Livelihood Vulnerability of Rice Farmers of Tamil Nadu, India to Climate Variability and Extremes

A thesis submitted

in partial fulfillment for the award of the degree of

Doctor of Philosophy

by

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01 July 2021

Certificate

This is to certify that the thesis titled ***Livelihood Vulnerability of Rice Farmers of Tamil Nadu, India to Climate Variability and Extremes*** submitted by **Rajkumar R.**, to the Indian Institute of Space Science and Technology, Thiruvananthapuram, in partial fulfillment for the award of the degree of **Doctor of Philosophy**, is a bona fide record of the original work carried out by him/her under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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Declaration

I declare that this thesis titled ***Livelihood Vulnerability of Rice Farmers of Tamil Nadu, India to Climate Variability and Extremes*** submitted in partial fulfillment for the award of the degree of **Doctor of Philosophy** is a record of original work carried out by me under the supervision of **Dr. C. S. Shaijumon**, and has not formed the basis for the award of any degree, diploma, associateship, fellowship, or other titles in this or any other Institution or University of higher learning. In keeping with the ethical practice in reporting scientific information, due acknowledgments have been made wherever the findings of others have been cited.

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Acknowledgements

First and foremost I am extremely grateful to my research supervisor Dr. C. S. Shaijumon, Associate professor, Indian Institute of Space Science and Technology, Thiruvananthapuram for his guidance, patience and encouragement during the course of my study.

I would like to acknowledge my gratitude to Dr. Lekshmi V. Nair (HoD, Department of Humanities) and other faculty members of the Department of Humanities, IIST, Dr. Ravi V., Dr. Babitha Justin and Dr. Gigy J. Alex for their support and guidance. I convey my gratitude to Dr. V. K. Dadhwal (Director, IIST), Prof. Y.V.N. Krishna Murthy (Registrar, IIST), Prof. Raju K. George (Dean R&D), Prof. Kuruvilla Joseph (Dean, Student Activities), Shri. Abdunnasar A. (Library Officer, IIST), The Hostel Manager IIST, and all the people in the institute administration for their support and encouragement.

My sincere gratitude towards my doctoral committee members, Dr. Manju S. Nair, and Dr.Shinoj P. for their insightful feedback and encouragement throughout the period of this study.

I am highly indebted to Dr. B. Gopakumar and Dr. Deepak Gopalakrishnan, for their invaluable assistance during the course of study. Their perseverance and academic support motivated me during the tough phases of the study.

I am grateful to all my friends in the Department of Humanities, Shiyas, Monisha Mohan, Pavanam, Aswathy, Rithwik, Syam, Soumya chechi, Bhavya chechi, and others for their helps and support.

I am indebted to all my friends and family who were always so helpful in numerous ways. Special thanks to Sarath Babu, Nikhil Raj, Mahesh, Richu Sebastian and Gayathri G. R. I also, acknowledge the helps provided by My friends Yadu C. R. and Veera Kalimuthu for my field visits and interviews related to the study. I have no words to express my deepest thanks to Anu Kuriakose who was very supportive throughout this journey of research and always wishes for my success.

My parents were a constant source of support during this work. I acknowledge my sincere gratitude for them.

Rajkumar R.

Abstract

Climate variability and extremes pose substantial challenges to life and livelihoods at global and regional scales. Recent decades have witnessed an increase in the frequency and severity of extremes in temperature and rainfall across the world. These changes in climate have had critical impact on agriculture. In India, agriculture is the largest livelihood providing sector in the economy accommodating nearly half of the nation's work force. Apart from the dependence of such a large share of population on this sector, the viability of agriculture as a means of livelihood is also affected by the structural issues such as the increasing fragmentation of agricultural land, decline in public investment, low accessibility to institutional credit. In this context, the present study examined the degree to which various socio-economic and biophysical factors make the livelihoods of rice farmers of Tamil Nadu, India vulnerable.

The present study started by examining the extent of variability and extremes in temperature and rainfall over the Tamil Nadu region. The analysis was performed over the seven agro-climatic zones of Tamil Nadu. The study used statistical methods such as EEMD, SPEI, and HWMId to identify the variability in temperature and rainfall, spatio-temporal patterns of droughts, and the spatio-temporal characteristics of heat waves and warm nights respectively. The analysis of extreme rainfall episodes was performed using the classification scheme of IMD. The study has used high-resolution temperature and rainfall data from the IMD for the period 1951-2016. The robustness of the results was tested using the Mann-Kendall trend (M-K) test and the Kolmogorov-Smirnov (K-S) test. An initial analysis of the temperature and rainfall data revealed visible changes in patterns starting in the early 1980s. Hence, we decided to divide the data in to two equal sub-periods 1951-1983 and 1984-2016. Also, our analysis of weather sensitivity of rice yield considers the data for the years 1985-86 and 2015-16, we found this division compatible to the context of our study. Later in the study, the K-S test suggested statistically robust differences in the distribution of data between the selected sub-periods.Overall, the study observed statistically significant increase in the variability and extremes in temperature and rainfall over Tamil Nadu. The frequency and severity of extremes increased after the 1980s and the period after 2000 witnessed some of the most severe episodes of heat waves, warm nights, droughts, and extreme rainfall over Tamil Nadu. Further, the study examined the extent to which rice yield

was influenced by the variability and extremes in temperature as well as rainfall. The study used the results of the first objective and the district level time series data on the area, yield, area under HYV, and the area under irrigation for achieving this objective. A Fixed Effects Panel Regression model was used to identify the weather sensitivity of rice yield in the three cultivating seasons and a multiple linear regression model was used to examine the weather sensitivity of rice yield at district level. The study observed that the rice yield was highly weather sensitive in the Kuruva season and the sensitivity was the least in Samba season. Finally, the study assessed the vulnerability of rice farmers of Tamil Nadu using the results derived in the analysis of the first two objectives and a field survey conducted in the Cauvery Delta region. The study observed that the rice farmers in Trichy and Thanjavur districts, those farmers cultivated in the Samba season, and those belonged to small farm size category were highly vulnerable to the climate variability and extremes. It was also observed that, besides the biophysical components, the socio-economic factors also played a substantial role in constituting the vulnerability of the sample households.

The results in the study indicated that urgent policy interventions are required to prevent the adverse effects of climate variations in the region, to promote beneficial diversification of livelihoods, to provide more coverage of institutional credit and insurance among the small farmers, and to improve sanitation facilities at household level.

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Abbreviations

ECDF	Empirical Cumulative Distribution Function
EMD	Empirical Mode Decomposition
EEMD	Ensemble Empirical Mode Decomposition
GDP	Gross Domestic Product
GMST	Global Mean Surface Temperature
HYV	High Yielding Variety
IMD	India Meteorological Department
LDI	Livelihood Diversification Index
LSAT	Land Surface Air Temperature
LVI	Livelihood Vulnerability Index
SDG	Sustainable Development Goal
SPEI	Standardized Precipitation and Evapotranspiration Index
SPI	South Peninsular India
SST	Sea Surface Temperature

Chapter 1

Introduction

1.1 Climate change, variability and extremes under current global warming

The global mean surface temperature (GMST) has warmed by approximately 1°C between 1885 and 2017 and is increasing at a rate of approximately 0.2°C per decade (IPCC, 2018). However, this increase has not been uniform across time and space. Warming above and below the global average has been experienced over many regions and periods. The observed mean surface air temperature over the global land area has increased considerably more than the combined GMST for the same period (Arneth et al., 2019). Similarly, the land surface air temperature (LSAT) in the Northern Hemisphere has increased at a faster rate than the LSAT in the southern hemisphere (Trenberth et al., 2007) and a visible shift is observed in the rate of increase between the periods 1901-1950, 1951-2012, and 1979-2012 (Hartmann et al., 2013). Recently Donat and Alexander (2012) observed significant distributional shifts towards higher values in both maximum and minimum temperatures over most regions of the world and the changes were greater for daily minimum (night-time) temperatures than for daily maximum (daytime) temperatures.

This warming climate is characterised by substantial variability in the global LSAT, an increase in precipitation variability, large scale dryness, increase in the frequency and severity of extreme precipitation, heat waves and warm nights across the world. Empirical evidence suggests that approximately three fourth of the variance in annual global LSAT was caused by the variations in the sea surface temperatures (SST). These SST variations, in turn, are attributed to "external radiative forcing associated with greenhouse gas, aerosol, volcanic and solar forcing" (Hoerling et al., 2008). The global warming also causes the precipitation variability to rise. The analysis using observational data and model simulations suggest that precipitation variability increases in response to warming over majority of the regions of the world (Pendergrass et al., 2017). In the case of extremes in temperature and rainfall, Fischer and Knutti (2015) observed that the current warming explains approximately one fifth of the the moderate daily precipitation extremes and nearly three fourth of the moderate daily hot extremes over land. In the recent past, the period 1980-2010 witnessed twelve percentage more record breaking extreme rainfall events compared to that expected in a stationary climate (Lehmann et al., 2015). In the case of drought, however, due to the "lack of direct observations, geographical inconsistencies in the trends, and dependencies of inferred trends on the index choice" current evidence does not suggest any global scale trends (Hartmann et al., 2013) although warming is considered to have a major role in determining the spatio-temporal characteristics of drying in the recent decades (Dai, 2011).

Over Indian region, the mean surface temperature has increased significantly during the last century with maximum temperature having a dominant role (Kumar et al., 1994). In the recent decades, the contribution of minimum temperature to the warming has also increased significantly (Kothawale and Rupa Kumar, 2005) with significant spatio-temporal variations. The literature suggests an upward trend in the variability as well as temperature extremes in the recent decades over Indian region (Kothawale et al., 2010a; Srivastava et al., 2017). Another notable aspect of warming over Indian region is the significant increase in the frequency, magnitude and duration of extreme temperature events. Kothawale et al. (2010b) observed an increasing trend in the hot days and warm nights in the pre-monsoon period during 1970-2005. Rohini et al. (2016) and Mazdiyasni et al. (2017) observed a substantial increasing trend in the frequency, total duration and maximum duration of heat waves over the Indian region, especially over Southeast and Northwest India during 1961-2013. Mishra et al. (2017a) observed a considerable increase in the frequency of heatwaves during the period 1951-2015, with the period after 1990 witnessing the five most severe heat waves in the entire record. Mukherjee and Mishra (2018) observed significant increase of concurrent hot day and hot night events over Indian region except Indo-gangetic area, after 1984. More specifically, warm nights have increased more rapidly than day time heat events. These heat events are projected to increase multi-fold under various warming scenarios (Mishra et al., 2017a; Mukherjee and Mishra, 2018) and pose significant impacts on public health (Mishra et al., 2017a; Mazdiyasni et al., 2017) as well as agricultural yield (Hatfield and Prueger, 2015)

Along with temperature, the rainfall characteristics of Indian region have been a subject to multitude of studies. Over central India, an increasing trend of extreme rainfall events and a declining trend of moderate rain events have been observed (Goswami et al., 2006; Rajeevan et al., 2008). A pan India study by Dash et al. (2009) suggests that the number of moderate rain days averaged over the whole of India has significantly decreased during the summer monsoon season and the number of heavy rain days considered over the entire country show some indications of increase, though the trend is not statistically significant. Results from the study of Guhathakurta et al. (2011) noted that while the intensity of extreme rainfall events are rising considerably over Saurashtra and Kutch, Coastal Andhra Pradesh, Odisha, West Bengal, and parts of North East India etc, a decreasing trend in the intensity and frequency of severe rainfall events are also observed over Chattisgarh, Jharkhand and some other parts of North India. At the same time, studies have identified that the drought events are also increasing over the Indian region. Kumar et al. (2013); Mishra and Liu (2014); Mallya et al. (2016).

1.2 The economic impacts of climate change

"Climate change is the mother of all externalities" and it is "larger, more complex, and more uncertain than any other environmental problem"(Tol, 2009). Initial attempts to assess the economic impacts of climate change focused on the extent to which the climate variations in a a given period determines the social welfare in that period (Fankhauser and Tol, 2005; Tol, 2010). In a more inclusive approach, Fankhauser and Tol (2005) observed that, with a constant savings rate, the investment will reduce in proportion to the decline in output caused by climate change, the capital accumulation effect of which, in turn, will retard future production and future consumption per capita. once the the savings rate is not constant, the future oriented agents would adjust their savings behaviour to cushion the effect of future climate change. This also suppresses growth prospects in both absolute and per capita terms. The extent of these effects will also be influenced by the changes in labour productivity and the rate of technical progress. A historical analysis of the impacts of climate change in the 20$^{\text{th}}$ century century (Tol, 2013) suggests that climate change had both positive and negative effects in the economy. The positive effects pertain to the Carbon dioxide fertilization of crops and a reduction in the energy demand for heating whereas the climate change exerts negative influence on water resources and public health. The study also observed that climate change was beneficial to most countries until 1980, and global mean impact was positive in the 20th century. Recent evidence (Carleton and Hsiang, 2016) suggest that climate change has substantial influence on agriculture, morbidity and mortality, violence, conflicts, energy consumption, labour productivity and supply, migration, and the gross domestic product (GDP) across the world.

One of the major impacts of climate change pertains to public health. Extremely warm temperature is an important determinant of human mortality with prolonged periods of exposure to extreme temperature causing “heatstroke, heat exhaustion, heat syncope, and heat cramps”(Kilbourne, 1997). Anderson and Bell (2009) observed that sustained periods of extreme heat events pose a higher risk over individual days of higher temperatures, even though the heat wave duration is as short as two days, and that duration and intensity of the heat wave influence the mortality risk. In the case of people aged above sixty five years, minimum temperature is observed to have substantial effect on excess mortality than maximum temperatures (Nicholls et al., 2008). In the Indian context, it was observed that the mortality associated with weather is more of a rural phenonmenon, and it is significantly clustered around the growing seasons. A one standard deviation increase in the number of degree-days over 32°C was observed to cause an approximately eight percent increase in mortality rate in the rural India (Burgess et al., 2014).

The climate change also impacts the economy through reduction in labour productivity. Dunne et al. (2013) observed that globally heat stress has caused an approximately ten percent reduction in the labour capacity in the recent decades. The loss of work capacity has already affected countries like Ethiopia (0.14%), USA (0.17%), Costa Rica (0.20%), China (0.31%), Cambodia (1.65%), and India[1] (Kjellstrom et al., 2018). While there are substantial contributions to the existing knowledge regarding the impact of labour productivity of those working outdoors, poorer countries and regions, other workers who are substantially exposed to the variations, in the modern economies the output is produced from diverse production environments ranging from agricultural fields to fully air-conditioned offices the overall impacts on labour productivity are relatively less understood (Day et al., 2019).

The impact of climate change on the economy is also manifested through the energy sector. Empirical evidence suggests that weather has a statistically robust influence on the demand for electricity, with effects that are of considerable magnitude (Eskeland and Mideksa, 2010; Gupta, 2016). On a global scale, there is an overall reduction in consumption of energy for heating and cooling due to the the adaptation to climate changes, wherein, the decrease in the energy requirement for heating more than compensates the increase in energy requirement for cooling (Labriet et al., 2015). On a regional scale, the analysis performed in Europe suggests that the demand for heating is expected to decline in Northern Europe whereas the demand for cooling is expected to climb up in Southern Europe. In

[1] India currently losses two percent of annual work hours and this may increase to eight percent by the end of the century

the countries such as Greece, Cyprus, Italy, Spain, Malta, and Turkey the increased cooling offsets the decreased heating demand while in most of Europe, the findings are consistent with the global average Eskeland and Mideksa (2010). In China and USA, the energy demand for both heating and cooling were found to be important and the net effect of climate change may by highly region specific (Labriet et al., 2015). In India, the estimates of Gupta (2016) indicate that climate change will raise the electricity demand by 6.7 percent with 4 percent GDP growth and 8.5 percent with 6 percent GDP growth by 2030 with reference to a stationary climate.

Water resources are another important channel through which climate change impacts the economy. The sustainable development goals (SDG) envisaged by the United Nations calls for urgent interventions to ensure "Clean water and sanitation for all". The water scarcity is already very high in India, North-East China, countries of middle east and Africa, some South and Eastern European countries, and parts of United States (Gain et al., 2016). On a global scale and thirty nine percent of the population[2] are estimated to be living in regions exposed to water scarcity and the patterns of climate change are expected to expose more people towards an increase in water scarcity than a decline in water scarcity (Gosling and Arnell, 2016). In the case of India, the water resources in the subcontinent are under the severe threat from climate change in due to the changes in the intensity and magnitude of rainfall, ground water recharge, floods, and droughts (Goyal and Surampalli, 2018).

1.3 Climate variations and agriculture

One of the major ways which the economy of a country is affected by the variations in climate is through the variations in agriculture (Carleton and Hsiang, 2016). Climate influences output, quality of output, yield, area under cultivation and cropping intensity (Yoshida, 1978; Porter and Semenov, 2005; Hatfield and Prueger, 2015; Iizumi and Ramankutty, 2016). On a global scale, around 30 percent of the variance in year-to-year yield changes was explained by the climate variations for all crops with with 18 percent to 44 percent of the explained variance attributable to climate extremes (Lobell and Field, 2007; Ray et al., 2015; Vogel et al., 2019). The soybean and maize cultivating regions in Northeast China and Argentina, rice cultivating regions in Asia, and wheat in Australia, and spring wheat cultivating regions of Europe have been observed as highly susceptible to the variability and extremes in climate (Iizumi and Ramankutty, 2016; Vogel et al., 2019). Evidence from rice cultivation in Indonesia (Naylor et al., 2007), study on the output of

[2]As in 2000

maize, rice and sorghum in Tanzania Rowhani et al. (2011) and study on association between Philippine rice production and El Nino Southern Oscillation (Naylor and Falcon, 2010) identified significant influence of climate variability especially annual, inter-annual and seasonal variations in rainfall on crop yield.

Studies in Indian context also concur the same. Krishna Kumar et al. (2004) identified significant correlation between monsoon rainfall and food grain production wherein both cereals as well as pulses production were observed to be predictably responsive to precipitation. A review of studies (Mall et al., 2006) on the impact of climate change on Indian agriculture also points at the dependency of Indian agriculture on climate even after various advances made in the post green revolution period. A marked asymmetry in the food grain production and Gross Domestic Product (GDP) of India in the response to monsoon variability has been observed with the magnitude of a negative impact of drought or deficit rainfall is found to outweigh the positive impact of a surplus rainfall (Gadgil and Gadgil, 2006). Further, the farm level net revenue in India is found to be significantly sensitive to climate variables even in the presence of annual weather and price variables (Kumar and Parikh, 2001). Auffhammer et al. (2012) observed significant nonlinear relation between the monsoon characteristics and the rice yield in India. The negative impact of reduced rainfall was higher during drought periods, and the positive impact of higher rainfall became negative during periods of extreme rainfall. According to the study, the cumulative rice yield would have been 5.67% higher in the absence of climate change. A regional analysis of weather sensitivity performed by Pattanayak and Kumar (2020b) suggested that the yield losses in rice due to variations in the weather was higher in the Southern India than in the Northern India during the period 1969-2007. Multi crop studies performed in the Indian context (Guiteras, 2009; Birthal et al., 2014) suggest that rice is one of the highly vulnerable crop in the current and future scenarios of warming. From these accounts, it is evident that temperature and precipitation have significant influence on India's agricultural sector both at the grass root level as well as at the aggregate level.

1.4 Importance of the Study

Agriculture plays a substantial role in the Indian economy. It provided the "original stimulus" to the acceleration of overall economic growth in the country (Balakrishnan and Parameswaran, 2007); it is the single largest livelihood provider in Indian economy accommodating more than half of the nation's work force (Motkuri and Naik, 2016); and it contributes 14.4 per cent of the GVA (Government of India, 2019). The existence and growth of this sector has important implications on poverty, employment, food security and nutritional status of the population. However, the sector did not receive the required policy attention. The history of implementation of land reforms in India is not impressive. During the period between 1947 and 2007, only 4.89 million acres of land were redistributed and only 5.4 million households received land ((Mishra, 2007) cited in Ramakumar (2012)). Latest evidence shows substantial decline in the size of land holdings, and a significant increase in 'landlessness'[3] (Yadu and Satheesha, 2016). This is further reflected in the occupational distribution as well. The census data reveals a steep decline in the number of cultivators coupled with a visible increase in the number of agricultural labour between 1991-2011 (Motkuri and Naik, 2016). Yadu and Satheesha (2016) provides more detailed picture of this scenario based on the National Sample Survey Office's (NSSO) 70th round. According to them, there is continuing land fragmentation in the country which makes cultivation an unviable means of livelihood. As a result, the small and marginal land holders move to the informal sector for wage employment primarily. This transition, according to them, from peasants to those who engage in household farming and wage labour, is the hallmark of the contemporary agrarian question in India. In the case of capital formation, though there was an accelerated pace in capital formation in the agriculture during the first three decades since independence (Mishra, 1996), the critical sectors such as irrigation did not receive the adequate attention (Ramakumar, 2012). The rate of growth in capital formation fell substantially in the eighties owing to a decline in public investment (Mishra, 1996) and the decline in public investment continued up to 2012-13 (Roy, 2017).

The case of incentive environment is also no different. The support systems - input subsidy support, credit support, marketing support and price support - introduced in the National Agricultural Strategy (NAS) were instrumental in regaining food security in the country. The nationalisation of banks played a crucial role in improving access to credit facilities in rural areas. Still, the overall benefits of the program was limited to certain well endowed regions and sections of the farmers, particularly those who cultivated rice and wheat. The benefits accrued to these "well-endowed" were not extensive enough to compensate the stagnation in rest of the sector (Ramakumar, 2012). In the post reform period, the institutional support to agriculture declined gradually. It involved dismantling of quantitative restriction of 470 agriculture products, reduction of tariffs on agricultural imports, more liberalised imports of seeds, gradual reduction of fertilizer subsidies, reduction

[3] 'landlessness' here, is understood in terms of cultivation which generates some income for the family. Therefore all households owning less than 1 acre (0.40 Ha) are classified as "effectively landless" (Basole and Basu, 2011).

of power subsidies in some parts of the country and opening up of power sector to private investment and dilution of priority sector lending (Vakulabharanam, 2005). Both input subsidies (Sen (1992) cited in Ramakumar (2012)) as well as agricultural credit (Narayanan, 2016) are observed as having significant direct influence on the adoption and usage of inputs. While input subsidies showed an increase as a fraction of the Gross Domestic Product (GDP) in agriculture in the post reform period, there relative share in the total GDP showed a declining trend (Ramakumar, 2012). Similarly, the share of agricultural credit as a fraction of the Gross Domestic Product (GDP) in agriculture also showed a rising trend though it has nearly stagnated as proportion of the total GDP (Mohan, 2006). This contributed to more distress since the post reform policies provided for an increase in the input prices (Ramakumar, 2012).

The current state of agriculture rightly reflects the policy paralysis particularly in the post-reform period. The appalling performance of India in the eradication of poverty, undernourishment, and disguised unemployment is widely attributed to the failure in addressing the stark realities existing in the agriculture sector, particularly the contemporary agrarian question Reddy and Mishra (2008); Ramakumar (2012); Yadu and Satheesha (2016); Roy (2017). Structural issues such as increasing fragmentation of agricultural land, augmenting pressure of labour, decline in public investment, stunted subsidies and stagnation in the growth of agricultural credit has made the farming as an unviable option for livelihood for majority of the farmers. This is reflected in the semi-proletarianisation[4] (Yadu and Satheesha, 2016), indebtedness, farmers' suicides (Reddy and Mishra, 2008), and the deterioration in the growth of agriculture as a whole and across the major crops cultivated Roy (2017). It is therefore important to see how do these farmers, the majority of whom are actually finding agriculture as a refuge in the absence of gainful employment in other sectors, fare in a warming scenario characterised by increasing variability and extremes in temperature as well as rainfall.

1.5 Research Problem

Evidence suggests that the current warming scenario is characterised by increase in the frequency and severity variability and extremes in climate and concurrence of the same is projected to make life and livelihood more difficult in the affected areas. Tamil Nadu is a rain shadow region and therefore it is more exposed to the vagaries of climate, particularly

[4]Semi-proletarianization is a situation in which migrant workers' households are forced to participate in both household farming and wage labour to earn decent living (Humphries, 1990).

the monsoon. Also, it is one of the major rice growing regions of the country. On the other hand there is widespread distress in agricultural sector instigated by structural issues, policy paralysis and lack of institutional support. Agriculture has become an unviable livelihood option for small and marginal landholders who form the majority of farmers. This is more relevant in the case of Tamil Nadu where land inequality (Rawal, 2008) and indebtedness (Reddy and Mishra, 2008) are higher than most of the Indian states. In this context, the present study examines the extent to which the livelihoods of the rice farmers of this region are vulnerable to the variability and extremes in climate. Rice farmers are selected as the representative category since rice is the prominent crop cultivated in Tamil Nadu and is a major livelihood option for many.

1.6 Objectives

The study aims to;

1. Study the extent of variability and extremes in temperature and rainfall over the Tamil Nadu region,

2. Identify the extent to which yield of rice is influenced by the variability and extremes in temperature as well as rainfall,

3. Identify the extent to which the rice farmers of Tamil Nadu adapts to the climate variability and extremes

1.7 Hypothesis

- Climate variability and extremes affect the crop yield and thereby influence the livelihoods of the farmers

- The socio-economic background of farmers determine the farmers' ability to adapt to climate variability and extremes.

1.8 Organization of the Thesis

The Thesis is presented in eight chapters.

Chapter 1 - Background and Introduction provides a brief introduction to the thesis. It discusses the background and significance of the research topic, details of the research problem, the objectives and hypotheses. The chapter concludes by providing details of the organisation of the thesis.

Chapter 2 - Review of Literature provides a detailed analysis of existing literature on vulnerability and its essential components. The chapter summarises the limitations and scopes in the present research and provides the rationale of the present work by the researcher.

Chapter 3 - Materials and Methods discusses the details of the study area, the data collected and the various methods employed to achieve the stated objectives of the thesis. This chapter provides details of the conceptual and analytical frameworks used in the thesis.

Chapter 4 - Climate Variability and Extremes over Tamil Nadu provides a detailed analysis of the variability and extremes in temperature and rainfall over Tamil Nadu region. The chapter has captured various policy relevant spatio-temporal patterns of the climate variability and extremes over the state.

Chapter 5 - Weather Sensitivity of Rice Yield in Tamil Nadu explains the weather sensitivity of rice yield in Tamil Nadu region using a fixed-effects panel data regression for the three major rice seasons in Tamil Nadu. The district level weather sensitivity is estimated using a multivariate linear regression. The weather sensitivity is measured in terms of the contribution of weather variables towards the variations in the crop yield.

Chapter 6 - Socio economic factors influencing Sensitivity and Adaptivity capacity of Farmers: a case study in Cauvery Delta region of Tamil Nadu provides a detailed analysis of the socio-economic profile and adaptive capacity of the rice farmers of Tamil Nadu. A brief overview of the farmers' perceptions is also provided in this chapter.

Chapter 7 - Livelihood Vulnerability of Rice Farmers provides the analysis and explanation of vulnerability of various categories of rice farmers based on the sample data selected from the seven districts of Cauvery Delta region.

Chapter 8 - Findings and Suggestions summarises the major findings of the study, provides the policy implications of the findings of the present study on the basis of the existing literature. The suggestions for improving the livelihood conditions of the farmers and the scope for future research is also provided.

Chapter 2

Review of Literature

This chapter reviews the existing literature pertaining to the vulnerability and adaptation in agricultural and rural sectors to climate variability and extremes. The chapter discusses various definitions, conceptual frame works, measurement methods in the vulnerability research tradition, vulnerability studies conducted at the global and national levels, and lists out the research gaps, scope and relevance of the present study.

2.1 Vulnerability: Temporal evolution of the concept and its framework

Vulnerability implies the state of being exposed to the possibility of being harmed (Oxford Dictionary of English, 2015). The origin of the word 'vulnerability' can be traced back to two Latin words - *vulnus* (a wound), and *vulnerare* (to wound). The word vulnerable is derived from the Late Latin word *vulnerabilis*. The Romans used this term to imply the state of a soldier lying wounded on a battlefield, i.e., injured and therefore at risk from further attack. Vulnerability, therefore, in its original sense, is defined primarily by the existing damage of a system (Kelly and Adger, 2000). In academia, the term vulnerability is defined, framed, and operationalised from a wide range of research contexts. Table 2.1 shows the various definitions of vulnerability used in the academic literature.

In the research literature, vulnerability as a concept initially appeared in the hazards related studies (Cairns and Dickson, 1977; Zajic and Himmelman, 1978; Gabor and Griffith, 1980). Timmerman (1981), listed some of the early attempts to define vulnerability and resilience, and also explained some of the basic models used to describe the paradigms of social systems under stress from the hazards perspective. According to him, resilience and reliability are the two important components influencing the vulnerability of society.

Resilience, in his study, referred to the ability of societies to overcome a hazard and reliability implies preparing shields against hazards. Vulnerability can arise out of the lack of resilience as well as reliable defences. While modern complex societies prefer reliable defences over resilience, the vulnerability arising out of the failure of reliable defences can be more damaging since the failure of the shield might possibly reveal the lack of absorptive capacity beneath it.

Watts and Bohle (1993) attempted to integrate various strands of conceptualisations on vulnerability to offer a generic model incorporating a multidimensional space and the tripartite causal structure of vulnerability. This causal structure is generated by integrating the elements of entitlement approach (Sen, 1981, 1987), enfranchisement approaches (Ribot et al., 2010), and social relations of production (Chitty, 2000). A similar discussion on the causal structure of vulnerability can be found in Ribot (1995) as well. According to them, enfranchisement through empowerment as discussed in Watts and Bohle (1993) provides a counter balance to the ongoing political-economic processes that contribute towards vulnerability. Such a counter balance was perceived as necessary to progress towards a sustainable development trajectory in the context of environmental variability and change.

However,Cutter (1996) observed that significant confusions and contradictions on the meaning of the concept, 'measurement', and the causes of spatial outcomes associated with vulnerability research. She identified three distinct thematic orientations in vulnerability research. The first theme focuses on the risk-hazard-exposure orientation and considers vulnerability as a pre-existing condition. The second theme considers vulnerability as social response or more precisely, a tampered societal response. The third orientation focuses on the geographical dimensions of vulnerability and considered vulnerability as hazard of place. This diversity was evident in the measurement methods as well. In the case of causal linkages and spatial outcomes of vulnerability also considerable bifurcations existed between the works that focus on the social and the ones emphasizing geographical aspects of vulnerability. Accordingly, she integrated the biophysical and the social vulnerabilities to identify the vulnerability of a region. Vulnerability as such was defined as a function of the hazard potential[1]. The hazard potential when filtered through the social fabric of society[2] determines the overall social vulnerability of the place. The hazard potential filtered through the geographic context[3] determines the biophysical or technological vulnerability. The integration of these two yields the vulnerability of the place.

[1]combination of risks and mitigation

[2]socio-economic indicators, cognition of risk, individual or societal ability to respond

[3]site and situation, proximity

Table 2.1: Definitions of Vulnerability

Author	Definition
Cairns and Dickson (1977) [4]	Vulnerability is defined as the ability to reverse irreversible damage
Zajic and Himmelman (1978) [5]	Vulnerability (to hazardous materials spills) is defined and calculated in terms of population density, frequency of transportation, levels of hazardousness of the chemicals and emergency plans formulated for each community
Gabor and Griffith (1980)	Vulnerability will refer to the threat to which a community is exposed taking into account not only the properties of the (chemical) agents involved but also, the ecological situation of the community and the general state of emergency preparedness at any given point in time.
Timmerman (1981)	Vulnerability is defined as the degree to which a system or part of a system may react adversely to the occurrence of a hazardous event. The degree and quality of that reaction are partly conditioned by the system's resilience
UNDRO (1982)	Vulnerability is the degree of loss to a given element or set of elements at risk resulting from the occurrence of a natural phenomenon of a given magnitude
Susman et al. (1984)	vulnerability is the degree to which the different social classes are differently at risk.
Kates (1985)	Vulnerability is the capacity to suffer harm and react adversely
Pijawka and Radwan (1985)	Vulnerability is a threat or interaction between risk and preparedness. It is the degree to which hazardous materials threaten a particular population and the capacity of the community to reduce the risk or adverse consequences of adverse materials releases

[4] cited in Timmerman (1981)
[5] cited in Timmerman (1981)

Wilhite et al. (1987)	Vulnerability is a function of the type of production system and degree of development
Bogard (1989)	Vulnerability is defined as the inability to take effective measures to insure against losses
Chambers (1989)	Vulnerability refers to the exposure to contingencies and stress, and difficulty coping with them. Vulnerability has thus two sides: an external side of risks, shocks and stress to which an individual or household is subject; and an internal side which is defencelessness, meaning a lack of means to cope without damaging loss
Mitchell (1989)	Vulnerability is the potential for loss
Liverman (1990)	Distinguishes between the biophysical (vulnerability in geographical space) and socio-economic (vulnerability in social space) aspects of vulnerability
Downing (1991)	Vulnerability has three connotations: it refers to a consequence (e.g. famine) rather than a cause (e.g. are vulnerable to hunger); and it is a relative term that differentiates among socio-economic groups or regions, rather than an absolute measure of deprivation.
von Braun (1991)	Vulnerability is the outcome of an interaction between environmental and socio-economic factors both in the long and short terms
Dow (1992)	Vulnerability is defined as the differential capacity of groups and individuals to deal with hazards, based on their positions
Watts and Bohle (1993)	The space of vulnerability is defined by three distinctive processes represented by entitlement, empowerment and political economy, which are theoretically derived, and which constitute in tandem a causal structure of hunger

Blaikie et al. (1994)	The characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard. It involves a combination of factors that determine the degree to which someone's life and livelihood is put at risk by a discrete and identifiable event in nature or in society
Cutter (1996)	Vulnerability is a function of the hazard potential (combination of risks and mitigation). The hazard potential when filtered through the social fabric of society (socio-economic indicators, cognition of risk, individual or societal ability to respond) determines the overall social vulnerability of the place. The hazard potential filtered through the geographic context (site and situation, proximity) determines the biophysical or technological vulnerability. The integration of these two yields the vulnerability of the place.
Adger and Kelly (1999)	Individual vulnerability is determined by access to resources and the diversity of income sources, as well as by the social status of individuals or households within a community. The collective vulnerability of a nation, region or community is determined by institutional and market structures, such as the prevalence of informal and formal social security and insurance, and by infrastructure and income.
Kelly and Adger (2000)	vulnerability is defined in terms of the ability or inability of individuals and social groupings to respond to, in the sense of cope with, recover from or adapt to, any external stress ? placed on their livelihoods and well being.
McCarthy et al. (2001)	The degree to which a system is susceptible, or unable to cope with adverse effects of climate change, including climate variability and extremes
Fussel (2007)	A vulnerable situation is characterised by vulnerability of a system's attribute(s) of concern to a hazard with a specific temporal reference.

The work of Kelly and Adger (2000) shed lights on the origin of the concept as well as its theoretical dimensions. They classified vulnerability studies into three categories namely, the studies that consider vulnerability as 'starting point', as an overarching 'focal point', and as an 'end point'. Vulnerability assessment is a potential 'starting point' of impact analysis in the conceptual frameworks which identified the likely sensitivities of a system in terms of limited capacity to respond to stress. Studies following this approach defines vulnerability in terms of adaptive capacity (Watts and Bohle, 1993; Cutter, 1996). Yet another set of studies, especially those pertaining to famine and natural hazards set vulnerability as an overarching concept or a 'focal point'. Here, vulnerability is defined in terms of the 'exposure to stress and crises, capacity to cope with stress, the consequences of stress and the related risks of slow recovery'. Finally, there are studies that consider vulnerability assessment as the 'end point' of impact analysis. In such studies involve a sequence of analysis beginning with projections of future emission trends, development of consequent climate scenarios, analysis of biophysical impacts under the projected scenarios and the identification of adaptive options. At the end stage, if any residual consequences remain, they constitute vulnerability. The definition given by Kelly and Adger (2000) consider vulnerability assessment as the starting point of the impact analysis and the definition in approaches vulnerability as the end point of impact analysis.

Smit et al. (2001) has provided one of the widely used conceptualisations of vulnerability. They defined vulnerability to climate change as "the degree to which a system is susceptible, or unable to cope with adverse effects of climate change, including climate variability and extremes, and vulnerability is a function of the character, magnitude and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity". Here, exposure referred to 'the nature and degree to which a system is exposed to significant climatic variations', sensitivity referred to the 'degree to which a system is affected by or responsive to climate stimuli (note that sensitivity includes responsiveness to both problematic stimuli and beneficial stimuli)' and adaptive capacity referred to 'the potential or capability of a system to adapt to (to alter to better suit) climatic stimuli or their effects or impacts'. These definitions were created on the basis of widely held conventions and are generic in nature.

Another important classification of vulnerability concepts is made by O'Brien et al. (2004). He categorised vulnerability research in to 'end point' and 'starting point' classifications of vulnerability. Vulnerability in the end point tradition represents the expected net impacts of a given level of global climate change, after accounting for possible adaptations. This is most relevant in the context of mitigation and compensation policy. Vulnerability according to the starting-point interpretation focuses on reducing internal socio-economic vulnerability to any climatic hazards. This interpretation addresses primarily the needs of broader social development as well as those of adaptation policy. It exists in a broader agreement with the political economy approach.

Adger (2006) conducted a historical overview of the divergent methods and research traditions in vulnerability research. According to him, the entitlement tradition and the natural hazards research tradition acted as the seedbeds for ideas which eventually translated into the current research on vulnerability of social and physical systems in a more integrated manner. The studies in the entitlement tradition mainly emphasized the social differentiation of vulnerability while the studies belonging to the hazards tradition mainly focused on the differential impacts of hazards. An integration of these two tradition was observed in Blaikie et al. (1994) in their ‘Pressure and Release’ model. This model held that the physical or the biological hazards represent one pressure and characteristic of vulnerability and that the cumulative progression of vulnerability constitutes an additional pressure, from root causes through to local geography and social differentiation. The disasters that result from the additive pressures of hazard and vulnerability are, in fact, a combination of these two pressures. Along with the integration of the two antecedents in the pressure and release model, Adger (2006) considered the systems oriented research approach as an improvement in the analysis of vulnerability. The systems approach (Turner et al., 2003a) considers vulnerability as a property of a social-ecological system, and seek to elaborate the mechanisms and processes in a synthesized manner.

Fussel (2007) presented a generally applicable conceptual framework of vulnerability that combined a nomenclature of vulnerable situations and a terminology of vulnerability concepts based on the distinction of four fundamental groups of vulnerability factors and characterizes the vulnerability concepts employed by the main schools of vulnerability research. According to him, the generally applicable conceptual framework for vulnerability assessment has six dimensions; Temporal reference (current vs. future vs. dynamic), Sphere (internal vs. external vs. cross-scale), Knowledge Domain (socio-economic vs. biophysical vs. integrated), Vulnerable System, Attribute of Concern, and Hazard. Here, household income, social networks, access to information etc. constitute ‘Internal Socio-economic’ category while national policies, international aid, globalisation etc come under the ‘External Socio-economic’ category. Similarly, topography, environmental conditions and land cover belong to ‘Internal Biophysical category’ while storms, earthquakes and sea level change come under ‘External Biophysical’ category.

Even though, the conceptualisation of vulnerability in Economics is much younger when compared to the climate change literature, the core of vulnerability framework owes to the concepts of poverty in Economics significantly. Kumar et al. (2007) analysed 'vulnerability' used in the 'poverty' literature with the conceptualisations in the climate change vulnerability literature. According to them, while economic analysis generally gives more emphasis on the measurability of the concept. In the case of vulnerability, this requirement of measurability is not balanced by an equally strong focus on conceptualisation and the development of analytical frameworks. In the context of 'poverty', the references to vulnerability are broadly identified as vulnerability to poverty, vulnerability as a symptom of poverty, vulnerability as part of the multi-dimensional nature of poverty, and vulnerability as an outcome of poverty (Prowse, 2003).

While the vulnerability to poverty and vulnerability to climate change are ex-ante measures attempting to provide useful insights about future scenarios, they differ significantly in the focus and spatio-temporal dimensions of the framework (Kumar et al., 2007). Both approaches analyse the externalities that expose people into poverty or to climate change and pull them back from them. For example, McCulloch and Calandrino (2003) involves a similar discussion wherein vulnerability is defined as the probability of being below the poverty line in any given year. The study observed that 30 percent of the households fell below the poverty line at some stage and a majority of them stayed there for one or two years only. However, those who experienced poverty for longer years may lose their ability to exit from such a situation. Here, when the analyses are in terms of 'means of human welfare', poverty and vulnerability reflect a transient phenomena, and when the studies analyse vulnerability in terms of outcomes or 'ends of human welfare', it reflects chronic poverty and vulnerability[6].

In the second approach, 'vulnerability as a symptom of poverty' considers vulnerability as a cause and consequence of poverty. Here, the mutually reinforcing nature of vulnerability-poverty nexus is emphasised. In the third category, 'vulnerability as a part of the multi-dimensional nature of poverty' considers vulnerability as "part of an expanded poverty concept"[7] and in the fourth one, vulnerability considered as an outcome of poverty. Kumar et al. (2007) makes certain comparisons between 'vulnerability to poverty' and 'vulnerability to climate change'. In vulnerability to poverty, the outcome is specific while the shocks contributing to the outcome is not specific. On the other hand, shocks are specific in climate change literature while the outcome of the shock on the entity is not

[6] Prowse (2003) discusses the notions of transient and chronic poverty in the analyses of 'vulnerability to poverty'.

[7] Morduch (1994)

specific. Poverty analysis is mainly concerned with household level vulnerability while climate change analysis is conducted at regional as well as national scales. The temporal scale of poverty is short while that of climate change vulnerability is longer. However, apart from these differences, Kumar et al. (2007) identified significant similarities between the vulnerability metrics of both streams and argue that these two streams can be linked by introducing the notion of sensitivity.

The recent Economics literature involves significant discussions about adaptive capacity to climate variability, extreme events, and long term changes. Castells-Quintana et al. (2018) focuses on the adaptation gaps across various sections of society even when the socio-economic impacts of weather remains the same. According to them, adaptation to climate change happens at two intertwined dimensions. At one level, it involves making the existing space or sector more resilient and on another level it involves migration across spaces and sectors. Poor people and regions are more exposed to the manifestations of climate change and they often miss beneficial adaptation options because of informational and institutional constraints, infrastructure bottlenecks, the smaller scale of economic activity, aversion to experimentation from precarious livelihoods and lack of credit and financial services.

Another stream of research focuses on a value based approach to the vulnerability in climate change (O'Brien and Wolf, 2010). The values-based approach holds that the effects of climate change cannot always be measured through objective or scientific means. Integrating perspectives on human values into assessments of vulnerability and adaptation thus requires the inclusion of new methodologies into climate change assessments, for instance, the studies that examine the relation between climate change and culture, religion, world-views, ethics, and psychology or, in other words the studies that capture the subjective dimensions of climate change. A value based approach has political implications, for it inevitably points to the role of power hierarchies and interests in prioritizing the values of some over those of others. It also focuses on the limits to adaptation set by the subjective factors tied to differential and dynamic values and how adaptation measures are carried out. Thomas et al. (2019) from the same research tradition emphasis on the importance of coordinated efforts from the stakeholders in shaping the availability, dissemination, and use of knowledge at a local scale and community level such that the scientific information will meaningfully contribute to adaptive responses to climate change.

Vulnerability is a concept analysed in multiple dimensions and research contexts. It is constructed and operationalised according to the concerned research tradition, knowledge domain, study objectives, subject under consideration etc. This has led to the emergence of a multitude of studies with diverse methods and variables. As the conceptual understanding of vulnerability evolves, these common threads and dimensions are observed as getting accepted across knowledge domains. However, though the broader frame remains the same, assessment measures and methods continue to remain different. Despite the diversity in measurement and reading, the vulnerability assessments have produced observations that are consistent across various research traditions.

2.2 Methodological Framework of Vulnerability

While there are innumerable studies that offered conceptual contribution to the vulnerability research, there has always been considerable mismatches between theoretical definitions and operational definitions. Therefore, it is important to mention some of the major contributions in the operationalisation /measurement of vulnerability particularly in the context of climate change.

Kelly and Adger (2000) defined vulnerability in terms of the ability or inability of individuals and social groupings to respond to, in the sense of cope with, recover from or adapt to, any external stress placed on their livelihoods and well-being. Accordingly, vulnerability is operationalised to study the changing patterns of vulnerability to the tropical storm impacts in Vietnam at the household and community level. The social vulnerability comprised of poverty, inequality and institutional adaptation. Poverty represented marginalisation in the society which narrowed down coping and resistance strategies. Inequality, represented the degree of collective responsibility, informal and formal insurance and underlying social welfare function, and institutional adaptation represents the architecture of entitlements that determines the resilience in the society; and the role of institutions as channels for developing collective perceptions of vulnerability. The study used both quantitative and qualitative data for the analysis of vulnerability.

O'Brien et al. (2004) developed a methodology to map vulnerability to multiple stressors and assessed the vulnerability of India's Agricultural sector to climate change and globalisation, at subnational level. The approach consisted of four main steps: (1) developing a national vulnerability profile for climate change at the district level; (2) developing a national vulnerability profile for an additional stressor at the district level; (3) superimposing profiles to identify districts in India that are "double exposed" and (4) conducting case studies in selected districts to assess differential vulnerability for any particular sector within the nation. For developing a vulnerability profile for climate change, the authors followed the conceptualization of vulnerability given by IPCC Third Assessment Report

McCarthy et al. (2001).

Schröter et al. (2005) introduced a generally applicable methodological approach that will guide vulnerability assessments towards a common end, even when the specific techniques employed differ from case to case. It is an eight step method of assessing vulnerability. The eight steps include (1) Defining the study area and stakeholders, (2) develop knowledge about the stakeholders, the ecosystem services they value and why, and the drivers of vulnerability in the study area, (3) Hypothesizing who is vulnerable to what, (4) Developing a causal model of vulnerability (5) Find indicators for the elements of vulnerability (6) Operationalise model(s) of vulnerability (7) Project future vulnerability, and (8) Communicate vulnerability creatively.

Brenkert and Malone (2005) used a Vulnerability-Resilience Indicator Prototype (VRIP) method to estimate and compare national vulnerability-resilience indices against a global index. Following the definition of McCarthy et al. (2001), the study assumed that vulnerability of a region is a function of three factors - exposure, sensitivity and adaptive capacity. To assess vulnerability the study looked at the response to climate exposure, expressed as sensitivities to climate, and societal coping and adaptive capabilities. The indicators of (negative) sensitivities and the (positive) coping/adaptive capacities are aggregated to a single vulnerability index.

Polsky et al. (2007) used a common and replicable schema for representing and organizing the findings of a given vulnerability assessment - a Vulnerability Scoping Diagram (VSD). The VSD attempts to structure vulnerability assessments and it requires the researchers to specify and organize the five features of their research project: (1) the hazard and associated outcomes to be mitigated, (2) the exposure unit, and the (3) dimensions, (4) components, and (5) measures of the vulnerability process in question, in a particular graphical way. The outcome of populating a VSD is a set of components and indicators that satisfy the demands of Step 5 of the "Eight Steps" (Schröter et al., 2005) (developing a place-based set of indicators relating to exposure to global change drivers, and the associated sensitivities and adaptive capacities of the human-environment system). However, populating a VSD itself is a challenging task and it requires subjective judgments of the researchers. Also, to facilitate the construction of comparable global change vulnerability assessments requires a significant number of vulnerability assessments to adopt this method to structure their indicator sets using VSD.

Eakin and Bojorquez-Tapia (2008) developed a classification procedure to handle the diverse types of variables describing the household characteristics (e.g. continuous, nominal and ordinal), and can provide a basis for comparing, weighting and aggregating such data into a single index. They followed the idea that the standard forms of multivariate classifications are insufficient in handling diverse types of variables (Sneath et al. (1973) cited in Eakin and Bojorquez-Tapia (2008)). Accordingly, the study used a multi- criteria decision analysis (MCDA) that assigns weights to indicators, and employed fuzzy logic to assign households to vulnerability classes. The result is a method for creating an index of vulnerability that is context-specific in both the selection as well as in the weighting of the indicators. The study used the fuzzy logic for the final categorisation of household level livelihood vulnerability to climatic risks in such a way that the analysis reveals how different structures of livelihood assets and activities contributes to household sensitivity and capacities in a region characterized by stagnant incomes, declining farm productivity, increasing market stress, and variable climatic conditions.

Hahn et al. (2009) devised the Livelihood Vulnerability Index (LVI) to estimate climate change vulnerability in the Mabote and Moma Districts of Mozambique. The LVI used multiple indicators to assess the extent of natural disasters and climate variability, social and economic characteristics of households that shape adaptive capacity, and current health, food, and water resource characteristics that determine the sensitivity to climate change impacts. The LVI can be constructed as a composite index comprised of seven major components and by aggregating the seven components into IPCC's three contributing factors of vulnerability - exposure, sensitivity, and adaptive capacity. The LVI formula provides equal weights to all major components using a balanced weighted average approach where each sub-component contributes equally to the overall index.

Hinkel and Klein (2009) developed a tool for assessing the vulnerability of coastal areas to sea level rise. The tool is called DIVA (Dynamic and Interactive Vulnerability Assessment). DIVA is a dynamic, interactive and flexible software tool that enables users to produce quantitative information on a wide range of coastal vulnerability indicators, for the climatic and socio-economic scenarios and adaptation strategies specified by the user, on national, regional and global scales, covering all coastal nations. The DIVA method consists of two parts: a modelling framework and a semi-automated development process. The modelling framework sets the model to be built by providing a general a priori conceptualization of the system to be modelled. However, only those phenomena that can be expressed using the framework's concepts can be modelled and the development process facilitates integration on the process level. It frames the iterative specializing of the framework's general concepts to the needs of the specific problem to be addressed. The tool also allows end-users to conduct their own assessments interactively as opposed to model developers running their own model and publishing a selection of the results in a report.

Seo (2010) examined whether an integrated farm that owns both crops and livestock is more resilient under global warming than a farm specialized in particular crops using a micro-econometric method in which each farmer is assumed to maximise their farm net revenue by choosing an agricultural system. The independent variables included soils, climate, water flows and socio-economic variables. Country dummy variables are also tested to see if country specific conditions such as different development stages, agricultural policies and trade agreements make a substantial difference. Major agricultural prices such as beef, maize and millet prices are also tested. The authors used a multinomial logit choice model with livestock-only-farm as the base case. The control variables are water flows, soils, electricity provision and country specific dummies. In order to interpret these climate parameter estimates, the authors computed the changes in the probability to choose each system when climate is disturbed by a small degree. The impacts of climate change on the profit for each system after half a century is also measured by the computing the difference between the profit in the future and the profit at present based on the estimates and climate predictions using the Atmospheric Oceanic General Circulation Models (AOGCMs).

Albizua and Zografos (2014) used the Q methodology to explore the values and perceptions of affected actors and decision-makers in the context of climate change in the Ebro Delta, in Catalonia.The main goal of Q is to pursue the scientific study of subjectivity, i.e. its study in an objective and structured manner by combining statistical analysis with the use of factor analysis and qualitative information using in-depth interviews. Q looks for correlations between subjects across a sample of variables and tries to explain why certain patterns exist in the data. In Q method, representation of Q is measured by the extent to which statements of the respondents are representative of the diversity of views over the topic in question. The first phase of the study used in-depth interviews to generate statements that would comprehend the diversity of views on the vulnerability and adaptation in the region. In the second phase, the study identified the values that are relevant in the society and differences in perceptions among various stake holders.

Gerlitz et al. (2017b) developed a Multidimensional Vulnerability Index to measure the multi-dimensional livelihood vulnerability in the Hindu Kush Himalayas (HKH). It represented three dimensions of vulnerability: exposure, sensitivity, and adaptive capacity. Each of these dimensions is broken down into a number of components, and each component is represented by a number of indicators. The MLVI was developed using the Alkire-Foster approach of multidimensional index construction (Alkire and Foster, 2011). The MLVI can be used as a single-value index or decomposed into its three main dimensions, 12 components, and 25 vulnerability indicators. The method conceptualised vulnerability based on the definition provided in McCarthy et al. (2001) and combined a modified version of a Livelihood Vulnerability Index framework (Hahn et al., 2009) with the AF method of multidimensional index construction. For the purposes of the MLVI, the unit of analysis is the household. The aim is to measure the current livelihood vulnerability status of households, that is, to identify households that have a high potential to be negatively affected by climatic and other changes. Consequently, the identification is based on household-level characteristics. The VACA (Vulnerability and Adaptive Capacity Assessment) questionnaire covered the thematic areas of household consumption, food security, water security, health and healthcare, access to basic facilities, accessibility, housing, education, assets, gender inequality, and exposure and resilience to shocks and medium-term climatic and environmental changes, representing the 12 components of vulnerability represented by the three dimensions. The MLVI identifies vulnerable households by counting vulnerabilities across dimensions (identification), answers the question how vulnerable a given population is (aggregation), and is able to describe in which way people are vulnerable (decomposition).

Sun et al. (2019) used a new panel data grey combined method of comprehensive grey relational analysis (CGRA) and Max-CGRA clustering, which is applied to identify the key factors of regional agricultural drought vulnerability (RADV) in China's Henan Province. The factor index system of RADV is constructed from three aspects of exposure, sensitivity and drought resistance ability. Then, the panel data CGRA method and Max-CGRA clustering method are proposed, respectively. Finally, the key factors of RADV are identified by the proposed grey combined method, and the corresponding managerial implications are put forward. The panel data grey combined method has been validated and found useful to solve the key scientific problem urgently in the early warning of Henan Province agricultural drought.

Apart from these, a variety of measures are employed in the analysis of vulnerability in various research contexts. The 'Local Vulnerability Index', (Naude et al., 2009) used for the subnational regions in South Africa, Household Vulnerability Index (HVI) used in Ncube et al. (2016), the agent based modelling (ABM) framework used in Acosta-Michlik and Espaldon (2008), the Southern Africa Vulnerability Initiative (SAVI) (O'Brien et al., 2009) etc. are some of the measurement approaches used to assess vulnerability to climate change at the household and community levels. However, indicator-based vulnerability assessment measures, have been widely used as they allow the incorporation of biophysical and socio-economic components of vulnerability, and are relatively simple to conduct and easy to communicate to the public and policymakers (Tonmoy et al., 2014).

2.3 Global Climate Change: Manifestations, Impacts, and Vulnerability in Agriculture

The global warming and the resultant changes in climate create substantial challenges to the well being of the natural and human systems. Assessment of the manifestations of climate change over a region, therefore, is a prerequisite in the examination of vulnerability of a region. A wide variety of studies have examined the patterns of temperature and rainfall in the context of global warming. Table 2.2 provides an overview of selected studies that describe the observational evidence and projections regarding the variability and extremes in climate on global as well as regional scales. In the recent decades, the global temperatures have been showing significant tendencies towards warmer temperature regimes (Donat and Alexander, 2012) with significant shifts in the location, scale and shape parameters. Along with the increase in the mean temperatures, the increase in the yearly variability can cause damaging extremes (Katz and Brown, 1992; Schär et al., 2004). The analysis by Schär et al. (2004) suggests that a heat wave like the one happened in the Europe in 2003 can be traced back to a temperature regime with increasing year wise variability. At the same time, the frequency of heat extremes increases in accordance with climatic warming (Rahmstorf and Coumou, 2011). Although, this pattern of increase in temperature extremes is observed over various parts of the world, robust evidence of this acceleration comes from Europe and the Mediterranean, Asia, and Oceania (Hartmann et al., 2013).

In the case of rainfall, the variability and extremes are observed as increasing under climatic warming and this is occuring at a higher rate than that expected in the absence of climate change (Pendergrass et al., 2017; Fischer and Knutti, 2015; Lehmann et al., 2015). The intensification in the global monsoon precipitation is attributed partly to an expansion of the area receiving monsoon globally (Hsu et al., 2011) and an increase in summer monsoon precipitation in the Northern Hemisphere (Wang et al., 2012). This amplification in rainfall is applicable over the drier regions of the world as well (Donat et al., 2016) In the case of drought, however, the available observational evidence does not suggest any global-scale trends (Hartmann et al., 2013). However, the increased evaporative demand is observed to create drying trends in different parts of the world (Cook et al., 2014) and most of the Americas, southern and central Africa, southern Europe, Australia and southeast Asia are expected to experience a rise in the incidence and magnitude of droughts substantially by the second half of this century (Dai, 2013).

Table 2.2: Selected Studies on the Global Patterns of Temperature and Rainfall Extremes under Warming

Study	Spatial scale/ Region	Subject of study	Methods	Findings
Rahmstorf and Coumou (2011)	Russia	The effect of warming trends on heat records	Derived distribution functions for the number of extremes expected in non-stationary climates, both for extremes exceeding a fixed threshold and for record-breaking events, and employed Monte Carlo simulations to analyse the effect of nonlinear climatic trends	The number of heat extremes decreases as short term variability in temperature increases, whereas a climatic warming increases the number of heat extremes. However, the dependence of record-breaking extremes on the warming trend is highly non-linear. Extreme events increase in a changing climate.
Donat and Alexander (2012)	Global scale	Changes in the respective probability density functions of both variables using two 30-year periods; 1951-1980 and 1981-2010	Probability Density Functions were developed using HadGHCND data set.	The distributions of both daily maximum and minimum temperatures have significantly shifted towards higher temperatures during 1981-2010 compared to 1951-1980 in almost all regions of the world, while changes in variance are spatially heterogeneous and often less significant. Changes are greater for daily minimum temperatures than for daily maximum temperatures.
Dai (2013)	Global scale	How drought might change under increasing GHGs	Computed self-calibrated PDSI with the Penman-Monteith potential evapotranspiration. Analysis of coupled climate model simulations under intermediate future GHG emissions scenarios from the Coupled Model Inter-comparison Project phase 3 (CMIP3) and the new phase 5 (CMIP5).	Increase in the frequency and severity of droughts are likely most of the Americas, southern Europe, southern and central Africa, Australia and southeast Asia by the second half of this century.
Cook et al. (2014)	Global	The relative contributions of changes in precipitation and evaporative demand to global and regional drying patterns	Using the GCM output available from the CMIP5, historical experiments were run for the years 1850-2005 and simulations were performed for the RCP8.5 scenario (2006-2099). The PDSI and 12-month SPEI were used for understanding the causes, inception, and termination of discrete drought events.	Increased evaporative demand will play a critical role in spreading drought beyond the sub-tropics and into the Northern Hemisphere mid-latitudes, regions of globally important agricultural production.

Sillmann et al. (2014)	Global	Observed and model-simulated changes in temperature extremes for recent decades at global and regional scales	Used HadEX2 global gridded observational data set of temperature and precipitation extremes. The historical simulations from 1971-2005 are combined with simulations using the RCP4.5 forcing scenario to cover the analysis period. Decadal trends were calculated using the ordinary least squares (OLS) linear trend slope.	While there exists a discrepancy in global Tmean trends between observations and simulations over the warming hiatus period, that does not generally extend to temperature extremes.
Lehmann et al. (2015)	Global	Analysis of differences in the frequency of observed record-breaking daily precipitation events from that expected in a stationary climate	The Clausius-Clapeyron model consisting of ensembles of precipitation time series which are composed of a thermally induced long-term non-linear trend and added stochastic year-to-year variability	We find an increase of 12% in the number of record-breaking rainfall events compared to that expected in the absence of climate change for the period 1981-2010. The explanation of this long-term increase in record-breaking anomaly requires rising temperatures as well. The temperature driven moisture increase has significantly added to the intensification of extreme rainfalls after 1980.
Russo et al. (2015)	Europe	Analysis of the magnitude and frequency of observed and projected heat waves	Heat wave magnitude index daily (HWMId) applied to maximum and minimum temperatures.	Europe experiences an enhanced probability for heatwaves comparable to or greater than the magnitude, extent and duration of the Russian heatwave in 2010. The probability of experiencing a major European heatwave in the coming decades is higher in RCP8.5 than RCP4.5 scenario even though global mean temperature projections do not differ considerably
Donat et al. (2016)	Global	how precipitation totals and extremes are changing in different regions	Analysis of changes in total precipitation (PRCPTOT) and annual-maximum daily precipitation (Rx1day) in the HadEX2 observational data set 15 and in GCM simulations from the CMIP Phase 5	Observations showed robust ($p \leq 0.05$) increases in both precipitation indices in the dry regions and in the Rx1day index in the wet regions, with slope values of $1-2\%$ per decade. Projections showed strong mean increases in total and extreme precipitation averaged over dry regions.

These results point towards an increase in the climate stress over majority of the food baskets across the world under warming and therefore necessitates the assessments of impacts and adaptations in these regions and systems. The Table 2.3 shows the impact of climate variability and change on the agriculture over different parts of the world.

The Table 2.3 shows the impact of climate change and variability on agriculture in different regions of the world. This category of studies examine the response of a system (here it is agriculture) to the variations in climate. Various methodologies have been adopted in the impact analyses to bring in more clarity regarding the vulnerability of the specific systems under study. Peng et al. (2004) and Welch et al. (2010) have used data from farm level experiments to study the response of rice yield to the variations in climate. On the other hand, Lobell and Field (2007); Teixeira et al. (2013), and Ray et al. (2015) have considered the case of multiple crops and a larger spatial scale to get a much broader picture of the phenomena under study.

However, Fischer et al. (2005) and Felkner et al. (2009) attempt to incorporate the socio-economic aspects in the analysis of climate impact of crop yield. In the work of Felkner et al. (2009), the analysis using the DSSAT model and economic model brought out contrasting results regarding the vulnerability as the economic model included farm level adaptations in it. It was then observed that, although farmers are not able to neutralize the impact of climate change, they can adapt to the changes by making use of the beneficial aspects of change. According to Fischer et al. (2005), the impacts of climate change are mostly region specific and adaptations at the local level can successfully reduce otherwise larger negative impacts. The incorporation of adaptations in the impact analysis framework therefore brings out results that are more inclusive and relevant to the human dimensions of the issue.

The framework of vulnerability is therefore unique as it facilitate the analysis of the adaptations of the system under study in a more detailed and customized manner. The Table 2.4 provides a detailed overview of vulnerability studies performed across the world in the context of climate change. As shown in the table, vulnerability studies vary substantially in their conceptual affiliations and measurement approaches. Adger and Kelly (1999) used a semi structured interview schedule and a combination of quantitative and qualitative approaches to measure the social vulnerability of coastal Vietnam to Climate variability and extremes. The study asserted the region specific nature of vulnerability and the meaninglessness of aggregations of vulnerability results. Cutter et al. (2003) in their analysis of social vulnerability in the USA, observed that vulnerability has a multidimensional space and a casual structure. The multidimensional space is represented by various indicators.

Table 2.3: Selected Studies on the Global Patterns of Impact of Climate Variations on the Crop Yield

Study	Spatial scale/ Region	Subject of study	Methods	Findings
Peng et al. (2004)	Global	Impact of projected global warming on rice yields	Correlation and partial correlation analysis of farm level weather data and data from irrigated field experiments performed at the IRRI farm from 1992 to 2003	In the dry season, maximum temperature was not related to rice yield. Increases in night temperature had a negative effect on the yield of irrigated rice in the dry season. In the wet season, grain yield and yield attributes were not related to minimum temperature, maximum temperature, or solar radiation
Fischer et al. (2005)	Global	Socio-economic and Climate Change Impacts on Agriculture:	Employed AEZ- BLS modeling framework under five emission scenarios specified in the IPCC Special Report on Emission Scenarios and five GCM outputs.	Climate change will additionally modify agricultural activities and possibly widen the gap between developed and developing countries. Impacts of climate change are mostly region specific and adaptations at the local level can successfully reduce otherwise larger negative impacts. Globally, only small percentage changes from the baseline reference are found in the case of cereal production.
Lobell and Field (2007)	Global scale	The impact of climatic trends on crop yields 1961-2002	Multiple linear regressions with first differences in yield and first differences in response variables	At least 29% of the variance in year-to-year yield changes was explained by the climate variations for all crops. The climate driven yield change for 1981-2002 was the highest for wheat and the lowest for rice.
Felkner et al. (2009)	Thailand	crop yield impacts from likely climate changes	Soil science crop modeling, weather simulators, and global climate change modeling into an integrated economic model of multi-stage rice production	DSSAT Predicted decrease in aggregate yields with respect to the neutral climate simulations for both high and low emissions scenarios by 3.53% and 13.79%, respectively. In contrast the economic model predicted declining yield under higher emissions and increasing yield under low emissions. Overall, farmers were unable to offset the negative effects of the extreme climate change. However, they are able to cope with milder climate change and even benefited slightly from small increases in rainfall.
Welch et al. (2010)	Asia	The relative sensitivity of rice yield to changes in Tmin, Tmax, and radiation	Fixed effects panel data regression model	Temperature and radiation had robust effects during the vegetative and ripening phases of irrigated rice. Higher minimum temperature reduced yield, whereas higher maximum temperature raised it.

Teixeira et al. (2013)	Global	Spatial assessment of heat stress risk at a global level for four key crops, wheat, maize, rice and soybean	FAO/IIASA Global Agro-Ecological Zones Model (GAEZ), Heat stress intensity index and production damage index	Global suitable land area under risk of heat stress is higher for wheat and is followed by rice in the baseline climate (Base; 1971-2000). In the future scenario (A1B; 2071-2100) however, more land area under rice will be at risk than wheat. Rice in South Asia and wheat in Central Asia experience relatively higher damage in the current climate.
Ray et al. (2015)	Global	Variations in maize, rice, wheat and soybean crop yields worldwide due to the recent climate variability	Performed 27 linear regression equations with detrended crop yields and 27 combinations of climate variables for 13,500 political units	70% of maize harvesting regions, 53% of rice harvesting regions, 79% of wheat harvesting regions and 67% of soybean harvesting regions experienced the influence of climate variability on crop yields. 41% of variations in maize yield, 32%of rice yield variability, 36%of the year-to-year yield variability in wheat and 36%of the yield variability in soybean are explained by climate variability

However, this study also observed location specific nature of vulnerability and the importance of location specific geographical and political processes which may not be directly represented in the measurement but influence the vulnerability of the place under consideration.

Luers et al. (2003) analysed vulnerability as the expected value of the sensitivity of selected variables of concern to identified stressors divided by the state of the variables of concern relative to a threshold of damage. This study also realised the multidimensional nature of vulnerability and found that, in the Yanqui valley of Mexico, farmers are more vulnerable to the fluctuations in the market than a 1% change in the temperature. However, the analysis of multidimensional vulnerability in the Hindu Kush Himalayas (Gerlitz et al., 2017a) and the analysis of livelihood vulnerability in Ghana (Williams et al., 2020) suggested that the environmental factors constituting the exposure of a region were relatively more influential in determining the vulnerability status of that region.

The studies performed by Eakin and Bojorquez-Tapia (2008) in Mexico and Rurinda et al. (2014) in Zimbabwe revealed an even more complex picture of the vulnerability profiles. According to Eakin and Bojorquez-Tapia (2008), households have a degree of membership in specific vulnerability classes, reflecting the complexity of their livelihood and asset profiles in the structure of their vulnerability. Rurinda et al. (2014), on the other hand made a similar observation, that both poor and wealthier households are vulnerable depending on the specific climatic exposure and the resources at their disposal, highlighting a more complex picture of the association between vulnerability and poverty.

Thus the studies provide more detailed and comprehensive picture of the various contributing factors of vulnerability as they advance from exposure to sensitivity and adaptive capacity. Further, the assessments that incorporated adaptive capacity provided more insights regarding the multidimensionality and complexity of vulnerability which in turn can shed lights in to the niche areas of policy.

2.4 Vulnerability Studies in the Indian Context

One of the earliest references of deficient rainfall and droughts over the Indian region can be traced back to the report of the Indian Famine Commission 1878 (1880). The commission observed unusual episodes of drought and significant fluctuations in annual rainfall concurrent with the sunspot cycle causing devastating famines in the subcontinent. The report identified "(1) the western and southern parts of the North-Western Provinces and that portion of the Punjab territory which lies east of the Satlej; (2) the western and northern

Table 2.4: Selected Studies on the Vulnerability of Agriculture and Rural livelihoods

Study	Spatial scale/ Region	Subject of study	Methods	Findings
Adger and Kelly (1999)	Vietnam	How vulnerability is related to the structure of economic relations and the entitlements which govern them	Qualitative data analysis based on a semi-structured interview	The processes that determine vulnerability manifest at the local, national, regional and global levels. But the state of vulnerability itself is associated with specific groups within societies. Therefore, aggregation of vulnerability profile constructed for one region or social system to a larger setting or to another geopolitical system is inappropriate. Also, a global-scale analysis of social vulnerability is not meaningful except in so far as it deals with the vulnerability of the global community itself
Cutter et al. (2003)	USA	Construction of an index of social vulnerability to environmental hazards for the United States of America.	A Social Vulnerability Index was constructed using an additive model that computes a summary score of 11 factors contributing to vulnerability.	Social vulnerability considered vulnerability as a multidimensional concept that helps to identify those characteristics and experiences of communities (and individuals) that enable them to respond to and recover from environmental hazards. However, social vulnerability is location-specific. The variations in the geographical and political processes in counties have an influence on the declaration of hazards rather than a common analytical framework.
Luers et al. (2003)	Mexico	Development of a new measurement method for agricultural vulnerability and its application in the in the semi-arid region of the Yaqui Valley	Measuring vulnerability as the expected value of the sensitivity of selected variables of concern to identified stressors divided by the state of the variables of concern relative to a threshold of damage.	Farmers are more vulnerable to the fluctuations in the market than a 1% increase in temperature. Improved management practices can overcome the constraints imposed by poor soil types. Vulnerability is a multidimensional issue.

Eakin and Bojorquez-Tapia (2008)	Mexico	Rural livelihood vulnerability in the state of Tamaulipas, México	Indicator based study. Multi-criteria decision analysis (MCDA) and fuzzy logic are used to weigh household attributes according to their relative importance in driving household vulnerability	Households have a degree of membership in specific vulnerability classes, reflecting the complexity of their livelihood and asset profiles in the structure of their vulnerability.
Gbetibouo et al. (2010)	South Africa	The vulnerability of South African agriculture to climate change and variability.	A composite index of various indicators weighted using Principal Component Analysis	The regions most exposed to climate change and variability do not always overlap with those experiencing high sensitivity or low adaptive capacity but a combination of medium-level risk exposure and medium to high levels of social vulnerability.
Rurinda et al. (2014)	Zimbabwe	The nature and sources of vulnerability of smallholder farmers to climate variability and change	Detailed characterisation of farming livelihood systems, farmer perceived climatic exposure and adaptation options, and analysis of long-term climatic data	The analysis of household vulnerability to climate variability and change suggested a complex picture in which, the vulnerability cannot be related simply to poverty. It was observed that both poor and wealthier households are vulnerable depending on the specific climatic exposure and resources at their disposal
Gerlitz et al. (2017a)	Hindu Kush Himalayas	The vulnerability of households in the HKH region	Multidimensional Vulnerability Index	Among the 16 surveyed districts, the Khotang district of the Kosi sub-basin showed the highest MLVI value. The districts Lohit and Udayapur showed the highest absolute contribution of lack of adaptive capacity while Khotang and Lakhimpur districts exhibited higher values of sensitivity. Regarding the dimension exposure, the highest absolute contribution was found in Khotang and the highest relative contribution in Hunza-Nagar district. Vulnerabilities related to high exposure to environmental and socio-economic shocks were the most influential factors in determining the vulnerability of a region.

Williams et al. (2020)	Ghana	vulnerability among smallholder horticultural farming households to climate variability	Livelihood Vulnerability Index	Out of the two regions (Nsawam and Keta), the smallholder farmers of Keta, the coastal area was found to be more vulnerable to climate variability and extremes. The incidences of climate variability and extremes were higher over Keta and the region did not have proper early warning systems. Further weak performance in health, food security and adverse production conditions worsened the condition of the region even though its capacity to adapt was higher than Nsawam.

states of Rajputana and of the central plateau which border on the North-Western Provinces; (3) the districts of Bombay above the Western Ghats, and the districts of Madras above the Eastern Ghats, together with the southern and western region of Hyderabad and all Mysore, except the strip lying close along the Western Ghats; (4) the districts of Madras along the east coast and at the extremity of the peninsula" as the regions worst affected by droughts.

Blanford (1884) conducted one of the earliest investigations on the Indian monsoon rainfall and made a significant observation regarding the occurrence of drought over certain parts of the Indian subcontinent. The contention put forward in this work is that the unusual snowfall in the north-western Himalayas promotes the development of dry north-west winds in over the Western plains of India and thereby act as predictor variable to forecast the occurrences of drought over North-Western and Western India. His later work (Blanford, 1886) divided the Indian subcontinent in to 25 homogeneous rainfall zones (Panda, 2013), calculated the annual rainfall data for 1867-1885 using 500 rain gauge stations, and observed “intervals of drought" or ‘prolonged dry spells between active spells of monsoon’ (Gadgil, 2003). An overview of studies on the variability and extremes in temperature and rainfall is provided in Table 2.5

Table 2.5: Selected Studies on the Variability and Extremes in India

Studies	Phenomena under study	Findings
Kulkarni (2012); Roxy et al. (2015)	Indian Summer Monsoon Rainfall	Decline in monsoon circulation and the amount of rainfall over south-west and core monsoon region (1976-2004) and central-east and northern regions of India, along the Ganges-Brahmaputra-Meghna basins and the Himalayan foothills (1901-2012)
Goswami et al. (2006); Rajeevan et al. (2008); Mishra and Liu (2014); Roxy et al. (2017); Mukherjee et al. (2018); Mishra (2019)	Extreme Rainfall	Increase in the frequency and magnitude of extreme rain events over central India, western India, north eastern India and southern India

Goswami et al. (2006); Mishra and Liu (2014); Mishra (2019); Nageswararao et al. (2019); Rajkumar et al. (2020)	Light and Moderate Rainfall	There are reductions in low to moderate rain events over central India, western India, north eastern India amd south peninsular India
Kumar et al. (2013); Mallya et al. (2016); Pai et al. (2017a); Rajkumar et al. (2020)	Drought	south India, central Maharashtra, the Indo-Gangetic Plains, north and northwest India have experienced an increase in the frequency of severe droughts in recent decades
Ratnam et al. (2016); Rohini et al. (2016); Panda et al. (2017); Joshi et al. (2020)	Heatwaves	all regions of India except the Indo-Gangetic Plains experienced significant increase in the heat waves in recent decades, particularly the north, northwest, central and the eastern coastal regions of India
Revadekar et al. (2012); Panda et al. (2017); Mukherjee and Mishra (2018)	Warm nights	Significant increase in the night time temperature extremes observed over the south peninsular India and the northern parts of India. While both the day time and nighttime temperature extremes have increased, the warm spells in nighttime temperatures have been increasing more rapidly than the heat waves

As shown in the table there is a general decline in the monsoon rainfall in recent decades over the core monsoon regions in the country. However, this decline is mostly reflected in the share of light and moderate rain events in the total rainfall as the heavy and extreme rainfall events have been observed as increasing and intensifying considerably over Indian region, particularly central India, western India, northeastern India and southern India. This phenomena of general decline in rainfall coupled with an increase in the extreme rainfall and a decline in light and moderate rainfall has been observed as contributing to considerable drying in different regions of the world Trenberth (2011) and the increased evaporative demand under warming can intensify this pattern. In the case of temperature, the recent decades have been characterised by increases in extreme events both in the day time and night time temperatures. More importantly, while both the day time and night-time temperature extremes have increased, the warm spells in nighttime temperatures have been increasing more rapidly than the heat waves (Mukherjee and Mishra, 2018). On a spatial scale, though the southern Indian regions are comparatively less exposed to the extremes in temperature, large regions of southern India, East and West coasts, are projected to be severely affected in the near future (Murari et al., 2015). As the mean number of heatwave days in India increases, the mortality rate associated with heat waves in the country is also projected to increase from 46 to 82% (Mazdiyasni and AghaKouchak, 2015) since the regions where agricultural workers who spend sizable time outside are large in share are observed as highly vulnerable to the projected amplifications in heat waves (Im et al., 2017).

These changes in the temperature and rainfall characteristics in the recent decades can have substantial implications on the crop yield as well as livelihoods in the Indian agriculture. Studies focusing on multiple crops have observed that wheat and rice are relatively more vulnerable in the current scenario. Though wheat is more vulnerable to the variations in current climate, the projected changes in climate are expected to impact the yield of rice more adversely. This is particularly important for rice cultivation in Indian region since the rice in south Asia is relatively more vulnerable to the vagaries in current climate than the rice in other regions (Teixeira et al., 2013). The Table 2.6 summarises the weather sensitivity of Indian agriculture with special focus on the rice cultivation.

The results in general suggest significant negative effects of climate change on the agricultural sector. Projections are, indeed, suggesting more damaging estimates of weather sensitivities of crop yields. While Guiteras (2009) observed that high yielding varieties or technological progress need not reduce the vulnerability of crops to climate change and farmers can cope only by adjusting the input use, none of the other studies denied the possibility of beneficial adaptations. The importance of region specific studies are also emphasised (Pattanayak and Kumar, 2020b). Table shows studies that Incorporated the adaptations in their analytical framework.

Table 2.6: Selected Studies on the Impact of Climate Variations on Indian Agriculture

Studies	Crops	Region	Findings
Saseendran et al. (2000)	Rice	Kerala, India	On an average over the state, the rice maturity period is projected to shorten by 8% and yield increase by 12%. When temperature elevations only are taken into consideration, the crop simulations show a decrease of 8% in crop maturity period and 6% in yield. The temperature sensitivity experiments have shown that for a positive change in temperature up to 5°C, there is a continuous decline in the yield. For every one degree increment the decline in yield is about 6%.. Rice yield in Kerala is very much sensitive to rainfall.
Kumar and Parikh (2001)	Farm level net revenue of 20 crops-bajra, jowar, maize, rice and wheat, barley, cotton, groundnut, gram, jute, other pulses, potato, ragi, tur, rapeseed and mustard, sesame,soybean, sugarcane, sunflower and tobacco	All India	The overall impacts due to the climate change scenario of a 2.08°C rise in temperature and a 7% increase in precipitation are negative and about 8.4% of the total net-revenue for India. The temperature increase results in significant negative impacts, while the higher precipitation considered under the scenario increases the net-revenue. Overall, the negative impacts due to temperature change more than compensate for the small positive impacts due to precipitation change. Impacts estimated for a range of temperature changes revealed that the temperature response function is of inverted 'U' shape, i.e., with higher climate change the losses would be greater.
Guiteras (2009)	Rice, wheat, jowar (sorghum), bajra (millet), maize and sugar	All India	In the degree days approach, the aggregate impact was found to be negative for all three scenarios, with mildly positive precipitation effects were outweighed by negative temperature effects. The temperature bins approach also produced results similar to the degree days approach in the medium term. However, the long term results were not as damaging as in the degree days approach. The study observed that high yielding varieties are more sensitive to the fluctuations in climate and that technological progress need not reduce climate vulnerability of crops. The evidence on adaptation suggests that the true welfare impact of a climate shock may be slightly overemphasized by the effect on yields, since farmers can reduce their input use farmers could respond to a harmful shock through double cropping. A fall in the wage by nearly two percent was also observed in response to a one-degree temperature increase

Auffhammer et al. (2012)	Rice	All India	Significant non-linear relation between the monsoon characteristics and the yield were observed. The negative impact of reduced rainfall was higher during drought periods, and the positive impact of higher rainfall became negative during periods of extreme rainfall. In the post-monsoon period, the negative impact of minimum temperature was found highly significant and higher in magnitude. The simulation results suggested that the cumulative yield would have been 5.67% higher in the absence of climate change
Kumar et al. (2014)	Wheat	Indo-Gangetic Plains	Yield levels are significantly negatively correlated with the current seasonal mean minimum temperatures in the range of 12 to 18°C and with mean maximum temperatures of 21 to 31°C. Though the magnitude of impacts are different, the direction of impact is similar in both RCM and GCM based assessments. Negative impacts are less severe in the B1 and B2 emission scenarios as compared to the A2and A1b scenarios. Timely sowing of wheat crop, adoption of improved and heat-tolerant varieties under increased input amount and efficiency regimes can not only offset yield reduction but also result in an increase in yield up to the mid-century.
Birthal et al. (2014)	Value of output (Output x farm harvest prices) of Rice, wheat, pearl millet, sorghum, finger millet, maize, barley, pigeon pea, chickpea, groundnut, rapeseed, sesame, and mustard, castor, safflower, linseed, soybean, sunflower, sugarcane and cotton	All India (200 Districts)	A 1°C rise in the Rabi temperature reduces the gross value of output per hectare by 4%. A similar increase in the Kharif temperature reduces it by 5.6%. In the arid and semi-arid tropics, the impact is higher. A 1°C increase in the Kharif temperature reduces the gross value of output by 9.2%. The damages due to temperature are partially offset by irrigation. The effect of Kharif rainfall is positive and significant in all the zones.
Pattanayak and Kumar (2014)	Rice	All India	The study observed that a higher minimum temperature during the vegetative and reproductive phases improved yield, while, a higher minimum temperature during the ripening phase decreased rice yield. Similarly, a robust negative effect of maximum temperature was also observed. The rice yield increased with higher rainfall, and had an inverse relation with incoming solar radiation. The simulation analysis suggested that the all-India Kharif Rice yield would have been $\approx 8.4\%$ (or cumulative 172 million tons) higher in the absence of climate change.
Pattanayak and Kumar (2020b)	Rice	Eastern and Southern regions of India	Simulation of impacts due to changes in historical climate revealed evidence of yield losses during 1969-2007 in the Southern (8%) and Eastern India (5%). Weather sensitivity of rice yield was observed to vary across regions. The assessment of climate change impacts at the regional level requires region-specific estimates of crop yield sensitivity to weather using disaggregated data on crop and weather variables

Vulnerability assessments over Indian region are diverse in their analytical framework. However, in the present context we have considered mainly the indicator based measurement approaches. As shown in the Table 2.7, there are both national and region scale studies. Although, O'Brien et al. (2004) and Brenkert and Malone (2005) covered larger area, these studies emphasis the importance of local level adaptation and policy support. Brenkert and Malone (2005) further observed the importance of both thematic as well as region specific policy support. Most of the studies in the later periods are therefore strictly location specific, emphasising the significant role of local factors in shaping the vulnerability of a system. Another important contribution in the analysis of vulnerability assessment is the incorporation of the idea of temporal evolution of vulnerability (Patnaik et al., 2013). Patnaik et al. (2013) conducted vulnerability assessments in the same location and observed substantial influence of previous levels of vulnerability in determining the present vulnerability. Another important contribution is the sustainable livelihoods approach of classifying the units of study according to their livelihood strategies (Aulong and Kast, 2012). Aulong and Kast (2012), in their analysis, identified 6 groups of homogeneous farmers linked with 3 types of livelihood strategies. The application of multiple assessment framework on the same region are performed in O'Brien et al. (2004), Ravindranath et al. (2011) and Sam et al. (2017) to get a detailed picture of vulnerability. Vulnerability assessments over Indian subcontinent share substantial insights regarding the diverse factors and contexts that shaped the vulnerabilities of various regions and communities. Continuous assessments of vulnerability are necessary in order to reveal the combinations of development strategies and various shocks that shape the outcomes of progress. It also calls for thematic interventions rather than asserting the space based differentials in policy decision making.

Table 2.7: Selected Studies on the Vulnerability of Agriculture and Rural livelihoods

Study	Subject	Region	Methods	Finding
O'Brien et al. (2004)	Mapping vulnerability to multiple stressors	India	Indicator based assessment	Districts of Rajasthan, Gujarat, Madhya Pradesh, southern Bihar and in western Maharashtra were identified to be double exposed to vulnerability. The study revealed that, poorly equipped farmers, inadequate institutional support and supports that disproportionately benefit farmers in the exposed districts and local level adaptations can play a substantial role in reducing vulnerability
Brenkert and Malone (2005)	Climate change vulnerability assessment	India	Vulnerability Resilience Indicator Prototype	Total protein intake and water availability are the largest contributors of vulnerability in India. Several conflicting factors such as high sensitivity to food security and high economic capacity were observed together for states which in turn points to the need for sector level and state level interventions separately
Aulong and Kast (2012)	Assessment of the vulnerability of South Indian farmers to global change at two periods of time: medium-term (2030-2040) and long term (2045-2065)	South India	Indicators and Analytic Hierarchic Process (AHP) method	From the official typology of Indian farmers based on operational land size, the study developed their own farmers' typology using again sustainable livelihood approach classifying farmers according to their current livelihood strategy. The study identified 6 groups of homogeneous farmers that linked to 3 specific livelihood strategies. The vulnerability measures are constrained by the dynamic of the bio-physical and socio-economic factors and cannot grasp the much faster dynamics of the decision making processes
Ravindranath et al. (2011)	A quantitative approach for assessing the vulnerability of the three key sectors of agriculture, water and forest.	North East India	Composite Indices - Agricultural Vulnerability Index, Water Vulnerability Index, and Forest Vulnerability Index	Currently vulnerable districts to become more vulnerable in the future scenario (AVI). Regions characterised as highly vulnerable to floods were identified as vulnerable to droughts as well (WVI). Except some districts, the vulnerability of districts belonging to all categories to increase in the future scenario (FVI)

Pandey and Jha (2012)	Climate change vulnerability of rural communities in the lower Himalayas	Srinagar, Uttrakhand	Climate Vulnerability Index	The selected households were classified into those staying near to and away from the district headquarters. It was observed that along with the sensitivity and adaptive capacity the information and perceptions played a substantial role in determining the vulnerability profile
Varadan and Kumar (2015)	The relative agricultural vulnerability of various districts of Tamil Nadu state in India to Climate Change.	Tamil Nadu	Agricultural Vulnerability Index	The study observed that all districts in an agro-climatic zone do not fall under the same category of vulnerability, that is vulnerability is influenced by factors that are too local in nature. Addressing those factors should consider the requirements of the local communities
Sam et al. (2017)	Livelihood and socio-economic vulnerability of rural farming households that are affected by drought.	Odisha	Livelihood Vulnerability Index, Socio-economic Vulnerability Index	Both LVI and SeVI showed similar results. Increasing the formal education, diversifying livelihood strategies etc. Systemic changes that account for the local requirements are necessary
Patnaik et al. (2013)	Socio-economic vulnerability for the coastal districts of Odisha	Odisha	Composite index	Incorporates the temporal evolution of vulnerability by constructing the index for three years 2001, 2006 and 2011 and identified strong correlation between present and past vulnerability.

2.5 Major Research Gaps

The existing research has made diverse coverage of a wide range of issues pertaining to the vulnerability of agriculture and livelihoods. Substantial contributions have been made in the conceptual as well as methodological spheres of vulnerability. However, one important grey area in the vulnerability research is the complex structure of vulnerability. This is well discussed in the works of Eakin and Bojorquez-Tapia (2008) and Rurinda et al. (2014). That is, households can be differently vulnerable reflecting the complexity of their livelihood strategies and asset profiles and can form specific vulnerability classes representing the degree of their vulnerability. This actually goes beyond the widely performed location based vulnerability assessments. Aulong and Kast (2012) in their study identified 6 groups of homogeneous farmers linked with 3 types of livelihood strategies. In the Indian context, studies exploring this dimension of vulnerability are very rare. Another important research gap pertains to the operation of the concept sensitivity in the vulnerability frameworks. In general, vulnerability frameworks consider sensitivity in terms of the factors causing sensitivity and not by sensitivity itself. O'Brien et al. (2004) is an exception to this. O'Brien et al. (2004) has used a climate sensitivity index to measure the sensitivity in their vulnerability assessment. Finally, only household level studies can make in depth analyses of adaptation processes and local level factors influencing the farmers perceptions and decisions therein. While the number of studies following this approach has increased in the recent years, that alone does not make this approach less important. Since every vulnerability assessment pertains to a specific location or a community, the importance of household level studies is only increasing. Apart from these gaps, the present study also includes a historical analysis of climate variability and extremes over the study area, the results of which are incorporated in the vulnerability assessment framework.

Chapter 3

Methodology and Data

This chapter provides a detailed account of the study area, data collected, materials and methods employed to collect and analyse data to achieve the stated objectives of the study. This chapter is divided in to four sections. Section 1 provides the details of the study area; section 2 discusses the details of the data collected; section 3 accounts for the various research methods used in the analysis of data; and section 4 provides the limitations of the study.

3.1 Study area and data

Tamil Nadu is located in the southern part of India between $8°15' - 13°30'$N and $76°30' - 82°00'$E. It lies in the leeward side of the Western Ghats - an elevated rim of the Deccan Plateau, located in the path of the Southwest monsoon. As a result of ensuing rain shadow effect, this region has a distinct rainfall pattern in comparison with the regions located to the west of Western Ghats (Gunnell, 1997). The region's dry sub-humid climate has been exhibiting a shift to semi-arid climate recently (Raju et al., 2013). Also, Tamil Nadu is one of the major rice cultivating states in the country and the land inequality[1] and indebtedness of farmers in this state is larger than many other Indian states (Rawal, 2008; Reddy and Mishra, 2008). Tamil Nadu has an area of 1,30,058 km^2 and is classified in to eight agro-climatic zones by the India Meteorological Department (IMD), Chennai, in its district level agro-meteorological advisory bulletin (Figure 3.1). The geographical, climatological, and socioeconomic features of the region has motivated us to select this region to study about the livelihood vulnerability of rice farmers to climate variability and extremes.

In order to study the climate variability and extremes, the study used the daily gridded rainfall data set with a horizontal resolution $0.25° \times 0.25°$ for 66 years from 1951 to 2016 for

[1]This is explained in detail in the Chapter 1

Indian region developed by India Meteorology Department (Pai et al., 2014) and the daily gridded minimum and maximum surface temperature data set with a horizontal resolution $1^\circ \times 1^\circ$ for 66 years from 1951 to 2016 for Indian region developed by India Meteorology Department (Srivastava et al., 2009) in this study.

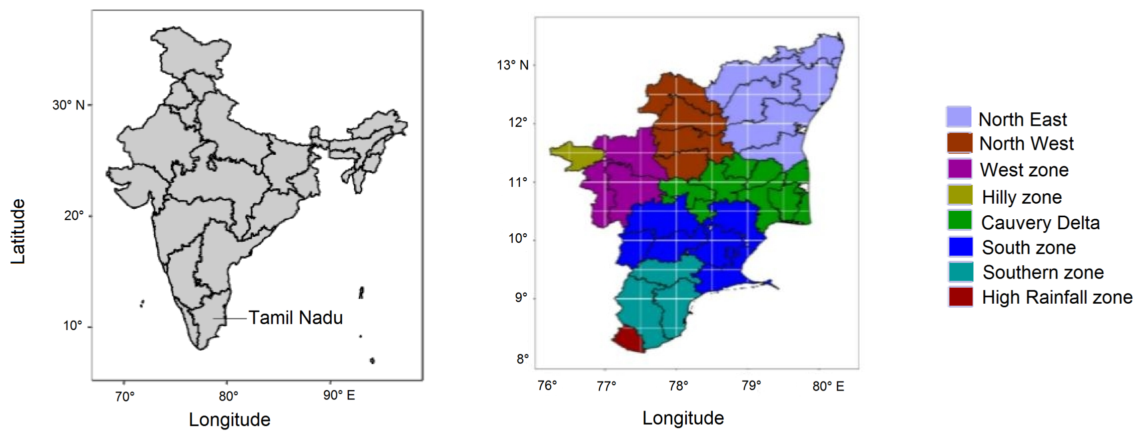


Figure 3.1: Agro-climatic zones of Tamil Nadu, India

The temperature data set was developed for the whole Indian region for the period from 1951 to the present day using the observations from 395 quality-controlled stations based on a modified version of Shepard's angular distance weighting algorithm (Srivastava et al., 2009). The rainfall dataset was developed for the period from 1901 to the present day from the daily rainfall records from 6,995 rain gauge stations in India using an inverse distance weighted interpolation (IDW) scheme (Pai et al., 2014). Since the temperature and rainfall data were available at different horizontal resolutions and the study involved the analysis of the spatial patterns of association between heat waves and droughts, we readjusted the resolution of temperature data and generated grid boxes of $0.25^\circ \times 0.25^\circ$ dimension (Fig. 2) using bilinear interpolation method in the 'GrADS' software (Doty and Kinter III, 1995). The 1×1 degree gridded temperature data was re-gridded to 0.25×0.25 degree. The annual values for minimum and maximum temperatures (mean) and rainfall (sum) were obtained from each grid point in the study area for 1951-2016. To study the spatial patterns of variability, the data from the grid points where both temperature and rainfall data were available (see Figure 3.2) were averaged in to zonal values for each zones shown in Figure 3.1. The grid boxes shown in Figure 3.2 cover 110947.81 km^2, i.e., 85.31% of the total land area of Tamil Nadu. Data, from this grid box level, were then aggregated to the district level to estimate the impact of climate variations on rice cultivation in each district. For the analysis of districts that are outside this grid, temperature and rainfall data were extracted from available grid points in the best proximity of the relevant regions.

The annual and seasonal data pertaining to the area, production, yield, the area under high yielding varieties, the area under irrigation for the period between 1985-86 and 2015-16 were collected from the Directorate of Statistics, Government of Tamil Nadu, National Digital Library and the Central Library of Tamil Nadu Agricultural University. Here also, the period of study was fixed considering the minimum requirement for a statistically robust estimation of weather sensitivity.

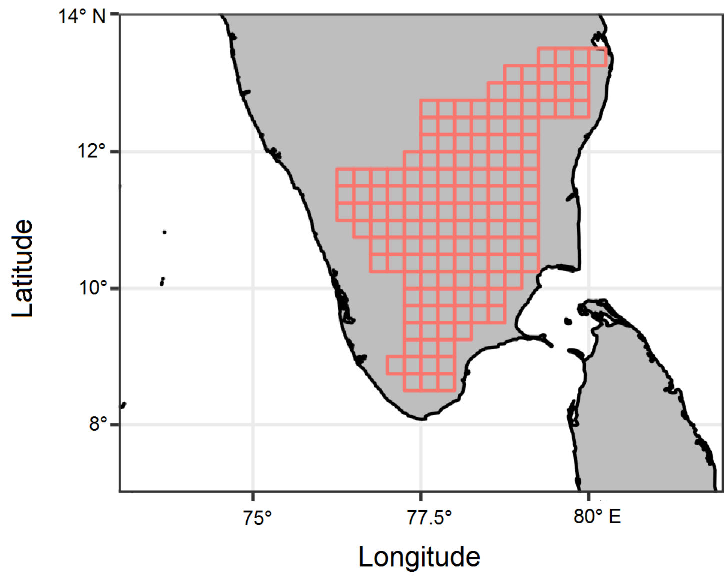
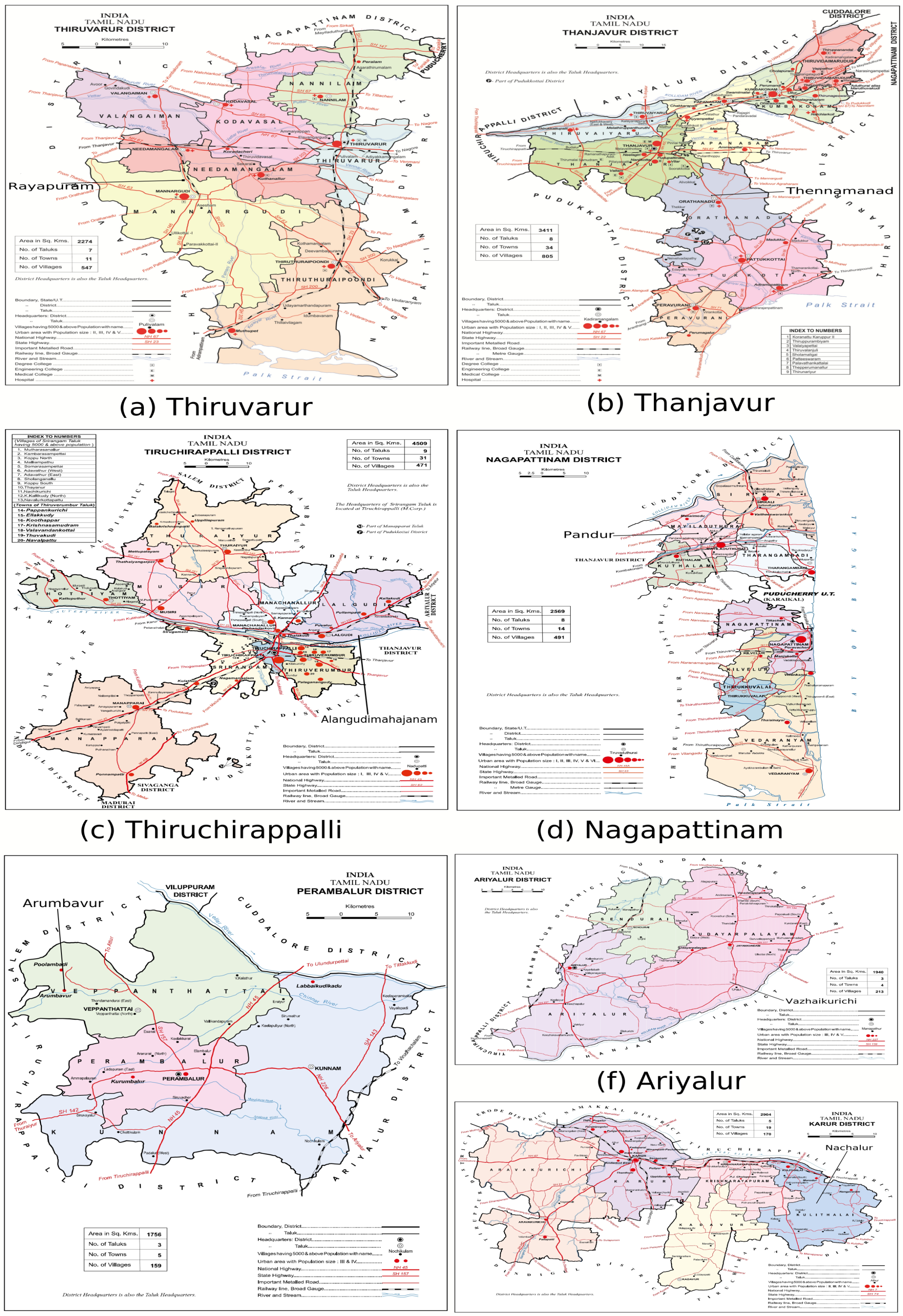


Figure 3.2: Area covered in the study

A field survey was conducted among the rice cultivating farmers in the Cauvery Delta[2] Region of Tamil Nadu. In the field survey, a well-structured interview schedule was used. The basic unit of analysis was the operational holder[3]. This follows the definition of operational holding as “all land which is used wholly or partly for agricultural production and is operated as one technical unit by one person alone or with others without regard to the title, legal form, the size or location” (Government of India, 2011a). According to the

[2]Cauvery Delta zone is known as the rice bowl of the state

[3]“An operational holder is a person who has the responsibility for the operation of the agricultural holding and who exercises the technical initiative and is responsible for its operation. If the holding is being operated either by one person or by a group of persons who are the members of the same household, such holding will be considered as an individual holding cultivating rice. If the persons sharing the responsibility of cultivation in an agricultural holding, they are considered as joint holders. The present study considers both individual and joint operational holders” (Government of India, 2011a)



(a) Thiruvarur
(b) Thanjavur
(c) Thiruchirappalli
(d) Nagapattinam
(e) Perambalur
(f) Ariyalur
(g) Karur

Figure 3.3: Map of the study areas showing the districts and villages of Cauvery Delta region, Tamil Nadu

data from Agricultural Census 2010-11, the total number of operational holdings in Tamil Nadu is 8098747 out of which 3675039 (45%) units are under paddy cultivation. From that, 1157667 (32%) rice farmers reside in the Cauvery Delta Region and out of that 742568 (64%) are individual operational holders. Using the representative sample for proportions method (Cochran, 1977) (See section A.1 of Appendix A), the minimum required sample size was estimated as 384. The Cauvery Delta region, as defined by the IMD, consist of seven districts. The study used expert sampling method for selecting one village each from the seven districts of the agro-climatic zone. A panel consisting of academic experts and the officials of the department of agriculture (Office of the Joint Director of Agriculture) in the concerned district. From each district, a "rice village" was selected based on the share of operational holders cultivating paddy. The selected villages are Rayapuram in Thiruvarur district, Thennamanad in Thanjavur, Alangudimahajanam in Thiruchirappalli (Trichy), Pandur in Nagapattinam, Arumbavur in Perambalur, Vazhaikurichi in Ariyalur, and Nachalur in Karur district. Figure 3.3[4] shows the location of selected villages in the respective districts. The researcher surveyed 400 rice farmers against the estimated minimum requirement of 384. However, 5 respondents were removed due to incomplete response to most of the questions in the interview schedule. In the estimated sample size, each of the selected villages were given weights based on the share of rice farmers in the concerned district in the total rice farmers in Cauvery Delta zone. In the next stage, we used stratified random sampling for selecting the farm households on the basis of the size of their farms (Small and marginal, Semi medium, Medium, Large). Here also, their proportion in the sample was decided according to the share of each category among the total number of individual operational holders in at the district level. From each category, farmers were selected from the list of operational holders available at village level using random numbers generated in 'R' software. In the case of medium and large farmers, their share in population represented by the sample was too small. Also, among these farmers we had to drop some respondents due to their non-availability and non-response to the majority of the questions in the interview schedule. In those cases farmers belonging to these categories were included in the sample purposively to ensure representation. Approximately 9 farmers (0.03% of the estimated sample size) were so added to the estimated sample size. Table 3.1 shows the distribution of the sample across the study districts.

[4]Source: Government of India (2011b)

Table 3.1: Primary Data Collection from Seven Districts of Cauvery Data

District	Village	Weightage	District Level Sample	Small and Marginal ≤ 2 Ha	Semi Medium $> 2 \leq 4$ Ha	Medium $> 4 \leq 10$ Ha	Large > 10 Ha
Ariyalur	Vazhaikurichi	5.11%	20	17	2	0	1
Karur	Nachalur	2.63%	11	10	1	0	0
Nagappattinam	Pandur	18.87%	74	66	5	3	0
Perambalur	Arumbavur	2.84%	13	13	0	0	0
Thanjavur	Thennamanad	27.83%	108	84	12	10	2
Thiruvarur	Rayapuram	20.20	80	56	12	12	0
Thiruchirappalli	Alangudimahajanam	22.40	89	66	17	5	1
Total	742568	100.00%	395	302	49	25	4

A well-structured interview schedule was used for the collection of primary data. The interview schedule was prepared after an extensive survey of literature and the interaction with expert members. The interview schedule was further reviewed after a pilot survey consisting of 20 samples. The interview schedule consisted of 6 sections. The section 1 pertains to the socio-demographic characteristics of the operational holders and consisted of 5 questions and 10 sub questions. In the section 2, questions related to the socioeconomic profile, poverty, migration, water, sanitation and health care were asked. There were 17 questions and 7 sub questions in this section. The section 3 included questions regarding the status of livestock and poultry owned by the operational holder. There was 1 question and 5 sub questions in this section. The section 4 is concerned with the assets and liabilities of the operational holder and had 4 questions and 2 sub-questions. The section 5 consisted of 9 questions related to the cultivation patterns and perceptions of the operational holder, and the section 6 was reserved for specific remarks from the farmers and observations of the enumerator (if any) made during the interview. The interview schedule is provided in the section A.2 of Appendix A.

3.2 Methodology

3.2.1 Conceptual framework

In the present study, we follow the IPCC definition of vulnerability which defined vulnerability as ‘the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity’. We incorporated the concept of household livelihood security (Frankenberger and McCaston, 1998) to this definition of vulnerability to bring out the extent to which various socioeconomic and biophysical factors combine together to constitute the vulnerability of rice farmers of Tamil Nadu. The household livelihood security is defined as “adequate and sustainable access to income and resources to meet basic needs’. The basic needs here include food, potable water, health facilities, educational opportunities, housing, time for community participation and social integration (Frankenberger and McCaston, 1998). This approach is also consistent with the concept of livelihood sustainability proposed by Chambers and Conway (1991). The concept of livelihood sustainability maintains that a livelihood is sustainable when it can “cope with and recover from stress and shocks, and maintain or enhance its capabilities and assets, and provide sustainable opportunities for the next generation”. Accordingly, this study considers that ability of the farmers to cope with the effects of climate change, climate variability and extremes depends on a combination of factors including the extent of livelihood security, the sensitivity of their major crop to weather variations, and the extent of variability and extremes in temperature and rainfall to which their livelihoods are exposed to. Table 3.4 provides the details of the various components and sub-components of the livelihood vulnerability, their dimensions, functional relation with vulnerability and explanations regarding their measurement.

3.2.2 Measurement methods

3.2.2.1 Ensemble Empirical Mode Decomposition

The anomaly time series of temperature and rainfall across seven agro-climatic zones were detrended using Ensemble Empirical Mode Decomposition (EEMD) to obtain the variability. The EEMD is a noise assisted, adaptive time-frequency data analysis method. It is an improvement of Empirical Mode Decomposition(EMD) that will decompose data, $x(t)$, in terms of IMFs, c_{j}, and a residual component r_{n}, i.e.,

$$x(t) = \sum_{j=1}^{n} c_{\mathrm{j}}(t) + r_{\mathrm{n}}(t) \tag{3.1}$$

In the Equation 3.1, the residual component, $r_{\mathrm{n}}(t)$, could be a constant, a monotonic function, or a function that contains only a single extrema from which no more oscillatory IMFs can be extracted. This definition of residual is almost identical to the definition of the trend when the data span in the trend definition covers the whole data length (Huang et al., 1998).

An important drawback of EMD has been mode mixing. Mode mixing is a situation in which a single IMF consists of signals of different scales or a signals of the same scale residing in different IMFs. Ensemble EMD (EEMD) analysis is an improved version of EMD in which a finite random white noise is introduced initially to the time series to populate whole time–frequency space uniformly with the constituting components of different scales. It fills the time scales that may not be part of the data to prevent mixing of different time scales into the same mode in the EMD analysis. In the EEMD method, the EMD is applied many times to the time series (with added noise) and the signal extracted through an ensemble average of the modes extracted. Here, all data are amalgamations of signal and noise. EEMD has been successfully applied to analyse non-stationary geo-physical time series (Wu and Huang, 2009). For decompositions, the ratio of the standard deviation of the added noise series is 0.2 times the standard deviation of the original data, and the number of trials was set to 200. The rainfall trend over the period of analysis given here are obtained from the from the residual, r_n. The EEMD was conducted using R package Rlibeemd (Luukko et al., 2016). A detailed explanation of EEMD is provided in the section A.3 of Appendix A.

3.2.2.2 Standardized Precipitation Evapotranspiration Index

This study has used Standardized Precipitation Evapotranspiration Index (SPEI) for the analysis of the spatio-temporal patterns of drought across Tamil Nadu. SPEI is a multi-scalar drought index which is suitable for the analysis of droughts under a warming climate (Vicente-Serrano et al., 2010). The calculation of SPEI requires precipitation as well as temperature data. The temperature data is used for the calculation of potential evapotranspiration (PET or ET_0). PET refers to "the rate at which evaporation from soils and transpiration by plants takes place when the water available for this process is non-limiting. It depends on climatic conditions, specifically the radiative energy of the sun, wind, the vapour deficit of the air, and temperature" (DESERTLINKS, 2004). Using a log-logistic regression, the monthly climatic water balance (difference between precipitation and PET) is converted to standardized units. For this study, we used a modified Hargreaves method (Droogers and Allen, 2002) to calculate the PET. Accordingly, in the present study, a drought event is defined as a period that begins as SPEI falls below 0 and stays continuously negative for at least 3 months. The drought ends with a positive value of the SPEI (Dayal et al., 2017). In the present study, therefore, a modified version of Hargreaves method (Droogers and Allen, 2002) has been adopted. It requires maximum and minimum temperature, precipitation and the geographical location of the region of interest.

Table 3.2: Categorization of dryness/wetness range by the SPEI

Categories	SPEI values
Extreme dryness	less than -2
Severe dryness	-1.99 to -1.5
Moderate dryness	-1.49 to -1.0
Near normal	-1.0 to 1.0
Moderate wetness	1.0 to 1.49
Severe wetness	1.50 to 1.99
Extreme wetness	more than 2

The typical values of SPEI range between -2.5 and 2.5 corresponding to exceedance probabilities of approximately 0.006 and 0.994, respectively, even though the theoretical limits are $-\infty, +\infty$ (Kumar et al., 2013). Table 3.2 provides the categorization of dryness/wetness extent by SPEI (Yu et al., 2014). As such a six month SPEI was calculated for each grid box since this time scale was observed as significant as far as agriculture is concerned. The six month scale SPEI implies that the data for current and past five months were used for the calculation of the SPEI for the current month and the entire past data was given equal weight. Along with the area affected, we estimated the duration, intensity as well as severity of droughts over the Tamil Nadu region by adopting a functional definition of drought. The severity S of a drought is given by:

$$S = \sum_{i=1}^{D} -(SPEI) \tag{3.2}$$

Where $i = 1$ is the start of a drought event when the SPEI becomes negative and continues for at least 3 months. D is the total duration of the drought from its onset to termination, and I, the intensity, is the minimum SPEI for a given drought event (Yevjevich, 1967; Dayal et al., 2017). The computation of SPEI was done by R package 'SPEI' (Beguería and Vicente-Serrano, 2017). The trend lines for drought analysis were plotted using 'ggplot2' package (Wickham, 2016) in R using the linear regression method.

3.2.2.3 Extreme rainfall analysis

This study made use of the classification scheme developed by India Meteorology Department (IMD) for rainfall events to examine the extreme rainfall events over Tamil Nadu (Table 3.3).

Table 3.3: Classification of rainfall events based on one day rainfall amount over a grid

IMD classifications of rainfall event	Rainfall (R) in a day in mm
Light	$0.0 < R \leq 10.0$
Moderate	$10.0 < R \leq 35.5$
rather heavy	$35.5 < R \leq 64.4$
Heavy	$64.4 < R \leq 124.4$
Very Heavy	$124.4 < R \leq 244.4$
Exceptionally heavy	$R > 244.4$

Accordingly, for various rainfall categories, we estimated the the area affected (in km^2) and their respective shares in the annual rainfall for 1951-2016 at the grid box level and are explained at the agro-climatic zone level. The trend lines for extreme rainfall analysis were plotted using 'ggplot2' package (Wickham, 2016) in R using linear regression method.

3.2.2.4 Heat-wave magnitude index daily

To examine the characteristics of heat waves over Tamil Nadu region, India, we used the Heat-wave magnitude index daily (HWMId) (Russo et al., 2015). A heat wave, according to this method is a situation in which the maximum temperature exceeds the daily threshold for the reference period (1981-2010) for at least three consecutive days. The threshold for a given day d as mentioned here is the 90th percentile of daily maximum temperature, centered on a 31 day window A_d as defined by Eq 3.3 where, $\bigcup$ is the union of sets and $T_{y,i}$ is the daily maximum temperature of the day i in the year y. The daily magnitude M_d is computed by Eq: 3.4. With T_d representing the daily maximum temperature on day d of the heatwave, T_{30y75p} and T_{30y25p} representing the 25th and 75th percentile values, respectively, of the time series composed of 30 year annual maximum temperatures within the reference period (1981-2010). HWMId magnitude is the sum of the magnitude of the consecutive days composing a heatwave and HWMId is the maximum magnitude of the heat waves in a year (Russo et al., 2015). The difference between T_{30y75p} and T_{30y25p} (Interquartile Range - IQR) is used as the heatwave unit as it represents a non-parametric measure of the variability and implies that if the T_d for a heat wave day equals T_{30y75p}, its corresponding magnitude value provided by Equation 3.4 will be 1. Accordingly, if the magnitude on the day d is 3, it implies that the temperature anomaly on the day d with respect to the T_{30y25p} is 3 times the Interquartile Range which is the definite pre-determined heatwave magnitude unit (Russo et al., 2015). HWMId has been observed as capturing events that are perceived as heatwaves by a broader public when compared with the previous indices (Ceccherini et al., 2017; Russo et al., 2015).While the original HWMId considers the event with maximum magnitude over the whole year as a heat wave, we modified it to include all events that exceeded the daily temperature threshold for at least three consecutive days. Following Russo et al. (2015), the event with the maximum magnitude in Tmax (Tmin) in a year is termed as heat wave (warm night) and the suboptimal episodes are referred to as warm spells in daytime (night-time) temperature. We calculated the HWMId for each grid box using the HWMId function in R package extRemes (Gilleland and Katz, 2016).

$$A_d = \bigcup_{y=1981}^{2010} \bigcup_{i=d-15}^{d+15} T_y, i \tag{3.3}$$

$$M_d(T_d) = \frac{T_d - T_{30y25p}}{T_{30y75p} - T_{30y25p}} \tag{3.4}$$

The robustness of the results was tested using the Mann-Kendall trend (M-K) test and the Kolmogorov - Smirnov (K-S) test. The M-K test is a non-parametric rank-based trend test that does not assume normality of the distribution of the time series (Shadmani et al., 2012). As a result, this test has been widely used in hydro-meteorological studies to detect monotonic trends (Shadmani et al., 2012; Gocic and Trajkovic, 2013). We divided the entire study period into two sub-periods of 33 years (1951-83 and 1984-2016) each and performed two-sample KS test with the alternative hypothesis that the Empirical Cumulative Distribution Function (ECDF) of the first distribution is greater than the ECDF of the second. The K-S test is also a distribution free and non-parametric test used to analyse if two data sets differ significantly. Any robust difference in the distribution favouring the alternate hypothesis implies that, for most values of x, the fraction of the values in the first half that is strictly greater than x is clearly less than the fraction of the values of the second half that is strictly greater than x. In other words, the values of the second half are larger than the values of the first half for the same cumulative fraction.

3.2.2.5 Regression Analysis

The present study further examined the extent to which the variability in temperature and rainfall causes variability in the rice yield over Tamil Nadu region. To study the weather sensitivity of rice yield in the three major cultivating seasons, fixed-effects panel regression analyses were performed. The data was detrended using EEMD and standardised to avoid multicollinearity. The choice of the regression model (between fixed and random effects models) was made on the basis of the Hausman test.

$$y_{it} = W_{it}\gamma + N_{it}\beta + c_i + \theta_t + \phi_{it} + \epsilon it \tag{3.5}$$

y_{it} represents the yield in the agroclimatic zone i in the year t. W_{it} represents the weather variables and N_{it} denotes the non-weather variables. The weather variables include solar radiation, maximum and minimum temperatures, rainfall, HWD[5], WND[6], SPEI, the fraction of area receiving extreme rainfall and average drought intensity while the fraction of area under high yielding varieties and the fraction of area irrigated constituted the non-weather variables. The variables c_i and θ_t represent the zone fixed and time fixed-effects respectively. ϵ_{it} denotes the error term (Auffhammer et al., 2012; Pattanayak and Kumar, 2020a). The seven agroclimatic zones of Tamil Nadu (Southern zone, South zone, Cauvery Delta, Hilly zone, West zone, Northwest zone, and Northeast zone) were considered for the analysis of weather sensitivity of rice yield during the period between 1985-86 and 2015-16.

The results were tested for Heteroscedasticity (Breusch-Pagan Test), Serial correlation (Wooldridge, 2002) (Wooldridge, 2010) and cross-sectional dependence (Pesaran CD test). We further computed the heteroscedasticity consistent robust standard errors which also account for serial correlation and cross sectional dependence Arellano et al. (1987). Five best models were selected and presented in the analysis part. Out of the five models, one model includes only weather variables. The estimations were performed using R package 'plm' (Croissant et al., 2008; Millo, 2017; Croissant et al., 2019).

In order to examine the weather sensitivity of rice yield at the district level, we used a multiple linear regression model (Eq. 3.6).

$$y_i = \beta_0 + \beta_1 w_i + \beta_2 n_i + \epsilon_i \tag{3.6}$$

where y_i represents the rice yield in the $i^t h$ district, w_i and n_i represent the weather and non-weather factors, and ϵ_i represents the error coefficient. For the district level analysis also, we used the detrended and standardised data. From each model, the R^2 value was partitioned by averaging over orders and the relative importance of each variable was

[5]HWD refers to the sum of magnitudes of all daytime warm spells in a selected period (Zampieri et al., 2017)

[6]WMD refers to the sum of magnitudes of all night-time warm spells in a selected period (Zampieri et al., 2017)

Table 3.4: Various components and sub-components comprising the Livelihood Vulnerability Index (LVI) used for the rice farmers of Tamil Nadu

Dimension	Major component	Minor component	Explanation of minor components	Functional relationship with vulnerability	Source
Adaptive Capacity	Socio demographic profile	Dependency ratio	Ratio of the population under 15 and over 65 years of age to the population between 65 years of age to the population between 15 and 64 years of age.	Vulnerability increases as dependency ratio increases	United Nations, Department of Economic and Social Affairs PD (2013); Gerlitz et al. (2014)
		Gender of the operational holder	Percentage of households where the household head/operational holder is female.	Female operational holders are asuumed as more vulnerable than their male counterparts	Hahn et al. (2009); Deressa et al. (2010); Arun (2012); Gerlitz et al. (2017a)
		Lack of educational attainment	Education levels of the members of the household are ranked and the average of minimum and maximum rank values is taken as the educational attainment score of the household. The inverse of the educational attainment score is taken as the proxy for lack of educational attainment.	Educational attainment reduces vulnerability. Lack of educational attainment increases vulnerability	Brenkert and Malone (2005); Lutz et al. (2014); Gerlitz et al. (2017b)
	Livelihood strategies	Proportion of migrant households	Percentage of households with at least one migrant member	Migrant households are considered as more vulnerable than non-migrant households	Black et al. (2011); Viswanathan and Kavi Kumar (2015); Singh et al. (2018)
		Livelihood diversification index	The inverse of (the number of livelihood activities +1) reported by a household. A household that farms, engage in wage labour, and run a small shop will have a Livelihood Diversification Index $LDI = 1/(3+1) = 0.25$	Higher LDI implies less diversification and higher degree of vulnerability	Ellis (1999); Panda et al. (2013)
		Agricultural diversification Index	The inverse of (the number of agricultural activities +1) reported by a household. A household that cultivates paddy, cotton, and have cattle will have a Agricultural Diversification Index $ADI = 1/(3+1) = 0.25$	Higher ADI implies less diversification in agricultural activities and higher degree of vulnerability	Hahn et al. (2009); Gerlitz et al. (2017a)

Table 3.4: Various components and sub-components comprising the Livelihood Vulnerability Index (LVI) used for the rice farmers of Tamil Nadu

Dimension	Major component	Minor component	Explanation of minor components	Functional relationship with vulnerability	Source
	Social networks	Lack of participation in SHGs	Percentage of households who does not participate in SHGs	Lack of participation in SHGs increases vulnerability	Desai and Joshi (2013); O'Reilly et al. (2017); Kumar et al. (2019)
		Lack of assistance from SHGs	Percentage of households who have not received any financial assistance from SHGs	Lack of assistance in SHGs increases vulnerability	Fafchamps and Minten (2002); Okten and Osili (2004)
		Lack of assistance from friends and family	Percentage of households who have not not received any assistance from friends and family	Lack of assistance from friends and family increases vulnerability	Fafchamps and Minten (2002); Okten and Osili (2004)
		Lack of insurance coverage	Percentage of households who does not have any insurance coverage	Lack of insurance coverage increases the vulnerability of operational holders	Fafchamps and Minten (2002); Okten and Osili (2004)
		Lack of assistance from cooperative institutions	Percentage of households who have not received any financial assistance from cooperative institutions	Lack of assistance from cooperative institutions can increase vulnerability	Fafchamps and Minten (2002); Okten and Osili (2004)
		Lack of assistance from government	Percentage of households who have not received any financial assistance from government	Lack of assistance from the government can make the operational holder more vulnerable	Fafchamps and Minten (2002); Okten and Osili (2004)
Sensitivity	Food	Cooking fuel	Cooking fuels used in each household are ranked and the average of minimum and maximum rank values is taken as the fuel score of the household. The inverse of the fuel score is used in the index.	Better cooking fuel provides a hygeinic means of absorption of available food. Better cooking fuel reduces vulnerability and vice versa	Frankenberger and McCaston (1998); Agarwal (2018); Menghwani et al. (2019)
		Lack of women and child care programmes access	Percentage of households without access to women and child care programmes	Access to Women and Child Care programmes reduces vulnerability	World Bank (1986); Webb and Harinarayan (1999); Swaminathan and Bhavani (2013)

Table 3.4: Various components and sub-components comprising the Livelihood Vulnerability Index (LVI) used for the rice farmers of Tamil Nadu

Dimension	Major component	Minor component	Explanation of minor components	Functional relationship with vulnerability	Source
	Water	Drinking water issues	Number of drinking water issues faced by a household	Drinking water issues increase vulnerability	Lindenberg (2002); Brenkert and Malone (2005); Hahn et al. (2009); Swaminathan and Bhavani (2013)
		Drinking water storage index	The inverse of (the number of water storage facilities +1) reported by a household. A household who has underground tank and overhead tank will have a water storage Index $WSI = 1/(2+1) = 0.3$	Higher the water storage index higher will be the vulnerability	Lindenberg (2002); Brenkert and Malone (2005); Hahn et al. (2009); Swaminathan and Bhavani (2013)
		Irrigation water issues	Number of irrigation water issues faced by a household	Irrigation water issues increases vulnerability	Bouman et al. (2007); Bouman (2009); World Bank (2019)
	Health	Proportion of households without toilet	Proportion of households without toilet	Higher the proportion of households without toilet facility, higher will be the vulnerability	Frankenberger and McCaston (1998); O'Reilly and Louis (2014)
		Proximity to medical facility	Hospitals were ranked on the basis of their levels (eg. a primary health centre is assigned a rank 1, a community health centre is ranked 2). The inverse of the sum of scores of such hospitals available in the district in which the household lives (this is based on the awareness of the household regarding various medical and health facilities available in their district) is taken as the hospital proximity index. A person who is aware of a Taluk level hospital, district hospital and a medical college (or super speciality hospital) in their district will have a hospital proximity index $HPI 1/(3+4+5) = 0.083$	Proximity to medical facility reduces vulnerability	De Haan and Zoomers (2005); Obrist et al. (2007); O'Reilly et al. (2017)

Table 3.4: Various components and sub-components comprising the Livelihood Vulnerability Index (LVI) used for the rice farmers of Tamil Nadu

Dimension	**Major component**	**Minor component**	**Explanation of minor components**	**Functional relationship with vulnerability**	**Source**
	Weather sensitivity	Weather sensitivity of rice yield	The R^2 of weather variables	Weather sensitivity increases vulnerability	O'Brien et al. (2004); Varadan and Kumar (2015)
Exposure	Climate variability and extremes	Average variability in maximum temperature (last 6 years)	Average of variability values obtained using EEMD	Higher the variability, higher will be the vulnerability	Hahn et al. (2009); Varadan and Kumar (2015)
		Average variability in minimum temperature (last 6 years)	Average of variability values obtained using EEMD	Higher the variability, higher will be the vulnerability	Hahn et al. (2009); Varadan and Kumar (2015)
		Average variability in rainfall (last 6 years)	Average of variability values obtained using EEMD	Higher the variability, higher will be the vulnerability	Hahn et al. (2009); Varadan and Kumar (2015)
		Number of warm spells in daytime temperature (last 6 years)	Number of warm spells in daytime temperatures obtained using HWMId	Higher the number of warm spells, higher will be the vulnerability	Hahn et al. (2009)
		Number of warm spells in night-time temperature (last 6 years)	Number of warm spells in night-time temperatures obtained using HWMId	Higher the number of warm spells, higher will be the vulnerability	Hahn et al. (2009)
		Average severity of droughts (last 6 years)	Average severity of droughts calculated using SPEI	Higher the severity, higher will be the vulnerability	Hahn et al. (2009)
		Number of extreme rainfall episodes (last 6 years)	Average number of extreme rainfall episodes obtained using the criteria of IMD	Higher the number of extreme rainfall episodes, higher will be the vulnerability	Hahn et al. (2009)

Table 3.5: Various components and sub-components comprising the Adaptive Capacity dimension in the Livelihood Vulnerability Index (LVI-IPCC)

Dimension	Major component	Minor component	Explanation of minor components	Functional relationship with vulnerability	Source
Adaptive Capacity	Socio demographic profile	Ratio of working age group to dependents	Ratio of the population between 15 and 64 years of age to the sum of the population under 15 and over 65 years of age.	Vulnerability decreases as the ratio of working age group increases	United Nations, Department of Economic and Social Affairs PD (2013); Gerlitz et al. (2014)
		Gender of the operational holder	Percentage of male operational holders	Male operational holders are assumed as less vulnerable than their female counterparts	Hahn et al. (2009); Deressa et al. (2010); Arun (2012); Gerlitz et al. (2017a)
		Educational attainment	Education levels of the members of the household are ranked and the average of minimum and maximum rank values is taken as the educational attainment score of the household.	Educational attainment reduces vulnerability	Brenkert and Malone (2005); Lutz et al. (2014); Gerlitz et al. (2017b)
	Livelihood strategies	Proportion of households without migrant members	Percentage of households without a migrant member	Migrant households are considered as more vulnerable than non-migrant households	Black et al. (2011); Viswanathan and Kavi Kumar (2015); Singh et al. (2018)
		Average number of livelihood options	Average of the number of livelihood activities reported by a household	More diversification implies lesser degree of vulnerability	Ellis (1999); Panda et al. (2013)
		Average number of agricultural activities engaged	Average of the number of agricultural activities engaged reported by a household	Higher the number of agricultural activities implies lesser degree of vulnerability	Hahn et al. (2009); Gerlitz et al. (2017a)
	Social networks	Participation in SHGs	Percentage of households who participate in SHGs	Participation in SHGs reduces vulnerability	Desai and Joshi (2013); O'Reilly et al. (2017); Kumar et al. (2019)
		Assistance from SHGs	Percentage of households who have received any financial assistance from SHGs	Assistances from SHGs reduces vulnerability	Fafchamps and Minten (2002); Okten and Osili (2004)

Table 3.5: Various components and sub-components comprising the Adaptive Capacity dimension in the Livelihood Vulnerability Index (LVI-IPCC)

Dimension	Major component	Minor component	Explanation of minor components	Functional relationship with vulnerability	Source
		Assistance from friends and family	Percentage of households who have received any assistance from friends and family	Assistance from friends and family reduces vulnerability	Fafchamps and Minten (2002); Okten and Osili (2004)
		Insurance coverage	Percentage of households who have insurance coverage	Insurance coverage reduces the vulnerability of operational holders	Fafchamps and Minten (2002); Okten and Osili (2004)
		Assistance from cooperative institutions	Percentage of households who have received any financial assistance from cooperative institutions	Assistance from cooperative institutions can reduce vulnerability	Fafchamps and Minten (2002); Okten and Osili (2004)
		Assistance from government	Percentage of households who have received any financial assistance from government	Assistance from the government can make the operational holder less vulnerable	Fafchamps and Minten (2002); Okten and Osili (2004)

identified using the method proposed by Lindeman et al. (1980). The share of variation in rice yield explained by the weather variables together was calculated and kept as a proxy for the weather sensitivity of rice yield. This computation was performed using R package 'relaimpo v2.2-3' (Grömping, 2006).

3.2.2.6 Vulnerability Analysis

To measure the vulnerability, we used the method adopted by Hahn et al. (2009) to calculate the Livelihood Vulnerability Index. It is a composite index consisting of seven major components designed to assess the extent of vulnerability to livelihood risks resulting from climate change. However, in our analysis, there are 3 dimensions, 8 major components, and 27 indicators. The major components used in the present study are; Socio-Demographic Profile, Livelihood Strategies, Social Networks, Health, Food, Water, Weather Sensitivity and Climate Variability and Extreme Events. Each of these components consist of several minor components that are prepared on the basis of extensive literature review and field survey. Table 3.4 provide a detailed overview of this framework of analysis. The table also provides an explanation of how each sub-component was quantified and their functional relation with vulnerability.

Following Hahn et al. (2009), the present study also uses the balanced weighted average scheme (Sullivan, 2002). In this approach weights are assigned in such a way that each of the eight components contributes equally to the overall vulnerability of the households. The components measured in various scales are standardized using Eq 3.7.

$$Sd_i = \frac{actual_i - min_i}{max_i - min_i} \tag{3.7}$$

where sd_i is the standardised value of the i^th component, $actual_i$ refers to the actual value of the i^th component, min_i represents the minimum value of the i^th component, and max_i refers to the maximum value of the i^th component. We have also adopted some of the assumptions in Hahn et al. (2009) underlying the components such as LDI, ADI etc. The LDI assumes that a person engaged in more than one livelihood activity is less vulnerable and vice versa. The standardised values of the sub-components were averaged using Eq. 3.8

$$M_d = \frac{\Sigma_{i=1}^{n} Sd_i}{n} \tag{3.8}$$

where M_d denotes the major component, $\Sigma_{i=1}^{n} Sd_i$ refers to the sum of the i sub-components, and n is the number of sub-components in the major component under consideration. The values for the eight major-components were averaged using Eq. 3.9.

$$LVI_d = \frac{\Sigma_{i=1}^{8} W_{Mi} M_{di}}{\Sigma_{i=1}^{8} W_{Mi}} \tag{3.9}$$

where LVI_d , the Livelihood Vulnerability Index for district d (if the analysis is performed for districts), equals the weighted average of the eight major components. The weights of each of the major component, W_{Mi}, are determined by the number of sub-components that constitute each major component and are included to ensure that all sub-components contribute equally to the overall LVI. We performed three sets of vulnerability assessments in this study. The first assessment is performed across the seven districts of the Cauvery Delta region, the second analysis was performed across the three major cultivating seasons to see the differential vulnerability across those who cultivate in different seasons, and the third one was performed for each of the farmer category. In the case of the farmer category, the index here includes only the sensitivity and adaptive capacity parameters of the index calculating metric.

We further calculated the LVI-IPCC developed by Hahn et al. (2009) since it incorporates the IPCC definition of vulnerability. The LVI-IPCC, categorises the 8 major components in to three dimensions of vulnerability. The dimension 'exposure' covers the climate variability and extremes occurred in the study region in the past 6 years. The 'sensitivity' dimension combines the components food, water, health, and weather sensitivity. The component 'adaptive capacity' includes the components socio-demographic profile, livelihood strategies and social networks. Instead of merging the major components into the LVI in a single step, they are first combined according to the above mentioned categorization scheme using the equation 3.10

$$Dim_d = \frac{\Sigma_{i=1}^{n} W_{Mi} M_{di}}{\Sigma_{i=1}^{n} W_{Mi}} \tag{3.10}$$

where Dim_d is the IPCC-defined contributing dimension (exposure, sensitivity, or adaptive capacity) for district/season d, M_{di} represents the major components for district d indexed by i, W_{Mi} is the weight of each major component, and n is the number of major components in each contributing dimension. Once exposure, sensitivity, and adaptive capacity were computed, the three contributing dimensions of vulnerability were combined using the following equation 3.11

$$LVI\ IPCC_d = (E_d - A_d) * S_d \tag{3.11}$$

where $LVI\ IPCC_d$ is the LVI for district/season d expressed using the IPCC vulnerability framework, E is the exposure score for district/season d, A is the adaptive capacity score for district d, and S is the calculated sensitivity score for district d. The LVI–IPCC score ranges between -1 (least vulnerable) to 1 (most vulnerable). In order to calculate the LVI-IPCC, we modified the way of incorporating the various component indicators in the index score. This is shown in the table 3.5.

3.3 Limitations

- The time frame and the resources available for the researcher limited the possibility of field surveys at regular intervals in the study area to develop a panel data set to measure the adaptive capacity of rice farmers in the study area.
- Index values used in the study are considered as relative values to be compared within the study sample only as they are standardized using the maximum and minimum values of the study population.
- The usage of indicators and indices oversimplify the complex reality of vulnerability and there is inherently no straightforward way to validate indices comprised of disparate indicators (Vincent, 2007; Hahn et al., 2009).
- Since we selected only one village from each of the seven study districts, this may not provide an adequate representation of the population characteristics of the study district.

Chapter 4

Climate variability and extremes over Tamil Nadu region

Global warming and the resulting climate change necessitates a thorough examination of the patterns in temperature and rainfall as a prerequisite to the assessment of the vulnerability of natural and human systems. Accordingly, the present chapter is constructed to serve as a statistical documentation of the variability and extremes in temperature and rainfall over the study area. The first section of the chapter provides a brief review of the spatio-temporal patterns of the climate variability and extremes over the Indian region. The second section includes a discussion section which compares the results of the present study with the results of the existing studies of national and international importance to arrive at a comprehensive understanding of the climate variability and extremes over Tamil Nadu region. We used various statistical methods and tests which are provided in detail in the Chapter 3. The third section of the study summarizes the findings of the present chapter.

4.1 Spatio-temporal patterns of Climate Variability and Extremes over Tamil Nadu

The study examined the patterns in the variability as well as extremes in temperature and rainfall over Tamil Nadu region using the temperature and rainfall data sets for an extended period 1951-2016 although the period of analysis in the present study is 1985-2016. The EEMD analysis decomposed the data in to various cycles and the residual trend and the analysis employing SPEI and HWMID revealed the patterns of extreme events in rainfall and temperature respectively.

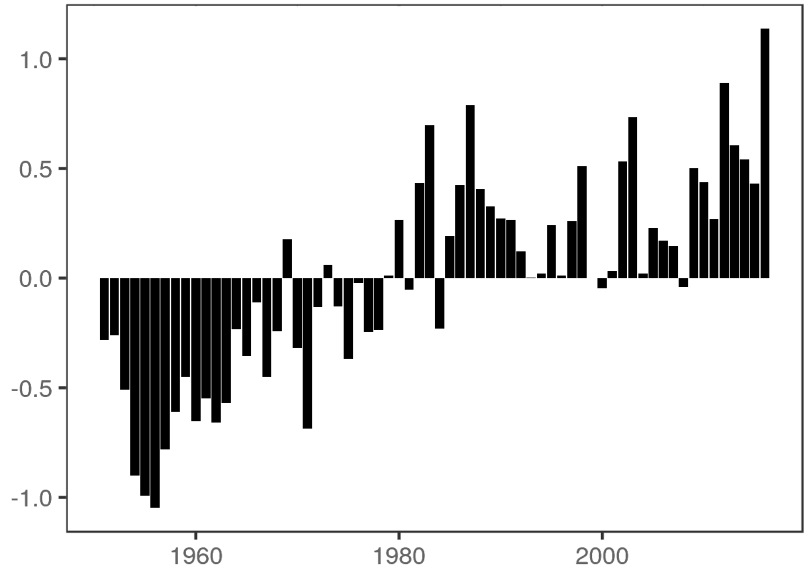


Figure 4.1: The anomaly in maximum temperature over Tamil Nadu from 1951 to 2016

4.1.1 Variability Maximum Temperature

Figure 4.1 illustrates the anomaly in the annual maximum temperature over Tamil Nadu during 1951-2016 period. As seen in the figure, the change in the maximum temperature anomaly has been a secular one over Tamil Nadu during 1951-2016. A distinct shift can be seen since the beginning of 1980s with respect to the climatological mean. Most of the years after 1980,are characterised with positive anomalies in the maximum temperature, in contrast to the period prior to 1980. Figure 4.2 shows the intrinsic mode functions c_j and the trend component (residue) r_n for the maximum temperature anomaly obtained by performing the EEMD analysis. Each IMF represents variation in the signal at a specific time scale. The frequency and amplitude of the rainfall signal at various time scales influence the overall characteristics of the time series. They are expressed in terms of the variance contribution rate (Bai et al., 2015) (Table 4.1). As seen from Table 4.1, for the maximum temperature there a statistically significant ($p < 0.01$) increasing trend is observed for the whole period, even though there is a tendency to flatten the curve in the second half (The last panel of the 4.2). The trend component explains 74.46% of the total variation in the annual temperature anomaly series. The first three IMFs, IMF 1, IMF 2 and IMF 3 have a periodicity of quasi 4 years, quasi 5 years and quasi 7 years respectively. These inter-annual components together contribute nearly 18% of the total variability in maximum temperature. The 4$^{\text{th}}$ and 5$^{\text{th}}$ IMFs are the inter-decadal cycles and these modes explain around 7%

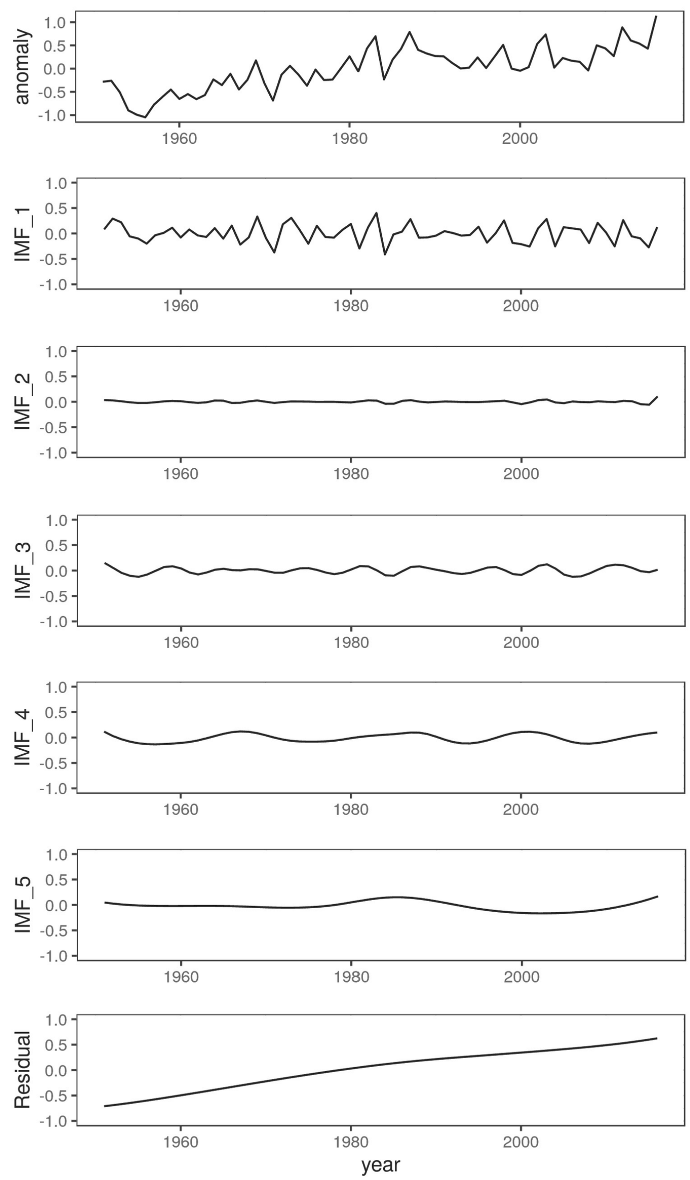


Figure 4.2: The IMF and Trend components of the anomaly in maximum temperature over Tamil Nadu from 1951 to 2016

Table 4.1: Variance contribution rates of various components towards anomaly in maximum temperature

Region	IMF Components	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	Residual
Tamil Nadu	Period (year)	4	5	7	17	33	
	VCR (%)	16.05	0.29	2.11	3.19	3.89	74.46

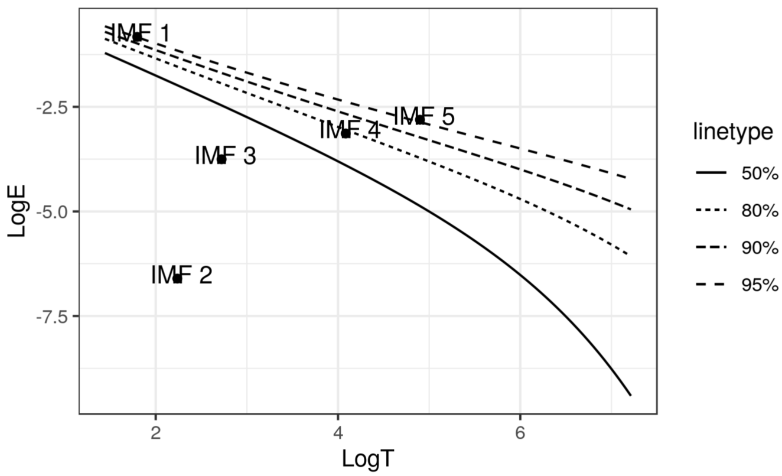


Figure 4.3: Statistical significance of the IMFs of the anomaly in maximum temperature

to the anomaly series. The statistical significance of each IMF, tested following the equations A.16 and A.17 (Wu and Huang, 2004), is shown in Figure 4.3. It has been observed that the IMF 5 is significant at 95% and the IMF 1 is located between 90% and 95% significance levels. Figure 4.4 provides the reconstructed inter-annual and inter-decadal variability (as adopted from Bai et al. (2015)) of maximum temperature along with the original anomaly series and the trend component. The inter-annual cycle is constructed using the first three IMFs and the trend whereas the inter-decadal cycle comprises the last two IMFs and the trend. Figure 4.4 shows that the significant variabilities in the maximum temperature anomaly are better explained by the inter-annual cycle, although some of the notable departures from the mean signal corresponds to the reconstructed inter-decadal variability as well. It is clear that rather than the inter-annual cycles, the inter-decadal cycles have become increasingly anomalous since 1980s. We further performed a similar analysis at regional level over Tamil Nadu. Figure 4.5 shows the trend in temperature anomaly over the agro-climatic zones of Tamil Nadu. As we can observe from the figure, Tamil Nadu has been a homogeneous region in terms of the anomaly in maximum temperature. All agro-climatic zones experienced a slight flattening of the trend line in in the second half of

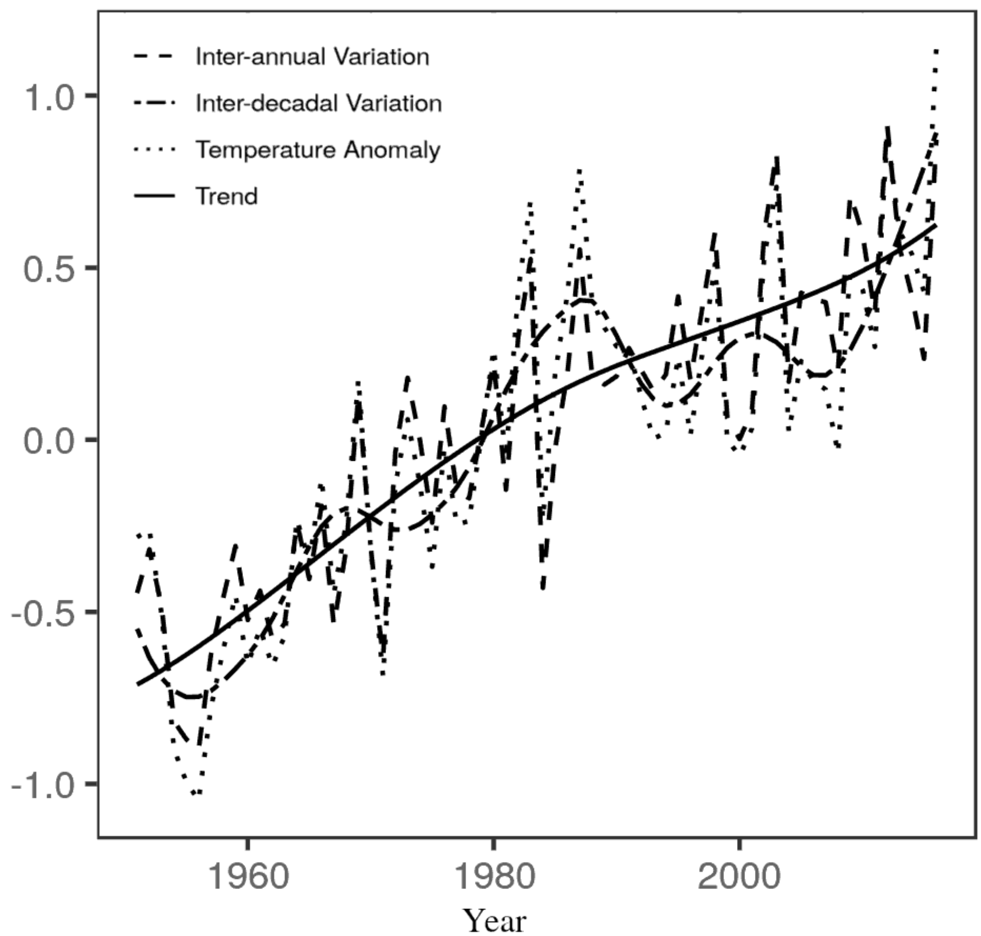


Figure 4.4: The trend, inter-annual variation and inter-decadal variation of anomaly in maximum temperature over Tamil Nadu from 1951-2016

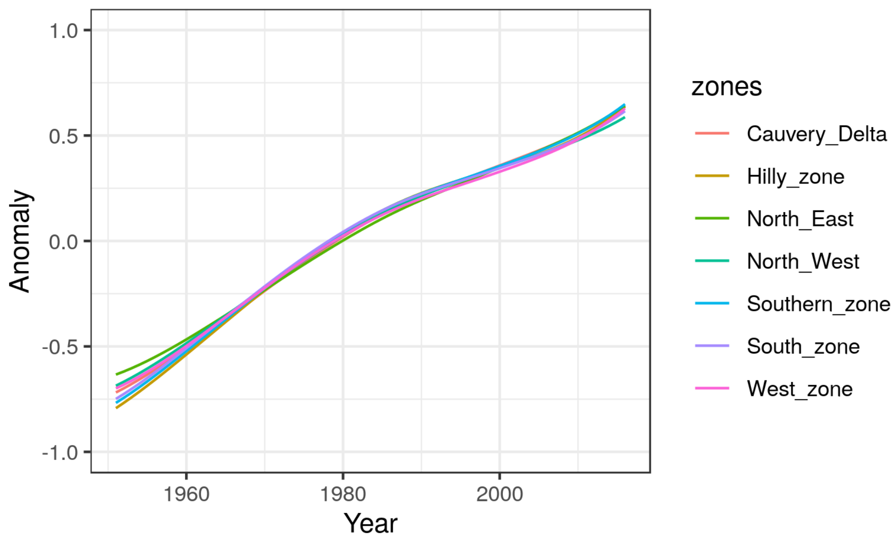
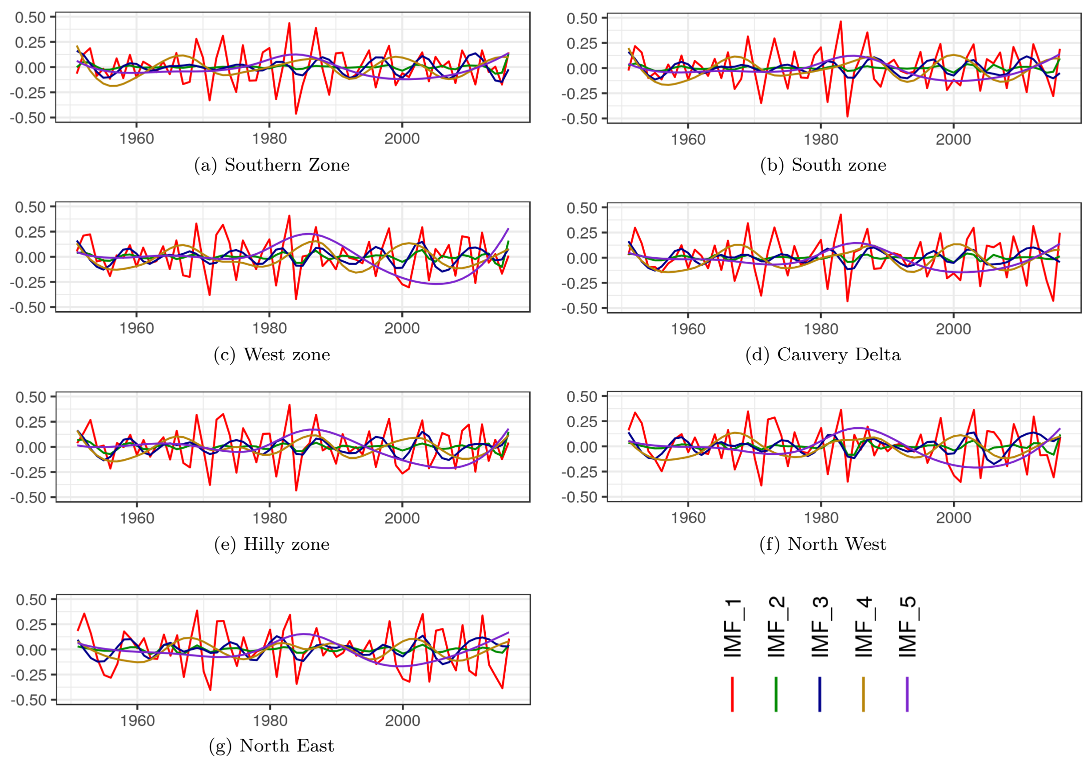


Figure 4.5: The trend of anomaly in maximum temperature over the agro-climatic zones of Tamil Nadu from 1951-2016

the observation period.

Figure 4.6 shows the variability of anomaly in maximum temperature over the agro-climatic zones of Tamil Nadu. In general the inter-annual variability can be seen as reducing after 1980s and the inter-decadal cycle is seen as amplifying during this period. The figure shows that the pattern of variability is more or less similar for all agroclimatic zones except for Cauvery Delta and North East zone. These zones on the Coromandel coast witnessed an increase in the variability in maximum temperature in the latter half, particularly after 2000. Table 4.2 shows the regional pattern of variance contribution rates of relevant IMFs and the trend component in determining the general characteristics of the anomaly in maximum temperature across various agro-climatic zones of Tamil Nadu. The dominant trend component is statistically highly significant. On an average, the trend component explains nearly 70% of the general characteristics of the maximum temperature implying a consistent increase of the same over Tamil Nadu region. The inter-annual cycles over Cauvery Delta and the North East zones as well as the inter-decadal cycles over West, Hilly and North West zones have amplified in the latter half of the study period and the influences of these components have been observed as statistically significant.



(a) Southern Zone
(b) South zone
(c) West zone
(d) Cauvery Delta
(e) Hilly zone
(f) North West
(g) North East

Figure 4.6: The variability of anomaly in maximum temperature over the agro-climatic zones of Tamil Nadu between 1951 and 2016

Table 4.2: Variance contribution rates of various components towards the anomaly in maximum temperature

Region	Components	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	Residual
Southern zone	Period (year)	3	5	7	17	34	
	VCR (%)	13.76	0.27	2.19	3.59	2.42	77.77***
South zone	Period (year)	4	6	7	17	34	
	VCR (%)	16.05	0.24	1.88	3.98	2.41	75.44***
West Zone	Period (year)	4	5	7	17	31	
	VCR (%)	15.64	0.60	2.40	3.72	9.04**	68.59***
Cauvery Delta	Period (year)	4	5	7	17	34	
	VCR (%)	17.24*	0.18	1.78	3.73	3.03	74.05***
Hilly zone	Period (year)	4	5	8	15	24	
	VCR (%)	15.09	0.53	2.14	2.70	4.79**	74.76***
North West	Period (year)	4	6	8	17	31	
	VCR (%)	17.84	0.55	2.79	3.27	5.81**	69.74***
North East	Period (year)	4	5	7	14	34	
	VCR (%)	21.11*	0.25	2.47	2.52	3.92*	69.74***

*** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

4.1.2 Heat Waves / Extremes in Maximum Temperature

The study used the Heat-wave magnitude index daily (HWMId) (Russo et al., 2015) to examine the characteristics of heat waves over Tamil Nadu region, India. According to this method, a heat wave, is a situation in which the maximum temperature exceeds the daily threshold (Equation 3.3) for the reference period (1981-2010) for at least three consecutive days. The magnitude of the heatwave is estimated by equation 3.4.

Figure 4.7 shows that there has been a marked increase in the frequency, magnitude and duration over heat waves since 1951. Particularly, the period after 1980 witnessed more frequent heat waves over the region. While the heat waves between 1980 and 2000 were frequent and more intense in general when compared to the periods before and after that, the period after 2000 witnessed two of the most damaging heat waves in the recent history of the region. These droughts of 2003 and 2016 lasted 23 and 30 days respectively and had magnitude values above 30. Table 4.3 shows a highly significant ($\alpha = 0.01$) increasing trend over all agro-climatic zones of the region.

The increase in the frequency of heat waves has been observed over most parts of Tamil Nadu. Similarly, a general intensification in the heat waves has been observed over all agro-climatic zones of the region. However, as seen in the figure 4.8 (panels a and b), the

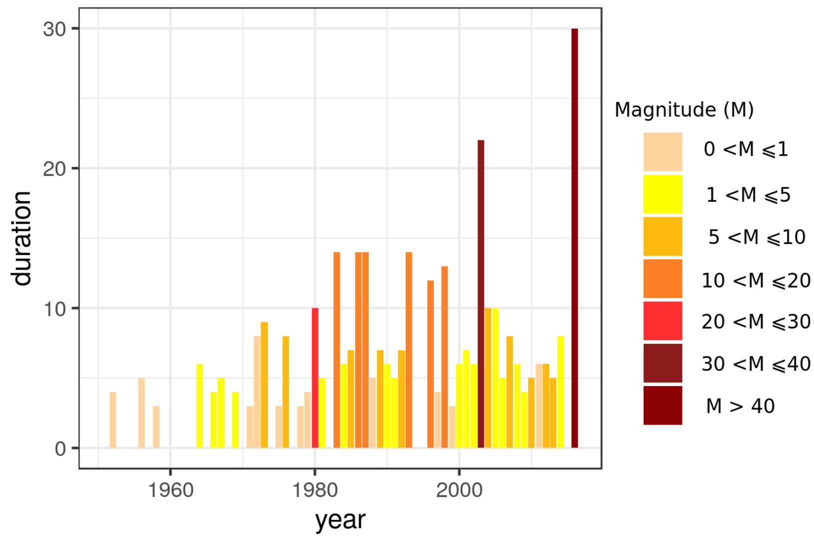


Figure 4.7: Heat waves over Tamil Nadu - Frequency, magnitude and duration between 1951 and 2016

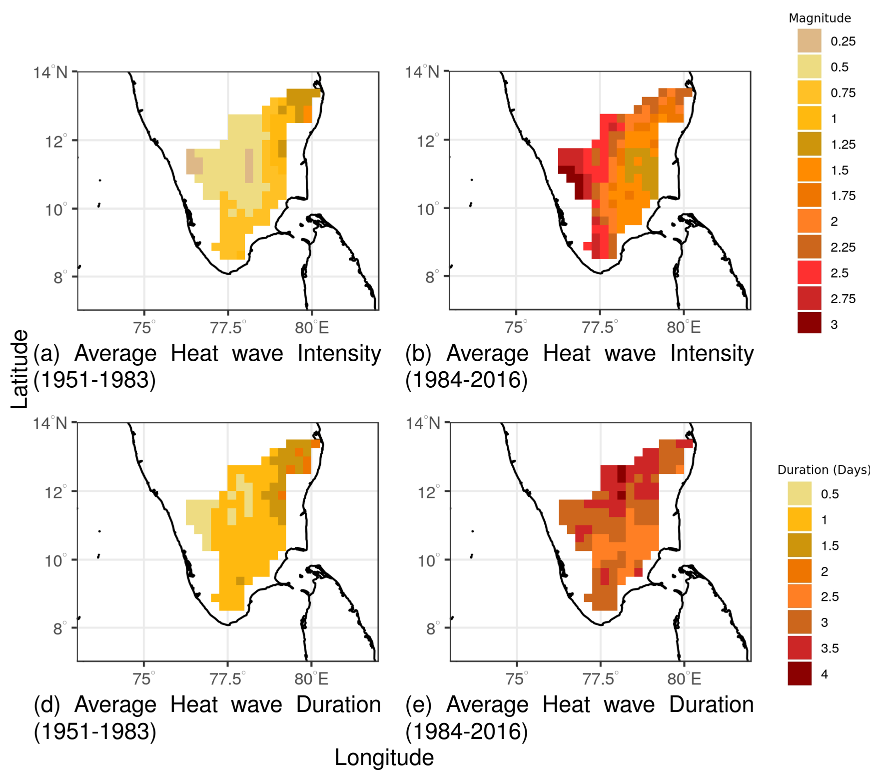


Figure 4.8: Heat waves over Tamil Nadu - Frequency, magnitude and duration between 1951 and 2016

Table 4.3: Results of the statistical tests for changes in heat waves during 1951-2016

Region	Test Statistic	Critical Values		
		Area affected	Magnitude	Duration
Southern zone	τ	0.411***	0.362***	0.351***
	D	0.455***	0.455***	0.394***
South zone	τ	0.379***	0.380***	0.394***
	D	0.485***	0.515***	0.485***
West Zone	τ	0.339***	0.319***	0.332***
	D	0.485***	0.455***	0.455***
Cauvery Delta	τ	0.319***	0.283***	0.296***
	D	0.455***	0.424***	0.424***
Hilly zone	τ	0.327***	0.312***	0.306***
	D	0.424***	0.424***	0.424***
North West	τ	0.369***	0.335***	0.351***
	D	0.545***	0.515***	0.485***
North East	τ	0.264***	0.285**	0.314***
	D	0.364**	0.455***	0.455***
Tamil Nadu	τ	0.381***	0.373***	0.379***
	D	0.515***	0.515***	0.545***

τ denotes Kendall's Tau. D denotes the Kolmogorov-Smirnov (K-S) test statistic. ***Statistically significant trends at the 1% significance level. **Statistically significant trends at the 5% significance level. *Statistically significant trends at the 10% significance level.

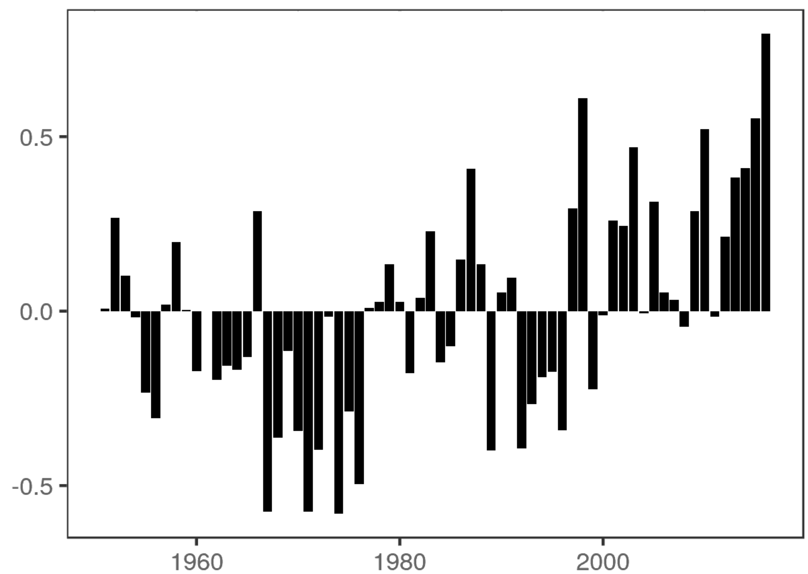


Figure 4.9: The anomaly in minimum temperature over Tamil Nadu from 1951 to 2016

western parts of Tamil Nadu experienced the more intense heat waves in the second half of the study period. It is also worth notable that the mean heat wave intensity for the period 1951-84 was the smallest over these regions. Similarly, the panels c and d of the figure 4.8 show an increase in the mean duration of the heat waves during 1984-2016. While all the regions experienced an increase in the duration, it was particularly higher in the grid boxes located in the North West, north-east and some boxes in the West as well as the South zones. The K-S test statistic suggests that there has been a statistically significant increase ($\alpha = 0.01$) in the share of higher values of heat wave magnitude and duration in the latter half of the study period.

4.1.3 Variability in Minimum Temperature

Unlike the case of maximum temperature, one cannot find a secular change in the minimum temperature anomaly during 1951-2016. However, the figure 4.9 shows that there has been a substantial increase in the frequency and magnitude of positive anomalies since 1980, particularly since 1996. The minimum temperature anomaly time series was decomposed using EEMD method and the relative contribution as well as the statistical significance of each component was tested.

Figure 4.10 shows the IMF and the trend components of the minimum temperature anomaly time series. The minimum temperature anomaly has a statistically significant

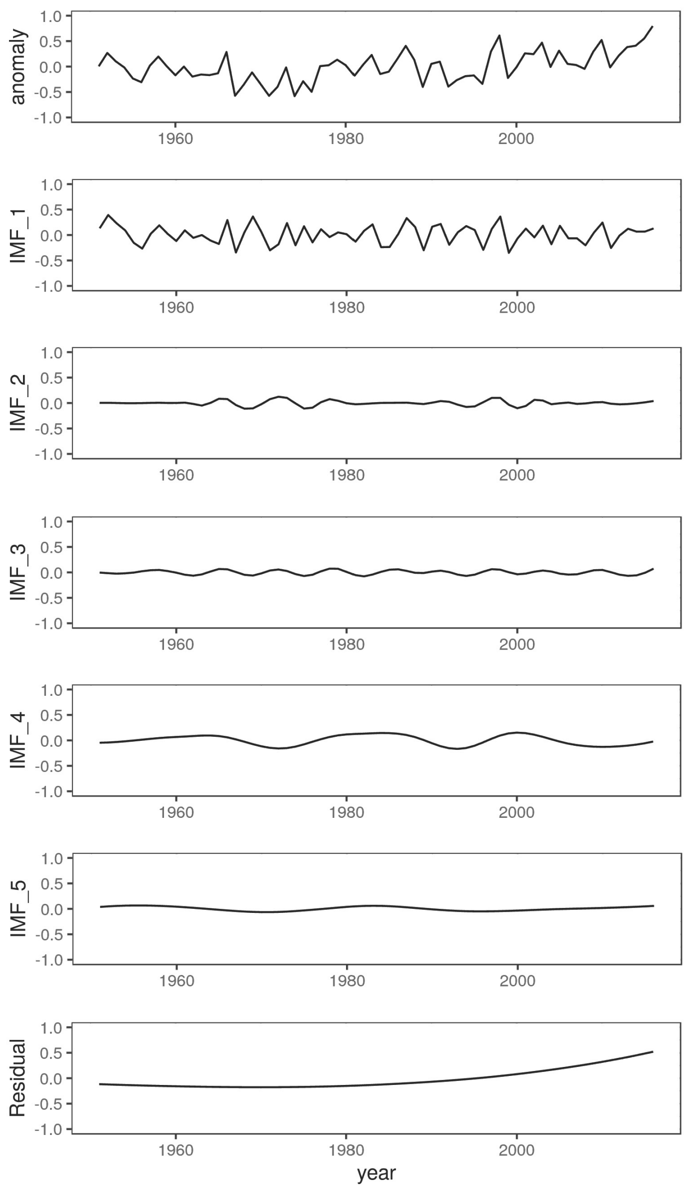


Figure 4.10: The IMF and Trend components of the anomaly in minimum temperature over Tamil Nadu from 1951 to 2016

Table 4.4: Variance contribution rates of various components towards anomaly in minimum temperature

Region	IMF Components	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	Residual
Tamil Nadu	Period (year)	4	6	7	21	32	
	VCR (%)	39.43	2.79	2.00	10.76	1.88	43.13

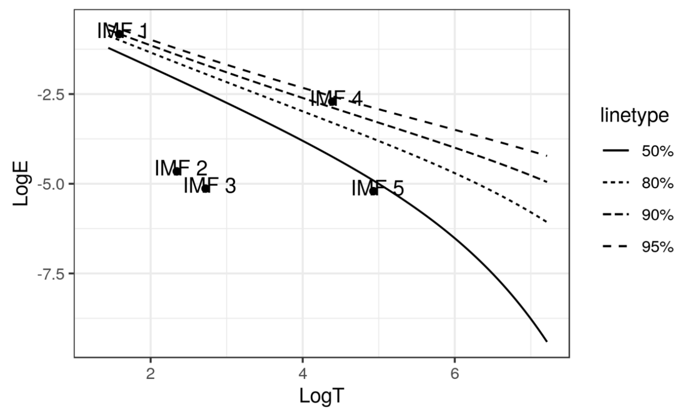


Figure 4.11: Statistical significance of the IMFs of the anomaly in minimum temperature

($\alpha = 0.05$) monotonic nonlinear trend which moves upward only after 1980. Table 4.4 shows the contribution of each components displayed in the figure 4.10 towards the actual anomaly time series. The trend component explains 43.13% of the variation in minimum temperature anomaly. This is relatively less when compared to the contribution of the trend component towards the maximum temperature. Further, the inter-annual variability, which comprises of the first three IMFs explains nearly 44% of the variation in minimum temperature while the inter-decadal cycles, IMFs 4 and 5 contributes about 12.5% of the variation on the original time series. The periodicity of the IMFs of both maximum and minimum temperatures does not differ considerably. Figure 4.11 shows the statistical significance of various components of the minimum temperature anomaly time series. Apart from the trend, the significance test identified IMF 1 ($\alpha = 0.1$) and IMF 4 ($\alpha = 0.1$) as significant. Figure 4.12 illustrates the reconstructed trend, inter-annual variation and inter-decadal variation of the anomaly in minimum temperature over Tamil Nadu from 1951-2016. Compared to the maximum temperature, the inter-decadal signal has considerable influence on the overall characteristics of the minimum temperature. Many significant departures from the mean are not completely in line with the inter-annual cycle and hence the major characteristics of the time evolution of minimum temperature over Tamil Nadu cannot be represented well, solely in terms of the the inter-annual variability. On the other

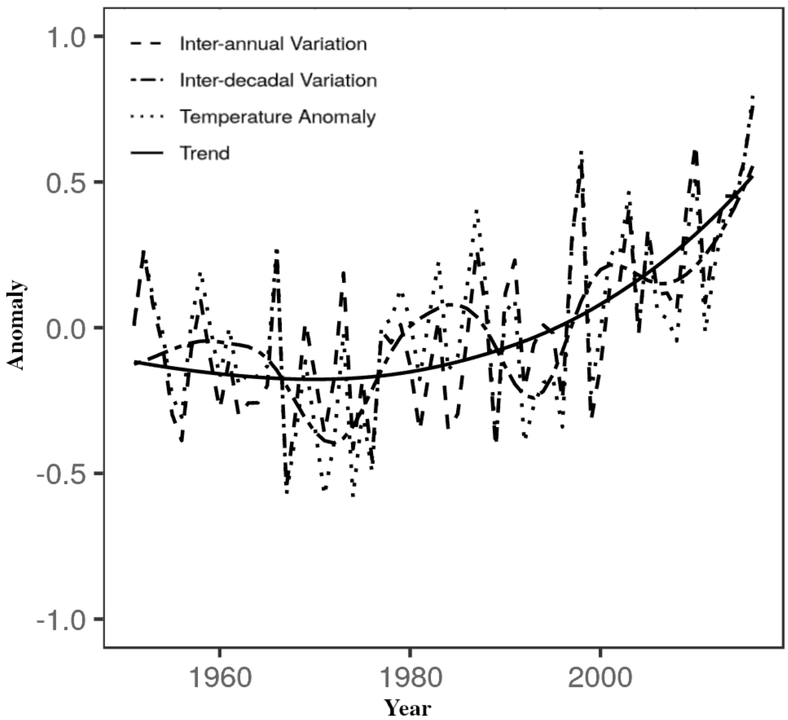


Figure 4.12: The trend, inter-annual variation and inter-decadal variation of anomaly in minimum temperature over Tamil Nadu from 1951-2016

hand, the influence of a strong decadal signal is evident from Figure 4.12 throughout the period. Here also, as the trend gets strengthened, the other cycles tend to converge with the trend component. On a regional scale the trend lines of minimum temperature does not synchronize as in the case of maximum temperature. Figure 4.13 therefore suggests that the minimum temperature over Tamil Nadu is not that homogenous at an intra-regional level, (when compared with the case of maximum temperature), despite the observed increasing trend in the recent decades over all agro-climatic zones.

Figure 4.14 shows the variability of anomaly in minimum temperature over the agro-climatic zones of Tamil Nadu. Unlike the maximum temperature, the variability in minimum temperature has been higher even before 1980s, and the inter-annual cycles can be seen as amplifying between 1980 and 2000. In the case of minimum temperature as well, while there is a general tendency of various cycles to converge in the recent years, the pattern of variability is not the same across various agro-climatic zones. The north-east zone has experienced higher variability when compared with other agro-climatic zones. While the converging tendency of various modes in the recent years is more visible over the South, Southern and the Delta zones, the inter-annual modes over the Hilly zone and

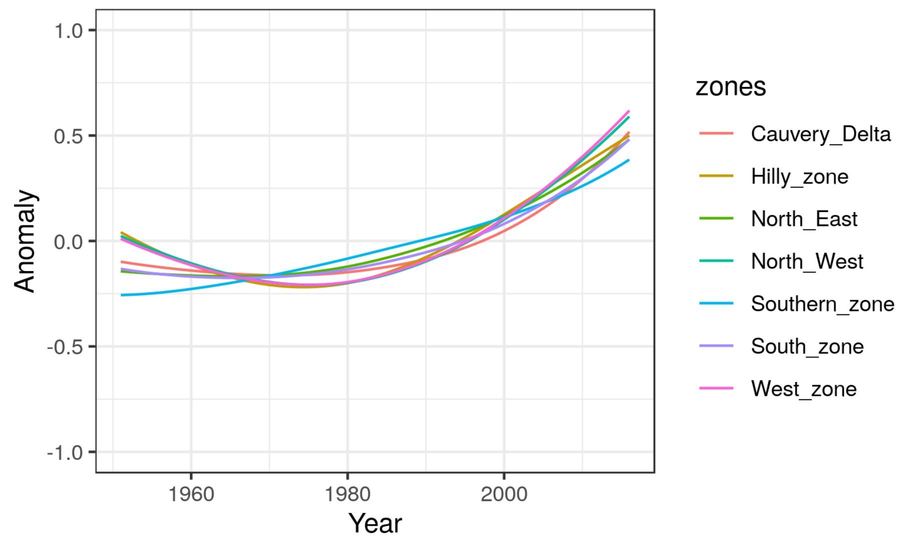


Figure 4.13: The trend of anomaly in minimum temperature over the agro-climatic zones of Tamil Nadu from 1951-2016

the West zone
show the tendency to amplify in the recent years as well. Table 4.5 shows the relative contributions of each components in explaining the general characteristics of the minimum temperature anomaly over various agro-climatic zones of Tamil Nadu as well as their level of statistical significance. As seen in the table, the trend component contributed between 33% to 49% of the variations in the original time series. The inter-annual mode IMF 1 explains a substantial share of the general characteristics of the anomaly in minimum temperature. Over the north-east, Cauvery Delta and Southern zones, this mode is dominant than the trend component. The first IMFs over the north-east, north-west, Hilly zone, Cauvery Delta and the West zone were observed as statistically significant ($\alpha = 0.1$). Another significant component of the minimum temperature anomaly is the fourth IMF, the inter-decadal cycle with a periodicity of approximately 20 years. The contribution of this cycle ranged between 9% and 14%.

4.1.4 Warm Nights / Extremes in Minimum Temperature

In order to investigate the extremes in night time temperature, the analysis using HWMId method was applied on the minimum temperature data over Tamil Nadu. Similar to the case of heat waves, this method captures the warm spells having the highest magnitudes in every year. Figure 4.15 shows the frequency, magnitude and duration of warm nights over

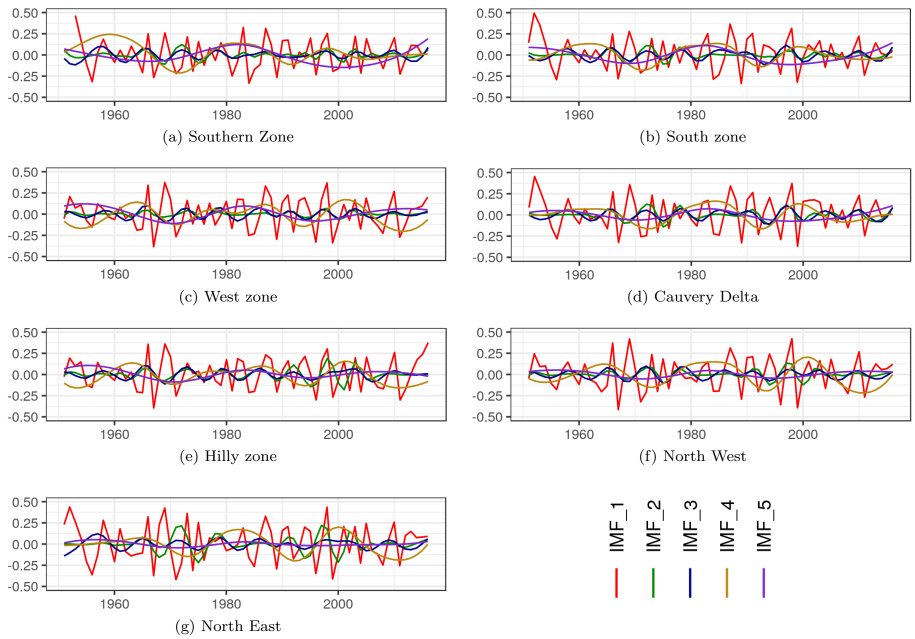


Figure 4.14: The variability of anomaly in minimum temperature over the agro-climatic zones of Tamil Nadu between 1951 and 2016

Table 4.5: Variance contribution rates of various components towards anomaly in minimum temperature

Region	IMF Components	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	Residual
Southern zone	period (years)	4	5	7	22	34	
	VCR (%)	38.21	2.07	2.50	13.78**	7.75*	35.69***
South zone	period (years)	4	6	7	21	33	
	VCR (%)	38.89	2.07	3.39	9.38*	6.54	39.73***
West Zone	period (years)	4	6	7	19	32	
	VCR (%)	32.41*	0.62	1.96	10.98**	4.59	49.44***
Cauvery Delta	period (years)	4	6	7	21	30	
	VCR (%)	42.56*	3.66	3.04	9.28	2.85	38.61***
Hilly zone	period (years)	4	6	7	21	27	
	VCR (%)	34.86*	3.88	2.55	9.70*	2.68	46.33***
North West	period (years)	4	6	7	20	32	
	VCR (%)	34.70*	2.15	2.19	13.82**	1.08	46.07***
North East	period (years)	4	7	8	22	31	
	VCR (%)	44.78*	7.20	2.61	11.58*	0.58	33.25***

*** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

Tamil Nadu region.

The results from the below figure suggests that the Tamil Nadu region has experienced warm nights of various magnitudes throughout the period of study. The period after 1980 experienced substantial increase in their frequency of warmer nights (Figure 4.15). The years 1980, 1998, 2004 and 2016 witnessed warm nights of relatively higher magnitudes. The extreme nigh time temperature incident of 2016 lasted more than a month and had a magnitude greater than 30. The Hilly zone, the West zone, the north-east zone and the north-west zone experienced statistically significant increasing trends in the area affected, intensity and duration of night time extreme temperatures.

Figure 4.16 shows the spatial patterns of change in the magnitude and duration of warm nights over Tamil Nadu. The panels a and b show the change in the mean intensity and the panels c and d show the change in the duration. Along with a general intensification over the whole region, the 30 year mean of the extreme night time temperature increased substantially over the West and north-west zones of Tamil Nadu. These regions witnessed a five times increase in the magnitude of warm nights, the change in magnitude was the least over the grid boxes located in the Southern zone of Tamil Nadu. The K-S test (Table 4.6) also suggests a statistically significant increase in the fraction of higher values of magnitude in the West zone, the Hilly zone, the north-west and the north-east zones. This pattern is more or less similar in the case of duration also. The western parts of Tamil Nadu, the West zone, the north-west zone, and some parts of the north-east zone witnessed five times higher duration values in the second half. The K-S test of duration values also suggest statistically highly significant (4.6) change in the second half over these regions.

4.1.5 Variability in rainfall

Figure 4.17 shows the anomaly in rainfall over Tamil Nadu. As seen in the figure, the yearly precipitation over Tamil Nadu does not involve substantial variations in general. However, considerably larger anomalies are seen around 1980, and after 2000. In order to understand the observed variability in detail, the annual precipitation anomaly time series for the period 1951-2016 was decomposed using the EEMD method. Figure 4.18 shows the various components of rainfall anomaly over Tamil Nadu. The figure indicates that, the precipitation anomaly over Tamil Nadu consists of five IMF components and a trend component. The IMF 1 has a periodicity of nearly 4 years, while the IMFs 2 and 3 spans approximately 6 and 8 years respectively (Table 4.7). These inter-annual modes explain nearly 85% of the total variation in the original time series. On the other hand, the inter-

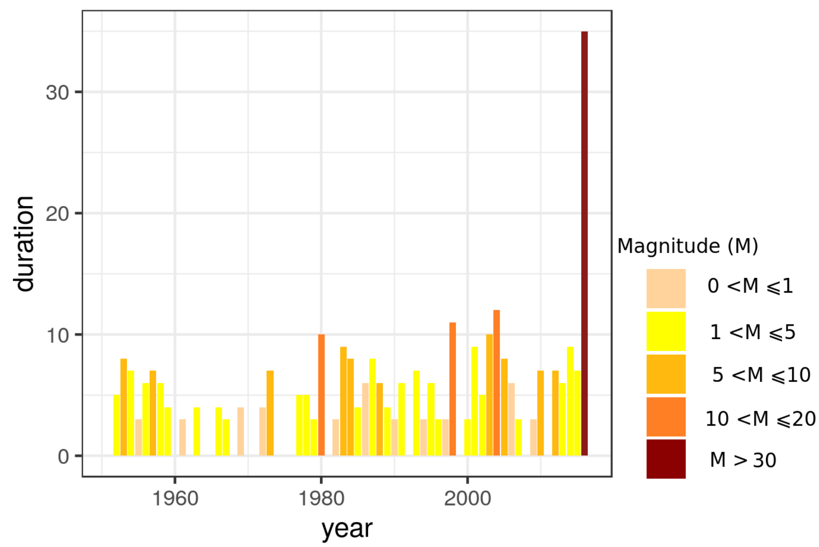


Figure 4.15: Warm nights over Tamil Nadu - frequency, magnitude and duration between 1951 and 2016

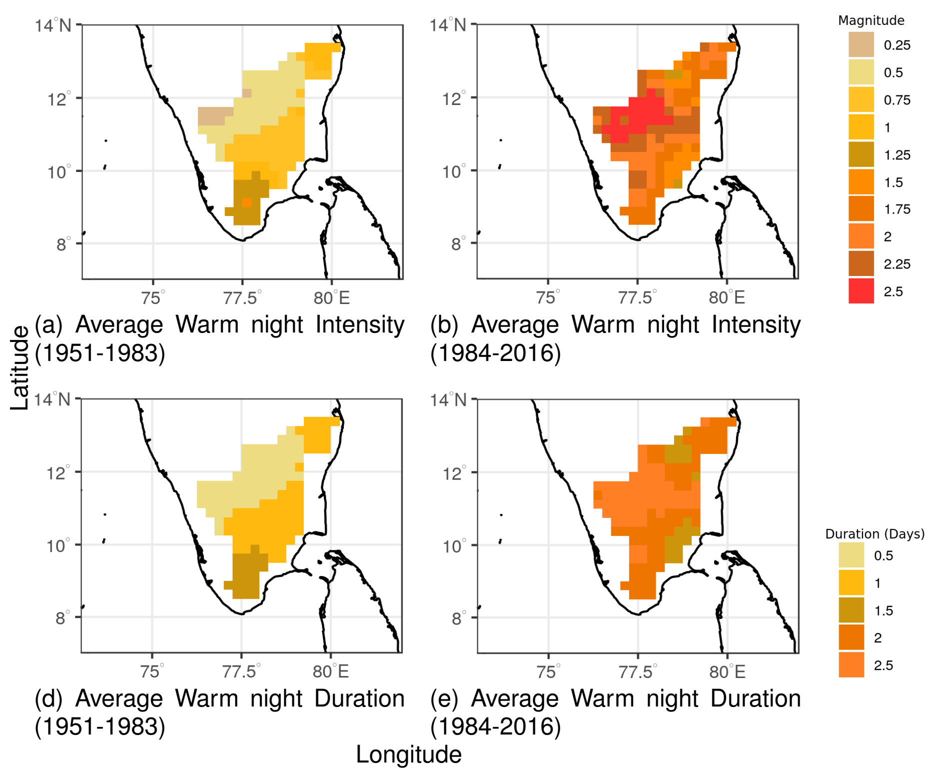


Figure 4.16: Warm nights over Tamil Nadu - frequency, magnitude and duration between 1951 and 2016

Table 4.6: Results of the statistical tests for changes in warm nights during 1951-2016

Region	Test Statistic	Critical Values		
		Area affected	Magnitude	Duration
Southern zone	τ	-0.0823	0.0111	0.00433
	D	0.0303	0.0606	0.0909
South zone	τ	-0.00691	0.035	0.0515
	D	0.0909	0.0909	0.182
West Zone	τ	0.159*	0.175*	0.238**
	D	0.242	0.182	0.424***
Cauvery Delta	τ	0.0811	0.0853	0.0944
	D	0.152	0.152	0.152
Hilly zone	τ	0.33***	0.345***	0.365***
	D	0.364**	0.364**	0.394***
North West	τ	0.229**	0.257***	0.333***
	D	0.394***	0.394***	0.424***
North East	τ	0.193**	0.202**	0.160*
	D	0.364**	0.303**	0.303**
Tamil Nadu	τ	0.135	0.179*	0.201**
	D	0.242	0.242	0.333**

τ denotes Kendall's Tau. D denotes the Kolmogorov-Smirnov (K-S) test statistic. ***Statistically significant trends at the 1% significance level. **Statistically significant trends at the 5% significance level. *Statistically significant trends at the 10% significance level.

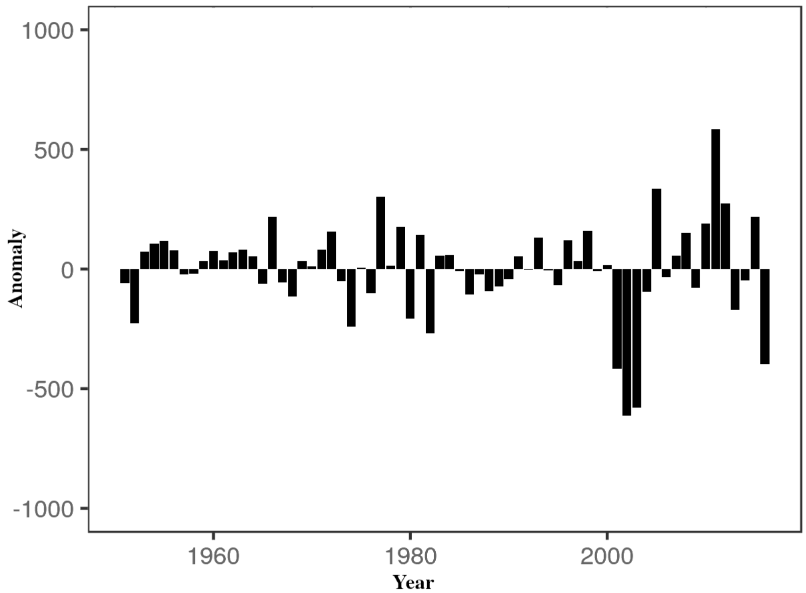


Figure 4.17: The anomaly in rainfall over Tamil Nadu from 1951 to 2016

decadal modes, IMFs 4 and 5, span approximately 15 and 62 years and explain nearly 13% of the total variation in the time series. The trend component which is more or less horizontal, explains only 2 percentage of the variations in the time series. As seen in figure 4.18, the inter-annual cycles of rainfall anomaly have amplified considerably after 2000.

Figure 4.19 shows the statistical significance of various IMFs discussed above. The figure suggests that the inter-annual mode, IMF 3 is highly significant ($\alpha = 0.05$) and the inter-decadal cycle IMF 5 is significant at 10% level. Also, it is seen that the IMF 1 and IMF 4 are found to be significant between 90% and 80% significance levels. The MK test suggested that the trend component is not significant, although it shows a slight positive trend during the period of observation.

Figure 4.20 shows the reconstructed inter-annual and inter-decadal variations plotted along with the original rainfall anomaly time series and its trend component. It is evident that the actual variability in precipitation anomaly is largely consistent with the inter-annual cycle throughout the period. However, some of the major deficient rainfall periods were associated with the dry phase of the inter-decadal cycle also. Thus the reconstruction of various cycles into inter-annual and inter-decadal modes illustrates the the extent to which the various components explain their respective contributions towards the general characteristics of the rainfall anomaly time series over the region.

Figure 4.21 shows the trend in rainfall anomaly across the various agro-climatic zones

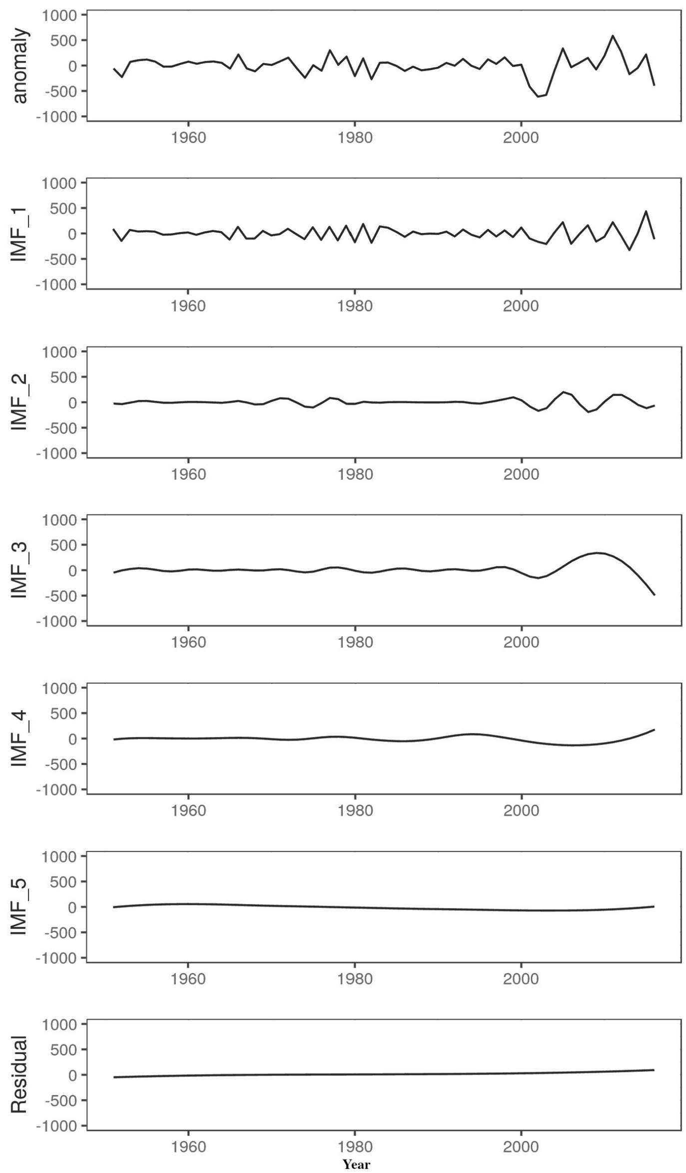


Figure 4.18: The IMF and Trend components of the anomaly in rainfall over Tamil Nadu from 1951 to 2016

Table 4.7: Variance contribution rates of various components towards anomaly in rainfall

Region	IMF Components	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	Residual
Tamil Nadu	Period (years)	4	6	8	15	62	
	VCR (%)	36.99	11.60	36.10	8.53	4.39	2.39

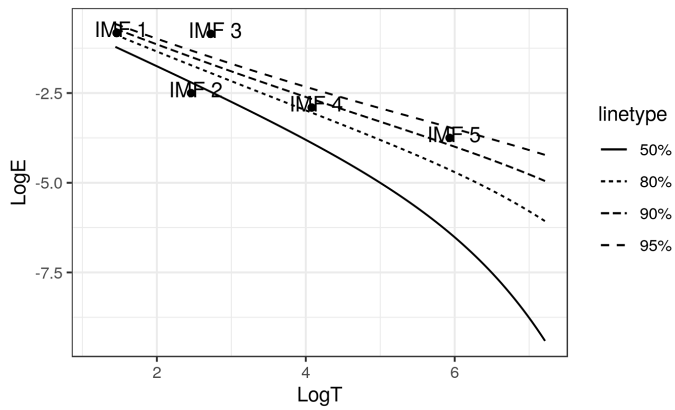


Figure 4.19: Statistical significance of the IMFs of the anomaly in rainfall over Tamil Nadu

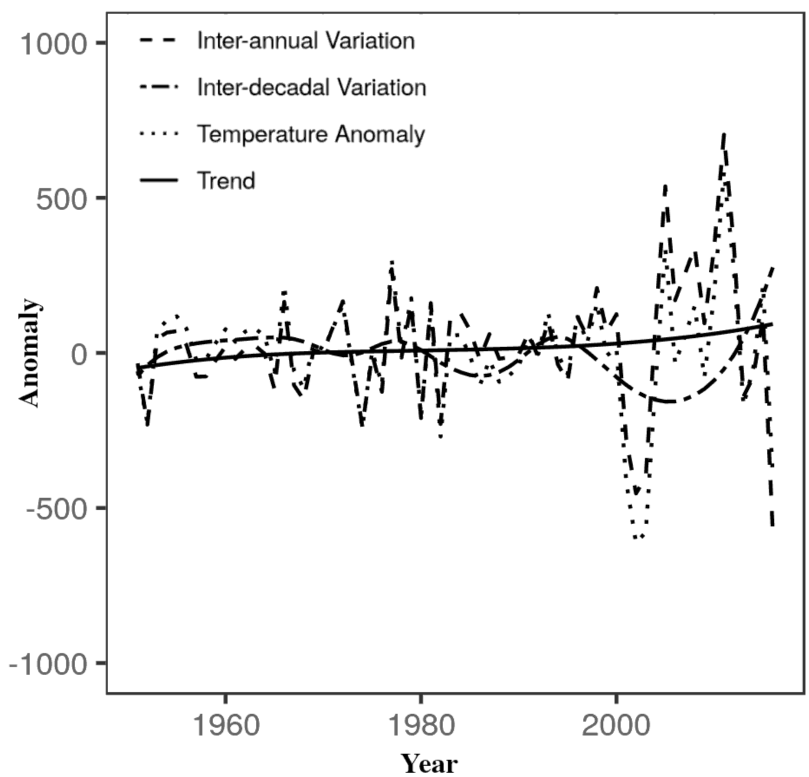


Figure 4.20: The trend, inter-annual variation and inter-decadal variation of anomaly in rainfall over Tamil Nadu from 1951-2016

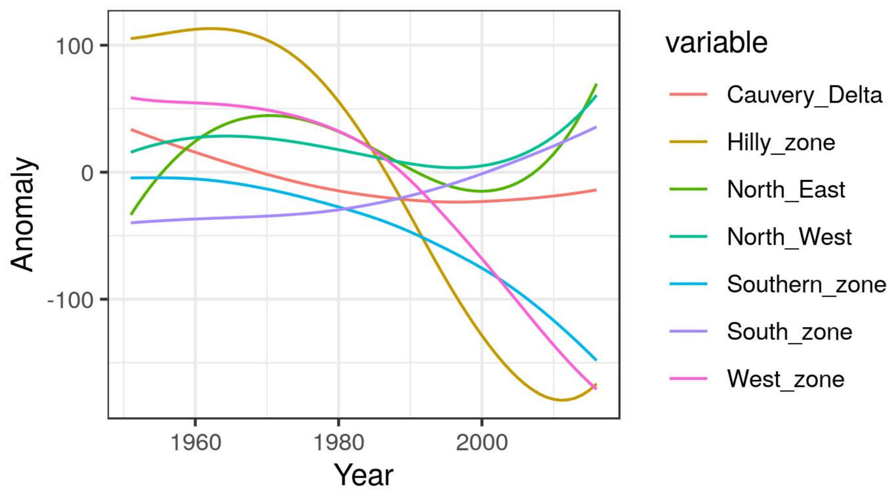
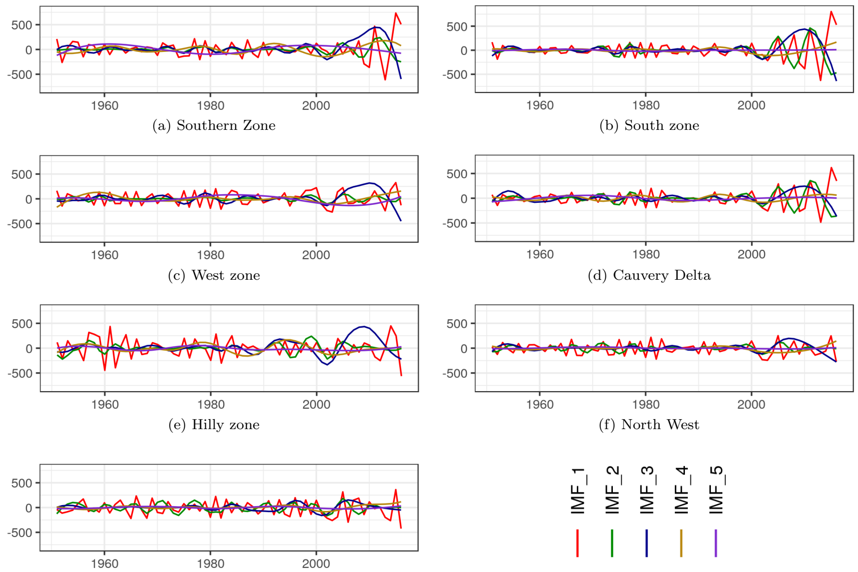


Figure 4.21: The trend of anomaly in rainfall over the agro-climatic zones of Tamil Nadu from 1951-2016

of the region. It is pretty clear from the figure that the precipitation trends over various zones differ from one another. This suggests that there is considerable heterogeneity in the precipitation over Tamil Nadu at a sub regional level. Importantly, statistically significant ($\alpha = 0.05$) downward trends are observed over the West zone and Hilly zone. As provided in Table 4.8, these trend components explain 10.98% and 14.58% of the variation in the rainfall over the respective regions. While, the trend components over the rest of the zones are not statistically significant and have negligible role in determining the general characteristics of the rainfall over the concerned regions, the difference among them substantiates that there is considerable intra-zonal heterogeneity in rainfall over Tamil Nadu .

Figure 4.22 shows the IMFs of rainfall anomaly over the seven agro-climatic zones of Tamil Nadu. Table 4.8 shows the periodicity and contribution of each component towards the general characteristics of rainfall over the respective regions. The IMF has a periodicity ranging from 3 to 4 years, IMF 2 has a periodicity ranging from 6 to 7 years and IMF 3 has a periodicity of 8 to 11 years. For Southern zone, South zone and Cauvery Delta, this IMF belong to the inter-annual cycle. However, for rest of the zones, this mode is part of the inter-decadal cycle. The periodicity of the fourth IMF ranges between 16 and 17 years while that of the IMF 5$^{\text{th}}$ IMF falls between 24 to 37 years. They contribute between nearly 4% and 17% of the variation in rainfall. As seen in the figure 4.22, the rainfall over Tamil Nadu generally does not involve much variability. However, the Hilly zone is an exception to this. This agro-climatic zone has been experiencing considerable variability in since the



(a) Southern Zone
(b) South zone
(c) West zone
(d) Cauvery Delta
(e) Hilly zone
(f) North West
(g) North East

Figure 4.22: The variability of anomaly in rainfall over the agro-climatic zones of Tamil Nadu between 1951 and 2016

beginning of the period under observation. All agro-climatic zones except the north-west zone and the north-east zone experienced considerably higher variability after 2000. It is also visible that the inter-annual modes, particularly the IMF 1 and the IMF 3. This increase in the variability is the largest since 1950s.

4.1.6 Extremes in Rainfall

The analysis of various categories of rainfall based on the classification provided in Table 3.3, suggests that only three incidences of “exceptionally heavy" rainfall have been observed over Tamil Nadu during 1951-2016. The first one was observed in 1978. 754.4 km2 land area in the Hilly zone (the Nilgiris district) received 246 mm rainfall. The second incident happened in 2007. Nearly, 3002 km2 area of the North-East zone received “exceptionally heavy" rainfall. The third one also happened over the same zone in 2015. Nearly 2250 km2 area, including the state capital Chennai, witnessed floods due to this “exceptionally heavy" rainfall. Figure 4.23 shows the spatial patterns of change in the remaining five categories of rainfall during the 1951-2016. The panel a of the figure 4.23 suggests that there has been a considerable decline in the occurrence of light rainfall over all agro-climatic zones of Tamil Nadu. This is particularly notable over the western parts of the Southern zone and South zone, over the Hilly zone as well as on some boxes lo-

Table 4.8: Variance contribution rates of various components towards anomaly in annual rainfall

Region	IMF Components	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	Residual
Southern zone	Period (years)	3	6	8	17	33	
	VCR (%)	47.57	7.00	28.82*	8.58	5.72	2.30
South zone	Period (years)	4	7	8	17	37	
	VCR (%)	44.20	25.02	27.03**	3.04	0.15	0.56
West Zone	Period (years)	3	6	10	17	32	
	VCR (%)	39.36	2.88	29.43**	9.03	8.32*	10.98**
Cauvery Delta	Period (years)	3	6	8	17	35	
	VCR (%)	49.71	26.17	17.04	4.45	2.09	0.53
Hilly zone	Period (years)	4	6	11	17	30	
	VCR (%)	43.50	8.42	24.80**	7.5	1.19	14.58**
North West	Period (years)	3	6	11	17	35	
	VCR (%)	60.03	10.36	22.25	6.26	0.55	0.54
North East	Period (years)	4	6	11	16	24	
	VCR (%)	66.65	17.23	9.92	3.97	0.79	1.45

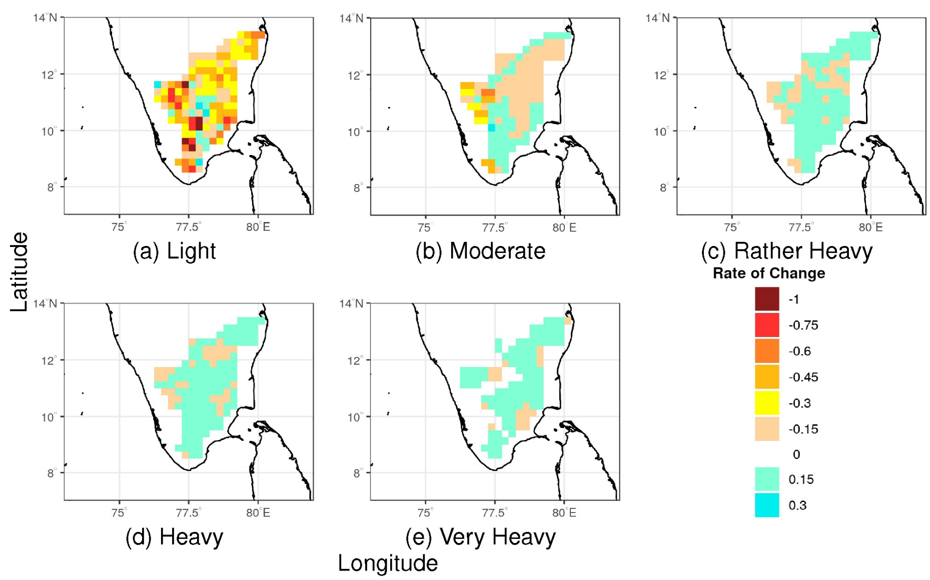


Figure 4.23: The rates of changes in various categories of rainfall over Tamil Nadu from 1951-2016, Source: Rajkumar et al. (2020)

Table 4.9: Results of the statistical tests for changes in various categories of rainfall during 1951-2016

Region	Test Statistic	Critical Values					
		Extreme Rainfall Area			Extreme Rainfall Share		
		VHR	HR	RHR	VHR	HR	RHR
Southern zone	τ	0.265***	0.193**	0.146*	0.261***	0.217**	0.171**
	D	0.212	0.303**	0.182	0.212	0.303**	0.303**
South zone	τ	0.060	0.160*	0.244***	0.055	0.153*	0.229***
	D	0.091	0.212	0.363**	0.090	0.212	0.364**
West Zone	τ	0.086	0.123	0.073	0.089	0.155*	0.1
	D	0.121	0.242	0.273*	0.121	0.303**	0.303**
Cauvery Delta	τ	0.105	0.076	0.070	0.103	0.079	0.073
	D	0.121	0.121	0.152	0.121	0.182	0.212
Hilly zone	τ	0.132	0.044	0.061	0.129	0.102	0.046
	D	0.121	0.030	0.091	0.152	0.121	0.212
North West	τ	0.112	0.056	0.002	0.095	0.033	0.097
	D	0.182	0.212	0.121	0.181	0.090	0.182
North East	τ	0.021	0.068	0.044	0.007	0.078	0.189**
	D	0.121	0.182	0.121	0.152	0.152	0.273*
Tamil Nadu	τ	0.108	0.125	0.175**	0.094	0.113	0.213**
	D	0.182	0.212	0.273*	0.182	0.212	0.303**

Source: Rajkumar et al. (2020)
τ denotes Kendall's Tau. D denotes the Kolmogorov-Smirnov (K-S) test statistic. ***Statistically significant trends at the 1% significance level. **Statistically significant trends at the 5% significance level. *Statistically significant trends at the 10% significance level.

cated in the north-east zone. The panel b shows that there has been a general decline in the incidence of moderate rainfall as well. This trend is observed over the Southern zone, Hilly zone, Cauvery Delta, the north-east and the north-west zones. On the other hand, the three heavy rainfall categories, “rather heavy", “heavy" and “very heavy", has shown an increasing trend.

The Table 4.9 shows the results of the statistical tests for changes in various categories of rainfall during 1951-2016. The results in the table concurs with the patterns shown in the Figure 4.23. Accordingly, there is a statistically significant increasing trend in both the area receiving the three heavy rainfall categories and their respective shares in the total annual rainfall over the Southern zone. On the other hand, the South zone has experienced significant changes in the area and share of heavy and rather heavy rainfall. Over the West zone, the D statistic suggests a significant change in the area receiving the “rather heavy" rainfall during 1984-2016, while both the M-K (τ) and the K-S test statistics (D) suggest an increase in the share of “heavy" and “rather heavy" rainfall categories over time. Another region with significant results is the north-east zone. This zone has a significant increasing trend in the share of rather heavy rainfall, and an increase in the share of higher values in the latter half of the period of observation.

4.1.7 Droughts

The pattern of drought across the agro-climatic zones of Tamil Nadu was studied using the SPEI - multi scalar drought index sensitive to warming. The drought, as defined in the present study, is a period which begins when SPEI falls below 0 and stays continuously negative for a minimum period of 3 months. The drought ends with a positive value of SPEI. The time scale used in the present study is 6 months since this time scale was observed as significant as far as agriculture is concerned.

The present study has analysed the frequency, magnitude, and severity of drought events over Tamil Nadu region. Figure 4.24 illustrates the spatial distribution of the same. The panels a and b of the figure suggest and interesting pattern. The number of drought events over Tamil Nadu declined in the latter half of the study period, under the warming climate. Some grid boxes in the north-west zone and some grid boxes in the South zone are exceptions to this observation. The majority of the locations to the north of the South zone experienced a decline in the number of droughts during the period 1984-2016 compared to that of 1951-1983. However, this decline in the drought frequency was accompanied by a general increase in the drought intensity over the region. Though this shift does not suggest a substantial increase in the 30 year mean of drought intensity in the second half, the spatial extent of this increase has to be noted. A large majority of the grid boxes experienced a similar increase in the mean intensity.

Further, the K-S test statistic in Table 4.10 suggests that the increase in the area under drought in the second half is statistically significant for certain regions such as Cauvery Delta, north-west and the north-east zones only. Also, while the mean drought intensity does not show any marked increase, the yearly maximum intensity has a statistically significant increasing trend. The highly significant values for the τ and D statistics suggest that while the change in the mean intensity was not at an alarming rate, there is statistically significant increase in the share of high intensity droughts during the second half. Further, the 30 mean severity of droughts nearly doubled in the second half of the study period. The statistical tests for the same provided in the Table 4.10 also suggest an overall increase in

Table 4.10: Results of the statistical tests for changes in droughts during 1951-2016

Region	Test Statistic	Critical Values		
		Area affected	Intensity	Severity
Southern zone	τ	0.056	-0.272***	-0.072
	D	0.061	0.394***	0.212
South zone	τ	0.120	-0.268***	-0.032
	D	0.182	0.515***	0.212
West Zone	τ	0.116	-0.267***	-0.206**
	D	0.182	0.424***	0.394***
Cauvery Delta	τ	0.17*	-0.297***	-0.103
	D	0.334**	0.455***	0.273*
Hilly zone	τ	0.202**	-0.340***	-0.107
	D	0.242	0.424***	0.242
North West	τ	0.19**	-0.288***	-0.175**
	D	0.364**	0.242	0.273*
North East	τ	0.155*	-0.191**	-0.131
	D	0.303**	0.242	0.273*
Tamil Nadu	τ	0.168*	-0274***	-0.221***
	D	0.272*	0.364**	0.394***

source: Rajkumar et al. (2020)
τ denotes Kendall's Tau. D denotes the Kolmogorov-Smirnov (K-S) test statistic. ***Statistically significant trends at the 1% significance level. **Statistically significant trends at the 5% significance level. *Statistically significant trends at the 10% significance level.

larger severity values over Tamil Nadu region in the second half of the study period.

4.2 Climate Variability over Tamil Nadu in a Broader Spatial Context

The observed global mean surface temperature for the decade 2006-2015 was approximately 0.87°C higher than the mean surface temperature for the period 1850-1900 (IPCC, 2018). In India, a consistent acceleration has been observed in the maximum, minimum, and the mean temperatures over the north-western and southern regions, and a cooling tendency over the north-eastern regions extending south-westward across the central India between 1951 and the 2000s (Ross et al., 2018). Results of similar nature has been observed by Nengzouzam et al. (2018) as well. In broad agreement with the above findings,

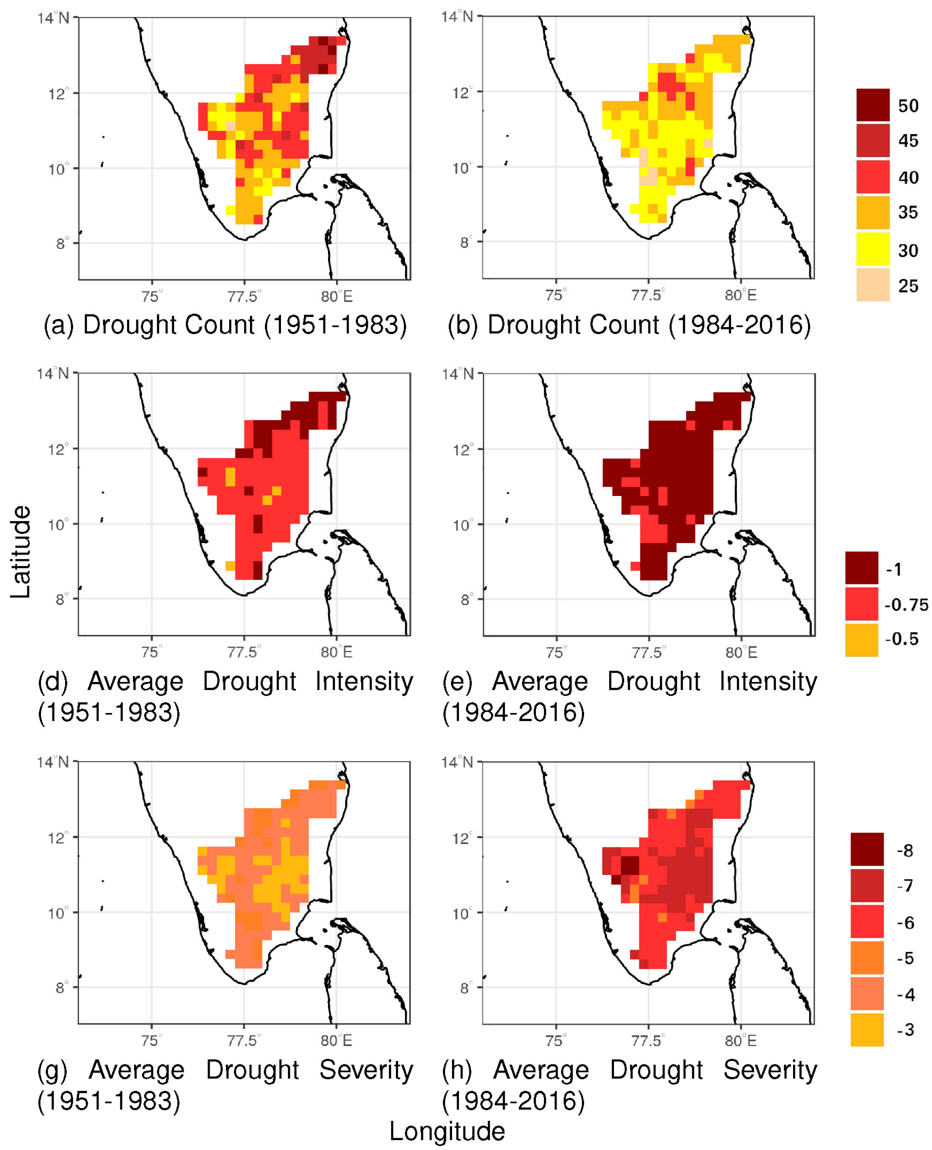


Figure 4.24: Droughts over Tamil Nadu - frequency, intensity and duration between 1951 and 2016, Source: Rajkumar et al. (2020)

the results of the present study conducted over Tamil Nadu, located on the Southeastern coast of India, suggests that there has been a consistent increasing trend in the maximum temperature over Tamil Nadu. The maximum temperature increased by 0.87°C during the decade 2007-2016 in comparison with the mean value for the period 1951-1980. The trend lines of maximum temperature anomaly (Figure 4.5) suggest that Tamil Nadu has been a homogeneous region in terms of maximum temperature, and there is a tendency of the trend line to flatten slightly in the second half. On the other hand, the minimum temperature over Tamil Nadu does not have a secular trend. It had a somewhat declining trend till the 1970s and started increasing only in the 1980s. Compared to the period 1951-80, the minimum temperature for the period 2007-16 was higher by 0.45°C. The trend lines for various agro-climatic zones across the region (Figure 4.13),suggest that Tamil Nadu is relatively less homogeneous for of minimum temperature compared to the maximum temperature. The trends observed here are in agreement with the findings of Srivastava et al. (2017) based on all-India data. These observations also concur with the observations of Kumar et al. (1994) since a dominance of maximum temperature in the overall change can be seen throughout the study period, although the minimum temperature has started gaining considerable momentum in the latter half of the study. It is also pertinent to note that, the minimum temperature temperatures have increased at a faster pace in the recent decades than the maximum temperatures. This is also consistent with the patterns observed nationally (National Climate Centre (2014) cited in Rohini et al. (2016)). Along with the trend, the study considered the variability part also. In the case of maximum temperature, the anomaly time series did not show any significant variability, as the trend component explained nearly 70% of the characteristics of the time series. However, the minimum temperature has been observed as more variable in comparison with the maximum temperature. The inter-annual cycle was observed as explaining approximately 45% of the variations in the time series across the agro-climatic zones. The inter-annual cycle remained more or less consistent during both halves of the period of observation. However, trend component showed significant upward mobility in the second half.

On a global scale, evidence suggests a clear increase in the frequency of temperature extremes in the current warming scenario (Hartmann et al., 2013; Fischer and Knutti, 2015). Despite the slowdown in the increase in global mean surface temperature that began around 1998, the temperature extremes witnessed a continuous increase. This implies that the trends in temperature extremes need not necessarily go parallel to the trends in the mean temperatures Seneviratne et al. (2014); Sillmann et al. (2014). Consistent with the global trends, the Indian region also witnessed a substantial increase in the frequency of heat waves during 1951-2015, experiencing some of the most damaging heat waves 1998-2015 (Mishra et al., 2017b). On a spatial scale, concurrent hot day and hot night (CHDHN) events were observed as experiencing an increase of about three events (3-day CHDHN) per year in the post-1984 period in the western, north-eastern, and the southern parts of India, with the night time temperature extremes increasing more rapidly than daytime events Mukherjee and Mishra (2018). Pai et al. (2017b) suggests that the north, north-west, central, east India and north-east part of the SPI experienced considerable increase in the summer season heat waves (April-May-June). The results of the present study concur significantly with the relevant spatio-temporal patterns mentioned in these studies. It observed a significant increase in the frequency, duration and magnitude of both heat waves and warm nights over Tamil Nadu, which belongs to the South Peninsular India. On a spatial scale, the western parts of Tamil Nadu, that located closer to the Western Ghats experienced the largest increase in mean heat wave intensity during the latter half of the study. However, heat wave duration was higher over the northern side of Tamil Nadu. In the case of the warm spells in night time temperature as well, the central and western areas of Tamil Nadu experiences the largest change in the magnitude and duration. These observations are more compatible with the findings of Sharma and Mujumdar (2017) which suggests increased occurrence of heat waves along the Western Ghats region of Tamil Nadu.

The current warming scenario is also characterized by visible changes in the variability and extremes in precipitation across the world. Seager et al. (2012) suggested that the hydro-climatic variability on an inter-annual scale intensifies as a result of global warming. However, a later analysis observed that the daily, monthly, annual and decadal scales variability in precipitation have been increasing substantially over a large fraction of global land area in response to the warming. This magnitude of the change in variability is greater than the change in the mean precipitation and lesser than the change in the extremes for most land areas Pendergrass et al. (2017). Over Indian region, the variabilities of different time scales are often associated with sea surface temperature anomalies and the evidence has been insufficient to suggest that the variability or the epochal changes of the Indian Monsoon Rainfall (IMR) are affected by the global warming (Kripalani et al., 2003). However, Naidu et al. (2015) suggests that the summer monsoon rainfall over most parts of Indian region has decreased during the recent three decades of the global warming. The patterns of rainfall variability over Tamil Nadu is dominated by the north-east Monsoon Rainfall (NEMR) since the region receives receives around $40-60\%$ of its annual rainfall during the North-East Monsoon season (October to December) (Sreekala et al., 2018). Over Tamil Nadu region, the present study observed a statistically insignificant upward trend in the annual rainfall anomaly time series for the period 1951-2016. The analysis of trend further revealed the intra-regional heterogeneity of rainfall anomaly. This is contrary to the existing observation (Krishna Rao and Jagannathan, 1953) that Tamil Nadu is fairly homogeneous in terms of rainfall. More interestingly the study observed substantial amplification in both the inter-annual as well as in the inter-decadal modes after 1980. At a regional scale, all regions except the north-east and north-west zones displayed substantial amplification in the inter-annual and inter-decadal modes after 2000.

This variability in rainfall manifests in more perceivable forms such as extreme rainfall events and droughts. Globally, more extreme precipitation events are projected in response to global warming Lau et al. (2013). This increase in precipitation extremes are not limited to the wet regions of the world but affects the dry regions as well (Donat et al., 2016). In India, various parts of the subcontinent witnessed substantial increase in extreme precipitation events. Over Central India, Goswami et al. (2006); Rajeevan et al. (2008); Roxy et al. (2017) observed significant increase in extreme rainfall along with a decline in the moderate rain events. Roxy et al. (2017) further, observed that both the frequency as well as the intensity of extreme rainfall events are increasing over central India. Over the western coast of India, Pattanaik and Rajeevan (2010); Pai et al. (2015) observed significant positive trends in the very heavy rainfall and negative trends in moderate rain events. Over north-east India, significant increasing trends were observed by Pattanaik and Rajeevan (2010); Mishra and Liu (2014). Over South Peninsular India (SPI), Nageswararao et al. (2019) observed an increase in high-intensity rain events and a significant decline in the light and moderate rain events during the NEMR seasons of 1959-2016. Independent analysis by the researcher (Rajkumar et al., 2020) revealed a general intensification of rainfall over Tamil Nadu region during 1951-2016. This intensification, however, was accompanied by decline in the light and moderate rainfall.The results for Tamil Nadu region, therefore, exist in concurrence with the findings at the national level.

In the case of drought, the current evidence does not suggest any global-scale trends with sufficient ‘confidence’ due to “the lack of direct observations, geographical inconsistencies in the trends, and dependencies of inferred trends on the index choice" (Hartmann et al., 2013). However, the regional scale studies over India suggest significant patterns of droughts in the recent decades. Significant increasing trends in the area and intensity of various categories of droughts have been observed over the north and north-west India (Kumar et al., 2013; Pai et al., 2017a). The Indo-Gangetic plains, central Maharashtra, and parts of coastal south India were observed as experiencing increase in the duration, severity, and spatial spread of droughts in recent decades (Mallya et al., 2016). An independent analysis by the researcher (Rajkumar et al., 2020) finds broader domains of agreement with the existing literature and has identified certain crucial differences as well. Accordingly, the results for Tamil Nadu (Rajkumar et al., 2020) suggests that there has been a decline in the number of droughts over the region during 1984-2016. While a statistically significant increase was observed in the maximum intensity of droughts between the two sub-periods, the change in the mean intensity has not been much alarming. However, the significant increase in the duration of drought events has resulted in a marked increase in the mean drought severity for the period 1984-2016.

The results from the present study suggest that the Tamil Nadu region experiences notable patterns of change in the temperature and precipitation that are comparable at both national and global levels. In the case of temperature, along with the change in mean temperature, the trend and the variability in the observed temperature can indicate the occurrence of extremes to an extent. In fact, the statistical theory of extremes suggests that the frequency of extremes is more sensitive to the changes in the variability (scale parameter) of the distribution (Katz and Brown, 1992). In the study related to the unusual heat wave of Europe in 2003, Schär et al. (2004) observed that the increasing year to year variability in summer temperature might be able to explain the heat wave of Europe in 2003. Over Indian region, many factors have been observed as influencing the temperature variability and extremes. Kothawale et al. (2010a) suggested a positive relation between maximum temperature anomaly and El Nino and an opposite relation between La Nina. Chowdary et al. (2014) observed that the ENSO and Indian Ocean warming/cooling are dominant factors responsible for inter-annual air-temperature variability over India. The heat waves over India are found predominantly during the pre-monsoon months. This is true in the case of Tamil Nadu as well since most of the heat waves are observed in the months of April and May. The El Nino is associated with a delay in the onset of the Indian Summer Monsoon and causes weakening of south westerlies over the Arabian sea and clear skies over the Indian region which in turn causes warmer and longer heat waves (Murari et al., 2016). Further, 'the anomalous persistent high with anti-cyclonic flow, clear skies and depleted soil moisture', have also been identified as responsible for the incidence of heat waves over India (Rohini et al., 2016).

In the case of precipitation as well, the ENSO plays a dominant role in determining the patterns of variability as well as extremes. In the case of the Indian Summer Monsoon (ISM), there is an inverse relation with ENSO and most of the severe droughts in India are associated with the ENSO events Azad and Rajeevan (2016). However,Tamil Nadu receives $40 - 60\%$ of its annual rainfall from October to December(during the NEMR season) (Sreekala et al., 2018). The NEMR is relatively more variable than the ISM both spatially as well as temporally **?**. In the case of the NEMR over South Peninsular India (SPI) the positive phases of ENSO, IOD, and EQUINOO promotes excess monsoon and the La Nina years have a relatively higher probability of experiencing a deficient rainfall (**?**). The excess rainfall years 1951, 1963, 1965, 1969, 1972, 1977, 1987, 1994, 2015 and the deficient rainfall of 2002 were associated with El Nino and the deficient rainfall of 1974, 1984, 1988, 1995 and the excess rainfall events of 1956 and 2010 were associated with coexisting La Nina events (Nageswararao et al., 2019). However, the independent analysis by the researcher (Rajkumar et al., 2020) observed that the years 1955, 1966, 1976, 1978, 1983, 1985, 1990, 1991, 1992, 1996, 1999, 2005, 2007, 2008 had experienced higher fractions of the area receiving “very heavy" rainfall events, along with an increasing trend and the years 1952, 1953, 1982, 1983, 1989, 1996, 2001, 2003, 2004, 2013, 2014, 2016 had experienced widespread droughts in Tamil Nadu. The analysis by Rajkumar et al. (2020) has also observed a decreasing trend in light rainfall. It is also worthwhile to note that the light rainfall is a major component of precipitation over the Tamil Nadu region. A decline in the frequency of light rainfall along with an increase in intense rain events has been observed over various parts of India as well as the world under warming (Goswami et al., 2006; Roxy et al., 2017). This, in turn, would cause a fall in the soil moisture and an increase in the number of dry spells even when the precipitation, in general, gets intensified (Trenberth, 2011). We therefore infer that the similar factors might be responsible for the drought patterns over Tamil Nadu as well.

4.3 Summary and Findings

The present chapter analysed the spatio-temporal patterns of climate variability and extremes over Tamil Nadu region, India. The study used EEMD method to examine the variability in temperature and rainfall. The extremes in maximum and minimum temperature were studied using HWMId method. The patterns of extreme rainfall was studied on the basis of a classification scheme issued by the India Meteorological Department. The analysis of drought was conducted using the SPEI method. The study used an extended period 1951-2016 to identify and project the changes happened in the recent decades which include the study period. The statistical significance of the results obtained were tested using the Mann-Kendall test and the Kolmogrove - Smirnov test. The results were compared with the existing studies of national and global relevance. The major findings of the study are:

1. The maximum and minimum temperatures exhibit statistically significant increasing trends for the period 1951-2016. While the trend in maximum temperature gets flattened slightly in after 1980, the trend in minimum temperature anomaly increases sharply during 1984-2016

2. The variability in maximum temperature declines after 1980s. However, Cauvery Delta and the north-east zone are an exception to this. These zones exhibited an amplification in the inter-annual variability. The variability in minimum temperature showed a general tendency of decline after 1980.

3. Tamil Nadu region experienced statistically significant increase in the frequency, intensity and duration of heat waves after 1980. The grid cells located in the western part of Tamil Nadu experienced the largest change in the 30 year mean magnitude between the two sub-periods. In the case of 30 year mean duration, the northern parts of Tamil Nadu witnessed the largest change. Further, the area affected, maximum intensity and duration of heat waves showed statistically significant increasing trend as well as distributional change during the period under observation.

4. The warmest spells in night time temperature exhibited statistically significant increase in the frequency, intensity and duration of heat waves after 1980. The changes in 30 year mean intensity and duration were observed over the western parts of the state. Higher values of mean duration were also observed for the grid cells belonging to the Cauvery Delta as well. Statistically significant changes in the area affected, maximum intensity and duration are observed over the West zone, Hilly zone, north-west and the north-east zones during 1984-2016.

5. The precipitation over Tamil Nadu did not show any statistically significant trends. However, the regional level analysis showed considerable heterogeneity in the rainfall anomaly across various agro-climatic zones of the region. The declining trends of the West zone and that of the Hilly zone were found statistically significant. All zones except the north-east zone witnessed significant increase in the variability at inter-annual as well as in the inter-decadal cycles after 2000.

6. The analysis of various categories of rainfall suggested a general increase in the frequency of heavy rainfall categories and a decline in the frequency of moderate and light rainfall events. The increase in the area affected, and share was observed mainly over the Southern and the South zone. In the case of “rather heavy" rainfall,

significant trends and changes in the area and share was observed over the West zone as well. A significant change in the share of “rather heavy" rainfall was observed over the north-east zone also.

7. The study of drought patterns revealed that Tamil Nadu has been a chronically drought prone region throughout the period of study. The region witnessed a decline in the drought count between the two sub-periods 1951-1983 and 1984-2016. However, the same period witnessed an increase in the mean intensity and severity over the region. Although the change in intensity was not at an alarming rate, it was widely spread throughout the region. The period 1984-2016 also witnessed marked increase in the mean drought severity mainly due to the substantial rise in the duration in the latter half. Significant test results suggest that relevant changes in the area affected were found over the agro-climatic zones located north of the South zone while the maximum intensity had a significant increase over almost all zones. The change in maximum severity was observed over the West zone, Cauvery Delta, north-west and the north-east zones.

8. Literature suggests the increase in the temperature anomalies, influence of oscillations such as ENSO, NAO and depletion of soil moisture have been instrumental increasing the temperature variability as well as extremes. On the other hand, the various deficient and excess rainfall years over Tamil Nadu have been associated in the literature with relevant episodes of ENSO, NAO and EQUINOO. Further, the decline in the frequency of light rainfall along with a rise in intense rain events has been observed over Tamil Nadu. This pattern of rainfall, has been observed globally as leading to a fall in the soil moisture and increasing the number of dry spells even when the precipitation intensity increases. The resulting depletion in soil moisture, in turn, acts as a catalyst for the extremes in temperature as well. The above factors might have played a significant role in shaping the spatio-temporal patterns of climate variability over Tamil Nadu

Chapter 5

Sensitivity of Rice Yield in Tamil Nadu to Climate Variability and Extremes

An important component in the analysis of vulnerability concerns with the extent to which a system is sensitive to the external shock to which it is exposed. The present study considers rice cultivation as the main livelihood option of the farmers. Therefore the weather sensitivity of rice yield is taken as the proxy for the sensitivity of livelihoods of the farmers. This chapter documents the weather sensitivity of rice yield to the variability and extremes in temperature as well as rainfall. Two major approaches have been adopted in this part of the analysis. To get an overall picture of weather-rice yield relation for the period between 1985-1986 and 2015-2016 for the entire Tamil Nadu region, we used a multivariate fixed effects panel data regression model with data for the seven agroclimatic zones in the region. Further, at the district level, we computed used a multiple linear regression model to estimate the sensitivity aspect. The section 1 in the chapter provides an overview of the rice cultivation in Tamil Nadu, the section 2 examines the weather sensitivity of rice yield in the three with the results of the analysis while the second part discusses the results with the findings from the existing literature. The section 3 of the chapter discusses the results with the existing observations in literature and the section 4 summarises the findings of the study. The details of the data, methods and tests used in this chapter are detailed in the Chapter 3.

5.1 Rice cultivation and yield in Tamil Nadu

Tamil Nadu is one of the major rice cultivating regions in India with 4% of the area under rice in the country and 5.17% in total production. Rice is the principal crop cultivated in the state occupying 42% of the total cropped area and accounting for 65% of the total food grains production in the State. While the season and varieties of rice cultivated in the state varies across regions, three dominant seasons can be identified as representative of all these sub seasons. They are, Kuruva - spanning from April to July. Early Kar, Kar and Sornavari

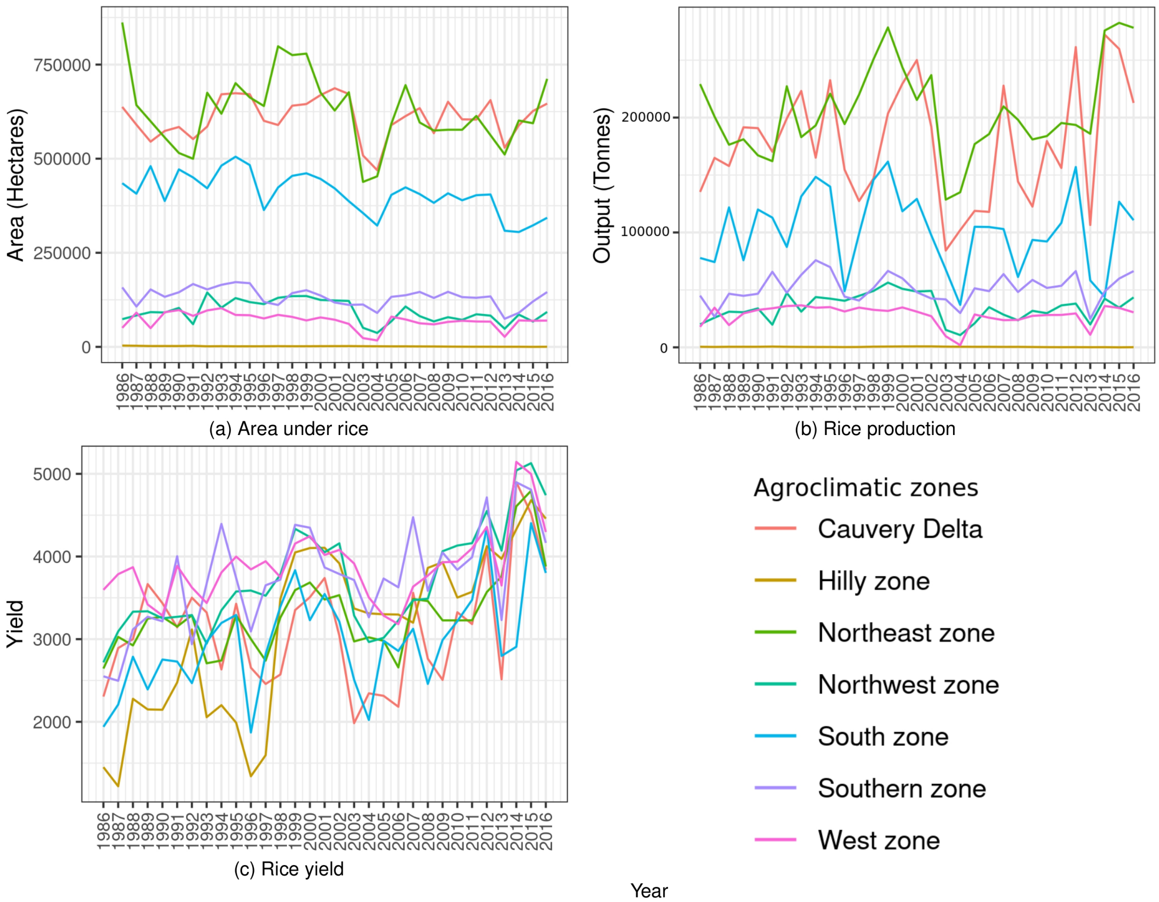


Figure 5.1: Area, production, and yield of rice across agroclimatic zones, Tamil Nadu 1986-2016

are the sub seasons during the Kuruva season in Tamil Nadu. The second season spans between August and November. This season is called Samba season. Early Samba, Late Samba, Thaladi, Pishanam, Late Pishanam, Late Thaladi are the sub cultivation seasons during the Samba season. The third season is the Navara season which starts from December and ends in March. Generally, the varieties cultivated during Kuruva and Navara seasons are short duration varieties. The majority of the farmers cultivate rice during the Samba season due to favourable climatic conditions. The Kuruva season contributed more than the Navara season. The average yield rate of rice per hectare during Kuruva season is more than those in Samba and Navara seasons (Sivagnanam, 2014). Figure 5.1 shows the changes in the area, production and yield under rice in Tamil Nadu between 1985-86 and 2015-2016.

The area under rice in Tamil Nadu decreased gradually from 2264293 hectares in 1985-86 to 2000213 hectares in 2015-16. South zone and the Northeast zone experienced relatively higher rates of decline in the area under cultivation during the period of study (Figure 5.1a). The production of rice increased from 5370490 tonnes in 1985-86 to 7374681 tonnes in 2015-16. This increase in output mainly happened on account of the increase in production in two agroclimatic zones, Cauvery Delta and Northeast zone (Figure 5.1b). The yield of rice increased from 2372 Kg/Ha in 1985-86 to 3687 Kg/Ha in 2015-16. The figure, thus suggests that the increase in the rice output in Tamil Nadu happened mainly on account of the increase in the yield and this increase involved substantial fluctuations as well (Figure 5.1c). The average yield during the study period was 3090 Kg/Ha with a standard deviation of ± 508 Kg/Ha. A considerable part of the changes in rice yield is can be attributed to the advances in seed-fertilizer-irrigation technologies and to the various schemes introduced as a part of National Food Security Mission. However, the possible role of weather factors are also cited in explaining the patterns of rice output and yield in Tamil Nadu in the recent decades. (Sivagnanam, 2014). The further sections analyse the weather sensitivity of rice yield at district and agroclimatic zone levels between 1985-86 and 2015-16.

5.2 Weather Sensitivity of Rice Yield

In this section, the results of the the statistical modelling approaches to empirically estimate the historical weather sensitivity of rice yield are presented. The subsection 1 provides the results of the fixed effects panel regression performed for the three dominant agricultural seasons in Tamil Nadu and the subsection 2 explains the results of the multiple linear regression performed at district level.

5.2.1 Climate Response Function Estimated using Fixed Effects Panel Data Model

Table 5.1 presents four models based on the estimated regression equations for the rice yield in the Kuruva season. The model 1 includes the year to year variability in solar radiation, maximum and minimum temperatures, rainfall and non-weather factors such as area under high yielding varieties (HYV) and area irrigated. The model 2 includes variations in solar radiation, heat wave magnitudes, warm night magnitudes, SPEI, and non-weather variables.

Table 5.1: Regression Estimates for Kuruva Rice 1985-86 to 2015-16

	Dependent variable: Rice Yield				
	Model 1	Model 2	Model 3	Model 4	Model 5
Solar Radiation (AM)	−0.033	−0.005			-0.041
	(0.123)	(0.168)			(0.148)
Solar Radiation (JJ)	0.100	−0.082			-0.014
	(0.158)	(0.088)			(0.091)
Maximum temperature (AM)	0.058				
	(0.109)				
Maximum temperature (JJ)	0.028				
	(0.142)				
Minimum temperature (AM)	0.197				
	(0.126)				
Minimum temperature (JJ)	0.032				
	(0.114)				
Rain (AM)	−0.151*			−0.103***	
	(0.090)			(0.013)	
Rain (JJ)	0.026			0.057	
	(0.116)			(0.129)	
Heat waves (AM)		0.156***	0.146***	0.119**	0.172***
		(0.045)	(0.044)	(0.055)	(0.043)
Heat waves (JJ)		0.774***	0.756***	0.711***	0.657***
		(0.091)	(0.114)	(0.053)	(0.078)
Warm nights (AM)		−0.198***	−0.193**	−0.200**	-0.155
		(0.072)	(0.084)	(0.088)	(0.101)
Warm nights (JJ)		0.035	0.024	0.043	0.075
		(0.077)	(0.067)	(0.049)	(0.070)
SPEI(AM)		−0.266	−0.317**		-0.135
		(0.166)	(0.148)		(0.148)
SPEI (JJ)		0.161	0.104		0.151
		(0.281)	(0.325)		(0.269)
Drought Intensity (AM)				−0.241	
				(0.285)	
Drought Intensity (JJ)				0.191	
				(0.282)	
% of area receiving extreme rainfall (AM)			−0.091***	−0.045*	
			(0.030)	(0.027)	
% of area receiving extreme rainfall (JJ)			0.035	−0.032	
			(0.048)	(0.068)	
% of area irrigated	0.073**	0.065**	0.053*	0.066***	
	(0.032)	(0.027)	(0.028)	(0.022)	
% of area under HYV	0.113	−0.351***	−0.349***	−0.288***	
	(0.107)	(0.068)	(0.076)	(0.038)	
Observations	217	93	93	93	93
R^2	0.055	0.296	0.310	0.317	0.240
Adjusted R^2	−0.201	−0.296	−0.269	−0.308	-0.345
F Statistic	0.985 (df = 10; 170)	2.101** (df = 10; 50)	2.248** (df = 10; 50)	1.860* (df = 12; 48)	2.049* (df = 8; 52)

Notes: *p<0.1; **p<0.05; ***p<0.01

Source: Computed by the author

The model 3 includes year to year variations in the magnitudes of heat waves, warm nights, SPEI, share of area receiving extreme rainfall, and non-weather variables. The model 4 includes variations in rainfall, variations in the magnitudes of heat waves, warm nights, drought (extracted from SPEI), fraction of area receiving extreme rainfall and non-weather variables, and the model 5 includes solar radiation, heat waves, warm nights and SPEI. Out of these four models, the second and third models are found significant at 95% significance level and the fourth model is significant at 10% significance level.

The table shows that the yield response towards certain variables are consistent across models. The variable rainfall during the months April and May exerts a significant negative influence on the rice yield (models 2 ($p \leq 0.1$) and 4 ($p \leq 0.01$)). On the other hand, the yield responds positively to the increase in the magnitudes of heat waves ($p \leq 0.01$) and negatively to the magnitudes of warm nights ($p \leq 0.01$). While heat waves during the first two and last two months have this significant direct influence on rice yield, the magnitude of warm nights for the the months June and July does not have any effects on the rice yield. What is noteworthy in this result is that, while the rice yield exhibit opposing sensitivities to the variations in heat waves and warm nights, the net effect is positive since the heat wave has beneficial influence on the rice yield through out the growing season and therefore outweighs the negative effect of minimum temperature. Another important influence on the yield belongs to the SPEI. The SPEI has an inverse relation with the rice yield, that the positive values of SPEI (wetness) corresponds to a negative response in rice yield and negative values in the SPEI (drought) corresponds to a positive response in the rice yield. In a similar response, models 3 and 4 suggest that rice yields exhibit negative response to the variations in the area receiving extreme rainfall. However, there is a robust and direct relationship between rice yield and area under irrigation. Rice yield varies positively to the variations in the area under irrigation. This is consistent across all models. However, models 2, 3, and 4 suggest a significant inverse relation between rice yield and the area under high yielding varieties.

Table 5.2 shows the diagnostic tests performed for the kuruva season. A Hausman test was conducted for each model before deciding whether to run a fixed effects or random effects model. The null hypothesis was that 'the individual random effects are exogenous' and the alternate hypothesis was set as 'one model is inconsistent'. The p values below the $\alpha = 0.05$ rejects the null hypothesis, and suggests that the random effects equation is inconsistent. As a result, it was decided to perform the fixed effects regression. The models were then tested for serial correlation. We used Wooldridge's test auto correlation in panel data (Wooldridge, 2010). This test is applicable to any fixed effects panel model, particularly to 'short' panels with small T and large n (Croissant et al., 2008). The test suggested that there is no serial correlation between the variables in the models ($p \leq 0.1$).

Table 5.2: Diagnostic Tests - Kuruva Season

Test	Model 1	Model 2	Model 3	Model 4	Model 5	Null/Alternate Hypothesis
Hausman	χ^2=47.69 (0.0494)	χ^2=167.88 (2.2e-16)	χ^2= 56.037 (2.02e-08)	χ^2=81.14 (2.501e-12)	χ^2=161.88 (2.2e-16)	H_1 = One model is inconsistent
Serial Correlation (Wooldridge's test)	F = 5.1112 (0.02481)	F = 3.2471 (0.07498)	F = 2.8705 0.09375)	F = 3.0916 (0.08217)	F = 3.1105 (0.09498)	H_1 = serial correlation
Heteroscedasticity (Breusch-Pagan test)	BP = 10.524 (0.8802)	BP = 12.432 (0.4116)	BP = 13.307 (0.3471)	BP = 12.884 (0.5357)	BP = 12.407 (0.4171)	H_0 = Homoskedasticity
Cross-sectional Dependence (Pesaran CD test)	z = 8.8225 (2.2e-16)	z = 3.9182 (8.923e-05)	z = 4.4547 (8.403e-06)	z = 4.1186 (3.812e-05)	z = 3.4525 (8.412e-05)	H_1= cross-sectional dependence

Notes: p-values in parenthesis correspond to test statistic under the null hypothesis.

We further tested the models for heteroscedasticity using the Breusch-Pagan test. The higher p values suggest that there is no heteroscedasticity among the variables. The test cross sectional dependence using Pesaran's CD test (Pesaran et al., 2004) suggested that there is cross sectional dependence among the variables. Therefore we refined the model by computing heteroscedasticity consistent robust standard errors that also account for serial correlation and cross sectional dependence (Arellano, 1987).

The yield response of rice in the Samba season is provided in the Table 5.3. Tamil Nadu receives the major share of its total annual rainfall during this period from August to November. Also, this period is generally free from heat waves and warm nights. Therefore the variables used in the models are year to year variability in solar radiation, maximum temperature, minimum temperature, rainfall, extreme rainfall (extreme rainfall events), fraction of area receiving extreme rainfall, SPEI, fraction of irrigated area and the fraction of area under high yielding varieties. Out of the four models presented, the model 1, 3 and 4 are statistically significant at 5% significance level and model 2 and 5 are significant at 10% level.

During Samba season also, the maximum temperature variation yields a positive response in the rice yield. Models 3 and 4 and 5 suggest nearly similar rates of sensitivity of rice yield towards the variations in maximum temperature ($p \leq 0.05$). However, this positive influence does not extent to the latter half of the growing season (ON). Also, it is not capable to offset the negative influence exerted by the variations in the minimum temperature. In the case of minimum temperature, all models invariably confirm this negative response ($p \leq 0.05$).

Table 5.3: Regression Estimates for Samba Rice 1985-86 to 2015-16

	Dependent variable: Rice yield				
	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)
Solar Radiation AS	0.018	0.023	0.049		
	(0.119)	(0.122)	(0.111)		
Solar Radiation ON	0.081	0.070	0.051		
	(0.104)	(0.101)	(0.116)		
Maximum Temperature AS	0.209	0.186	0.289*	0.285*	0.203
	(0.168)	(0.177)	(0.166)	(0.158)	(0.151)
Maximum Temperature ON	0.040	0.055	0.063	0.096	0.116
	(0.126)	(0.122)	(0.149)	(0.102)	(0.100)
Minimum Temperature AS	0.026	0.028	−0.001	0.008	0.051
	(0.148)	(0.151)	(0.157)	(0.157)	(0.144)
Minimum Temperature ON	−0.458***	−0.440**	−0.405**	−0.413**	−.410**
	(0.175)	(0.188)	(0.200)	(0.187)	(0.176)
Rain AS	−0.036	−0.005	0.023	0.015	0.031
	(0.096)	(0.068)	(0.102)	(0.109)	(0.112)
Rain ON	0.144*	0.135	0.065	0.059	0.086
	(0.079)	(0.087)	(0.076)	(0.066)	(0.081)
SPEI AS		0.173			
		(0.232)			
spei_ON		−0.052			
		(0.176)			
Drought Intensity (mean) AS			0.098	0.105	0.093
			(0.097)	(0.099)	(0.115)
Drought Intensity (mean) ON			−0.091	−0.087	0.056
			(0.112)	(0.116)	(0.115)
% area with extreme rainfall AS			−0.103	−0.104	0.118
			(0.073)	(0.072)	(0.077)
% area with extreme rainfall ON			0.148**	0.145**	0.129**
			(0.069)	(0.068)	(0.065)
% area irrigated	0.150	0.146	0.153	0.154	
	(0.123)	(0.121)	(0.122)	(0.120)	
% area under HYV	0.116***	0.115***	0.113***	0.111***	
	(0.029)	(0.026)	(0.026)	(0.027)	
Observations	217	217	217	217	0.217
R^2	0.106	0.110	0.132	0.131	0.096
Adjusted R^2	−0.136	−0.144	−0.129	−0.117	-0.148
F Statistic	2.006** (df = 10; 170)	1.731* (df = 12; 168)	1.809** (df = 14; 166)	2.114** (df = 12; 168)	1.808* (df = 10; 170)

Notes: *p<0.1; **p<0.05; ***p<0.01

AS represents the month August-September and ON, the months October-November

Therefore, in the Samba season, the net effect of temperature variations on the rice yield is negative. In the case of rainfall, there are not sufficient evidence to suggest a substantial influence, though the model 1 shows positive yield response ($p \leq 0.1$) to the variations in rainfall, the standard errors are relatively high in the other models to suggest any significant influence. However, models 3 and 4 suggest that the rice yield in the Samba season varies positively with the variations in the fraction of area receiving extreme rainfall. Neither, SPEI nor drought showed any significant influence on the rice yield. In this season also, rice yield responds positively to the variations in the area receiving irrigation. However, the results included high standard errors and were not significant as in the case of Kuruva season. High yielding varieties, however, has a robust positive influence on the rice yield in the Samba season unlike the negative influence in the Kuruva season.

Table 5.4: Diagnostic Tests - Samba Season

Test	Model 1	Model 2	Model 3	Model 4	Model 5	Null/Alternate Hypothesis
Hausman	χ^2= 50.14 (2.516e-07)	χ^2= 124.08 (2.2e-16)	χ^2= 124.08 (2.2e-16)	χ^2= 40.62 (1.318e-05)	χ^2= 62.68 (1.25e-05)	H_1 = One model is inconsistent
Serial Correlation (Wooldridge's test)	F = 0.30038 (0.5842)	F = 0.288 (0.5923)	F = 0.10002 (0.7521)	F = 0.43334 (0.5111)	F = 0.13302 (0.7121)	H_1 = serial correlation
Heteroscedasticity (Breusch-Pagan test)	BP = 17.403 (0.36)	BP = 17.501 (0.489)	BP = 22.906 (0.2935)	BP = 23.447 (0.1023)	BP = 18.401 (0.2489)	H_0 = Homoskedasticity
Cross-sectional Dependence (Pesaran CD test)	z = 6.4884 (8.678e-11)	z = 6.4639 (1.021e-10)	z = 6.5991 (4.137e-11)	z = 7.390 (1.467e-13)	z = 6.380 (1.037e-11)	H_1= cross-sectional dependence

Notes: p-values in parenthesis correspond to test statistic under the null hypothesis.

The diagnostic tests are shown in the table 5.4. The Hausman test suggested fixed effects regression against random effects ($p \leq 0.01$). The Wooldridge's test, however, suggested the presence of serial correlation among the variables in the model. The Breusch-Pagan test, suggested that the null hypothesis claiming homoscedasticity in the data is true, and the Pesaran CD test suggested the presence of cross sectional dependence among the variables in the data. Therefore, we generated robust standard errors (Table 5.3) that are heteroscedasticity consistent and which account for serial correlation as well as cross sectional dependence, based on Arellano (1987).

Table 5.5 shows the estimates of the response function of rice yield in Navara season. Four models combining the variables, year to year variations in solar radiation, maximum and minimum temperatures, rainfall, SPEI, drought (extracted from SPEI), fraction of area under extreme rainfall, fraction of area irrigated and the fraction of area using HYVs, are generated. Farmers of Hilly zone in Tamil Nadu has not cultivated in this season for more than a decade. Therefore, this region is not considered for the analysis, and the sample size for this season is 186. Out of the four models presented, the models 2 and 4 are significant at 10% level and the model 3 is significant at 5% level. The model 1 was not found significant at all.

Table 5.5: Regression Estimates for Navara Rice 1985-86 to 2015-16

	Dependent variable: Rice Yield				
	Model 1	Model 2	Model 3	Model 4	Model 5
Solar Radiation DJ	−0.028	−0.071	−0.052	−0.061	−0.024
	(0.128)	(0.119)	(0.108)	(0.123)	(0.133)
Solar Radiation FM	−0.540***	−0.507***	−0.518***	−0.589***	−0.420***
	(0.106)	(0.084)	(0.126)	(0.117)	(0.154)
Tmax DJ	−0.048	−0.117	−0.145	−0.109	−0.119
	(0.082)	(0.143)	(0.143)	(0.145)	(0.109)
Tmax FM	−0.035	0.052	0.108	0.059	0.126
	(0.114)	(0.045)	(0.085)	(0.054)	(0.183)
Tmin DJ	−0.192	−0.235	−0.210	−0.239	−0.198
	(0.235)	(0.278)	(0.273)	(0.270)	(0.269)
Tmin FM	0.198	0.222	0.212	0.190	0.256*
	(0.171)	(0.144)	(0.156)	(0.157)	(0.145)
Rain DJ	0.110	−0.212*	−0.209**	−0.139	
	(0.147)	(0.110)	(0.103)	(0.101)	
Rain FM	−0.115	−0.052	−0.079	−0.064	
	(0.072)	(0.067)	(0.078)	(0.073)	
SPEI DJ		−0.350			
		(0.233)			
SPEI FM		0.356			
		(0.313)			
Drought Intensity DJ			−0.426*		
			(0.224)		
Drought Intensity FM			0.648***		
			(0.214)		
Drought Severity DJ					−0.439**
					(0.219)
Drought Severity FM					0.626***
					(0.242)
% Area receiving Ext Rainfall DJ		0.204**	0.159	0.171	
		(0.094)	(0.122)	(0.115)	
% Area receiving Ext Rainfall FM		−0.162**	−0.152*	−0.157**	
		(0.067)	(0.078)	(0.072)	
Extreme Rainfall DJ					0.021
					(0.155)
Extreme rainfall FM					−0.082
					(0.074)
% Area irrigated	−0.032	−0.039	−0.039	−0.039	
	(0.078)	(0.072)	(0.075)	(0.070)	
% Area under HYV	−0.154*	−0.161*	−0.178*	−0.162*	
	(0.087)	(0.089)	(0.096)	(0.085)	
Observations	186	186	186	186	186
R^2	0.087	0.148	0.189	0.133	0.128
Adjusted R^2	−0.206	−0.160	−0.103	−0.162	−0.153
F Statistic	1.340 (df = 10; 140)	1.682* (df = 14; 136)	2.266*** (df = 14; 136)	1.767* (df = 12; 138)	2.052** (df = 10; 140)

Notes: *p<0.1; **p<0.05; ***p<0.01

DJ represents the month December-January and FM, the months February-March

As shown in the table, all models invariably confirm that there is a robust negative influence exerted by the variations in solar radiation during the months of February and March ($p \leq 0.01$). Similarly the variations in the area under HYVs also have an inverse relation with the rice yield across the models ($p \leq 0.1$). While both maximum and minimum temperatures exhibited opposing sensitivities in rice yield between the first two and last two months, the standard errors were too high to assert any robustness in these results. Models 2 ($p \leq 0.1$) and 3 ($p \leq 0.05$) suggested significant inverse relation between rainfall in the months of December and rice yield. However, as suggested by model 2 this negative influence of rainfall becomes positive once the intensity of rainfall becomes extreme in the initial months of this season ($p \leq 0.05$). However, in the latter half of the growing season, the influence of extreme rainfall becomes negative ($p \leq 0.05$). Also, the Navara rice yield exhibited opposing sensitivity to drought intensity during the first half and the second half of the growing season. During the months of December and January the rice yield responded positively to drought ($p \leq 0.1$) while it responded negatively to droughts during the months February and March ($p \leq 0.01$). The variations in the area under irrigation did not have any significant influence over the rice yield during this season.

Table 5.6: Diagnostic Tests - Navara Season

Test	Model 1	Model 2	Model 3	Model 4	Model 5	Null/Alternate Hypothesis
Regression based Hausman test	χ^2=39.427 (2.137e-05)	χ^2=42.083 (0.0001199)	χ^2= 54.825 (9.279e-07)	χ^2=49.399 (1.781e-06)	χ^2= 52.025 (97.278e-06)	H_1 = One model is inconsistent
Serial Correlation (Wooldridge's test)	F = 3.0142 (0.08427)	F = 4.3475 (0.03849)	F = 7.1968 (0.007991)	F = 4.4988 (0.0353)	F = 7.3442 (0.007829)	H_1 = serial correlation
Heteroscedasticity (Breusch-Pagan test)	BP = 120.93 (0.1391)	BP = 24.771 (0.1682)	BP = 41.869 (0.001846)	BP = 23.215 (0.1424)	BP = 38.791 (0.1862)	H_0 = Homoscedasticity
Cross-sectional Dependence (Pesaran CD test)	z = 6.9333 (4.11e-12)	z = 7.3241 (2.405e-13)	z = 7.1308 (9.981e-13)	z = 7.2413 (4.443e-13)	z = 7.1349 (7.945e-13)	H_1= cross-sectional dependence

Notes: p-values in parenthesis correspond to test statistic under the null hypothesis.

Table 5.6 shows the diagnostic tests performed for Navara season regression estimations. The Hausman test suggested that the random effects model is inconsistent ($p \leq 0.01$). Wooldridge's test for serial correlation suggested that there are no serial correlations among the variables used in the models ($p \leq 0.05$). The Breusch-Pagan test suggested that there is no homoscedasticity in the model and the Peasran's CD test suggested the presence of cross-sectional dependence among the variables in the models ($p \leq 0.01$). Based on these diagnostic tests, we used the robust standard errors for the estimation of the model, generated based on the method of Arellano (1987) which accounts for both serial correlation as well as cross sectional dependence.

The panel data analyses performed for the three rice cultivating seasons in Tamil Nadu suggested the presence of diverse climatic factors influencing the yield of rice. Rice cultivation in Tamil Nadu is well irrigated and use high yielding varieties. The rice yield exhibited opposing sensitivity to the variations in heat waves and warm nights during the

Kuruva season. The net effect, although, suggested that heat waves has a positive impact on the rice yield. In the Samba season, however, the positive effect of heat waves was not able to offset the negative effect of variations in minimum temperature, making the net effect negative. In the Navara season, both maximum and minimum temperatures exhibited opposing sensitivities between the first and second half of the growing season. However, these yield response to temperature variations was not significant in this season. In the case of rainfall, rice yield exhibited negative sensitivities to rainfall, particularly extreme rainfall in general, though some estimations suggested slight positive influence. Drought was not found to have significant negative effects on the rice yield generally, although a negative response was observed with the droughts of initial part of Navara season. The influence of certain variables, such as heat waves and warm nights have a very region specific character which these models were unable to bring out. The models with only weather variables did not exhibit any patterns that are substantially different from the other models. Therefore, we performed time series regression for the Kuruva and Navara season to incorporate the influence of these extremes on the rice yields.

5.2.2 Climate response function estimated at district level using multiple linear regression Model

Table 5.7 shows the weather sensitivity of rice yield in Tamil Nadu estimated at district level using season scale data for the period 2009-10 to 2015-16. We performed multiple linear regressions using various combinations of 12 variables - maximum temperature (Tmax), minimum temperature (Tmin), heat waves (Hmag), warm nights (Wmag), rainfall (rain), SPEI representing dry and wet extremes, fraction of area irrigated and the share of area with high yielding varieties. We also checked the combined effect of certain variables on rice yield. The results of which are provided in the table. We had 21 observations for each variable, 3 each from every year representing the major cultivating seasons. Each model provided in the table represents the statistically most significant combination of variables for the respective district. The table also provides the coefficient of determination of each model and the statistical significance of the F statistic.

Table 5.7: Regression estimates of weather sensitivity of rice yield in Tamil Nadu at district level for the period 2009-10 to 2015-16

District	Intercept	Tmax (Early)	Tmax (Late)	Hmag	Tmin (Early)	Tmin (Late)	Wmag	Rain (Early)	Rain (Late)	SPEI	Irrigation	HYV	Combined effects of variables[a]	R^2	Weather R^2	α value for F-statistic
Kancheepuram	-0.03			-0.48*			0.32			0.39	-0.31	0.64		0.40	0.28	0.15
Thiruvallur[b]	-0.18	-2.93*	-0.58	-0.07	2.81	1.01	-0.03	0.15	-1.33**	1.14*	-0.34	0.58	0.79	0.83	0.75	0.05
Cuddallore[b]	-0.14	0.45	2.37**	-0.48	-0.01	-1.17	0.28	0.40	1.21*	-0.38	-0.42		-0.41	0.57	0.55	0.50
Villupuram	0.04			-0.11			0.04			0.32	5.41	-5.10		0.14	0.04	0.80
Vellore[c]	-0.12	-0.32	0.15					1.85**	-1.35**		-0.13	0.13		0.50	0.50	0.1
Thiruvannamalai	-0.02	0.50	0.69	-0.27*	-1.46	-0.80	-0.60**	0.004	-0.38	-0.22	-12	10		0.78	0.53	0.1
Salem[d]	0.00	0.31	-1.08		-1.19	0.39				0.004	-0.78	0.72		0.68	0.65	0.05
Namakkal[c]	-0.01	0.56**	-0.17		-0.92***			0.11	-0.19		1.09	-1.01		0.85	0.81	0.05
Dharmapuri[e]	0.62*	-1.56	-1.27		-0.18	2.48**				-0.55	0.67	-0.54	-0.66**	0.51	0.23	0.25
Krishnagiri[e]	-0.27			0.12			0.12			1.59***	-2.93	3.15	0.35	0.50	0.33	0.1
Coimbatore[f]	-0.39**	-1.24***	0.21	-0.15	0.07	1.87***	-1.50**	0.59**	-0.26	-1.27**	-199.26	199.93	-2.80**	0.93	0.69	0.01
Thiruppur[d,e]	-0.005			-0.15			0.01			0.38	9.71	-9.42		0.33	0.21	0.25
Erode[e]	0.13	-0.45	-0.44		-0.03	0.89*				-0.25	10.37	-9.86	-0.13	0.79	0.32	0.01
Tiruchirapalli	-0.02			0.07			0.08			-0.22	-8.74	8.95		0.17	0.09	0.7
Karur[c]	0.01	-0.67***	0.64***	-0.85***			0.45**	-0.19	-0.015		180.2	-180		0.85	0.58	0.01
Perambalur[g]	0.26	0.55	-1.72*	1.05**	-3.57	2.43*	-0.02	0.54	0.06	0.20	-20.67	19.54	-0.37	0.71	0.50	0.25
Ariyalur[g]	0.25*	0.52	2.44***	0.26	-3.55***	0.55	0.94***	-0.24	0.30	0.30	7.28***	-3.94***	-0.29**	0.95	0.40	0.01
Pudukkottai[d, e]	-1.63**	0.22	-1.51*		-0.63	1.13				-0.00	18.89***	-21.68***	1.71***	0.83	0.22	0.01
Thanjavur[d]	0.00	-0.96	-0.39		0.75	0.95		0.33	0.23					0.32	0.32	0.45
Thiruvarur[d]	0.00	0.48	0.063		-1.50	0.83				-0.024				0.31	0.28	0.45
Nagapatinam	0.00			0.11			0.03			0.04	3.37	-3.53		0.23	0.08	0.55
Madurai	0.01			-0.05			0.47*			-0.18	-11.13	11.49		0.46	0.22	0.30
Theni	-0.07	1.98**	-0.15	0.18	-2.24**	-1.13	0.13	1.34***	0.90**	-1.25**	-193.47	194.67		0.80	0.65	0.05
Dindigul	-0.03			-0.27			0.46			-0.60**	15.34	-15.10		0.44	0.39	0.1
Ramanathapuram	-0.03	0.07	-2.62**	0.00	-0.42	0.68	-0.029	1.02**	-0.05	-0.82*	-2.53*	0.77***		0.77	0.62	0.1
Virudhunagar[g]	0.76***	-3.05***	-0.85***	-0.54***	0.80	1.81***	3.80***	1.50***	-0.16	-0.90**	16.58***	-15.94***	-0.82***	0.95	0.81	0.01
Sivagangai[b]	0.02	1.49	-4.16**	0.74**	-4.34**	4.13**	-0.48	1.84**	-0.70*	-1.49**	0.87	-2.62	-0.80**	0.80	0.73	0.1
Thirunelveli[e]	-0.14			0.03			-0.10			-0.09	-5.84	6.00	0.14	0.31	0.28	0.8

Thoothukudi[d]	0.39	-0.91	-0.20		0.38	-0.01				-0.09	-9.84	10.49	-0.41^{*}	0.47	0.25	0.35

[a] Combined effects of various independent variables have been included in the models

[b] The combined effect of Hmag and SPEI is included in the model

[c] The extreme values of temperature and rainfall (Hmag, Wmag and SPEI) for the early and late seasons were used in the place of actual values (Tmax, Tmin and Rain).

[d] Rainfall for whole season was used in the place of SPEI.

[e] The combined effect of Irrigation and HYV is included in the model.

[f] The combined effect of Wmag and SPEI is included in the model.

[g] The combined effect of Hmag and Wmag is included in the model

*** Represents estimates that are significant at $\alpha = 0.01$

** Represents estimates that are significant at $\alpha = 0.05$

* Represents estimates that are significant at $\alpha = 0.1$

Source : Author's calculations

Out of the 29 districts studied, the weather and non-weather variables used in the models were able to explain the yield variations in rice in 15 districts at a statistically highly significant level ($p \leq 0.1$). In the remaining districts, the models explained only a very smaller portion of yield variation in rice. In thirteen districts, the weather variables explained more than 50 per cent of the variability in the yield of rice. In nine districts, the weather variables explained between 25 and 49 per cent of the variations in rice yield. In five districts, statistically significant estimates were obtained for individual variables, bu the overall models were not significant or explained the variations in the dependent variable sufficiently. In eight districts, neither the model nor any individual variables were statistically significant.

In the Northeast zone, statistically significant ($p \leq 0.1$) models were obtained for Thiruvallur, Vellore, and Thiruvannamalai districts. In Thiruvallur, the model explained 56 per cent of the variation in rice yield whereas in Thiruvannamalai and Vellore, the model explained 51 percent and 26 percent of the variability in rice yield respectively. In Kancheepuram, although the model was not significant at least at 10 % level, it explained 20 per cent of the variation in rice yield. The intercept value was not significant in any of the districts. In Kancheepuram, while the overall model was not significant, the magnitude of heat waves in the region had an adverse influence of the rice yield ($p \leq 0.1$). In Thiruvallur also, the variations in maximum temperature had a highly negative influence on the yield of rice ($p \leq 0.1$). Apart from Tmax, the rice yield in Thituvallur was significantly affected by the variations in the late season rainfall ($p \leq 0.05$) as well as the dry and wet extremes ($p \leq 0.1$). While the late season rainfall had a more than proportionate negative impact, the rice yield responded positively to wet extremes and affected negatively by dry extremes in Thiruvallur. In Cuddalore district, although the model was not statistically significant, two variables, variations in Tmax in the late season ($p \leq 0.05$), and rainfall in the late season ($p \leq 0.1$) influenced the rice yield positively. In Vellore, SPEI had a positive relation with the rice yield in the early half of the season ($p \leq 0.05$) while it was negatively correlated with the rice yield in the second half ($p \leq 0.05$). It implies that rice yield increased with wet extremes in the early season and decreased with dry extremes in the first half and responded to these variables in an opposite fashion in the latter half of the cultivating season. In Thiruvannamalai district, rice yield responded negatively to the variations in day time ($p \leq 0.1$) and night time ($p \leq 0.05$) extremes in temperature. While the model was statistically significant and explained about 50 % of the variations in rice yield, none of the other variables had significant coefficients. In this zone, approximately 28 percent to 100 percent of the variations in the models are exclusively explained by the weather variables.

In the Northwest zone, the models for the districts, Salem ($p \leq 0.05$), Namakkal ($p \leq 0.05$), and Krishnagiri ($p \leq 0.1$) were statistically significant. In Salem, the model explained 68 % of the variations in the rice yield while in Namakkal and Krishnagiri, the models explained 85 % and 50 % of the variability in the rice yield respectively. In Dharmapuri, although the model explained 51 % of the variations in rice yield, the overall model was not statistically significant. In the models, weather variables explained 45 - 95 percent of the total variability in rice yield explained by the models. In Salem, none of the individual variables had statistically robust coefficient while in Namakkal, the rice yield exhibited opposing sensitivity to the variations in the magnitude of heat waves and warm nights in the early half of the cultivating season. The Hmag variable had a positive relation with the rice yield ($p \leq 0.05$) while the rice yield was negatively correlated with Wmag ($p \leq 0.01$). In Dharmapuri, the positive effects of minimum temperature (late season) ($p \leq 0.05$) and the negative effects of irrigation and high yielding varieties together ($p \leq 0.05$) were found to influence rice yield, although the overall model was not statistically robust. In Krishnagiri, the dry and wet extremes (as represented by SPEI) was found to exert a disproportionate and highly robsut direct effect on the rice yield ($p \leq 0.01$). Rice yield varied by about 1.59 units for every unit change in SPEI towards wet extremes and vice versa.

In the West zone, the models for the districts, Coimbatore ($p \leq 0.01$) and Erode ($p \leq 0.01$) were statistically significant. The model for Thiruppur district was not significant at least at 10 % level and explained only 11 per cent of the variation in rice yield. In the case of Coimbatore, the model explained 82 % of the variations in rice yield. Here, rice yield exhibited an inverse relation with the variability in early season Tmax ($p \leq 0.01$), while a highly positive change was detected with changes in late season Tmin ($p \leq 0.01$). However, Wmag representing the variability in the magnitude of extremes in minimum temperature, had a negative impact on the rice yield ($p \leq 0.05$). Also, rice yield in coimbatore has a positive relation with early season rainfall ($p \leq 0.05$) but a negative relation with SPEI ($p \leq 0.05$). This implies that rice yield responds positively to the variations in normal rainfall but extreme rainfall has a negative influence on it. Also, the interaction of this SPEI with variability of nighttime extremes in temperature also has a net negative influence on the rice yield in Coimbatore ($p \leq 0.05$). In Erode, although the model explained 65 % of the variations in rice yield, only the effect of variations in minimum temperature was found statistically significant. The rice yield varied positively with variations in minimum temperature in the later half of the cultivating season ($p \leq 0.1$).

In Cauvery Delta zone, only two districts - Ariyalur and Karur had statistically robust models explaining the variance in rice yield. In Ariyalur, the model explained 88 % of the variability in rice yield ($p \leq 0.01$) whereas the model accounted for 70 % of the variations in rice yield in Karur ($p \leq 0.01$). Although the model for Perambalur district explained 27 % of the rice yield variations, the overall model was not statistically significant at least at 10 % level. In Trichy district, none of the weather or non-weather variables could significantly explain the variation in rice yield. In Karur, at the same time, opposing sensitivity in the rice yield were observed to changes in heat wave magnitude during the early and late halves of the cultivating seasons. During the early half, the rice yield responded negatively to the variations in Hmag ($p \leq 0.01$) while in the later half a positive correlation of almost similar magnitude was observed between rice yield and Hmag ($p \leq 0.01$). Also, the rice yield was negatively influenced by the overall variations in maximum temperature during the growing season ($p \leq 0.01$). Rice yield, on the other hand, varied positively with variations in the magnitude of warm spells in nighttime temperatures ($p \leq 0.05$). In Perambalur, the rice yield responded positively to the variations in late season Tmin ($p \leq 0.1$) and varied in the inverse direction to the changes in late season Tmax ($p \leq 0.1$). However, the variations in the magnitude of heat waves during the growing season had a positive influence on the rice yield in Perambalur ($p \leq 0.05$). In Thanjavur, Thiruvarur, and Nagapattinam, the variables in the model were not statistically robust in explaining the variation in rice yield.

In the South zone, Pudukkottai, Theni, Dindigul, Ramanathapuram, and Sivagangai districts had statistically significant models explaining climate-rice yield relationship. In Pudukkottai, the model explained 70 % of the variations in rice yield and was significant at 1 % level. In Pudukkottai, apart from the direct relationship between rice yield and maximum temperature variations in the latter half of the growing seasons ($p \leq 0.1$), variations in the share of area under irrigation and high yielding varieties ewre observed to influence the rice yield profoundly. Rice yield varied directly with the area under irrigation ($p \leq 0.01$) while it exhibited an inverse relation with the area under HYVs ($p \leq 0.01$). However, the combined effect of irrigation and rice yield was a positive influence on the yield of rice ($p \leq 0.01$). In Madurai, however, none of the variables had a robust influence of the yield of rice. The overall model, however, explained 15 % of the variations in the yield. In Theni, the model explained 56 % of the variation in the crop yield and the model was found significant ($p \leq 0.05$). In Theni, the crop yield responded positively to the variations in early season Tmax ($p \leq 0.05$), but the variations in the early season nighttime temperature influenced the rice yield adversely and in a way that can offset the positive influence of variations in Tmax ($p \leq 0.05$). Similarly, variability in the early season rainfall ($p \leq 0.01$) and late season rainfall ($p \leq 0.05$) influenced the rice yield positively, though the yield responded negatively to extreme wetness ($p \leq 0.05$). In Dindigul, the model explained 25

% of the variations in rice yield and was significant at 10 % level. Here also, the rice yield varied inversely with the SPEI ($p \leq 0.05$) suggesting that the yield in adversely influenced by extreme wetness. In Ramanathapuram, the overall model was statistically significant ($p \leq 0.1$) and explained 49 % of the variations in rice yield. Rice yield in Ramanathapuram responded positively to the variations in early season rainfall ($p \leq 0.05$) and the area under HYVs ($p \leq 0.01$), and negatively to the variations in late season Tmax ($p \leq 0.05$), SPEI ($p \leq 0.1$) and irrigation ($p \leq 0.1$). In Sivagangai district, Hmag during the whole cultivating season ($p \leq 0.05$), Tmin in the late season ($p \leq 0.05$), rainfall in the early season ($p \leq 0.05$) and responded negatively to the variations in late season Tmax ($p \leq 0.05$), early season Tmin ($p \leq 0.05$), late season rainfall ($p \leq 0.1$) and SPEI ($p \leq 0.05$). The combination of heat waves and SPEI also had a negative influence on the rice yield ($p \leq 0.05$). Overall, the model explained 51 % of the variations in the crop yield ($p \leq 0.1$).

In the Southern zone, only Virudunagar district had a statistically significant ($p \leq 0.01$) model. It explained 87 % of the variation in the rice yield in the district. In Virudunagar, the variations in early season and late season Tmax as well as the Tmax extremes had a profound negative impact on the rice yield ($p \leq 0.01$). However, a positive relation capable of offsetting this negative influence is exerted by the variability and extremes in minimum temperature ($p \leq 0.01$). Also, the rice yield is positively related to early season rainfall ($p \leq 0.01$) but negatively correlated with the extremes in rainfall ($p \leq 0.05$). The rice yield exhibited significant opposing sensitivities towards the variations in the fraction of area under irrigation and HYV ($p \leq 0.01$). The combination of these variables also had a significant negative influence on the rice yield ($p \leq 0.01$). In Thirunelveli, the model was not at all significant and did not explain any of the variations in the rice yield. In Thoothukkudi, however, the model explained 12 % of the variations in rice yield and suggested that the combined influence of variation in the area under irrigation and HYV has a negative influence on the rice yield ($p \leq 0.1$).

5.3 Weather sensitivity of rice yield in a larger context

In the present study, we empirically examined the weather sensitivity of rice yield in Tamil Nadu region, India using fixed effects panel data models and multiple linear regression models. Using the fixed effects regression model, we assessed the response of rice yield in the three major rice cultivating seasons of the region - Kuruva, Samba, and Navara separately. We used the data for the period between 1985-86 and 2015-16 for the fixed effects models. The study further performed a district level analysis of weather sensitivity using a multiple linear regression method with seasonal data from 2009-10 to 2015-16. The rice yield exhibited significant responses to weather and non-weather variables in both fixed effects and linear regression models. The results are comparable to the results estimated in regional, national and global contexts.

In general, the yield capacity of rice is primarily a function of its vegetative and reproductive phases. The variations in temperature influences the physiological processes involved in grain production and impacts the rice yield (Krishnan et al., 2011). In the present study, we tested the influence of the variability and extremes in maximum and minimum temperatures as well as the influence of solar radiation on the rice yield. Our results for the Kuruva season suggested that rice yields responded positively to the variations in the magnitude of warm spells in daytime temperature (both April-May and June July) and negatively to the variations in warm spells in night-time temperature (April-May). In the Samba season, also a similar response is observed as rice yield responded positively to changes in maximum temperature (August-September) and was influenced negatively by the variations in minimum temperature (October-November). In the Navara season, the rice yield responded negatively to the variations in both maximum and minimum temperatures. However, the estimate for the influence of temperature on rice yield for the Navara seaosn was not statistically robust. These results are broadly consistent with the observations of Welch et al. (2010) that the rice in tropical and subtropical Asia exhibited opposing sensitivities towards maximum and minimum temperature. The inverse relationship of changes in minimum temperature and yield is observed widely in rice specific studies (Peng et al., 2004; Auffhammer et al., 2012; Pattanayak and Kumar, 2014, 2020b) in India and abroad. However, none of these studies suggest positive influence of variations in maximum temperature on rice yield. At the district level, rice yields in Cuddalore, Namakkal, Perambalur, Ariyalur and Theni exhibited positive response to variations in maximum temperature; the rice yields in Thiruvalluar, Coimbatore, Ramanathapuram, and Virudhunagar exhibited negative responses to variations in maximum temperature; and the rice yields in Karur exhibited opposing sensitivities towards variations in maximum temperature in the early and late halves of growing seasons while the rice yields in Perambalur and Sivagangai exhibited opposing sensitivities towards variations in maximum temperature in the late half of the growing season and the variations in the magnitude of warm spells in daytime temperature. In the case of minimum temperature, the rice yields in Dharmapuri, Erode and Virudhunagar exhibited positive relation with the variations in minimum temperature; the rice yields in Thiruvannamalai, Namakkal and Theni exhibited inverse responses to variations in minimum temperature; and the rice yields in Coimbatore, Ariyalur, and Sivagangai exhibited opposing sensitivities to the variations in early and late season minimum temperatures. The models for Kuruva and Samba seasons did not show any significant influence of solar radiation on the rice yield while the Navara rice responded negatively to the variations in solar radiations in the latter half of the season.

Rice is mostly grown in flooded or submerged conditions and it is highly sensitive to variations in water availability (Bouman et al., 2007; Bouman, 2009). Rainfall during the ripening stage is observed to influence rice yield positively (Welch et al., 2010). Kumar and Parikh (2001) observed that higher precipitation has a beneficial influence in the winter and autumn seasons and exert detrimental influence during the spring and summer. In agreement with these contentions, the present study observed that, on an average, rice yields responded negatively to variations in rainfall during Kuruva (April-July) and Navara (December-March) seasons. In Samba season, one model showed a positive influence of rainfall on the yield of rice in the later half of the cultivation period. This observation also, is broadly consistent with the findings of (Welch et al., 2010). At district level, rice yields generally exhibited opposing sensitivities towards the variations in rainfall during the early and later halves of the cultivating season. Rainfall during the early half had a positive effect on the rice yield while the rice yield showed an inverse relation with rainfall during the later half of the cultivating season. This observation is generally contrary to the findings in certain widely cited studies. In Auffhammer et al. (2012), rice yield exhibited inverse relation with the rainfall during early and later halves of the cultivating season. In Pattanayak and Kumar (2020b) rice yield responded negatively to the rainfall during early half of the cultivating season and exhibited a positive relation with rainfall in the later half over South India. However, our results are consistent with the findings of Pattanayak and Kumar (2014) for the Kharif rice in Inda. The Kharif rice in India responded positively to the variations in rainfall and responded negatively to the rainfall changes in the latter half of the cultivating season.

Apart from the influence of rainfall on the rice yield, the present study also checked the relation between rice yield and extreme rainfall. The influence of extreme rainfall is measured in terms of the fraction of area receiving extreme rainfall. In the district level analysis, the variable SPEI is modified to include values below -1 and the values above +1 to account for the dry and wet extremes. We could observe that the rice yield responded negatively to the variations in the fraction area receiving extreme rainfall during Kuruva season, the rice yield had a positive relation with variations in extreme rainfall in the Samba season, and the rice yield exhibited opposing sensitivities to the early season and late season variations in extreme rainfall in the Navara season. In the early half of the growing season, a positive relation was observed and an inverse relation was seen in the latter half. Revadekar and Preethi (2012) observed a strong positive correlation between extreme rainfall during June-August period and Kharif rice yield in India. Our results for Samba season are broadly consistent with this observation. However, Auffhammer et al. (2012) suggests that the extreme rainfall during the south-west monsoon has a negative influence on the rice yield. At the district level, the rice yield in Thiruvalluar and Krishnagiri districts displayed a significant positive relation with extreme wetness (SPEI) while all other districts showed a negative yield response towards extreme wetness.

Along with extreme rainfall, drought is another important component influencing the rice yield. Drought is measured in terms of SPEI. Negative values of SPEI are extracted and drought intensity and severity are calculated based on the methods discussed in Chapter 3. We observed that drought did not have any significant influence on the Kuruva and Samba rice yield. However, Navara rice yield displayed significant negative response to drought during the early half of the growing season and a positive response to the drought during the later half. Since the rice yield in Tamil Nadu is mostly irrigated, the negative effect of drought is relatively less. This is equally reflected in the district level analysis as well. At the district level, only Krishnagiri and Thiruvalluar experienced negative influence of droughts. Further, the rice yield in Kuruva season exhibited a significant positive relation with irrigation while the relations between Samba and Navara rice yields and irrigation were not statistically significant. Using a district level panel data model, Auffhammer et al. (2012) and Pattanayak and Kumar (2014) observed a small but positive and highly significant relation between rice yield and irrigation. The models for Ariyalur, Pudukkottai, Ramanathapuram and Virudhunagar districts suggested significant influence of area irrigated on the rice yield. Similarly, the present study observed an inverse relation between rice yield and the area under high yielding varieties. This was observed in two major cultivating seasons - Kuruva and Navara and across districts as well. However, our results for Samba season suggests a significant positive relation between rice yield and the area under HVY. This observation is in agreement with the results of Auffhammer et al. (2012) and Pattanayak and Kumar (2014) for Kharif rice in India.

5.4 Summary and Findings

The present chapter examined the sensitivity of rice yield in Tamil Nadu to the variations in weather and non-weather factors. We used a fixed effects panel data model to study the response of rice yield to the variations in weather across three major cultivating seasons in

Tamil Nadu. The diagnostic tests such as Hausman's test, Wooldridge's test for serial correlation, Breusch-Pagan test for heteroscedasticity, and Pesaran CD test for cross-sectional dependence were performed. Based on the results of the diagnostic tests, we estimated heteroscedasticity consistent robust covariance matrix and SEs that also account for and autocorrelation and cross-sectional dependence. At the district level, we performed multiple linear regression analysis. The major findings of this chapter are;

1. Rice cultivation in Tamil Nadu has been increasing mainly on account of the increase in the yield of rice.

2. The yield of rice in Kuruva season is highly sensitive to the variations in extremes in temperature and precipitation. The rice yield exhibit opposing sensitivities to the variations in heat waves and warm nights. However, the beneficial influence of heat waves on the the rice yield outweighs the negative effect of minimum temperature. Also, while the rice yield is inversely related to extreme rainfall, the rice yield has increased in response to the droughts in the growing season possibly due to the presence of irrigation. The fraction of area irrigated has a direct relation to the yield of rice in Kuruva season.

3. In the Samba season, rice yield is positively influenced by the variations in maximum temperature. However, the negative influence of minimum temperature variations is the dominant factor in the Samba season. Also, the rice yield in Samba season responded positively to the variations in the area receiving extreme rainfall and the area under HYV.

4. In the Navara season, the Solar radiation, rainfall and extreme rainfall exert a strong negative influence on rice yield.

5. At the district level, the weather and non-weather variables used in the models were able to explain the yield variations in rice in 15 districts at a statistically highly significant level. Weather variables contributed a major share in the overall variability in the yield of rice. In five districts, statistically significant estimates were obtained for individual variables, but the overall models were not significant or explained the variations in the dependent variable sufficiently.

Chapter 6

Socio economic factors influencing Sensitivity and Adaptive Capacity capacity of Farmers: a case study in Cauvery Delta region of Tamil Nadu

6.1 Introduction

In this chapter we analyse the factors that constitute the sensitivity and adaptive capacity of the sample households. Based on an extensive literature survey and inputs from the field visit we have included twenty socio-economic factors that determine the sensitivity and adaptive capacity of the sample households under a warming climate characterised by increasing variability and extreme events. These factors are broadly grouped under six major components - socio-demographic profile, livelihood strategies, social networks, food security, water security, and health security. Among these components, the socio-demographic profile, livelihood strategies, and social networks represent the extent to which the households are able to adapt to the variations in climate whereas food security, water security, and health security determine the extent to which the farmers are sensitive to these variations (Hahn et al., 2009).

6.1.1 Socio-demographic Profile

Socio-demographic profile provides an overview of the social and economic resources available to the household. The components of socio-demographic profile are of considerable importance resource management, decision making, and strategic planning at the household level (Gerlitz et al., 2014). In the present study, socio-demographic profile of a household is defined in terms of three variables - dependency Ratio, percentage of female operational holders and the educational attainment of the household.

6.1.1.1 Dependency Ratio

Dependency ratio refers to the ratio of the number of children (0-14 years old) and older persons (65 years or over) to the number of persons belonging to the working-age population (15-64 years old). The dependency ratio is considered as “a good initial approximation to assess the degree of economic-demographic dependency in a society" United Nations, Department of Economic and Social Affairs PD (2013) and reflects the manoeuvrability of the households to adapt to drivers of change (Gerlitz et al., 2014).

The tables 6.1 and 6.2 illustrate the patterns of dependency among the rice farmers of Tamil Nadu. Among the sample households, 46.32 percent has a dependency ratio higher than the national average value for the year 2015, 0.52[1], and 53.67 percent of the farmers have dependency ratio values smaller than the national average. As seen from the tables, majority (73.16 per cent) of the households have a low dependency ratio (0-1). The dependency ratio is relatively higher among the farmers in Nagapattinam and Thanjavur districts. The dependency ratio was more or less similar for all farm size categories. A notable observation in this analysis is that 8.35 percent (33 households) of the households had all the current members above 65 years of age. Majority (84.84 percent) of these households senior were small farmers. The dependency ratio of Tamil Nadu is generally better among the Indian states. Among the sample households as well, the dependency ratio is relatively small. However, among the various farm size categories the small farmers are more disadvantaged in terms of dependency ratio, which, in turn may affect their ‘manoeuvrability’ in the context of climate change.

6.1.1.2 Gender of the Operational Holder

Vulnerability studies generally assume that the extent of vulnerability is different for male and female headed households. Generally, female headed households are considered as more vulnerable to the impacts of climate change (Hahn et al., 2009; Gerlitz et al., 2017a). However, this approach of ‘feminisation of poverty’ has been widely disputed internationally (Arora-Jonsson, 2011). Empirical studies, however continue to assume differential vulnerability of female and male headed households. Bayard et al. (2007); Hassan and

[1] calculated from United Nations (2019)

Nhemachena (2008), and Deressa et al. (2010) observed that men performed better in managing farms and taking decisions pertaining to adaptation and Arun (2012) observed that female farmers faced discrimination in interventions and institutional support. In view of these evidences, the present study considered gender of the operational holder as a variable

Table 6.1: Dependency ratio of farmers sorted on the basis of their districts

Dependency Ratio	Districts							
	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
0 - 1	16 (80%)	11 (100%)	52 (70.27%)	12 (92.31%)	71 (65.74%)	60 (75%)	67 (75.28%)	289 (73.16%)
1.01 - 2	1 (5%)	0	13 (17.57%)	0	21 (19.44%)	11 (13.75%)	9 (10.11%)	55 (13.92%)
2.01 - 3	1 (5%)	0	5 (6.75%)	0	5 (4.63%)	4 (5%)	2 (2.25%)	17 (4.3%)
3.01 - 4	0	0	0	0	1 (0.93%)	0	0	1 (0.25%)
Inf	2 (10%)	0	4 (5.41%)	1 (7.69%)	10 (9.3%)	5 (6.25%)	11 (12.36%)	33 (8.35%)
Total	20 (100%)	11 (100%)	74 (100%)	13 (100%)	108 (100%)	80 (100%)	89 (100%)	395 (100%)

Source: author's calculation

Table 6.2: Dependency ratio of farmers sorted on the basis of their categories

Dependency Ratio	Farmer Categories				
	Large	Medium	Semi Medium	Small	Total
0 - 1	3 (75%)	22 (73.34%)	36 (73.47%)	228 (73.08%)	289 (73.16%)
1.01 - 2	1 (25%)	4 (13.34%)	5 (10.20%)	45 (14.42%)	55 (13.92%)
2.01 - 3	0	2 (6.67%)	4 (8.16%)	11 (3.53%)	17 (4.3%)
3.01 - 4	0	0	1 (2.04%)	0	1 (0.25%)
Inf	0	2 (6.67%)	3 (6.12%)	28 (8.97%)	33 (8.35%)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

influencing the adaptive capacity assuming differential capacity to adapt among male and female headed households.

The tables 6.3 and 6.4 show the gender-wise distribution of farmers across districts and farm size categories. Among the 395 operational holders surveyed, only 9.62 percent were females. In majority of the cases, senior female members of the household had to take charge of the cultivation following the demise of the male head of the household or when the male head migrated to other states for a long period for employment purposes. Majority of the female headed operational holders were small farmers and mainly cultivated in Samba and Navara seasons. Thanjavur district had the largest number of female headed households followed by Nagapattinam district.

6.1.1.3 Educational attainment of the household

Evidence from vulnerability research suggest that higher levels of education is associated with better capacity to adapt to climatic changes (Brenkert and Malone, 2005; Deressa et al., 2010; Lutz et al., 2014; Gerlitz et al., 2017b). According to Lutz et al. (2014), education enhances cognitive capacities of individuals, and enables them to develop awareness and perception about risks and influences their decisions regarding risk mitigation strategies. More specifically, Lutz et al. (2014) observed that preventive measures such as living in low-risk areas, stockpiling emergency supplies etc. were higher among educated households and they experienced less in terms of loss of life, morbidity and damages. Further, the study also observed that educated households coped better to loss of income and psychological impacts of natural disasters. In general vulnerability studies consider the educational attainment of the head of the household for the analysis of vulnerability. However, the household heads often make decisions in consultation with the family members particularly when there are well educated members in the family (Singh et al., 2016). Female members are observed as contributing substantially to strategic decisions among farm households (Quentin, 2010). Therefore, we considered incorporating the educational attainment of the whole family instead of using the education of the household head. We assigned incremental values for each higher levels of education starting from 0 for no education and 8 for post graduate level education. The educational attainment of the family was then represented by the mean of maximum and minimum values for education in a household. The tables 6.5 and 6.6 represent the educational attainment of farmers of Tamil Nadu represented by this education score.

Table 6.3: Gender of the operational holders sorted on the basis of their districts

Gender of OPH	Districts							
	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
Female	1 (5 %)	0	9 (12.20 %)	0	19 (17.60 %)	5 (6.20 %)	4 (4.50 %)	38 (9.62 %)
Male	19 (95 %)	11 (100 %)	65 (87.80 %)	13 (100 %)	89 (82.40 %)	75 (93.80 %)	85 (95.50 %)	357 (90.38 %)
Total	20 (100 %)	11 (100 %)	74 (100 %)	13 (100 %)	108 (100 %)	80 (100 %)	89 (100 %)	395 (100 %)

Source: author's calculation

Table 6.4: Gender of the operational holders sorted on the basis of their categories

Gender of the OPH	Farmer Categories				
	Large	Medium	Semi Medium	Small	Total
Female	0	1 (3.30%)	4 (8.20%)	33 (10.60%)	38 (9.62%)
Male	4 (100%)	29 (96.70%)	45 (91.80%)	279 (89.40%)	357 (90.38%)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

Table 6.5: Educational attainment of the operational holders sorted on the basis of their districts

Education Score	Districts							
	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
0 - 2	8 (40%)	6 (54.55%)	26 (35.14%)	5 (38.46%)	29 (26.85%)	26 (32.50%)	27 (30.34%)	127 (32.15%)
2 - 4	8 (40%)	2 (18.18%)	40 (54.05%)	8 (61.54%)	63 (58.34%)	38 (47.50%)	45 (50.56%)	204 (51.65%)
4 - 6	3 (15%)	2 (18.18%)	8 (10.81%)	0	16 (14.81%)	16 (20%)	14 (15.73%)	59 (14.94%)
6 - 8	1 (5%)	1 (9.09%)	0	0	0	0	3 (3.37%)	5 (1.27%)
Total	20 (100%)	11 (100%)	74 (100%)	13 (100%)	108 (100%)	80 (100%)	89 (100%)	395 (100%)

Source: author's calculation

Table 6.6: Educational attainment of the operational holders sorted on the basis of their categories

Education score	Farmer Categories				
	Large	Medium	Semi Medium	Small	Total
0 - 2	0	2 (6.67%)	11 (22.45%)	114 (36.54%)	127 (32.15%)
2 - 4	3 (75%)	16 (53.34%)	25 (51.02%)	160 (51.28%)	204 (51.65%)
4 - 6	1 (25%)	12 (40%)	11 (22.45%)	35 (11.22%)	59 (14.94%)
6 - 8	0	0	2 (4.08%)	3 (0.96%)	5 (1.27%)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

As seen in the tables 6.5 and 6.6, majority of the farm households of Tamil Nadu have decent educational attainment with most of the farmers sending their children at least up to graduation levels. The educational attainment is relatively higher in the districts Thanjavur, Thiruvarur, and Trichy. In the farm size category-wise classification, it is interesting to note that households with largest educational attainment belonged to small and semi-medium households. Also, the share of households with lower educational attainment decreases with increase in the farm size. For the small households, educating their children is clearly a way out towards a better livelihood scenario.

6.1.2 Livelihood Strategies

An important component in the process of adaptation is the various strategies adopted by the farmer households to cope with the manifestations of climate change impacts. Livelihood strategies provide flexibility and provide a buffering ability to cope with perturbations (Marschke and Berkes, 2006). This section provides an overview of livelihood strategies adopted by the farmer households of Tamil Nadu. The indicators used to represent livelihood strategies are, a) the percentage of migrants among farm households, b) livelihood diversification, and c) the diversification of agricultural activities.

6.1.2.1 Percentage of Migrants

Migration plays an important role in the adaptation process of farm households. Migration provides new opportunities, networks and resources in the host regions, and provides an option to diversify the household livelihoods, support climate adaptation ,and build societal resilience in the regions of origin (Scheffran et al., 2012). Also, migration is emerging as a key livelihood strategy in rural India (Singh et al., 2018) and the benefits from remittance, knowledge and social networks from the host region are enhancing the adaptive capacity of migrating households (Jha et al., 2018). Environmental change is a major factor influencing the motivation to migrate. It creates circumstances that force and attract people to migrate, and also limits the capacity of the households to migrate (Black et al., 2011). Evidence from India suggests that weather-induced distress in agriculture could lead to migration from rural to urban areas in India. A 1 % decline in rice yield leads to a nearly 2 % increase in the rate of out-migration from a state while a similar decline in wheat yield causes a 1 % increase in the rate of out-migration (Viswanathan and Kavi Kumar, 2015). In the present study, therefore migration is considered as a proxy for distress among the agrarian households.

Table 6.7: Percentage of migrant households among the operational holders sorted on the basis of their districts

Number of Migrants	Districts							
	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
0	12 (60.%)	11 (100%)	53 (71.60%)	11 (84.6%)	74 (68.50%)	71 (88.80%)	82 (92.10%)	314 (79.50%)
1	3 (15%)	0	19 (25.70%)	2 (15.40%)	29 (26.90%)	6 (7.50%)	5 (5.60%)	64 (16.20%)
2	4 (20%)	0	2 (2.70%)	0	2 (1.90%)	3 (3.80%)	2 (2.20%)	13 (3.30%)
3	0	0	0	0	2 (1.90%)	0	0	2 (0.50%)
4	1 (5%)	0	0	0	1 (0.90%)	0	0	2 (0.50%)
Total	20 (100%)	11 (100%)	74 (100%)	13 (100%)	108 (100%)	80 (100%)	89 (100%)	395 (100%)

Source: author's calculation

Table 6.8: Percentage of migrant households among the operational holders sorted on the basis of their categories

Number of Migrants	Farmer Categories				
	Large	Medium	Semi Medium	Small	Total
0	2 (50%)	26 (86.70%)	38 (77.60%)	248 (79.50%)	314 (79.50%)
1	1 (25%)	3 (10%)	6 (12.20%)	54 (17.30%)	64 (16.20%)
2	1 (25%)	1 (3.30%)	4 (8.20%)	7 (2.20%)	13 (3.30%)
3	0	0	1 (2%)	1 (0.30%)	2 (0.50%)
4	0	0	0	2 (0.60%)	2 (0.50%)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

The tables 6.7 and 6.8 illustrate the patterns of migration among the farm households of Tamil Nadu region. The present study incorporates both national as well as international migration in the analysis. The tables suggest that migration is relatively low among the rice farmers of Tamil Nadu with 79.49 percent of the sample households does not have any migrant member. There were 64 families with one migrant member, 13 families with 2 migrant members and 2 families with 3 migrant members and 2 families with 4 migrant members. Thanjavur district had relatively larger share of the migrant households followed by Nagapattinam. Among the four farmer categories, small operational households had the largest share of migrant members. This was followed by semi-medium households.

6.1.2.2 Livelihood Diversification Index

Livelihood diversification is primarily an autonomous response to survival issues. Turner et al. (2003b) considers livelihood diversification as “an overarching strategy aimed at reducing risks and increasing options in the face of hazards used world-wide and across economic classes and political economies, in some cases at the cost of reduced material well being". Such diversifications often contribute positively to livelihood sustainability by reducing the proneness to stress and shocks (Ellis, 1999). While the diversification of incomes other than agriculture is a promising adaptation strategy in the face of adverse impacts of a changing climate, the scope of this strategy depends on the off-farm activities available in the respective areas (Panda et al., 2013). Tables 6.9 and 6.10 show the extent of livelihood diversification among the rice farmers of Tamil Nadu.

Since migration was considered separately in the previous section, this analysis of livelihood diversification does not include migration as a variable. It includes only those employment opportunities available locally in the respective areas. It was observed that the rice farmers of Cauvery Delta Region, Tamil Nadu engaged in casual wage labour, skilled works, ran small shops and other trading activities locally. Some of the farmers found opportunities in the services sector, both government and private within their locality.

Table 6.9: Livelihood diversification among the operational holders sorted on the basis of their districts

LDI	Districts							
	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
0.125	0	0	0	0	1 (0.90 %)	1 (1.20 %)	0	2 (0.50 %)
0.143	0	0	0	0	0	1 (1.20 %)	0	1 (0.30 %)
0.200	0	0	0	0	1 (0.90 %)	1 (1.20 %)	0	2 (0.50 %)
0.250	1 (5 %)	0	9 (12.20 %)	0	10 (9.30 %)	5 (6.20 %)	5 (5.60 %)	30 (7.60 %)
0.334	6 (30 %)	2 (18.20 %)	36 (48.60 %)	3 (23.10 %)	33 (30.60 %)	28 (35 %)	25 (28.10 %)	133 (37.70 %)
0.500	13 (65 %)	9 (81.80 %)	29 (39.20 %)	10 (76.90 %)	63 (58.30 %)	44 (65 %)	59 (66.30 %)	227 (57.50 %)
Total	20 (100 %)	11 (100 %)	74 (100 %)	13 (100 %)	108 (100 %)	80 (100 %)	89 (100 %)	395 (100 %)

Source: author's calculation

Table 6.10: Livelihood diversification among the operational holders sorted on the basis of their categories

LDI	Farmer Categories				
	Large	Medium	Semi Medium	Small	Total
0.125	0	0	0	2 (0.60 %)	2 (0.50 %)
0.143	0	0	0	1 (0.30 %)	1 (0.30 %)
0.200	0	0	0	2 (0.60 %)	2 (0.50 %)
0.250	2 (50 %)	0	1 (2 %)	27 (8.70 %)	30 (7.60 %)
0.334	2 (50 %)	12 (40 %)	18 (36.70 %)	101 (32.40 %)	133 (37.70 %)
0.500	0	18 (60 %)	30 (61.20 %)	179 (57.40 %)	227 (57.50 %)
Total	4 (100 %)	30 (100 %)	49 (100 %)	312 (100 %)	395 (100 %)
Total	4 (100 %)	30 (100 %)	49 (100 %)	312 (100 %)	395 (100 %)

Source: author's calculation

Here, a livelihood diversification index (LDI) was constructed to study the extent of diversification. LDI is the inverse of (the number of livelihood activities +1) reported by a household (Hahn et al., 2009). The larger the number of livelihood options engaged by a household the smaller will be the LDI.

As seen from the tables a large majority of the farmers in the region depend on farming as the sole livelihood option (57 %). Diversification is generally higher in Thiruvarur, Thanjavur and Nagapattinam districts and is too low among the farmers of Ariyalur, Karur and Perambalur. Category-wise, livelihood diversification is generally higher among small farmers although more than 50 % of them depend solely on rice cultivation. The fraction of farmers depending exclusively on rice cultivation is higher among medium and semi-medium farmers.

6.1.2.3 Diversification of agricultural activities

This is a measure similar to that of the livelihood vulnerability index. A farmer who cultivate more than one crop and raises animals, and collects natural resources will be less vulnerable to the impact of climatic changes than a farmer who depends exclusively on a single crop Hahn et al. (2009); Gerlitz et al. (2017a). The diversification of agricultural activites by a household is measured in terms of an index called agricultural diversification index (ADI). Similar to the LDI, the ADI is the inverse of (the number of agricultural livelihood activities +1) reported by a household. Tables 6.11 and 6.12 illustrate the extent of diversification of agricultural activities among agricultural households of Cauvery Delta Region, Tamil Nadu.

The rice farmers of Cauvery Delta region cultivated cotton, black gram, sesame, ground nut, coconut, pumpkin, sugarcane, vegetables, reared cattle, buffalo, ovine, and poultry. The analysis using ADI suggests that majority of the farmers had one or two agricultural activities other than rice cultivation. There were two farmers who did not cultivate even rice during the last three to four years. One of them belonged to Perambalur district and the other one was from Thanjavur district. While approximately 25 percent of the farmers cultivated only rice, the rest had at least poultry. The diversification was relatively higher in Thanjavur district followed by Thiruvarur and Nagapattinam while it was relatively low in Karur, Perambalur and Ariyalur. The diversification was widely prevalent among small farmers followed by semi-medium and medium farmers. Most of the farmers cultivated black gram, sesame, and ground nut during the Kuruva season and cultivated rice in the other seasons.

Table 6.11: Diversification of agricultural activities among the operational holders sorted on the basis of their districts

ADI	Districts							
	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
0.111	0	0	0	0	1 (0.90 %)	0	0	1 (0.30 %)
0.125	0	0	0	0	3 (2.80 %)	0	0	3 (0.80 %)
0.143	0	0	0	0	2 (1.90 %)	0	0	2 (0.50 %)
0.167	0	0	4 (5.40 %)	0	0	2 (2.50 %)	0	6 (1.50 %)
0.200	0	0	11 (14.90 %)	0	2 (1.90 %)	11 (13.80 %)	8 (9 %)	32 (8.10 %)
0.250	2 (10 %)	2 (18.20 %)	31 (41.90 %)	0	27 (25 %)	21 (26.20 %)	19 (21.30 %)	102 (25.80 %)
0.334	6 (30 %)	8 (72.70 %)	23 (31 %)	7 (53.80 %)	52 (48.10 %)	22 (27.50 %)	29 (32.60 %)	147 (37.20 %)
0.500	12 (60 %)	1 (9.10 %)	5 (6.80 %)	5 (38.50 %)	20 (18.50 %)	24 (30 %)	33 (37.10 %)	100 (25.30 %)
1	0	0	0	1 (7.70 %)	1 (0.90 %)	0	0	2 (0.50 %)
Total	20 (100 %)	11 (100 %)	74 (100 %)	13 (100 %)	108 (100 %)	80 (100 %)	89 (100 %)	395 (100 %)

Source: author's calculation

Table 6.12: Diversification of agricultural activities among the operational holders sorted on the basis of their categories

LDI	Farmer Categories				
	Large	Medium	Semi Medium	Small	Total
0.111	0	0	0	1 (0.30%)	1 (0.30%)
0.125	0	0	0	3 (1%)	3 (0.80%)
0.143	0	0	1 (2%)	1 (0.30%)	2 (0.50%)
0.167	0	0	1 (2%)	5 (1.60%)	6 (1.50%)
0.200	1 (25%)	4 (13.30%)	5 (10.20%)	22 (7.10%)	32 (8.10%)
0.250	0	9 (30%)	10 (20.40%)	83 (26.60%)	102 (25.80%)
0.334	1 (25%)	6 (20%)	22 (44.90%)	118 (37.80%)	147 (37.20%)
0.500	2 (50%)	11 (36.70%)	10 (20.40%)	77 (24.70%)	100 (25.30%)
1	0	0	0	2 (0.60%)	2 (0.50%)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

6.1.3 Food

Food security implies that "all people, at all times, have physical, social, and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (Food and Agriculture Organization, 1996). Food security is an integral component of livelihood security. The idea of household livelihood security includes "adequate and sustainable access to income and resources to meet basic needs (including adequate access to food, potable water, health facilities, educational opportunities, housing, time for community participation and social integration)" (Frankenberger and McCaston, 1998). The assessments of vulnerability, in general, focus on the absence of these securities that constitute the vulnerability of a system (Webb and Harinarayan, 1999).This section examines the factors that constitute the food and nutritional insecurity among the farm households of Tamil Nadu. As a proxy for food security, use of various cooking fuels among the farmer households was measured. For nutritional security, we measured the coverage of Women and Child Care (WCC) programmes among the farmers in the region. Before considering cooking fuel as the variable representing the food security component in the region, we studied the coverage of public distribution system among the sample farmers. The Public Distribution System (PDS) is one of the major interventions by Government of India to tackle food insecurity and hunger in the country. As the implementing agency, Tamil Nadu state government has performed substantially well in ensuring universal access to essential commodities through its public distribution system (Anuradha, 2018). Among the 395 sample farmers, 393 farmers had ration cards and availed the services from the PDS. Therefore, we decided to consider cooking fuel as a proxy for the command of household over food.

6.1.3.1 Cooking fuel

Availability and access to adequate cooking energy is considered as an essential element in food security (Agarwal, 2018). In developing countries, approximately 2.4 billion households still use conventional bio fuels such as charcoal, firewood, cattle dung, and crop residues for cooking and heating (Vira et al., 2015). In India, the fraction of population depending on solid fuels for cooking is 75 percent in the rural areas and nearly 25 percent in the urban areas (Faizan and Thakur, 2019). The inherent disadvantages of the traditional fuels include arduous and time-consuming nature of fuel collection, difficulty in controlling combustion process, and inefficient heat exchange (Viswanathan and Kumar, 2005) and there is clearly a hierarchy

Table 6.13: Choice of cooking fuel among the operational holders sorted on the basis of their districts

	Districts							
Cooking fuel	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
Firewood	4 (20 %)	8 (72.70 %)	69 (93.20 %)	9 (69.20 %)	86 (79.60 %)	75 (93.80 %)	85 (95.5 %)	336 (85.10 %)
Kerosene	0	1 (9.10 %)	5 (6.80 %)	1 (7.70 %)	9 (8.30 %)	0	4 (4.50 %)	20 (5.10 %)
LPG	17 (85 %)	10 (90.90 %)	72 (97.30 %)	12 (92.30 %)	79 (73.10 %)	4 (5 %)	36 (40.40 %)	230 (58.20 %)
Electricity	16 (80 %)	3 (27.30 %)	17 (23 %)	5 (38.50 %)	22 (20.40 %)	7 (8.80 %)	3 (3.40 %)	73 (18.50 %)
Total	20 (100 %)	11 (100 %)	74 (100 %)	13 (100 %)	108 (100 %)	80 (100 %)	89 (100 %)	395 (100 %)

Source: author’s calculation

Table 6.14: Choice of cooking fuel among the operational holders sorted on the basis of their categories

	Farmer Categories				
Cooking Fuel	Large	Medium	Semi Medium	Small	Total
Firewood	1 (25 %)	28 (93.30 %)	42 (85.70 %)	265 (84.90 %)	336 (85.10 %)
Kerosene	0	0	4 (8.20 %)	16 (5.10 %)	20 (5.10 %)
LPG	3 (75 %)	13 (43.30 %)	25 (51 %)	189 (60.60 %)	230 (58.20 %)
Electricity	3 (75 %)	5 (16.70 %)	7 (14.30 %)	58 (18.60 %)	73 (18.50 %)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author’s calculation

of choices with regard to the cooking fuel depending on the socioeconomic circumstances of the households (Menghwani et al., 2019). Thus, along with the availability and accessibility, access to improved and healthy means of cooking therefore reflect the command of the household over food choices and represent the ability of a household to absorb the food under healthy circumstances. Tables 6.13 and 6.14 show the district wise and category wise distribution of fuel choices among the sample households.

As seen in the table firewood is the dominant fuel used by the sample household. Around 85 percent of the farmers prefer firewood for cooking. This is followed by LPG. 58 per cent of the sample households have LPG connection. Electric cooking equipments are used by approximately 18 percent of the households while kerosene has become the least preferred fuel for cooking. Across districts, the usage of firewood is highest in Trichy followed by Thiruvarur and Nagappattinam, and is Lowest in Ariyalur district. The share of LPG using households is highest in Nagappattinam followed by Perambalur, Karur and Ariyalur. The usage of LPG is the lowest in Thiruvarur followed by Trichy. The preference for electricity as a means of cooking is higher among the farmers of Ariyalur while kerosene is the least used means of cooking in all districts. Table 6.14 suggests that only one out of the four large farmers use firewood for cooking while the remaining three use LPG and electricity for cooking. Firewood is the dominant fuel for cooking among all the other categories, though a majority of them have LPG connections.

6.1.3.2 Women and child care programmes

In 1986, the seminal report by World Bank (World Bank, 1986) defined food security as “access by all people at all times to enough food for an active and healthy life". According to the report, starvation, chronic under-nutrition, and specific nutrient deficiencies are the major manifestations of hunger. It implies that nutritional security is central to the idea of food security. The policy focus as such shifted towards ensuring availability and accessibility of essential commodities on a macro scale. Swaminathan and Bhavani (2013) asserts the need to bring about a paradigm shift from the concept of food security at the aggregate level to one of nutrition security at individual levels. One of the major contentions put forward by various studies analysing nutritional vulnerability is the inherent differentials in vulnerability among certain age/gender categories. More specifically, women and children are recognized as intrinsically vulnerable to nutrition deficiencies (Webb and Harinarayan, 1999). In the present study, therefore, we consider the coverage of women and child care programmes among the sample farmers as proxy for nutritional security.

Table 6.15: Coverage of women and child care programmes among the operational holders sorted on the basis of their districts

	Districts							
WCC	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
Beneficiaries	18 (90 %)	11 (100 %)	25 (33.80 %)	9 (69.20 %)	73 (32.40 %)	79 (98.80 %)	84 (95.50 %)	299 (75.90 %)
Non-beneficiaries	2 (10 %)	0	49 (66.20 %)	4 (30.80 %)	35 (67.60 %)	1 (1.20 %)	4 (4.50 %)	95 (24.10 %)
Total	20 (100%)	11 (100%)	74 (100%)	13 (100%)	108 (100%)	80 (100%)	89 (100%)	395 (100%)

Source: author's calculation

Table 6.16: Coverage of women and child care programmes among the operational holders sorted on the basis of their categories

	Farmer Categories				
WCC	Large	Medium	Semi Medium	Small	Total
Beneficiaries	4 (100 %)	24 (80 %)	41 (85.40 %)	230 (73.70 %)	299 (75.90 %)
Non-beneficiaries	0	6 (20 %)	7 (14.60 %)	82 (26.30 %)	95 (24.10 %)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

As seen in table 6.15, majority of the households are covered by women and child care programmes run by the government agencies. However, Nagappattinam district is an exception to this. Only one third of the total sample from this district receive benefits of these nutritional security programmes. The coverage of these programs is high in Karur, Thiruvarur, Trichy and Ariyalur districts and is moderate in Thanjavur and Perambalur. Across, various categories of farmers, a similar pattern of coverage can be seen with a minimum of 70-80 percent of households are covered by WCC programmes. Among the large farmers, the coverage is 100 per cent while it is 85 per cent among the semi-medium farmers.

6.1.4 Water

Water has an important role in the livelihood security of households and the availability and access to clean water has been used widely in the assessments of livelihood security as well as vulnerabilities (Lindenberg, 2002; Hahn et al., 2009; Kakota et al., 2011; Gerlitz et al., 2017a). In the present study we study the availability and quality issues pertaining to both drinking water and irrigation water among the rice farmers of Tamil Nadu.

6.1.4.1 Drinking water

Drinking water is an important component of household livelihood security (Frankenberger and McCaston, 1998). The absorption of available food depends crucially on the availability of adequate drinking water (Swaminathan and Bhavani, 2013). Vulnerability studies consider water security as an essential component influencing the sensitivity and adaptive capacity at both individual and community levels (Brenkert and Malone, 2005; O'Brien et al., 2004; Hahn et al., 2009; Gerlitz et al., 2017a). In Tamil Nadu, many areas of the state experience challenges with respect to the availability (TWAD Board, 2018) and quality of drinking water (Government of Tamil Nadu, 2014).

Table 6.17: Drinking water issues among the operational holders sorted on the basis of their districts

	Districts							
Drinking Water	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
Insufficient Availability	4 (20 %)	1 (9.10 %)	2 (2.70 %)	1 (7.70 %)	18 (16.70 %)	4 (5.20 %)	1 (1.30 %)	31 (8.10 %)
Irregular Supply	12 (60 %)	0	21 (28.40 %)	2 (15.40 %)	70 (64.80 %)	35 (45.50 %)	4 (5.10 %)	144 (37.70 %)
Bad Taste	0	0	10 (13.50 %)	0	0	3 (3.90 %)	6 (7.60 %)	19 (5 %)
Bad Odour	0	0	0	0	0	0	4 (5.10 %)	4 (1 %)
Colour	0	0	1 (1.40 %)	0	0	0	1 (1.30 %)	2 (0.50 %)
Cloudy	1 (5 %)	0	21 (28.40 %)	0	1 (0.90 %)	1 (1.30 %)	0	24 (6.30 %)
Low Pressure	0	0	6 (8.10 %)	0	4 (3.70 %)	9 (11.70 %)	4 (5.10 %)	23 (6 %)
Seasonal shortage	5 (25 %)	0	7 (9.50 %)	8 (61.50 %)	15 (13.90 %)	28 (36.40 %)	5 (6.30 %)	68 (17.80 %)
Salt	4 (20 %)	0	3 (4.1 %)	1 (7.70 %)	0	21 (27.30 %)	30 (38 %)	59 (15.40 %)
Others	1 (5 %)	1 (9.10 %)	0	0	9 (8.30 %)	0	2 (2.50 %)	13 (3.40 %)
Total	20 (100 %)	11 (100 %)	74 (100 %)	13 (100 %)	108 (100 %)	80 (100 %)	89 (100 %)	395 (100 %)

Source: author's calculation

Table 6.18: Drinking water issues among the operational holders sorted on the basis of their categories

Drinking Water	Farmer Categories				
	Large	Medium	Semi Medium	Small	Total
Insufficient Availability	0	4 (13.80%)	5 (11.10%)	22 (7.20%)	31 (8.10%)
Irregular Supply	2 (50%)	9 (31%)	24 (53.30%)	109 (35.90%)	144 (37.70%)
Bad Taste	0	2 (6.90%)	3 (6.70%)	14 (4.60%)	19 (5%)
Bad Odour	0	0	0	4 (1.30%)	4 (1%)
Colour	0	0	0	2 (0.70%)	2 (0.50%)
Cloudy	0	3 (10.30%)	1 (2.20%)	20 (6.60%)	24 (6.30%)
Low Pressure	0	2 (6.90%)	5 (11.10%)	16 (5.30%)	23 (6%)
Seasonal shortage	1 (25%)	6 (20.70%)	7 (15.60%)	54 (17.80%)	68 (17.80%)
Salt	1 (25%)	7 (24.10%)	5 (11.10%)	46 (15.10%)	59 (15.40%)
Others	0	2 (6.90%)	1 (2.20%)	10 (3.30%)	13 (3.40%)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author’s calculation

Table 6.19: Water storage facilities among the operational holders sorted on the basis of their districts

	Districts							
Storage facility	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
Underground Storage	7 (35%)	4 (36.40%)	21 (28.40%)	2 (15.40%)	37 (34.30%)	13(16.20%)	20 (23.80%)	104 (26.33%)
Overhead storage	7 (35%)	2 (18.20%)	15 (20.30%)	6 (46.20%)	15 (13.90%)	16 (20%)	16 (19%)	77 (24.56%)
Vessels	20 (100%)	11 (100%)	73 (98.60%)	13 (100%)	101 (93.50%)	77 (96.20%)	81 (91.01%)	376 (95.19%)
Total	20 (100%)	11 (100%)	74 (100%)	13 (100%)	108 (100%)	80 (100%)	89 (100%)	395 (100%)

Source: author's calculation

Table 6.20: Water storage facilities among the operational holders sorted on the basis of their categories

	Farmer Categories				
Drinking Water	Large	Medium	Semi Medium	Small	Total
Underground Storage	2 (50%)	29 (30%)	20 (40.80%)	73 (23.80%)	104 (26.33%)
Overhead storage	3 (75%)	14 (46.70%)	13 (26.50%)	47 (15.30%)	77 (24.56%)
Vessels	4 (100%)	28 (93.30%)	45 (91.80%)	299 (95.83%)	376 (95.19%)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

In general, the sample farmers faced a wide range of issues with regard to the availability and quality of drinking water. Majority of them face more than one issue, and use treatment methods and adopt storage facilities to address them. Table 6.17 shows the district wise distribution of drinking water issues among the sample households. Regarding the availability of water, only a small share of farmers faced difficulties in availability. However, a larger fraction of them faced the issue of irregular supply. A majority of farmers from Thanjavur and Ariyalur reported irregular supply of drinking water followed by 45 percent of the farmers in Thiruvarur. The sample households did not feel much bad about the taste, colour and odour of the drinking water, although a small fraction of them, particularly those from Nagappattinam district reported cloudy nature of drinking water. Seasonal shortage was reported by a few farmers, mainly from Perambalur and Thiruvarur district and the issue of salt content was reported mainly by the farmers of Trichy district. We further analysed the storage facilities available in the sample farmers households. The tables 6.19 and 6.20 show the district level and category wise distribution of storage facilities among the sample farmers. As shown in the table, vessels are the widely used water storage facility among the farmers. Nearly all farmers (approximately 95 per cent) use vessels for storing water. Underground storage facilities are the next preferred ones, mainly because of the absence of plumbing arrangements in the households and due to the low pressure in pipe water. Overhead tanks are used by a relatively smaller share of farmers. We can see a clear differential in the share of households using overhead water tanks as we move from large to small farmers.

6.1.4.2 Irrigation Water

Rice is a water intensive crop, with the production of 1 Kg of rice requiring around 800 litres to nearly 5000 litres of water (Bouman, 2009). The crop is highly sensitive to water stress. As the soil water content falls below saturation, the growth and yield formation of rice are adversely affected, mainly through reduction in the leaf surface area, rate of photosynthesis, and sink size. Similarly, an increase in salt stress causes osmotic stress, salinity, and nutrient imbalances and yield reduction in rice. While, chemical contamination is also an adverse factor affecting the rice yield, the influence of this factor is more prevalent on the aquatic biodiversity, including fish and shrimp, which constitute important source of protein for the rural poor and a supplementary source of income for the small farmers (Bouman et al., 2007). In the case of Tamil Nadu, the average annual rainfall (921 mm) is well below the national average (1200 mm) and the per capita availability of water

Table 6.21: Irrigation water issues among the operational holders sorted on the basis of their districts

Issues	Districts							
	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
Insufficient Availability	15 (75%)	1 (9.10%%)	16 (21.62%)	5 (38.46%)	64 (59.26%)	14 (17.50%)	3 (3.37%)	118 (29.87%)
Irregular Supply	14 (70%)	2 (18.18%)	13 (17.57%)	0	61 (56.48%)	19 (23.75%)	8 (8.99%)	117 (29.62%)
Bad Taste	0	0	0	0	2 (1.85%)	1 (1.25%)	0	3 (0.76%)
Low Pressure	4 (20%)	0	33 (44.59%)	1 (7.69%)	20 (18.52%)	31 (38.75%)	15 (16.85%)	104 (26.33%)
Seasonal shortage	16 (80%)	2 (18.18%)	42 (56.76%)	11 (84.62%)	70 (64.81%)	42 (52.50%)	24 (26.96%)	207 (52.41%)
Salt	1 (5%)	0	39 (52.70%)	1 (7.69%)	2 (1.85%)	11 (13.75%)	33 (37.08%)	77 (19.49%)
Others	0	2 (18.18%)	0	0	7 (6.48%)	1 (1.25%)	0	10 (2.53%)
Total	20 (100%)	11 (100%)	74 (100%)	13 (100%)	108 (100%)	80 (100%)	89 (100%)	395 (100%)

Source: author's calculation

Table 6.22: Irrigation water issues among the operational holders sorted on the basis of their categories

Issues	Farmer Categories				
	Large	Medium	Semi Medium	Small	Total
Insufficient Availability	1 (25%)	9 (30%)	9 (18.36%)	99 (31.73%)	118 (29.87%)
Irregular Supply	1 (25%)	9 (30%)	9 (18.36%)	98 (31.41%)	117 (32.15%)
Bad Taste	2 (50%)	0	1 (2%)	0	3 (0.76%)
Low Pressure	1 (25%)	15 (50%)	19 (38.78%)	69 (22.12%)	104 (26.33%)
Seasonal shortage	1 (25%)	11 (36.67%)	29 (59.18%)	166 (53.21%)	207 (52.41%)
Salt	1 (25%)	6 (20%)	10 (20.41%)	70 (22.44%)	77 (19.49%)
Others	0	1 (3.34%)	0	9 (2.89%)	10 (2.53%)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

in the state is about 750 cubic meters a year compared to the national average of 2,100 cubic meters. Apart from the requirements in agriculture sector, the existing water sources are already under severe stress due to increased demands from urban centres, industries, hydro power, fisheries, environmental flows, and community use (World Bank, 2019). The irrigation development in the state has reached its potential, and the potential utilization of groundwater in the state is more than 85 percent of the available resources (Amarasinghe et al., 2009). Further, a number of areas in Tamil Nadu experiencing challenges with regard to the availability and contamination of ground water and surface water (TWAD Board, 2018; Government of Tamil Nadu, 2014).

As shown in the tables 6.21 and 6.22, nearly one third of the operational holders faced difficulties sufficient availability and regular supply of irrigation water. Particularly, those from Ariyalur, Thanjavur and Nagapattinam faced these issues in large percentages. Apart from this majority of farmers faced seasonal shortages ($\approx$ 52 %) and a third of the total farmers reported low pressure, so that the water did not reach their farms adequately. Salinity in the ground water is a major issue in the coastal districts of Tamil Nadu. Among the sample farmers, more than 50 per cent from Nagapattinam district and a considerable share of farmers in Trichy reported increased salt content in irrigation water. The category wise distribution of these issues suggest that the availability issues are pervasive among the small farmers, compared to the other categories.

6.1.5 Health

This section discuses the health component of livelihood vulnerability. The health component is analysed in terms of sanitation and proximity to public medical facility. For sanitisation, we chose the variable, toilet facility among the farmer households.

6.1.5.1 Better toilet facility

Sanitation and hygiene are essential components in food security. They play a substantial role in determining the the ability to biologically utilize the food consumed (Swaminathan and Bhavani, 2013) and ensure livelihood security (Frankenberger and McCaston, 1998). A critical part of maintaining improved standards of public health and hygiene is building toilets and getting people to use them (O'Reilly and Louis, 2014). In the case of Tamil Nadu, according to the Census of India (2011), the state has has the sixth highest number of households that do not have latrines in the country, with 76.8 per cent of its rural households

Table 6.23: Toilet status among the operational holders sorted on the basis of their districts

Toilet status	Districts							
	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
Toilet with flush	15 (75 %)	11 (100 %)	60 (81.10 %)	13 (100 %)	63 (58.30 %)	64 (80 %)	69 (78.40 %)	295 (74.90 %)
Pit latrines	0	0	0	0	4 (3.70 %)	3 (3.80 %)	9 (10.20 %)	16 (4.10 %)
No toilets	5 (25 %)	0	14 (18.90 %)	0	41 (38 %)	13 (16.20 %)	10 (11.40 %)	83 (21.10 %)
Total	20 (100%)	11 (100%)	74 (100%)	13 (100%)	108 (100%)	80 (100%)	89 (100%)	395 (100%)

Source: author's calculation

Table 6.24: Toilet status among the operational holders sorted on the basis of their categories

Toilet status	Farmer Categories				
	Large	Medium	Semi Medium	Small	Total
Toilet with flush	4 (100 %)	29 (96 %)	43 (87.76 %)	219 (70.12 %)	295 (74.90 %)
Pit latrines	0	1 (3.30 %)	0	15 (4.80 %)	16 (4.10 %)
No toilets	0	0	6 (12.20 %)	77 (24.80 %)	83 (21.10 %)
Total	4 (100 %)	30 (100 %)	49 (100 %)	312 (100 %)	395 (100 %)

Source: author's calculation

live without latrines (O'Reilly et al., 2017). Therefore, following Gerlitz et al. (2017a), the present study considered the type of toilet facility as an indicator for the sanitation component.

As shown in the table 6.23, $\approx$ 75 per cent of the households had toilet with flush. However, Thanjavur district is an exception to this with only 58 per cent of the farmers had toilets with flush. Apart from this, a small per cent of the farmers had pit latrines. Pit latrines included ventilated improved pit latrines, composting toilets etc. However, it is worth noting that 21 per cent of the farmers did not have toilets. While some areas had community level toilets, open defecation is widely prevalent in the sample regions. District wise, Thanjavur and Ariyalur had relatively high share of households without any toilet facility. The category-wise analysis (Table 6.24) suggests that almost every one in the large and medium category had toilets while there were a few semi-medium farmers without a toilet facility. In the case of small farmers, majority of the pit latrines were used by them and $\approx$ 25 per cent of the farmers in this category did not have any toilets.

6.1.5.2 Proximity to Public Health Facility

Adequate and sustainable access to resources is central to the security of livelihoods. Access to resources and livelihood opportunities is "governed by social relations, institutions and organizations, and it includes power as an important explanatory variable" (De Haan and Zoomers, 2005; O'Reilly et al., 2017). Weaker sections of the society are not only more exposed to health risks than their better off counterparts, but have less resistance to diseases, and less access to preventive and curative interventions (Obrist et al., 2007). Tamil Nadu state has one of the better public health networks in India, with a separate directorates for public health services and medical education. The public health services coordinate the primary and community health services at the grass-root level with the support of local self governments. The activities involve prevention of epidemics, sanitation, spreading health awareness, essential medical facilities and even psycho social interventions (Vijaykumar et al., 2006; World Bank, 2009).

As mentioned in the previous paragraph, Tamil Nadu has a relatively better public health system. Six out of the seven districts considered here has medical colleges. So the responses analysed here represents more about the awareness of the sample households regarding the public health facilities in their proximity. Hospital proximity is assessed in terms of an index, which is the inverse of the sum of ranks assigned to various public health facilities that the respondent is aware of. The tables 6.25 and 6.26 show the hospital

Table 6.25: Hospital proximity among the operational holders sorted on the basis of their districts

	Districts							
Hospital proximity	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
0 - 0.05	0	0	0	0	11 (10.19 %)	1 (1.25 %)	0	12 (3.03 %)
0.051 - 0.1	16 (80 %)	11 (100 %)	23 (31.08 %)	13 (100 %)	96 (88.89 %)	79 (98.75 %)	86 (96.63 %)	324 (82.03 %)
0.11 - 0.15	4 (20 %)	0	51 (68.92 %)	0	0	0	1 (1.12 %)	56 (14.18 %)
0.21 - 0.25	0	0	0	0	0	0	2 (2.25 %)	2 (0.51 %)
Inf	0	0	0	0	1 (0.93 %)	0	0	1 (0.25 %)
Total	20 (100 %)	11 (100 %)	74 (100 %)	13 (100 %)	108 (100 %)	80 (100 %)	89 (100 %)	395 (100 %)

Source: author's calculation

Table 6.26: Hospital proximity among the operational holders sorted on the basis of their categories

	Farmer Categories				
Hospital proximity	Large	Medium	Semi Medium	Small	Total
0 - 0.05	0	1 (3.34 %)	2 (4.08 %)	9 (2.88 %)	12 (3.03 %)
0.051 - 0.1	4 (100 %)	28 (93.34 %)	45 (91.84 %)	247 (79.17 %)	324 (82.03 %)
0.11 - 0.15	0	1 (3.34 %)	2 (4.08 %)	53 (16.99 %)	56 (14.18 %)
0.21 - 0.25	0	0	0	2 (0.64 %)	2 (0.51 %)
Inf	0	0	0	1 (0.32 %)	1 (0.25 %)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

proximity index and the corresponding number of farmers arranged according to their district and category. In the tables, smaller values of the index correspond to higher proximity and vice versa. The tables suggest that majority of the farmers had relatively higher hospital proximity which, in turn, reflects the better public health system in this state. In the district wise classification, only Nagapattinam had a major share of farmers with a relatively lower proximity, followed by Ariyalur. Majority of those who have a lower hospital proximity in these districts belong to small farmer households (see table 6.26).

6.1.6 Social Networks

Social relations or social capital play substantial roles in shaping the livelihoods of the people. The social categories of "eligibles and ineligibles" are often created by the collective livelihood actions of the society that include and exclude others from access to resources. The dynamics of this inclusion and exclusion are often governed by property relations, social or physical characteristics such as race, gender, language, ethnicity, or religion De Haan and Zoomers (2005). In Tamil Nadu, caste relations altered the sanitation interventions and decisions about adoption of the latrines provided (O'Reilly et al., 2017). Similarly, various types of social groupings can shape and reshape the various factors constituting livelihoods. In the present study, we adopt participation in self help groups (SHGs), assistance from SHGs, assistance from friends and family, assistance from cooperatives, and assistance from insurance schemes and government as variables.

6.1.6.1 Participation in SHGs

SHGs are an increasingly common effort to overcome the barriers of collective actions. They are "membership-based organizations" that function on the basis of collective responsibility and mutual support to achieve the individual objectives of the members through education, access to credit, and linkages to development projects. The target group envisioned in the formation of SHGs was the women who were outside the network of the formal credit agencies (Kumar et al., 2019; Desai and Joshi, 2013). SHGs were observed to increase the participation of women in household decisions, civic activities (Desai and Joshi, 2013), make awareness about public entitlements, avail public assistance, develop wider social networks and better mobility, exercise democratic rights in the public sphere (Kumar et al., 2019), and played instrumental roles in mitigating the effects of natural disasters (Prabhakaran and Kartha, 2019).

Table 6.27: SHG Participation among the operational holders sorted on the basis of their districts

SHG Participation	Districts							
	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
Member HHs	6 (30 %)	8 (72.70 %)	29 (39.20 %)	4 (30.80 %)	50 (46.30 %)	37 (46.20 %)	46 (51.70 %)	180 (45.60 %)
Non-member HHs	14 (70 %)	3 (27.30 %)	45 (60.80 %)	9 (69.20 %)	58 (53.70 %)	43 (53.80 %)	43 (48.30 %)	215 (54.40 %)
Total	20 (100 %)	11 (100 %)	74 (100 %)	13 (100 %)	108 (100 %)	80 (100 %)	89 (100 %)	395 (100 %)

Source: author's calculation

Table 6.28: SHG Participation among the operational holders sorted on the basis of their categories

SHG Participation	Farmer Categories				
	Large	Medium	Semi Medium	Small	Total
Member HHs	0	10 (33.30 %)	21 (42.90 %)	149 (47.80 %)	180 (45.60 %)
Non-member HHs	4 (100 %)	20 (66.70 %)	28 (57.10 %)	163 (52.20 %)	215 (54.40 %)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

As seen in the figures 6.27 and 6.28, nearly half of the total respondents participate in SHGs. SHG participation is relatively higher among the operational holders of Karur and Trichy and lowest among the respondents of Ariyalur. As seen in the table 6.28, there is an inverse relation between land size and SHG participation. Smaller farmers tend to participate in SHGs in large shares and vice versa.

6.1.6.2 Assistance from social networks

Social networks have a significant role in determining the access to financial assistance. Empirical evidence suggests that community and family networks are important in knowing a place to borrow, as well as for loan approval and this works particularly in the case of the poor and women in enhancing the access to credit and financial assistance. Social networks are observed to have a considerably higher influence in determining the access to credit than other socioeconomic factors of a household (Fafchamps and Minten, 2002; Okten and Osili, 2004). Therefore the present study considered the financial assistance (including credit) received by the household as a proxy for their networking skills. Tables 6.29 and 6.30 shows the district wise and category wise distribution of assistance received by the sample households.

The tables suggest that friends and family forms the largest source of financial assistance in the sample districts. Approximately 81 per cent of the sample households look to their friends and kins for assistance in need. This was followed by cooperatives. Farmer cooperatives play a major role in providing the operational holders with access to credit, seeds and other assistance. Government is the next preferred source of assistance among the farmers. However, the knowledge and access to government assistance varies substantially across the districts. Thiruvarur and Karur has relatively higher shares of farmers fetching government assistance while it is the lowest in Ariyalur. Only 20 percent of the sample households received assistance from insurances while the fraction of households receiving assistance from SHGs is the lowest among the five sources. The category wise analysis suggest that nearly all categories have a more or less similar access to all sources compared to the general picture of knowledge and access to assistance sources in the region.

Table 6.29: Social network financial benefits among the operational holders sorted on the basis of their districts

Social network financial benefits	Districts							
Source of benefits	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy	Total
SHG	6 (30 %)	0	0	0	6 (5.50 %)	4 (5 %)	2 (2.25 %)	18 (5.06 %)
Friends and family	16 (80 %)	9 (81.80 %)	56 (75.70 %)	11 (84.60 %)	88 (81.50 %)	69 (86.20 %)	71 (79.80 %)	320 (81 %)
Cooperatives	16 (80 %)	6 (54.50 %)	34 (45.90 %)	10 (76.90 %)	61 (56.50 %)	48 (60 %)	51 (57.30 %)	226 (57.20 %)
Insurance	7 (35 %)	0	35 (47.30 %)	0	21 (19.40 %)	16 (20 %)	2 (2.20 %)	81 (20.50 %)
Government	2 (10 %)	4 (36.40 %)	24 (32.40 %)	4 (30.80 %)	23 (21.30 %)	67 (83.80 %)	19 (23.80 %)	143 (37 %)
Total	20 (100%)	11 (100%)	74 (100%)	13 (100%)	108 (100%)	80 (100%)	89 (100%)	395 (100%)

Source: author's calculation

Table 6.30: Social network financial benefits among the operational holders sorted on the basis of their categories

Social network financial benefits	Farmer Categories				
Source of benefits	Large	Medium	Semi Medium	Small	Total
SHG	0	1 (3.30 %)	4 (8.20 %)	13 (4.17 %)	18 (5.06 %)
Friends and family	4 (100 %)	25 (83.30 %)	42 (85.70 %)	249 (79.80 %)	320 (81 %)
Cooperatives	3 (75 %)	6 (86.70 %)	35 (71.40 %)	162 (51.90 %)	226 (57.20 %)
Insurance	2 (50 %)	7 (23.30 %)	9 (18.40 %)	63 (20.20 %)	81 (20.50 %)
Government	1 (25 %)	19 (63.30 %)	22 (44.90 %)	101 (33.30 %)	143 (37 %)
Total	4 (100%)	30 (100%)	49 (100%)	312 (100%)	395 (100%)

Source: author's calculation

6.2 Farmers' Perceptions on Climate Change

Apart from these factors, the awareness and perceptions of farmers about climate change are influential in their adaptations. During the field visits, the researcher collected notes on the perceptions of farmers regarding the patterns of temperature, rainfall, and their expected influence on the crop yield. In general, it is observed that farmers are well aware of the changes in temperature and rainfall, and also that these changes are part of a larger phenomena pertaining to 'human actions'. Apart from their idea on deforestation, pollution of rivers, and the pollution by factories, almost none of the farmers seemed to have specific knowledge on how farming contribute towards climate change.

Overall, 88.60% of the sample respondents perceived a reduction in rainfall in the recent years, while 4.60% and 6.70% perceived an increase in rainfall and no change in rainfall respectively. Approximately 88 per cent of the farmers, who observed the reduction in rainfall also, suggested an increase in dry spells and 97% suggested an increase in extreme rainfall episodes recently. Also, majority of the farmers (61%) asserted an overall increase in the severity of drought conditions in the state.

To the question regarding a change in temperature, almost every respondent has experienced the increase in both daytime and night-time temperatures. However, to the specific question regarding heat waves only a few (12%) suggested an increase recently. Apart from temperature and rainfall, approximately 38% of the farmers suggested an increase in the pest attacks recently.

Farmers, in general, believed that the climate, particularly rainfall has become unreliable in the recent decades. As a result none of the sample respondents cultivate depending on the seasonal rainfall. They take cultivation decisions based on the availability of water by means of irrigation. However, nearly 70% of the farmer believe that the variations in climate have substantial influence on the yield of rice. 25 per cent of the farmers believed that the recent erratic nature of rainfall adversely affects their crop yield. For approximately 17% of the farmers, delay in the onset of monsoon, and for 28 per cent, the early ending of the seasonal rainfall is harmful to the crop yield. While, nearly 25% of the farmers believed that floods are an important factors damaging their crops, a few (3 respondents) suggested that floods increase water levels, and are good for cultivation in the long-run.

6.3 Summary and Findings

This chapter analysed the socioeconomic factors that influenced the sensitivity and adaptive capacity of the rice farmers using the sample taken from the Cauvery Delta region, Tamil Nadu. The socio-demographic profile, livelihood strategies, food and nutritional security, water security, health and sanitation status, social networks and financial benefits among the sample farmers. The indicators representing these broader components were analysed across districts and farmer categories to identify the characteristics and patterns.

1. The analysis of socio-demographic profile suggested that majority of the sample households have a dependency ratio lower than the national average. However, the analysis revealed the presence of households in which all members were above 65 years of age. Such households were mainly found in Thanjavur and Thiruvarur districts and majority of them were small farmers. The small farmers also had the largest share of female headed households or female operational holders, and were mainly observed in Thanjavur and Thiruvarur districts. Further, the analysis of educational attainment suggested that the operational holders, irrespective of their educational and asset backgrounds, gave more emphasis of the education of their children. The respondents with largest educational attainment belonged to the small and semi medium farmer households, and in Ariyalur, Karur and Trichy districts.

2. The study observed that the sample households adopted diverse strategies to cope with the risks involved in cultivation. Around 20 per cent of the families, mostly from small farmers, had at least one migrant member in the family. Similarly, more than one third of the families engaged in at least one off farm employment within their locality and more than one third of the households engaged in an additional farm activity other than rice cultivation.

3. The study considered the command over cooked food as an inseparable component of food security and nutritional security. It was observed that only 58 per cent of the farmers had access to clean and safe fuel. majority of the farmers ($\approx 85\%$) a large majority of which was constituted by small farmers ($\approx 79\%$) used fire wood as the cooking fuel. Firewood is the dominant fuel for cooking among all the other categories, though a majority of them have LPG connections. Further, the analysis of nutritional security suggested that more than 75 % of the households received the benefits of WCCs. However, the coverage of nutritional security programmes

was low in Nagappattinam district with only one third of the total sample from this district were covered in the WCC programmes.

4. The sample households faced diverse issues pertaining to the availability and quality of drinking water. Supply issues were generally higher in Thiruvarur and Thanjavur while quality issues were mostly reported from Trichy and Nagapattinam districts. The severity of water crisis is evident from the fact that almost all households, irrespective of their farm size or location, used to store water in vessels. Even those having underground and overhead water storage facilities used to store water in vessels. Supply issues were widely prevalent in irrigation water also. The salinity in the water was another major issue affected the irrigation. This was mainly reported by the farmers from Nagapattinam, Trichy and Thiruvarur districts.

5. The analysis of health and sanitation among the sample households revealed that nearly 20 per cent of the total households, almost all of them belonging to small farm size category, did not have toilets. In regions without much community level initiatives, this is a direct indication of prevalence of open defecation in the sample region. It is also noted that, despite the poor performance in sanitation, majority of the farmers had relatively higher hospital proximity to public health facilities which, in turn, reflects the better public health system and initiatives in this state.

6. In the study region, nearly half of the total respondents participated in SHGs. With smaller farmers tend to participate in SHGs in large shares and large farmers participating less, we observed an inverse relation between land size and SHG participation. A large majority of the sample households received financial assistance from their friends and families and then from cooperatives. Only 20 percent of the sample households received assistance from insurances and the fraction of households who reported SHGs as financially beneficial was less than 20 per cent.

Chapter 7

Livelihood Vulnerability of Rice Farmers

The previous chapters in this study have identified and quantified various biophysical and socioeconomic factors that influence the livelihoods of rice farmers in Tamil Nadu. In this chapter we combined these components and their respective indicators into a vulnerability profile of the rice cultivating households in Tamil Nadu. At first, we assessed the vulnerability of rice farmers across the seven study districts to account for the location-specific factors that constitute vulnerability. We further assessed the vulnerability of their livelihoods across the three major cultivating seasons in the region. The nature and extent of climate stimuli and the sensitivity of rice yield towards these changes vary across seasons. Also, the combination of farmers who cultivate in each season are different and so is their vulnerability. Lastly we examined the vulnerability of rice farmers belonging to various categories of classified on the basis of the size of their landholding. The livelihood vulnerability was assessed using both LVI as well as LVI-IPCC (See Chapter 3) methods. The calculation of LVI-IPCC requires that components socio-demographic profile, livelihood strategies, and social networks represent the adaptive capacity of the households while in calculating LVI, we modified these variables in such a way that they represent the lack of adaptive capacity of the households. The remaining portions in this chapter are arranged as follows. Section 1 explains the LVI and LVI-IPCC across the seven study districts in the region. Section 2 explains the LVI and LVI-IPCC across the three cultivating seasons in Tamil Nadu. Section 3 explains the LVI across various categories of farmers in the region and the section 4 provides the summary and major findings of the chapter.

7.1 LVI and LVI-IPCC across the seven study districts of Tamil Nadu

Table 7.1: Livelihood Vulnerability Index (LVI) standardised sub-component values for the seven study districts of Tamil Nadu

Indicators	**Districts**						
	Ariyalur	**Karur**	**Nagapattinam**	**Perambalur**	**Thanjavur**	**Thiruvarur**	**Trichy**
Dependency ratio	0.74	0.28	0.94	0.00	1.00	0.73	0.53
Gender of the operational holder	0.28	0.00	0.69	0.00	1.00	0.35	0.26
Lack of educational attainment	0.72	1.00	0.01	0.52	0.01	0.04	0.00
Proportion of migrant households	1.00	0.00	0.71	0.38	0.79	0.28	0.20
Livelihood diversification index	0.60	1.00	0.00	0.90	0.38	0.30	0.62
Agricultural diversification Index	0.86	0.31	0.00	1.00	0.33	0.35	0.50
Lack of participation in SHGs	1.00	0.00	0.78	0.98	0.62	0.62	0.49
Lack of assistance from SHGs	0.00	1.00	1.00	1.00	0.84	0.86	0.94
Lack of assistance from friends and family	0.59	0.42	1.00	0.15	0.45	0.00	0.61
Lack of insurance coverage	0.26	1.00	0.00	1.00	0.59	0.58	0.95
Lack of assistance from cooperative institutions	0.00	0.75	1.00	0.09	0.69	0.59	0.67
Lack of assistance from government	1.00	0.64	0.70	0.72	0.85	0.00	0.81
Cooking fuel	0.00	0.10	0.15	0.12	0.33	1.00	0.71
Lack of women and child care programmes access	0.15	0.00	1.00	0.46	0.49	0.02	0.07
Drinking water issues	1.00	0.00	0.67	0.63	0.77	0.97	0.46
Drinking water storage index	0.04	0.16	0.47	0.00	0.54	0.74	1.00
Irrigation water issues	1.00	0.00	0.70	0.40	0.78	0.46	0.19
Proportion of households without toilet	0.66	0.00	0.50	0.00	1.00	0.43	0.30
Proximity to medical facility	0.87	0.00	1.00	0.46	0.05	0.05	0.08
Weather sensitivity of rice yield	0.64	1.00	0.00	0.84	0.48	0.40	0.02
Average variability in maximum temperature (last 6 years)	0.51	0.79	0.00	1.00	0.19	0.10	0.91
Average variability in minimum temperature (last 6 years)	0.00	0.68	1.00	0.09	0.28	0.39	0.53
Average variability in rainfall (last 6 years)	0.00	0.69	0.11	0.28	0.51	0.12	1.00
Number of warmspells in daytime temperature (last 6 years)	0.43	1.00	0.14	0.00	0.57	0.14	0.86
Number of warmspells in nighttime temperature (last 6 years)	0.00	1.00	0.00	0.00	0.29	0.00	0.71
Average severity of droughts (last six years)	0.17	0.16	0.04	0.00	0.48	1.00	0.44
Number of extreme rainfall episodes (last 6 years)	0.25	1.00	0.08	0.25	0.33	0.00	0.50

Source : Author's calculations

The table 7.1 presents the standardised LVI sub-component values for rice farmers in each study district. The actual values of these LVI sub-components are provided in the table B.2 in Appendix B. The table 7.2 shows the composite LVI for these districts. Overall, Thanjavur district showed greater vulnerability in the socio-demographic profile (SDP) index (0.671) and Perambalur had the least vulnerability index value (0.175). Tamil Nadu has one of the lowest dependency ratio in India according to the Census 2011 (0.52) (Rajan and Mishra, 2019). Among the sample farmers, five out of seven districts had a dependency ratio higher than the state level ratio. The dependency ratio of Perambalur and Karur districts were lower than the state level estimate. We also encountered households with all current members are above the 60 years old. The percentage of female operational holders was the highest in highest in Thanjavur (17.60%) and the lowest in Karur and Perambalur (0%) (see table 7.2). Similarly, the educational attainment was highest in Karur and lowest in Thiruchirappalli (Trichy).

Table 7.2: Livelihood Vulnerability Index (LVI) values for the seven study districts of Tamil Nadu

Major component	**Ariyalur**	**Karur**	**Nagapattinam**	**Perambalur**	**Thanjavur**	**Thiruvarur**	**Trichy**
Socio-demographic profile	0.583	0.426	0.550	0.175	0.671	0.373	0.262
Livelihood strategies	0.821	0.438	0.236	0.761	0.499	0.310	0.441
Social networks	0.475	0.635	0.747	0.658	0.673	0.440	0.746
Food	0.076	0.051	0.576	0.291	0.408	0.509	0.389
Water	0.678	0.054	0.609	0.345	0.698	0.721	0.550
Health	0.762	0	0.749	0.229	0.525	0.237	0.187
Weather sensitivity	0.64	1	0	0.84	0.48	0.4	0.02
Climate variability and extremes	0.194	0.760	0.196	0.231	0.379	0.25	0.707
LVI	**0.473**	**0.481**	**0.470**	**0.418**	**0.542**	**0.388**	**0.532**

Source: author's calculation

With regard to the livelihood strategies, Ariyalur was the most vulnerable (0.821) and and Nagapattinam district was the least vulnerable (0.236). In Ariyalur, 40% of the sample households had migrant members in the family whereas only 28 % of the families in Nagapattinam had migrant members. In Karur district, none of the farmer households had a migrant member (see table B.2). Viswanathan and Kavi Kumar (2015) observed that weather-induced agricultural distress cause migration from rural to urban areas in India. A 1 % decline in rice yield leads to a nearly 2 % increase in the rate of out-migration from a state while a similar decline in wheat yield causes a 1 % increase in the rate of out-migration. Around 49% of the migrants from the sample farm households moved to other cities or nearby states for employment purposes whereas 51% migrated to foreign countries for employment. In the case of livelihood diversification, on an average, the farmers in Nagapattinam engaged in at least 1 additional activity other than agriculture whereas the farmers in a large majority of the sample farmers in Karur engaged in agriculture only. Within agriculture also, the farmers in Nagapattinam engaged at least in 2 more agricultural activities other than rice cultivation while most of the sample rice farmers in Perambalur did not cultivate any other crops nor did they had cattle or poultry.

In terms of the participation and support from social networks, Nagapattinam (0.747) and Trichy (0.746) were highly vulnerable and Thiruvarur (0.440) was the least vulnerable. As seen in the table 7.4, SHG participation is less than 50% in the sample districts except Karur and Trichy. However, only a negligible fraction of the households reported that they received financial assistance from SHGs following a crop failure or climate related hazard. However, according to the Tamil Nadu Corporation for Development of Women (TNCDW - `http://www.tamilnadumahalir.org/`), the state has been successful in mobilising women involved in agricultural activities into SHGs and the state has approximately 7 lakh SHGs functioning in the state wherein 4.71 lakh are in rural areas. The SHGs have been able to provide Rs.604.76 crores as economic assistance as on 31/07/2020. Hence the responses from sample households, except from those in Ariyalur district regarding the assistance from SHGs seem broadly inconsistent with the prevailing situation in the state. All households from Ariyalur who participated in SHGs also acknowledged receiving financial assistance from SHGs. It was observed that friends and families were the most preferred source of credit among the sample farmers. Around 80% of the sample farmers received assistance from their relatives during crop failures. In the case of insurance coverage, 47% of the farmers acknowledged receiving assistance from insurance companies while none of the farmers in Karur and Perambalur districts received insurance assistance. Similarly, only 2% of the farmers from Trichy district received insurance assistance whereas the percentage of farmers who received insurance assistance was 19.40% and 20% in Thanjavur and Thiruvarur districts. After friends and family, cooperative institutions catered the requirement of economic assistance by the sample farm households. 80% of the sample households in Ariyalur and 46% of the sample farm households received assistance from cooperative institutions. Further 83.80% of the farm households in Thiruvarur acknowledged receiving government assistance while only 10% of the households in Ariyalur received assistance from the government sources (Table 7.4). Accordingly, the LVI-IPCC frame work suggests that Thiruvarur district has the highest adaptive capacity (0.614), while the adaptive capacity of sample farm households Nagapattinam (0.377) and Thanjavur (0.378) districts is the lowest.

Table 7.3: Livelihood Vulnerability Index (LVI-IPCC) standardised sub-component values for the seven study districts of Tamil Nadu

Indicators	**Districts**						
	Ariyalur	**Karur**	**Nagapattinam**	**Perambalur**	**Thanjavur**	**Thiruvarur**	**Trichy**
Ratio of working age group to dependents	0.26	0.72	0.06	1.00	0.00	0.27	0.47
Percentage of male operational holders	0.72	1.00	0.31	1.00	0.00	0.65	0.74
Educational attainment	0.51	0.19	0.34	0.00	0.98	0.89	1.00
Households without migrant members	0.00	1.00	0.30	0.62	0.23	0.73	0.80
Livelihood diversification	0.40	0.00	1.00	0.09	0.71	0.85	0.38
Average number of agricultural activities engaged	0.03	0.47	1.00	0.00	0.66	0.63	0.41
Participation in SHGs	0.00	1.00	0.22	0.02	0.38	0.38	0.51
Assistance from SHGs	1.00	0.00	0.00	0.00	0.16	0.14	0.06
Assistance from friends and family	0.41	0.58	0.00	0.85	0.55	1.00	0.10
Insurance coverage	0.74	0.00	1.00	0.00	0.41	0.42	0.05
Assistance from cooperative institutions	1.00	0.25	0.00	0.91	0.31	0.41	0.33
Assistance from government	0.00	0.36	0.30	0.28	0.15	1.00	0.19
Cooking fuel	0.00	0.10	0.15	0.12	0.33	1.00	0.71
Lack of women and child care programmes access	0.15	0.00	1.00	0.46	0.49	0.02	0.07
Drinking water issues	1.00	0.00	0.67	0.63	0.77	0.97	0.46
Drinking water storage index	0.04	0.16	0.47	0.00	0.54	0.74	1.00
Irrigation water issues	1.00	0.00	0.70	0.40	0.78	0.46	0.19
Proportion of households without toilet	0.66	0.00	0.50	0.00	1.00	0.43	0.30
Proximity to medical facility	0.87	0.00	1.00	0.46	0.05	0.05	0.08
Weather sensitivity of rice yield	0.64	1.00	0.00	0.84	0.48	0.40	0.02
Average variability in maximum temperature (last 6 years)	0.51	0.79	0.00	1.00	0.19	0.10	0.91
Average variability in minimum temperature (last 6 years)	0.00	0.68	1.00	0.09	0.28	0.39	0.53
Average variability in rainfall (last 6 years)	0.00	0.69	0.11	0.28	0.51	0.12	1.00
Number of warm spells in daytime temperature (last 6 years)	0.43	1.00	0.14	0.00	0.57	0.14	0.86
Number of warm spells in night-time temperature (last 6 years)	0.00	1.00	0.00	0.00	0.29	0.00	0.71
Average severity of droughts (last six years)	0.17	0.16	0.04	0.00	0.48	1.00	0.44
Number of extreme rainfall episodes (last 6 years)	0.25	1.00	0.08	0.25	0.33	0.00	0.50

Source : Author’s calculations

The components food, water, health and weather sensitivity represent the factors that constitute the sensitivity of the livelihoods of the sample farm households in Tamil Nadu. As seen in the Table 7.2, Nagapattinam (0.576) and Thiruvarur (0.509) were more vulnerable in terms of food. Here, food is represented by the absorption component of food security (Swaminathan and Bhavani, 2013; Agarwal, 2018) as well as coverage of nutrition security programmes. We used cooking fuel as a proxy for hygienic method for absorbing the available food. The measure we adopted accounts for the hierarchy (Viswanathan and Kumar, 2005) in cooking fuel usage. It was observed that Ariyalur district had a relatively better cooking fuel index (0.40) and the farmers of Thiruvarur had the worst cooking fuel index (0.93). Though the usage of firewood for cooking has been wide spread among the sample farmers, the very low usage of LPG as a means of cooking has been influential in the case of Thruvarur. In the case of WCC programmes, we observed that 66.2% of the sample households from Nagapattinam district were not covered in any of the WCC programmes whereas all of the sample farmers in Karur, 98.80% in Thiruvarur and 90% of the sample farmers in Ariyalur were covered in WCC programmes.

Apart from food, an important component that influence the sensitivity of the livelihoods of the sample households is water. Based on the pilot survey conducted in the region, we included 9 issues and an open question (others) in the interview schedule that are prevalent in the region with regard to the drinking water. In the case of irrigation we included 6 issues and ‘others’ option in the interview schedule. A water score was computed for both drinking water and irrigation water. The water score measured the ratio of the number of issues faced by the respondent to the total number of issues listed in the interview schedule. As shown in the table 7.2, sample households in Thiruvarur district are more vulnerable (0.721) than the farmers in other districts. Karur was found least vulnerable (0.054) in terms of water related indicators. The index values for Thanjavur (0.698), Ariyalur (0.678), and Nagapattinam (0.609) were closer to the vulnerability index for the most vulnerable district. The issues pertaining to the drinking water was relatively higher in these districts. However, the sample households from Ariyalur, Perambalur, and Karur districts had relatively better water storage facilities and farmers in Karur and Perambalur experienced relatively less number of issues pertaining to the irrigation water. Issues pertaining to irrigation water can make the rice cultivation more sensitive to climate stress and retard possibilities of diversification of livelihood options of the farmers.

The next important component influencing the sensitivity of the livelihoods of the sample households is the health component of their security. The health component is measured in terms of hospital proximity and sanitation. In terms of the health component, sample households in Ariyalur (0.762) and Nagapattinam (0.749) were more vulnerable and Trichy (0.187) and Karur (0.00) were the least vulnerable. The awareness about proximate public health facilities was quantified and taken as one proxy for the health component. The hospital proximity index ranged between 0.06 and 0.10. Higher hospital proximity index (HPI) represents less awareness about proximate public health facilities and vice versa. Thanjavur (0.05) and Thiruvarur had the lowest vulnerability in terms of the HPI and Nagapattinam was the most vulnerable in terms of hospital proximity (1.00). The sanitation component was measured in terms of the percentage of households without toilet. Thanjavur district had the largest fraction of sample households without toilet (38%) and Perambalur had no households without toilets.

The sensitivity of the livelihoods of the rice farmers also depend on the weather sensitivity of their crop yield. The weather sensitivity of crop yield is estimated in terms of the R^2 of the regression model with rice yield as the dependent variable. The R^2 provides an estimate on the percentage of variation in the dependent variable explained by the model used. For this study we decomposed the R^2 value and identified the relative contribution of each variable towards the total variation in the dependent variable. The sum of weather relative contributions of weather variables in the model towards the overall variation in the rice yield was taken as the proxy for the weather sensitivity of rice yield. The study observed that the weather sensitivity of rice yield was higher in Karur (0.58) and Perambalur (0.50) and the lower in Nagapattinam (0.08) and Trichy (0.09) districts (Table B.2). Thus, on the basis of the above mentioned components of sensitivity, the study observed that Nagapattinam was the most sensitive district (0.560) followed by Thanjavur (0.555) and Ariyalur (0.544) and Karur was the least sensitive district (0.158) (Table 7.4).

Table 7.4: Livelihood Vulnerability Index (LVI-IPCC) values for the rice farmers in seven study districts of Tamil Nadu

Dimensions	Ariyalur	Karur	Nagapattinam	Perambalur	Thanjavur	Thiruvarur	Trichy
Adaptive Capacity	0.422	0.464	0.377	0.398	0.378	0.614	0.421
Sensitivity	0.544	0.158	0.560	0.364	0.555	0.507	0.353
Exposure	0.194	0.760	0.196	0.232	0.379	0.250	0.707
LVI-IPCC	**-0.124**	**0.047**	**-0.101**	**-0.061**	**0.0001**	**-0.185**	**0.101**

Source: author's calculation

The variability and extremes in temperature and rainfall constituted the exposure component for the sample farmers in each study district. Karur (0.760) and Trichy (0.707) districts were highly exposed to the variability and extremes in climate whereas Ariyalur

(0.194) and Nagapattinam were the least exposed (0.196) (Table 7.4). Perambalur and Trichy witnessed the largest variability in maximum temperature whereas the variability in minimum temperature was higher in Nagapattinam and karur. Karur also witnessed the relatively higher variability in rainfall and higher numbers of warm spells in daytime and night-time temperatures along with Trichy. Further, Tricv experienced relatively higher severity in droughts along with Thiruvarur, and the number of extreme rainfall episodes was higher in Karur and Trichy (Table 7.1). Accordingly, based on the vulnerabilities in major components, the overall LVI at district level is calculated (Table 7.2). The LVI in this study ranges between 0 and 1 with 1 being the most vulnerable and 0 is the least vulnerable. It was observed that livelihoods of rice farmers of Thanjavur district are relatively more vulnerable (0.542) in the context of the increase in the variability and extremes in climate. Thanjavur was followed by Trichy (0.532) and Karur (0.481). Thiruvarur was identified as the least vulnerable district (0.388). The livelihood vulnerability estimated on the basis of LVI-IPCC method is provided in Table 7.4. The LVI-IPCC ranges between -1 and 1 with -1 represents the least vulnerable and 1 represents the most vulnerable systems. The table suggests that, Trichy district is the most vulnerable (0.101) followed by Karur (0.047) and Thanjavur (0.0001). In the cases of Trichy and Karur, high exposure was the main reason behind the vulnerability of rice farmers in these regions whereas in the case of Thanjavur high sensitivity was the influential factor behind the vulnerability. Although, the sensitivity factor was high in Thiruvarur district, the adaptive capacity of the sample farmers in Thiruvarur was the highest (0.614) and hence they became the least vulnerable to climate variability and extremes.

7.2 LVI and LVI-IPCC across the three cultivating seasons of Tamil Nadu

Farmers were asked about the seasons they usually cultivate. The response revealed that all farmers do not cultivate rice in all the three seasons. Some cultivate in the first two seasons, some in the second two seasons and some cultivate exclusively in Samba season. Since the weather characteristics and sensitivity of the rice crop, and the combination of farmers cultivating in each season are not similar we made an assessment of vulnerability across the three seasons. It was observed that the farmers cultivating in the Navara season were more vulnerable (0.667) than those cultivating in the Samba and Kuruva seasons (Table 7.6). The relatively low educational attainment (mean education score is 2.98 - Table B.5), and relatively higher proportion of female operational holders (10% - Table B.3) were the reasons for this increased vulnerability of this group of farmers. These group of farmers were also observed to be the most vulnerable in terms of livelihood strategies as well (0.667). Among these farmers, livelihood diversification as well as diversification in agricultural activities are relatively low, though they are not too behind in terms of actual values. Further, in terms of social networks, the farmers who engaged in Samba rice cultivation were observed to be more vulnerable (0.795) than others. From the table B.5, it can be inferred that the farmers cultivating in Kuruva season were more capable in obtaining financial assistance from SHGs, friends and families, insurance, cooperative institutions and even government. Their vulnerability index value for social networks was very low (0.167) compared to the other two groups. Thus, in terms of the LVI-IPCC

Table 7.5: Livelihood Vulnerability Index (LVI) standardised sub-component values for three rice cultivating seasons of Tamil Nadu

Minor component	**Cultivating Season**		
	Kuruva	**Samba**	**Navara**
Dependency ratio	1.00	0.23	0.00
Gender of the operational holder	0.00	0.67	1.00
Lack of educational attainment	0.00	0.72	1.00
Proportion of migrant households	0.47	1.00	0.00
Livelihood diversification index	0.09	0.00	1.00
Agricultural diversification Index	0.50	0.00	1.00
Lack of participation in SHGs	1.00	0.16	0.00
Lack of assistance from SHGs	0.00	0.88	1.00
Lack of assistance from friends and family	0.00	1.00	0.27
Lack of insurance coverage	0.00	0.72	1.00
Lack of assistance from cooperative institutions	0.00	1.00	0.94
Lack of assistance from government	0.00	1.00	0.96
Cooking fuel	1.00	0.00	0.89
Lack of women and child care programmes access	0.00	1.00	0.77
Drinking water issues	1.00	0.27	0.00
Drinking water storage index	0.00	1.00	0.90
Irrigation water issues	0.00	1.00	0.44
Proportion of households without toilet	0.00	1.00	0.92
Proximity to medical facility	0.00	0.88	1.00
Weather sensitivity of rice yield	1.00	0.00	0.21
Average variability in maximum temperature (last 6 years)	0.00	0.77	1.00
Average variability in minimum temperature (last 6 years)	0.00	0.58	1.00
Average variability in rainfall (last 6 years)	0.16	1.00	0.00
Average number of warmspells in daytime temperature (last 6 years)	1.00	0.00	0.25
Average number of warmspells in nighttime temperature (last 6 years)	1.00	0.00	0.13
Average severity of droughts (last six years)	0.00	1.00	0.12
Average number of extreme rainfall episodes (last 6 years)	0.26	1.00	0.00

Source : Author's calculations

framework, it was observed that the Kuruva cultivating farmers had the highest adaptive capacity among the farmers cultivating in the three seasons. They were followed by Samba cultivating farmers (0.336) and those cultivated in Navara season (0.236).

The table 7.6 shows the major components that constitute the vulnerability of households cultivating in each season. It is shown in the table that in terms of food and nutritional security, the sample farmers cultivating in the Navara season are more vulnerable (0.827). Those who cultivate in Kuruva and Samba had same vulnerability value (0.500) suggesting moderate vulnerability. The differences in terms of cooking fuel index is relatively small among the three categories. However, the coverage of WCC programmes is considerably high among Kuruva cultivating farmers and low among Samba cultivating farmers (Table B.3).

Table 7.6: Livelihood Vulnerability Index (LVI) values for the three cultivating seasons of Tamil Nadu

Major component	**Kuruva**	**Samba**	**Navara**
Socio-demographic profile	0.333	0.540	0.667
Livelihood strategies	0.354	0.333	0.667
Social networks	0.167	0.795	0.695
Food	0.500	0.500	0.827
Water	0.333	0.756	0.447
Health	0.000	0.938	0.961
Weather sensitivity	1.000	0.000	0.214
Climate variability and extremes	0.346	0.621	0.357
LVI	**0.314**	**0.625**	**0.585**

Source: author's calculation

In terms of water security also, the Samba cultivating farmers are more vulnerable (0.756) and Kuruva cultivating farmers are the least vulnerable (0.333). The Samba cultivating farmers face more irrigation water related issues than the Kuruva and Navara cultivating farmers. In terms of health and sanitation, the Navara cultivating farmers are more vulnerable (0.961). However, the Samba cultivating farmers are also highly vulnerable (0.938) in terms of health and sanitation facilities. Here, while the hospital proximity is the same for all categories, the proportion of farmer households without toilet is relatively very high among Samba and Navara cultivating farmers.

Table 7.7: Livelihood Vulnerability Index (LVI-IPCC) standardised sub-component values for three rice cultivating seasons of Tamil Nadu

Minor component	**Cultivating Season**		
	Kuruva	**Samba**	**Navara**
Dependency ratio	0.00	0.67	1.00
Gender of the operational holder	1.00	0.33	0.00
Lack of educational attainment	1.00	0.31	0.00
Proportion of migrant households	0.50	0.00	1.00
Livelihood diversification index	1.00	0.50	0.00
Agricultural diversification Index	0.20	1.00	0.00
Lack of participation in SHGs	0.00	0.83	1.00
Lack of assistance from SHGs	1.00	0.12	0.00
Lack of assistance from friends and family	1.00	0.00	0.06
Lack of insurance coverage	1.00	0.27	0.00
Lack of assistance from cooperative institutions	1.00	0.00	0.06
Lack of assistance from government	1.00	0.00	0.04
Cooking fuel	1.00	0.00	0.89
Lack of women and child care programmes access	0.00	1.00	0.77
Drinking water issues	1.00	0.27	0.00
Drinking water storage index	0.00	1.00	0.90
Irrigation water issues	0.00	1.00	0.44
Proportion of households without toilet	0.00	1.00	0.92
Proximity to medical facility	0.00	0.88	1.00
Weather sensitivity of rice yield	1.00	0.00	0.21
Average variability in maximum temperature (last 6 years)	0.00	0.77	1.00
Average variability in minimum temperature (last 6 years)	0.00	0.58	1.00
Average variability in rainfall (last 6 years)	0.16	1.00	0.00
Average number of warm spells in daytime temperature (last 6 years)	1.00	0.00	0.25
Average number of warm spells in night-time temperature (last 6 years)	1.00	0.00	0.13
Average severity of droughts (last six years)	0.00	1.00	0.12
Average number of extreme rainfall episodes (last 6 years)	0.26	1.00	0.00

Source : Author's calculations

One of the major factor contributing to the vulnerability of farmers cultivating in different seasons is the sensitivity of the rice variety cultivated in each season towards the variations in climate. As seen in tables 7.6 and B.3, the rice yield in Kuruva season is relatively more sensitive to the variations in climate. The sensitivity component in the table 7.8 accounts for the food, water, health, and weather sensitivity components in the table 7.6. The tables suggest that the livelihoods of Samba (0.643) and Navara (0.641) cultivating farmers are more sensitivity towards the variations in climate whereas the livelihoods of Navara cultivating farmers are moderately sensitive (0.346) irrespective of the high sensitivity of Navara season rice yield towards the variability and extremes in climate.

The table 7.5 shows the standardised sub-component values for the exposure in the table 7.8 and the component climate variability and extremes in the table 7.6. According to the

Table 7.8: Livelihood Vulnerability Index (LVI-IPCC) values for the three cultivating seasons of Tamil Nadu

Dimensions	**Kuruva**	**Samba**	**Navara**
Adaptive Capacity	0.725	0.336	0.263
Sensitivity	0.375	0.643	0.641
Exposure	0.346	0.621	0.357
LVI-IPCC	**-0.142**	**0.183**	**0.0607**

Source: author's calculation

table, the variability in maximum and minimum temperature is relatively high in Samba and Navara seasons, while it is too less in the Navara season. In the case of rainfall, the variability is high in Samba season while it is very less in Kuruva and Navara seaosns. The warm spells in both daytime and night-time temperatures were more experienced during the Kuruva season. The presence of these extremes were observed in the Navara season in small numbers and no temperature extremes were observed during the Samba season. However, it was observed that both droughts severity and the number of extreme rainfall episodes were higher during the Samba season. Thus the exposure to climate variability and extremes was high in Samba season (0.621) whereas it was moderate in Navara (0.357) and Kuruva (0.346) seasons. Overall, the vulnerability constituted by the eight sub-components of LVI (Table 7.6) is higher in Samba season (0.625) followed by Navara season (0.585). However, in Kuruva season, the livelihood vulnerability of farmers to climate stress is relatively less (0.314). A similar pattern is visible in LVI-IPCC (Table 7.8) as well. High exposure, high sensitivity, and low adaptive capacity has caused high vulnerability of livelihoods in the Samba season (0.183) whereas moderate exposure, high sensitivity and low adaptive capacity resulted in the vulnerability (0.0607) of rice farmers cultivating in the Navara season. In the Kuruva season, both exposure and sensitivity were moderate and adaptive capacity was high, causing very low vulnerability (-0.142).

7.3 LVI and LVI-IPCC across the various categories of farmers of Tamil Nadu

We further examined the vulnerability of farmers belonging to four landholding based categories. The sample rice farmers have classified in to large, medium, semi-medium and small on the basis of their operated landholding. Table B.1 represent the actual values for each sub-component in the LVI measurement framework, the table 7.9 provides the standardised sub-component values for each category of rice farmers in Tamil Nadu, and the table 7.10 represents the LVI values for the various categories of farmers. The tables suggest that small farmers are the most vulnerable in terms of the socio-demographic profile (0.672) followed by semi-medium farmers (0.651). Though the dependency ratio was higher among the medium farmers (0.93), the dependency ratio was generally higher among all farmer groups (Table B.1). Further, among the small farmers, the share of female operational holders was higher (10%) and the educational attainment was lower. In this assessment, small farmers were closely followed by semi-medium farmers. Although, small farmers were observed as more vulnerable in terms of their socio-demographic profile, they were relatively less vulnerable in terms of livelihood strategies with and index value of 0.437 (Table 7.10). However, the interpretation of this component is a bit complicated. In terms of proportion, half of the large farm households had migrant members. However, they were employed in white collar jobs abroad. However, majority of the migrants belonging to the small and semi-medium households worked in the near by states and mostly engaged in casual labor. Further, majority of the large farmers had other businesses or employments besides agriculture while livelihood diversification was relatively low among all the other categories. Similarly, large farmers mostly cultivated rice, and they cultivated rice in all seasons. They did not do much diversification in cropping although majority of them had cattle. In the case of semi-medium and medium farmers, diversification of livelihood activities was relatively low, although they considerable fraction of them cultivated sesame/black gram and owned cattle or poultry. In terms of social networks small farmers were the most vulnerable (0.696) and medium farmers were the least vulnerable (0.428). Although, large farmers did not participate in SHGs or or obtained assistance from them or government, all of them received assistance from friends and families and had insurance coverage. They also received assistance from cooperative institutions. In the case of medium farmers, while the participation and assistance from SHGs or friends and family, majority of them were able to get assistance from cooperative institutions and government sources. A majority of the semi-medium farmers were able to depend their friends and family, and cooperative institutions in times of crises. In the case of small farmers, they also depended considerably on friends and family and their access to other sources were relatively lower than that of other categories.

Table 7.9: Livelihood Vulnerability Index (LVI) standardised sub-component values for various categories of rice farmers Tamil Nadu

Minor component	**Farmer Category**			
	Large	**Medium**	**Semi-medium**	**Small**
Dependency ratio	0.00	1.00	0.59	0.02
Gender of the operational holder	0.00	0.31	0.77	1.00
Lack of educational attainment	0.00	0.17	0.59	1.00
Proportion of migrant households	1.00	0.00	0.25	0.20
Livelihood diversification index	0.00	1.00	1.00	0.90
Agricultural diversification Index	1.00	0.41	0.00	0.22
Lack of participation in SHGs	1.00	0.31	0.10	0.00
Lack of assistance from SHGs	1.00	0.59	0.00	0.45
Lack of assistance from friends and family	0.00	0.83	0.71	1.00
Lack of insurance coverage	0.00	0.84	1.00	0.94
Lack of assistance from cooperative institutions	0.34	0.00	0.44	1.00
Lack of assistance from government	1.00	0.00	0.48	0.78
Cooking fuel	0.00	1.00	0.81	0.61
Lack of women and child care programmes access	0.00	0.76	0.55	1.00
Drinking water issues	0.10	1.00	0.68	0.00
Drinking water storage index	0.00	0.46	0.59	1.00
Irrigation water issues	0.00	1.00	0.58	0.71
Proportion of households without toilet	0.00	0.00	0.49	1.00
Proximity to medical facility	0.51	0.00	0.10	1.00

Source : Author's calculations

The table 7.10 shows the components of sensitivity of livelihoods of the sample farmers. It is seen that, in terms of food and nutritional security, medium farmers were found to be the most vulnerable (0.880) followed by small (0.803) and semi-medium farmers (0.683). This is because, even though both firewood and LPG are the most prevalent methods of cooking among the sample households, the usage of LPG for cooking was relatively higher among small farmers and the usage of firewood was higher among the medium and semi-medium farmers. Similarly, the share of beneficiaries of WCC programmes was higher among the semi-medium and large farmers and was relatively lower among the medium and small farmers.

Table 7.10: Livelihood Vulnerability Index (LVI) values for the various categories of farmers of Tamil Nadu

Major component	**Large**	**Medium**	**Semi-medium**	**Small**
Socio-demographic profile	0	0.493	0.651	0.672
Livelihood strategies	0.667	0.470	0.416	0.437
Social networks	0.556	0.428	0.455	0.696
Food	0	0.880	0.683	0.803
Water	0.033	0.819	0.615	0.568
Health	0.253	0	0.296	1
LVI	**0.313**	**0.509**	**0.512**	**0.674**

Source: author's calculation

In the case of water, drinking water and irrigation water issues were widely prevalent among the medium farmers than among the large and small farmers. However, the medium and semi-medium farmers had better storage facilities when compared to the small farmers. Hence, according to the table 7.10, medium farmers were relatively more vulnerable (0.819) in terms of water security. Semi-medium farmers were also relatively more vulnerable (0.615) than the small and large farmers. In the health component, small farmers were highly vulnerable (1.00) while large (0.253) and semi-medium (0.296) farmers were moderately vulnerable and the medium farmers were the least vulnerable (0.00). Among the small farmers, 25% did not have toilets in their houses whereas 12% of the semi-medium farmers also reported as not having toilets. Further, the awareness about the public health facilities in the proximity was very low among the small farmes. However, the awareness about public health facilities was low among large farmers as well. The large farmers mostly depended on private hospitals or nursing homes nearby. Accordingly, assuming that weather sensitivity and exposure are constant among these farmer categories, a LVI was constructed based on the adaptive capacity and sensitivity components. The index suggests that, in a given climate scenario, the livelihoods of the small farmers are the most vulnerable (0.674), followed by semi-medium (0.512), and medium (0.509) categories. Vulnerability is very moderately low for the large farmers (0.313).

7.4 Summary and Findings

In this chapter, we consolidated the biophysical and socioeconomic factors that constitute the vulnerability of the livelihoods of the sample rice farmers of Tamil Nadu region. The various indicators representing the components and dimensions of vulnerability were standardised across three corss sections - geographical location (district), cultivating season, and farmer category. The livelihood vulnerabilty of the sample farmers was computed using the equation 3.9. The major findings of this chapter are;

1. The analysis across the districts revealed that Thanjavur district was the most vulnerable according to the LVI framework. Thanjavur was followed by Trichy, Karur, Ariyalur, Nagapattinam, Perambalur, and Thiruvarur. In the case of Thanjavur, the high vulnerability was caused on account of the socio-demographic profile of the farmers, lack of beneficial social networks, and the lack of water security were the major factor determining the vulnerability. In Trichy and Karur districts, lack of beneficial social networks coupled with high incidence of variability and extremes in climate formed the dominant components of vulnerability of the farmers. In Karur, the weather sensitivity was the highest. In the Ariyalur district, weaknesses in livelihood strategies, lack of water and health security, formed extent of vulnerability in the district. In Nagapattinam as well, the lack of beneficial social networks, and the lack of water and health security were influenced the overall vulnerability of the rice farmers in the region. In Perambalur, weak livelihood strategies, lack of beneficial social networks, and high weather sensitivity constituted the vulnerability profile of the farmers. The sample households from Thiruvarur were the least vulnerable among the whole sample. Here, only the issues pertaining to the water security, and moderate weather sensitivity were influential. According to the LVI-IPCC framework, Trichy district was the most vulnerable followed by karur, Thanjavur, Perambalur, Nagapattinam, Ariyalur, and Thiruvarur. In Trichy, the exposure was one of the highest, and the farmers exhibited moderate sensitivity and moderate adaptive capacity in the context of climate stress. In Karur, the exposure was the highest and adaptive

capacity was moderately high whereas the sensitivity was very less. In Thanjavur, moderate exposure and adaptive capacity coupled with higher sensitivity constituted the major determinants of the vulnerability profile of the farmers. In Perambalur, exposure was relatively low and sensitivity and adaptive capacity components were generally moderate. In Nagapattinam and Ariyalur, the exposure was relatively low, the sensitivity component was moderately high, and the adaptive capacity was moderate. Thiruvarur had high adaptive capacity, moderately high sensitivity and very low exposure.

2. The analysis across seasons using LVI revealed that the farmers cultivating in the Samba season are more vulnerable, and those cultivating in the kuruva season are the least vulnerable. Those cultivating in the Navara season exhibited moderately high vulnerability. Among the farmers who preferred to cultivate in the Samba season, the lack of beneficial social networks, issues pertaining to water security and health insecurity were relatively high and they experienced high incidence of climate variability and extremes in the season. In the case of Navara farmers, they were weak in socio-demographic profile, social networking, livelihood strategies, food and health security although they experienced relatively low incidence of climate stress. In the case of Kuruva season, all components except food security and weather sensitivity were moderate in nature. Similar results were produced by LVI-IPCC as well. According to the LVI-IPCC framework, the farmers cultivating in the Kuruva season had the highest adaptive capacity, and they exhibited moderate sensitivity and had moderate exposure as well. In the case of those cultivating in the Navara season, they had low adaptive capacity, high sensitivity and moderate exposure. The farmers cultivating in the Samba season had moderate adaptive capacity, high sensitivity and high exposure.

3. The analysis across farmer categories suggested that the small farmers were the most vulnerable and were followed by semi-medium and medium and large categories. The small farmers were vulnerable for majority of the components representing the sensitivity and adaptive capacity of the livelihoods. Medium and semi-medium category farmers exhibited more or less similar characteristics. Both these categories of farmers were highly vulnerable in terms of food and water security. in the case of large farmers, they were found more vulnerable only in terms of livelihood strategies. However, although majority of them have migrant members, most of them are abroad and are better off when compared with the migrant members belonging to

other categories.

Chapter 8

Findings and Suggestions

The global mean surface temperature has increased by more than 1°C above the pre-industrial level. This increase in temperature has caused unprecedented changes across the human and natural systems. The variability and extremes in rainfall, temperature etc., have witnessed substantial increase in different parts of the world. In India, the last five decades experienced an increase in the frequency and magnitude of extreme rain events over central India, western India, northeastern India, and southern India whereas, an increase in the frequency of severe droughts have been observed over south India, central Maharashtra, the Indo-Gangetic Plains, north, and north-west India. Nearly every region in India experienced increase in the warm extremes in temperature in these decades. This increase in the variability and extremes in climate constituted substantial challenges to the existence and progress of various natural and human systems across the country. Agriculture, forests, water resources, mountain, and coastal ecosystems etc., have been particularly affected. In the case of agriculture, it is the largest livelihood providing sector in Indian economy and it accommodates nearly half of the nation's work force. Apart from the dependence of such a large share of population on this sector, the viability of agriculture as a means of livelihood is also affected by the structural issues such as the increasing fragmentation of agricultural land, decline in public investment, stunted subsidies, and stagnation in the growth of agricultural credit. It is, therefore, important to examine the degree to which various socio-economic and biophysical factors make the livelihoods of farmers vulnerable.

In the present study, therefore, we examined the livelihood vulnerability of rice farmers of Tamil Nadu to climate variability and extremes. The study considered that weather sensitivity of yield varies across different crops. Since rice is a prominent crop constituting nearly half of the total food grain production in the country, we selected rice farmers as the subjects of the study. Further, Tamil Nadu, is predominantly an agricultural state where rice is the major crop. Based on the literature review, the following research objectives were decided.

The first objective was to study the extent of variability and extremes in temperature and rainfall over the Tamil Nadu region. The study used temperature and rainfall data from IMD for examining the major changes in the climate variability and extremes during 1984-2016 with reference to 1951-2016. The study utilised a robust statistical tool namely the Ensemble Empirical Mode Decomposition (EEMD) method to measure the variability in temperature and rainfall. In order to measure the spatio-temporal characteristics of droughts and extreme rainfall events, the study used the Standardised Precipitation Evapotranspiration Index (SPEI) and a classification scheme based on daily rainfall (IMD). Further, the study investigated the time evolution of heat waves and warm nights over Tamil Nadu using the Heat-wave magnitude index daily (HWMId). The statistical robustness of the results was tested using the Mann-Kendall trend test and the Kolmogorov-Smirnov test.

The second objective of the study was to identify the extent to which rice yield is influenced by the variability and extremes in temperature as well as rainfall. The study used the result analysis of the first objective and the district level time series data on the area, yield, area under HYV, and the area under irrigation for achieving this objective. A Fixed Effects Panel Regression model was used to identify the weather sensitivity of rice yield in the three cultivating seasons and a multiple linear regression model was used to examine the weather sensitivity of rice yield at district level.

The third objective was to examine the socio-economic factors that constitute the vulnerability of rice farmers. In order to achieve this objective, a primary survey was carried out among the rice farmers of Cauvery Delta region to identify the socio-economic factors that constitute the sensitivity and adaptive capacity at household level. The study used the Livelihood Vulnerability Index method proposed by Hahn et al. (2009) to assess the overall vulnerability of the rice farmers. This method involved two ways of calculating the vulnerability index. The first one is a composite index approach and consisted of seven major components: Socio-demographic profile, Livelihood strategies, Social networks, Health, Food, Water, and climate variability and extremes. In the present study we added one more component - Weather sensitivity of rice yield. This component represents the extent to which the variation in rice yield is explained by the weather variables. The second one organises the eight major components into the three dimensions in the IPCC definition framework. The exposure dimension is measured in terms of the component climate variability and extremes. The sensitivity component is measured by assessing the weather sensitivity of rice yield, current state of the food and water security and health status of the farmers. The dimension adaptive capacity represents the demographic profile of a district, the types of livelihood strategies employed, and the strength of social networks. In the composite index approach, however, adaptive capacity represents the lack of these factors. Thus the analysis of livelihood vulnerability involved twenty seven indicators representing eight major components and three dimensions of vulnerability. The following findings were obtained from the analyses performed in the present study.

1. The temperature and rainfall over Tamil Nadu exhibited substantial variability and extremes in the recent decades. In the case of temperature, both the maximum and minimum temperature showed significant increasing trends. The inter-annual variability played a dominant role in determining the overall characteristics of the minimum temperature, while the overall variability was relatively less for maximum temperature during 1984-2016 with reference to the previous three decades.

2. There was a general decline in the variability in maximum temperature, but, the Cauvery Delta region was an exception for this. The total variability in maximum temperature over Cauvery Delta exhibited an increase during 1984-2016, due to an increase in the inter-annual scale variability. Within the Cauvery Delta region, the district level analysis suggested that the variability in maximum temperature was relatively higher in Perambalur, Trichy, and Karur districts whereas the variability in minimum temperature was higher in Nagapattinam, Karur, and Trichy during 2011-2016. Similarly, the season level analysis suggested that the variability in maximum and minimum temperature was higher in Navara season followed by Samba season during 2011-2016.

3. The study observed robust increase in the frequency, magnitude, and duration of heat waves over Tamil Nadu during 1951-2016. The incidences of heat waves became more frequent and intense after 1980. The most severe heat waves between 1951 and 2016 occurred in 2003 and 2016. These episodes lasted for 23 and 30 days respectively. Although, every location in the state experienced an increase in the incidence of heat waves during 1984-2016, the shift in intensity was more evident over the areas closer to the western border of the state. Unlike heat waves, warm nights were more frequent from 1951 itself, with occasional incidences of larger intensity and duration. The most severe warm night event in the entire study period occurred in 2016. The episode lasted up to 35 days. In the case of warm nights, the South zone, West zone, and Northeast zones witnessed the largest increase in the number of episodes in the second half of the study period, whereas the shift in duration and intensity was considerably larger over central Tamil Nadu.

4. In the Cauvery Delta region, Karur and Trichy districts experienced the largest number of warm spells in daytime and night-time temperatures during 2011-2016. Karur witnessed 14 daytime warm spells and 14 night-time warm spells during 2011-2016 whereas Trichy experienced 13 daytime warm spells and 12 night-time warm spells during the same period. Across seasons, Kuruva season has witnessed the largest number of warm spells in daytime (36) and night-time (39) temperatures in the six years starting from 2011. While Navara season witnessed nine warm spells in daytime temperature and five in night-time temperature, Samba season did not experience any episodes of warm spells during 2011-2016.

5. In the case of rainfall, the variability in the annual rainfall anomaly time series across Tamil Nadu ranges between -400 mm to +400 mm. The present study observed an amplification of inter-annual scale variability in rainfall over all agro-climatic zones except the Northeast zone after 2000, causing excess and deficient rainfall years that cross this range. In the Cauvery Delta, Trichy and Karur districts experienced relatively higher variability in annual rainfall whereas across seasons, the Samba season exhibited the largest rainfall variability between 2011 and 2016.

6. The study observed a general increase in the occurrence of heavy rainfall categories and a decline in the frequency of light and moderate rainfall events. There was an increase in the area affected by heavy rainfall categories, and an increase in the share of these types of rainfall events was observed over the Southern and the South zone. In the case of "rather heavy" rainfall, significant trends and changes in the area and share was observed over the West zone. A significant change in the share of "rather heavy" rainfall was observed over the Northeast zone also. In the Cauvery Delta, Karur and Trichy districts witnessed twelve and six extreme rainfall episodes during 2011-2016, whereas Tamil Nadu experienced sixty two extreme rainfall episodes in the Samba season and twenty two episodes in the Kuruva season during this period.

7. The results from the present study suggest that Tamil Nadu is a chronic drought-affected region. The region witnessed a decline in the number of drought episodes between the two sub-periods, i.e., 1951-1983 and 1984-2016. However, the same period witnessed an increase in the area affected, mean intensity and severity over the region. As a result, Tamil Nadu is at risk of becoming a drought hot spot under the current warming scenario. It is important to note that the mean drought severity over Tamil Nadu during 2011-16 was higher in the Samba season followed by Navara

season. In the Cauvery Delta, Thiruvarur and Thanjavur districts exhibited relatively higher values of drought severity.

8. The analysis of sensitivity of rice yield towards weather and non-weather factors suggest that the response of rice yield was different towards variables of similar nature in different seasons. However, a general impression is that rice yield responded directly towards variations in the maximum temperature, whereas the variations in minimum temperature exerted a negative influence on the rice yield. Rice yield was inversely correlated to the variations in rainfall in the Kuruva and Navara seasons, while in the Samba season, it responded positively to the rainfall variations. There was no negative response to the drought episodes, possibly due to the presence of irrigation and high yielding varieties of seeds. Irrigation and HYV seeds have positively influenced the rice yield. In general, the weather sensitivity of rice yield is the highest in Kuruva season and is the lowest in the Samba season. Among the districts of Tamil Nadu, robust contributions of weather variables towards the changes in the rice yield were observed in sixteen districts. In the Cauvery Delta, the weather sensitivity of rice yield was higher in Karur, Perambalur, and Ariyalur and was lower in Nagapattinam and Trichy districts.

9. The socio-demographic profile represents the potential for adaptation among the sample households (Deressa et al., 2010). The analysis of socio-demographic profile considered three factors - dependency ratio, gender of the operational holders, and educational attainment of the household. The analysis of these components across the farm size categories revealed that small farmers were the most vulnerable in terms of their socio-demographic profile and large farmers were the least vulnerable. Similarly, the analysis across districts of the Cauvery Delta suggested that farmers from Thanjavur district were the most vulnerable in terms of socio-demographic profile and those from Perambalur and Trichy districts were relatively less vulnerable. Also, the analysis at seasonal level suggested that those who cultivate in the Navara season are the most vulnerable and those who cultivate in the Kuruva season are the least vulnerable.

10. The analysis of Livelihood strategies considered migration, livelihood diversification, and diversification of agricultural activities among the sample households. It was observed that the semi-medium and small farmers had to engage in more livelihood activities than the large farmers in order to survive. Hence the vulnerability score of large farmers is higher in this category. Across the districts, it was observed that

sample farmers from Ariyalur and Perambalur districts were the more vulnerable and those from Nagapattinam and Thiruvarur were less vulnerable in terms of their livelihood strategies. The analysis of different seasons suggested that the farmers cultivating in Navara season were the most vulnerable and those cultivating in Samba season were the least vulnerable.

11. The analysis of social networks considered the participation of sample farmers in SHGs, financial assistance they received from SHGs, friends and family, cooperative institutions, insurance companies, and government sources. It was observed that majority of the sample farmers received assistance from their friends and family. It was followed by cooperative institutions. Although, more than one third of the farmers participated in SHGs, the percentage of farmers who reported to have received financial assistance from SHGs was too negligible. Insurance coverage and the assistance of government sources were also less among the sample farmers. Among the various farm size categories, the small farmers were highly vulnerable in terms of the strength of social networks while medium farmers were the least vulnerable in terms of social networks. In the Cauvery Delta region, the sample farmers from Nagapattinam and Trichy were highly vulnerable in terms of their social networks whereas those from Thiruvarur were less vulnerable. The analysis of different seasons revealed that the farmers cultivating in the Samba season were the most vulnerable whereas those cultivating in Kuruva season were least vulnerable.

12. The present study considered cooking fuel and the coverage of WCC programmes as a proxy for the food and nutrition security of the households. It was observed that nearly eighty five percent of the farmers used firewood and fifty eight percent used LPG as the cooking fuel. It was also observed that farmers used firewood even though they have LPG connection and electric means of cooking. The vulnerability assessment in the present study suggests that, among the various farm size categories, medium and small farmers were observed as most vulnerable and the large farmers were observed as the least vulnerable. Among the study districts of the Cauvery Delta, the farmers of Nagapattinam district were the most vulnerable in terms of food and nutrition security, whereas, the farmers of Ariyalur were the least vulnerable. Across the seasons, those cultivated in the Navara season were the most vulnerable while the farmers who cultivated in the Samba and Kuruva seasons had similar vulnerability score.

13. The study considered drinking water issues, water storage facilities, and irrigation

water issues to represent the water security of the sample households. The farmers faced diverse issues pertaining to the availability and quality of drinking water. In Thiruvarur and Thanjavur, water supply issues were generally higher, while from Trichy and Nagapattinam districts, water quality issues were mostly reported. Issues related to water supply were widely prevalent in the case of irrigation water also. Water salinity was also a major issue affected the irrigation in Nagapattinam, Trichy, and Thiruvarur districts. Overall, the study observed that the farmers of Thiruvarur district were the most vulnerable in terms of water security. The farmers of Thanjavur, Ariyalur, and Nagapattinam districts were also relatively more vulnerable in terms of water security. The farmers of Karur district were the least vulnerable. Among the farm size categories, the medium farmers were the most vulnerable and the large farmers were the least vulnerable. Further, it was observed that those cultivating in the Samba season were the most vulnerable and those cultivating in the Kuruva season were the least vulnerable.

14. The analysis of health security considered the proximity to public health facilities and the percentage of households without toilet. The study observed that twenty one percent of the sample households did not have toilet. The study also observed that there is very good network of public health facilities in the sample area and the people are well aware of the facilities available. In terms of health security, the small farmers were the most vulnerable category while medium farmers were the least vulnerable. The farmers of Ariyalur and Nagapattinam were highly vulnerable and the farmers in Karur and Trichy districts were the least vulnerable. The season level analysis suggested that the farmers cultivating in the Navara and Samba seasons were highly vulnerable in terms of health security.

15. The overall vulnerability assessment of the farmers belonging to various farm size categories suggested that small farmers were the most vulnerable category followed by semi-medium and medium farmers. The large farmers were found to be the least vulnerable among all farmers. In the case of small farmers, it was observed that they made fairly better attempts to diversify their livelihoods. The major causes of higher vulnerability of the small farmers in the study area are the relatively low educational attainment, more female operational holders, lack of access to beneficial networks in the society, higher proportion of households exclusively using fire woods for cooking, and a larger percentage of households without toilet. In the case of semi-medum farmers, they performed relatively better in terms of livelihood strategies and

had better health and sanitation security. In the case of medium farmers, better health security and social networks reduced their vulnerability.

16. The vulnerability assessments (LVI and LVI-IPCC) of farmers located across the seven districts suggest that the farmers of Thanjavur and Trichy districts are highly vulnerable. According to LVI method, farmers in Thanjavur district are the most vulnerable, whereas, according to the LVI-IPCC, the farmers in Thanjavur are second to those in Trichy district in terms of vulnerability. In both methods, the farmers in Thiruvarur district were the least vulnerable among the sample farmers. According to the LVI-IPCC, although both Karur and Trichy districts were highly exposed to the climate variability and extremes, low sensitivity and better adaptive capacity made the vulnerability of Karur district moderate when compared to Trichy. In the case of Thiruvarur, the exposure was low but sensitivity was high. However, high adaptive capacity caused less vulnerability to the farmers in Thiruvarur.

17. The analyses of vulnerability (LVI and LVI-IPCC) across seasons suggest that the farmers cultivating in the Samba season are more vulnerable. In samba season, exposure is high, however, the weather sensitivity of rice yield is the lowest. The farmers are highly sensitive in terms of their food, water, and health securities and they have moderate adaptive capacity. In the Navara season, the exposure is moderate and weather sensitivity of rice yield is less. However, the adaptive capacity of farmers cultivating in this season is low and the overall vulnerability is moderate. In the case of Kuruva season, there is moderate exposure to climate variability and extremes and highest weather sensitivity of rice yield. However, the socio-economic factors constituting sensitivity and adaptive capacity are having high index values such that farmers cultivating in Kuruva season have the lowest vulnerability.

8.1 Policy Implications

Tamil Nadu region has been experiencing an increase in the variability and extremes in temperature and rainfall in the recent decades. These changes coupled with the socio-economic characteristics determine the overall vulnerability of the rice farmers in the region. It was observed that small farmers, having relatively low livelihood security are at the highest risk from the increase in climate variability and extremes. Based on our findings, the following perspectives that are relevant to policy are suggested.

1. Tamil Nadu region has been experiencing an increase in the number of heat waves and warm spells in daytime temperatures. The associated heat stress may cause decline in the productivity of labour and result in an increase in morbidity and mortality among the farmers who regularly work outdoors. This is more important since Tamil Nadu belongs to the southern part of India which is expected to be severely affected by heat waves by the end of the twenty-first century (Murari et al., 2015).

2. The study observed that Tamil Nadu region has been experiencing a significant increase in the minimum temperature in the recent decades. Also, the warm spells in nigh-time temperatures are increasing over Tamil Nadu. The variations in minimum temperature is widely considered as a better predictor of excess mortality (Nicholls et al., 2008) and it also points towards an increase in the concurrent heat waves and warm nights over Tamil Nadu (Rajkumar et al. 2021) which can trigger morbidity as well as excess mortality in the region.

3. The study observed an increase in the extreme rainfall events and a decline in the occurrence of moderate and light rainfall events over Tamil Nadu. Although some of our results pertaining to this observation are not statistically robust, there is definitely a pattern. These results are consistent with the findings of Nageswararao et al. (2019) which observed a significant decline in light and moderate rain events and an increase in high-intensity rain events over the Southern Peninsular India during the NEMR seasons of 1959-2016. This pattern is observed over different parts of India (Goswami et al., 2006; Mishra and Liu, 2014) and is expected to a cause decline in soil moisture and a increase in the number of dry spells even when rainfall in general, intensifies (Trenberth, 2011). In this context, we suggest policies to promote water conservation, water recharge, and optimal usage of water for domestic as well as agricultural uses in the region.

4. The results of the present study suggests an increase in the intensity and severity of droughts in Tamil Nadu. This issue requires policy attention since the ground water level in many areas of Tamil Nadu are very low. Since the droughts here are measured using SPEI, these results could be a warning of an upcoming water crisis in the region. In the case of Tamil Nadu, a shift from dry sub-humid climate to semi-arid climate has also been observed over the region recently (Raju et al., 2013).

5. Our results suggests that, in general, the variations in minimum temperature causes a negative response in the rice yield. This is consistent with the findings of Welch et al.

(2010) which identified opposing sensitivities of yield in the irrigated rice growing areas of tropical and subtropical regions of Asia towards the variations in maximum and minimum temperature. This can be more detrimental in the near future, since, the maximum temperature is also rising and the rice yield is expected to respond negatively to the variations in maximum temperature beyond a limit.

6. The present study observed that small farmers are the most vulnerable even though they attempt to diversify their livelihoods more. It is therefore, suggested to promote beneficial diversification of livelihood activities among the farmers.

7. The present study observed that, majority of the sample farmers were depending the friends and family for their financial needs. This is particularly affecting the small farmers whose social networks are relatively weak. Therefore we suggest adequate policy interventions to promote the availability and access to institutional credit among the farmers. Also, the enhancement of the coverage of insurance policies is important in the present context.

8. The results of the present study suggest that the farmers continue to depend on fire wood as a means to cook food although majority of them have LPG connections. This fuel stacking behaviour among the households in Tamil Nadu was earlier observed in Malaiarasan et al. (2019) and was attributed to the income elastic demand of fuels among them. Adequate policy interventions are required to make improvements in this issue.

9. The present study observed that nearly twenty percentage of the sample households did not have toilet. It is ironical that some of these villages were officially declared as open defecation free by the government. We recommend urgent policy interventions to ensure adequate toilet facility universally in the region.

10. We recommend specific policy interventions in the Cauvery Delta region, in order to accommodate the vulnerable farmers and enable them to undertake beneficial adaptations in under a warming climate.

8.2 Scope for future work

1. The sample farmers were selected from one village each from every district in the Cauvery Delta. Considering more villages and a larger sample size could provide

more representative character to the results. Also, taking samples from other regions of Tamil Nadu is important to ensure this representative nature.

2. It is important to undertake surveys at regular intervals in the region to observe the periodic changes in the socio-economic characteristics that constitute vulnerability.

3. A comparative analysis with a region from another state would fetch more meaningful results.

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List of Publications

Refereed Journals

1. Rajkumar, R., Shaijumon, C. S., Gopakumar, B., and Gopalakrishnan, D. (Accepted for Publication). Recent Patterns of Extreme Temperature Events over Tamil Nadu, India. *Climate Research*

2. Rajkumar, R., Shaijumon, C. S., Gopakumar, B., and Gopalakrishnan, D. (2020). Extreme rainfall and droughts over Tamil nadu, India. *Climate Research*, 12(12):124012, https://doi.org/10.3354/cr01600.

3. Rajkumar, R., Shaijumon, C. S. (2019). Vulnerability: A Note on the Concept, Measurements and Application in Indian Agriculture,. *International Journal of Social Science and Economics Research*, 4(3), 1908-1926.

Refereed Conferences

1. Conference 1

2. Conference 2

Others

Appendix A

A.1 Selection of Sample Size

The following formula was used in this study to fix the sample size

$$n_0 = z^2pq/e^2 \tag{A.1}$$

$$1.96^2(0.5)(1-0.5)/0.05^2 = 384 \tag{A.2}$$

wherein n is the sample size, z is the critical value for the desired confidence level, p is the estimated proportion of an attribute that is present in the population, $q = 1 - p$ and e is the desired level of precision. For a sample size of a large population whose degree of variability is not known. Assuming the maximum variability, which is equal to 50 percent $(p = 0.5)$ [1] and taking 95 percent confidence level with ± 5 percent precision, the equation A.2 sets the required minimum sample size.

A.2 Interview schedule used in the study

The study used the following interview schedule for collecting the primary data from the operational holders of selected study areas. The interview schedule contains 36 questions and 24 sub-questions, mainly classified into six sections. The questions represented the various components of vulnerability analysis performed in the study.

[1]Since a proportion of 0.5 indicates the maximum variability in a population, it is often used in determining a more conservative sample size

Indian Institute of Space Science and Technology
Department of Humanities

PhD Research Work on

Assessment of Vulnerability of Rice Farmers of Tamil Nadu, India to Climate Variability

Interview Schedule

(The information is used only for research purpose and will be kept confidential)

I) General Profile of the Operational Holder

1. Name and Age of the informant ....
2. Name, age and Gender of the operational holder ....
3. If informant and operational holder are different, reason..
4. Village, Taluk and District ....

- Codes for reason for substitution of original household/Operational holder: Operational holder busy -1, members away from home -2, operational holder non-cooperative -3, others -9.
- Codes for gender of the head of the household: Female-1 Male-2 Others-3
- Age as on 1st April 2018.

5. Details of family members

Sl. No. (1)	Member (2)	Relation to the head (3)	Sex (4)	Age (5)	Religion (6)	Social Group (7)	Marital status (8)	Education (9)	Occupation (10)
a.									
b.									
c.									
d.									
e.									
f.									

- Codes for item 3: self –1, spouse of head –2, child –3, spouse of child – 4, grand child –5, father/mother-6, father-in-law/ mother-in-law – 7, brother / sister-8, brother-in-law/ sister-in-law/ other relatives – 9, servant/employees/ other non-relatives –10.
- Codes for item 6: Hinduism-1, Islam-2, Christianity -3, Sikhism-4, Jainism-5, Buddhism-6, Judaism-7 Others-9
- Codes for item 7: Scheduled tribe-1, Scheduled caste-2, Other backward class-3, Others-9
- Codes for item 8: Unmaried-1 Married-2 Divorced-3 Separated-4 Others-5 (Please specify)
- Codes for item 9: Primary-1 Secondary-2 SSLC-3 Graduation-4 Professional-5 Illiterate-6 Others-7 (Please specify)
- Codes for item 10: Farmer-1 Wage labourer-2 Skilled worker-3 Petty Trader(shop keeper)-4 Self-employed-5 Service Government-6 Service Private-7, Homemaker-8, Student-9, Retired-10, Unemployed-11, Others-12 (Please specify)

II) Specific Socioeconomic Profile. Questions pertaining to the Poverty, Migration, Water, Sanitation and Health care will be asked in this section

1) What is the type of your ration card? [ ] PHH – 1, NPHH – 2, Old Ration Card – 3, No Ration Card – 0.

2) What type of fuel is used for cooking? [ ] Wood [ ] Electricity [ ] Kerosene [ ] LPG [ ] Others (specify)

3) Does any of the female members of the family has a share in the ownership of land? [ ] Yes -1, No -2

4) What is the source of water for the following usages? (Secondary sources are those sources the household use to access when water is not available or not accessible in the primary sources)

Usage	Primary	Secondary
a) Drinking/ Cooking		
b) Washing Cloths		
c) Bathing		
d) For Cattle or Poultry		
e) Gardening		
f) Irrigating		
g) Other usages		

Codes for sources: Owned Pipe Connection – 1, Neighbour's Pipe Connection -2, Public Tap -3, Tanker(Public) -4, Tanker(Private) -5 Owned Protected Well -6, Neighbour's Protected Well -7, Protected Public Well -8, Owned Unprotected Well -9, Neighbour's Unprotected Well -10, Unprotected Public Well -11, Bore Well -12, Rainwater Harvesting System -13, Canal Water -14, River, Stream, Lake, Pond -15.

5) Have you faced shortage of water anytime during the last 12 months? [ ] Yes –1, No – 2.

6) During the last 12 months, did you face any of the following problems with the water that you use for drinking/cooking? [ ] (More than one answer possible)
Codes for water problems: Insufficient water availability – 1, irregular supply -2, Bad Taste -3, Bad Odour -4, Colour -5 Water was cloudy -6, Low water pressure -7, Seasonal shortage -8, Salt content in water -9, Other (specify) -10.

7) During the last 12 months, did you face any of the following problems with the water that you use for irrigation? [ ] (More than one answer possible)
Codes for water problems: Insufficient water availability – 1, irregular supply -2, Bad Taste -3, Bad Odour -4, Colour -5 Water was cloudy -6, Low water pressure -7, Seasonal shortage -8, Salt content in water -9, Other (specify) -10.

8) What kind of facility do you have for storing water from the connection/canal inside the compound?
Underground Tank [ ], Overhead Tank [ ], Vessels [ ], No Storage Facility [ ]

9) Do you have an electricity connection? [ ] Yes -1, No -2

10) What type of toilet facility does your household has? [ ]
Codes for toilet facility: Flush to piped sewer system -1, Flush to septic tank -2, Pit latrine -3, Composting Toilet -4, Others (specify) -5, No facilities – 6.

11) What kind of health care facilities are available in your area? (More than one answer possible)

	Health Facilities Available
Village	
Taluk	
District	

Codes for healthcare facilities: Primary Health Center -1, Community Health Center -2, Taluk Hospital -3, Small Private Hospital -4, District Hospital -5, Medical College- 6, Public Super Specialty Hospital -7, Private Super Specialty Hospital -8, Public Multi Specialty Hospital -8, Private Multi Specialty Hospital -9, Nursing Home -10.

12) Do you have access to Women and Child care programmes like ICDS? [ ] Yes -1, No-2

13) Do any female or male members of your household work in your farm? [ ]
Female -1, Male -2, Both -3, No -0.

14) Do any adult female and male members of your household live and work in a different town or village within the country? [ ]
Female within – 1, Female abroad – 2, Male within – 3, Male Abroad – 4, Nil - 0

15) Does any of the migration during last 12 months relate to crop failure due to climate activity? [ ] Yes -1, No -2

16) Is there any self-help group functioning in your area? [ ] Yes -1, No -2

17) Do any of the family members participate in any of the self help groups? [ ] Yes -1, No -2

III) Questions on Asset Ownership and Transactions of the Household

1) Livestock and/or poultry owned by the operational holder as on 01.04.2018?

Item		**Number**
Cattle (both cross-bred cattle and non-descript)	**(a) female over 2 years** (i) cow : in milk	
	(ii) cow : dry	
	(b) male cattle over 2 years (i) for work/ breeding	
	(c) others	
Buffalo	**(a) female over 2 years** (i) buffalo : in milk	
	(ii) buffalo : dry	
	(b) males over 2 years (i) male buffalo for work/breeding	
	(c) others	
ovine and other mammals (sheep, goat, pig, rabbits, etc.)		
poultry birds (hen, cock, chicken, duck, duckling, other poultry birds, etc.)		
Others		

IV) This section focuses on the financial asset and liability profile of the household

1) Does the household have savings in any of the listed institutions?

[ ] (more than one answer possible)

Codes for financial institutions: Bank Deposits -1, Post office savings -2, NSC, KVP -3, Deposits with NBFCs -4, Deposits with Cooperative societies -5, Deposits with microfinance institutions -6, Others (Please specify) -7, No -8.

2) Does the household take part in any of the following schemes?

[ ](more than one answer possible)

Codes for saving schemes: MDS with Cooperative Banks/Societies -1, Chitties with private chit funds -2, Other small chit schemes -3, Provident funds/ pension funds/ NPS other contributory pension schemes -4, Others (Please specify) -5, No -6.

3) Does the household have investments in any of the following schemes?

[ ] (more than one answer possible)

Codes for investment schemes: Stocks and shares -1, Mutual fund -2, Debentures -3, ULIPs -4, Life insurance -5, Bullion and Ornaments -6, Others(Please specify) -7, No -8.

4) Debt Profile of the household (As on 01.04.2018)

1.	Major source of borrowing	
2.	Purpose of loan	

- **Codes for major source of borrowing**: Government -01, Co-operative society/bank -02, Commercial bank incl. regional rural bank -03, Provident fund -04. Public sector non-banking Financial corporation/institution/company-05, Self-help group-bank linked (SHG-BL) -06, Self-help group, non-banking financial companies (SHG-NBFC) – 07, Other institutional agencies -08, Landlord – 09, Professional moneylender – 10, input supplier – 11, Relatives and friends – 12 doctors, lawyers & other professionals -13, Others – 09.
- **Codes for purpose of loan**: Capital expenditure in farm business- 01, Current expenditure in farm business- 02, Capital expenditure in non-farm business -03, current expenditure in non-farm business-04, expenditure on litigation-05, repayment of debt-06, for housing-07, for other household expenditure -08, financial investment expenditure-09, for education -10, for medical treatment-11, others-12, others-13.

V) Questions in this section pertain to the cultivation practices and patterns of the operational holder.

1) How long have you been cultivating rice ? [ ]

1. ≤ 5 years	2. ≤ 10 years	3. ≤ 15 years	4. ≤ 20 years	5. ≤ 25 years	6. ≥ 25 years

2) Do you cultivate rice in all cropping seasons? [ ] Yes-1, No-2

3) If not, please specify the seasons that you usually prefer to cultivate [ ] Kuruva-1, Samba-2, Navara-3 (more than one answer possible)

4) Cropping pattern and crop schedule in the last agricultural year

Season	Crop	Variety	Area (Ha)	Month of Sowing	Month of Harvesting	Source of Irrigation (Codes as in 2(e))

5) Area under cultivation for Paddy [ ]

Codes for area under paddy: < 0.5 Ha – 01 , 0.5 < 1 Ha - 02, 1 < 2 Ha -03, 2 < 3 Ha -04, 3 < 4 Ha -05, 4 < 5 Ha -06, 5 < 7.5 Ha -07, 7.5 < 10 Ha -08, 10 < 20 Ha-09, ≥ 20 Ha-10.

6) Do you think rainfall variations influence your cultivation even if you irrigate your land? [ ] Yes-1, No-2, Not sure-3.

7) Do you think temperature changes influence your cultivation even if you irrigate your land? [ ] Yes-1, No-2, Not sure-3.

8) During the last one year , did any of the following climate shocks caused crop loss in rice cultivation [ ] (More than one answer possible, give number also)
Codes for climate shocks: Drought- 01, Erratic rainfall- 02, Extreme rainfall in monsoon seasons-03, High night temperature-04, Heat waves-05, Floods-06, No climate shocks-07,Others (please specify)-08

9) Who of the following assisted the household to deal with the difficult phases in life (financially) [ ] Family-1, Insurance company-2, Government-3, NGOs-4, Cooperatives/SHGs-5

10) Do you have soil health card? [ ] Yes - 1, No – 2

VI) This section includes specific remarks from the farmers and observations of the enumerator (if any) made during the interview.

A.3 Ensemble Empirical Mode Decomposition

The EEMD is a noise assisted, adaptive time-frequency data analysis method. It is an improvement of Empirical Mode Decomposition(EMD) which decomposes data, $x(t)$, in terms of Intrinsic Mode Functions(IMFs), c_j and a residual trend component. An IMF is a simple oscillatory mode in which the number of extrema and the number of zero crossings are either equal or differ by at most one, and the mean value of the envelope defined by the local maxima and local minima equals zero (Huang et al., 2003). The IMFs are extracted through a sifting process. The sifting process starts with identifying all local extrema of the data $x(t)$ and connecting them with a cubic spline to form the upper $U(t)$ and lower $L(t)$ envelop curves. Then the difference between the data and the local mean (Equation A.3) of envelops are obtained.

$$m(t) = \frac{(U(t) + L(t))}{2} \tag{A.3}$$

The local mean so obtained $(m(t))$ is subtracted from the original signal $x(t)$ to get the first component $h_1(t)$.

$$h_1(t) = x(t) - m(t) \tag{A.4}$$

If $h_1(t)$ does not comply with the definition of IMF, the steps implied by equations A.3 and A.4 has to be repeated taking $h_1(t)$ as the new $x(t)$ until $h_{1k}(t)$ satisfies to be an IMF.

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t) \tag{A.5}$$

Once $h_{1k}(t)$ qualifies the definition of an IMF, it is designated as an IMF component.

$$h_{1k}(t) = c_1(t) \tag{A.6}$$

This process is repeated by taking the residual ($r(t) = x(t) - c(t)$) as data until the residue contains no more than one extremum (Wang et al., 2010). The sifting process will stop when the difference standard deviation is smaller than a predetermined value as shown by equation A.7 (Wang et al., 2010).

$$SD = \sum_{t=0}^{T} \left[\frac{h_{1(k-1)}(t) - h_{1k}(t)}{h_{1(k-1)}(t)}\right]^2 \tag{A.7}$$

To prevent the EMD from repeating the sifting too many times and causing the IMFs to lose the physical meaning, the SD (generally 0.2-0.3) should be used (Bai et al., 2015).

Finally, the original signal can be constructed as shown by equation A.9 wherein the sum of IMFs $\sum_{j=1}^{n} c_j$ represents the variability in the data and r_n represents the adaptive trend component.

An important drawback of EMD is mode mixing, in which a single IMF consists of signals of different scales or a signals of the same scale residing in different IMFs. Ensemble EMD (EEMD) analysis is an improved version of EMD in which a finite random white noise is introduced initially to the time series to populate whole time-frequency space uniformly with the constituting components of different scales. It fills the time scales that may not be part of the data to prevent mixing of different time scales into the same mode in the EMD analysis. In the EEMD method, the EMD is applied many times to the time series (with added noise) and the signal extracted through an ensemble average of the modes extracted. Here, all data are amalgamations of signal and noise. EEMD has been successfully applied to analyze non-stationary geo-physical time series(Wu and Huang, 2009).

Assuming that all data are amalgamations of signal ($x(t)$) and noise ($w_i(t)$),

$$x_i(t) = x(t) + w_i(t) \tag{A.8}$$

the EEMD decomposes the noise ($w_i(t)$) added data set $x_i(t)$ in to relevant intrinsic mode functions (IMFs) c_j and the residual component r_n.

$$x_i(t) = \sum_{j=1}^{n} c_j + r_n \tag{A.9}$$

Here, in r_n, n is the number of IMFs removed. While the added white noise (w^i) may result in noisy results in individual trials, it populates the time-frequency space uniformly with the constituting components of different scales. Since the noise is different for each trial, it gets canceled out in the ensemble mean of trials. The white noise declines following Equation A.10 (Wu and Huang, 2009).

$$ln\epsilon_n + \frac{\epsilon}{2} lnN = 0 \tag{A.10}$$

Here the residual component represents the trend or the monotonic function having only one extrema and $\sum_{j=1}^{n} \mathrm{c_j}$ is the variability obtained after removing the trend. Following the decomposition of the data, we conducted Hilbert transform of each of the IMF components and obtained the instantaneous frequency and amplitude

$$y(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d^{\tau} \tag{A.11}$$

wherein the P indicates the principal value of the singular integral. With the Hilbert transform, the analytic signal is defined by equation

$$z(t) = x(t) + iy(t) = a(t)e^{i\theta(t)} \tag{A.12}$$

in which $a(t) = \sqrt{x^2 + y^2}$, and $\theta(t) = \arctan(\frac{y}{x})$. Here, $a(t)$ is the instantaneous amplitude, and θ is the phase function, and the instantaneous frequency is represented by this equation.

$$\omega = \frac{d(\theta)}{d(t)} \tag{A.13}$$

Now the original data can be represented as real part as defined in Equation A.14 (Huang, 2014; Huang and Wu, 2008).

$$x(t) = Re\Big\{ \sum_{j=1} n a_j(t) \exp\left[i \int \omega_j(t) dt \right] \Big\} \tag{A.14}$$

The effect of signal fluctuation frequency and amplitude in each scale on the general characteristics of the original data is referred to as the variance contribution rate and is defined by the Equation A.15 (Bai et al., 2015; Guo et al., 2016).

$$VCR_i = \frac{var(c_i(t))}{\sum_{i=1}^{n} var(c_i(t)) + var(r_n(t))} \times 100 \tag{A.15}$$

A statistical significance test (Wu and Huang, 2004) was conducted to check if an IMF component contains actual meaning with regard to the original data. The energy density E_k of the k^{th} IMF as defined by the equation A.16

$$E_k = \frac{1}{N} \sum_{j=1}^{N} |c_n(j)|^2 \tag{A.16}$$

is related to the averaged period (T_k) of the IMFs through the equation A.17.

$$\ln \bar{E}_k + \ln \left\{ \bar{T}_k \right\}_{\alpha} = 0 \tag{A.17}$$

In the equations A.16 and A.17, N is the length of the IMF component and $c_k(j)$ denotes the k^{th} IMF. Equation A.17 implies that $\bar{E}_k$ is the mean of E_k when N approaches infinity. As illustrated by Figures (fill figures), with $\ln\{\bar{T}_k\}$ in the x axis and $\ln \bar{E}_k$ in the y axis the relation between energy density and averaged period can be expressed by a straight line the slope of which equals -1. Theoretically, the IMF component of the white noise should get distributed on this line. However, at application levels there can be sight deviations from this line (Bai et al., 2015). Therefore, the confidence interval for the energy spectrum distribution of white noise is defined by the equation A.18.

$$\ln \bar{E}_k = -\ln\left\{\bar{T}_k\right\}_\alpha \pm \alpha\sqrt{2/N}e^{\ln\left(\left\{\bar{T}_k\right\}_{\alpha/2}\right)} \tag{A.18}$$

In the equation A.18, α is the significance level.

For decompositions, the ratio of the standard deviation of the added noise series is 0.2 times the standard deviation of the original data, and the number of trials was set to 200. The rainfall trend over the period of analysis given here are obtained from the from the residual, r_n. The EEMD was conducted using R package Rlibeemd (Luukko et al., 2016).

A.4 Standardized Precipitation Evapotranspiration Index

This study has used Standardized Precipitation Evapotranspiration Index (SPEI) for the analysis of the spatio-temporal patterns of drought across Tamil Nadu. SPEI is a multi-scalar drought index which is suitable for the analysis of droughts under a warming climate (Vicente-Serrano et al., 2010). The calculation of SPEI requires precipitation as well as temperature data. The temperature data is used for the calculation of potential evapotranspiration (PET or ET_0). There are three methods available for the calculation of PET, namely Thornthwaite method, Penman-Monteith (PM) method and Hargreaves method. Thornthwaite method requires only monthly mean temperature and latitude value. The PM method requires a crop parameter, insolation, saturation water pressure, atmospheric surface pressure along with the minimum and maximum temperature. While the PM method is formally adopted by several international agencies as a standard procedure for computing PET, it demands a massive volume of data and a number of variables, the data for which are often not available for many locations of the world (Vicente-Serrano et al., 2010). In the present work, therefore, a modified version of Hargreaves method (Droogers and Allen, 2002) has been adopted. It requires maximum and minimum temperature, precipitation and the geographical location of the region of interest.

$$ET_0 = 0.0013 \times 0.408RA \times (T_{avg} + 17.0) \times (TD - 0.123P)^{0.76} \tag{A.19}$$

Here RA represents monthly mean daily incoming solar radiation($MJm^{-2}d^{-1}$), T_{avg} is the monthly mean temperature (°C), TD is the difference between the maximum and minimum monthly temperatures (°C) and P represents monthly total precipitation (mm). The numeric values are multipliers and offset values used in the Modified Hargreaves equation (see Equation A.19). Once the PET is estimated, the climatic water balance is calculated using

$$D_i = P_i - PET_i \tag{A.20}$$

The calculated D values can be aggregated at different time scales. The difference $D_{i,j}^k$ in a given month j and year i depends on the chosen timescale k. The accumulated difference for one month in a particular year i with a 6-month time scale is calculated using the following equation

$$X_{i,j}^k = \sum_{l=j-k+1}^{j} (D_{i,l}) \tag{A.21}$$

where $n \geq k$. Further, a log-logistic distribution was fitted to the series of D to obtain SPEI. The probability density function of the log-logistic distributed variable is expressed as:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)\left[1 + (\frac{x-\gamma}{\alpha})\right]^{-2} \tag{A.22}$$

where, α, β and γ are scale, shape and origin parameters respectively, for D values in the range ($\gamma > D > \infty$). The probability distribution function of the D series is given by:

$$F(x) = \left[1 + \left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \tag{A.23}$$

The modeled values of $F(x)$ from log-logistic distribution is observed as adapting better to the empirical values of $F(x)$ from different regions of the world, independently of the climate characteristics and the time scale of analysis. With $F(x)$, SPEI can be obtained as the standardized values of $F(x)$ following the classical approximation of (Abramowitz and Stegun, 1965) cited in (Vicente-Serrano et al., 2010),

$$SPEI = W - \frac{C_0 + C_1W + C_2W^2}{1 + d_1W + d_2W^2 + d_3W^3} \tag{A.24}$$

where $W = \sqrt{-2\ln(P)}$ for $P \geq 0.5$ is the probability of exceeding a determination D value, $P = 1 - F(x)$. If $P > 0.5$, then P is replaced by $1 - P$ and the sign of the resultant SPEI is reversed. The constants are $C_0 = 2.515517, C_1 = 0.802853, C_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269$, and $d_3 = 0.001308$ ((Yu et al., 2014; Vicente-Serrano et al., 2010)). The typical values of SPEI range between -2.5 and 2.5 corresponding to exceedance probabilities of approximately 0.006 and 0.994, respectively, even though the theoretical limits are $-\infty, +\infty$ ((Kumar et al., 2013)). Table 3.2 provides the categorization of dryness/wetness grade by SPEI ((Yu et al., 2014)). As such a six month SPEI was calculated for each grid box since this time scale was observed as significant as far as agriculture is concerned. The six month scale SPEI implies that the data for current and past five months were used for the calculation of the SPEI for the current month and the entire past data was given equal weight.

Appendix B

B.1 LVI Sub-component values

Table B.1: Livelihood Vulnerability Index (LVI) sub-component values for various categories of rice farmers Tamil Nadu

Minor component	**Component Form**	**Farmer Category**					
		Large	**Medium**	**Semi-medium**	**Small**	**Maximum**	**Minimum**
Dependency ratio	Ratio	0.69	0.93	0.83	0.69	0.93	0.69
Gender of the operational holder	Proportion of female OPH	0.00	3.30	8.20	10.60	10.60	0.00
Educational attainment	Inverse of the education score	0.26	0.30	0.38	0.46	0.46	0.26
Proportion of migrant households	ratio	0.50	0.13	0.22	0.21	0.50	0.13
Livelihood diversification index	index	0.29	0.43	0.43	0.42	0.43	0.29
Agricultural diversification Index	index	0.38	0.35	0.33	0.34	0.38	0.33
Percentage of households who do not participate in SHGs	percentage	100.00	67.00	57.10	52.20	100.00	52.20

Percentage of households who have'nt received assistance from SHGs	percentage	100.00	96.67	91.84	95.51	100.00	91.84
Percentage of households who have'nt received assistance from friends and family	percentage	0.00	16.70	14.30	20.20	20.20	0.00
Percentage of households who doesn't have insurance coverage	percentage	50.00	76.70	81.60	79.80	81.60	50.00
Percentage of households who have'nt received assistance from cooperative institutions	percentage	25.00	13.30	28.60	48.10	48.10	13.30
Percentage of households who have'nt received assistance from government	percentage	75.00	36.70	55.10	66.70	75.00	36.70
Cooking fuel	Inverse of the fuel index	0.46	0.76	0.70	0.64	0.76	0.46
Percentage of households who are not covered by women and child care programmes	Percentage of households not covered under wcc	0.00	20.00	14.60	26.30	26.30	0.00
Drinking water issues	Drinking water score is the ratio of the number of issues experienced by the household to total number of issues listed	0.10	0.12	0.11	0.10	0.12	0.10
Drinking water storage index	WSI	0.33	0.39	0.40	0.45	0.45	0.33
Irrigation water issues	Drinking water score is the ratio of the number of issues experienced by the household to total number of issues listed	0.13	0.18	0.16	0.17	0.18	0.13
Proportion of households without toilet	proportion of households without toilet	0.00	0.00	0.12	0.25	0.25	0.00
Proximity to medical facility	HPI	0.07	0.06	0.06	0.07	0.07	0.06

Source : Author's calculations

Table B.2: Livelihood Vulnerability Index (LVI) sub-component values for seven study districts of Tamil Nadu

Indicator	**Districts**								
	Ariyalur	**Karur**	**Nagapattinam**	**Perambalur**	**Thanjavur**	**Thiruvarur**	**Trichy**	**Maximum**	**Minimum**
Dependency ratio	0.71	0.32	0.88	0.08	0.93	0.70	0.53	0.93	0.08
Gender of the operational holder	5.00	0.00	12.20	0.00	17.60	6.20	4.50	17.60	0.00

Lack of educational attainment	0.61	0.68	0.41	0.55	0.41	0.42	0.41	0.68	0.41
Proportion of migrant households	0.40	0.00	0.28	0.15	0.31	0.11	0.08	0.40	0.00
Livelihood diversification index	0.44	0.47	0.39	0.46	0.42	0.41	0.44	0.47	0.39
Agricultural diversification Index	0.43	0.33	0.28	0.45	0.34	0.34	0.37	0.45	0.28
Percentage of households who do not participate in SHGs	70.00	27.30	60.80	69.20	53.70	53.80	48.30	70.00	27.30
Percentage of households who have'nt received assistance from SHGs	70.00	100.00	100.00	100.00	94.44	95.00	97.75	100.00	70.00
Percentage of households who have'nt received assistance from friends and family	20.00	18.20	24.30	15.40	18.50	13.80	23.20	24.30	13.80
Percentage of households who doesn't have insurance coverage	65.00	100.00	52.70	100.00	80.60	80.00	97.75	100.00	52.70
Percentage of households who have'nt received assistance from cooperative institutions	20.00	45.50	54.10	23.10	43.50	40.00	42.70	54.10	20.00
Percentage of households who have'nt received assistance from government	90.00	63.60	67.60	69.20	78.70	16.20	76.20	90.00	16.20
Cooking fuel	0.40	0.46	0.48	0.46	0.57	0.93	0.77	0.93	0.40
Percentage of households who are not covered by women and child care programmes	10.00	0.00	66.20	30.80	32.40	1.20	4.50	66.20	0.00
Drinking water issues	0.14	0.02	0.10	0.09	0.11	0.13	0.07	0.14	0.02
Drinking water storage index	0.40	0.41	0.43	0.40	0.44	0.45	0.47	0.47	0.40
Irrigation water issues	0.25	0.06	0.19	0.14	0.21	0.15	0.10	0.25	0.06
Proportion of households without toilet	0.25	0.00	0.19	0.00	0.38	0.16	0.11	0.38	0.00
Proximity to medical facility	0.09	0.06	0.10	0.08	0.06	0.06	0.06	0.10	0.06
Weather sensitivity of rice yield (R^2)	0.40	0.58	0.08	0.50	0.32	0.28	0.09	0.58	0.08
Average variability in maximum temperature (last 6 years)	0.06	0.08	0.03	0.09	0.04	0.04	0.08	0.09	0.03
Average variability in minimum temperature (last 6 years)	0.01	0.05	0.07	0.01	0.03	0.03	0.04	0.07	0.01
Average variability in rainfall (last 6 years)	31.18	188.04	56.76	95.86	147.89	58.33	258.31	258.31	31.18

Number of warmspells in daytime temperature (last 6 years)	10.00	14.00	8.00	7.00	11.00	8.00	13.00	14.00	7.00
Number of warmspells in nighttime temperature (last 6 years)	7.00	14.00	7.00	7.00	9.00	7.00	12.00	14.00	7.00
Average severity of droughts (last six years)	3.90	3.85	3.31	3.15	5.25	7.55	5.08	7.55	3.15
Number of extreme rainfall episodes (last 6 years)	3.00	12.00	1.00	3.00	4.00	0.00	6.00	12.00	0.00

Source : Author’s calculations

Table B.3: Livelihood Vulnerability Index (LVI) sub-component values for three rice cultivating seasons of Tamil Nadu

Minor component	**Season**				
	Kuruva	**Samba**	**Navara**	**Maximum**	**Minimum**
Dependency ratio	0.79	0.75	0.73	0.79	0.73
Gender of the operational holder	7.00	9.00	10.00	10.00	7.00
Lack of educational attainment	0.37	0.41	0.42	0.42	0.37
Proportion of migrant households	0.20	0.21	0.19	0.21	0.19
Livelihood diversification index	0.42	0.42	0.42	0.42	0.42
Agricultural diversification Index	0.34	0.33	0.34	0.34	0.33
Percentage of households who do not participate in SHGs	58.50	55.00	54.30	58.50	54.30
Percentage of households who have'nt received assistance from SHGs	93.29	95.13	95.37	95.37	93.29
Percentage of households who have'nt received assistance from friends and family	30.50	42.40	41.70	42.40	30.50
Percentage of households who doesn't have insurance coverage	70.70	77.40	79.90	79.90	70.70
Percentage of households who have'nt received assistance from cooperative institutions	30.50	42.40	41.70	42.40	30.50
Percentage of households who have'nt received assistance from government	53.50	61.70	61.40	61.70	53.50
Cooking fuel	0.68	0.66	0.67	0.68	0.66
Percentage of households who are not covered by women and child care programmes	20.70	25.60	24.50	25.60	20.70
Drinking water issues	0.11	0.10	0.10	0.11	0.10
Drinking water storage index	0.42	0.44	0.44	0.44	0.42
Irrigation water issues	0.15	0.17	0.16	0.17	0.15
Proportion of households without toilet	0.12	0.22	0.21	0.22	0.12
Proximity to medical facility	0.07	0.07	0.07	0.07	0.07
Weather sensitivity of rice yield (\$Rˆ2\$)	0.24	0.10	0.13	0.24	0.10
Average variability in maximum temperature (last 6 years)	0.00	0.02	0.02	0.02	0.00
Average variability in minimum temperature (last 6 years)	0.01	0.03	0.04	0.04	0.01
Average variability in rainfall (last 6 years)	10.12	27.16	6.77	27.16	6.77
Average number of warmspells in daytime temperature (last 6 years)	36.00	0.00	9.00	36.00	0.00
Average number of warmspells in nighttime temperature (last 6 years)	39.00	0.00	5.00	39.00	0.00
Average severity of droughts (last six years)	3.49	8.20	4.08	8.20	3.49
Average number of extreme rainfall episodes (last 6 years)	22.00	62.00	8.00	62.00	8.00

Source : Author's calculations

B.2 LVI-IPCC sub-component values for adaptive capacity

Table B.4: Livelihood Vulnerability Index (LVI-IPCC) sub-component values for seven study districts of Tamil Nadu

Indicator	Districts	Districts	Districts	Districts	Districts	Districts	Districts		
	Ariyalur	**Karur**	**Nagapattinam**	**Perambalur**	**Thanjavur**	**Thiruvarur**	**Trichy**	**Maximum**	**Minimum**
Ratio of working age group to dependents	0.29	0.68	0.12	0.92	0.07	0.30	0.47	0.92	0.07
Percentage of male operational holders	95.00	100.00	87.80	100.00	82.40	93.80	95.50	100.00	82.40
Educational attainment	2.85	2.68	2.76	2.58	3.10	3.05	3.11	3.11	2.58
Proportion of households without migrant members	99.60	100.00	99.72	99.85	99.69	99.89	99.92	100.00	99.60
Average number of livelihood options	1.40	1.18	1.73	1.23	1.57	1.65	1.39	1.73	1.18
Average number of agricultural activities engaged	1.50	2.09	2.81	1.46	2.35	2.31	2.02	2.81	1.46
Percentage of households who participate in SHGs	30.00	72.70	39.20	30.80	46.30	46.20	51.70	72.70	30.00
Percentage of households who have received assistance from SHGs	30.00	0.00	0.00	0.00	5.56	5.00	2.25	30.00	0.00
Percentage of households who have received assistance from friends and family	80.00	81.80	75.70	84.60	81.50	86.20	76.80	86.20	75.70
Percentage of households who has insurance coverage	35.00	0.00	47.30	0.00	19.40	20.00	2.25	47.30	0.00
Percentage of households who have received assistance from cooperative institutions	80.00	54.50	45.90	76.90	56.50	60.00	57.30	80.00	45.90
Percentage of households who have received assistance from government	10.00	36.40	32.40	30.80	21.30	83.80	23.80	83.80	10.00

Source : Author's calculations

Table B.5: Livelihood Vulnerability Index (LVI-IPCC) sub-component values for three rice cultivating seasons of Tamil Nadu

Minor component	**Cultivating Season**				
	Kuruva	**Samba**	**Navara**	**Maximum**	**Minimum**
Ratio of working age group to dependents	0.21	0.25	0.27	0.27	0.21
Percentage of male operational holders	93.00	91.00	90.00	93.00	90.00
Educational attainment	3.27	3.07	2.98	3.27	2.98
Proportion of households without migrant members	0.80	0.79	0.81	0.81	0.79
Average number of livelihood options	1.57	1.56	1.55	1.57	1.55
Average number of agricultural activities engaged	2.28	2.32	2.27	2.32	2.27
Percentage of households who participate in SHGs	41.50	45.00	45.70	45.70	41.50
Percentage of households who have received assistance from SHGs	6.71	4.87	4.63	6.71	4.63
Percentage of households who have received assistance from friends and family	69.50	57.60	58.30	69.50	57.60
Percentage of households who has insurance coverage	29.30	22.60	20.10	29.30	20.10
Percentage of households who have received assistance from cooperative institutions	69.50	57.60	58.30	69.50	57.60
Percentage of households who have received assistance from government	46.50	38.30	38.60	46.50	38.30

Source : Author's calculations