A Changing Climate in Sri Lanka: Shifts, Perceptions, and Potential Adaptive Actions

By

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For my dad.

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CHAPTER 1

INTRODUCTION

1.1. Overview

How to adapt to climate change and allocate increasingly scarce water resources for agriculture is a question that confronts water managers in almost every nation on Earth. In many countries, agriculture often accounts for more than 80% of national water use [*Gleick*, 2003]. In major grain producing countries that number is even higher. Faced with increasing demand and a changing climate, the scenario that water managers must face grows more challenging every day. Anthropogenic climate change is shifting weather patterns and increasing uncertainty. Some areas of the globe will see an increase in precipitation, while others will see a decrease. Almost all regions are predicted to see an increase in precipitation intensity [*IPCC*, 2007]. Temperature is also rising due to increased concentrations of CO_2 in the atmosphere. Global average temperatures are expected to increase, with the poles warming more than the lower latitudes [*IPCC*, 2007]. Higher temperatures and changes in precipitation distribution and intensity are expected to create more frequent and severe periods of drought and extreme wetness. Drought and extreme wet periods are of particular interest to farmers and agricultural water managers because the appropriate application of water is integral to achieving a successful crop.

Other factors also contribute to the challenge that adaptation planners and water managers face. Anthropogenic land use changes are also affecting both regional and local climates. Land use changes have been tied to the urban heat island effect [*Kalnay and Cai*, 2003], changes in river discharge [*Costa et al.*, 2003], and a variety of other adverse effects [*Foley et al.*, 2005]. The El Nino - Southern Oscillation (ENSO) phenomenon and changes in local sea surface temperatures have also been shown to have strong influence on global and regional weather patterns [*Wang et al.*, 2000]. When changes in weather patterns associated with land use changes and the natural variability of ENSO are combined with the changes occurring due to global change the task of making adaptation and water management decisions becomes increasingly complex and incredibly difficult.

Social and human factors add further to that complexity. Global population reached 7 billion people in early 2012, and population is expected to increase to 8.0 billion by 2025 and 9.2 billion by 2050. Most of that growth will take place in the developing world – Africa and Asia in particular [*UNDP*, 2010]. Population growth, and development in general, are occurring primarily in cities. In 2008, 50% of the world's population was living in cities for the first time ever. By 2050, that number will be 70% [*UNDP*, 2010]. Food production will necessarily have to increase in order to feed the growing number of people. In Asia, where rice is a staple of the local diets, that means a need to grow more rice. Demand for electricity will increase as countries generally develop and as more people move to cities. Increased agricultural activities will require more water for irrigation, and more water will be needed to run both thermoelectric and hydroelectric power plants [*Gleick*, 1994]. Adaptation planners and water managers will have to balance the competing demands of agricultural and urban water users.

In order to begin to confront the challenges facing adaptation planners and water managers, an interdisciplinary approach is needed. The Mahaweli River Watershed (MRW) in Sri Lanka provides an excellent case study for exploring both the natural and social factors that influence water management behaviors on multiple scales. In their 2001 report, the IPCC placed Sri Lanka into the *small island nations vulnerable to climate change* category. In Sri Lanka, temperatures are increasing [*Basnayake et al.*, 2004] and precipitation has exhibited a downward trend [*Chandrapala et al.*, 1996a]. In addition to the changing climate, Sri Lanka as a whole, and the MRW in particular, are subject to a mélange of social, political, and economic stressors. The MRW serves as the primary agricultural region of the country and the main water source for irrigation, hydropower generation, and drinking water. The MRW is also undergoing dramatic social change due to a national development program that is relocating landless peoples from densely populated areas to land in the MRW [*Abeysinghe*, 1990]. With the changing climate and the changing social dynamics, the MRW presents a natural experiment for studying how water management decisions for agriculture are made in a changing climate.

1.2. Structure of Dissertation

The work presented in this dissertation represents an interdisciplinary approach to the problem of water availability and use in Sri Lanka. In Chapter 2, a software tool for calculating the Palmer drought severity indices is presented. This tool was created to ease the arduous task of calculating one of the world's most widely used drought indices, the Palmer Drought Severity Index. By easing the calculation requirements, the transparent, easy-to-use tool enables scientists from all backgrounds to make use of drought indices in their work. This tool has been used to contribute to a program to inform decision makers about drought in Sri Lanka [*Munasinghe et al.*, 2014].

Chapter 3 presents research on the changing patterns of precipitation in Sri Lanka. With an eye towards planned adaptation to climate change, this research evaluates the spatial and temporal changes in Sri Lankan precipitation patterns. We find that while there have been only slight shifts in the spatial patterns, there have been significant changes in the timings of the onsets of the two Sri Lankan monsoons. At the end of the chapter, the tool presented in Chapter 2 is applied to Sri Lankan precipitation and temperature data and preliminary results of a study of changing patterns of drought are presented.

In Chapter 4, a study of perceptions of environmental change is discussed. We find that the perceived changes in the environment experienced by farmers in Sri Lanka often do not match the measured changes in the environment. This disparity between perceived and actual changes can impact the adaptive capacity of the farmers.

In Chapter 5, agent-based modeling is shown to be an effective way to join the physical and social sciences. In this study, a proposed seasonal forecasting initiative is evaluated by looking at how the way a farmer makes his decisions impacts how much skill is required of any forecast.

Finally, Chapter 6 offers ideas for future work and provides a summary of the findings of this dissertation.

CHAPTER 2

A TOOL FOR CALCULATING THE PALMER DROUGHT INDICES

2.1. Introduction

Drought affects every region and every climate - from tropical rice paddies in Asia, to the historic cities of continental Europe, to the Great Plains of the United States. Yet, what drought means to a Sri Lankan rice farmer may be completely different than a Nebraskan corn farmer's idea of drought. A means of quantifying drought in a spatially comparable manner is needed for a variety of uses, including emergency management, policy decisions, and academic research.

Originally developed in the 1960s by Wayne Palmer [*Palmer*, 1965], the Palmer Drought Severity Index (PDSI) provides a method for quantifying, and comparing, drought across different regions. Four inputs are needed for the calculation of the PDSI: temperature, precipitation, latitude of the location of interest, and the available water capacity (AWC) of the soil, which is a constant also known as the field capacity (Table 2.1). The four inputs are used to compute a water balance for the area of interest, which then serves as the basis for the calculation of the PDSI.

Table 2.1 | Units of inputs needed for PDSI calculation

Input	Unit
Temperature	Fahrenheit
Precipitation	Inches
Latitude	Degrees
Available Water Capacity (AWC)	Inches

A detailed explanation of the PDSI calculation procedure is given by *Alley* [1984], but a short synopsis is given here for clarity. The calculation procedure starts with a monthly water balance based on the temperature, precipitation, latitude (used as a measure of solar energy), and the AWC of the soil. The soil is divided into two layers – a top layer of 1 in. and a second layer that is the AWC. Evapotranspiration in the water balance is calculated using the Thornthwaite method.

Coefficients calculated as part of the water balance are used in two ways. The first is to calculate the Climatically Appropriate For Existing Conditions (CAFEC) precipitation. The CAFEC precipitation is the “normal” precipitation amount for that location for a given month. The difference between the measured precipitation and the CAFEC precipitation, along with results of the water balance, informs the calculation of the Z-Index. The Z-Index is a short-term soil moisture anomaly.

The Z-Index is then used to calculate X, which is the PDSI value for that month. Before the final X is selected, three different X values are calculated. X1 is severity of a wet spell that is not yet established; X2 is the severity of a dry spell that is not yet established; X3 is the severity of a dry or wet spell that has become established. A drought or wet spell is considered established when the absolute value of X is greater than 1. X1, X2, or X3 is chosen through a series of situational rules and backtracking procedures to be the final X, or PDSI value, for that month [*Alley*, 1984].

In addition to the PDSI, other Palmer drought indices include the Z-Index, the Palmer Hydrological Drought Index (PHDI), and the Palmer Modified Drought Index (PMDI) [*Palmer*, 1965; *Karl*, 1986; *Heddinghaus and Sabol*, 1991]. The PMDI is the operational version of the PDSI. When forecasting using historic values, care should be taken to differentiate between the PDSI and PMDI. The Z-Index and PHDI are computed during the calculation of the PDSI.

All four Palmer indices are widely reported and used, both in the United States and internationally [*Karl et al.*, 1990; *Dai et al.*, 2004; *Dai*, 2011; *D'Arrigo et al.*, 2008]. The National Oceanic and Atmospheric Administration (NOAA) reports weekly values for the three indices on a climatological division scale. Historic monthly values on the division scale are available through NOAA's National Climatic Data Center (NCDC) climate monitoring website (http://www1.ncdc.noaa.gov/pub/data/cirs/).

While the PDSI is widely used, a number of problems have been noted. *Alley* [1984], *Karl* [1983,1986], *Guttman* [1991] and *Guttman et al.* [1992] have all noted issues with the sensitivity of the PDSI to the potential evapotranspiration (PET) equations and calibration periods, as well as the lack of true spatial comparability.

In addition to the more technical objections to use of the PDSI, there are also two general problems that seriously impede its use: computational complexity and a lack of transparency. As outlined in *Alley* [1984], there are a multitude of computations required, many of which follow somewhat ambiguous procedures. Most of the studies that make use of the PDSI do not provide the methods of calculation, so it is difficult to compute the PDSI independently when doing research. Various computer codes for the calculation of the PDSI are available online, but they lack transparency and can often be difficult to use.

Researchers are thus forced to use PDSI values supplied by NOAA, NCDC, or some other party. Since the supplied values are only available for the continental U.S., and usually at the climatological division scale, a researcher is out of luck if her area of interest is abroad or at a smaller scale. By using the tool presented here to calculate the PDSI for individual climate stations, *Duncan et al.* [In Preparation] have demonstrated differences between the supplied climatological division PDSI value and calculated station values within the same division.

In order to make the PDSI more accessible to those who wish to make us of it, we present an easy to use, well documented, and transparent MATLAB tool for calculating the monthly PDSI, PHDI, and Z-Index at any spatial scale and any location.

2.2. Methods

An initial version of the tool was created after consulting the available literature that gave details about the calculation processes [*Palmer*, 1965; *Alley*, 1984; *Steinemann*, 2003; *Karl*, 1986; *Heddinghaus et al.*, 1991]. This version of the code was able to replicate the example table (Table 12) given in *Palmer* [1965]. To test the robustness of the tool, the NCDC FORTAN code (available at ftp://ftp.ncdc.noaa.gov/pub/software/palmer/pdi.f) for computing the PDSI was run using data from a number of climate divisions in climatically diverse regions of the country. The same climate division data was then run through our MATLAB tool, and the two sets of PDSI values were compared.

Discrepancies between the two sets of PDSI values were addressed in a methodical manner. Working up from the water balance, through the Z-Index, and finally to the PDSI calculation, two discrepancies were found that resulted in a difference between the MATLAB tool values and NCDC values. One discrepancy is that the NCDC code makes use of a transformed Thornthwaite potential evapotranspiration (PET) equation [*Hobbins et al.*, 2008]. Justification for the use of this transformed equation could not be found in the literature. Our MATLAB code uses PET equations found in *Thornthwaite* [1948] and *Hamon* [1961].

The other discrepancy is in the water balance calculation. Calculation of the PDSI relies on a water balance based on a two-bucket system, where there is a surface layer with a storage capacity of 1 in. and an underlying layer with a storage capacity of AWC - 1 in. During months where PET exceeds precipitation and where the difference between PET and precipitation exceeds the 1 in. stored in the surface layer, evaporative losses in the underlying layer are expected to occur. These losses are given by the equation

$$L_U = \frac{[(PE - P) - L_S]S_U}{AWC}, \tag{2.1}$$

where L_U is the loss from the underlying layer, PE is potential evapotranspiration, P is precipitation, L_S is the loss from the surface layer, S_U is the amount of water stored in the underlying layer at the start of the month, and AWC is the combined moisture capacity of both layers [*Alley*, 1984]. NCDC adds an additional inch to the AWC, making the equation

$$L_U = \frac{[(PE - P) - L_S]S_U}{AWC + 1}. \tag{2.2}$$

A justification for this change could not be found, but there appears to be little physical reasoning behind it. While adding an inch to the denominator of one equation seems to be a minor change, doing so has an effect on the PDSI values generated later. Our MATLAB code uses Equation (2.1) when computing the water balance. For researchers interested in replicating the NCDC results, our tool can easily be modified, following directions in the user manual, to run in exactly the same manner as the NCDC program. (Note: The NCDC code was changed in April 2013 to use Equation (2.1) instead of Equation (2.2)).

The effect of the two deviations from the NCDC code was evaluated by calculating the monthly PDSI for 117 years (1895-2011) for five climatically different climatological divisions (AL-1, AZ-5, KS-5, WA-1, and NY-2) and comparing them against the published PDSI values from the NCDC archives.

2.3. Results

The tool executes a series of events – loading the required inputs, calculating the water balance, calculating the Z-Index, and finally calculating the PDSI and PHDI (Figure 2.1). PDSI_Central, the main function within the PDSI code, launches five sub-functions when appropriate (Figure 2.2). Due to the sensitivity of the PDSI to its calibration coefficients outlined by *Karl* [1986], the tool includes the option to use either the NCDC calibration period or the full record as a calibration period. Since the PET calculation method can perform differently in different climates [*van der Schrier et al.*, 2011; *Lu et al.*, 2005], multiple PET calculation methods are also provided.

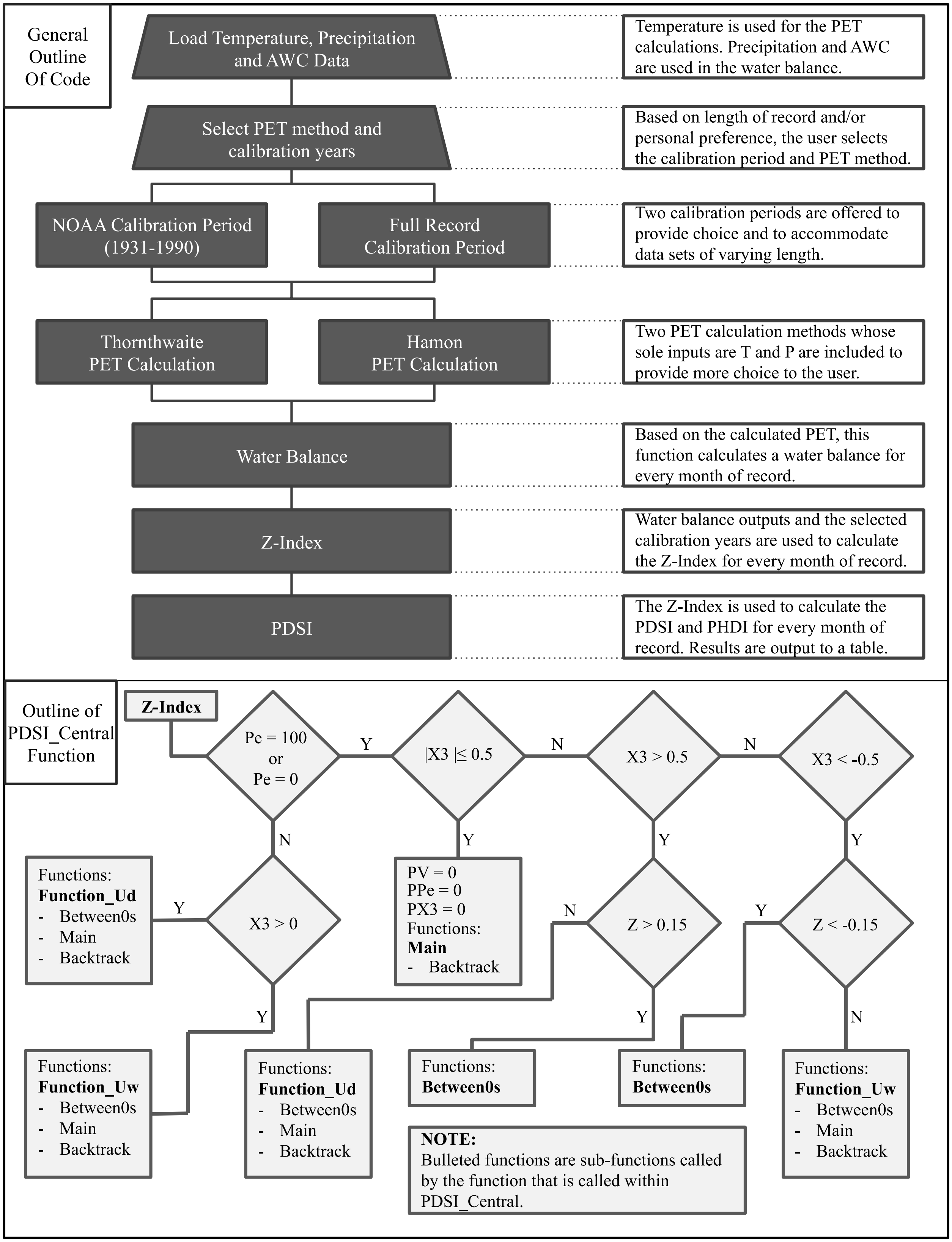

Figure 2.1 | General Outline of the Tool and the PDSI_Central Function

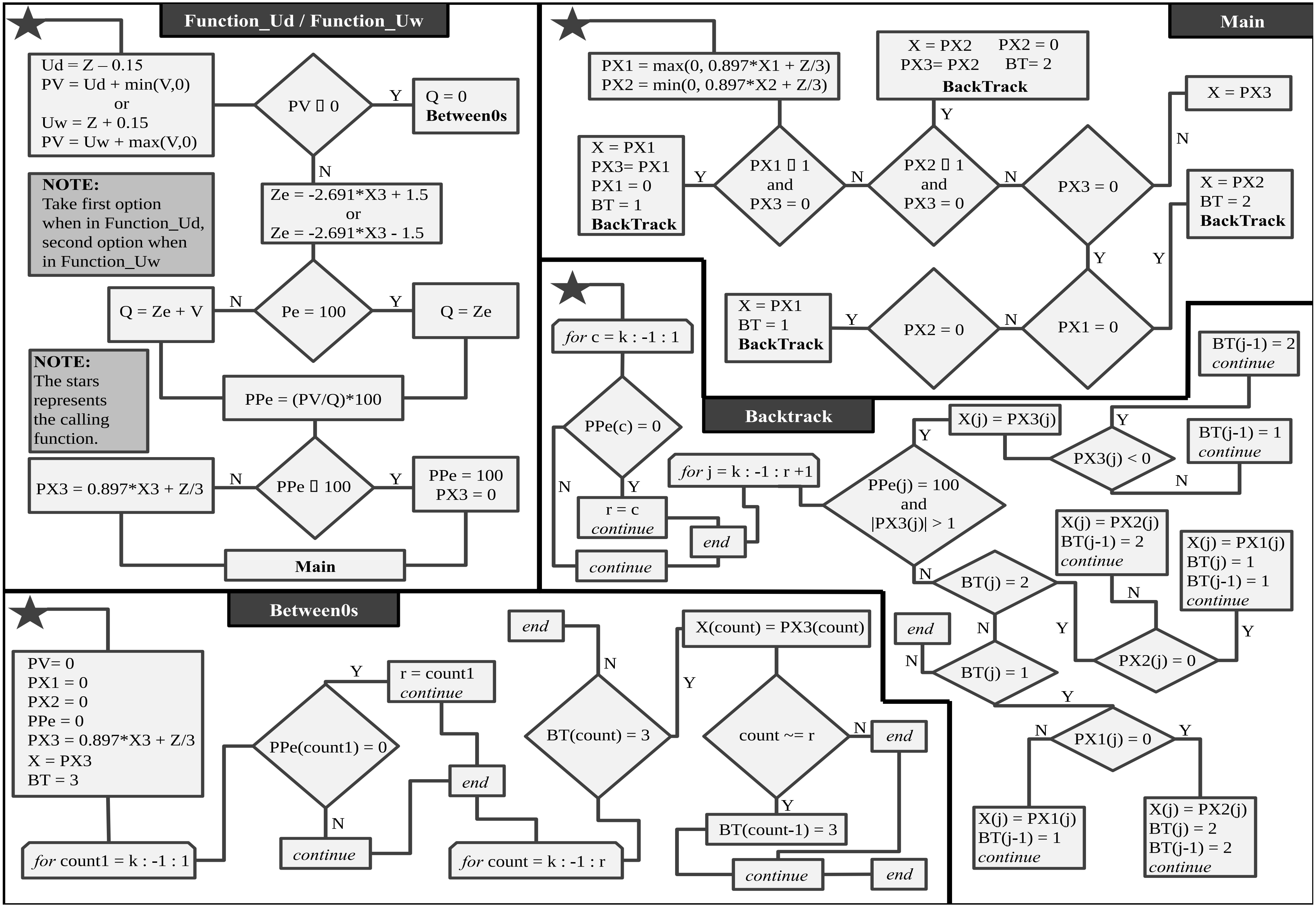

Figure 2.2 | Outline of function files called by PDSI_Central

Differences between our results and the NCDC values were analyzed by calculating the root mean square error (RMSE) between them, computing the percentage of observations where the sign of the PDSI values were opposite, and finding the percentage of observations where the absolute value of the difference between the values was greater than one (Table 2.2). A runs test was also performed on the differences between our results and the NCDC values to determine any persistence in the differences. The null hypothesis of a random order of positive and negative differences was rejected at the $p=0.05$ level for all five climate divisions. Differences for AL-1, AZ-5, and WA-1 were biased negatively, while differences for KS-5 and NY-2 were biased positively.

Table 2.2 | Differences Between Results From the MATLAB Tool and NCDC Values

Statistic	Average	Max.	Min.
RMSE	0.44	0.82 (AZ-5)	0.24 (NY-2)
Opposite Sign (%)	2.75	4.06 (AZ-5)	1.64 (NY-2)
Difference more than one (%)	2.45	3.42 (AZ-5)	1.50 (NY-2)

2.4. Discussion

Based on a graphical user interface, our MATLAB tool for calculating the Palmer drought indices requires minimal computer skill, and the code is well commented and documented to improve understanding of the underlying processes. Although there are minimal differences between the code in our tool and the NCDC code, our code accurately reflects the literature, which results in increased transparency and ease of use. Despite the differences between our tool and the NCDC values, the differences in results are small enough that the two can still be compared if one wishes to do so. For example, the typical error between the two values is on the order of 0.1 – 0.3 compared with a typical range of PDSI values -4.0 to 4.0. These differences are almost invisible from an operational standpoint and would likely have only minor effects on more rigorous statistical analysis. With an easy to use method of calculating the PDSI and its associated indices, scientists and policy makers can easily quantify drought and use those numbers in research or policy decisions. The increased transparency this tool provides also allows users to better understand the processes involved in the calculation of the PDSI.

CHAPTER 3

SHIFTS IN PATTERNS OF RAINFALL AND DROUGHT IN SRI LANKA

3.1. Introduction

Developing, monsoon-dependent nations are among the most vulnerable to climate change [*Brooks et al.*, 2005]. While many of these countries are clumped in Sub-Saharan Africa and South Asia, their vulnerability has international implications for food security [*Lobell*, 2008], international conflict [*Reuveny*, 2007], and human health [*Patz et al.*, 2005]. To better understand the potential effects of climate change on these vulnerable nations, global trends and expected changes do not suffice; more local analyses are needed [*Wilbanks et al.*, 1999]. These country- or region-specific studies can be used to reduce vulnerability, guide the disbursement of development funds, and inform adaptation planning.

Most adaptation occurs in response to extreme events, although some adaptive actions are done in anticipation of future climatic conditions. Planned adaptation to climate change is often done at the government scale [*Wilby et al.*, 2009] and is built into larger, national plans [*Adger et al.*, 2007] that use information about past and projected climates to assess current and planned policies, practices, and infrastructure [*Füssel*, 2007]. Proper assessment requires asking questions such as how will the climate change, does the change matter to the practice or policy under review, and how will the risks of acting too early or late be balanced? [*Füssel*, 2007]

In the vulnerable South Asian region, Sri Lanka provides a microcosm for this type of localized study. The country is dependent on the South Asian monsoon for much of its annual rainfall. Sri Lanka is also rapidly developing after a long civil war, providing an opportunity for strong adaptation planning polices to be put in place. Many of Sri Lanka's neighbor countries, namely India, Pakistan, and Bangladesh, are also dependent on the South Asian monsoon and are in various stages of development. Future changes in the monsoon are uncertain [*Kripalani et al.*, 2007; *Palmer et al.*, 2002; *Ashfaq et al.*, 2008], which complicates adaptive planning efforts. This uncertainty is complicated by the monsoon's relationship with El Niño – Southern Oscillation (ENSO) events [*Fedorov et al.*, 2000; *Kumar*, 2006] , including potential climate change impacts on ENSO. [*Shukla et al.*, 1983; *Yeh et al.*, 2009]

Sri Lankan weather patterns are dominated by two seasonal monsoons: *Maha,* the Northeast monsoon, which runs from December to February, and *Yala,* the Southwest monsoon, which runs from May to September [*Wickramagamage*, 2010]. The country is divided into three climatic zones – wet, intermediate, and dry. The wet zone in the southwest of the country , receives an annual rainfall of more than 2500 mm from both monsoons; the dry zone primarily in the north , receives less than 1750 mm of annual rainfall mainly from the *Maha* monsoon [*Zubair*, 2002]. The monsoons in Sri Lanka are strongly related with ENSO patterns [*Zubair*, 2002; *Zubair et al.*, 2006; *Kane*, 1997]. Given the dominance of the monsoons and the Sri Lankan climate's strong relationship with ENSO, the uncertainty surrounding climate change effects on the monsoon and ENSO is troubling for planners in Sri Lanka.

Here we present a local analysis to help assess how global changes in the South Asian monsoon may already be affecting local climate. To do so, we identify changing rainfall patterns, both spatial and temporal, in Sri Lanka. Although there have been previous statistical studies of Sri Lankan rainfall patterns [*Wickramagamage*, 2010; *Suppiah et al.*, 1984; *Malmgrem et al.*, 2007; *Puvaneswaran et al.*, 1993], this is the first to look at separate time periods to identify changes in climate.

3.2. Methods

To assess changes in the Sri Lankan rainfall patterns, both the spatial and temporal rainfall patterns are analyzed. Both analyses are done for two time periods – 1881-1980 and 1981-2011. Major irrigation infrastructure developments were initiated around 1980 [*Abeysinghe*, 1990] so results from an analysis of possible shifts in climate since then could have implications for adaptation planning.

3.2.1. Data

Monthly data for 29 precipitation stations are collected from the Meteorology Department of Sri Lanka. The 29 stations we use are the same 29 stations used by *Suppiah et al*. [1984], who presented an analysis of temporal patterns in rainfall for 1881-1980. Most stations have at least 110 years of monthly precipitation data, with some stations containing more than 140 years of data. The lone exception is Mullaitivu, which has more than 100 years of missing values, but Mullaitivu is included to replicate the analyses of *Suppiah et al.* [1984]. To fill in missing values in the data set, the ratio of precipitation values between all the stations is found for every month and the average monthly ratio between all stations is calculated. The coefficient of variation is then calculated for the entire time series of monthly ratios. When a station has a missing value, the station with the lowest coefficient of variation in that month's ratio and that had a precipitation observation is found. This station's rainfall value is multiplied by the average monthly ratio to fill in the missing value.

3.2.2. Spatial Pattern Analysis

Building on an earlier analysis [*Suppiah et al.*, 1984] of the spatial patterns of temporal variability, exploratory principal component analysis is performed for the time series of monthly anomalies for 29 stations for both time periods. This analysis seeks to identify patterns of temporal variability in rainfall and, therefore, uses the full time series. To remove the effects of seasonality we use standardized monthly rainfall anomalies. The mean and standard deviation of each month for each station (i.e., 29 stations) is calculated to find the standardized anomalies. For each station,

$$\overline{X_i} = \frac{1}{n}\sum_{y=1}^{y=n} X_{i,y} \,, \tag{3.1}$$

$$S_i = \left[\frac{1}{n-1}\sum_{y=1}^{y=n}(X_{i,y} - \overline{X_i})^2\right]^{1/2} , \tag{3.2}$$

$$Z_{i,y} = \frac{X_{i,y} - \overline{X_i}}{S_i} \,, \tag{3.3}$$

where $\bar{X}$ is the mean, S is the standard deviation, the Z values are the standardized monthly anomalies, i is the month (i.e., January (1) through December (12)), y indicates the time series, and n is the number of months in the time series.

We conduct a principal component analysis (PCA) on the covariance matrix of the standardized rainfall anomalies. For the analysis, n months were the observations and s stations were the variables [*Suppiah et al.*, 1984]. A scree plot of the eigenvalues, the variance attributed to each component, was used to decide on the number of components to retain [*Jolliffe*, 2002].

We followed the procedure of *Eder et al.* [1987] to compute the component loadings; the square root of each eigenvalue was multiplied by the coefficients of the corresponding eigenvector. We interpolated between stations using Delaunay triangulation and linear interpolation to represent component loadings on a contour plot.

To further our investigation into the spatial patterns of rainfall, we follow the approach used by *Wickramagamage* [2010] and perform a factor analysis. Factor analysis, used to promote interpretation of the patterns, is conducted on the correlation matrix of the monthly means for each station. For the factor analysis, stations are the *observations* and months are the *variables* [*Wickramagamage*, 2010]. Varimax rotation is used for the factor analysis. We used a scree plot to identify the number of factors to retain [*Jolliffee*, 2002].

3.2.3. Temporal Pattern Analysis

Shifts in temporal patterns are explored by analyzing the variance explained by the principal components, the factor loadings produced as part of the factor analysis, and a statistical analysis of rainfall amounts and variability.

The variance explained by the principal components and the contributions of the principal components to the monthly variances ware produced as part of the principal component analysis. The contribution to the monthly variance was calculated with the monthly scores (i.e., the representation of rainfall anomalies in the PC space); each month's scores for each of the 29 stations were summed and divided by the total sum of each month's scores for all stations.

By comparing the contributions to monthly variance and the factor loadings across the two time period, months with large shifts were selected for further analysis. To assess changes in timings of the monsoons, the mean rainfall and variance of rainfall for all stations for selected months are computed for two time periods, 1881-1980 and 1981-2011. The mean rainfalls of each time period are then compared using the paired t-test, which has a null hypothesis that the mean difference between the two time periods is zero. All stations in each period are then averaged and the difference between the time periods is found. A similar procedure is followed to determine changes in the variance. The two sample F-test is used to compare variances of the two time periods. The null hypothesis of the two sample F-test is that the data in each time period come from a normal distribution with the same variance. The variances across all stations are then averaged for each time period and the difference is found.

3.3. Results

Six principal components had eigenvalues greater than the mean; the scree plot revealed multiple “elbows” but two components are within the first “elbow”. These two components explain approximately 50% of the total variance (Table 3.1).

Table 3.1 | Variance explained by the first and second eigenvectors. Typical Maha (bolded) and Yala (italicized) months are highlighted.

	Percent Contributions					
Eigenvector	1			2		
Time Period	1881-1980		1981-2011	1881-1980		1981-2011
Variance Explained	42.3		38.9	8.7		10.5
Monthly Contributions	1881-1980	Change	1981-2011	1881-1980	Change	1981-2011
January	**57.7**	**-4.7**	**53.0**	**5.2**	**0.4**	**5.6**
February	**46.2**	**11.0**	**57.2**	**6.7**	**4.8**	**11.5**
March	44.0	5.6	49.6	6.5	1.7	8.2
April	34.0	0.1	34.1	6.4	0.4	6.8
May	*46.6*	*-18.3*	*28.3*	*7.2*	*1.7*	*8.9*
June	*26.0*	*-4.5*	*21.5*	*14.2*	*6.0*	*20.2*
July	*39.0*	*1.6*	*40.6*	*14.0*	*-0.1*	*13.9*
August	*37.6*	*-6.4*	*31.2*	*11.9*	*-0.2*	*11.7*
September	*41.8*	*-9.7*	*32.1*	*10.1*	*-1.6*	*8.5*
October	39.6	1.1	40.7	7.7	2.8	10.5
November	40.3	-11.4	28.9	7.6	4.0	11.6
December	**55.2**	**-5.7**	**49.5**	**7.3**	**0.9**	**8.2**

The spatial patterns of the first and second eigenvectors reveal two distinct spatial patterns of temporal variability (Figure 3.11), confirming the earlier analysis by *Suppiah et al.* [1984]. The first eigenvector, with its flat pattern and high contribution to the variance (Table 3.1), can be ascribed to the Northeast, or *Maha*, monsoon. The high monthly contributions in the *Maha* months (e.g., December to February) support this claim (Table 3.1). The second eigenvector, with its sharp gradient pattern and diminished, but still high, contributions to the variance, can be ascribed to the Southwest, or *Yala*, monsoon. Again, the high monthly contributions in the *Yala* months (e.g., May to September) support this claim (Table 3.1).

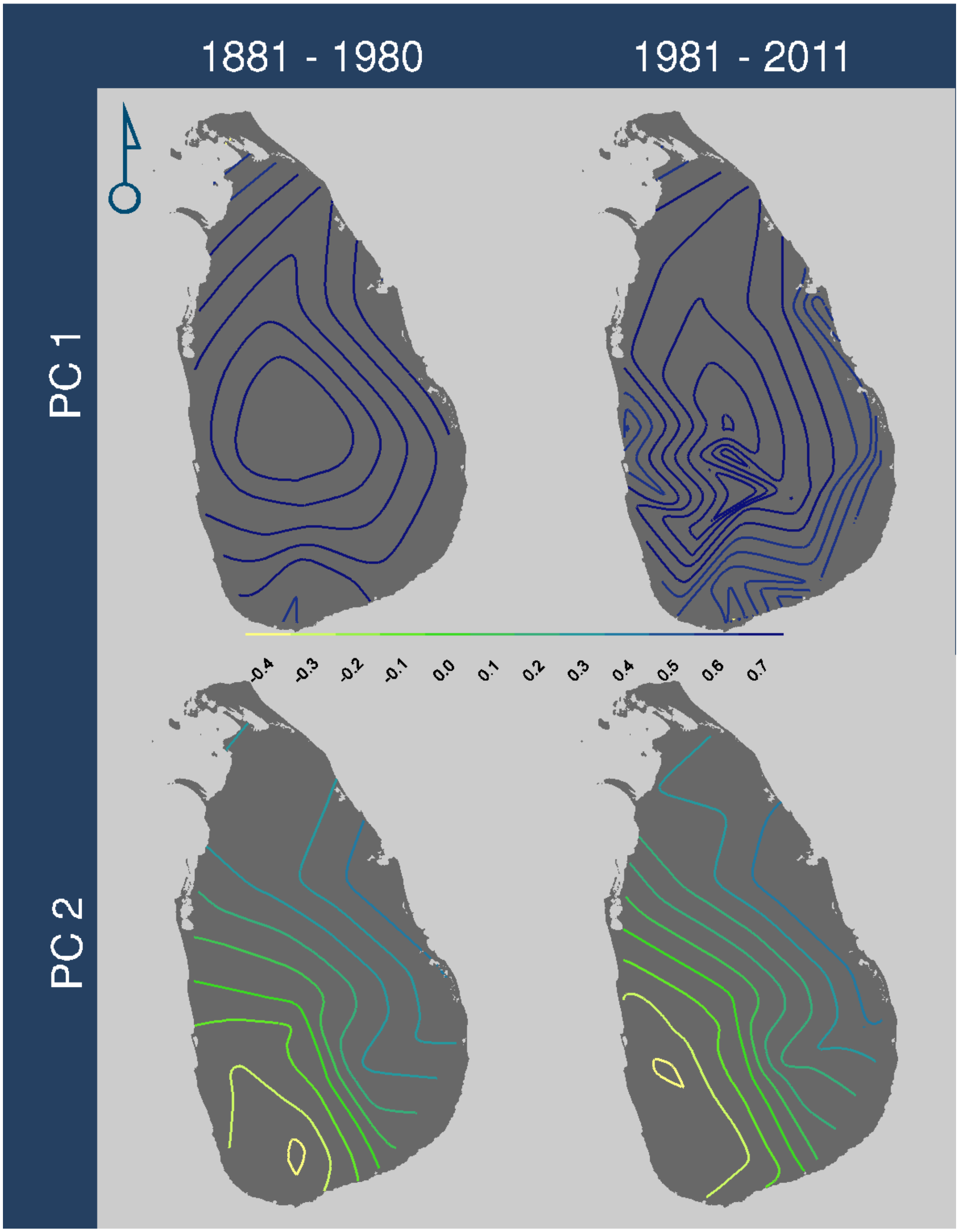

Figure 1.1 | The first two principal components for each time period. Contour lines represent the component loadings. The magnitudes are an indicator of the amount of variation in station rainfall anomalies that is explained by the component. The opposite signs in PC2 reflect an inverse relationship between the rainfall anomalies in the Northeast and Southwest.

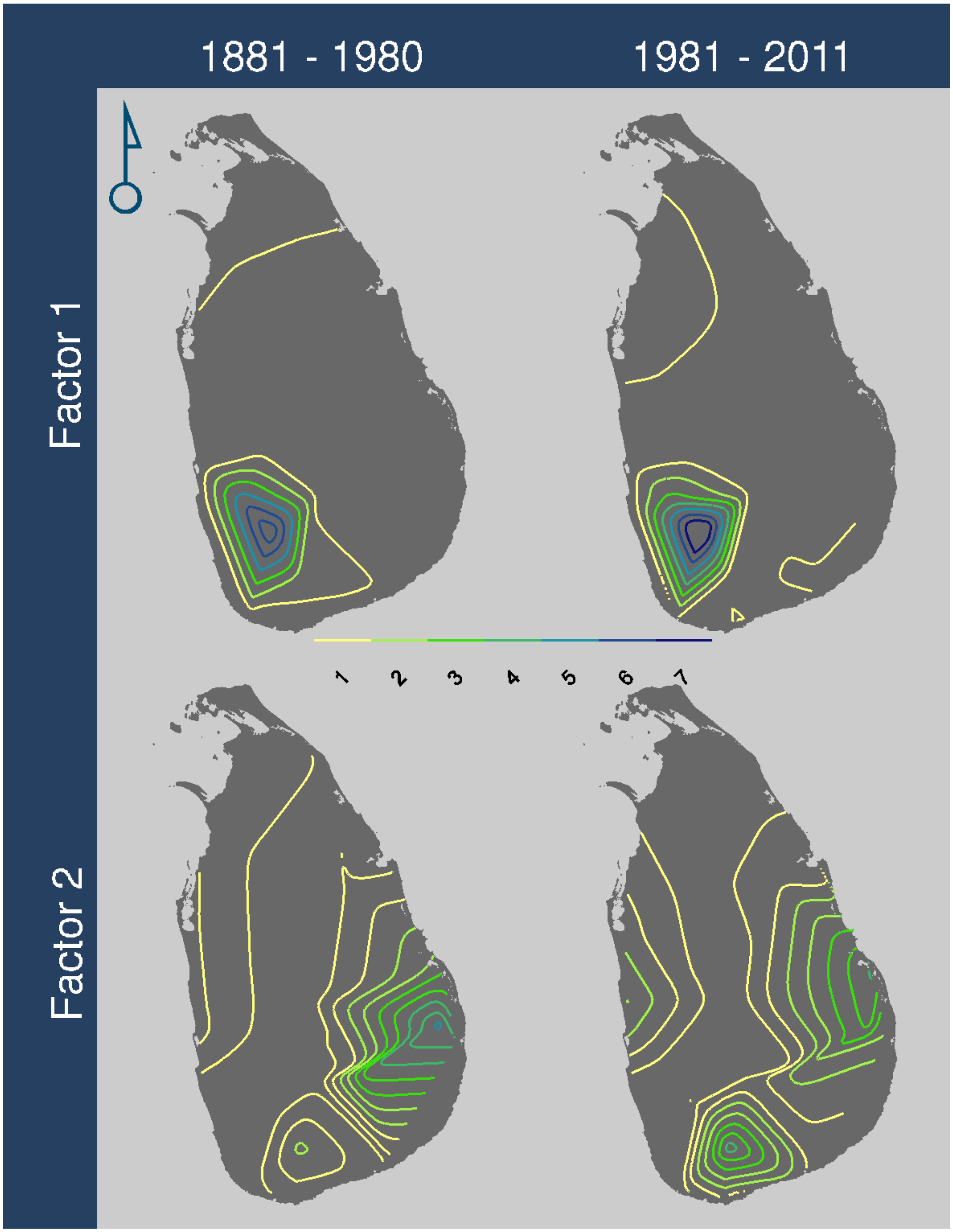

Figure 3.2 | The first two factors for each time period. Contour lines represent the factor scores, whose magnitudes can be taken as a measure of actual rainfall amounts.

The spatial patterns of the factor scores (Figure 3.2) indicate that Factor 1 represents the intermonsoonal months and the *Yala* monsoon and its concentration in the wet zone of the country, while Factor 2 represents the *Maha* monsoon and its broader distribution of rainfall. Looking at the factor loadings, these seasonal distinctions between the factors are confirmed (Table 3.2). Factor 1 represents the intermonsoonal periods (e.g., March, April, and October) and the *Yala* monsoon (e.g., May-September). Factor 2 is the *Maha* monsoon, with the highest loadings in the *Maha* months of December-February.

Table 3.2 | Factor Loadings. Typical Maha (bolded) and Yala (italicized) months are highlighted.

Factor	**1**			**2**		
Time Period	1881-1980	Change	1981-2011	1881-1980	Change	1981-2011
January	**-0.103**	**-0.023**	**-0.126**	**0.991**	**-0.095**	**0.896**
February	**0.423**	**-0.126**	**0.297**	**0.814**	**0.060**	**0.874**
March	0.824	-0.202	0.622	0.268	0.090	0.358
April	0.852	-0.166	0.686	-0.025	0.087	0.062
May	*0.929*	*-0.047*	*0.882*	*-0.140*	*0.054*	*-0.086*
June	*0.983*	*-0.030*	*0.953*	*-0.117*	*0.068*	*-0.049*
July	*0.965*	*0.003*	*0.968*	*-0.054*	*0.069*	*0.015*
August	*0.941*	*0.018*	*0.959*	*0.128*	*-0.025*	*0.103*
September	*0.973*	*-0.033*	*0.940*	*0.057*	*-0.025*	*0.032*
October	0.836	-0.074	0.762	-0.107	0.170	0.063
November	0.238	-0.057	0.181	0.326	0.318	0.644
December	**-0.264**	**0.029**	**-0.235**	**0.876**	**0.061**	**0.937**

Table 3.3 | Changes in means and variances for selected months. A significance level of p = 0.05 is used when rejecting the null hypotheses of equivalent means (paired t-test) and equivalent variances (two sample F-test).

	Paired t-test			**Two sample F-test**		
	Reject H_0?	*p*	Mean Change	Reject H_0?	*p*	Mean Change
February	Fail To	0.754	0.967	Yes	0.004	529
May	Yes	<.001	-24.4	Fail to	0.313	-5580
November	Yes	0.012	14.9	Yes	0.010	2490

3.4. Discussion

The timings of the monsoons in Sri Lanka appear to be changing. Our analysis suggests that the *Yala* monsoon may be beginning later than its customary May start time. This finding is supported by shifts in the Sri Lankan crop calendar [*Senalankadhikara et al*., 2009] and by similar shifts in the Indian monsoon [*Adamson et al.*, 2013]. For the *Maha* monsoon, our analysis suggests that the monsoon is tending to start earlier, in November instead of December. Spatial changes are less clear, but there does appear to be an increase in rainfall in the southern portion of the country during the *Maha* monsoon.

3.4.1. Spatial Patterns

For the principal components analysis, the months served as observations and the stations as variables. The eigenvectors themselves represent spatial patterns of temporal variation (Figure 3.1). Changes in the spatial patterns between the two time periods analyzed are very slight. The spatial patterns of the eigenvectors across the time periods show minimal shifts; nevertheless, there appears to be a slight pinching of the low component loadings in the center of the country, which indicates more variability in the *Yala* monsoon in the center of the country (Figure 3.1).

For the factor analysis, stations are the *observations* and months are the *variables* so the factor scores represent spatial patterns. The factor analysis of spatial rainfall patterns across the two time periods also shows only small shifts in the spatial patterns, though there does appear to be an increase in rainfall, as indicated by the higher factor scores, in the south of the country (Figure 3.2).

3.4.2. Temporal Patterns

Shifts in the temporal patterns of rainfall are much more pronounced than are the spatial shifts. The monthly contributions of the eigenvectors during the first 100 years of the data set show clear demarcations of both the *Maha* and *Yala* seasons (Table 3.1). In the 1981-2011 data, however, things appear to change. The *Maha* months continue to be strongly identifiable, but the *Yala* months are harder to distinguish and the second eigenvector accounts for more of the variance in many of the months. This indicates that the *Yala* monsoon is becoming more variable and unpredictable.

Indications of changing monsoon timings are apparent in the results of both the principal component and factor analyses. The large changes in the monthly contribution of the first eigenvector for some months (Table 3.1) and the large increase in the November loading in Factor 2 (Table 3.2) are both indicative of timing changes.

This assessment is further supported by changes in the mean rainfall and variability for some of the months identified in the principal components analysis: February, May, and November. In February, typically the final month of the *Maha* monsoon, the mean amount of rainfall stays the same, but the rainfall becomes more variable (Table 3.3). In May, at the start of the *Yala* season, mean rainfall decreases. In November, just before the start of the typical *Maha* monsoon, the mean amount of rainfall increases, as does the variability. All three changes indicate changes in the timings of the monsoons. The end of the *Maha* monsoon is becoming more variable, either ending earlier or extending later. The *Maha* monsoon also appears to be starting earlier, as indicated by the increased mean rainfall and variability in November. Although May is typically considered the start of the *Yala* monsoon, the changes in May seem to cast that into doubt. The very significant decline in the mean amount of rainfall indicates that May is no longer getting as much monsoonal rain.

3.5. Conclusion

Although there have been some shifts in rainfall patterns over the past 30 years, the changes identified here may be a prelude for more dramatic changes. Shifts from *the norm* are likely to have serious impacts on the management of resources and infrastructure in Sri Lanka, a country dependent on the agricultural sector both culturally and economically. With uncertain monsoon arrival times, planning for reservoir storage will become more difficult. Energy demand in the country is expected to increase dramatically over the next decade [*Amarawickrama et al.*, 2008], and when combined with increased irrigation needs [*De Silva et al.*, 2007], water managers will be under increasing pressure that may be amplified by changes in monsoon timings.

Developing, monsoon-dependent nations like Sri Lanka need to plan for how they will adapt to climate change. With uncertain changes to the monsoons and an increased pace of development, much will be demanded of planners and resource managers in the countries, as well as of the global institutions that provide much of the development funding. How successfully these countries adapt and continue to develop may have global ramifications. To assist adaptation planners in their work, local or regionally focused analyses similar to the one presented here must be conducted to assess how the regional climate has changed. Though they can be relatively simple, this type of analysis can help to identify changes and spur more detailed studies of potential future changes.

CHAPTER 4

PERCEIVED AND ACTUAL CHANGES IN THE SRI LANKAN CLIMATE

4.1. Introduction

While sophisticated statistical techniques such as those presented in Chapter 3 are able to reveal changes in the Sri Lankan climate, the people of Sri Lanka may have a harder time discerning any noticeable shifts, especially if they occur over the long time periods associated with anthropogenic climate change. It is widely regarded that anthropogenic climate change poses a serious and potentially catastrophic threat to human and natural systems worldwide [*IPCC*, 2007; *National Research Council*, 2010a]. People living in developing nations, such as Sri Lanka, are particularly vulnerable to the expected impacts of climate change due to geographic vulnerability, a lack of economic resources, less developed infrastructure and a heavy reliance on resource dependent livelihoods. It is now understood that the effects of anthropogenic climate change are already occurring, that continued warming is inevitable due to the level of greenhouse gas (GHG) concentrations already in the atmosphere, and that further and significant increases in global temperatures are very likely due to stalled national and international mitigation efforts [*IPCC*, 2007]. Consequently, research and policies designed to facilitate adaptation to climate change, in addition to mitigation, have been identified as global priorities worldwide [*IPCC*, 2007; *National Research Council*, 2010a].

In contrast to mitigation, which necessitates national and international coordination to be successful, adaptation can have immediate utility at even very small scales such as farm or village levels. However, there remain significant gaps in our understanding of how actors at this scale perceive of and respond to climate change, particularly in the absence of good information. Recently, the *National Research Council* [2010b] identified the question of how people, "understand, decide, and act in the climate context" as a major research priority (p. 101). In this paper, we focus specifically on the question of understanding, i.e., to what extent do people perceive changing climatic conditions in their local environment? In this paper we compare data of perceived changes in temperature and rainfall among smallholding farmers in Sri Lanka historical meteorological records to assess the capacity of farmer to detect changes in these parameters.

4.1.1. Perceptions of Environmental Change

The detection of a threat is a core component of theories that attempt to describe the psychological processes that lead to risk-reducing behaviors. In most cases, the recognition of a risk is a necessary but not sufficient condition for engaging in proactive efforts to remove or reduce risk. For example, the widely used protection motivation theory (PMT) [*Rippetoe & Rogers*, 1987; *Rogers*, 1983; *Rogers & Prentice-Dunn*, 1997] argues that people make two appraisals when faced with a potential threat. The first is a risk appraisal, in which an individual evaluates the likelihood that a threat will occur, and its severity if it does occur. This likelihood is the perceived probability of the occurrence of a threat, not the actual probability. Only if the risk (i.e., likelihood x severity) is considered high does a person move to the second appraisal in which she evaluates the extent to which she is capable of coping with the threat. Ultimately the theory predicts that an individual will be compelled to engage in risk-reducing actions when both the risk and coping appraisals are high. PMT and closely related theories (e.g., health belief model, theory of reasoned action) are heavily used in the field of health psychology where they have performed well, typically accounting for a moderate degree of variance in a variety of self-protective health behaviors [*Floyed et al.*, 2000]. *Grothmann &* Patt [2005] tested a modified version of PMT to predict actions to prevent future flood losses in a sample of German residents and found that it was more effective than a socio-economic model that considered only adaptive capacity.

Although there is an abundance of psychological research into risk perceptions and responses, the focus of much of this work has been on variability in perceptions of the likelihood or severity of a threat occurring, or the role of expectations and efficacy in coping responses. The detection of a threat itself has received less attention, in part because the importance of threat detection in provoking a threat response is relatively uncontroversial. However, the ability of individuals to detect environmental changes that could compromise their wellbeing is critical for understanding the capacity of individuals to respond to climate change. In addition, variability in the extent to which individuals detect change can inform the design of programs and policies intended to support adaptive capacity. For example, the influence of recent events on risk perceptions of future climatic changes, or the ability to detect slowly evolving vs. rapidly evolving changes, may have significant implications for the design of programs and policies to support adaptation.

It is widely recognized that those who are engaged in resource-dependent livelihoods hold extensive local knowledge of their surrounding environment that, in some cases, facilitates sustainable livelihood practices and adaptation to environmental stressors [*Alessa et al.*, 2008; *Berkes,* 2002; *King et al.*, 2008; *Mertz et al.*, 2009]. For example, *Thomas et al.* [2007] describe a nuanced understanding of recent changes in precipitation among small scale farmers in South Africa that largely correspond with spatial and temporal trends of physical measurements in the region, identified through self-organized mapping. The authors also found that, although climate change was only one of a number of risks identified by farmers, it was identified as a significant risk to livelihoods and respondents reported that they had taken a number of steps to cope with these impacts. Such adaptations included the commercialization of agricultural production, income diversification and modifications to cultivation practices.

While there is little doubt that farmers actively respond and adapt to the impacts of climate change, it is questionable whether individuals have the ability to accurately detect, characterize and preemptively respond to the type of gradual and highly variable environmental changes associated with anthropogenic climate change. For example, *Smit et al.* [1997] have shown that, despite known variability in year-to-year weather patterns, Canadian farmers disproportionately base their planting decisions for the upcoming year on the previous year's weather rather than assessing the probability of future weather conditions based on recent trends. Similarly, *Brondizio & Moran* [2008] interviewed smallholding farmers in the Amazon and found that over 50% did not remember one of the most significant droughts on record that had occurred just three years prior. These findings are consistent with the body of work in social and cognitive psychology suggesting that people use a variety of heuristics or "mental shortcuts" to process information efficiently and swiftly [*Kahneman et al.,* 1982; *Sunstein*, 2006; *Tversky and Kahneman,* 1973]. If farmers are capable of updating their expectations about the future climate based on new observations, there are likely to be significant time delays associated with this learning process as well as significant adjustment costs. *Kelly et al.* [2005] have argued that even if we assume that farmers engage in something akin to Bayesian updating, the degree of natural variability would require a farmer to observe data over an extended period of time before being able to detect deviations from normal variation. Their model estimates that there will be adjustment costs 100 years after a climatic change has occurred due to incomplete learning.

4.1.2. Objectives

The implications of these finding are that we cannot assume that local ecological knowledge within traditional communities will remain fully intact and useful against the backdrop of rapidly changing climate conditions, modernization, and changing demographics within rural communities. It is therefore critical to understand individual perceptions of climate change in a variety of contexts, and how these perceptions influence decision-making and behavior. Surprisingly little work has been done in a developing world context where the anticipated impacts are large. In this paper we examine perceptions of environmental change among a sample of paddy farmers within the agricultural dry zone of Sri Lanka. Drawing on the previous research reviewed above, we explore our primary research question:

(1) To what extent do farmers' perceptions of variability in temperature and precipitation reflect physical measurements in the region?

4.2. Materials and Methods

4.2.1. Study Area and Research Overview

These data were collected as part of a pilot survey designed to assess responses to water stress among paddy farmers living within the heavily agricultural dry zone of Sri Lanka. Sri Lanka is a nation undergoing tremendous economic, socio-political and environmental change. In 2008 the country saw the end of a violent 30-year civil war between Sri Lankan government forces and the separatist Liberation Tigers of the Tamil Eelam (LTTE) that caused the death and displacement of many thousands of persons, particularly in the north and the east of the country. Despite this protracted conflict, Sri Lanka is classified as a lower-middle-income country by The World Bank and scores relatively well on a number of world development indicators (e.g., access to electricity, life expectancy, infant mortality) compared to other countries in the region [*World Bank*, 2013]. Yet, like many nations in South and Southeast Asia, population growth and climate change introduce a number of threats to food security and economic development. Sri Lanka falls into the IPCC's category of "vulnerable small island nations" under serious threat from climate change impacts, including drought [*IPCC*, 2001]. Annual mean air temperature anomalies have shown significant increasing trends during recent decades, on the order of 0.016 C per year for the period of 1961 – 1990 [*Chandrapala*, 1996a]. Annual mean maximum air temperatures have also shown increasing trends in almost all stations with the maximum rate of increase about 0.021 C per year [*Basnayake & Vithnage,* 2004]. The mean annual precipitation has also decreased by 144mm during 1961-1990, which is a 7% reduction compared to 1931-1960 [*Chandrapala*, 1996b].

This preliminary pilot work is associated with a large interdisciplinary project to assess the impacts of climatic trends and water stress on rice production in Sri Lanka, and the adaptive responses of farmers to these trends. The Mahaweli River Watershed (MRW) region where this study takes place encompasses 75% of land area yet receives less than 40% of total rainfall, most of which falls during the monsoon season (October – March). When rainfall is insufficient, agricultural production (primarily rice), is buffered by an extensive irrigation system that delivers water to over 3,600 square kilometers (km^2) through a system of reservoirs, open channels and tunnels. The purpose of this pilot work was to assess the costs and feasibility of a larger study in the area, to develop and validate a survey instrument, and to refine the scope of the larger project. As a part of this pilot work, household surveys were administered to a sample of N=192 rice farmers in five communities located throughout the MRW. Surveys were administered as face-to-face interviews to the individual within the household who was designated as the person who makes the majority of decisions about rice cultivation. Typically this was the male head of household (79%); however, in some cases the female head of household was identified (21%). Respondents were asked a number of questions to gather information about (among other things) household demographics, wealth, access and use of various water sources, cultivation practices, and perceptions of environmental changes. The survey protocol was reviewed and approved by ethical review committees in Sri Lanka and the United States.

4.2.2. Site Selection and Sampling

Five communities were selected at the *Grama Niladhari* (GN) division level, which is the smallest administrative unit in Sri Lanka and typically represents one village or in some cases a few small villages. Initially, pilot sites were randomly selected from throughout the watershed based on the extent of paddy cultivation and population density. However, after completing surveys in the first community (Site T), it was determined that the time and cost required to complete the survey in these sites would be prohibitive. To remain within budget we reselected the remaining four communities to reduce their geographic dispersion. Two communities (P and G) were chosen from System C of the MASL Development Area, which is located on the border of the intermediate and the dry zones relatively close to the catchment area. This area is known to have relatively fewer problems with water scarcity. Two other sites (N and K) were chosen from System H, which is located entirely within the dry zone and is known to be a particularly drought-prone region [*Nandana et al.*, 2011]. Site T, the first community visited prior to the revision of the site selection procedures, is located partially within System D1 such that some residents were served by the irrigation system and others did not receive centrally managed irrigation water and instead relied on rainfall collected by a small village tank (reservoir).

To select the remaining four communities, we identified 310 GN divisions that fell within these two selected systems. Seven were removed from the sampling frame because the proportion of paddy land to households was over three standard deviations (SD) above the mean indicating a departure from the typical farming community that is comprised of households holding approximately 1-5 acres of paddy land. Urban or semi-urban areas, classified as having a paddy land to household ratio of below the 25th percentile, were also omitted (n=75). After these exclusions 228 divisions remained, 48 in System C and 180 in System H. Next, the GNs in each system were split into two equal groups based on the 50th percentile of population density (persons/hectare) and one community was randomly selected from each group resulting in two communities (one less densely and one more densely populated) in each of System C and H. See Figure 4.1 for the approximate location of the five communities.

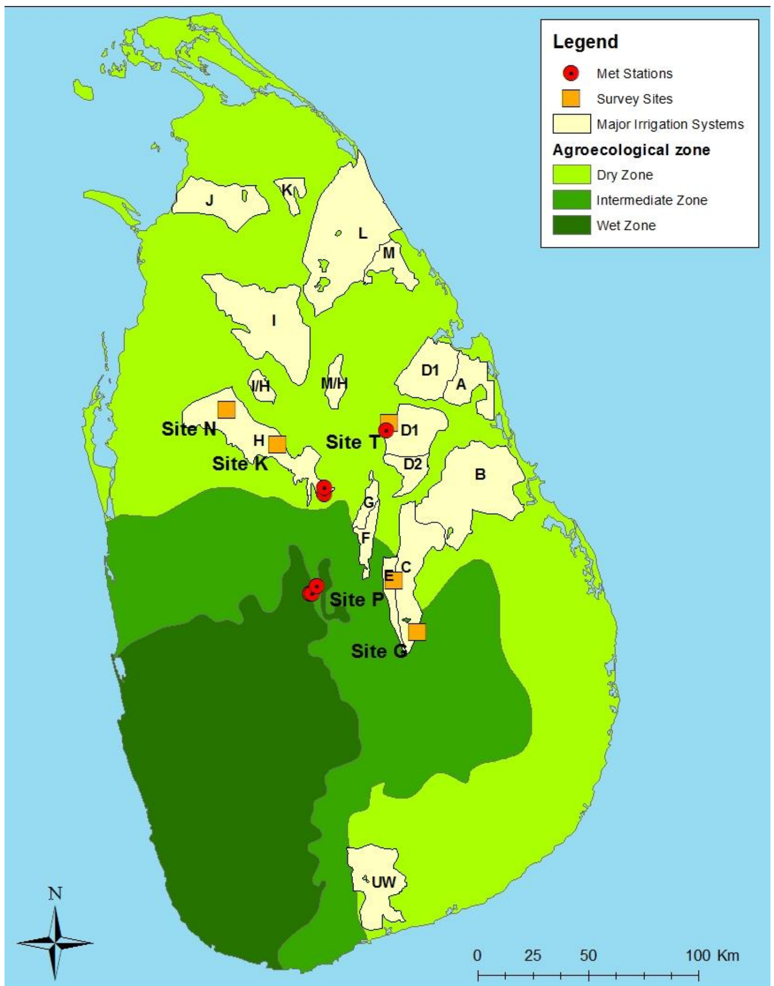

Figure 4.1 | The selected survey sites. Climatic zones and Mahaweli systems are also identified.

To select households the interviewers mapped the roadways in the village and proceeded to approach every *n*'th household where *n* was the total number of households in the division divided by 40, our target sample size per village. In cases where the head farmer was not available the interviewer was instructed to return at a later time. Data collection was restricted to daytime hours because of the long travel distance to the interviewers' overnight accommodations; therefore, some randomly selected households were not available to be interviewed during these times. In these cases the interviewer was instructed to approach the next household on the road. Demographic statistics of our sample compared to the 2011 census for the same communities are provided in Table 4.1. There was one notable discrepancy in that the average number of people per household was substantially larger in the sample than in the population. This may be due to the fact that only paddy farming households were sampled and these households tend to be less affluent than others in the community.

Responses to another survey conducted in the fall of 2013 are also included in this work. The sites of the survey are different from the ones described above, but the site selection process was similar. More of an emphasis was placed on including a mix of both Mahaweli system and local, rain-fed villages in the survey. 278 farmers were interviewed during this survey.

Table 4.1 | Demographic profile of the 2011 household sample compared to the 2011 census data.

	Site T		Site P		Site G		Site N		Site K	
	Sample	**Census**	**Sample**	**Census**	**Sample**	**Census**	**Sample**	**Census**	**Sample**	**Census**
Households	42	262	40	227	39	460	37	428	34	374
Persons per household	4.79	3.63	4.75	3.68	4.38	3.67	4.30	3.72	4.50	3.75
Gender										
% Male	50%	51%	52%	51%	47%	47%	51%	49%	48%	47%
Age										
% less than 15 years	22%	29%	26%	30%	22%	33%	27%	26%	24%	34%
% over 60 years	10%	10%	3%	7%	13%	9%	8%	10%	7%	6%
Drinking Water Source										
Well	93%	94%	95%	91%	98%	92%	69%	70%	88%	82%
Piped; Rural water project	2%	0%	-	-	-	6%	28%	29%	12%	8%
Surface	2%	5%	5%	-	-	2%	-	0%	-	-
Religion										
Buddhist	100%	nd	100%	nd	100%	nd	100%	nd	38%	nd
Muslim	-	nd	-	nd	-	nd	-	nd	59%	nd
Hindu	-	nd	-	nd	-	nd	-	nd	-	nd
Christian	-	nd	-	nd	-	nd	-	nd	3%	nd
Ethnicity										
Sinhalese	100%	nd	100%	nd	100%	nd	100%	nd	41%	nd
Sri Lankan Moor	-	nd	-	nd	-	nd	-	nd	59%	nd
Sri Lankan Tamil	-	nd	-	nd	-	nd	-	nd	-	nd

Note. '-' indicates that the value is zero or near zero; nd = no data available

4.3. Analyses and Results

4.3.1. Meteorological Record of Temperature and Rainfall

Meteorological and temperature data were obtained from the Sri Lankan Department of Meteorology and were analyzed using a simple trend analysis. Twenty years of monthly data (1991-2010) from meteorological stations that were physically close and climatically similar to the surveyed communities were used. A total of six stations were selected: three for sites K and N, two for sites P and G, and one for site T. Though no stations are located exactly in any of the communities, these stations can be assumed to be representative of the local conditions. Temperature gradients are relatively flat in the areas of the country where the survey sites are located. Although the exact amount of precipitation can vary from village to village, seasonal characteristics and trends tend to be consistent. Any missing values, of which there were few, were filled in using linear interpolation.

The data were analyzed by fitting linear trend lines. These trend lines were fit to the full time series for the temperature data, as well as the average annual values for the seasonal monsoon periods of *maha* (March-August) and *yala* (September – February). These linear trends were fit just to find the slope of the trend line to get an idea of the temperature and precipitation trends. No effort was made to calculate the significance of the trend. Some preliminary analysis indicates that 20 years of data is not sufficient to find a significant trend – a time series of 30-40 years may ultimately be required to find a significant trend. Overall trends from the past 20 years of temperature data suggest subtle warming of between 0.018 C and 0.02 C per year (see Figure 4.2) in all communities. These results are consistent with results found by *Chandrapala* [1996a] and *Basnayake & Vithanage* [2004].

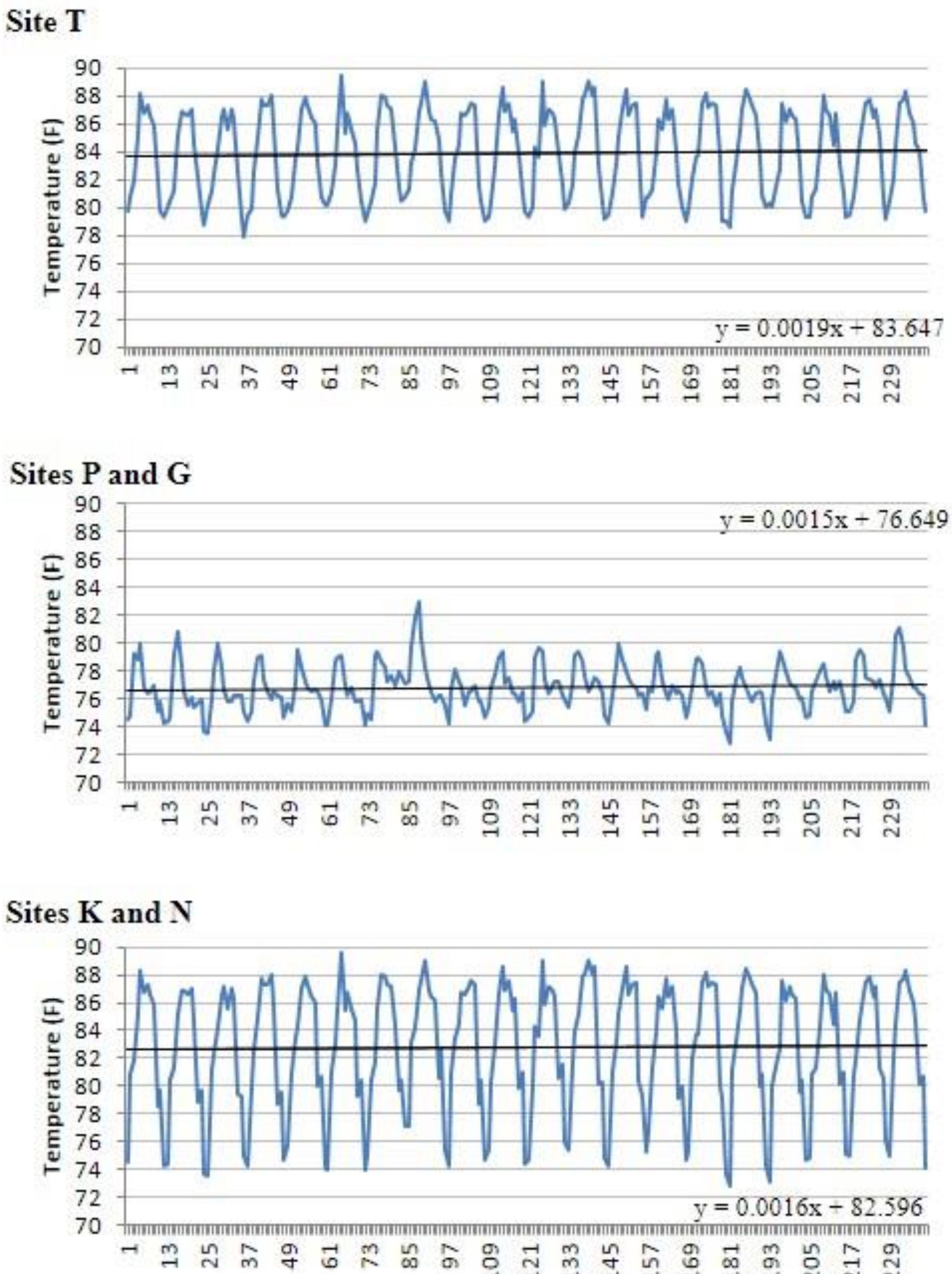

Figure 4.2 | Temperature data from the three meteorological areas over a 20-year time period (indicated on the x-axis in months). Figures fit a 20-year linear trend line.

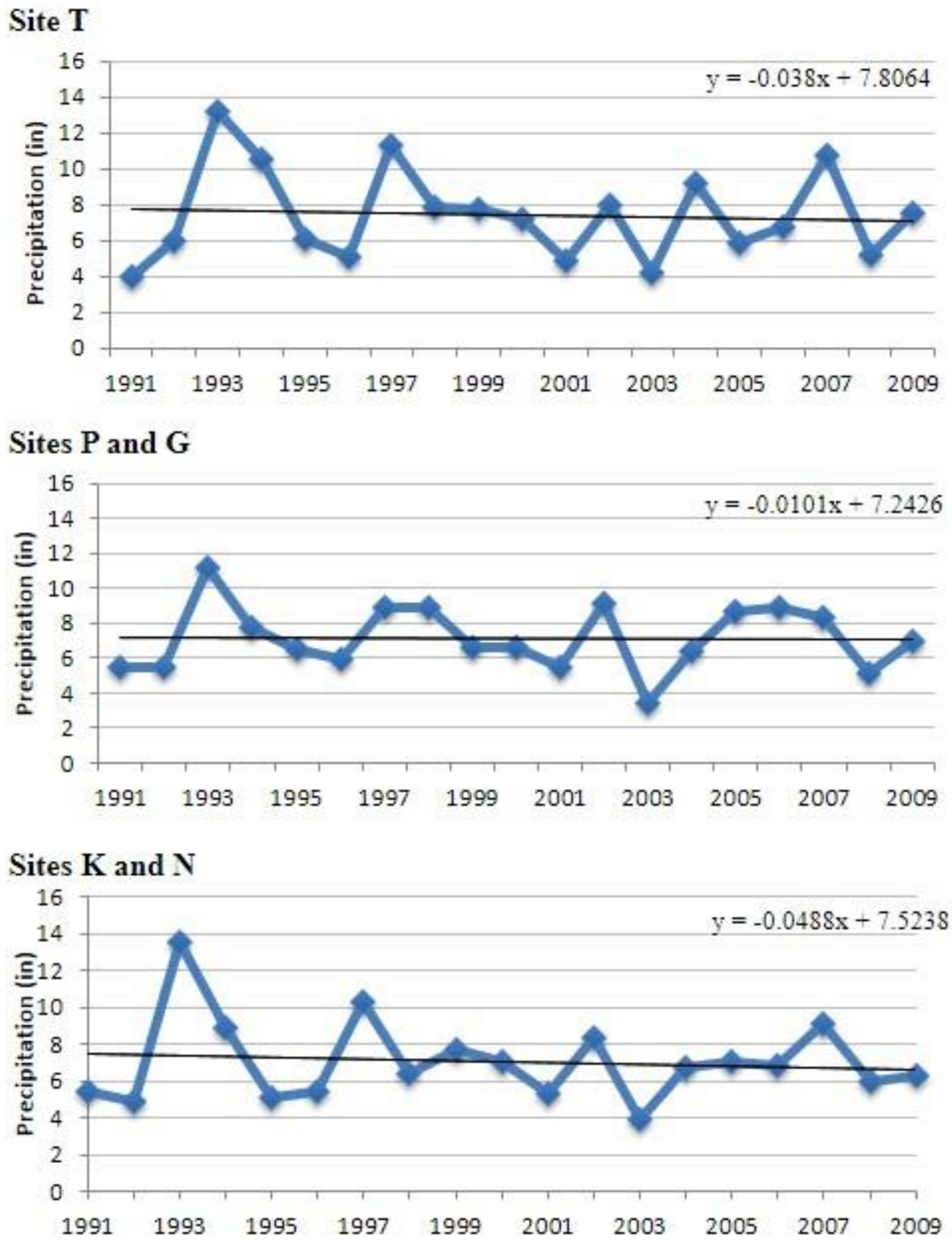

Figure 4.3 | Monthly average rainfall in Maha (Wet Season) from the three meteorological areas over a 20-year time period. Figures fit a 20-year linear trend line.

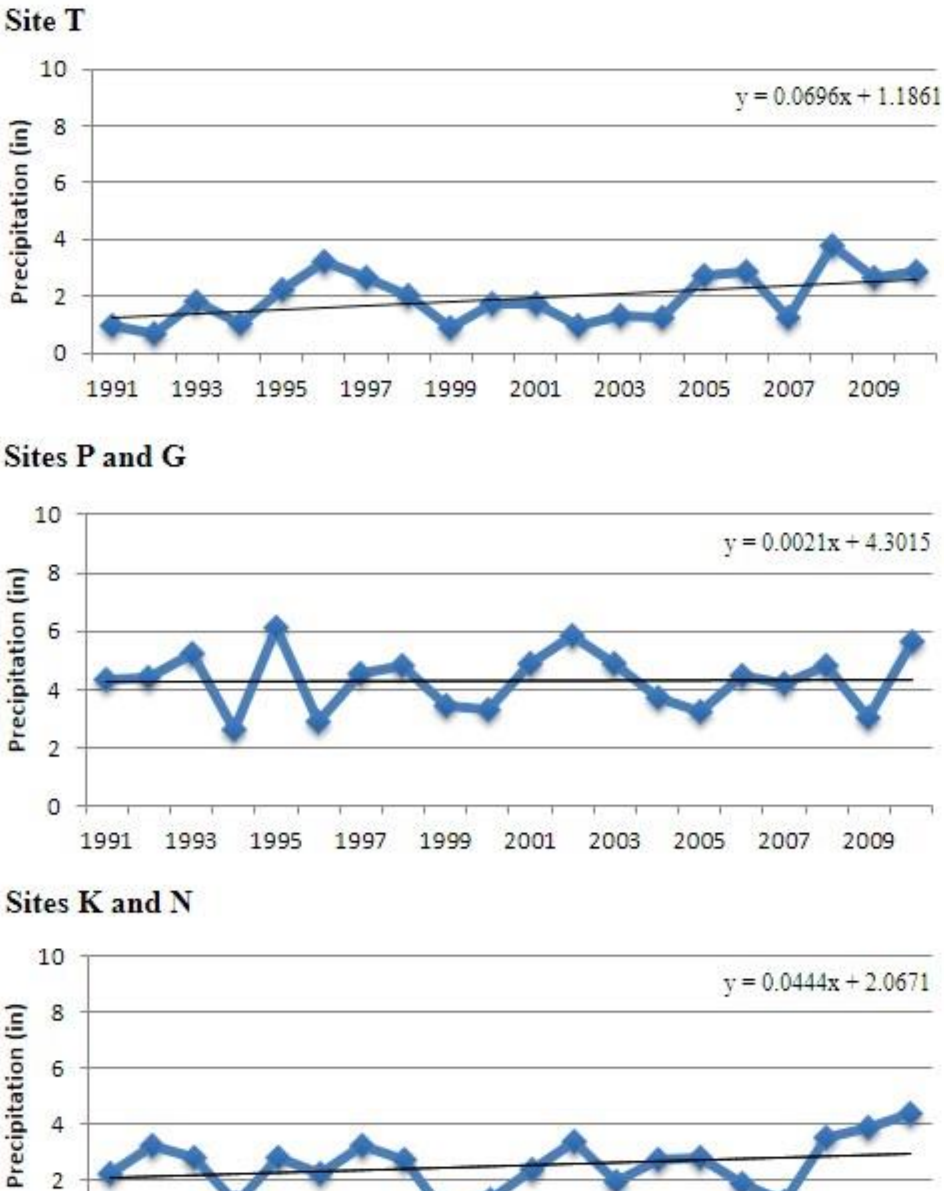

Figure 4.4 | Monthly average rainfall in Yala (Wet Season) from the three meteorological areas over a 20-year time period. Figures fit a 20-year linear trend line.

Monthly rainfall during the wet (*maha*) season from the past 20 years suggest that rainfall during the wet season has declined slightly in Sites T, K and N but has remained relatively stable in Sites P and G (Figure 4.3). There was a very slight negative trend in Sites P and G; however, the magnitude of this change was substantially less than in the other sites. Similar data for the dry (*yala*) season suggest that rainfall has slightly increased in Sites T, K and N, but has remained stable in Sites P and G (Figure 4.4).

4.3.2. Perceptions of Temperature and Rainfall Change

By comparing the actual meteorological records to perceived changes in temperature and rainfall, we can draw some preliminary conclusions about farmers' ability to detect changes in climatic conditions. First, we examine the accuracy of those perceptions. Drawing on the data presented in Section 4.3.1, if farmers are able to detect gradual changes in the climate we would expect the following hypotheses to be true:

1. Farmers in all study sites will report an increase in the temperature at a rate that is significantly better than chance (i.e., 33%).
2. (a) Farmers in Sites T, K, and N will report a decrease in wet season rainfall at a rate that is significantly better than chance. (b) Farmers in Sites P and G will report no change in wet season rainfall at a rate significantly better than chance.
3. (a) Farmers in Sites T, K and N will report an increase in dry season rainfall at a rate significantly better than chance. (b) Farmers in Sites P and G will report no change in dry season rainfall at a rate significantly better than chance.

A plurality of farmers in all sites reported an increase in temperature (Figure 4.5); however, there was substantial variability in the proportion of correct responses across communities, ranging from 48% (Site G) to 79% (Site K). To test Hypothesis 1 (H1), a series of chi-square tests were conducted to compare the observed distribution of perceived temperature change in each village to a hypothetical distribution of equal probabilities across the three levels (decrease, no change, increase). This hypothetical distribution of equal probabilities across the three levels is assumed to represent the hypothetical choices of a sample population that knows nothing about the weather. The even distribution also helps to keep things neat and to keep the statistics manageable. In the real world, this assumption may not hold up. Framing effects from the survey may push people towards either "increase" or "decrease". While further work is needed to determine if the equal distribution is a sound one, the assumption has little effect on the results of this study since all responses are considered, not just the statistically significant ones. To correct for family-wise error, a Bonferroni correction was applied in which the alpha threshold for statistical significance was set to $p < 0.01$. The results (summarized in Table 4.2) indicated that in Sites T, N and K, farmers perceived an increase in the temperature at a rate that was significantly better than chance, providing partial support for H1. However, in sites P and G, famers perceptions were no better than chance.

Table 4.2 | Chi-Square tests comparing perceived changes in the environment to a hypothetical distribution of equal probabilities by site.

		Temperature		Rainfall (wet)		Rainfall (dry)	
Sites	***N***	χ^2	***Sig.***	χ^2	***Sig.***	χ^2	***Sig.***
T	41	25.95	**	34.29	**	27.12	**
P	40	7.55		6.65		43.85	**
G	40	6.65		10.85	*	39.80	**
N	37	14.49	**	6.87		33.78	**
K	34	32.53	**	3.81		21.06	**

Note. To correct for family-wise error, a Bonferroni correction has been applied setting the alpha threshold for statistical significance to ^$p < .02$; *$p < .01$; *$p < .002$

A plurality of farmers in all locations also perceived a decline in rainfall during the *maha* season, ranging from 48% in Sites P and K to 76% in Site T. A series of χ^2 tests (Table 4.2) revealed that only the data from Sites T and G significantly differed from chance. In Site T, a significant majority of farmers accurately reported a decrease in Maha rainfall; however, in Site G, a significant proportion of farmers incorrectly reported a decline in rainfall. In the remaining sites, the percentage of respondents who reported a decline or no change in rainfall was not significantly different than base rates. These data provide little support for H2.

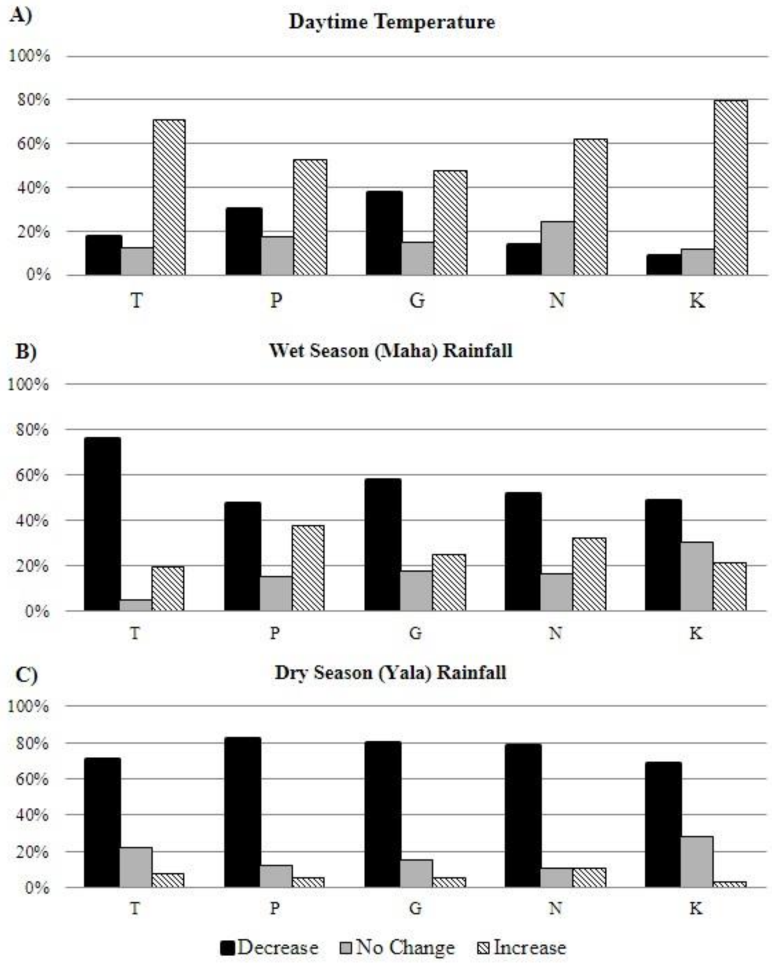

Figure 4.5 | Proportion of farmers by study site who perceived a decrease, increase, or no change in each climate parameter over the past 20 years.

Finally, with respect to changes in dry season rainfall, farmers in all locations demonstrated near unanimous agreement that rainfall has declined. Not surprisingly, given the level of agreement, the distribution of responses in all sites was significantly different than chance. However, in all sites the majority perception did not conform to the meteorological data that suggested there has been an increase in rainfall.

4.3.3. Perceptions of Shifts in Monsoon Timings

Jacobi et al. [In Preparation] identify shifts in the starts of the monsoons. They find that over the last 30 years, the *Maha* monsoon is starting earlier and the *Yala* monsoon is starting later. The survey conducted in the fall of 2013 asked participants about the timing of the start of the *Maha* monsoon. Respondents were asked to say, in their experience, whether the *Maha* monsoon was starting earlier, later, or if there was no change in the timings. 79.9% of participants responded that the *Maha* monsoon is starting later, and only 4% said it was starting earlier (Figure 4.6).

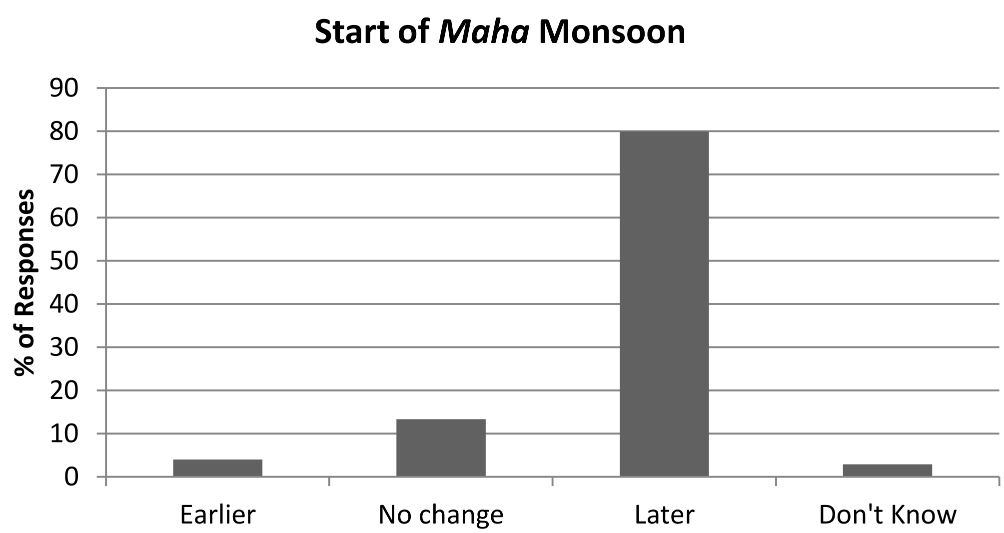

Figure 4.6 | Percentage of farmers who perceived changes in the start of the *Maha* monsoon.

4.4. Discussion

This study suggests that perceptions of environmental change by farmers in Sri Lanka often do not match the realities. The environmental change that participants are most likely to correctly perceive is the increase in daytime temperatures over the past 20 years (Figure 4.7). Yet this change, an average 0.02°C annual rise, is so slight that only someone with an accurate thermometer would be able to truly register this rise in temperature. Nevertheless, for this paper, we use the increases or decreases found by fitting trend lines to assess the correctness of the survey responses. This choice is made to remove ambiguity about the true direction of the change. The changes are so slight that "no change" could also be considered a correct response, but that could opens up the possibility of "decreasing" being correct as well since all the trends are so close to zero. Even if "no change" was counted as a correct response, the results would not change significantly. The range of "no change" responses falls somewhere between 10 and 20% of responses. If these were included as correct responses, the overall findings of this work would be no different. For the questions about rainfall and the start of the *Maha* monsoon, the percentage of respondents who accurately perceive a change decreases from 41% who correctly perceive a decrease in rainfall during the *maha* season to only 4% who correctly perceive the earlier start to the *Maha* monsoon (Figure 4.7). Similarly to the changes in temperature, changes in rainfall have been very slight over the past 20 years, which makes identifying the trend very difficult without some kind of measurement equipment.

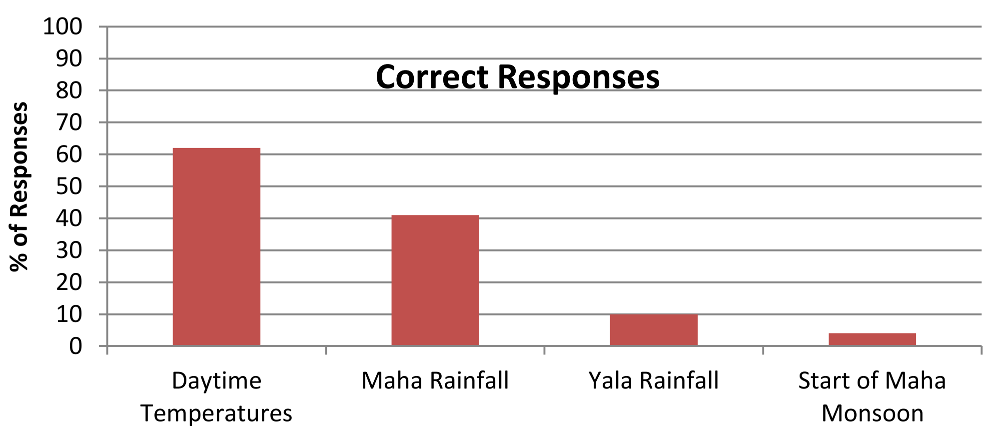

Figure 4.7 | Percentage of response who correctly perceived the measured changes in the climate.

Failure to correctly perceive changes in the environment can significantly reduce a farmer's ability to adapt. According to protection-motivation theory, if the farmer does not deem the risk of climate change high enough, he is unlikely to take adaptive action. The survey responses presented here suggest that farmers in Sri Lanka are unlikely to deem the risk of some climatic changes (i.e shifting monsoon timings) high enough to take action while also deeming other risks too high (i.e. decreases in precipitation). If this is the case, these farmers are potentially misallocating resources towards perceived threats that may not actually be threats while ignoring other, possibly more hazardous threats.

To assist farmers in identifying changes in their environment and to help spur adaptive action, a systematic forecasting program may be useful. In this same survey, 60% of participants said that the predictability of rainfall has decreased. As there is currently no seasonal forecasting program in Sri Lanka, many of the predictions that farmers are making are based on local or indigenous knowledge. A local non-governmental organization, Practical Action, is attempting to launch a more scientific seasonal forecasting program to help farmers identify what to expect for the upcoming growing season and to hopefully encourage adaptive behavior. The potential effects of this proposed seasonal forecasting program are explored more fully in Chapter 5 of this dissertation.

CHAPTER 5

SEASONAL FORECASTING AND FARMER BEHAVIOR

5.1. Introduction

Over the past 30 years, spatial and temporal patterns of precipitation and drought have been changing in Sri Lanka [*Jacobi et al.,* In preparation]. These changes are not just abstract phenomena – they have real consequences for the people and institutions of the country. Nevertheless, perceptions of the changes do not match the realities of the situation [*Carrico et al.*, In preparation]. For those dependent on the weather for their livelihoods, namely rice farmers, the combination of the uncertain climatic future and the disparity between perceived and actual changes in climate poses a great challenge to maintaining a sustainable lifestyle.

To help farmers, a local non-governmental organization, Practical Action, is planning on starting a seasonal forecasting program to provide actionable information to farmers prior to the growing seasons. Farmers currently receive only short-term (3-10 days) forecasts, which makes it difficult to truly plan for the upcoming growing season. A seasonal forecast would ideally better enable farmers to make more informed, adaptive decisions about what crops to grow, which varieties to use, and when to plant and harvest. Seasonal forecasts have proven to be effective at predicting rice yields in the Philippines [*Koide et al.*, 2013] and strong benefits of providing seasonal forecasts to farmers have been demonstrated [*Patt et al.*, 2004]. The forecasting skill (e.g. how accurately the forecast is able to predict the weather), and thus the usefulness of the forecast, that

Practical Action will be able to attain remains an open question. One study finds typical forecast skills of 18-45% [*Ungani et al.*, 2013]. Another seasonal forecasting tool developed specifically for Sri Lanka by the South Asian Association for Regional Cooperation (SAARC) Meteorological Research Centre (SMRC) was able to achieve hit scores, a measure of forecast skill, of 48 – 70 [*Basnayake et al.*, 2008]. There is also a strong relationship between precipitation and El Niño and the Southern Oscillation (ENSO) in Sri Lanka, which may make long-term forecasting easier [*Malmgren et al.*, 2003; *Zubair et al.*, 2008]. Nevertheless, achieving consistently good forecast skill will be a difficult task, especially given the observed changes in the weather patterns and changes likely to occur in the future.

During a recent research trip to Sri Lanka, and with the proposed seasonal forecasts in mind, we observed farmer behavior that became the motivation for this study. When visiting officials in the capital and farmers in their fields, we saw that the preference is to always grow rice. This can partly be explained by a strong national ethic of being self-sufficient in rice, the staple food of the Sri Lankan diet. While the pride in growing rice is understandable, the economics do not always make sense. A farmer could make considerably more money by growing a cash crop, such as onions [*SEPC*, 2012]. The view of some officials in the city was that farmers always want to grow rice because they are lazy; cash crops often require more labor than rice. Our observations in the field belie the stereotypical attribution of laziness as a reason for a preference for growing rice. One possibility for the farmers' preference for rice stems from the fact that even in a bad year, rice still yields enough to enable them to feed their families. Rice can be kept and stored, while cash crops must be sold almost immediately.

These different explanations for the same action raises the question of the decision model that farmers are using when choosing what crops to grow – are the farmers trying to maximize their gains or are they exhibiting loss aversion that leads to more rice growing? These questions map onto the two prevailing models of choice: expected utility theory and prospect theory.

Expected utility (EU) theory is the starting point for an understanding of decision making under uncertainty and a foundation of economic theory. Under EU, actors calculate the expected value - the sum of all possible outcomes of a decision, multiplied by their respective probabilities – for each decision option. When making a decision under EU, the actor attempts to maximize his or her expected value. Assuming that the actor's risk attitude is risk neutral, a utility function can be modeled with a one-unit increase in wealth corresponding to a one-unit increase in utility (Figure 5.1).

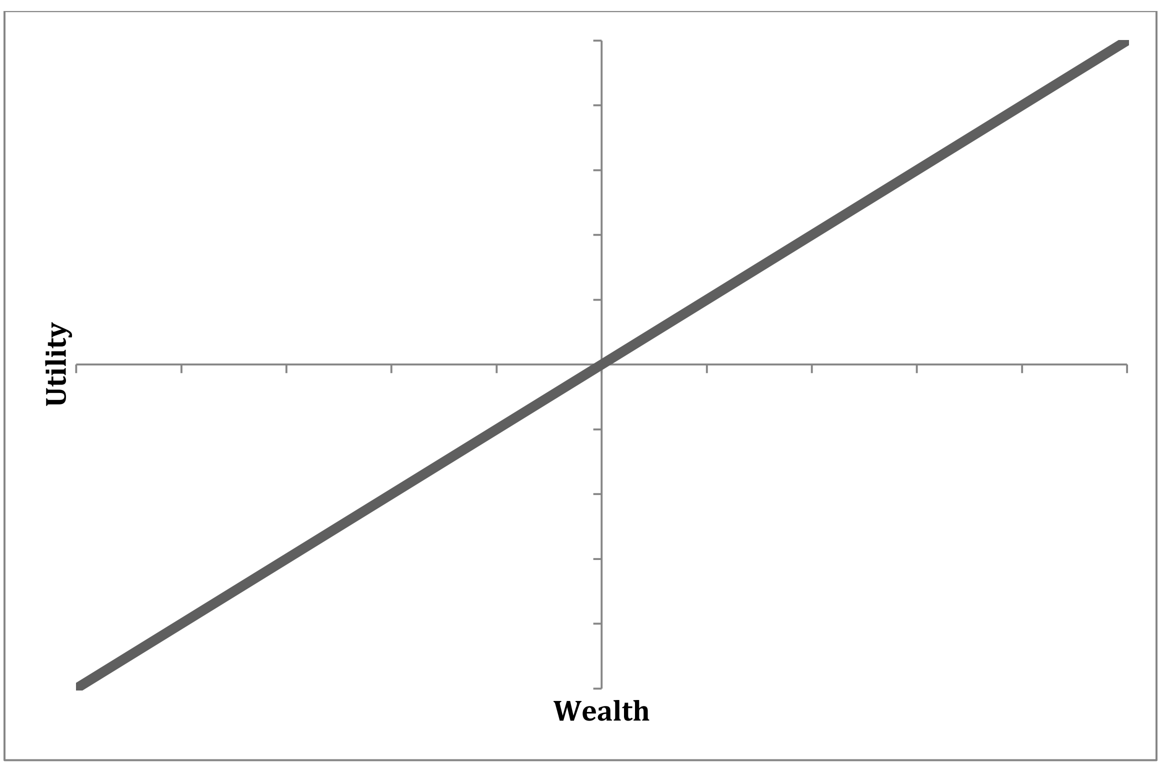

Figure 5.1 | Expected Utility curve

Two psychologists, *Kahneman & Tversky* [1979], developed prospect theory, which is a widely adopted description of how people evaluate risk, at least in controlled settings [*Barberis*, 2013]. Prospect theory has three distinguishing components. The first is reference dependence. Utility is gained from changes in wealth with respect to a reference point. For example, if one is expecting a raise at work, one sets one's reference to the new salary including the raise. If the raise doesn't come through, one experiences that as a loss even though one is still making the same amount of money as before because one's current salary is now below the reference point. The second component is loss aversion. Actors weight losses more heavily than gains. The third is diminishing sensitivity. As losses and gains continue to increase, the change in utility becomes smaller.

These three differentiators can be illustrated in the shape of the prospect theory utility curve (Figure 5.2). The origin is the reference point, the loss aversion can be seen in the steeper negative slopes, and the diminishing sensitivity is clear in the flattening of the curves. The prospect theory utility function is governed by two equations:

$$\text{if } x \geq 0 \qquad U = x^{\alpha} \text{ , and} \tag{5.1}$$

$$\text{if } x < 0 \qquad U = -\lambda(-x)^{\alpha} \text{ ,} \tag{5.2}$$

where x is the gain or loss relative to the reference point, U is the utility, α is the diminishing sensitivity parameter, and λ is the loss aversion parameter.

In this study, we aim to explore the relationship between decision models and the forecast skill of seasonal forecasting programs. For this investigation, we use an agent-based model (ABM).

Our goal in this study is not to simulate existing or proposed systems with extensive data or empirically grounded observations. Instead, we use the ABM as a means of generating hypotheses that can then be tested in the field.

ABMs are capable of simulating heterogeneous mixtures of agents and their environment. Agents can be anything from animals, to people, to corporations, and can have static and dynamic attributes. Models can consist of multiple types of agents, and agents within the same class can be heterogeneous. One of the main features of ABMs is the interaction between agents and their environment.

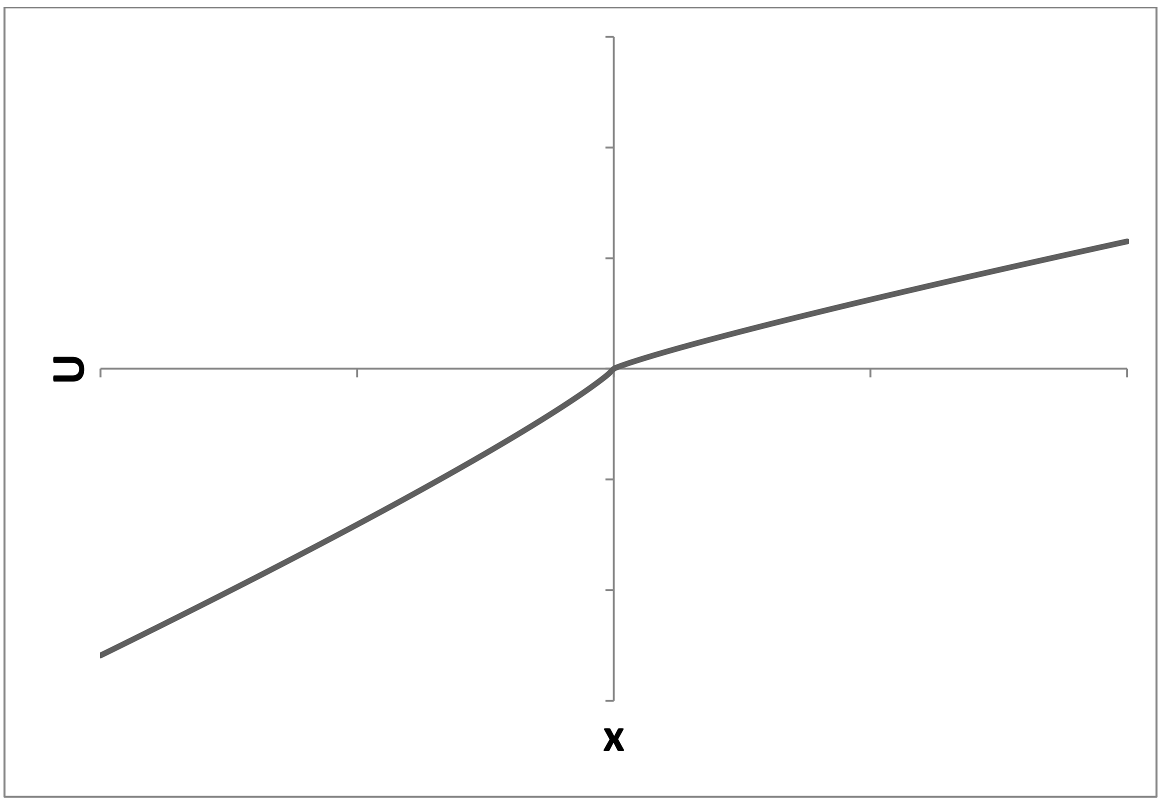

Figure 5.2 | Prospect theory curve. x is the difference from the reference point and U is the utility.

ABMs have recently been fruitfully applied to research on human-environment interactions and in agricultural research [*Schreinemachers & Berger*, 2011; *Berger*, 2001; *Bert et al.*, 2011]. For instance, *Ziervogel et al.* [2005] performed a similar study, though without varying the decision model component, and found that forecasts that do not achieve skill levels of 60-70% are unlikely to benefit farmers, and may even do more harm than good.

5.2. Methods

An agent-based model is used to test the influence of varying forecast skill, decision model, and a number of other variables (Table 5.1) on the cultivation decisions of farmers. The model is run 40 times for 110 steps at each combination of variables, resulting in 28,160 total runs and over 3 million simulated growing seasons.

Table 5.1 | Variables tested

Variable	Range
Prospect Theory as decision model	True or False
Voting to decide cultivation	True or False
Risk Parameter Heterogeneity	True of False
Farmer Skill Heterogeneity	True or False
Reference Point	Both crops, Rice, Onions, Community
Forecast Skill	0 – 1 in steps of 0.1

5.2.1. Study Area

The model is designed to capture key stylized features the Anuradhapura district of Sri Lanka. Anuradhapura is one of the country's largest rice producing districts and is located in the heart of the dry-zone. We choose to base our study here due to the availability of data in the region and the proximity to ADAPT-SL survey sites. The ADAPT-SL project, a National Science

Foundation sponsored project based at Vanderbilt University, is studying how small farming communities adapt and respond to changes in climate.

5.2.2. Data

Temperature and precipitation data at the Anuradhapura meteorological station are provided by the Meteorological Department of Sri Lanka. We calculate a time series of the Palmer Drought Severity Index (PDSI) by applying the tool provided by *Jacobi et al.* [2013]. We analyze the PDSI time series to determine the frequency of dry, normal, and wet years and find that normal years occur 60% of the time and dry and wet years each occur 20% of the time.

In the model simulations, farmers choose between rice and onions. Data on crop yields and their responses to water stress are collected from a variety of sources. Typical Sri Lankan rice and onion yields, as well as the cost of cultivation and farm-gate prices, are taken from data collected by the Agricultural Department of Sri Lanka [*SEPC*, 2012]. The data for *Yala* (the spring monsoon) years are used. Since only two years of data are available, the yields and associated profits and losses are systematically adjusted to better reflect the behavior of Sri Lankan farmers.

To adjust the rice yields we assume a maximum potential yield of 7 mt/ha. This is a value presented by *Bouman & Tuong* [2001] for an agriculturally similar site in India. Using rainfall data for Anuradhapura and data on the amount of irrigation water delivered to a community near Anuradhapura [*MASL*, 2013], as well as an analysis of relative yield as a function of water delivered by *Hijmans & Serraj* [2008], we are able to adjust the rice yields to obtain values for dry, normal, and wet years (Table 2). For example, the total water delivered to fields during a normal year by both rainfall and irrigation is approximately 700mm per year. Using the curve presented by *Hijmans & Serraj* [2008], we get a relative yield of 80% of the maximum potential yield, which in our case is 5.6 mt/ha. This value is very similar to values reported by the Agricultural Deparment of Sri Lanka.

Table 5.2 | Crop yields and profits used in the model

Weather	Dry		Normal		Wet	
	Yield (mt/ha)	Profit (Rs.)	Yield (mt/ha)	Profit (Rs.)	Yield (mt/ha)	Profit (Rs.)
Rice	2.8	42,616	5.6	85,232	6.3	95,886
Onions	3.7	180,005	1.5	72,975	0	-131,000

Data for onion yields is much sparser. Onions have a lower sensitivity to drought than rice [*Brouwer & Heibloem*, 1986], so it is assumed that they will do best when the weather is dry. Yields measured by the Agricultural Department are thus assigned as the “dry” yields (Table 2). As the amount of water delivered to the crops increases past some threshold, it is assumed that rot and pests will decrease the yields. Ultimately, in a wet year, there is so much water that the fields flood and the entire crop is lost.

5.2.3. Model Processes

The agent-based model used in this study is built in the agent-based modeling platform, NetLogo [*Wilensky*, 1999]. The general process of the model is illustrated in Figure 5.3.

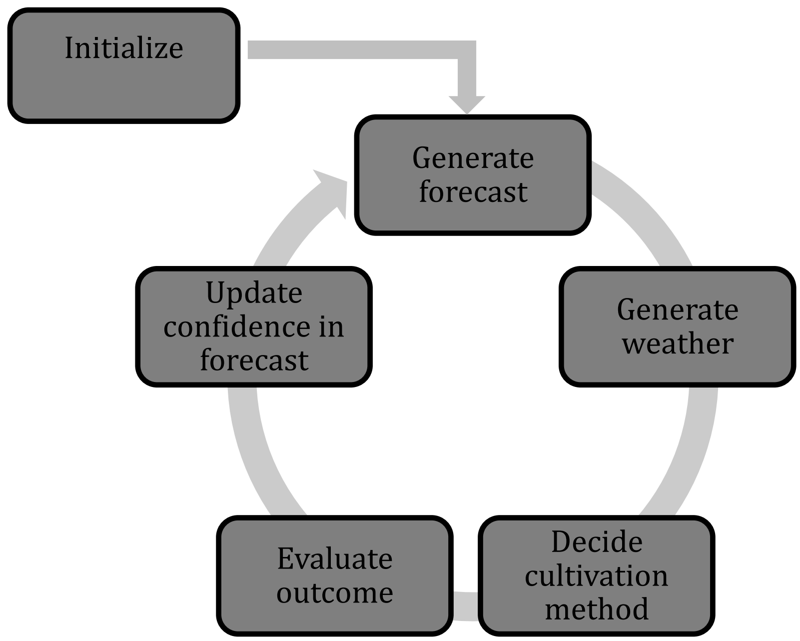

Figure 5.3 | General process of the agent-based model

When the model is initialized, 49 different farmers are created with initial values for their wealth, prospect theory parameters, and individual values for typically attained yields of rice and onions. 49 farmers are used in an attempt to minimize the computation time while still achieving a sufficient sample size. The values of the prospect theory parameters and typical yields can either be the same across all farmers or heterogeneous across the population, depending on what the modeler wishes to test. Additionally, each farmer is given an initial trust in the forecast. This trust, or confidence, in the forecast is initially set to zero – a farmer expects the weather to occur at the historic frequencies of 20% dry, 60% normal, and 20% wet, regardless of the forecast.

During initialization, global values that influence all farmers are set. These values include a global forecast confidence that is based on the forecast skill that is being tested. This confidence is the probability of getting a certain type of weather for a given forecast (p(w|f)) (Table 3). At zero skill, the probability of getting a certain type of weather is the same as the historic norms.

At perfect skill, the matrix is a 3x3 with ones along the diagonal. Each farmer uses the same matrix to determine his trust in the forecast, but the farmers' matrices are all initially set with zero skill while the global one is based on the actual forecast skill.

Table 5.1 | Probability of weather given forecast. p_x is the historic probability of that weather type. s is the forecast skill.

		Weather		
		Dry	Normal	Wet
Forecast	Dry	$p_d + s(1-p_d)$	$(1-s)p_n$	$(1-s)p_w$
	Normal	$(1-s)p_d$	$P_n + s(1-p_n)$	$(1-s)p_w$
	Wet	$(1-s)p_d$	$(1-s)p_n$	$p_w + s(1-p_w)$

Once the model is set-up, it is run for 70 steps to initialize the farmers' memories. Each step is one growing season. Each farmer has a memory of his yield and income for the last five instances of a given forecast. The 70 initialization steps are excluded from the analysis but are necessary to populate the memory with actual values.

When running the model, the first step is the generation of the forecast, which are categorical and are just given as dry, normal, or wet. This model choice realistically represents the type of forecast that may be delivered to farmers. Forecasts are generated with the same probabilities as the historic weather probabilities. Dry forecasts occur 20% of the time, for example. Once the forecast is generated, the actual weather that occurs is determined by using the actual forecast skill and the confidence matrix outlined in Table 3. The farmers know what the forecast is, but they do not know what the actual weather will be.

After the forecast and weather are determined, each farmer decides which of the two crops – rice or onions – he will grow based on the forecast and his confidence in the forecast. The farmer uses one of two methods to decide his cultivation, either expected value or prospect theory, depending on the modeler's choice. When using prospect theory, the farmer first sets his reference point based on the memory of his average income over the last five times the given forecast occurred. Making predictions with a reference-dependent decision model such as prospect theory requires the modeler to specify what the relevant reference point is and how agents estimate it. Koszegi and Rabin (2006) propose a decision model where a person's reference point is the probabilistic belief she has about outcomes. There are three different individual memory types and one community memory type we use to set the reference point under different runs to experiment with the effects of how the reference point is estimated. The three individual memory types are the average income from growing either crop, just rice, or just onions over the last five instances of the given forecast. The community memory type is the average of the median income in the community over the last five instances of the given forecast.

Once the reference point is set, the farmer calculates his expected utility for each crop. He does this by calculating how much money he would make growing both rice and onions under the three weather scenarios. If using prospect theory, the farmer subtracts the reference point from the expected income and converts that value to utility using Equations 5.1 and 5.2. The farmer then weights the three expected utilities – one each for dry, normal, and wet – by his personal values of the probability of the weather scenarios given the forecast. In mathematical notation, this can be expressed as

$$X = \sum p_{w_i|f} x_i \,, \qquad (5.3)$$

where X is the weighted sum of expected utilities, $p_{wi|f}$ is the probability of weather i given the forecast, and x_i is the expected utility under weather i. The farmer then chooses to grow the crop that provides the largest expected utility. If farmers are voting, the count of rice and onion growers is taken and all farmers are assigned the cultivation method of whichever count is larger.

Once all the farmers have decided what crop they will grow, the season is simulated and each farmer calculates his yield and income based on the crop he choose and the actual weather. The yield and associated income is based on the personal typical yields of each farmer but includes some randomness to simulate variations in pests and other factors that are generally determined by chance.

Before moving on to the next step, the farmers update their confidence in the forecast. This is done through Bayesian updating. Each farmer has three matrices used in the Bayesian updating – my-pa, a 1x3 matrix which is the probability of each type of weather; my-m, a 3x3 matrix where $m_{i,j}$ is the conditional probability of forecast *i* if the actual weather will be *j*; and my-confidence, a 3x3 matrix like the one presented in Table 3. When updating his trust in the forecast, a farmer first updates my-pa using a 10-year moving average,

$$pa(t+1) = 0.9 * pa(t) + 0.1 * I(w)\ , \tag{5.4}$$

where *I* is the identity matrix, w is the index for the weather (0 for dry, 1 for normal, and 2 for wet), and *I(w)* is the w'th row of the identity matrix.

After updating my-pa, the farmer then updates my-m. If the weather is *j*, column *j* of my-m is updated with a 10-year moving average using the same process as in Equation 5.4. Finally, the my-confidence matrix is updated using Bayes' theorem,

$$C_{i,j}(t+1) = \frac{m_{i,j}(t+1) * pa_j(t+1)}{\sum_k m_{j,k}(t+1) * pa_k}\ , \tag{5.5}$$

where i is the forecast, j and k are the weather, and C is the my-confidence matrix.

After all farmers have updated their confidence in the forecast, the numbers of farmers who grew rice and onions are outputted to a table and the process starts over again. The model is run 40 times for 110 steps (70 for initialization, 40 for simulation) for every combination of variables (Table 5.1).

5.2.4. Analysis

Model outputs are initially divided into 64 different groups, one for each combination of variables excluding forecast skill (our primary continuous independent variable of interest). Quadratic curves are fit to the outputs in each group using a least squares fit. To assess the effect of prospect theory on the outputs, the coefficients from the quadratic fits are grouped by prospect theory and expected value. The coefficients of the squared term are compared using two-sample t-tests with null hypotheses of equivalent means. Comparing the coefficients of the squared terms allow for an assessment of the convexity or concavity of the curves.

Visual inspection of the outputs reveals that behavior during dry forecasts is the main area of interest, due a large shift in the fraction of rice growers from low to high skill. A logistic regression is run on all the outputs that were generated when there was a dry forecast. A logistic-binomial model is used for this regression, allowing us to model the number of “successes” out of N trials, with the probability of success being fit to a logistic regression [*Gelman & Hill*, 2007]. In the case of this model, the "successes" are rice growers and N is equal to the total number of farmers.

The agent-based model simulations are then re-run with prospect theory, voting, risk parameter heterogeneity, and skill heterogeneity all set to true and with varying risk parameters of alpha (0.06, 0.88, 1.00) and lambda (1.00, 2.25, 3.50). Quadratic curves are fit to these outputs and a logistic regression is performed using the logistic-binomial model as well.

For an economic analysis, the optimal crop choice is determined by calculating the weighted sum (by the probability of weather for a given skill level) for both rice and onions and then taking the larger of the two. The actual profit for PT and EV is calculated by determining the fraction of farmers that grew rice and onions at a skill level and then multiplying that fraction by the weighted sum of profits for rice and onions. The difference between EV and PT is taken to determine the amount of money being either gained or lost compared to the counterfactual of the use of the other decision model.

5.3. Results

When looking at the general behavior of the farmers, there is not much variation between both the prospect theory and expected value curves and across the different levels of forecast skill (Figure 5.4). Looking at only the behaviors observed when a dry forecast occurs, however, reveals an interesting pattern of decreasing numbers of rice growers as forecast skill increases

(Figure 5.5). The mean prospect theory values for both all forecasts and just the dry forecasts are consistently higher than the mean expected value values.

A logistic regression on the number of rice growers when there is a dry forecast confirms that forecast skill and whether or not the farmer is using prospect theory to make his decisions are the main predictors for the probability of growing rice in a given year (Table 5.4). Fitting quadratics to the data also confirm that prospect theory and forecast skill are the main predictors of rice growing, though the memory type used to set the reference point does seem to have an effect on the shape of the prospect theory curve (Figures 5.6 - 9).

Another logistic regression run on results generated by varying the prospect theory parameters (Table 5.5) and visual inspection (Figure 5.10) reveals that the prospect theory parameters have an effect on the growing decisions of the farmers.

The economic impact of using the two different decision models is also made apparent (Table 5.6).

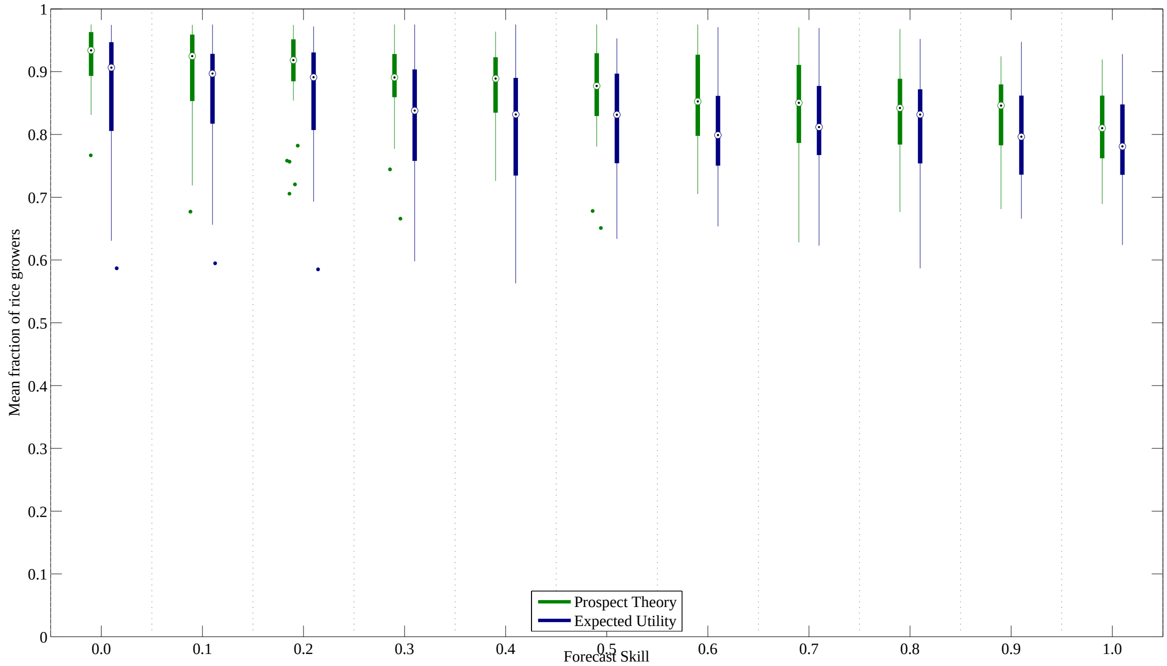

Figure 5.4 | Box and whisker plots of model outputs under all forecasts with voting turned off and risk and skill heterogeneity turned on. The central mark is the median, the edges of the boxes are the 25th and 75th percentiles, and the whiskers cover 99.3% of all the outputs.

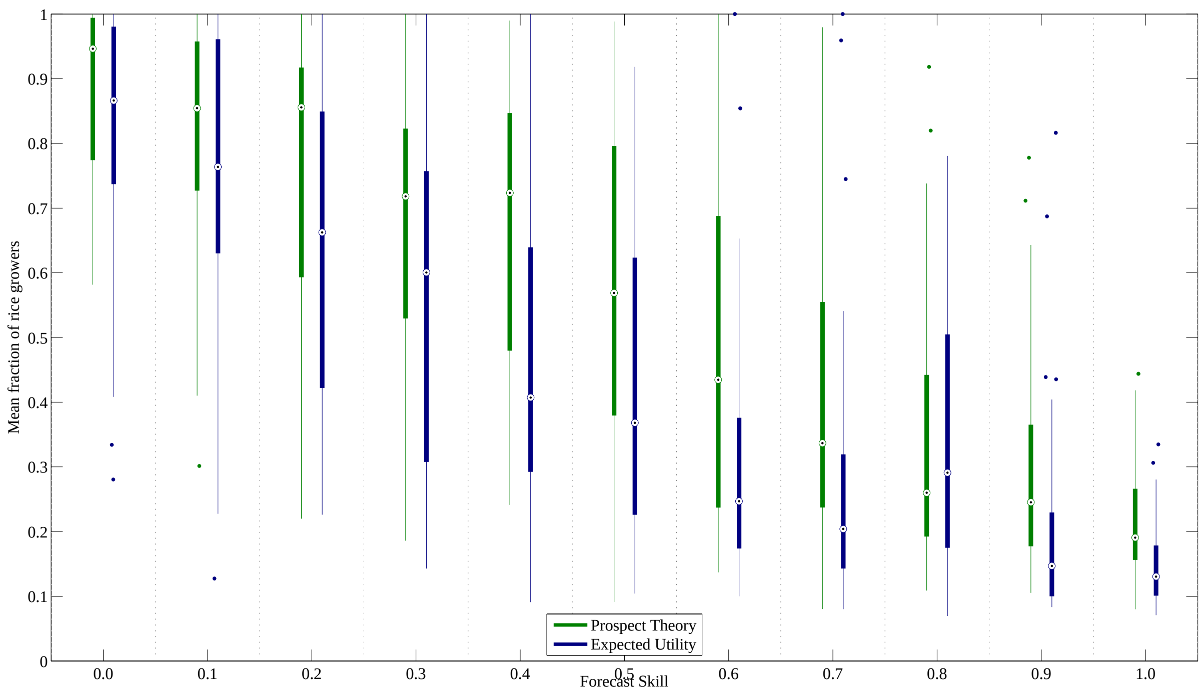

Figure 5.5 | Box and whisker plots of model outputs under only dry forecasts with voting turned off and risk and skill heterogeneity turned on. The central mark is the median, the edges of the boxes are the 25th and 75th percentiles, and the whiskers cover 99.3% of all the outputs.

Table 5.4 | Logistic regression of dry forecast behaviors. The outcome of the logistic regression is the probability of growing rice.

Predictor	Beta	SE	*p*	Beta / 4
Constant	1.405	0.014	0.000^{++}	0.351
Prospect Theory	0.45	0.009	0.000^{++}	0.112
Voting	0.02	0.009	0.030^{+}	0.005
Risk Parameter Heterogeneity	-0.015	0.009	0.105	-0.004
Farmer Skill Heterogeneity	-0.004	0.009	0.681	-0.001
Memory Type	-0.009	0.004	0.023^{+}	-0.002
Forecast Skill	-3.314	0.016	0.000^{++}	-0.829

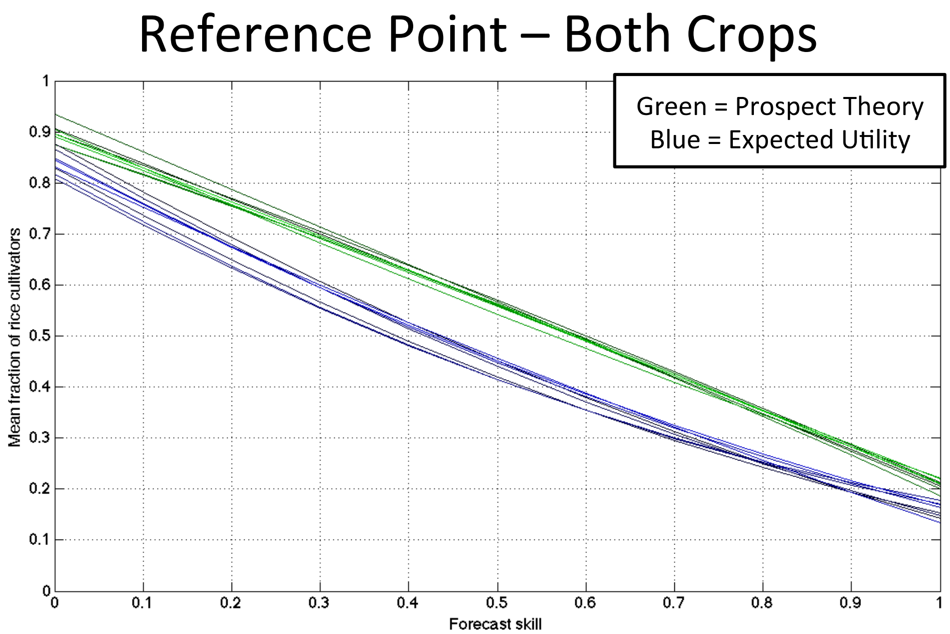

Figure 5.6 | Quadratics fit to model outputs. Each line represents a different combination of the risk heterogeneity, skill heterogeneity, and voting variables.

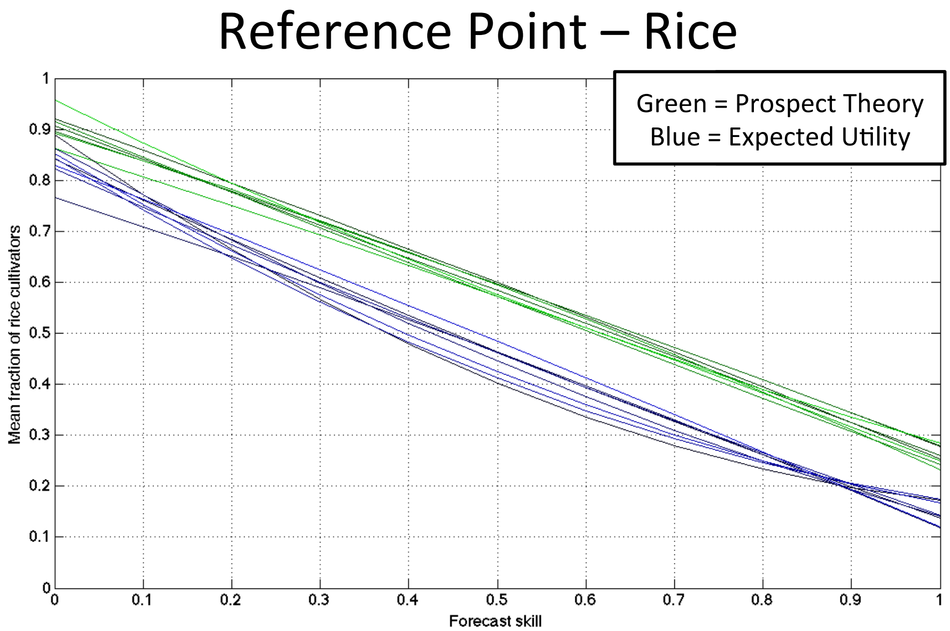

Figure 5.7 | Quadratics fit to model outputs. Each line represents a different combination of the risk heterogeneity, skill heterogeneity, and voting variables.

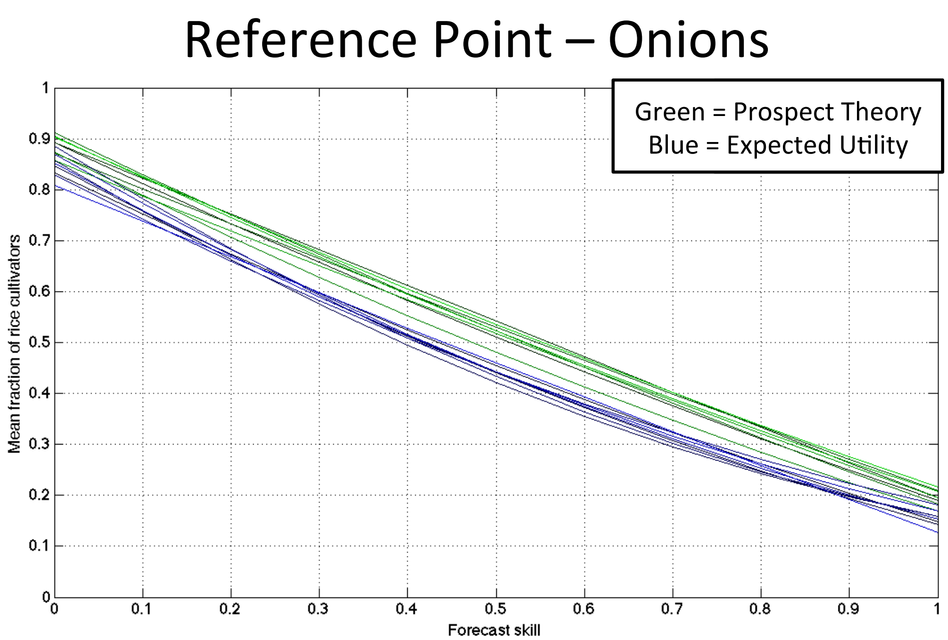

Figure 5.8 | Quadratics fit to model outputs. Each line represents a different combination of the risk heterogeneity, skill heterogeneity, and voting variables.

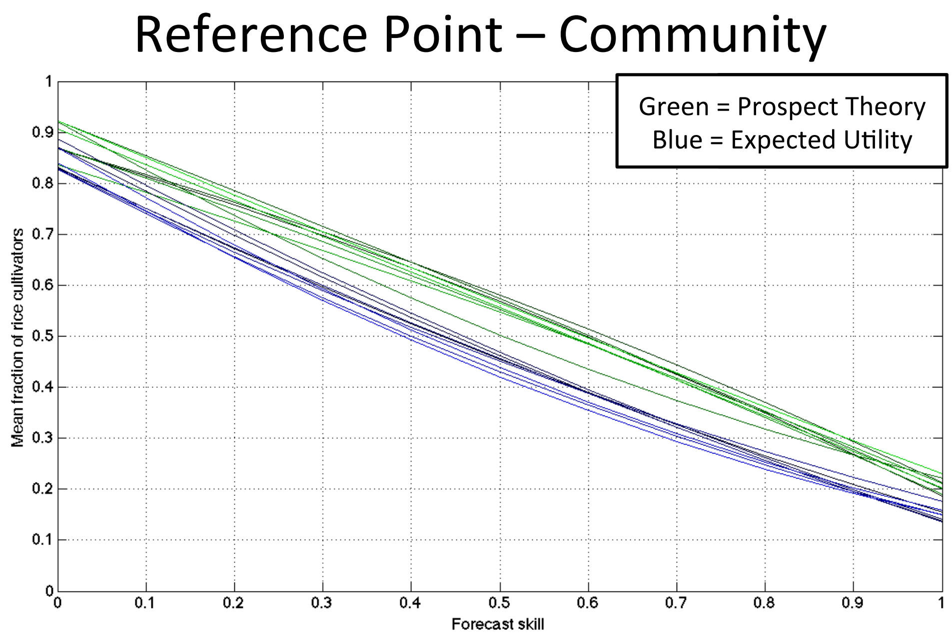

Figure 5.9 | Quadratics fit to model outputs. Each line represents a different combination of the risk heterogeneity, skill heterogeneity, and voting variables.

Table 5.5 | Logistic regression coefficients of dry forecast behavior with varying prospect theory parameters. The outcome of the logistic regression is the probability of growing rice.

Predictor	Beta	SE	*p*	Beta/4
Constant	1.047	0.031	0.000^{++}	0.262
Memory Type	-0.046	0.005	0.000^{++}	-0.011
Lambda	0.353	0.005	0.000^{++}	0.088
Alpha	-0.203	0.031	0.000^{++}	-0.051
Forecast Skill	-3.142	0.018	0.000^{++}	-0.786

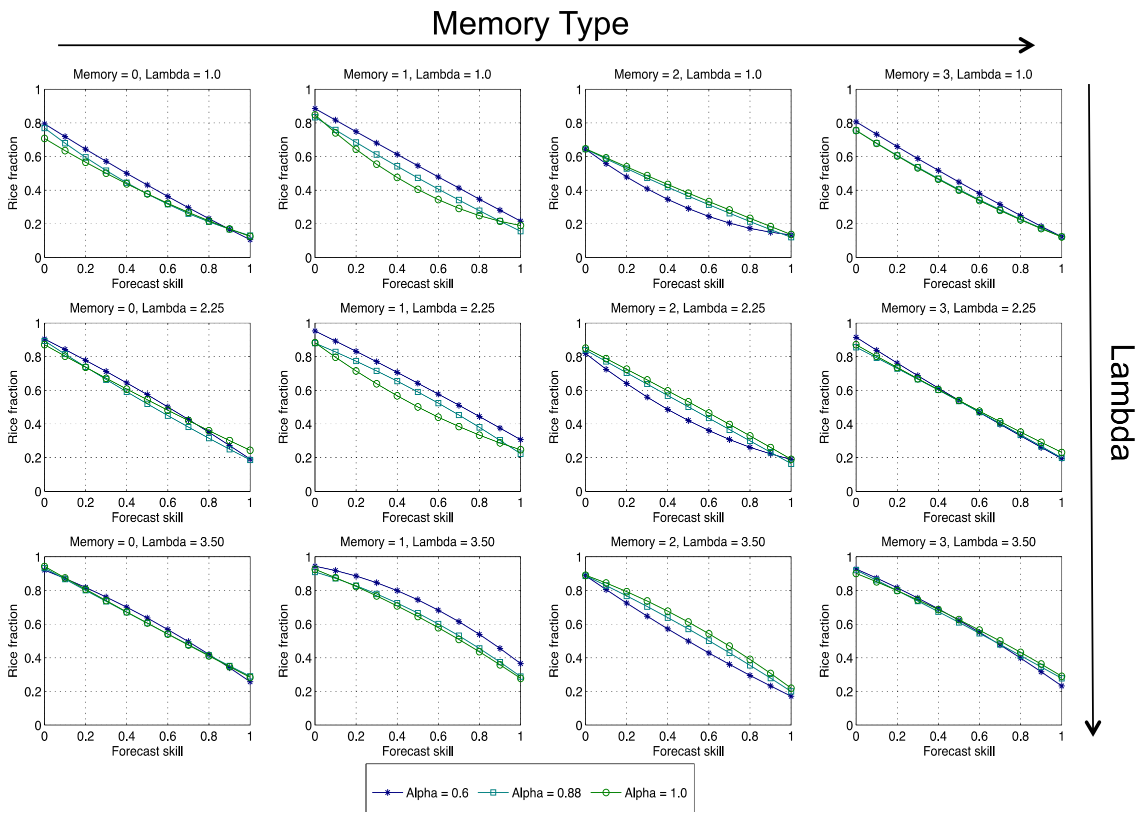

Figure 5.10 | The influence of the memory type used to set the reference point and the prospect theory parameters on the fraction of rice growers. Memory of 0 is both crops, 1 is rice, 2 is onions, and 3 is community.

Table 5.6 | Difference in Sri Lankan Rupees between the expected value of the average expected utility and prospect theory quadratic fits at each level of forecast skill.

Forecast Skill	Reference Point			
	Both	Rice	Onions	Community
	EU - PT	EU - PT	EU - PT	EU - PT
0	-1,440	-1,694	-1,014	-1,019
0.1	-731	-812	-485	-571
0.2	728	796	470	595
0.3	2,665	2,928	1,701	2,245
0.4	4,814	5,381	3,060	4,146
0.5	6,903	7,956	4,399	6,065
0.6	8,665	10,449	5,568	7,769
0.7	9,830	12,660	6,419	9,025
0.8	10,128	14,387	6,804	9,599
0.9	9,292	15,428	6,574	9,258
1	7,051	15,582	5,581	7,770
Total Difference	57,905	83,062	39,078	54,883

5.4. Discussion

The decision model used by farmers has important implications for both the farmers themselves and for Practical Action and their seasonal forecasting program. When looking at the behavior across all forecasts, farmers tend to grow rice around 90% of the time across both decision models and all levels of forecast skill (Figure 5.4). Yet, when looking at just the behavior observed under dry forecasts, the differential effects of the decision model and the level of forecast skill become obvious (Figure 5.5). The number of farmers growing rice decreases as forecast skill increases. Additionally, the range of responses under dry forecasts at each level of forecast skill is much larger than the range of responses under all forecasts. The dry forecasts are also the most important aspect of the proposed forecasting program.

A logistic regression of outputs under dry forecasts confirms that the decision model and the skill of the forecast are the main drivers behind the probability of growing rice in a given year (Table 5.4). Fitting quadratics to the outputs under dry forecasts provides an intuitive visual confirmation of this result and also reveals the slight effect that the reference point can have on the number of rice growers (Figures 5.6-9).

The differences observed across the decision models and the forecast skills under dry forecasts can be explained almost entirely by the loss aversion, a key component of prospect theory. Under both decisions models, farmers are evaluating their expected utility for all three weather scenarios and weighting those expected utilities by their personal probabilities of the different weather scenarios. At low forecast skill, the personal weather probabilities are close to the historic probabilities of 0.2 for dry, 0.6 for normal, and 0.2 for wet. Thus, the large loss that would be experienced if growing onions during wet weather and the lesser profits of growing onions during normal weather (Table 5.2) play a much larger role in the decision process than they would at forecast skills of 0.8 – 1.0 where the personal weather probabilities are closer to 0.9 for dry and 0.05 for normal and wet. Under prospect theory, these potential losses are then multiplied by the loss aversion parameter, which increases their weight. The increased weight of the losses lowers the total expected utility for onions under prospect theory and results in more farmers choosing to grow rice. Since gains and losses are weighted equally under expected utility theory, farmers are less sensitive to the potential losses that could be experienced by growing onions and are thus more likely to grow onions in the hope of achieving the dramatically higher profits available from growing onions under dry weather.

The decision model used by the farmers can have serious economic impacts (Table 5.6). At the lowest levels of forecast skill, the loss aversion exhibited by farmers using prospect theory works in the farmers' favor. The farmer makes more money by using prospect theory when the weather is most uncertain. By being loss averse, they are less likely to grow onions and don't expose themselves to total crop loss if the weather is wet. Expected utility theory has long been considered the decision model of the rational, wealth-maximizing actor [*Tversky & Kahneman*, 1986], so it is interesting to note that when the forecast has the least amount of skill, prospect theory actually does a better job of maximizing wealth, albeit in a very constrained scenario.

This effect disappears once the forecast gains a modicum of skill. At levels of skill that can be feasibly achieved (0.5 – 0.8), the difference between expected utility and prospect theory, on average, can be as much as 14,000 SLR per growing season (Table 5.6). The volatility of a farmer's income is expected to be higher when using expected utility theory because he will be betting wrong more frequently, but nevertheless, on average, he will make more money every growing season when the forecast has decent skill.

How the farmer sets his reference point also seems to have an effect on both the fraction of farmers who grow rice using prospect theory and on the economic differences between the decision models. When a farmer is using either the memory of both crops or the memory of how the community performed, the fraction of rice growers and the economic impacts are about equal. When the reference point is set to the average income when growing rice under the given forecast, the fraction of rice growers increases, as does the economic disparity. The opposite is true when the memory of onions is used to set the reference point (Figures 5.6-9; Table 5.6).

How the reference point affects the decision to grow rice under prospect theory is not yet fully understood and will require more analysis to describe the details of the process. Nevertheless, the behaviors observed by changing the reference point in the models offer the possibility of a significant contribution to the prospect theory literature, as how people set their reference points remains an important open question, and is likely context dependent [*Kőszegi & Rabin*, 2006; *Camerer*, 1998; *Barberis*, 2013].

The parameters that shape the prospect theory curve also have an impact on the fraction of rice growers (Figure 5.10). A logistic regression reveals the importance of the prospect theory parameters on the probability of growing rice (Table 5.5). As the loss aversion parameter (λ) increases from loss-neutral (1.00) to very loss averse (3.5), the convexity of the curves increase (Figure 5.10). This means that more farmers are growing more rice at almost all levels of forecast skill. This pattern of behavior makes sense, since growing onions opens the farmer up to the potential for a large loss. As the diminishing sensitivity parameter (α) increases from rapidly diminishing sensitivity (0.66) to no diminishing sensitivity (1.00), there are smaller, but still noticeable, changes. Except for in the case of onions as the reference point, a lower α almost always results in a higher fraction of rice growers. This pattern also makes sense, as the large gains that could be achieved by growing onions when the weather is dry become less important with rapidly diminishing sensitivity.

This work is conducted as part of a larger, multi-year, multi-disciplinary project that is working to understand how farming communities in Sri Lanka can adapt to changes in their climate and the factors that influence those decisions. As the project progresses, field research will need to be conducted that attempts to identify both the decision model used and the parameters of the model, especially given our finding that the parameter make a significant difference. Typical parameters for prospect theory are 2.25 for lambda and 0.88 for alpha, but these values were measured with subjects primarily in the U.S. [*Tversky & Kahneman*, 1992]. If prospect theory value functions are estimated on choices of Sri Lankan farmers, their values may be very different.

Understanding the farmers' decision model is especially important for Practical Action and its nascent seasonal forecasting program. If the goal of the program is to get more farmers to grow onions or some other cash crop during dry years, the decision model used can have a large impact on the forecast skill required. To get half of the farmers to grow onions instead of rice under a dry forecast, a forecast skill of around 0.45 is required if the farmers are using expected utility theory. In order to achieve the same rate of rice growers using prospect theory, the forecast skill would need to be close to 0.6. Given that the best forecast skill found in a study by *Ungani et al.* [2013] was 0.45, it is clear that a 0.15 increase in forecast skill is not trivial, especially with the dynamic nature of the Sri Lankan climate. Additionally, the forecast skills of 0.5 – 0.7 reported by *Basnayake et al.* [2008] can have large economic impacts on the farmers. As the forecast skill increases to 0.7 or 0.8, the difference between returns using expected utility and prospect theory grow to around 10,000 SLR (Table 5.6). The decision model used can thus have a large impact on the success of the seasonal forecasting program by either decreasing or increasing the forecast skill required to achieve the goals of the program.

As seasonal forecasts and other programs intended to help the people of developing nations adapt to climate uncertainty are introduced, serious attention must be paid to how people make decisions. As has been demonstrated here, the mental tools people use can determine the success or failure of an adaptive program.

CHAPTER 6

SUMMARY

6.1. Future Work

The work presented in this dissertation will hopefully serve as a launching pad for many future studies. The PDSI tool enables easy calculation of the PDSI for varying temporal and spatial scales. This allows for an analysis of the effects of downscaling drought indices to the local level [*Duncan et al.*, In Submission]. Further work is also needed on the study of perceptions of environmental change. Larger sample size surveys have been or will be conducted. The responses to these surveys, along with more rigorous meteorological assessments, can be used to better understand how people are perceiving and adapting to changes in their climate. These results can then be used to research and inform adaptation policy.

The agent-based model presented in Chapter 5 can be expanded in a number of ways. First, as more data is collected, the complexity of the model can be increased to better reflect observed behaviors. This could take the form of adding a third decision model or changing the trust updating procedure to better reflect how people actually update their perceptions. Second, the interactions between the farmers can also be made more complex. In the current model, farmers are making their decisions independent of the other farmers. This is not really the way it works in real life. Future iterations of the model should include more complex interactions between the farmers when making their decisions. Third, based on data collected by others on the project, the ABM can be used to model other observed phenomena. These models can remain at the farmer level, or decision making processes of government agencies can be modeled. Fourth, ABMs are excellent for hypothesis generation, and simple models that are capable of producing interesting hypotheses can be built quickly. Simulation models are much harder to build and require extensive amounts of data that is not currently available. Finally, ABMs allow NGOs like Practical Action to roughly evaluate their programs before implementation. If they discover that their forecast skill will be on the order of 0.6 – 0.8, an ABM allows them to get a rough estimate of the benefits or costs of the program and how it may impact farmers.

The weather patterns work can also be extended. By using the tool for calculating the Palmer Drought Severity Index (PDSI) presented in Chapter 2, the analysis presented here can be furthered to identify shifts in the spatial and temporal patterns of Sri Lankan drought. The PDSI uses inputs of precipitation, temperature, and a constant soil term, the Available Water Capacity (AWC), which is a measure of how much water the soil can hold. While changes in precipitation patterns have already been identified in the study presented here, studying patterns of drought may help to reveal how those changes interact with changes in temperature and the varying soil types found in Sri Lanka.

Work on this study has already started [*Gunda et al.*, In preparation]. Temperature and precipitation data from 13 stations provided by the Meteorology Department of Sri Lanka, as well as AWC values calculated based on soil types, were fed into the PDSI tool to calculate a monthly time series of PDSI values from 1881 to 2011. Principal component and factor analyses were then performed on the data in a manner identical to methods described above.

Table 6.1 | Variance explained by the first and second eigenvectors. Typical Maha (bolded) and Yala (italicized) months are highlighted.

	Percent Contributions					
Eigenvector	1			2		
Time Period	1881-1980		1981-2011	1881-1980		1981-2011
Variance Explained	35.7		36.9	12.0		15.0
Monthly Contributions	1881-1980	Change	1981-2011	1881-1980	Change	1981-2011
January	**41.97**	**4.02**	**45.99**	**11.27**	**-0.69**	**10.58**
February	**46.38**	**12.67**	**59.05**	**10.77**	**-2.24**	**8.53**
March	47.67	11.41	59.08	9.20	-0.12	9.08
April	36.83	14.14	50.97	9.07	0.77	9.84
May	*37.51*	*-4.01*	*33.50*	*10.44*	*5.81*	*16.25*
June	*30.71*	*-4.12*	*26.59*	*12.21*	*8.04*	*20.25*
July	*30.72*	*2.88*	*33.60*	*12.78*	*5.42*	*18.20*
August	*32.07*	*-2.6*	*29.47*	*14.45*	*3.61*	*18.06*
September	*34.79*	*-2.16*	*32.63*	*14.43*	*-0.08*	*14.35*
October	26.78	-7.28	19.50	14.80	3.19	17.99
November	**28.38**	-6.95	**21.43**	**12.91**	**7.14**	**20.05**
December	**34.18**	**-3.04**	**31.14**	**12.10**	**5.13**	**17.23**

Principal component analysis reveals both spatial and temporal changes in the patterns of temporal variability of drought. From 1981 – 2011, the first eigenvector accounts for more than half of the variability in drought for February, March, and April (Table 3.4), an increase of 11-14 percentage points. There is also a clear shift towards the north of the country, indicating more variable drought in the dry zone during the last 30 years (Figure 3.3).

Table 6.2 | Factor Loadings. Typical Maha (bolded) and Yala (italicized) months are highlighted.

Month	Factor 1		Factor 2	
	1881-1980	1981-2011	1881-1980	1981-2011
January	**0.882**	**0.637**	**0.418**	**0.638**
February	**0.913**	**0.695**	**0.387**	**0.648**
March	0.845	0.783	0.498	0.577
April	0.704	0.817	0.672	0.532
May	*0.642*	*0.876*	*0.678*	*0.404*
June	*0.691*	*0.882*	*0.644*	*0.422*
July	*0.596*	*0.844*	*0.786*	*0.509*
August	*0.480*	*0.646*	*0.848*	*0.724*
September	*0.324*	*0.588*	*0.916*	*0.742*
October	0.526	0.414	0.729	0.858
November	0.630	0.399	0.655	0.900
December	**0.747**	**0.651**	**0.621**	**0.730**

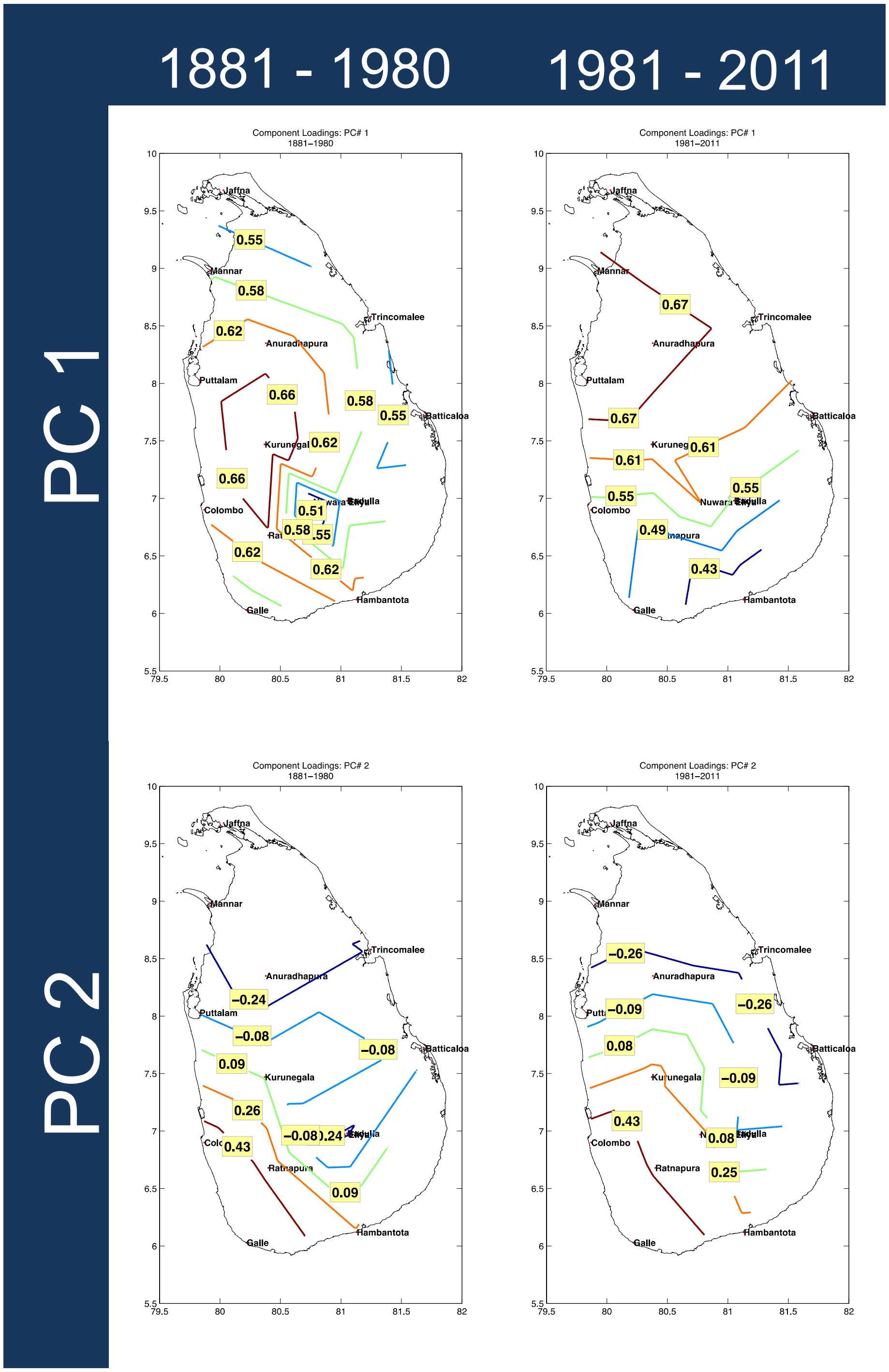

Figure 6.1 | The first two principal components for each time period. Contour lines represent the component loadings. The magnitudes are an indicator of the amount of variation in station drought anomalies that is explained by the component. The opposite signs in PC2 reflect an inverse relationship between the drought anomalies in the Northeast and Southwest.

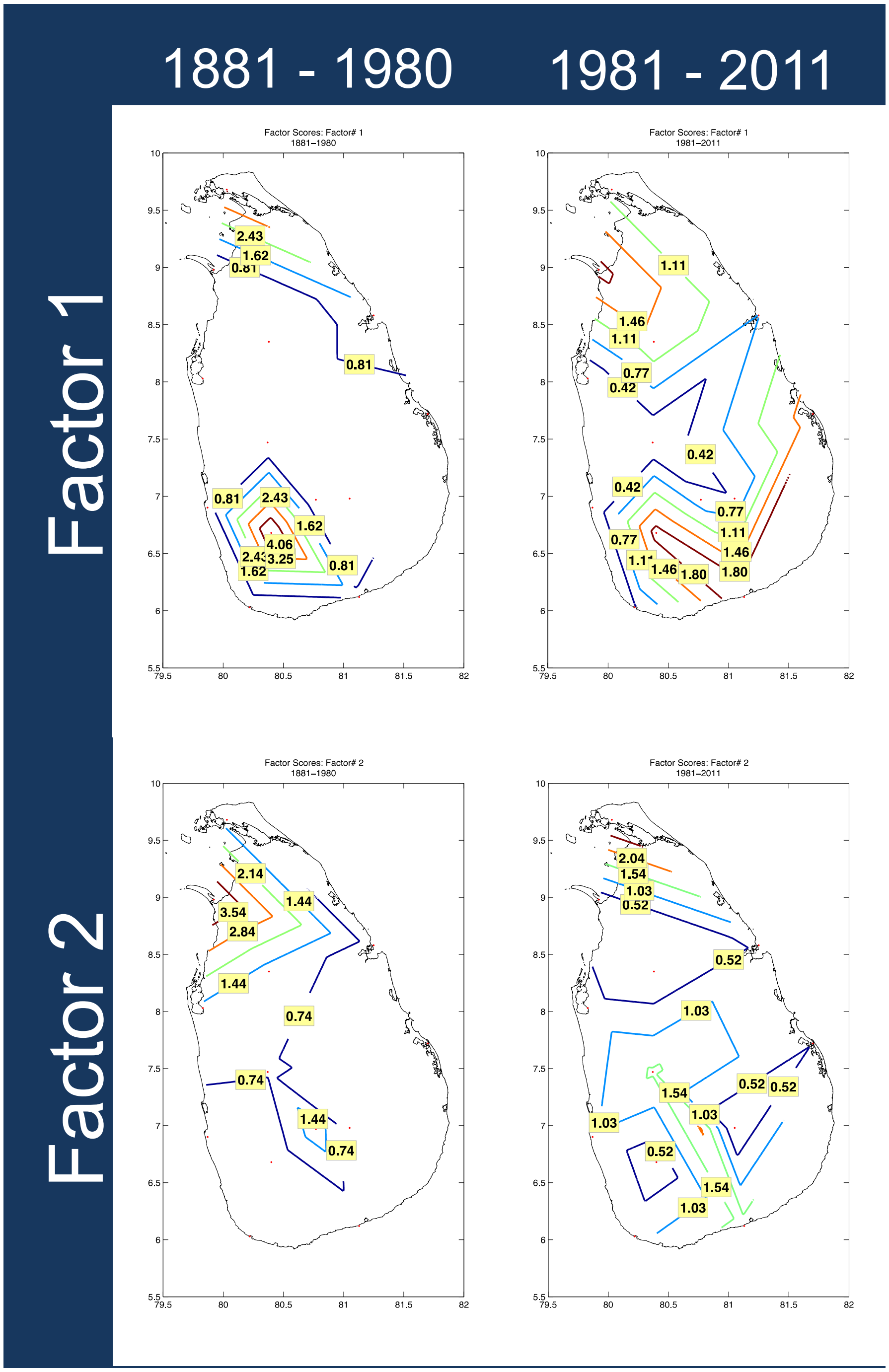

Figure 6.2 | The first two factors for each time period. Contour lines represent the factor scores.

Dramatic shifts in the spatial and temporal patterns are also revealed by the factor analysis. The months with the highest factor loadings are during the *Maha* months in the 1881-1980 time period. In the 1981-2011 time period, the months with the highest factor loadings are the *Yala* months. This is a complete flip in the temporal pattern (Table 3.5). The spatial patterns also show significant changes for both Factor 1 and Factor 2 (Figure 3.4).

These preliminary results require much further analysis to be fully understood. For example, it is not yet clear what the shifts identified by factor analysis mean. Whether an increase in the factor loading indicates a drying or wetting is not obvious and will require other types of analysis to complete the picture of changing drought in Sri Lanka. Nevertheless, it is clear that there have been changes in the patterns of drought over the last 30 years. How these changes impact the citizens and institutions of Sri Lanka depends on both their physical and social capabilities to adapt.

6.2. Conclusions

Research on adaptation to climate change must be an interdisciplinary pursuit. The challenges are too great and complex for any one discipline to tackle alone. The work presented in this dissertation attempts to adhere to the ideals of interdisciplinary research. Chapter 2 presents an easy-to-use tool that enables drought research to be conducted by scientists of all backgrounds. Chapter 3 examines how the climate of Sri Lanka is changing with the hope of better informing planners and managers in the country as they attempt to adapt to the observed changes. Chapter 4 highlights the difficulties in perceiving the gradual changes that are associated with climate change and showcases the importance of strong social science research in combating climate change. Finally, in Chapter 5, an attempt is made to combine social science research in the field of decision science with physical science research to explore the potential outcomes of a proposed program intended to help farmers adapt to climate change.

While this research is mainly focused on rural rice farmers in Sri Lanka, many of the lessons learned have broader impacts. Periodic assessments of climate change that are focused on human and ecological infrastructure are necessary for planned adaptation to climate change. Instead of only making plans after a big storm hits, adaptive planning should be a constant process of assessment, planning, and reassessment. Additionally, the importance of social science in climate change related research cannot be underestimated. It is humans who are impacted by the changes in climate and it is humans who have the potential to find a solution. Yet, if it is not understood how someone makes a decision or perceives changes in the environment, the best climate science in the world is unlikely to make a difference. Finally, tools like agent-based modeling and other integrative techniques are necessary for combining the physical and social sciences. One cannot be conducted in total ignorance of the other, and tools like ABMs allow for a relatively easy way to model the interactions between humans and their environment.

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