# The Water-Food Nexus: A Data-driven, Interdisciplinary Approach to Inform Decision Making in Sri Lanka

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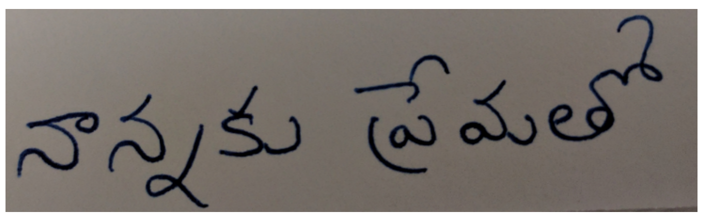


This dissertation work is dedicated to my father, whose unfailing love has been the linchpin of my achievements.

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LIST OF ACRONYMS

**ADAPT-SL** Agricultural Decision-making and Adaptation to Precipitation Trends in Sri Lanka

**AWC** available water capacity

**CNHS** coupled natural and human system

**COI** cone of influence

**CV** coefficient of variation

**CWTs** continuous wavelet transforms

**FIM** first intermonsoon

**IWRs** irrigation water requirements

**NEM** northeast monsoon

**PC** principal component

**PCA** principal component analysis

**PDSI** Palmer Drought Severity Index

**PET** potential evapotranspiration

**PM** Penman-Monteith

**SIM** second intermonsoon

**SPI** Standardized Precipitation Index

**SPI-9** Standardized Precipitation Index at a 9-month scale

**SWM** southwest monsoon

**WTCs** wavelet coherences

**XWTs** crosswavelet transforms

Abstract

My dissertation research aims to improve management of water resources for agriculture, which accounts for 70% of global freshwater withdrawals and 90% of global water consumption. Using Sri Lanka as a case study, we constructed Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index at a 9-month scale (SPI-9) agricultural drought indices. We then analyzed these indices for: 1) spatiotemporal patterns of drought in the country from 1880 to 2010 and 2) utility as drought monitoring tools. Our findings show that although the two indices exhibited similar physical patterns, with a strong, negative association between the Northeastern monsoon and El-Niño in recent decades. Important zonal distinctions were present between the indices concerning correlations to local metrics of drought impacts; PDSI correlated best with the intermediate zone districts, SPI-9 correlated best with dry zone districts, but neither index correlated well with the wet zone districts.

The drought analysis indicated that the northeast portion of the island (an important agricultural region) was becoming drier during the minor growing season, when water resources are already scarce. So we quantified and assessed patterns in irrigation water requirements (IWRs) for rice (the staple food of the country) over 20 years. Comparing IWRs with actual planting records indicates that shifting planting dates to earlier in the season is a low-cost adaptation that could yield IWRs savings of up to 6% in parts of the country. These potential water savings are particularly important given emerging climate change research of less water being available for irrigation during the minor growing season.

In certain parts of the country, however, water stress is already significant enough to warrant diversification away from rice production, a water-intensive process. Given that crop selection decisions are influenced by myriad factors besides weather, I led an interdisciplinary team of researchers (with backgrounds in hydrology, social psychology, human geography, and behavioral economics) to assess whether provision of seasonal forecasts to

farmers could inform their crop selections and lead to improved net agricultural incomes. For this mixed methods study, we compiled and analyzed data from numerous sources including meteorological assessments, games in the field, household surveys, interviews, and government reports. Our empirical findings were rolled into a single-agent system dynamics model, with which we explored the combined impact of a changing climate and varying crop economics on agricultural income. Our results indicate that, when water resources are scarce, farmer incomes could become stratified, potentially compounding existing disparities in farmers' financial and technical abilities to use forecasts to inform their crop selections. This analysis highlights that while policies and programs that promote production of certain crops may ensure food security in the short-term, the long-term implications of these dynamics need careful evaluation.

Beyond water and food, the convergence of limited supply and growing demand issues has prompted much needed conversations about interactions with other critical resources such as energy. For example, treatment of nitrates (a common agriculture-related water quality issue) requires energy investments, which depend on the same scarce water resources upon which agriculture also depends on in Sri Lanka. Given the complex physical and social factors (including governance shifts, climate change, population growth, and technology developments) govern these resource interactions, interdisciplinary research will become increasingly important for and all nations (including Sri Lanka) to help inform policies and strategies that efficiently manage resource use.

# Chapter 1

# Introduction

## 1.1 Background

Water is an important resource for various societal needs; currently, we have appropriated more than 50% of available renewable freshwater (*Srinivasan et al.*, 2012). This dissertation work focuses on the water needs for agriculture, which currently accounts for 70% of global freshwater withdrawals and 90% of global water consumption (*Doll and Siebert*, 2002; *Oki and Kanae*, 2006; *Comprehensive Assessment of Water Management in Agriculture*, 2007; *Khan and Hanjra*, 2009; *Mekonnen and Hoekstra*, 2011; *Hoekstra and Mekonnen*, 2012). Population growth, urbanization, rising incomes, and other factors are projected to increase food demand by 60% by 2050 (*UNESCO*, 2014). To meet this increased demand, irrigated agriculture is projected to expand and increase agricultural water withdrawals by 14% by 2030 (*Khan and Hanjra*, 2009; *UNESCO*, 2003).

Water constraints are further magnified by climate change impacts. Anthropogenic increases in greenhouse gas concentrations and other forcings (such as land use and aerosols) have resulted in a warming of  0.85°C between 1880 and 2012 (*IPCC*, 2014). The increase in greenhouse gas concentrations and temperature has triggered a chain of events including sea level rise, shrinking glaciers, and intensification of precipitation events (*IPCC*, 2014). All of these environmental changes have long-lasting impacts on the supply and demand of water resources for agriculture. Temperature and precipitation changes alone could lead to an increase in global irrigation requirements by another 20% above that projected from expanded irrigation areas alone (*Hanjra and Qureshi*, 2010). The United Nations projects that water scarcity will impact food scarcity more so than land scarcity (*Hanjra and Qureshi*, 2010).

Increasing temperatures as well as shifting rainfall patterns are expected to negatively impact global agricultural output (*Funk and Brown*, 2009; *Quiggin et al.*, 2010; *Lobell et al.*, 2011; *Gourdji et al.*, 2013). Although farmers have historically adapted to seasonal fluctuations in weather, they now face unprecedented shifts in climate patterns (*Morton*, 2007; *Senaratne and Scarborough*, 2011). Farmers in sub-Saharan Africa and South Asia are expected to be particularly impacted by climate change because these regions already have high temperatures and less adaptive capacity (*IPCC*, 2014; *Schmidhuber and Tubiello*, 2007; *Skoufias et al.*, 2011). Since agricultural systems exist in a social, ecological, and political context (*Comprehensive Assessment of Water Management in Agriculture*, 2007), sustainable water management analysis needs to incorporate the human component of agricultural systems into physical assessments. Specifically, research should recognize that in agricultural systems, which are a coupled natural and human system (CNHS), human decision-making is not just influenced by natural resource factors but also economic and psychological factors. Thus, an interdisciplinary systems approach will be crucial to informing assessments of water resource use in agriculture (*Grothmann and Patt*, 2005).

## 1.2 Study Region

Sri Lanka provides an interesting region for studying water requirements for agriculture due to its geographic isolation and large agricultural sector. As an island nation, all water resources for crop production are sourced from endogenous precipitation in Sri Lanka. Also, the nation's economy is closely tied with the agricultural sector; approximately 30% of the population and 65% of land is engaged in agricultural activities in the country, with approximately 34% of cultivated land being irrigated (*DCS*, 2001; *UNESCO*, 2003; *Imbulana et al.*, 2006; *Socio Economics & Planning Centre*, 2012). Since a significant portion of its economy is in climate-sensitive sectors, Sri Lanka is particularly vulnerable to climate change impacts (*Seo et al.*, 2005; *IPCC*, 2007).

Rainfall patterns in Sri Lanka are categorized into four periods: the northeast monsoon (NEM) spans December-February, the first intermonsoon (FIM) spans March-April, the southwest monsoon (SWM) spans May-September, and the second intermonsoon (SIM) spans October-November (*Suppiah*, 1996; *Malmgren et al.*, 2003; *Zubair et al.*, 2008). Spatial variability in rainfall, arising from cyclonic and orographic influences (*Zubair et al.*, 2008), delineates three climatic zones in the country: the wet zone, the intermediate zone, and the dry zone (*Thambyahpillay*, 1954; *Wickramagamage*, 2009). The wet zone receives most of its rain during the SWM and SIM and experiences more than 2,500 mm of rainfall annually (*Suppiah*, 1996; *Zubair*, 2002). The dry zone, which covers three-quarters of the island, predominantly receives rainfall during the SIM and NEM. Since the NEM is weaker than the SWM, the dry zone receives less than 1,750 mm annually, with semi-arid conditions present during the summer months (*Amarasinghe et al.*, 1999; *Zubair*, 2002). The intermediate zone is a transition zone and experiences conditions intermediate between the wet and dry zones.

As the staple food crop of the country, rice plays a large role in stabilizing food security in Sri Lanka (*Fernando*, 2010). Rice comprises 40% of all crop production and is grown throughout the country (*FAO*, 2014) (Figure 1.1); 800,000 farmers and their families as well as 30% of the land area in the nation is devoted to rice production (*De Silva et al.*, 2007). Currently, 87% of total freshwater withdrawals and 40% of freshwater consumption are attributed to growing rice (*UNEP-DHI Partnership*, 2007; *Davis et al.*, 2016). The high water demand for rice is primarily due to two factors: 1) crop requires a lot of water and 2) rice is typically grown in flooded fields; both of these factors lead to high potential evapotranspiration rates. Changing rainfall patterns have already started to affect paddy cultivation practices in Sri Lanka (*Senalankadhikara and Manawadu*, 2010).

Rice is cultivated during two seasons in Sri Lanka: Maha and Yala. A majority of rice production (62% in 2013) occurs during the Maha, the major growing season, which spans from August to January (Figure 1.2) (*Davis et al.*, 2016). The minor growing season, Yala, spans from February to July (*Zubair et al.*, 2008) (Figure 1.2). The two cultivation seasons coincide with monsoonal periods; Maha coincides with SIM and NEM while Yala coincides with FIM and SWM.

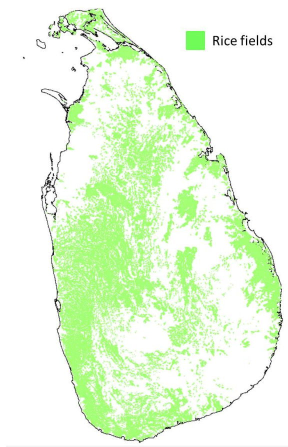



Figure 1.1: Location of Sri Lankan rice fields

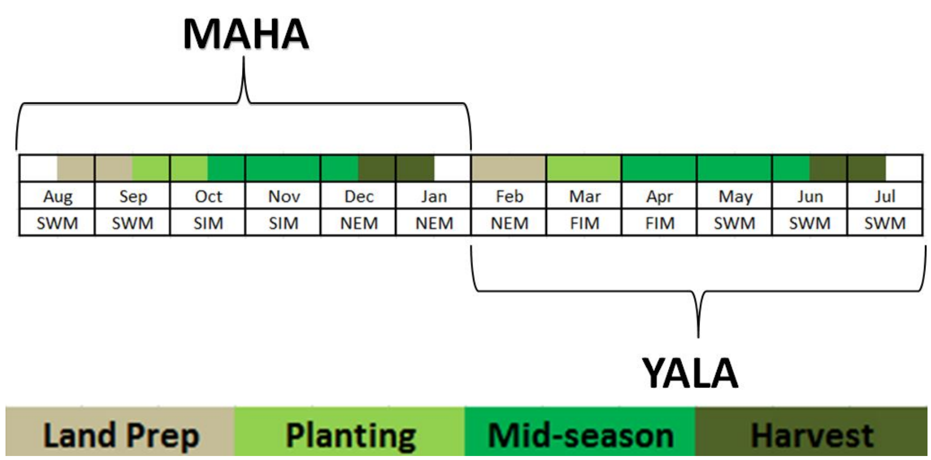



Figure 1.2: Sri Lankan monsoons and cultivation seasons

Seventy percent of the national paddy (i.e., unmilled rice) production is from the dry zone, a region where water resources are already stressed (*De Silva et al.*, 2007; *Withanachchi et al.*, 2014). Since the majority of the annual precipitation in the dry zone is received between October and December (*Amarasinghe et al.*, 1999), Sri Lankans have developed two distinct irrigation schemes to adapt to this uneven distribution of rain: 1) small artificial lakes and ponds (locally referred to as wewas) and 2) major irrigation systems, such as the Mahaweli system. Wewas store excess local runoff from the monsoons to provide water during the minor growing season (*Marambe et al.*, 2012; *Sakthivadivel, R.*, *N. Fernando, C.R. Panabokke*, 1996), while the Mahaweli system depends on interbasin transfers (*ARD, Inc.*, 2005; *Gunawardhana and Adikari*, 1981).

The rice production system in Sri Lanka, in particular, is a strongly CNHS and is deeply rooted in the local socio-political culture. Sri Lanka has a self-sufficiency policy for rice, which is set at 100% of domestic demand (*Imbulana et al.*, 2006). Various measures have been developed to support rice production, including credit, subsidized fertilizers, guaranteed price system, and crop insurance (*Pain*, 1986). Due to a combination of high yielding varieties, paddy expansion, and increased use of irrigation and fertilizer, rice production has steadily risen to meet this target. Sri Lanka has been almost entirely supplied by its own rice production since 2005 (*DCS*, 2014; *FAO*, 2014). Many traditional festival and religious practices are also associated with Sri Lankans' cultivation of rice (*Bouman et al.*, 2007; *FAO*, 2012); many identify rice farming not just as a livelihood but as a way of life (*Jayasuriya*, 1985).

## 1.3 Research Goal and Objectives

Given increasing need for water resources on the horizon (*UNESCO*, 2014), it has become increasingly important to efficiently manage our current resource use. The goal of this research is to improve management of water resources to advance food security in Sri Lanka. Agricultural research, once at the forefront in Sri Lanka (*Pain*, 1986), stagnated in the 1980s during the Civil War (*Wijesekera et al.*, 2006; *Mahbuba and Rousseau*, 2010), resulting in some inadequacies in Sri Lanka's research capabilities (*Sumathipala et al.*, 2003). So the early objectives of this dissertation establish a foundation of knowledge upon which subsequent chapters build.

In Chapter 2 we explore spatiotemporal patterns of agricultural drought over the last century. We then take a step further and translate this research effort to evaluate the utility of drought indices as drought monitoring tools. Our findings show that although the two indices exhibited similar physical patterns, important zonal distinctions were present between the indices concerning correlations to local metrics of drought impacts.

In Chapter 3, I describe work conducted in collaboration with Ashley Rivera, an undergraduate in Civil Engineering, to assess patterns in IWRs for rice and quantify the impact shifting a planting date can have on the irrigation system efficiency. We find that shifting planting dates to earlier in the season could yield IWR savings of up to 6% in parts of the country.

In certain parts of the country, however, water stress is significant enough to warrant diversification away from rice production. In Chapter 4, we assess whether the provision of a seasonal climate forecast could aid farmers with crop diversification. Given that crop selection decisions are influenced by a myriad factors besides weather, this objective considers interdisciplinary perspectives (including social psychology, behavioral economics, and human geography) represented in the Agricultural Decision-making and Adaptation to Precipitation Trends in Sri Lanka (ADAPT-SL) research group – the larger research effort in which this dissertation work is embedded (https://my.vanderbilt.edu/srilankaproject/). Our results indicate that, when water resources are scarce, farmer incomes could become stratified, potentially compounding existing disparities in farmers' financial and technical abilities to use forecasts to inform their crop selections. This analysis highlights that while policies and programs that promote production of certain crops may ensure food security in the short-term, the long-term implications of these dynamics need careful evaluation.

We conclude Chapter 5 with an outlook on other resource pressures on the horizon for Sri Lanka and other agricultural nations.

# Chapter 2

# Drought Characterization

## 2.1 Introduction

As the most frequent natural disaster in Sri Lanka, drought greatly affects crop production and livelihoods in this island nation (*Chithranayana*, 2008). Over half of all agricultural crop damage in Sri Lanka is due to drought (*Disaster Management Centre*, 2011). In 2003-2004, drought in two consecutive seasons affected nearly 1.5 million people, most of whom were subsistence farmers (*World Food Programme*, 2007). Drought also affects public health, hydropower generation, and other sectors of the Sri Lankan economy; protracted drought in 2001-2002 caused a 1% drop in gross domestic product (*Lyon et al.*, 2009). Climate change is expected to increase the frequency and severity of drought in the country (*Eriyagama et al.*, 2010).

Thus far, studies in Sri Lanka have predominantly focused on characterizing specific years of anomalous rainfall (*Jayamaha*, 1975); spatiotemporal patterns of rainfall (*Suppiah and Yoshino*, 1984a,b); and relationships among rainfall, rice production, and Southern Oscillation Index and other El Niño indices (*Suppiah*, 1996; *Malmgren et al.*, 2003; *Wickramagamage*, 2009; *Zubair*, 2002; *Suppiah*, 1997; *Kane*, 1998; *Zubair et al.*, 2005). A monthly Moisture Availability Index was developed to identify regions of Sri Lanka that are vulnerable to drought (*Chithranayana*, 2008), but it is unclear which years were used in the analysis. Standardized Precipitation Index (SPI) was characterized at a 3-month scale for the Anuradhapura district and identified 46 drought occurrences between 1951 and 2007 (*Ekanayake and Perera*, 2014). A study on the relationship between the SPI and drought relief payments in the country discovered the strongest correlation with a 9-month cumulative drought index (*Lyon et al.*, 2009); a significant difference in total rice production and yield between drought and non-drought years has also been discovered (*Fernando*, 2010).

A good correlation was found between weighted-average SPI and the PDSI for Idamelanda from 1960 to 2000 (*Bandara et al.*, 2010). However, these studies only characterized restricted time periods or regions of drought and none of them have assessed spatiotemporal patterns of drought across the nation.

Thus, the research objectives of this study are to evaluate: 1) spatial and temporal patterns of agricultural drought in Sri Lanka from 1881-2010 and 2) the utility of PDSI and SPI as agricultural drought monitoring tools for Sri Lanka. We assess agricultural drought using two well-known indices: the PDSI and SPI-9. Drought indices, such as PDSI and SPI-9, can facilitate reporting of drought conditions and development of drought management strategies (including contingency planning) (*UN*, 2009). We selected PDSI and SPI-9 because both indices are being used by Sri Lankan government agencies; SPI is widely used for local meteorological drought analysis and our research partners at the National Building Research Organization are evaluating PDSI as an indicator of agricultural drought. We analyze differences in the spatiotemporal patterns of PDSI and SPI-9 and consider whether such differences lead to a preferred drought monitoring tool for the country.

Spatiotemporal patterns of drought have been studied by coupling principal component analysis (PCA) with spectral analysis of the principal component (PC) scores (*Eder et al.*, 1987) or by coupling wavelets with PCA of significant periods of variance (*Elsanabary et al.*, 2014). We use a combination of these two approaches by first conducting PCA on the data (per *Eder et al.* (1987)) and then applying wavelets to the PCs (per *Elsanabary et al.* (2014)). Specifically, spatial patterns are identified by applying PCA of the PDSI and SPI-9 time series and temporal patterns are identified by wavelet analysis of the scores of the retained PCs. Our analysis shows similar spatiotemporal patterns of drought for both indices. An assessment of the utility of PDSI and SPI-9 as agricultural drought monitoring tools using correlation analysis suggests that different indices might be appropriate for each of the climatic zones in Sri Lanka.

## 2.2 Methods

### 2.2.1 Drought Indices

The PDSI is calculated by conducting a physical water balance of precipitation, evapotranspiration, recharge, and runoff (*Palmer*, 1965). The index assumes a two-layer model for soils; the calculations assume that the top soil layer has a field capacity of one inch and that moisture is only transferred to the second layer upon saturation of the first layer (*Palmer*, 1965; *Heim Jr*, 2002). When both layers are saturated, excess water becomes runoff. Precipitation occurring in a given month is first utilized to meet the evapotranspiration demand of that month; if precipitation is greater than evapotranspiration demand, then there is a positive moisture anomaly and vice versa. Each month's PDSI value is calculated based on the previous month's PDSI value as well as the moisture anomaly of the current month.

While PDSI was established as an indicator of meteorological drought, it has also been used to assess agricultural drought (*Rohli et al.*, 2008). The dimensionless values of PDSI range from -4 to 4, with negative numbers representing dry spells (*Hu and Willson*, 2000). A drought period begins when the index value reaches -1 and ends the first month when the moisture conditions begin an uninterrupted rise that ultimately erases the water deficit (*Keyantash and Dracup*, 2002). Because antecedent conditions are accounted for as a part of the PDSI calculations, the temporal scale of the PDSI is ambiguous; the time scale of PDSI is typically taken to be about 9 months (*Guttman*, 1998; *Heim Jr*, 2002). The data requirements for this index are monthly precipitation and temperature data, as well as the available water capacity (AWC) of the soil reservoir conceptualized in the water balance model. Additional information regarding the methodology and limitations of this index can be found in (*Palmer*, 1965), (*Alley*, 1984), and (*Briffa et al.*, 1994).

PDSI values for Sri Lanka were calculated using the MATLAB PDSI tool (*Jacobi et al.*, 2013). Potential evapotranspiration values were estimated using the Thornthwaite Method and the entire period of record was used for calibration. PDSI calculations on a time interval require boundary conditions to be imposed at the beginning and end. Those conditions bias results at times close to the beginning and end; but sufficiently far from the boundaries, results are insensitive to the boundary conditions (*Guttman*, 1991). We calculated PDSI on data from January 1875 to December 2013, obtaining stable values for 1881-2010.

The SPI is calculated by fitting all of the historical precipitation data at a meteorological station to a gamma distribution, which is then transformed to a Gaussian distribution (*McKee et al.*, 1993). The SPI values are standardized precipitation anomalies: the number of standard deviations by which the precipitation total for a time interval (e.g., 1-month, 3-month, or 9-month) differs from the long-term mean of that interval. At short time-scales (e.g., 1-month), SPI is considered as a meteorological drought indicator; when SPI captures long-term anomalies of precipitation (e.g., 3-month and 9-month), it is considered as an agricultural drought indicator (*Patel et al.*, 2007). Sri Lankans often capture rainfall during the NEM and use it for agricultural production in the SWM; therefore, a SPI scale longer than 6 months is needed to adequately capture this interplay between the two monsoon seasons. To be consistent with the approximate time scale of PDSI, SPI at a 9-month scale was selected for this initial analysis. Moreover, *Lyon et al.* (2009) find that 9-month timescales for drought indices produced the greatest correlation with agricultural drought, as measured by relief payment to farmers. SPI-9 values for each month incorporate precipitation information for the preceding 8 months. For example, SPI-9 for January 2009 requires precipitation values from May 2008 to January 2009.

SPI values range from -2 to 2. Similar to PDSI, SPI is dimensionless with negative numbers representing dry spells. SPI considers a drought period to begin when the index value reaches -1 and to end when the index value reaches 0 (*Morid et al.*, 2006). SPI-9 values were calculated using a MATLAB SPI tool (*Lee*, 2009). To be consistent with the PDSI calculations, the same data range (January 1875 to December 2013) was used with the SPI tool, with values from 1881-2010 retained for further analysis.

### 2.2.2 Data

Monthly precipitation and temperature data were obtained from the Meteorological Department of Sri Lanka for 13 stations with long-term records (Table 2.1). Approximately 13% of the temperature and 14% of the precipitation data were missing. Temperature anomalies of up to 1.7°C result in only minor effects on PDSI values (*Guttman*, 1991). Because the monthly temperature values at each station had a variance less than 1°C, missing temperature values at each station were estimated with the corresponding station's average monthly temperature value. This method produced comparable values (i.e., less than 1°C difference) to those estimated using the between-stations technique for missing monthly temperature values at Jaffna (*Thevakaran and Sonnadara*, 2013).

Missing precipitation values were filled in using the modified normal ratio method (*Young*, 1992). The modified normal method weights precipitation values from three stations to develop an estimate for the missing precipitation value; the three stations used for each estimation are identified using correlation coefficients. The weights were calculated using the equation,

$$w_i = \frac{r_i^2(n_i - 2)}{1 - r_i^2}, \tag{2.1}$$

where $w_i$ is the weight, $r_i$ is the correlation coefficient between the two stations, and $n_i$ is the number of points used to calculate the correlation coefficient (*Young*, 1992). For Sri Lanka, stations with high correlation coefficients were generally in the same climatic zone as the station with missing data.

To determine the AWC of soils near each of the meteorological stations, the soil type was first identified using a soil map for the country (*De Alwis and Panabokke*, 1972). Only two stations in the dry zone had published AWC values (*Mapa and Pathmarajah*, 1995). For the remaining stations, AWC estimates from similar soil types elsewhere in the world were used since soil water contents are strongly correlated with soil textures (*Minasny et al.*, 1999; *Hong et al.*, 2013).

Table 2.1: Summary of meteorological stations

| Stations | Latitude (N) | Longitude (E) | Altitude (m) | AWC (in) | Annual Precipitation (mm) | Annual Temperature (°C) |
|---|---|---|---|---|---|---|
| Anuradhapura | 8.35 | 80.38 | 92.5 | 3.82 | 1369 | 27.6 |
| Badulla | 6.98 | 81.05 | 669.6 | 8.11 | 1814 | 23.4 |
| Batticaloa | 7.72 | 81.7 | 7.8 | 3.27 | 1691 | 27.7 |
| Colombo | 6.9 | 79.87 | 7.3 | 8.11 | 2313 | 27.3 |
| Galle | 6.03 | 80.22 | 12.5 | 8.11 | 2288 | 26.8 |
| Hambantota | 6.12 | 81.13 | 15.5 | 3.27 | 1057 | 27.2 |
| Jaffna | 9.68 | 80.03 | 3.1 | 0.98 | 1285 | 27.8 |
| Kurunegala | 7.47 | 80.37 | 116.1 | 8.11 | 2066 | 27.1 |
| Mannar | 8.98 | 79.92 | 3.6 | 3.27 | 1033 | 28.0 |
| Nuwara Eliya | 6.97 | 80.77 | 1893.6 | 8.11 | 2084 | 15.5 |
| Puttalam | 8.03 | 79.83 | 2.1 | 0.98 | 1157 | 27.4 |
| Ratnapura | 6.68 | 80.4 | 34.4 | 8.11 | 3622 | 27.2 |
| Trincomalee | 8.58 | 81.25 | 23.9 | 3.27 | 1655 | 28.3 |

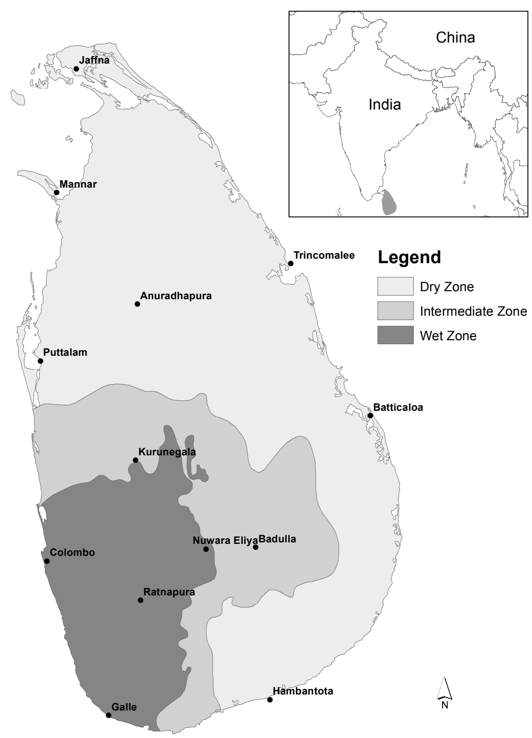



Figure 2.1: Meteorological stations with long-term monthly temperature and precipitation data used in the drought analysis

### 2.2.3 Spatial Analysis

PCA is a common method used to identify spatial patterns in climatic data (*Santos et al.*, 2010). By reducing dimensionality, PCA emphasizes relationships among variables (i.e., stations) and observations (i.e., monthly drought indices). Specifically, data for $k$ variables for a given time period: $X_1$, $X_2$,..., $X_k$ can be used to produce $k$ principal components ($PC_1$, $PC_2$,..., $PC_k$) for the same time period using linear combinations:

$$\begin{aligned}
PC_1 &= a_{11}X_1 + a_{12}X_2 + \ldots + a_{1k}X_k \\
PC_2 &= a_{21}X_1 + a_{22}X_2 + \ldots + a_{2k}X_k \\
&\ldots \\
PC_k &= a_{k1}X_1 + a_{k2}X_2 + \ldots + a_{kk}X_k
\end{aligned} \tag{2.2}$$

The PCs are, by definition, orthogonal and uncorrelated to each other. The coefficients of the linear combinations ($a$'s) are weights of the original variables in the PCs and are called loadings (*Santos et al.*, 2010). PCA is not affected by lack of independency in the original variables and while normality of the dataset is desirable, it is not essential, especially if the dataset is not excessively skewed (*Santos et al.*, 2010). The dataset of PC scores, which contains transformed data points from the original axis system to the axis system of the PCs, is the same length as the original dataset. Since PC loadings can be influenced by uneven distribution of data (*Karl et al.*, 1982), the PDSI and SPI-9 values at each station were weighted by the corresponding station's Thiessen polygon area prior to conducting the PCA (*Drosdowsky*, 1993; *Chung and Nigam*, 1999; *Wrublack et al.*, 2013); Thiessen polygons assign weights according to areas defined by points closest to each station.

From the original dataset of 13x1560, a 13x13 covariance matrix ($\Sigma$) was constructed to identify the eigenvalues. A covariance rather than a correlation matrix was used because the covariance matrix is useful for locating specific regions with high variance relative to the rest of the field (*Overland and Preisendorfer*, 1982; *Eder et al.*, 1987). So if we let $\phi$ be a n x n matrix, whose columns are eigenvectors of the covariance matrix and $\Lambda$ is a diagonal matrix whose elements are the eigenvalues ($\lambda$) of the covariance matrix, then

$$\Sigma\phi = \phi\Lambda. \tag{2.3}$$

The eigenvalues of the covariance matrix of the original variables are the variances of the PCs. Therefore, the PCs account for all of the variation in the original data, because the sum of the PC variances equals the sum of the covariance matrix eigenvalues. The amount of variance explained by each of the PCs decreases sequentially: $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_k \geq 0$. The matrix of eigenvectors, $\phi$, is a linear transformation which transforms the data points from the original axis system to the axis system of the PCs, where the variables are uncorrelated. The transformed values are called scores and the dataset of PC scores is the same size as the original dataset (i.e., 13x1560). The PC scores are represented by:

$$(PCScore)_{ik} = \sum_j O_{ij} L_{jk} \tag{2.4}$$

where $O_{ij}$ is the observation for month $i$ at station $j$, $L_{jk}$ is the loading of station $j$ on component $k$, and the $(PCScore)_{ik}$ is the component score for month $i$ on component $k$ and is summed over all 13 stations (*Eder et al.*, 1987). Monthly contributions (i.e., fraction of the total variance explained by the PC attributable to each month) for the retained PC scores were calculated by summing the PC scores for each month and dividing by the total variance at each station. Scree plot analysis, which compares the variance explained by each of the PCs and indicates that PCs within the first "elbow" should be retained, was used to decide on the number of PCs to retain (*Jolliffe*, 2002). Communalities, or the proportion of variance attributable to each station, were also calculated by summing the squared loadings of the retained PCs (*Eder et al.*, 1987). All of the principal component analysis was conducted in MATLAB.

Orthogonal rotations, which sometimes produce more physically explainable patterns, were implemented to facilitate interpretation (*Santos et al.*, 2010). The Varimax rotation preserves the orthogonality of the PCs but maximizes the sum of the variances of the squared loadings, which can result in a spatial clustering of the variables (*Drosdowsky*, 1993). Following the methods outlined in *Jolliffe* (2002), PCs were rotated using MATLAB commands. To visualize the spatial patterns in loadings, the coefficients of both unrotated and rotated PCs were interpolated using the inverse distance weighted technique in ArcMap 10.2.

### 2.2.4 Temporal Analysis

Wavelet analysis has been used in an array of geophysical studies to assess the Southern Oscillation, cold fronts, rainfall patterns, and dispersion of ocean waves (*Torrence and Compo*, 1998). Wavelets allow decomposition of a time series into time-frequency space so that dominant modes of variability can be explored over time. The Morelet wavelet, which is a plane wave modulated by a Gaussian window, was chosen for this analysis because it provides reasonable localization of both time and frequency (*Grinsted et al.*, 2004). The Morelet wavelet function is defined as:

$$\psi_0(\eta) = \pi^{-\frac{1}{4}} e^{-i6\eta} e^{-\frac{\eta^2}{2}}, \tag{2.5}$$

where $\eta$ is a nondimensional time parameter. Unlike windowed Fourier transform, wavelet analysis is scale independent and is thus not compromised by the aliasing of high- and low-frequency components that do not fall within the frequency range of chosen window lengths (*Torrence and Compo*, 1998). Wavelets are structured such that as the period increases, the amount of temporal information decreases (*Grinsted et al.*, 2004). Additional background information on wavelet theory can be found in *Torrence and Compo* (1998); *Grinsted et al.* (2004).

The MATLAB code provided by *Grinsted et al.* (2004) was used to generate continuous wavelet transforms (CWTs) of the scores of retained PCs from the spatial analysis. For each station, monthly means of PDSI and SPI-9 were removed from the records to define an anomaly time series as defined by:

$$\bar{X}_i = \frac{1}{n}\sum_{y=1}^{y=n} X_{i,y}$$
$$Z_{i,y} = X_{i,y} - \bar{X}_i \tag{2.6}$$

where $X$ are the original index data, $\bar{X}$ are monthly means, $Z$ are monthly anomalies, $i$ is the month (i.e., January (1) through December (12)), $y$ is the number of years in the time series, and $n$ is 130 years. Removing the monthly means of PDSI and SPI-9 from the records allowed us to focus on long-term forcings. The normality of the anomaly score time series was confirmed using Q-Q plots and the Shapiro-Wilk test. Because the dataset is finite, the monthly score anomalies were padded with zeros prior to generating the CWTs. Accordingly, errors occur at the beginning and end of the wavelet power spectra; outside the cone of influence (COI) is the region of the wavelet spectrum where these edge effects are important. Therefore, information outside the COI should be considered with caution. Significance levels at 95% of the observed spectra were determined relative to a background spectrum of red noise, commonly modeled with a first order autoregressive (AR1) process for geophysical phenomena (*Torrence and Compo*, 1998; *Grinsted et al.*, 2004).

Variations in the Niño 3.4 dataset (a measure of sea surface temperature from 5°N - 5°S, 120°W - 180°W) explain some of the variability in seasonal agricultural production (*Zubair et al.*, 2005). The relationship between the scores and monthly anomalies of Niño 3.4 (*Rayner et al.*, 2003) was assessed using crosswavelet transforms (XWTs) and wavelet coherences (WTCs). XWTs expose the common power between two CWTs and the relative phase in time-frequency space. WTCs show localized correlation coefficients in time-frequency space, and thus, can expose areas of significant coherence between two CWTs even when the common power is low (*Grinsted et al.*, 2004).

### 2.2.5 Drought Monitor Analysis

Five classes of drought were originally defined for PDSI while only three classes of drought were defined for SPI (*McKee et al.*, 1993; *Alley*, 1984). Palmer arbitrarily designated drought severity classes for PDSI (*Alley*, 1984). So to allow comparisons between the two index classifications, PDSI was re-categorized into three classes (*Morid et al.*, 2006).

Monthly impacts of drought on agricultural activity from 1974 to 2010 for 11 metrics were obtained at the district-level from the disaster management information system, DesInventar (*Disaster Management Centre*, 2011). These metrics include demographic, crop, and economic parameters such as the number of Grama Niladharis (GNs; i.e., lowest administrative division) affected by drought, loss of paddy, and relief payments (Table 2.2). The usefulness of PDSI and SPI-9 as agricultural drought monitoring tools was evaluated using correlation analysis between drought index time series and the corresponding district's agricultural metrics from DesInventar. We calculated correlations between the two drought indices and the 33 metrics for which we had sufficient data (i.e., at least 10 months of recorded drought in the district and an absence of significant autocorrelation in the metric) (Table 2.3).

Linear trend analysis was then conducted on PDSI and SPI-9 time series at stations that exhibited correlations with DesInventar metrics. Both PDSI and SPI-9 time series showed serial correlation, which affects the accuracy of estimated trends (*Yue et al.*, 2002). Therefore, linear trend analysis was conducted on individual monthly time series at each station. PDSI has a bimodal distribution owing to its computational structure (*Eder et al.*, 1987) while SPI-9 has a normal distribution. Therefore, the nonparametric Mann-Kendall test was used to assess the significance of trends at $\alpha = 0.05$ (*Hirsch et al.*, 1982).

Table 2.2: DesInventar metrics

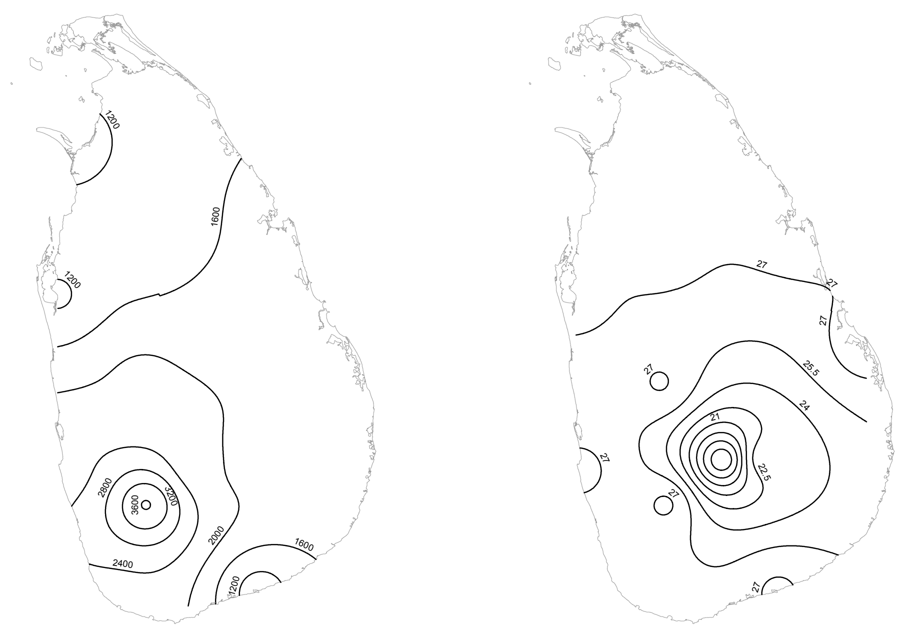
| |
|---|
| Damages in crops (hectares) |
| Number of families affected |
| Number of Grama Niladhari (GN) divisions affected |
| Loss for paddy and other crop (rupees) |
| Loss for paddy (rupees) |
| Loss for other farm (rupees) |
| Payment for relief (loss of other crop in rupees) |
| Payment for relief (loss of paddy in rupees) |
| Payment for relief (loss of total crop in rupees) |
| Payment for relief (livelihood option) |
| Relief cost (rupees) |

Table 2.3: Regression analyses conducted. Note: Regression analyses were not conducted for grey boxes due to either 1) too few samples or 2) autocorrelation issues

| DesInventar Metric | Anuradhapura (n=50) | Badulla (n=38) | Batticaloa (n=22) | Colombo (n=5) | Galle (n=5) | Hambantota (n=75) | Jaffna (n=8) | Kurunegala (n=90) | Mannar (n=6) | Nuwara Eliya (n=22) | Puttalam (n=41) | Ratnapura (n=20) | Trincomalee (n=30) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Damages in crops (hectares) | | | | | | | | | | | | | |
| Number of families affected | | | | | | | | | | | | | |
| Number of Grama Niladhari (GN) divisions affected | | | | | | | | | | | | | |
| Payment for relief (loss of total crop in rupees) | | | | | | | | | | | | | |
| Payment for relief (loss of paddy in rupees) | | | | | | | | | | | | | |
| Payment for relief (loss of other crop in rupees) | | | | | | | | | | | | | |
| Loss for paddy and other crop (rupees) | | | | | | | | | | | | | |
| Loss for paddy (rupees) | | | | | | | | | | | | | |
| Loss for other farm (rupees) | | | | | | | | | | | | | |
| Relief cost (rupees) | | | | | | | | | | | | | |
| Payment for relief (livelihood option) | | | | | | | | | | | | | |

## 2.3 Results

The 13 stations used in the analysis are well-distributed across the three climatic zones (Figure 2.1). The interpolated annual average temperature and precipitation maps developed using data from the 13 stations (Figure 2.2) are similar to finer scale maps developed by *Zubair et al.* (2010).




(a) Average Precipitation (mm)

(b) Average Temperature (°C)

Figure 2.2: Average weather patterns based on monthly data at the meteorological stations

The scree plots of PDSI and SPI-9 PCs show an elbow at the 2nd PC for both indices (Figure 2.3). Thus, the first two PCs of PDSI and SPI-9, which explain 67% and 69% of the total variance, respectively, were retained for further analysis. The unrotated PC 1 of both indices shows little variance and is flat or in phase while the unrotated PC 2s are out of phase (Figure 2.4). The unrotated PC 1s both show a general trend from the north to the southwest. In contrast, the unrotated PC 2s both show a general trend from the southwest to the north. February and March months contribute the most to PC 1 of

Table 2.4: Monthly contributions (as percentage of total variance) to principal component scores. February and March contribute the most to PC 1 of PDSI but the remaining PCs have relatively little variability in monthly contributions.

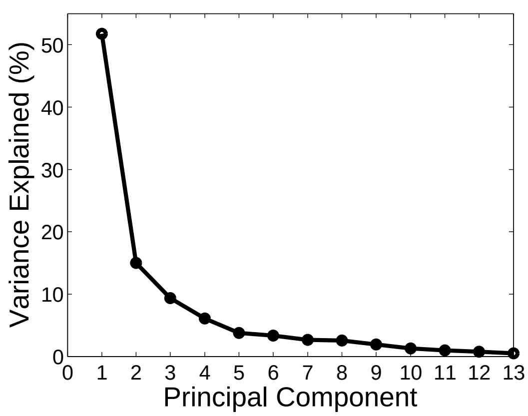
| | PDSI | | SPI-9 | |
|---|---|---|---|---|
| Month | PC 1 | PC 2 | PC 1 | PC 2 |
| Jan | 56.0 | 14.8 | 48.9 | 21.7 |
| Feb | 59.8 | 14.3 | 49.4 | 21.0 |
| Mar | 59.0 | 15.9 | 50.2 | 21.1 |
| Apr | 54.7 | 14.6 | 49.2 | 21.3 |
| May | 50.6 | 16.3 | 50.9 | 20.2 |
| Jun | 47.4 | 16.2 | 51.5 | 18.8 |
| Jul | 49.0 | 15.4 | 53.5 | 16.6 |
| Aug | 47.8 | 15.4 | 55.0 | 16.0 |
| Sep | 48.1 | 15.7 | 52.8 | 16.1 |
| Oct | 45.8 | 13.1 | 47.0 | 19.0 |
| Nov | 47.4 | 13.3 | 44.3 | 20.6 |
| Dec | 51.5 | 13.7 | 44.6 | 21.9 |

PDSI but the remaining PCs have relatively little variability in monthly contributions (Table 2.4). The station communalities indicate that the stations with the highest contributions are distributed across climate zones (Table 2.5). The rotated PCs clarify visually the similarities between the two PC 1s and the two PC 2s (Figure 2.5). The re-distributed percentages of variance corresponding to the rotated PCs are 50.9% and 15.9% for PDSI rotated PC 1 and 2, respectively and 46.8% and 22.5% for SPI-9 rotated PC 1 and 2, respectively.

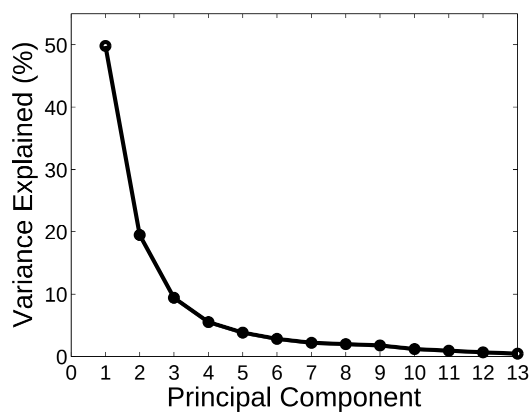
To evaluate the impact of the number of stations on spatial patterns, we conducted PCA on the rainfall data for the 30 stations in Sri Lanka with long-term data and compared these results to those from the rainfall data for the 13 stations used in the drought analysis (Figure 2.6). The spatial patterns are very similar between the two datasets, with a general south to north trend in PC 1 and an east to west trend in PC 2. These patterns increase our confidence that the 13 stations used in our drought index analysis adequately capture the spatial variability in the country (Figure 2.7).

Table 2.5: Communalities, proportion of variance attributable to each station. Stations with the highest contributions to PC loadings are distributed across the climatic zones.

| Climate Zone | Stations | PDSI | SPI-9 |
|---|---|---|---|
| Wet | Colombo | 0.12 | 0.14 |
| | Galle | 0.03 | 0.03 |
| | Nuwara Eliya | 0.01 | 0.01 |
| | Ratnapura | 0.87 | 0.88 |
| Intermediate | Badulla | 0.06 | 0.09 |
| | Kurunegala | 0.04 | 0.05 |
| Dry | Anuradhapura | 0.02 | 0.03 |
| | Batticaloa | 0.04 | 0.06 |
| | Hambantota | 0.00 | 0.01 |
| | Jaffna | 0.51 | 0.43 |
| | Mannar | 0.20 | 0.15 |
| | Puttalam | 0.08 | 0.11 |
| | Trincomalee | 0.02 | 0.03 |

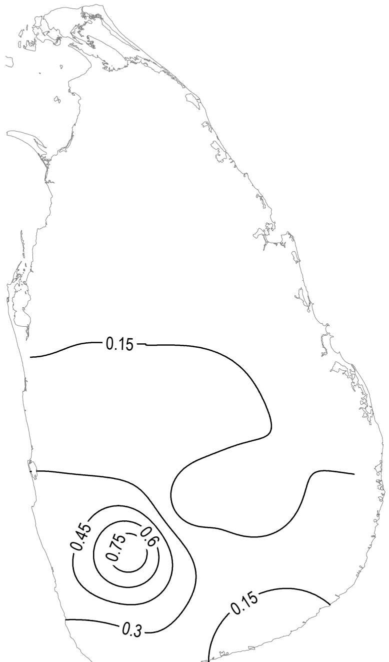


(a) PDSI

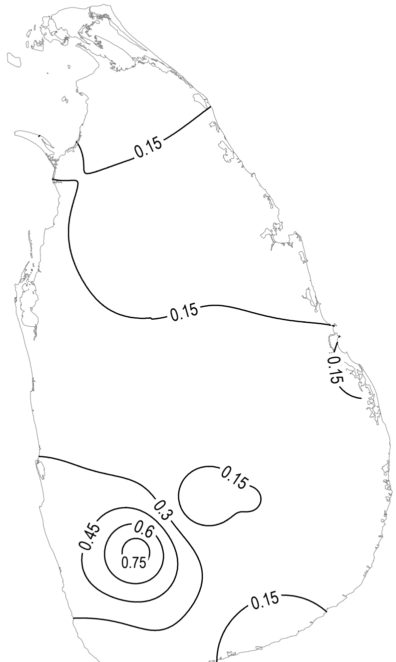


(b) SPI-9

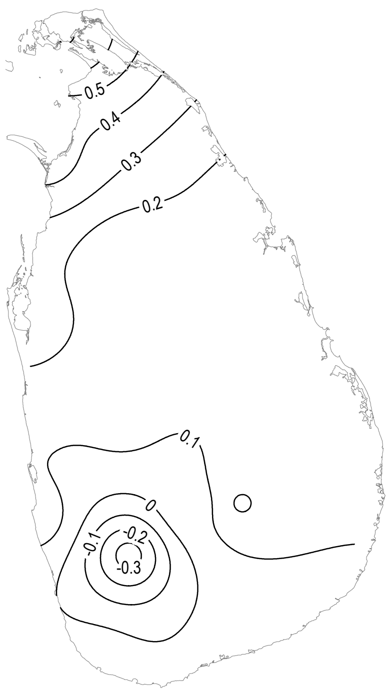
Figure 2.3: Scree plots of PDSI and SPI-9 datasets. Both plots show an elbow at PC 2.



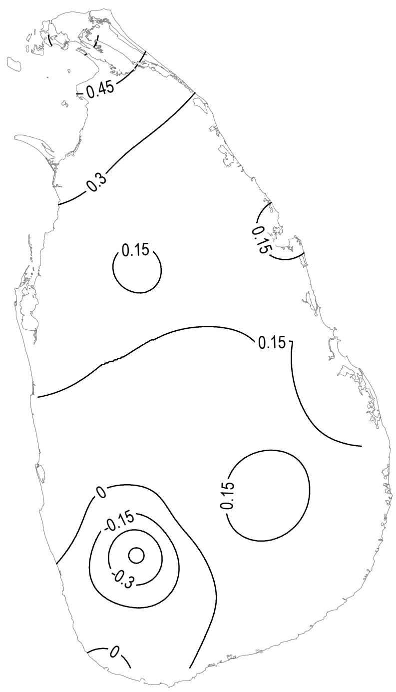

(a) PDSI Unrotated PC 1




(b) SPI-9 Unrotated PC 1



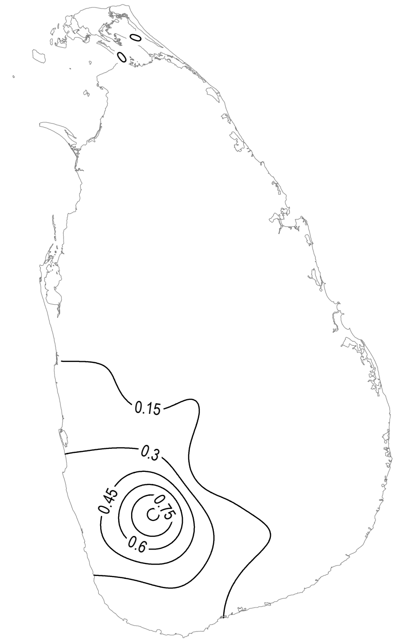

(c) PDSI Unrotated PC 2



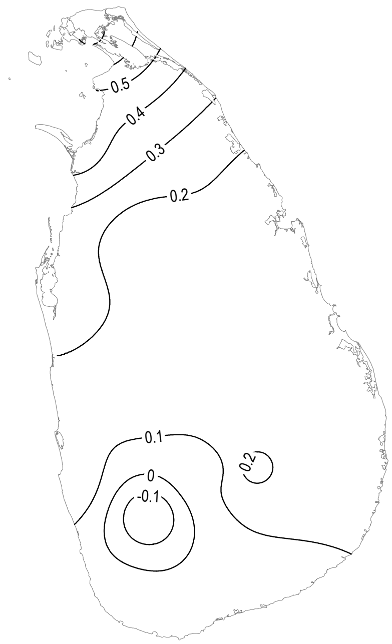

(d) SPI-9 Unrotated PC 2

Figure 2.4: Unrotated principal components of PDSI and SPI-9. Both PC 1s show a general trend from the north to the southwest while both PC 2s show a general trend from the southwest to the north.

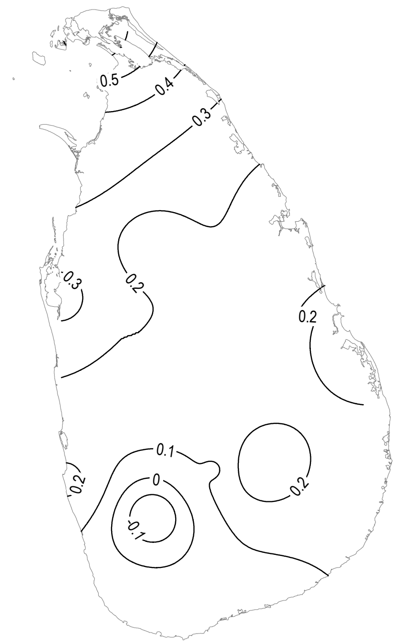

(a) PDSI Rotated PC 1




(b) SPI-9 Rotated PC 1




(c) PDSI Rotated PC 2




(d) SPI-9 Rotated PC 2

Figure 2.5: Rotated principal components of PDSI and SPI-9. The rotated components clarify visually the similarities between the two PC 1s and the two PC 2s.

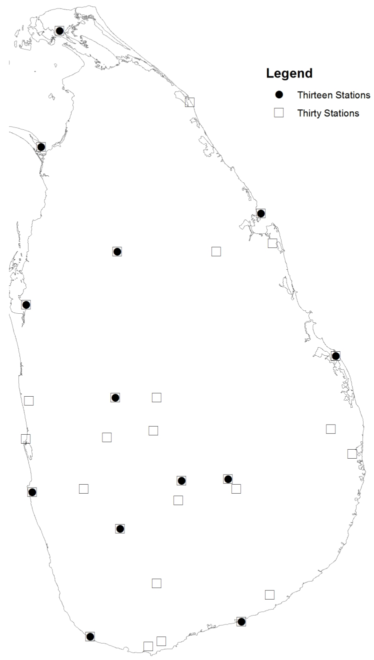
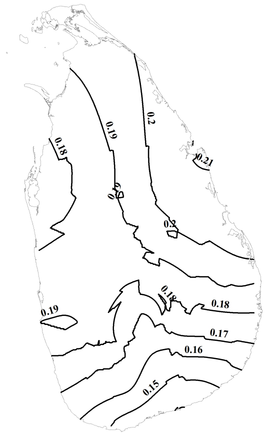
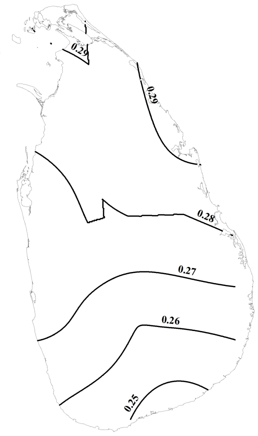


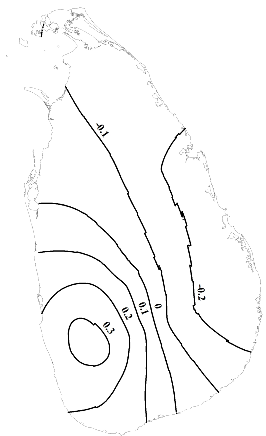

Figure 2.6: Patterns comparison: 30 stations vs 13 stations. Long-term rainfall data were available for the 30 stations in Sri Lanka (squares) while long-term temperature and rainfall data were only available at the 13 stations used in the drought study (circles).



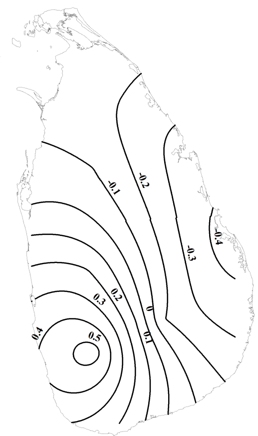

(a) PC 1: 30 Stations




(b) PC 1: 13 Stations




(c) PC 2: 30 Stations




(d) PC 2: 13 Stations

Figure 2.7: PCA comparison: 30 stations vs 13 stations. The spatial patterns are very similar between the two datasets, with a general south to north trend in PC 1 and an east to west trend in PC 2.

The confidence bands in the CWTs highlight the 1980s in the 4–6 year period range for PDSI Score 1 and in the 1–8 year period range for PDSI Score 2 (Figure 2.8). The confidence bands for SPI-9 also highlight the 1980s but in the 1–2 and 4–6 period range for Score 1 and in the 1–4 year range for Score 2 (Figure 2.9). While some of these regions could be spurious correlations, there is generally high power between 2 and 16 years in the CWTs for all four of the retained PC scores. The CWT of the Niño 3.4 dataset also shows significant power in the 2–4 year range from 1880 to 1920 as well as from 1960 to 2010, which is consistent with observations by *Torrence and Compo* (1998). There also appears to be a lengthening of frequency in the Niño 3.4 time series from 1970 to 1990 (Figure 2.10). The XWTs show significant common power between all of the scores and Niño 3.4 from 1980 to 2000. During this time period, Score 1 of each index shows a consistent anti-phase relationship (i.e., left-pointed arrows) with Niño 3.4 data during the 4–6 period range. Score 2 of PDSI also shows an anti-relationship with Niño 3.4 data in the 1980s during the 4–6 period range while Score 2 of SPI-9 does not show any clear relationships with the Niño 3.4 data. In general, the phase relationships varied greatly in the XWTs. Greater areas stand out as being significant in the WTCs compared to the XWTs. The WTCs of both Score 1s and PDSI Score 2 again show the anti-phase relationship with the Niño 3.4 data during 1980–1990 in the 4–6 period and varying phase relationships in the other regions.

(a) PDSI Score 1 (b) PDSI Score 2

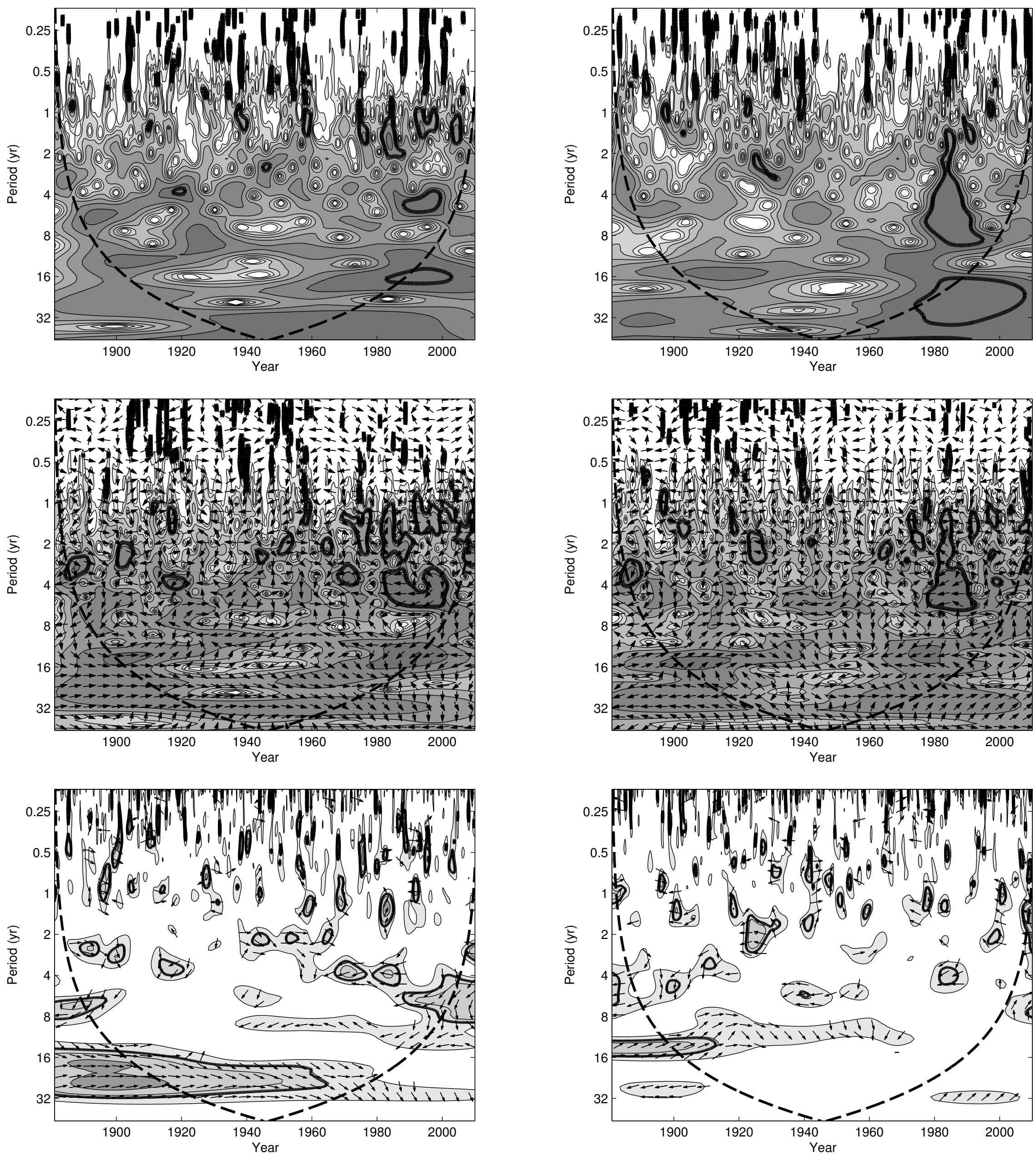



Figure 2.8: Wavelets of PDSI scores: Row 1=CWTs, Row 2=XWTs, and Row 3=WTCs. XWTs and WTCs were constructed using Niño 3.4 data. Areas with dark shading have high power. Significant regions are indicated by black lines and the COI by a dashed line.

(a) SPI-9 Score 1

(b) SPI-9 Score 2

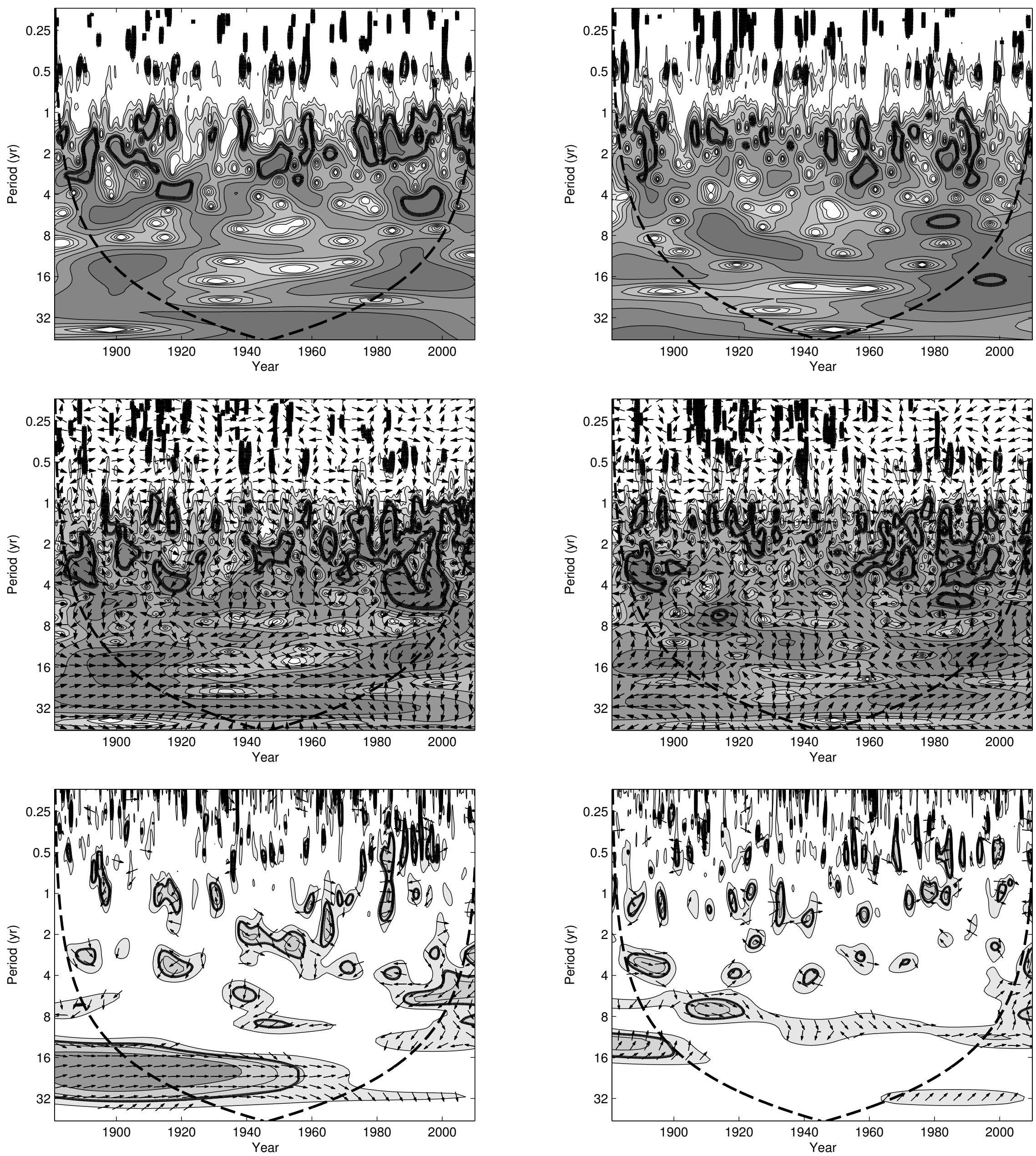



Figure 2.9: Wavelets of SPI-9 scores: Row 1=CWTs, Row 2=XWTs, and Row 3=WTCs. XWTs and WTCs were constructed using Niño 3.4 data. Areas with dark shading have high power. Significant regions are indicated by black lines and the COI by a dashed line.

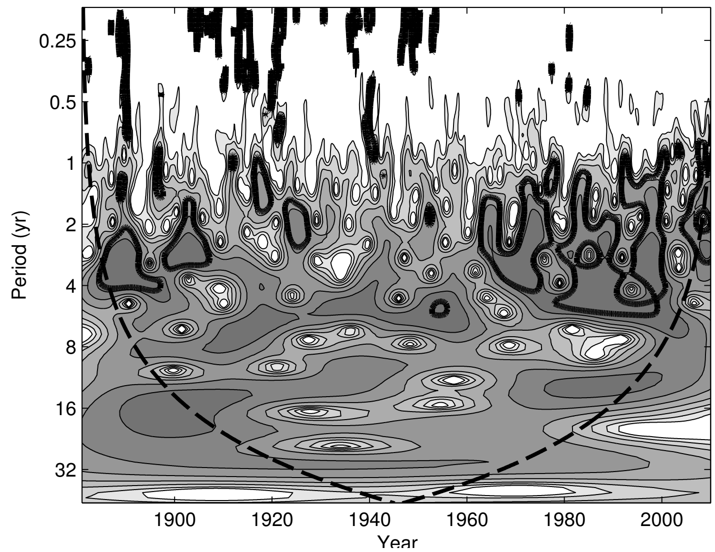



Figure 2.10: Continuous wavelet transform of Niño 3.4. Areas with dark shading have high power. Significant regions are indicated by black lines and the COI by a dashed line.

The PDSI and SPI-9 time series generally show some agreement in drought (see Figure 2.11 for an example). The overall correlation between PDSI and SPI-9 values is 0.65 (Table 2.6), with a range from 0.46 to 0.81 at individual stations. The PDSI and SPI-9 correlations follow climatic zones; the two drought indices have the strongest correlations in wet zone stations (0.74-0.81), followed by intermediate zone stations (0.73-0.74), and dry zone stations (0.46-0.60). Hambantota in the dry zone had a stronger correlation of 0.74 (Table 2.6).

PDSI defines more periods of drought and more numbers of months in drought than SPI-9 at all 13 stations (Figure 2.12). The SPI-9 data show that the wet zone has generally experienced less drought (<40 periods) than the intermediate zone (40-41 periods) and dry zone stations (>44 periods); Hambantota was an exception again in the dry zone with only 39 drought periods. The PDSI data do not follow any clear spatial patterns with regards to number of drought periods. By subtracting the percentages of months in each of the drought classes of SPI-9 from PDSI, a relative comparison of drought severity for the two indices was developed. This comparison shows that SPI-9 generally classifies more months as extreme drought than PDSI (Figure 2.13).

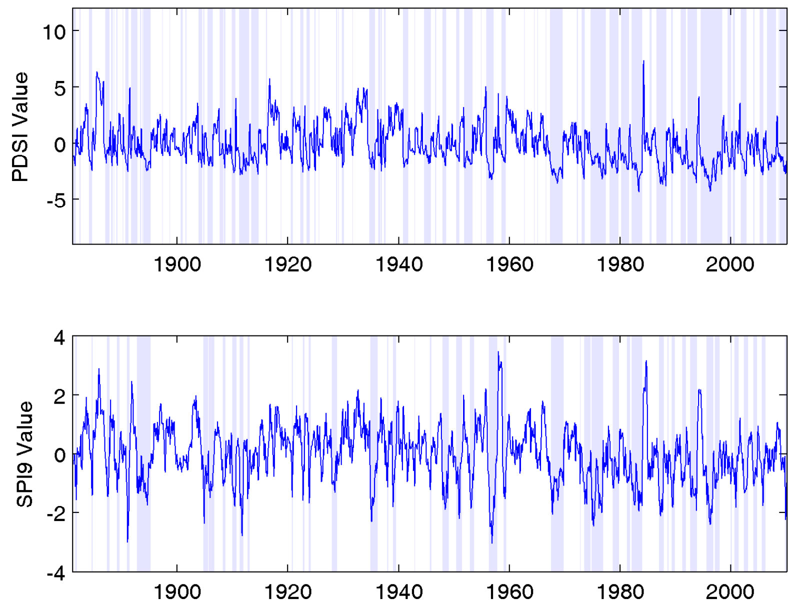



Figure 2.11: PDSI (top) and SPI-9 (bottom) time series for Anuradhapura. Drought periods colored in gray.

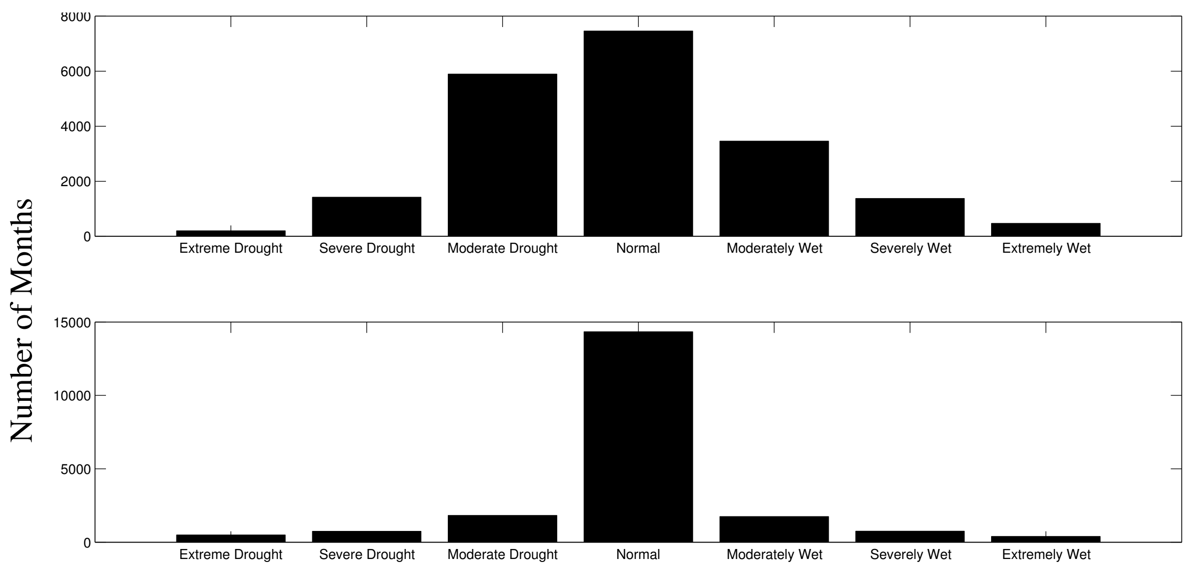



Figure 2.12: Differences in Drought Categories for PDSI (top) and SPI-9 (bottom).

Table 2.6: PDSI and SPI-9 Correlations

| Zone | Station | R-val |
|---|---|---|
| Wet | Colombo | 0.74 |
| | Galle | 0.81 |
| | Nuwara Eliya | 0.75 |
| | Ratnapura | 0.80 |
| Intermediate | Badulla | 0.73 |
| | Kurunegala | 0.74 |
| Dry | Anuradhapura | 0.60 |
| | Batticaloa | 0.46 |
| | Hambantota | 0.74 |
| | Jaffna | 0.47 |
| | Mannar | 0.55 |
| | Puttalam | 0.51 |
| | Trincomalee | 0.51 |
| | Overall | 0.65 |

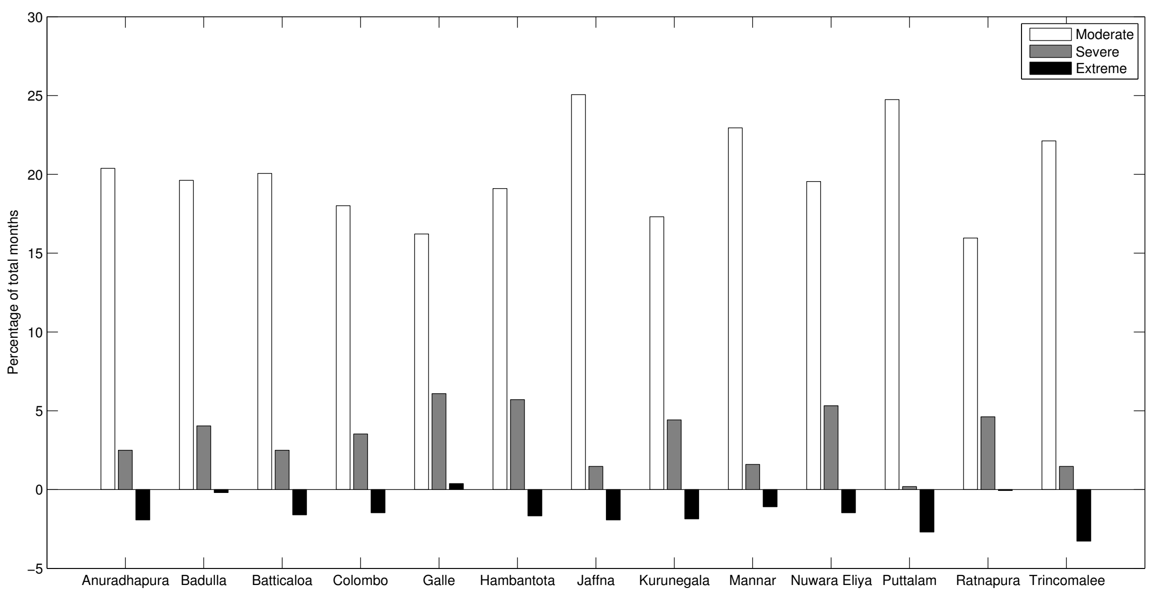



Figure 2.13: Differences in Drought Frequencies. Values are calculated as the difference in percentages of PDSI months and SPI-9 months in each category.

Economic and demographic metrics related to agriculture, rather than crop-specific metrics, showed significant correlations with drought indices (Table 2.7). The correlations

Table 2.7: Correlations with DesInventar agricultural metrics

| | District | Metric | R-val |
|---|---|---|---|
| PDSI | Badulla | Number of families affected | -0.37 |
| | Kurunegala | Loss for paddy (rupees) | 0.27 |
| | | Loss for other farm (rupees) | 0.24 |
| SPI-9 | Anuradhapura | Payment for relief (loss of other crop in rupees) | 0.33 |
| | | Loss for other farm (rupees) | 0.33 |
| | Puttalam | Payment for relief (livelihood option) | -0.36 |
| | Trincomalee | Number of Grama Niladhari divisions affected | 0.45 |

Table 2.8: Significant monthly linear trends ($\alpha$ = 0.05) with R-values in parentheses. All trends are decreasing.

| Stations | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Badulla | PDSI (0.28) | PDSI (0.25) | PDSI (0.24) | PDSI (0.22) | PDSI (0.29) | PDSI (0.36) | PDSI (0.27) | | | | | PDSI (0.24) |
| Kurunegala | PDSI (0.27) | | | | | | | PDSI (0.23) | PDSI (0.19) | PDSI (0.20) | | PDSI (0.22) |
| Anuradhapura | SPI-9 (0.23) | SPI-9 (0.22) | SPI-9 (0.20) | SPI-9 (0.20) | SPI-9 (0.20) | SPI-9 (0.22) | SPI-9 (0.22) | SPI-9 (0.22) | | | | SPI-9 (0.23) |

with the specific drought index varied depending on the climatic zone. The intermediate zone stations of Badulla and Kurunegala both significantly correlated with PDSI while the dry zone stations of Anuradhapura, Puttalam, and Trincomalee significantly correlated with SPI-9; none of the wet zone districts had significant correlations with either of the drought indices. The correlation results indicate that there is a counterintuitive, inverse relationship between drought and the number of families affected by drought in Badulla and relief payments for livelihood in Puttalam (Table 2.7). Linear trend analysis for PDSI shows that Badulla is experiencing drier conditions from December to July (Table 2.8). Kurunegala is also experiencing drier conditions during 5 months of the year. Of the dry zone stations, significant trends were only observed at Anuradhapura with monthly SPI-9 values decreasing from December to August (Table 2.8).

## 2.4 Discussion

Selection of a drought index as a monitoring tool is dependent on both the quantity of climate data and the ability of the index to consistently detect spatial and temporal variations of a drought event (*Morid et al.*, 2006). Both indices show similar spatial patterns for drought in Sri Lanka, with in phase PC 1s and out of phase PC 2s. Although, all of the months show similar contributions to PC loadings, PCs 1 and 2 could be physically interpreted as the NEM and SWM. The in phase PC 1s indicate that drought (and consequently non-drought) conditions are experienced uniformly across the island. This is consistent with the NEM, which brings rainfall to the entire island. The out of phase PC 2s indicate that drought conditions experienced in the southwest portion of the island are opposite those of the conditions experienced elsewhere on the island; the combination of negative loadings and negative score values signify higher index values in the southwest. This is consistent with the SWM, which brings rainfall to the southwest of the island but not elsewhere. Temporal analysis of the PC scores showed high power in the 4–6 year period range, consistent with the dominant modes of oscillations observed for rainfall (*Suppiah and Yoshino*, 1984b). The XWTs and WTCs showed a consistent anti-phase lag relationship between PC Score 1s and Niño 3.4 data during 1980–2000 in the 4–6 period range. This indicates a weakening of NEM during El Niño years in recent decades, which is consistent with findings by other researchers (*Zubair et al.*, 2008; *Zubair and Ropelewski*, 2006).

Although SPI is computationally simple and only needs precipitation data, the index does not account for the influence of temperature on water shortages. Alternatively, PDSI is constructed using a physical water balance model that incorporates evapotranspiration processes into the calculations but lack of data for parameters (such as site-specific AWC values) in Sri Lanka introduces uncertainties in the results (*Karl*, 1983). Furthermore, PDSI values can vary depending on the evapotranspiration equation used in the calculations (*Sheffield et al.*, 2012). While PDSI values were similar at the regional and global level for both the Thornthwaite and Penman-Monteith evapotranspiration equations (*van der Schrier et al.*, 2011), local comparisons of these estimates have not been conducted for Sri Lanka to date. These local comparisons of evapotranspiration models at multiple timescales (i.e., daily and monthly) are the focus of ongoing work in our research group.

While determination that one particular index is better overall than another index can rarely be made (*Heim Jr*, 2002), our study suggests that different indices might be appropriate for each of the climatic zones in Sri Lanka: PDSI for the intermediate zone stations and SPI-9 for the dry zone stations. Neither the PDSI nor SPI-9 correlated with the wet zone stations. PDSI and SPI-9 for the wet zone stations of Nuwara Eliya or Ratnapura did not correlate with any of the district-level agricultural metrics, possibly due to the limited recorded drought information in DesInventar at these locations (20 and 22 months, respectively). The remaining two wet zone stations, Colombo and Galle, had less than 10 months of recorded drought information and were thus excluded from the correlation analysis. Agricultural metrics showed strong correlations with PDSI values of Badulla and Kurunegala as well as SPI-9 values of Anuradhapura, Puttalam, and Trincomalee. Especially given the negative correlations between the drought indices and some of the DesInventar metrics, additional research is needed to verify the validity of using correlations with DesInventar metrics and to identify alternative agricultural metrics to select appropriate drought indices for the wet zone. Although there are some issues, the correlation analysis with the DesInventar drought metrics was a first step towards determining an adequate agricultural drought monitoring tool for Sri Lanka.

Continuing to study drought indices will assist national understanding of drought in the country, development of a drought monitoring system, and associated drought management strategies. Particular attention should be given to robust indices that reflect expected climate change impacts such as increasing temperatures (*Eriyagama et al.*, 2010) and strengthening of El Niño phenomena (*Dai et al.*, 1998). While variations in PDSI and SPI-9 drought classifications will have notable impacts on drought management if one of these indices is adopted as a basis for drought relief payment allocation, they do not seem to greatly influence the spatial distributions of the two drought indices. Our results show that Anuradhapura and Badulla have been experiencing drier conditions during March while Kurunegala has been experiencing drier conditions during September, when rice planting decisions are typically made for Yala and Maha, respectively (*Zubair et al.*, 2008). Since weather during these months could have large impacts on farming decisions, additional research is needed to understand the impacts of these patterns on actual crop production.

# Chapter 3

# Irrigation Water Requirements

## 3.1 Introduction

During the drought analysis in the previous chapter, we discovered that the northeast portion of the island (an important agricultural region) was becoming drier during the minor growing season, when water resources are already scarce. Various practices are currently being pursued in the country to adapt rice production to a changing climate, including cultivation of stress-resistant varieties (*Redman et al.*, 2011). Of the adaptation measures, shifting of the planting date is a low-cost strategy that is especially promising for resource-strained environments (*Hoanh et al.*, 2015).

Existing IWRs studies in Sri Lanka, however, either typically do not take into account the dry zone (e.g., (*Weerasinghe et al.*, 2000)), where 70% of the country's rice is grown (*DCS*, 2014; *Withanachchi et al.*, 2014) or they do not address the minor growing season (e.g., (*De Silva et al.*, 2007)), when rice is produced mainly under irrigated conditions (*Amarasingha et al.*, 2015). Furthermore, these studies only focus on average patterns. Given that irrigation agriculture accounts for 96% of water withdrawals in the drier areas of the country (*De Silva et al.*, 2007), an understanding of historical patterns of variability of IWRs during the minor growing season is critical for contextualizing estimates of future changes in IWRs and for informing current adaptation practices.

Therefore, the aim of this chapter is to characterize patterns in IWRs during the minor growing season in the main rice growing zones of Sri Lanka and to quantify the impact that shifting the planting date could have on reducing irrigation water needs, thereby improving the irrigation system efficiency. Our analysis of historical data indicates that significant gains can be achieved by planting early during the minor growing season in the dry and intermediate zones. This local-scale assessment of Sri Lanka IWRs contributes to

Table 3.1: Station profiles. Average climate data reported for minor growing season (March 1 – October 13).

| Station | Average Daily Rainfall (mm) | Average Daily Temperature (°C) | Nearby Irrigation System |
|---|---|---|---|
| Angunakolapelessa | 3.1 | 28.1 | Mahaweli System UW |
| Aralaganvila | 2.1 | 29.0 | Mahaweli System C: Ulhitiya Tank |
| Batalagoda | 4.5 | 27.8 | Wewa: Batalagoda Tank |
| Maha Iluppallama | 2.5 | 28.6 | Mahaweli System H: Kalawewa Tank |

the growing literature on the role that low-cost adaptation measures can play in mitigating detrimental impacts of climate change.

## 3.2 Methods

A detailed spatial assessment of IWRs cannot be conducted in Sri Lanka due to lack of daily meteorological data (*De Silva et al.*, 2007). Therefore, the IWRs analysis will be conducted on a station-by-station basis. Since the brunt of climate change impacts on water resources is expected to be borne by the dry zone of the country (*Eriyagama and Smakhtin*, 2010), this objective will particularly focus on stations in this region. After reviewing a list of available records, data was obtained for four stations located in districts with high paddy production (Figure 3.1). The data from the Meteorological Department of Sri Lanka includes daily rainfall, temperature, relative humidity, wind speed, and sunshine duration records from 1991-2010 (Table 3.1). The meteorological data were reviewed for quality issues prior to calculating IWRs.

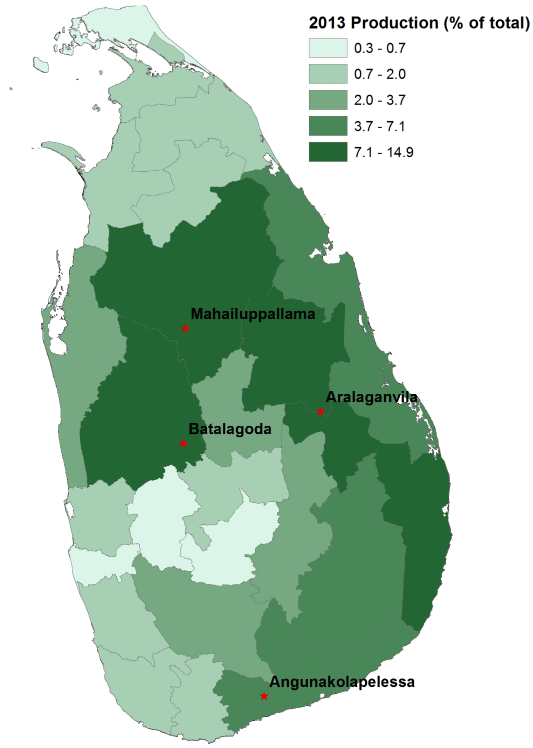



Figure 3.1: Stations used in IWRs analysis

### 3.2.1 IWR Calculations

In this analysis, we define IWRs as:

$$IWR = WD - P_{eff} \tag{3.1}$$

where $WD$ is the water demand and $P_{eff}$ is the effective rainfall (i.e., available water) (*Brouwer and Heibloem*, 1986); all units are in mm. Water demand is defined as:

$$WD = SAT + WL + PERC + ET_c \tag{3.2}$$

where $SAT$ is the soil saturation, $WL$ is the water layer, $PERC$ is the percolation and seepage, and $ET_c$ is the crop evapotranspiration (*Chapagain and Hoekstra*, 2011); all units are in mm.

Water is required during the land preparation stage and the growing period of rice, the latter of which is composed of the initial, development, mid-season, and late stages (Table 3.2). *SAT* is the amount of water used by farmers during land preparation to make it easier to till and level the field; the amount of water needed for this process is dependent on local soil characteristics. The three stations in the dry zone are predominantly underlain by reddish brown earth (RBE) soils while the intermediate zone station is predominantly underlain by low humic gley (LHG) soils (*Panabokke*, 1996). Because the RBE soils have high moisture-retaining clay content (*Stone*, 2015), we assume SAT is 250 mm for these stations. For LHG soils, which have sandy loam textures, we assume SAT is lower at 200 mm (*Panabokke*, 1996).

$WL$ is the amount of water farmers use to flood the fields to prevent weed growth during the initial growing period; farmers in Sri Lanka typically maintain a depth of 10 cm (*Stone*, 2015). *PERC* represents the amount of water lost due to drainage of water from the soil throughout the growing period; we assume the intermediate zone station has a percolation loss rate of 6 mm/day, while the dry zone stations lose water at a rate of 8 mm/day (*Weerakoon et al.*, 2010). $ET_c$ is the amount of water needed by rice due to evaporation and transpiration water losses throughout the growing period and is calculated as:

$$ET_c = ET_o * K_c \tag{3.3}$$

where $ET_o$ is the potential evapotranspiration (PET) (in mm) and $K_c$ is a dimensionless crop-specific coefficient, which varies for rice depending on the growing stage ((*Batchelor and Roberts*, 1983; *Batchelor*, 1984); Table 2). $ET_o$ (in mm/day) values were calculated using the Penman-Monteith method (*Allen et al.*, 1998):

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}, \tag{3.4}$$

where $R_n$ is the net radiation at the crop surface (MJ/m$^2$/day), $G$ is the soil heat flux density

(MJ/m$^2$/day), $T$ is the mean daily air temperature at 2m height (°C), $u_2$ is the wind speed at 2m height (m/s), $e_s$ is the saturation vapor pressure (kPa), $e_a$ is the actual vapor pressure (kPa), $\Delta$ is the slope vapor pressure curve (kPa/°C), and $\gamma$ is the psychrometric constant (kPa/°C).

The effective rainfall was calculated using a daily-adjusted dependable rain method:

$$P_{eff} = \begin{cases} 0.6P_{daily} - 0.3 & \text{if } P_{daily} \leq 2.3 \\ 0.8P_{daily} - 0.8 & \text{otherwise} \end{cases}, \tag{3.5}$$

where $P_{eff}$ is the effective rainfall and $P_{daily}$ is the daily rainfall (*FAO*, 2016); all units are in mm.

The IWR for any growing season depends on the date that rice is planted. To quantify the amount of irrigation water required to grow rice during the minor growing season, daily IWRs were summed over the land preparation and the growing stages for a given planting date (i.e., first day of the initial growing stage) to develop a seasonal estimate. Seasonal IWRs were calculated for planting dates ranging from March 22 to June 30; the range of planting dates were selected based on crop calendars (*IDSL*, 2014). We used a threshold of five consecutive days to address missing data; when there were five or fewer missing consecutive days of $P_{eff}$ or $ET_o$, missing data at a given station was imputed with data from the station with the highest correlation for the whole time series. Otherwise, the seasonal IWRs calculation was not conducted for that planting date. Although daily data is necessary for agricultural research (*Abeyasekera et al.*, 1983), they could lead to an overestimation of IWRs if daily net irrigation requirements are constrained to be greater than or equal to zero (*Doll and Siebert*, 2002). We address this issue by allowing daily IWRs to be negative, which takes into consideration the soil's ability to hold rainwater. The harvest and postharvest stages are not considered in the IWR calculations.

Table 3.2: Stage Lengths and Crop Coefficients

| Stages | Length (days) | Kc |
|---|---|---|
| Land Preparation | 21 | - |
| Initial Growing Stage | 20 | 1.1 |
| Developmental Stage | 25 | 1.1 |
| Mid-Season Growing Stage | 30 | 1.25 |
| Late Season Growing Stage | 30 | 1.0 |

### 3.2.2 Characterization and Adaptation Analysis

Variability of IWRs can be assessed using several metrics. An average IWR for each season (i.e., IWR averaged across all possible planting dates) should reflect temporal trends or other large-scale patterns related to climate. Intraseasonal variation of IWRs (i.e., IWR as a function of planting date for any given season) should reflect other changes, for example a change in the onset date of the monsoon. We use both interseasonal and intraseasonal metrics to explore patterns in IWR estimates.

Interseasonal analysis was conducted using average seasonal IWRs:

$$\overline{X_j} = \frac{\sum_{n=1}^{N} X_{i,j}}{N}, \tag{3.6}$$

where $X$ is the seasonal IWR for planting date $i$ and year $j$, $\overline{X_j}$ is the average seasonal IWR for year $j$, and $N$ is the number of days for which a seasonal IWR was calculated (maximum of 101). Variability in seasonal IWRs was quantified using coefficient of variation (CV). Interseasonal CV for each station was calculated by:

$$C_v = \frac{\sigma(\overline{X_j})}{\mu(\overline{X_j})}, \tag{3.7}$$

where $\sigma(\overline{X_j})$ and $\mu(\overline{X_j})$ are the standard deviation and mean, respectively, of the average seasonal IWRs. The intraseasonal CV is then:

$$C_{v,j} = \frac{\sigma_j(\overline{X_{i,j}})}{\mu_j(\overline{X_{i,j}})}, \tag{3.8}$$

where $\sigma_j(\overline{X_{i,j}})$ and $\mu_j(\overline{X_{i,j}})$ are the standard deviation and mean, respectively, of the seasonal IWR estimates for all of the planting dates $i$ for a given year $j$. Linear trend analysis was conducted both interseasonally (i.e., $\overline{X_j}$ as a function of $j$) and intraseasonally (i.e., $\overline{X_{i,j}}$ as a function of $i$ for each $j$); significance of linear trend analysis was evaluated using the nonparametric Mann-Kendall test and the slopes quantified using the Theil-Sen estimator method (*Theil*, 1992). Patterns in IWRs were assessed relative to sea surface temperatures from the Niño 3.4 dataset, which has been shown to explain some of the climate variability in Sri Lanka (*Gunda et al.*, 2016).

Intraseasonal patterns in IWRs were compared with actual planting date records from nearby agricultural communities to identify possible gains from shifting planting dates (Table 3.1); we assume that planting occurred 21 days after the initial water release dates listed in government records (including (*MASL*, 2004-2013)). Within each season, we identify periods of low IWRs (which we define as the lowest 25th percentile of values) to explore patterns in optimal planting dates. We quantify potential water savings from shifting planting dates by calculating:

$$WS_k = IWR_{avg,actual} - IWR_{avg,k}, \tag{3.9}$$

where $WS_k$ is the potential water savings for planting week $k$, $IWR_{avg,actual}$ is the average of the seasonal IWR estimates corresponding to the actual planting dates across the years, and $IWR_{avg,k}$ is the average of the seasonal IWR estimates across the years for each planting week $k$; all units are mm/season. Analyses were conducted in MATLAB and R.

## 3.3 Results

The three stations in the dry zone have higher and less variable seasonal IWRs (mean: 1625–1746 mm; interseasonal CV: 0.04–0.06) than Batalagoda (mean: 1163 mm; interseasonal CV: 0.11) (Figures 3.2 and 3.3). There are a number of years when the intraseasonal CV is notably greater than the interseasonal CV, particularly at Batalagoda and Maha Iluppallama (Figure 3.3). There are no systematic trends in either the CVs or average IWRs across the seasons (Figures 3.3 and 3.4). The lack of trends in IWRs is consistent with the general lack of trends in PET and precipitation observed over the course of the growing season at the four stations (Figures 3.5 and 3.6).

Intraseasonally, IWRs generally increase with planting date (Table 3.3). The general increase in IWRs as a function of planting date is consistent with increasing PET and decreasing rainfall patterns observed over the course of the minor growing season (Figures 3.7 and 3.8). In 2000, all four stations exhibit a significant negative trend in IWRs as a function of planting date (Table 3.3). Brief El Niño periods occurred in 1992, 1995, 1998, 2002, 2005, 2010 while La Niña periods occurred in 1996, 1999-2001, and 2008 (Figure 3.9).

The actual planting did not often coincide with the low IWRs periods, especially near the dry zone stations (e.g., Figure 3.10). Water savings calculations highlight that less irrigation water would be needed if rice were planted early in the season: before April 20th at Batalagoda and before May 1st at the dry zone stations (Figure 3.11). The potential maximum water savings presented in Figure 3.11 correspond to 2.8% at Batalagoda, 3.1% at Angunakolapelessa, 3.7% at Aralaganvila, and 6.4% at Maha Iluppallama of the corresponding station's average seasonal IWRs.

Table 3.3: Theil-Sen slopes of linear models fit to seasonal IWRs as a function of planting date. Significant positive slopes in red, significant negative slopes in blue, and non-significant slopes in black; $\alpha = 0.05$.

| Year | Angunakolapelessa | Aralaganvila | Batalagoda | Maha Iluppallama |
|---|---|---|---|---|
| 1991 | - | - | - | 2.6 |
| 1992 | -0.6 | 0.9 | - | 1.6 |
| 1993 | - | -1.0 | 2.5 | 3.3 |
| 1994 | -1.8 | 1.2 | -0.2 | -0.1 |
| 1995 | 3.1 | 1.5 | 6.0 | 6.0 |
| 1996 | -0.2 | 1.0 | -0.6 | -0.7 |
| 1997 | -0.4 | 2.5 | 2.9 | 2.8 |
| 1998 | -0.3 | 0.6 | 0.7 | 0.8 |
| 1999 | 0.6 | 0.8 | - | 2.4 |
| 2000 | -1.1 | -0.4 | -1.9 | -1.3 |
| 2001 | 1.7 | 2.8 | 3.0 | 3.8 |
| 2002 | 2.1 | 2.5 | 5.3 | 4.9 |
| 2003 | 2.4 | 2.5 | 2.0 | 1.4 |
| 2004 | 2.2 | 0.4 | -3.8 | 3.1 |
| 2005 | - | 1.8 | 3.1 | 3.9 |
| 2006 | - | - | 0.2 | 4.1 |
| 2007 | - | - | -0.5 | 0.9 |
| 2008 | - | 0.9 | 2.6 | 3.2 |
| 2009 | - | 2.4 | 0.7 | 0.1 |
| 2010 | - | 1.7 | 3.0 | 1.5 |

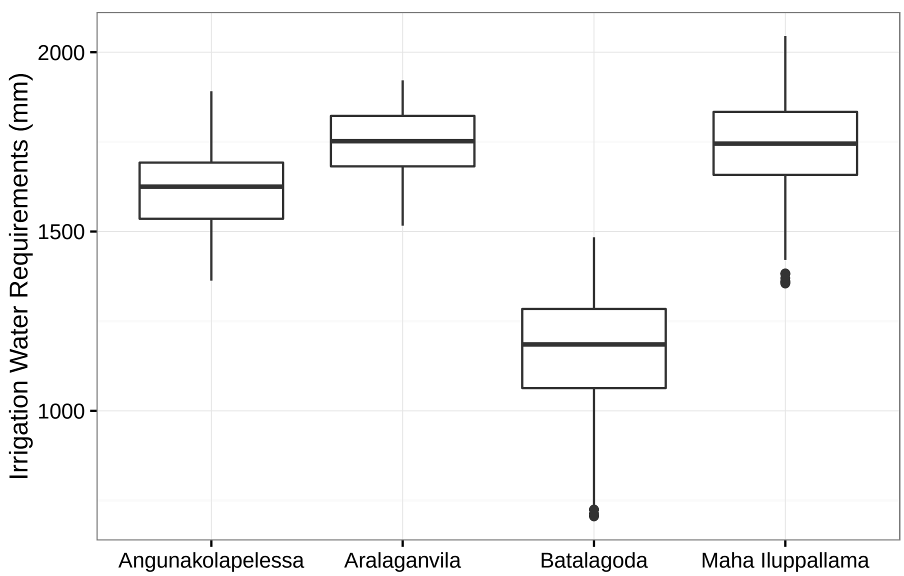



Figure 3.2: Distribution of seasonal IWRs at the four study locations.

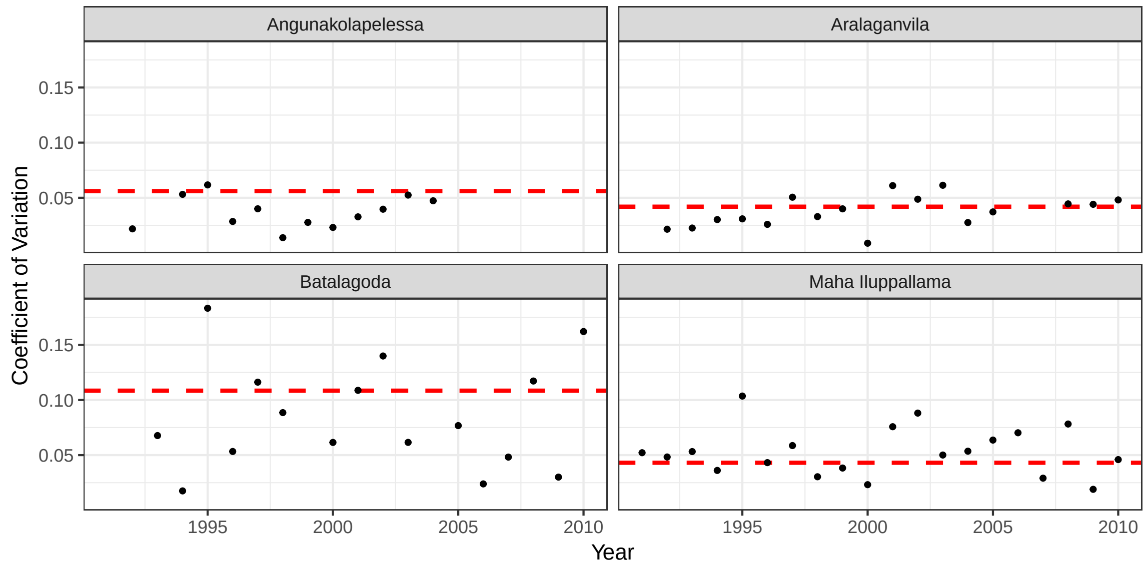



Figure 3.3: Intraseasonal coefficient of variation in irrigation water requirements (black points) compared to interseasonal coefficient of variation at each station (red dashed lines)

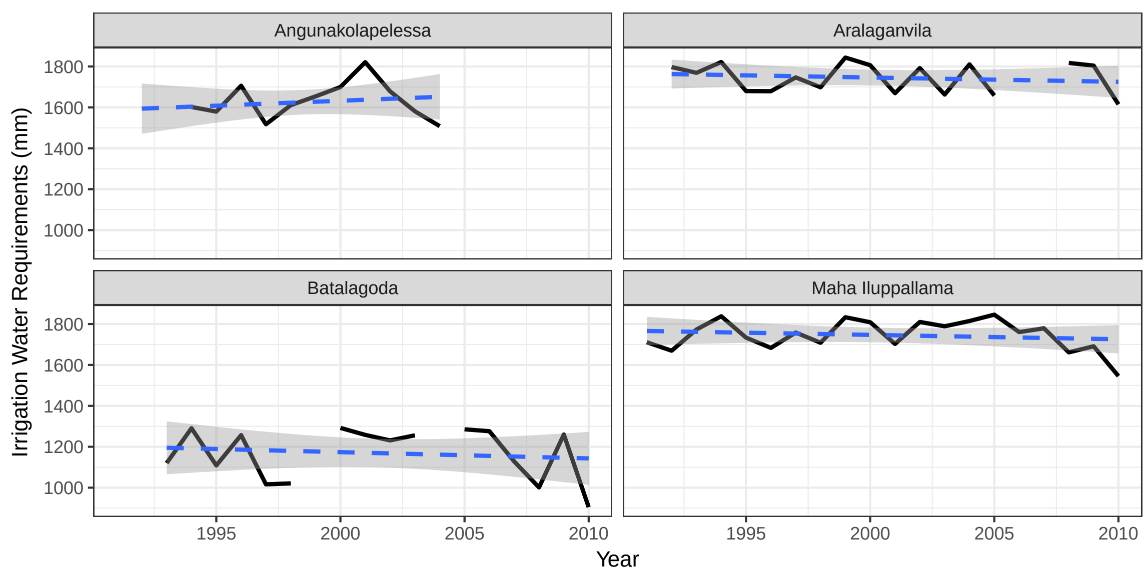



Figure 3.4: Average seasonal IWRs (black solid lines) fitted with a linear model fit (blue dotted lines) and corresponding 95% confidence interval (gray shaded areas). None of the slopes is significantly different from zero (p>0.05 for all).

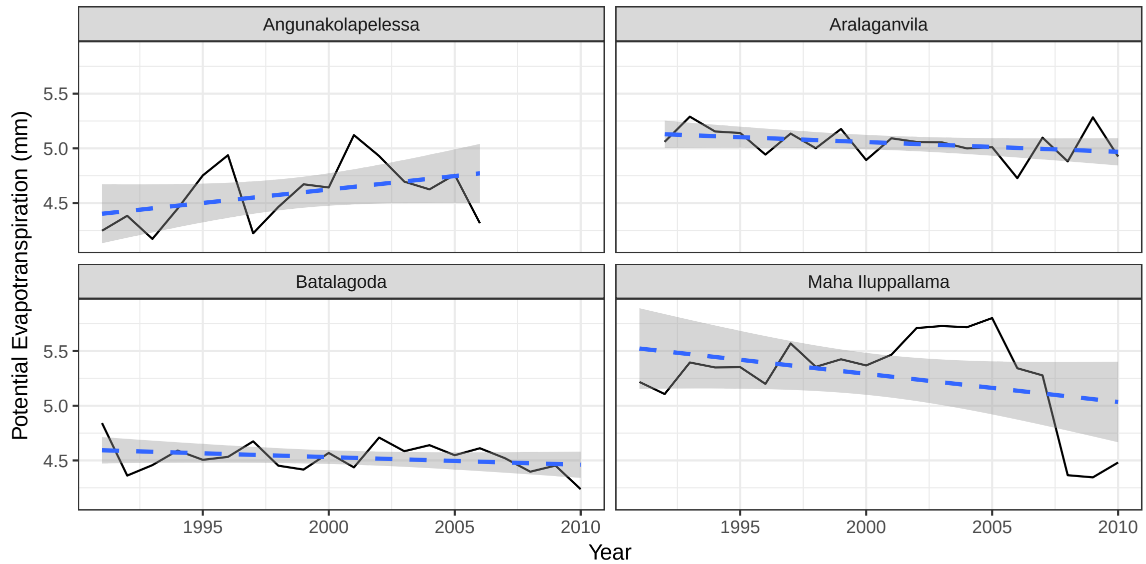



Figure 3.5: Average daily potential evapotranspiration (black solid lines) fitted with a linear model fit (blue dotted lines) and corresponding 95% confidence interval (gray shaded areas). Averages for minor growing seasons were calculated using daily data from March 1 to October 13. Angunakolapelessa has a small positive trend while Maha Iluppallama has a small negative trend. Aralaganvila and Batalagoda do not have slopes significantly different from zero (i.e., $p>0.05$).

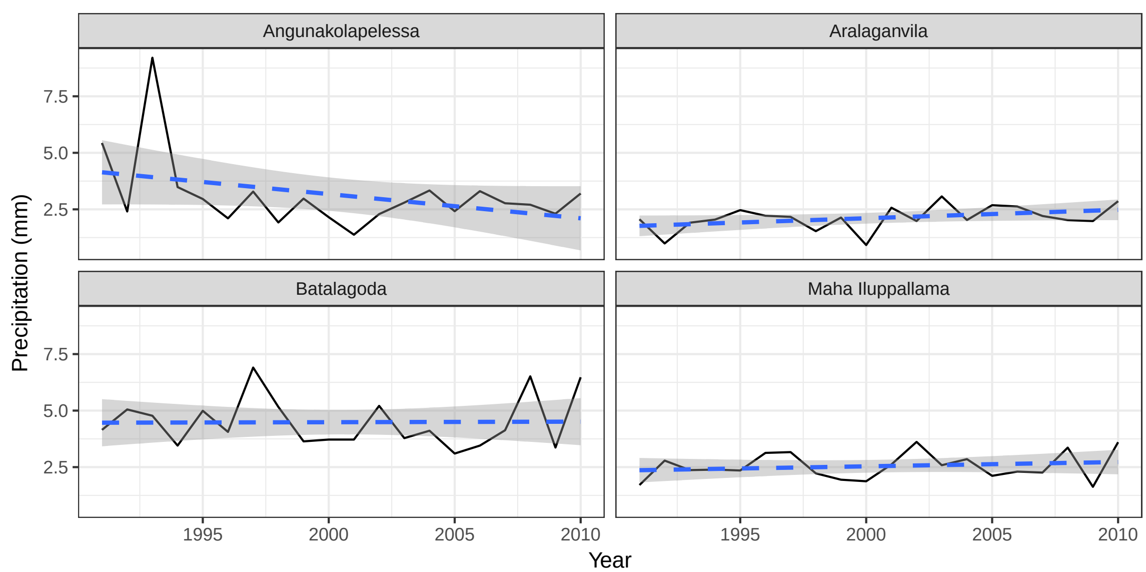



Figure 3.6: Average daily precipitation (black solid lines) fitted with a linear model fit (blue dotted lines) and corresponding 95% confidence interval (gray shaded areas). Averages for minor growing seasons were calculated using daily data from March 1 to October 13. Angunakolapelessa has a small negative trend while the remaining three stations do not have slopes significantly different from zero (i.e., $p>0.05$).

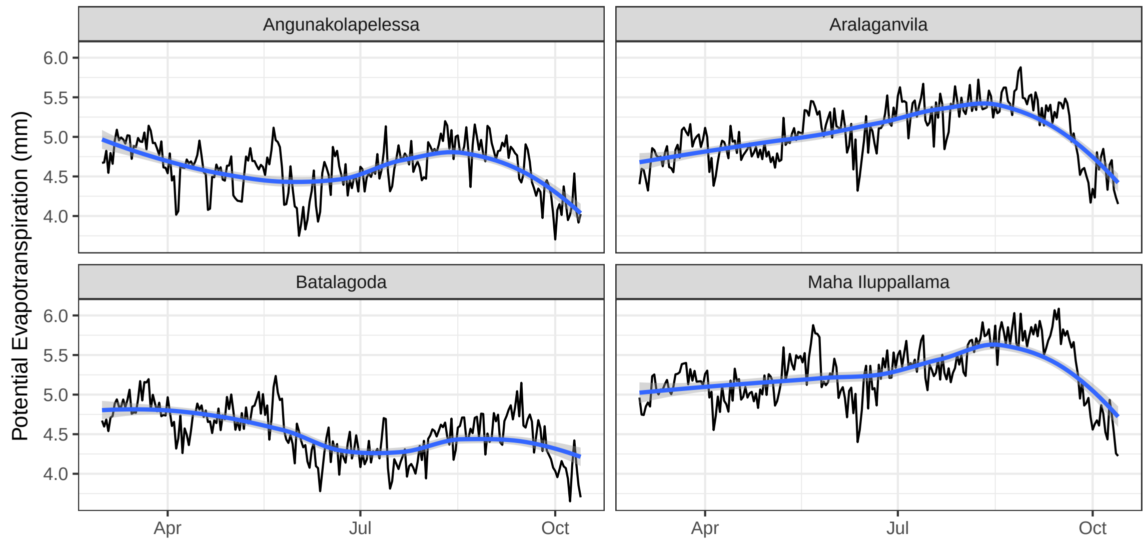



Figure 3.7: Potential evapotranspiration averaged across the years (black solid lines) fitted with a smoothed curve computed by loess (blue dotted lines) and corresponding 95% confidence interval (gray shaded areas). At Angunakolapelessa and Batalagoda, potential evapotranspiration decreases over the course of the minor growing season while at Aralaganvila and Maha Iluppallama, potential evapotranspiration generally increases over the course of the minor growing season.

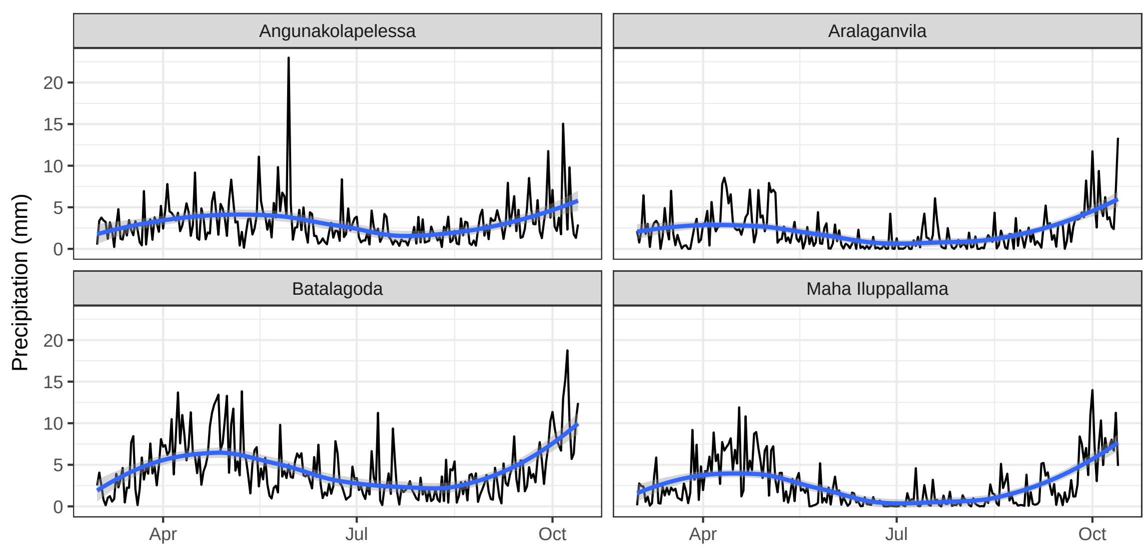



Figure 3.8: Precipitation averaged across the years (black solid lines) fitted with a smoothed curve computed by loess (blue dotted lines) and corresponding 95% confidence interval (gray shaded areas). At all four stations, there is generally high precipitation in early April.

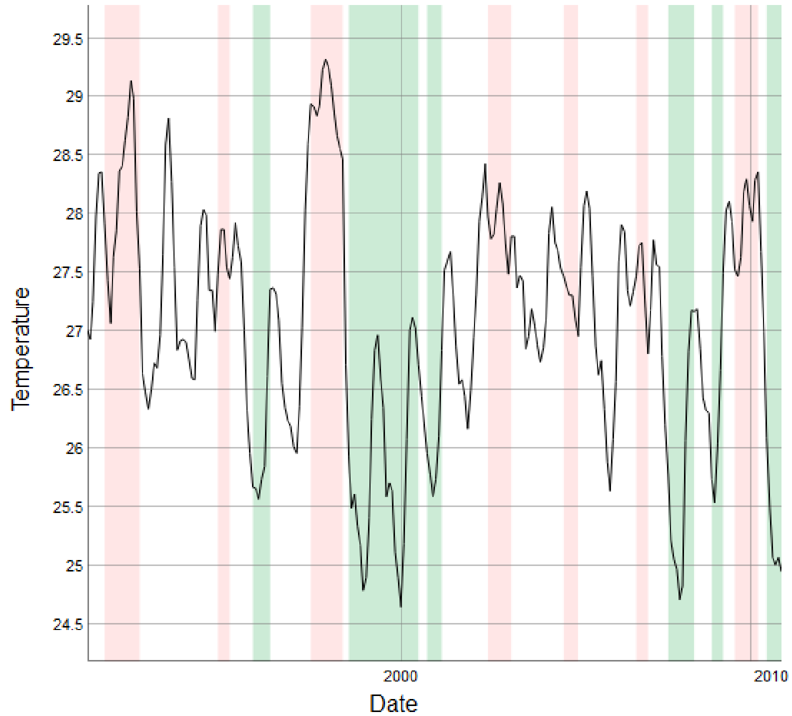



Figure 3.9: Sea surface temperature from the Niño 3.4 dataset with corresponding El Niño (pink) and La Niña (green) periods shaded.

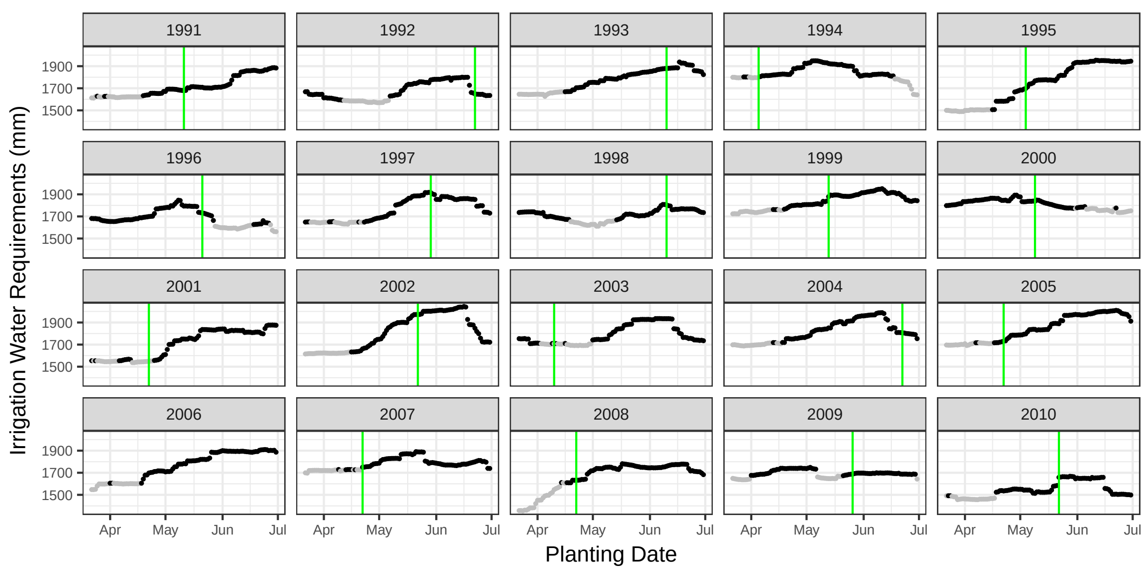



Figure 3.10: Seasonal IWRs as a function of planting date at Maha Iluppallama (points in gray are lower than that season's 25th percentile while points in black are greater than or equal to the 25th percentile). Vertical green line indicates actual date rice was planted; rice was not planted in the nearby irrigation area at Kalawewa tank during 2006.

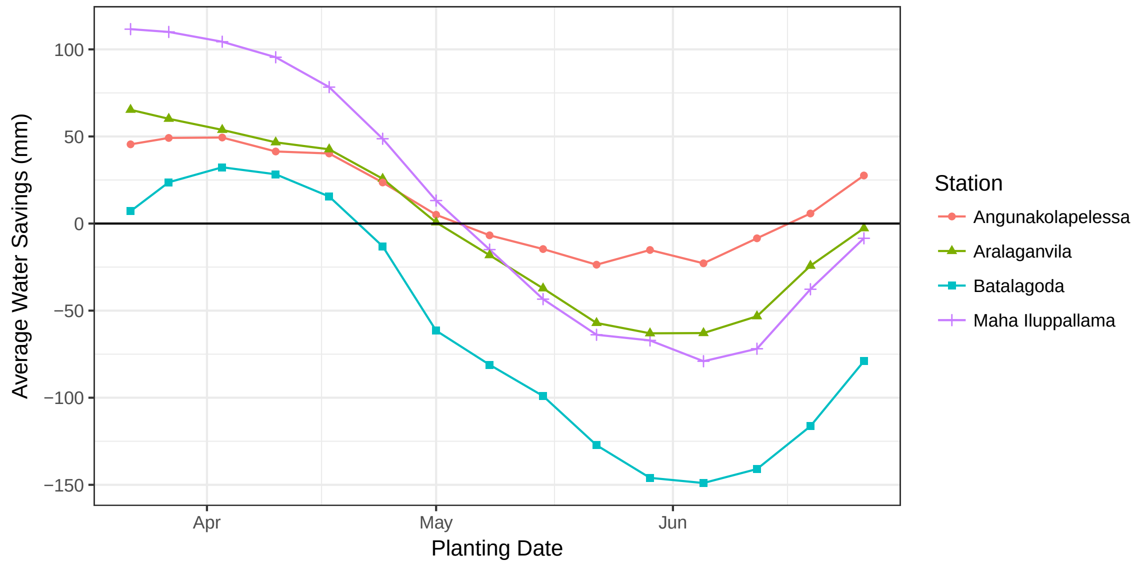



Figure 3.11: Potential average water savings in IWRs as a function of planting date for the 20 years analyzed.

## 3.4 Discussion

Our analysis characterizes IWRs and associated patterns for the main rice growing zones of Sri Lanka. Due to lack of access to historical data, this analysis was limited to a 20-year period at four stations. Although the station coverage is sparse, the previous chapter indicates that such patterns could still be good approximations of general patterns in the country. Batalagoda has lower IWRs than the three stations in the dry zone, which is consistent with the higher rainfall received in the intermediate climatological zone. The minor growing season IWRs for Batalagoda are similar to the estimates developed for the Nilwala basin (1012-1246 mm) (*Weerasinghe et al.*, 2000), which is also in the intermediate zone. IWRs for the dry zone have only been characterized for the major growing season (450-500mm) (*De Silva et al.*, 2007), so our average IWRs estimates of 1625-1746mm are among the first developed for the minor growing season for this region of the country.

In addition to average estimates, we also consider trends in IWRs both across and within seasons. Although increases in temperature have been observed in Sri Lanka (*Eriyagama and Smakhtin*, 2010), we do not observe any systematic trends in average seasonal IWRs across the study years (Figure 3.4). A combination of increasing PET and decreasing rainfall over the course of the minor growing season (Figures 3.7 and 3.8) drive increases in IWRs as a function of planting date; the notable exception was 2000 when a significant La Niña was present. The presence of a La Niña in 2000 could have delayed and stabilized the rainfall, causing the coefficient of variation to be relatively low during this period (Figure 3.3); the cause of the local high in coefficient of variation in 1995 for Batalagoda and Maha Iluppallama is unclear.

We also consider the variability in seasonal IWRs. IWRs at Batalagoda have a higher CV than the three dry zone stations (Figure 3.3), indicating that the intermediate zone has more variable weather. Furthermore, during certain years, the interseasonal CVs are notably lower than intraseasonal variability. For example, the intraseasonal CV at Batalagoda was 0.19 in 1995, which is much larger than the 0.11 interseasonal CV observed at the station across the 20 years. This indicates that day-to-day decisions would have had measurable impact on seasonal IWRs in 1995 at Batalagoda. Therefore, intraseasonal fluctuations should be considered alongside long-term changes during planning to minimize irrigation water demand and generally, improve management of water resources for agriculture.

Ideally, planting dates would coincide with rainfall onset to maximize crop yields (*Amarasingha et al.*, 2015). When timely rainfall forecasts are lacking, however, an understanding of historical patterns could help inform agricultural practices. If irrigation water is available, shifting planting dates to mid-April or earlier could improve irrigation water use efficiencies in Sri Lanka while delaying the planting date to June could result in losses (Figure 3.11). These dates coincide with the periods of high and low rainfall observed at the stations in the early April months and July months, respectively (Figure 3.8). These findings are consistent with studies (e.g., *Weerasinghe et al.* (2000); *Dharmarathna et al.* (2014)), which identify early April as the optimal planting period for the minor growing season in the intermediate zone based on historical data and future climate scenarios, respectively. However, in years where rainfall is scarce (e.g., in 2000), there may be little or no savings realized from the shifting of planting dates. Spatial variations amongst the zones are also important to recognize; more water savings can be achieved in the dry zone if planting occurs in late March (up to 6.4%) while intermediate zone water savings are highest during the first week of April (up to 2.8%). There are also differences among the dry zone stations; PET trends at Angunakolapelessa, which generally decrease over the course of the minor growing season, are more comparable to trends observed at Batalagoda in the intermediate zone than to the other two stations in the dry zone.

Although our analysis focuses on the irrigation water requirements of the minor growing season, it is worthwhile to note that this irrigation water is obtained through management of excess water from the preceding major growing season. The locally-managed wewa systems in the intermediate zone could potentially respond more rapidly to local rainfall onsets, thereby addressing the management challenge associated with high variability of IWRs in this region. Water releases in the dry zone, however, are based on available stored water across basins in the Mahaweli system. Given the relatively low interseasonal CVs at the dry zone stations, it would be particularly beneficial to systematically shift the planting date of rice earlier in these areas.

Shifting planting dates is a low-cost strategy since no additional resources need to be invested (e.g., purchasing different seed varieties). Although rice revenues are subsidized by the Sri Lankan government, there may be other drivers influencing farmers' selection of planting dates. This is an active area of research among social scientists on the ADAPT-SL project; in addition to rainfall onset and water release dates, we are also considering other factors influencing farmers' planting decisions, such as extreme weather events, labor dynamics, and recommendations by local extension officers. The general increasing trend observed in drought indices during the March planting month noted in the previous chapter may also be a contributing factor. Assuming historical water availabilities, Sri Lanka should be able to meet future demand by continuing to close yield gaps and increasing harvested areas (*Davis et al.*, 2016). However, high-resolution regional climate models for Sri

Lanka indicate that water resources in the dry zone of the country will be adversely affected by climate change (*Ashfaq et al.*, 2009). Furthermore, given research indicating less excess water being available during the major growing season in the future (*De Silva et al.*, 2007), it is all the more critical that water managers optimize planting dates for the minor growing season so that Sri Lankan farmers can continue to maintain self-sufficiency in their staple crop even under the pressures of a changing climate. Overall, our analysis contributes to the growing literature (such as *Kucharik* (2008); *Hu and Wiatrak* (2012); *Deryng et al.* (2011)) on the potential for shifting planting dates on improving crop production.

# Chapter 4

# Crop Diversification

## 4.1 Introduction

In certain parts of the country, however, water stress is already significant enough to warrant diversification away from rice production, a water-intensive process. However, crop selection decisions are influenced by myriad factors besides weather, such as economics (rice is heavily subsidized in Sri Lanka but other crops are subject to market dynamics), a farmer's prior experiences, and their behavioral attitudes.

Fortunately, strategies that help farmers adapt to climate change can benefit both farming productivity and revenue (*Di Falco et al.*, 2012). Although infrastructure-driven strategies (such as building new reservoirs) often drive policy conversations, soft adaptation techniques (such as seasonal forecasts) can also buffer farmers from climate risks (*Sovacool*, 2011). Access to weather information is often positively correlated to changes in farming practices (*Wood et al.*, 2014), with seasonal forecasts, in particular, having considerable potential to improve livelihoods in regions with high inter-annual rainfall variability (*Roncoli*, 2006; *Ash et al.*, 2007; *Ziervogel, G. and Opere, A. (editors)*, 2010; *Hansen et al.*, 2011). Such forecasts can be used by farmers, for example, to inform their crop diversification strategies by helping them decide which crops to plant (*Crane et al.*, 2010).

Both field and modeling approaches have been used to evaluate the impact of forecasts on agricultural communities (*Bharwani et al.*, 2005; *Patt et al.*, 2005; *Ziervogel et al.*, 2005; *Roncoli*, 2006; *Ash et al.*, 2007; *Everingham et al.*, 2008; *Crane et al.*, 2010; *Hansen et al.*, 2011; *Roudier et al.*, 2014; *Wood et al.*, 2014; *Choi et al.*, 2015; *Vervoort et al.*, 2016). Although field studies capture real-world responses to forecasts, their findings can be limited when longitudinal data are absent (*Patt et al.*, 2005; *Ash et al.*, 2007; *Hansen et al.*, 2011). Thus, empirically-grounded agricultural system models play a critical role in the assessment of forecast benefits since they allow for long-term assessment and can take into account the probabilistic realizations of the forecast (*Ash et al.*, 2007).

Given the complex and simultaneous interactions among biophysical, social, economic, and perceptual factors in farming communities, a CNHS framework is critical to developing a comprehensive understanding of the effectiveness of adaptation strategies (*Liu et al.*, 2007; *Nay et al.*, 2014). Accordingly, agricultural system models include complex dynamics to account for the various factors that shape farmers' immediate environments and subsequent decisions (*Graeub et al.*, 2016; *Jain et al.*, 2015). Although market dynamics are often incorporated into modeling studies (e.g., (*Acosta-Michlik and Espaldon*, 2008)), the combined impact of forecast use and different crop economics (i.e., costs and return dynamics of subsidized vs. market-driven crops) on farmer livelihoods has not received much attention. Research shows that garden farmers in the Limpopo province of South Africa who plant butternut squash, a more expensive crop with a perceived guaranteed return, would have much higher income in a drier climate scenario (*Bharwani et al.*, 2005). However, it is unclear, how the crop economics would have affected Limpopo farmers' incomes in a wetter climate scenario. Various countries around the world, including India, Qatar, and the United States have policies that incentivize production of certain crops (*Fader et al.*, 2013). Since subsidies and company contracts can greatly change the economics of crops and subsequent farmer decisions, the interplay between the physical and economic environments needs to be explicitly evaluated to develop a comprehensive understanding of seasonal forecast benefits and limitations.

Thus, the primary objective of this study is to assess the impacts of seasonal forecast use on crop diversification in a system with varying crop economics (i.e., costs and returns). The specific objectives we aim to evaluate for our study area are: 1) whether incorporating forecasts into planting decisions could generate higher net agricultural income for a farmer and 2) the role crop economics play in moderating the effect of different climate conditions on changes in a farmer's net agricultural income.

The dry zone of Sri Lanka, a region with a large agricultural sector and high inter-annual rainfall variability (*Gunda et al.*, 2016), serves as an ideal case study for this analysis for two reasons: 1) varying crop economics and 2) forecasts availability. The three main crops in the region (rice, soybean, and onion) have notably different crop economics: rice production is heavily subsidized and has a guaranteed market return while onions are subject to the dynamics of market supply and demand; soybean returns are partially buffered by futures contracts, whereby farmers enter agreements with businesses to buy the crop at a fixed price irrespective of subsequent market fluctuations. Furthermore, the Meteorological Department of Sri Lanka develops ternary seasonal forecasts (i.e., probabilities that rainfall will be dry, normal, and wet) and shares this information with other government agencies. Therefore, although available, seasonal forecasts are not currently directly shared with farmers.

To evaluate the objectives, this study draws upon diverse research expertise and incorporates methods and insights from several fields, including hydrology, social psychology, geography, and behavioral economics to develop an integrative model on a system dynamics platform. We use both quantitative and qualitative data to inform and develop our empirically-based model, including games in the field to develop decision rules regarding how farmers translate seasonal climate forecast information to farming decisions; when games are designed to emulate the local environment, farmers' hypothetical choices can approximate real-life behaviors and thus, provide considerable insight (*Kühberger et al.*, 2002; *Kang et al.*, 2011). Our simulation results suggest that by using seasonal forecasts, farmers' average agricultural income generally increases, albeit with greater variance in income than farmers that do not use the forecasts. Although further work is needed to understand the impact of social interactions on farmers' crop selection decisions, our analysis indicates that the current economic structure will aid livelihood improvement of a forecast-using farmer under a drier climate scenario and reduce income disparity under a wetter climate scenario. Our work extends the ongoing assessment of seasonal climate forecast benefits for farmer livelihoods both conceptually and methodologically by: 1) explicitly incorporating the impacts of crop economics on farmer livelihoods in a changing climate and 2) using games to derive forecast interpretation decision rules.

## 4.2 Methods

### 4.2.1 Site Description

Our study region is System MH, where approximately 56% of the working population is involved in agriculture (*DCS*, 2012). System MH, located in the Galenbindunuwewa district, is one of the irrigation systems managed by the Mahaweli Authority of Sri Lanka (Figure 4.1). The MH region is chronically water-stressed, in part due to its location in the dry zone. The Huruluwewa reservoir was constructed and later connected to Sri Lanka's major irrigation system to buffer the MH region from the high seasonal rainfall variability. However, decreasing rainfall coupled with minimal inflows from the Mahaweli system has meant that Huruluwewa is often rain-fed and under-capacity during the dry season (*De S. Hewavisenthi*, 1992; *MASL*, 2004-2013; *Abeynayaka et al.*, 2007; *Eriyagama and Smakhtin*, 2010; *Gunda et al.*, 2016).

When water is sufficient during the dry season (e.g., in 2015), farmers in MH predominantly grow rice (65% by area) followed by soybean (14%) and some onion (1%) for revenue; the remaining production area is either devoted to vegetables for household consumption (2.4%), maize (<1%), other crops (<1%), or left fallow (16%) (*Berundharshani and Munasinghe*, 2015). Growing rice is generally preferred over other food crops like soybean or onion because rice is the staple food of the country (*Brewer et al.*, 1992; *Weerakoon et al.*, 2011); soybeans are typically sold for use as animal feed while onions are a cash crop. The water requirements for soybeans are comparable to those of rice but soybeans are more tolerant of drought; in a drier climate, however, onions do much better (*Brouwer and Heibloem*, 1986). Generally, there is sufficient water in the Huruluwewa reservoir to grow onions more often than rice or soybean. However, the input and hired labor cost of growing onions is much greater, up to five times the cost for rice and soybean (*Department of Agriculture*, 2010–2011). The cost of planting rice is the lowest of the three crops due to various government support programs, such as heavily subsidized fertilizer specifically for rice (*Davis et al.*, 2016). An additional factor discouraging onion production is the volatility of returns associated with the crop relative to that of rice and soybean: the prices for onion are subject to market fluctuations while the returns for rice and soybean are relatively fixed, due to government price ceilings and futures contracts respectively (field notes). Farmers typically plant only one crop per field during the season given that the crops require different land preparation and management efforts. At the start of the season, if the reservoir levels are visibly low, farmers typically leave their fields fallow. Most of the farmers receive information about water availability from their farmer organization representatives, who meet with the Irrigation Engineer, Department of Agriculture, and other government officers (field notes).

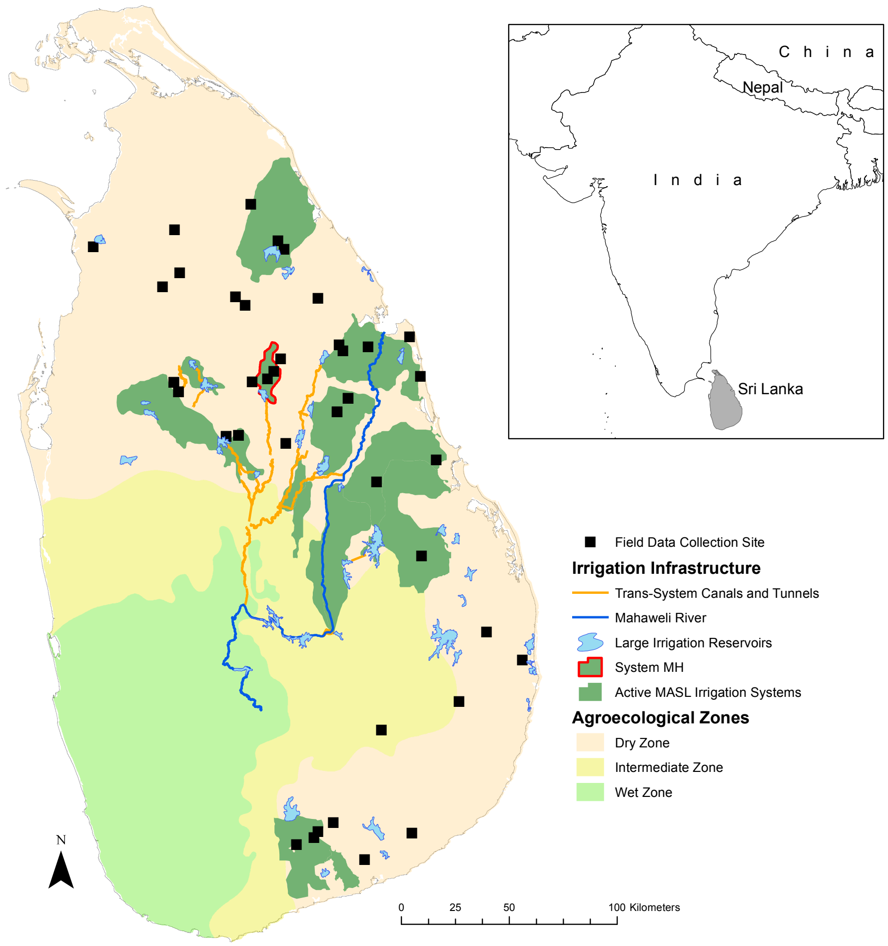



Figure 4.1: Study location and areas of field work

### 4.2.2 Model Development and Data Sources

The modeling effort is centered on a simplified representation of an individual farmer living in System MH. Interactions between individuals (i.e., social components) and extreme weather events were outside the scope of the model. The model is built on a system dynamics platform (specifically Powersim Studio 10 Expert) with a seasonal time step for a period of 64 dry seasons, which occur once per year. The system dynamics platform was selected because it provides a visual framework that allows for easier integration of the diverse variables in the study. The model we developed for this study has been made publically available and can be accessed via the openabm platform:

https://www.openabm.org/model/5395/version/1/view.

The three main components of the model structure are hydrological, economic, and behavioral (Figure 4.2). The objective of the model is to evaluate the impact of seasonal forecasts on a farmer's net agricultural income when their crop choices have different and variable costs and returns. Net agricultural income is defined as the difference between the costs and revenues associated with the crop the farmer plants on their field. In the model, net agricultural income is a function of the crops planted, actual seasonal weather, and market returns. Three climate scenarios are simulated in the model: 1) climate consistent with historical conditions, 2) drier climate, and 3) a wetter climate. Each season, the forecast is sampled from the specified climate scenario and the actual weather is subsequently sampled (moderated by the forecast skill) from the forecast. It should be noted that in the model, the forecast skill is defined as the percentage of time that the weather is drawn from the forecast, which is different from standard meteorological definitions of forecast skill. To understand the impact of the seasonal forecasts, the farmer's behavior when using seasonal forecasts ("Adaptive: Forecasts") is compared to: 1) a farmer who only uses climate conditions (i.e., the climate condition from which the forecast was sampled) to select crops ("Baseline: Climate") and 2) a farmer who consistently plants rice every season regardless of the weather ("Baseline: Rice Alone").

The model variables and assumptions, including how the various empirical data sources were consulted to define model variables and dynamics, are described in detail in Appendix A. A summary of the primary variables is provided in Table 4.1. Brief descriptions about the primary sources consulted for the model are provided below.

- Game: Since games can provide insight into decision processes (*Kühberger et al.*, 2002; *Castillo et al.*, 2011; *Kang et al.*, 2011; *Nay et al.*, 2014), we designed a contextualized, dynamic game to investigate how farmers in the field respond to and interpret weather forecasts within their specific environment. Specifically, the farmers were provided with a randomly selected seasonal forecast (Figure 4.3) and asked to select which crops (if any) they would plant for the season. Once the farmers' crop choices were recorded and associated costs paid to the banker, the wheel was spun to determine the actual weather and subsequent returns for the crops planted were paid to the farmers. The wheel was then reset for the next season. The farmers then planted crops given the new forecast and their current income. This process was repeated for a few rounds. The game was played with 49 farmers in System MH in January 2016, in 4 groups of 12-13 players per group. All of the crop selections made by the farmers were analyzed relative to the weather forecasts and other variables (e.g., education) to understand how farmers interpreted the probabilistic nature of the forecasts (additional details about the decision heuristics are provided in Appendix A). A description of the game method (including instructions) is provided in Appendix B.

- Surveys: The primary survey consulted (hereafter referred to as "ADAPT-SL Survey") was conducted for over 800 randomly selected dry zone rice farmers as part of the larger project in which this study is embedded. The ADAPT-SL Survey captures various information including farmer demographics and attitudes towards adaptation practices. The second survey consulted was a household survey (hereafter referred to as "System MH Survey") conducted during the 2015 dry season to characterize farming behaviors in the study area (*Berundharshani and Munasinghe*, 2015).

- Interviews: Data from 200 farmer interviews (140 of which were all conducted in and near System MH in late 2015) as well as interviews with officials (representing both governmental and non-governmental agencies) working on areas of irrigation, agriculture, and climate provided information about the context in which farmers make decisions.

Given the presence of stochastic variables in the model, each climate condition was simulated 1,000 times and the results were aggregated to capture general trends. Model outputs from Powersim were written to Microsoft Excel and processed in R. Given the stylized nature of our modeling effort, we focus on pattern-oriented modeling to qualitatively judge the ability of the model to reflect patterns observed in the real system (*Grimm et al.*, 2005). In addition to ensuring accurate formulation by reviewing output tables (*Rykiel*, 1996), we evaluated our model to ensure that it reproduced predicted patterns (*Ahmad and Simonovic*, 2000). Sensitivity analyses were conducted to understand the impacts of variable assumptions on model output. Each of the variable values explored in the sensitivity analysis (summarized in Table 4.2) was simulated 1,000 times and aggregated prior to comparisons.

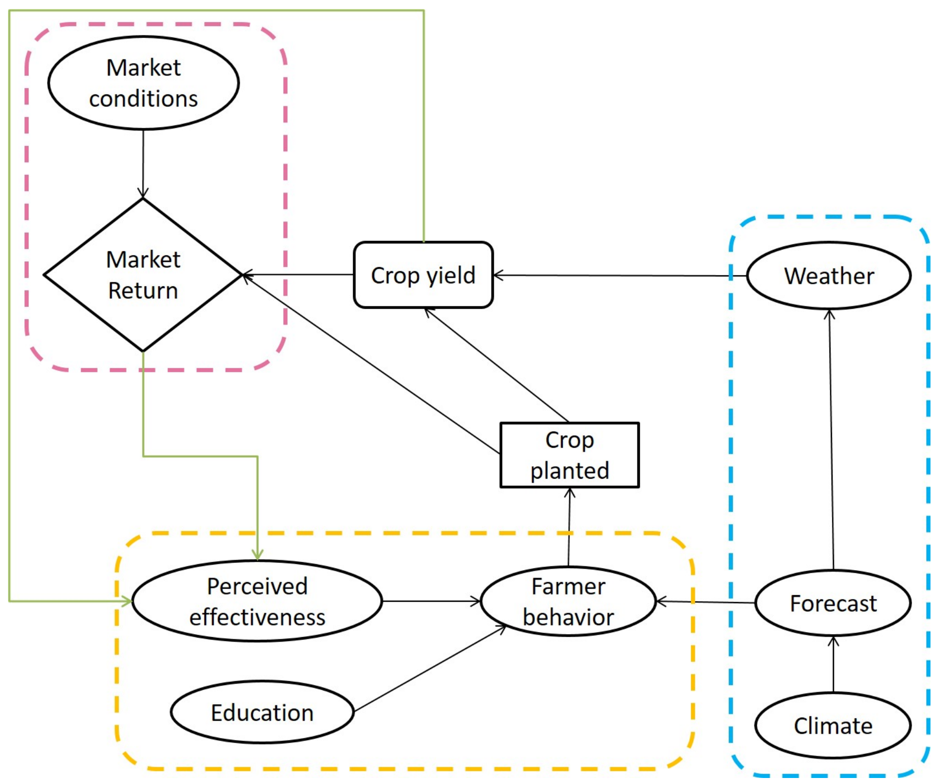



Figure 4.2: Influence diagram of hydrological (dashed blue), economic (dashed purple), and behavioral (dashed orange) components of the system dynamics model. The two green arrows indicate the updating process of the farmer's perceived effectiveness (i.e., prior experience) of the adaptation practice of crop diversification at the end of each season.

Table 4.1: Summary of the variables and related empirical data sources for the various model components

| Model component | Variable | Source | Notes |
|---|---|---|---|
| Hydrology | Climate scenarios | Academic literature | Historical climate is defined as 40% dry - 40% normal - 20% wet (additional details in the "Climate scenarios" subsection in Appendix A) |
| | Forecast skill | Interviews | The actual weather observed draws from the seasonal forecast 70% of the time (additional details in the "Actual weather" subsection in Appendix A) |
| Economic | Crop costs and returns | Government reports | Crop costs (including both labor and materials) and returns are derived from agricultural statistics of the region; onions are approximately 5 times the cost of rice and soybeans and also have a more variable return (additional details in the "Market return" subsection in Appendix A) |
| Behavioral | Interpretation of seasonal forecast | Game | Generally speaking, farmers preferred to plant soybean except when the probability of wet or dry weather is high, in which case farmers opted to plant rice or onions respectively (additional details in the "Crop decisions" subsection in Appendix A) |
| | Perceived effectiveness (e.g., weather forecast) | ADAPT-SL survey | As farmer's predictability of rainfall decreased, they were less likely to plant non-rice, or other food crops (additional details in the "Trust heuristics" subsection in Appendix A) |
| | Trust heuristics | Multiple sources | Farmer's trust is based on previous experiences and influences behavior in the future (additional details in the "Trust heuristics" subsection in Appendix A) |
| | Education | Game and ADAPT-SL survey | Survey data shows that farmers who are less educated were less likely to state that they could predict rainfall. Results from the game indicate that less educated farmers planted more rice even at low probabilities of wet season whereas more educated farmers moved more quickly towards planting rice as the probability of a wet season increased (additional details in the "Education" subsection in Appendix A) |
| Other | Crop yields | Government reports | Soy and rice have higher yields in wet climate while onions perform better in a dry climate (additional details in the "Crop yield" subsection in Appendix A) |

Table 4.2: Sensitivity analyses conducted

| Parameter | Initial Value | Distribution |
|---|---|---|
| Forecast skill | 70% | Uniform: 50% to 100% in 10% intervals |
| Initial trust in forecast | 80% | Uniform: 50% to 100% in 10% intervals |
| Threshold for losing trust in forecast | 30% | Uniform: 10% to 60% in 10% intervals |
| Initial trust in market | 70% | Uniform: 50% to 100% in 10% intervals |
| Threshold for losing trust in market | 50% | Uniform: 30% to 80% in 10% intervals |
| Market return expectations (ratio of actual to maximum values) | 0.8 | Uniform: 0.5 to 1.0 in 0.1 intervals |

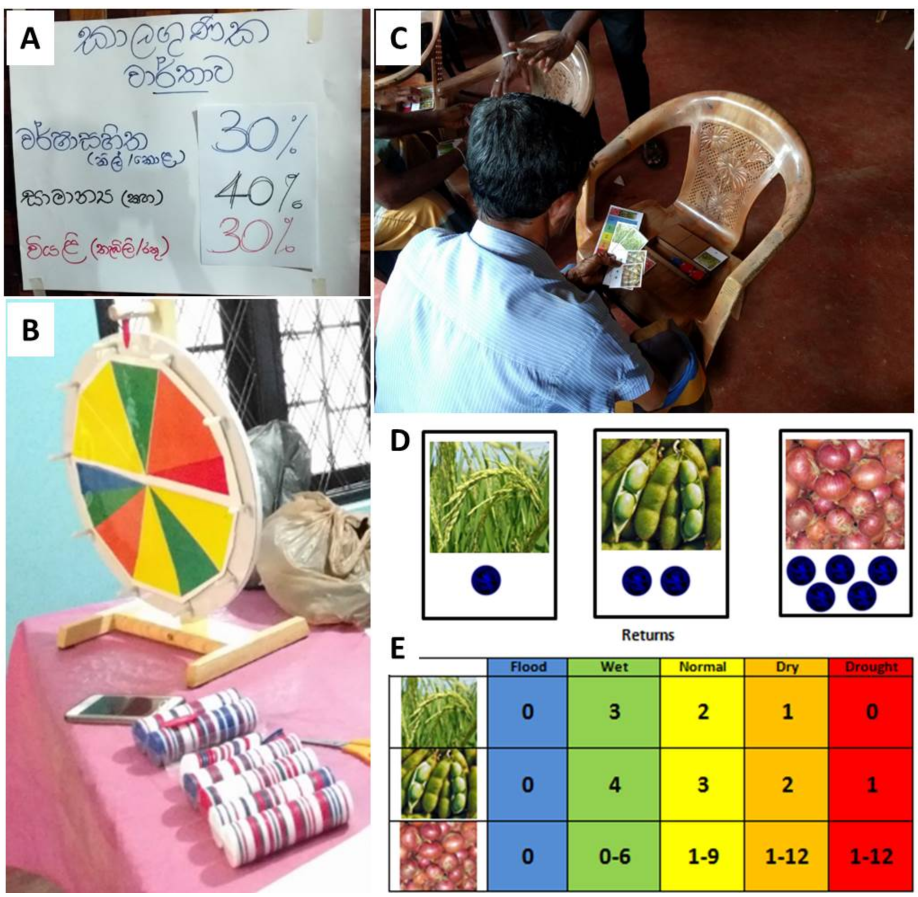



Figure 4.3: Playing games in the field: A) written presentation of forecast information, B) weather wheel with spinner and poker chips used as currency, C) farmer placing crop cards on fields to convey planting decisions, D) crop cards with associated planting costs, and E) yield return sheet showing relationships between crops, weather, and market returns. Both planting costs and yield returns are based on data from Department of Agriculture (2010-2011) and are normalized by 30,000 Sri Lankan Rupees (LKR).

## 4.3 Results

Model simulations for the three climate conditions show that, generally, the adaptive farmer has a higher average net agricultural income than either of the baseline farmers, especially under the drier climate scenario (Figure 4.4). However, the adaptive farmer's income has the largest CV of the three farmers in each of the climate scenarios (Table 4.3). The adaptive farmer has greater trust in the weather forecast over time especially in the drier climate scenario (Figure 4.5) while the farmer using general climate information has marginally greater trust in the market over time (Figure 4.6); the rice-alone farmer's trust in the market does not change over time since rice is not subject to market fluctuations (Figure 4.6). The adaptive farmer chooses all four crop options over the course of the simulation while the farmer using general climate information chooses between rice and soybeans (Figure 4.7).

When education levels are varied, results show that the less educated, adaptive farmer has lower average net agricultural income than the more educated, adaptive farmer in the historical and drier climate scenarios (Figure 4.8). In the wetter climate scenario, however, there is no difference in net agricultural income between the two farmers. Generally, the less educated, adaptive farmer has lower trust in the forecast and market than the more educated, adaptive farmer (Figures 4.9 and 4.10). The more educated, adaptive farmer generally plants more soybeans across the climate scenarios as well as more onions in the drier climate scenario (Figure 4.11).

All of the results above were simulated with a forecast skill of 70%, the current accuracy of Meteorological Department of Sri Lanka's forecasts. A sensitivity analysis of forecast skill shows that as forecast skill increases, the adaptive farmer's net agricultural income and trust in the forecast both generally increase as well (Figure 4.12). Changing the initial trust level of forecasts or threshold at which trust in the forecast is lost does not affect the adaptive farmer's net agricultural income (Figures 4.13 and 4.14). Changing the initial trust level of market or the threshold at which farmer loses trust in the market, however, both

Table 4.3: Coefficient of variation of farmers' net cumulative agricultural income

| | Historical Climate | Drier Climate | Wetter Climate |
|---|---|---|---|
| Adaptive: Forecast | 0.66 | 0.69 | 0.63 |
| Baseline: Climate | 0.63 | 0.64 | 0.62 |
| Baseline: Rice Alone | 0.61 | 0.62 | 0.61 |

have a significant impact on the farmer's net agricultural income (Figures 4.15 and 4.16). As the adaptive farmer's expected return for the market approaches the maximum return values, the farmer's net agricultural income decreases (Figure 4.17).

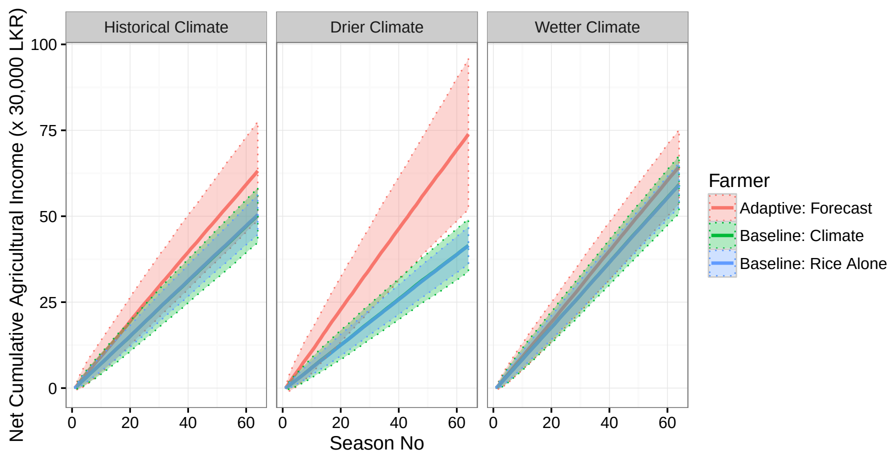



Figure 4.4: Net agricultural income of farmers across climate conditions. Solid lines represent average values while the shaded regions are +/- 1 standard deviation. The adaptive farmer generally has higher average net income, especially under the drier climate scenario, but also a greater standard deviation than the two baseline farmers.

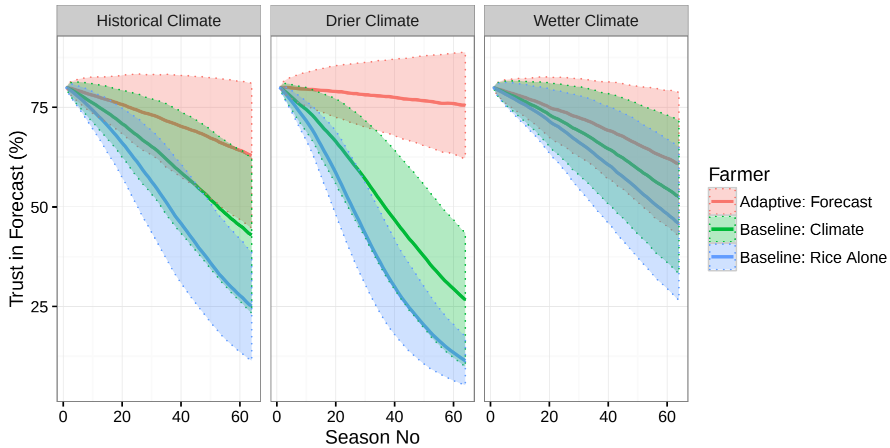



Figure 4.5: Trust in forecast over time. Solid lines represent average values while the shaded regions are +/- 1 standard deviation. The adaptive farmer has higher trust in the weather forecast than the baseline farmers, especially for the drier climate scenario when the standard deviation bounds of the adaptive farmer are outside the standard deviation bounds of the baseline farmers.

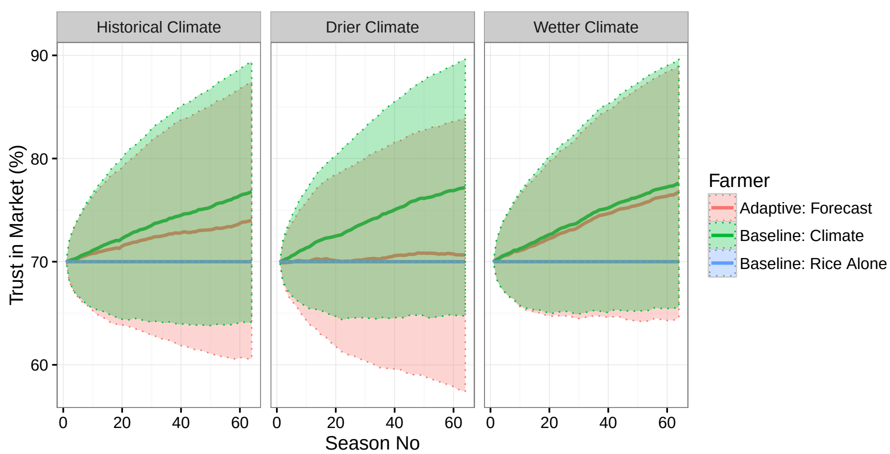



Figure 4.6: Trust in market over time. Solid lines represent average values while the shaded regions are +/- 1 standard deviation. Across the climate scenarios, both the adaptive and climate farmers have high standard deviations with the latter having marginally higher average trust over time; the only-rice farmer's trust in the market stays constant at 70% because their crop revenue is not subject to market fluctuations.

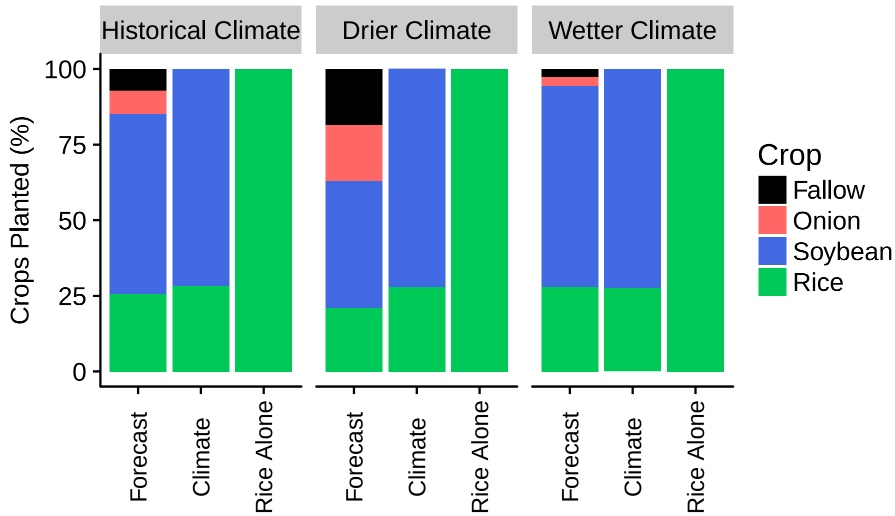



Figure 4.7: Crops planted by the adaptive (”Forecast”) and baseline farmers (”Climate” and ”Rice Alone”) across the three climate scenarios. The adaptive farmer is the only farmer who plants onions across the three climate scenarios.

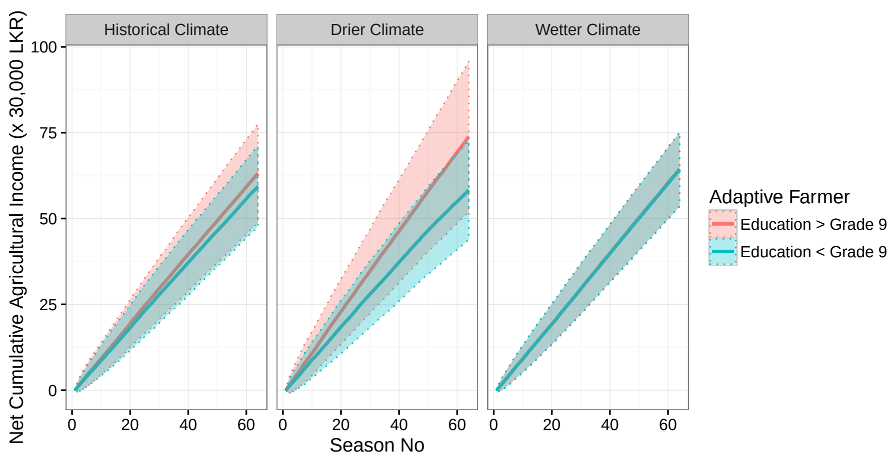



Figure 4.8: Net agricultural income as a function of the adaptive farmer’s education. Solid lines represent average values while the shaded regions are +/- 1 standard deviation. The more educated farmer has higher average net income than the less educated farmer in the historical and drier climate scenario but the two farmers have comparable net income in the wetter climate scenario.

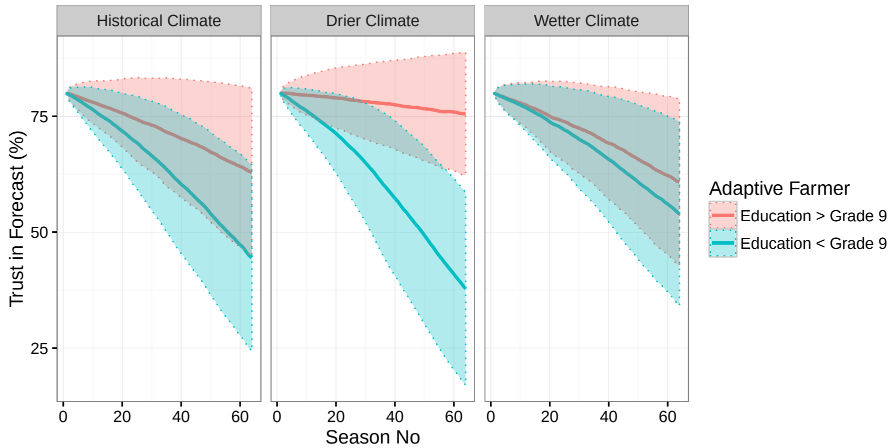



Figure 4.9: Trust in forecast over time as a function of the adaptive farmer's education. Solid lines represent average values while the shaded regions are +/- 1 standard deviation. The more educated farmer consistently has higher average trust in the weather (especially in the drier climate scenario) than the less educated farmer.

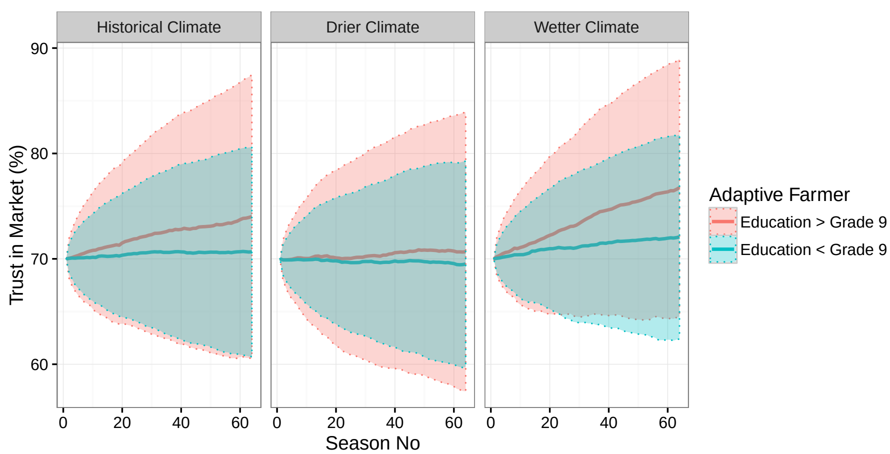



Figure 4.10: Trust in market over time as a function of the adaptive farmer's education. Solid lines represent average values while the shaded regions are +/- 1 standard deviation. The more educated farmer has higher average trust in market over time than the less educated farmer; however, the standard deviations for both farmers are very high.

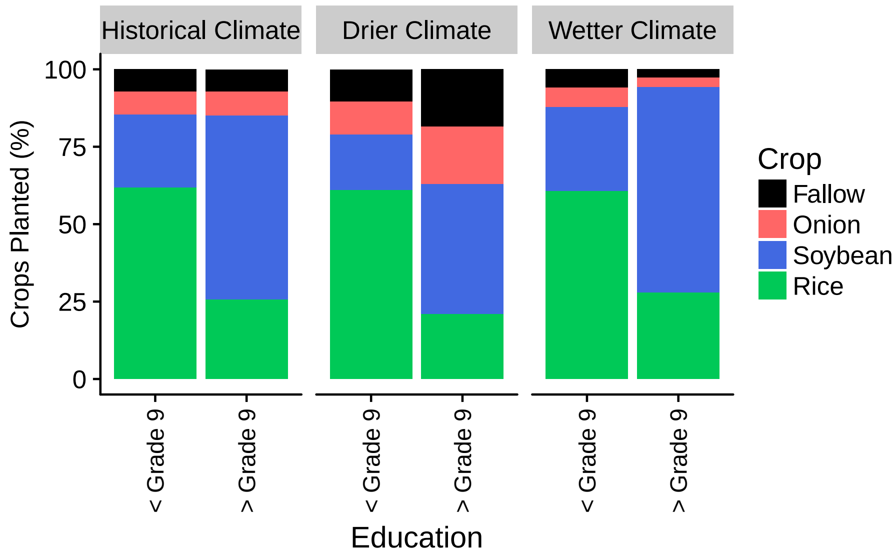



Figure 4.11: Crops planted across the three climate scenarios as a function of the adaptive farmer's education. The more educated farmer generally plants more soybean across the climate scenarios as well as more onions during the drier climate scenario.

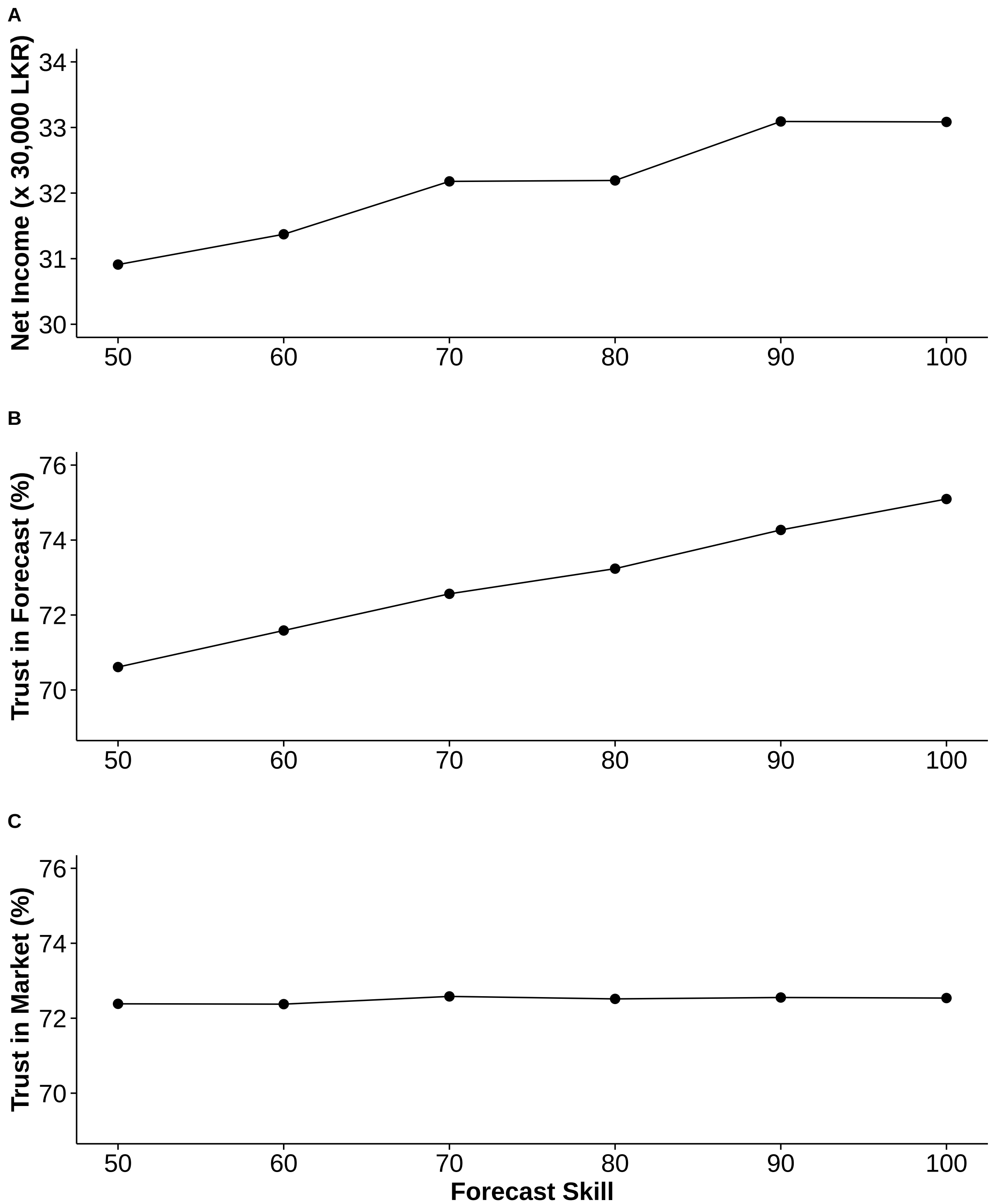



Figure 4.12: Sensitivity analysis of forecast skill. As forecast skill increases, the net agricultural income (A) and trust in forecast (B) both generally increase but there is no change in market trust (C).

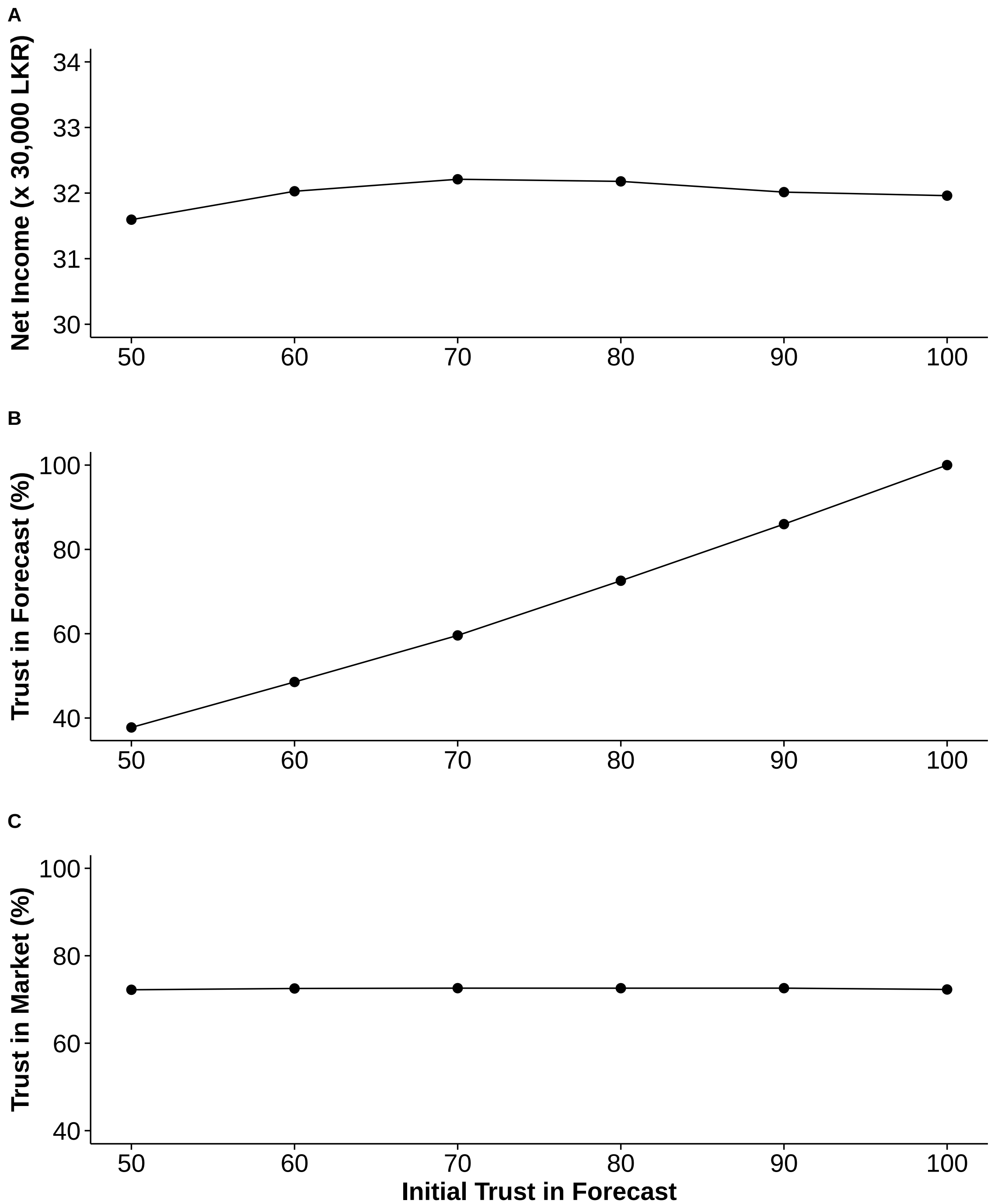



Figure 4.13: Sensitivity analysis of initial trust in forecast. As initial trust in the forecast increases, overall trust in the forecast for the adaptive farmer also increases (B) but there is minimal change in farmer's net agricultural income (A) and farmer's trust in the market (C).

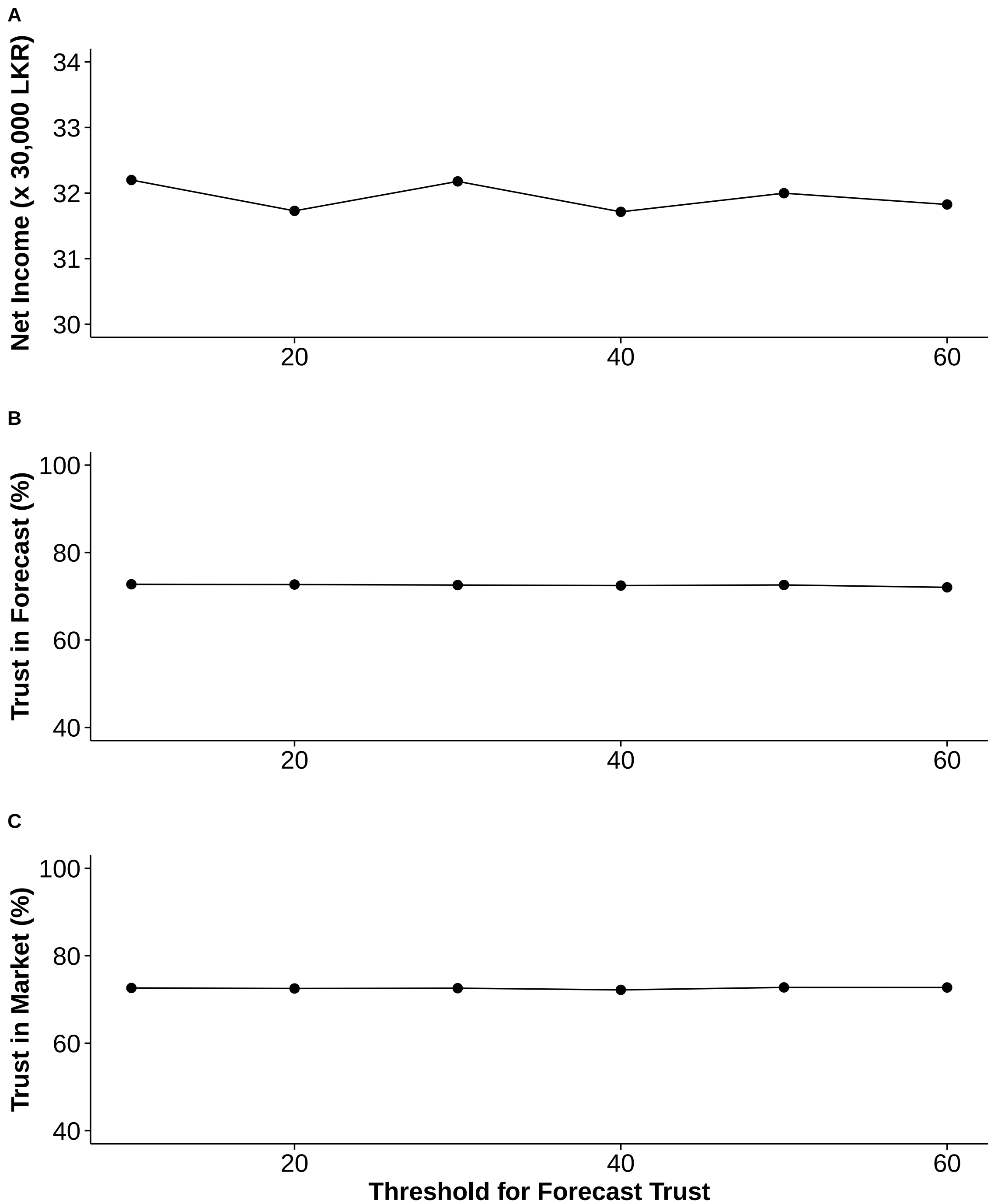



Figure 4.14: Sensitivity analysis of threshold at which the adaptive farmer loses trust in forecast. Changing the farmer's threshold for trusting the forecast has no notable impact on farmer's net income (A), trust in the forecast (B), or trust in the market (C).

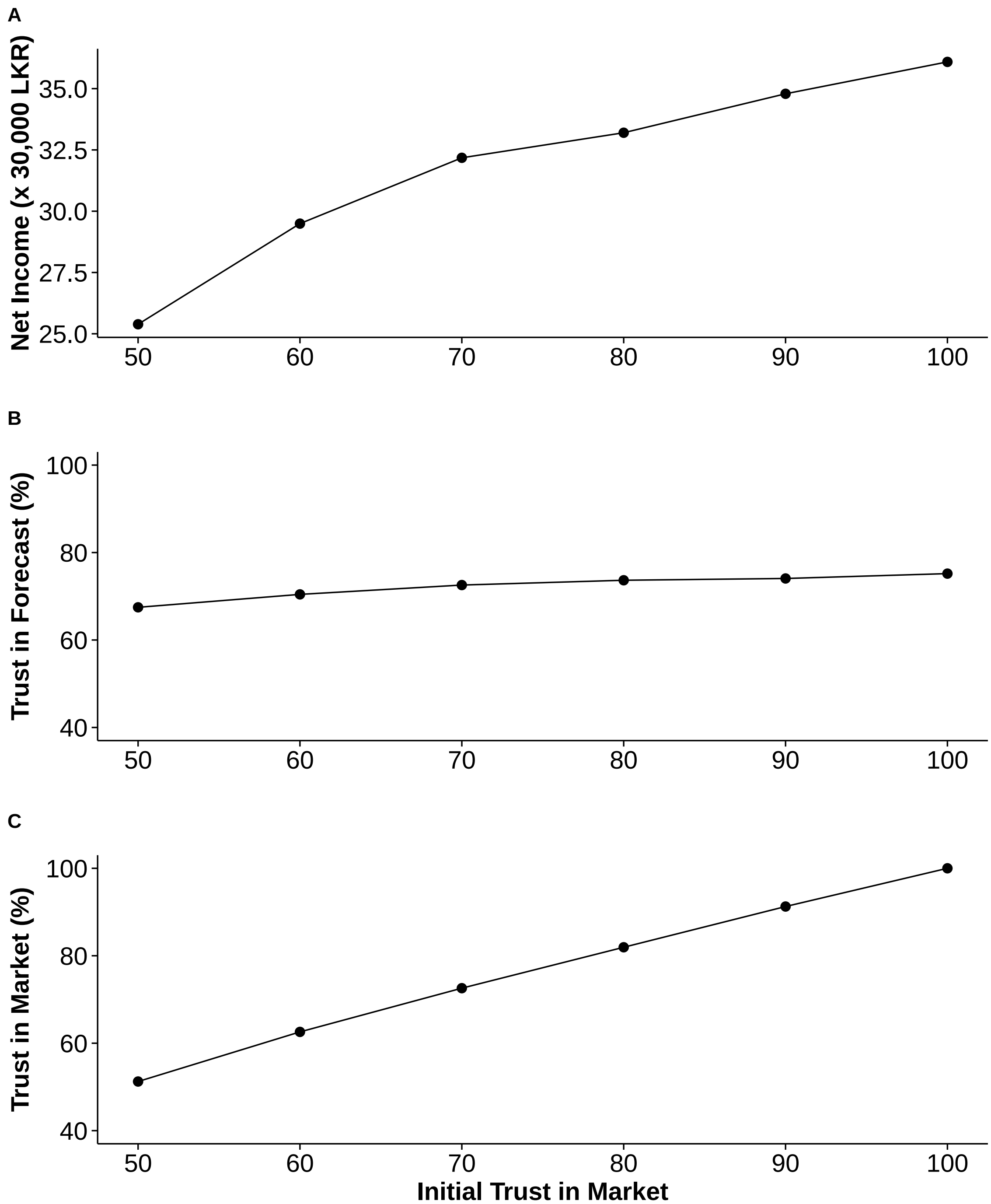



Figure 4.15: Sensitivity analysis of initial trust in market. As initial trust in the market increases, both farmer's net agricultural income (A) and the farmer's overall trust in the market (C) significantly increase but the farmer's trust in the forecast only marginally changes (B).

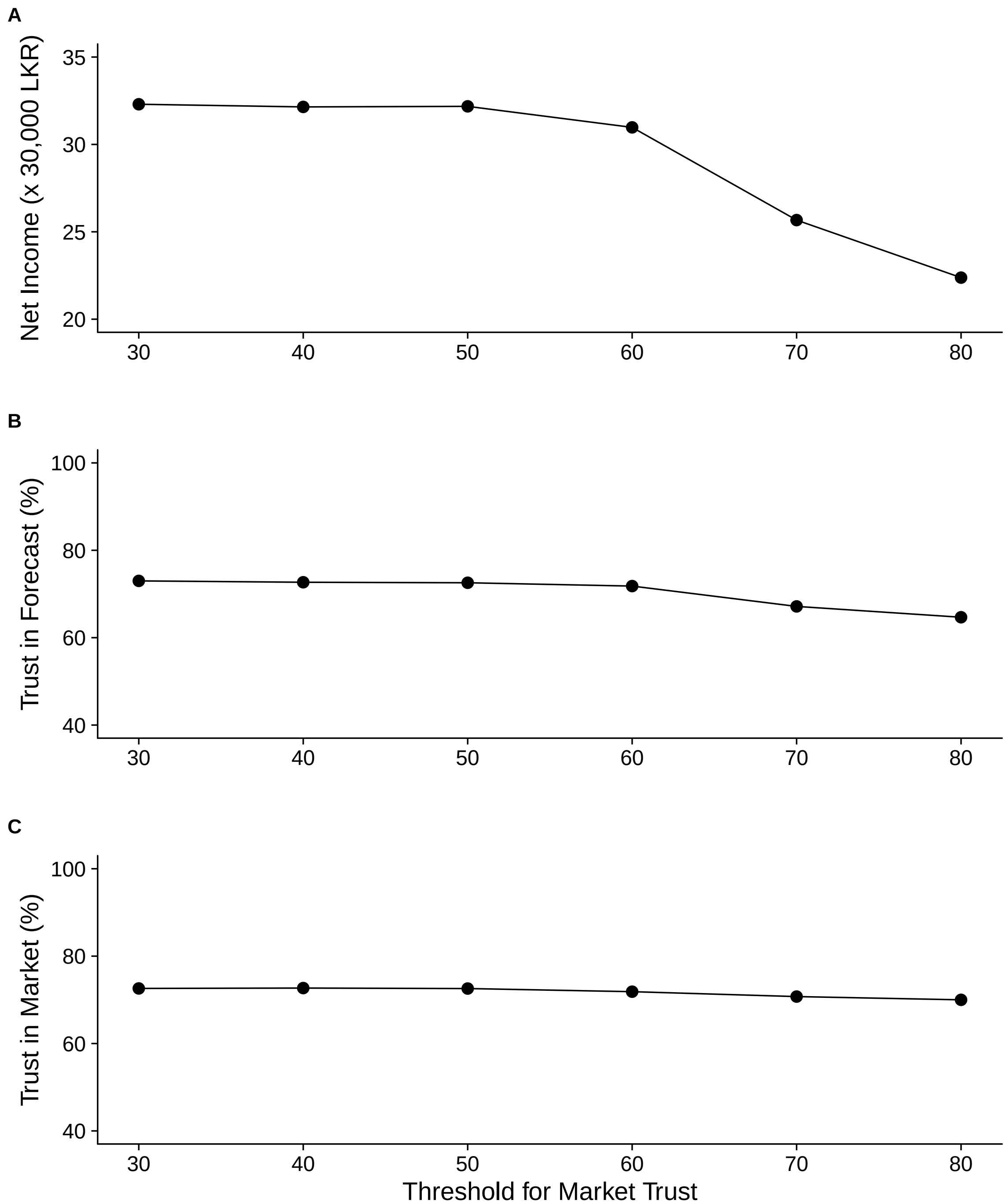



Figure 4.16: Sensitivity analysis of threshold at which the adaptive farmer loses trust in market. As a farmer's market threshold increases, their net income (A) decreases but there is no change in the farmer's trust in forecast (B) or trust in market (C).

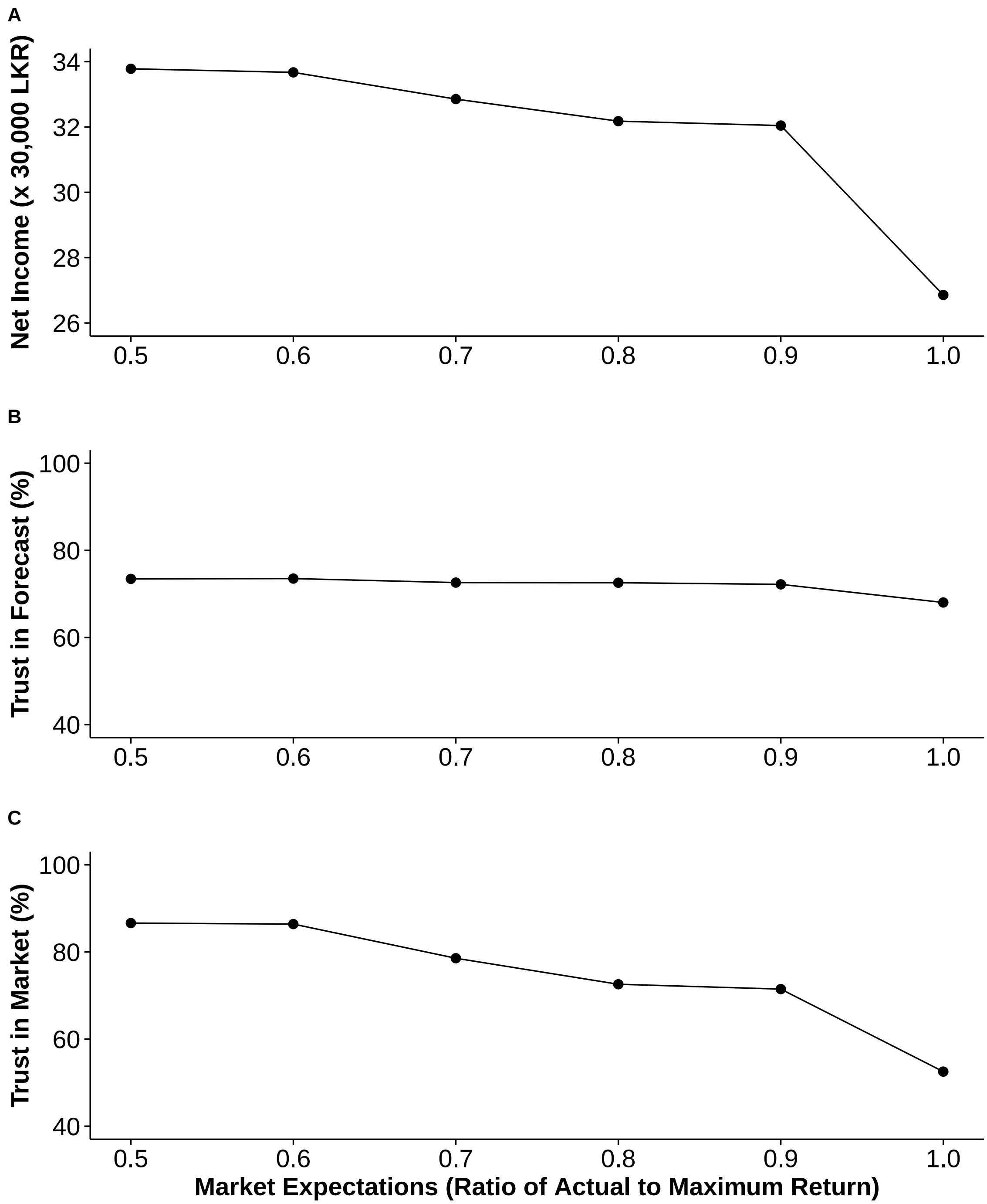



Figure 4.17: Sensitivity analysis of the adaptive farmer's expectation for market returns. As farmer's market expectations (ratio of actual return to maximum return) increase, their net income (A) and trust in the market (C) decrease but there is no change in the farmer's trust in the forecast (B).

## 4.4 Discussion

Our empirically-grounded simulation reproduces multiple patterns that are expected in the real system, thereby increasing the confidence with which we can interpret the model results. Notably, we would expect a farmer's cumulative net agricultural income to increase over time; farmers would pursue another livelihood if they were chronically losing money on their farming operations. We would also expect the farmer who only plants rice to have a lower CV in their net agricultural income than a farmer who depends on market-dependent crops. Both of these patterns are verified by our model outputs (Figure 4.4). Our current field data lack the resolution necessary to capture differences in net agricultural income as a function of education, so additional data collection is needed to assess the model results presented in Figure 4.8.

Consistent with empirical findings of *Patt et al.* (2005), our simulation indicates that the adaptation practice of using seasonal forecasts could improve economic outcomes. In other words, our model results show that by using forecast information, the adaptive farmer has higher average net agricultural income than a farmer who only plants rice or a farmer who selects crops based only on average climate information. The difference in income is primarily driven by the diverse portfolio of crops planted by the adaptive farmer over the 64 seasons in the simulation, specifically the prevalence of onions under the drier climate scenario. Crop diversification has been recognized as a significant factor in increasing resilience of agricultural systems (*Mijatović et al.*, 2013). However, structural constraints (such as subsidy programs) are a contributing factor in farmers' lack of interest in this adaptation strategy (*Lin*, 2011). Ongoing research on the ADAPT-SL project is considering the impact of an influx of onions on systematically driving down the returns for the crop.

When water resources are plentiful, on the other hand, similar income profiles emerge from differing mixes of crop choices. In particular, the adaptive farmer with greater than grade 9 education plants more soybeans than onions or rice but has the same average income as the adaptive farmer with less than grade 9 education. These dynamics highlight that the impact of the current crop economics of the crops on farmer livelihoods varies depending on the climate scenario, with the drier climate scenario benefiting farmers who are willing to take more risks (i.e., planting onions, a crop dependent on market dynamics) while the wetter climate scenario reduces income disparity between the farmers. Our results indicate that when resources are scarce, varying decisions (i.e., use of forecast vs just planting rice) could increase income disparities between groups. This is consistent with findings that disparities in natural resources can exacerbate income inequality (*Fum and Hodler*, 2010). The accumulation of wealth by some farmers can have a compounding effect, making these farmers more able to invest in new technologies, which increase production and income, and could further buffer them from environmental changes (*Reardon and Taylor*, 1996; *Reardon et al.*, 2000). Although increased rainfall variability is the dominant climate change impact expected in Sri Lanka, farmers in the dry zone have observed a shift in the local climate: droughts have been getting worse, an observation that is consistent with analysis of meteorological data in Chapter 2 (*Seo et al.*, 2005; *Esham and Garforth*, 2013; *Truelove et al.*, 2015; *Gunda et al.*, 2016). Since accurate perception of weather patterns has been shown to be a significant predictor of adaptation, it is not surprising that Sri Lankans have begun adapting by managing their farming practices or diversifying their income, with changing crops being the most popular on-farm adaptation strategy (*Esham and Garforth*, 2013; *Piya et al.*, 2013; *Truelove et al.*, 2015). Therefore, concerns about income disparities are not insignificant.

In addition to higher average incomes, the adaptive farmer (regardless of education levels) has higher income variability than the baseline farmers, a pattern generally observed across farmers using forecasts (*Ash et al.*, 2007). Farmers who lack the financial capital to buffer them from the income variability might be more reluctant to diversify away from rice, a crop with stable returns; a general reluctance to diversify has been noted by many field studies including *Thiruchelvam* (2010). An analysis of ADAPT-SL Survey data shows that high economic status was positively associated with planting non-rice food crops during the dry season (*Burchfield and Gilligan*, 2016), further indicating that crop diversification is not an equally accessible adaptation strategy. In our modeling effort, we assume that farmers have the necessary capacity to obtain loans as needed (i.e., their crop selections are not constrained by their actual bank accounts). This is in large part due to the presence of a debt economy in Sri Lanka. In future iterations, the model could be extended to explore the impact of economic as well as other constraints such as imperfect access to forecasts or markets and biophysical limitations on farmer livelihoods (*Peng et al.*, 2004; *Hansen et al.*, 2011; *Dilling and Lemos*, 2011; *Esham and Garforth*, 2013; *Berundharshani and Munasinghe*, 2015; *Roncoli*, 2006).

While farmers' understanding of the probabilistic forecasts has generally been mixed (with some arguing farmers are unable to understand them and some showing otherwise (*Patt et al.*, 2005; *Hansen et al.*, 2009; *Roncoli*, 2006; *Lemos et al.*, 2007; *Unganai et al.*, 2013), our games in the field show that farmers in System MH are responsive to forecasts, particularly to the probabilities of wet and dry seasons. Changes in the probability of a normal season did not seem to greatly influence farmers' crop selection, a pattern observed in other countries (*Grothmann and Patt*, 2005). Additionally, farmers' responses to forecasts were moderated by education, which was incorporated into our assessment, and coordination among farmers, which was outside the scope of this analysis. The impact of social interactions on attitudes towards use of climate information is not insignificant (*Thomas et al.*, 2007; *Acosta-Michlik and Espaldon*, 2008; *Crane et al.*, 2010; *Marshall et al.*, 2011; *Berger and Troost*, 2014; *Muita et al.*, 2016), and could positively influence farmers' adaptation (*Esham and Garforth*, 2013; *Truelove et al.*, 2015). Our findings in the field indicate changes in farmer behaviors when collaboration was encouraged (Appendix A). However, additional field work is needed to characterize the heterogeneity of farmers (e.g., differences in risk tolerances, prior experiences with extreme weather events such as floods, and perceptions of climate change) and determine the relative importance of social information vs a farmer's own experiences in influencing their adaptation behavior (*Berger*, 2001;

*Hansen et al.*, 2009; *Sabater and Sierra*, 2005; *Karali et al.*, 2014; *Pérez et al.*, 2016). Extending our single-agent model to incorporate multiple autonomous agents could enable us to actively explore the impacts of heterogeneity and coordination on farmer livelihoods, thereby improving our understanding of who might use forecast information (*Jain et al.*, 2015; *Vogel et al.*, 2015).

Consistent with findings from other studies (e.g., *Ziervogel et al.* (2005)), our sensitivity analysis confirms the importance of forecast skill on farmer outcomes; as the forecast skill increases, not only does the farmers' trust in the forecast increase but the increased accuracy results in higher agricultural income. For a fixed forecast skill, however, changing the farmer's initial trust levels or trust threshold for the forecast has minimal impact on the farmer's net income. Market-related variables such as the market trust threshold and the ratio of actual to maximum return, on the other hand, have large impacts on net income; as the farmer became more tolerant of risks with the market, the farmer was more likely to plant onions, the more profitable option. Therefore, providing farmers with more information about market conditions (currently lacking in Sri Lanka) could have a notable impact on farmers' financial outcomes underscoring the value of both production and market support as needed adaptations in a changing climate (*Acosta-Michlik and Espaldon*, 2008). As weather forecasting capabilities improve, we could extend this analysis to understand intra-seasonal dynamics (both in the market and weather), which would allow an integration of findings from the previous chapter (i.e., benefits of planting rice early) into the crop diversification context.

Although farmers have reported that adaptation strategies have improved crop productivity, lack of information on climate change has been a notable obstacle to their adaptation (*Esham and Garforth*, 2013). Overall, our research adds to the growing literature that providing forecasts to farmers has considerable potential for helping farmers adapt to the changing climate. Our results highlight the importance of understanding and incorporating the impact of varying crop economics on farmer decisions in adaptation assessments.

Additional data and research is needed to continue to characterize farmer behavior and to understand leverage points for enhancing adaptive capacity. This additional work is especially critical since our results indicate that when water resources are scarce (i.e., drier climate scenario), farmer incomes could become significantly stratified, potentially compounding existing disparities in farmer's financial and technical abilities to use forecasts to inform their crop selections. System MH is just one of many regions that promote the production of certain crops through subsidies. While such programs could ensure food security in the short-term, the long-term implications of these dynamics have received limited attention. Our modeling approach, which is publicly available via openabm, could be easily modified to look at the specific dynamics of varying crop economics in other regions of the world (e.g., in the Limpopo province of South Africa).

# Chapter 5

# Outlook

This dissertation research assessed water use for agriculture in Sri Lanka, with an emphasis on interdisciplinary assessments of climate change adaptations. In Chapter 2, we studied spatiotemporal patterns of agricultural drought in the country from 1880 to 2010 and learned (among other things) that the northeast portion of the island was becoming drier during the minor growing season, when water resources are already scarce. So we evaluated patterns in IWRs for rice (the staple food of the country) over 20 years and identified that shifting planting dates to earlier in the season is a low-cost adaptation that could yield IWR savings of up to 6% in parts of Sri Lanka. These potential water savings are particularly important given emerging climate change research of less water being available for irrigation during the minor growing season. In certain parts of the country, however, water stress is already significant enough to warrant diversification away from rice production, a water-intensive process. So we evaluated the utility of seasonal forecasts with an interdisciplinary approach that accounted for both physical and social factors governing farmers' crop selections. Our results indicated policies and programs that promote production of certain crops need careful evaluation given changing climate dynamics.

Beyond water and food, the convergence of limited supply and growing demand issues has prompted much needed conversations about interactions with other critical resources such as energy. These interactions are extremely complex because of spatial and temporal considerations as well as the combined impact of physical and social factors and emerging pressures including governance shifts, climate change, population growth, and technology developments. For example, given Sri Lanka's dependence on hydroelectricity, the nation has been well aware of tensions arising between food and energy during times of water scarcity (*Lyon et al.*, 2009). However, as the nation continues to increase its extraction of natural resources, more intricate dynamics will begin emerging.

For example, assessments to date have not accounted for the investments needed (in both natural resources or products) to manage agriculture-related water quality issues. The Government of Sri Lanka provides fertilizer subsidies to help farmers improve their yields (*Davis et al.*, 2016). This practice, however, has led to an overuse of fertilizers and subsequent contamination of water supplies (*Stone and Hornberger*, 2016). Treatment of nitrates from agricultural runoff requires energy investments (*Koparal and Öğütveren*, 2002), which depend on the same scarce water resources upon which agriculture also depends in Sri Lanka. Unfortunately, such unintended consequences of agricultural adaptations and policies are not uncommon (*Fezzi et al.*, 2015).

Insights gained from studying Sri Lankan agricultural systems (methodologically and beyond) transcend national borders. Notably, the changing dynamics of the agricultural CNHS due to natural and social pressures present an increasing need to be aware of intersecting resource issues. Although there are developmental and cultural differences between Sri Lanka and the United States, overarching challenges facing the nations are similar; as agricultural nations, both Sri Lanka and the U.S. are trying to produce more food while using less water per unit of output and ensuring rural people live productive lives (*UNESCO*, 2006). Similar to work by ADAPT-SL, researchers are engaging in interdisciplinary research to understand the feedbacks between natural and social pressures in the vulnerabilities of acequias, community-managed irrigation systems, in southwestern United States (*Fernald et al.*, 2015; *Turner et al.*, 2016). Given changing supply and increasing demands for critical resources, such interdisciplinary research will become increasingly important for all nations to inform optimal strategies for efficient resource management and to avoid unintended consequences of policy interventions.

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Appendix A

Model Overview, Design Concepts, and Details

# Model Overview, Design Concepts, and Details

## Overview

**Model Software:** Powersim Studio 10 Expert

**Purpose:** The purpose of this model is to evaluate the impact of seasonal forecasts on a farmer's net agricultural income. The net income is a function of the crops planted, actual seasonal weather, and market conditions. The farmer being simulated is a simplified representation of farmers in System MH.

**Entities, state variables, and scales:** The entity in this model is an adaptive farmer who uses seasonal forecast information to select crops. To understand the impact of the seasonal forecasts, the net income of the adaptive farmer is compared to a farmer who uses climate information instead of seasonal forecast information to select crops (hereafter referred to as "climate" farmer) and a farmer who plants only rice (hereafter referred to as "rice-alone" farmer) every season.

Both the climate and adaptive farmers are characterized by heuristics, wherein the farmer's experiences over time influence their future decisions. Based on findings from games played in the field, we also simulate the influence of education on the adaptive farmer's net income; a farmer with less than grade 9 education demonstrates more randomness in their crop selection decision. For all three planting approaches, the decisions are not constrained by a farmer's bank balance and are assumed to occur uniformly across the farmer's field, hypothetically assumed to be one acre. The three planting approaches were simulated for three climate scenarios: 1) climate consistent with historical conditions, 2) drier climate, and 3) a wetter climate.

The model is calendar-independent with each time step representing one dry (locally referred to as "yala") season. The simulations are run for 64 dry seasons, which occur once per year. There is no spatial distribution of fields, farmers, or weather within the model.

An overview of the model's components and layout in Powersim are provided in Figures A1 and A2 respectively.

**Process overview and scheduling:** The model actions are executed in the following order each season:

1. Season begins (and the adaptive farmer receives a weather forecast)
2. Farmer selects a crop based on their planting approach
3. Reality ensues with actual weather and market conditions
4. Farmer obtains a net agricultural income
5. Farmer updates their rationale for planting given actual weather and market experiences
6. New season begins

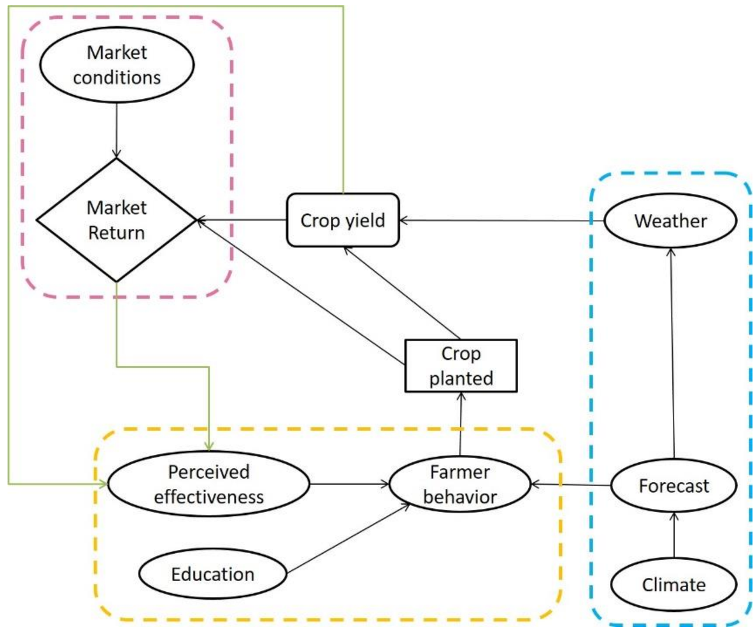


**Figure A1.** Influence diagram of hydrological (dashed blue), economic (dashed purple), and farmer behavior (dashed orange) components of the system dynamics model. The two green arrows note the updating process of the farmer's perceived effectiveness (i.e., prior experience) of the adaptation practice of crop diversification at the end of each season.

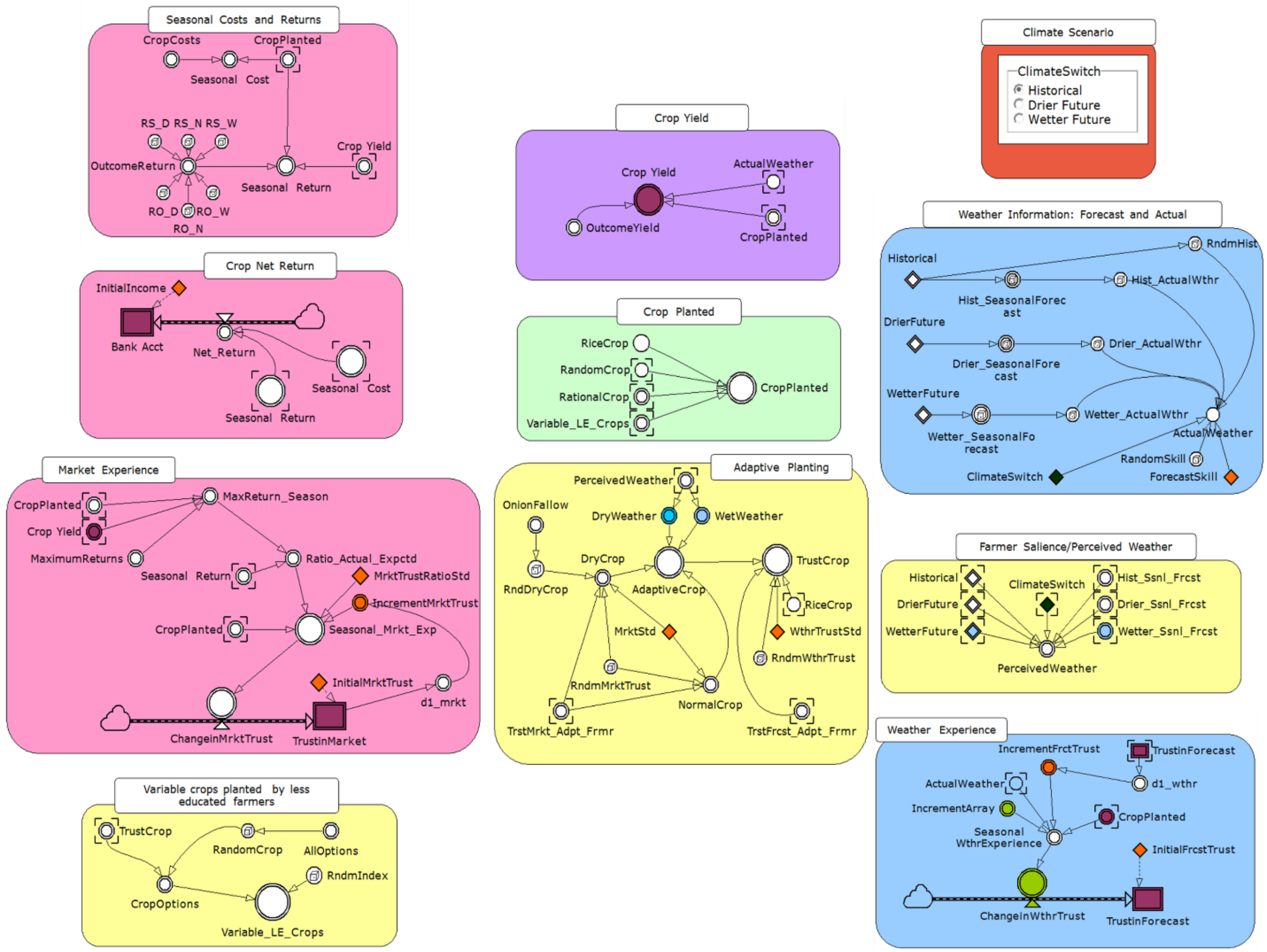


**Figure A2.** Snapshot of simulation set-up in Powersim Studio 10 Expert, a system dynamics software.

## Design Concepts

**Emergence and Observation:** The model's primary output is net agricultural income over time. Important secondary outputs include farmer's trust in forecast and trust in the market; these outputs emerge from how the farmer's planting decision compares to the season's realized weather and market conditions. Our analysis focuses on the impact of different planting approaches and climate conditions on the outputs of interest.  Even though changes in forecast and market trust do not influence the rice-alone farmer's planting decision, these outputs are generated for comparison purposes. Outputs from Powersim were written to Excel files and processed in R.

**Adaptation and Learning:** The rice-alone farmer does not adapt their decisions between seasons. The adaptive (and climate) farmer, on the other hand, updates their rationale for crop selection based on their experiences with the weather and market. If the farmer's trust in the forecast or market decreases below a threshold, the farmer becomes risk averse. Specific learning traits of the adaptive farmer are described in detail below.

**Objectives:** The farmer's objective is to maximize their net agricultural income. However, this objective is not explicitly incorporated into their planting approaches except implicitly as part of the risk aversion behaviors of the adaptive farmer.

**Prediction:** The rice-alone farmer predicts the return for their crop is constant, which is reflective of the current price floor policies for rice in Sri Lanka (Herath et al., 1982). The climate and adaptive farmers predict their crop returns will be at least 80% of their maximum return; if below this value, then their trust in the market decreases.

**Sensing:** The climate and adaptive farmers are assumed to have perfect knowledge of the climate conditions and seasonal forecasts respectively. These farmers are also assumed to have perfect knowledge of the maximum returns for crops but not the exact returns for soybean or onions.

**Interaction:** Although game findings indicate that farmer behaviors changed when they interacted with fellow players (Figure A3), this dynamic is outside the scope of model analysis. Therefore, there are no interactions in the model.

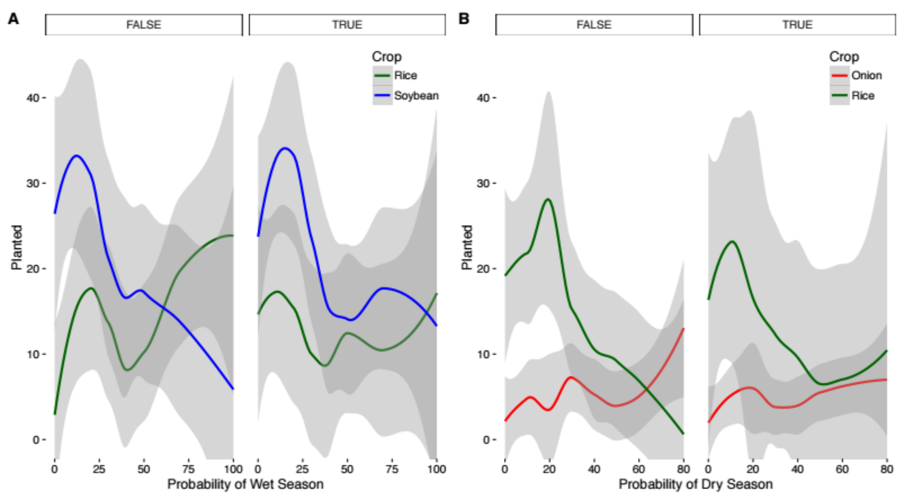


**Figure A3.** Impact of collaboration on farmer crop selections of A) rice vs soybean as a function of wet season probabilities and B) rice vs onion as a function of dry season probabilities. Lines represent average values while shaded regions represent 95% confidence interval for a LOESS fit to the data. When there is collaboration (i.e., condition is true) in rice-soybean comparison (A), farmers were more likely to plant soybean over a wider range of wet season probabilities. As for rice-onion comparison (B), when there is collaboration, farmers were more likely to plant rice over a larger range of dry season probabilities.

**Stochasticity:** There are two main stochastic components of the model: 1) weather and 2) market returns for soybean and onions. Each model run is initiated with one of three climate conditions from which the forecast and subsequently the weather are randomly generated (see subsections on "Climate scenarios" and "Actual weather"). The market returns for soybean and onions are randomly generated from a uniform distribution of a range of returns (see subsection on "Market return").

**Collectives:** There are no collectives in the model.

**Initialization:** Each model run is initialized with one of the three climate scenarios. All three farmers begin with net agricultural income of 0, 80% trust in the forecast, and 70% trust in the market; initial trust levels were chosen based on impressions gained from interviews in the field.

**Input Data:** In addition to the initialized values, the values in Table A1 are default parameters used in the model set-up across the climate scenarios.

**Table A1. Default parameter values used in model simulation**

| Parameter | Value |
|---|---|
| Forecast skill | 70% |
| Threshold at which trust in forecast is lost | 30% |
| Threshold at which trust in market is lost | 50% |
| Ratio of actual return to expected return at which farmer's trust in market is updated | 0.8 |

## Details

**Climate scenarios***:* The climate scenarios are binned in deciles across probabilities that rainfall during the season is dry, normal, or wet. A general trend towards drought at our study site has been observed by Gunda et al. (2016) but Seo et al. (2005) note that the dominant climate change being observed at a seasonal level in Sri Lanka is increased variability. Therefore, the three climate scenarios considered in the model are:

1. Historical climate during the dry season: 40% dry – 40% normal – 20% wet
2. Drier climate: 50% dry – 40% normal – 10% wet
3. Wetter climate: 30% dry – 40% normal – 30% wet

The historical probabilities were determined from assessing drought indices at Anuradhapura using 131 years of data generated by Gunda et al. (2016) (Figure A4). No extreme conditions (i.e., floods and droughts) are considered in the model. The categorical approach (i.e., dry, normal, and wet) is consistent with field findings, which indicate that local water managers generally think about water availability in categorical rather than quantitative terms (Burchfield and Gilligan, 2016).

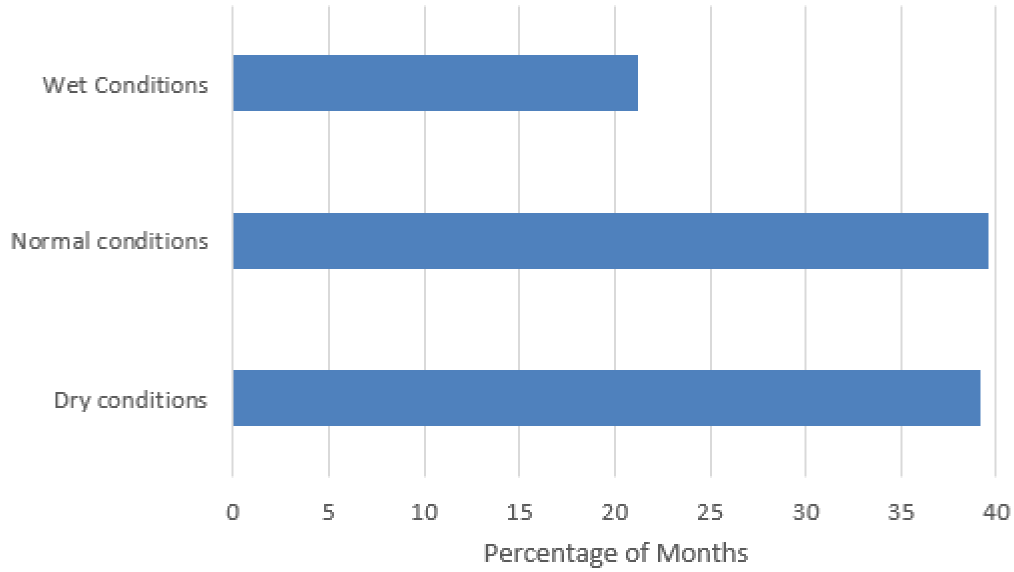


**Figure A4**. Percentage of months between 1881 and 2010 that were classified as wet, normal, and dry conditions based on the Palmer Drought Severity Index values at Anuradhapura. Data generated by Gunda et al. (2016).

**Seasonal forecasts:** For a given climate scenario, a seasonal forecast is generated by randomly sampling the corresponding climate probabilities.

**Actual weather***:* Actual weather is generated by randomly sampling the seasonal forecast but is moderated by the forecast skill. For a forecast skill of 70%, for example, the actual weather generated is drawn (on average) from the generated forecast probability 70% of the time and from historical conditions (regardless of the actual climate) the remaining 30% of the time. For a forecast skill of 100% then, the actual weather generated is drawn from the generated forecast probability 100% of the time.

**Crop options:** The adaptive (and climate) farmer has the option of planting rice, soybeans, onions, or leaving their field fallow.

**Crop decisions**: As aforementioned, both the climate and adaptive farmers select crops based on their ongoing experiences with the weather and market. Based on the game findings (Figure A5), both farmers use the following logic to translate the ternary weather probabilities to actual crop decisions:

- If the probability of wet weather is >=70%, plant rice
- Else if the probability of wet weather is <30% and the probability of dry weather is >=60%, plant onions or leave field fallow
- Else, plant soybeans

Based on the ADAPT-SL survey data, the farmer chooses to plant onions (instead of leaving their field fallow) 75% of the time. If the farmer's planting decisions do not match the actual weather, they lose trust in the forecast. If the farmer's trust in the forecast drops below a threshold (default: 30%), then the farmer exhibits risk averse behavior by just planting rice – a behavior observed and documented in many regions of South Asia, including Sri Lanka (Thiruchelvam, 2005; Hertzog et al., 2014; Jain et al., 2015). This model set-up also reflects our ADAPT-SL survey findings that as a farmer's predictability of rainfall decreased, they were less likely to plant non-rice, or other food crops (OFCs). Similarly, if the farmer's market return for a crop is not at least 80% of their expectations, they lose trust in the market. If the farmer's trust in the market drops below the threshold, they exhibit risk averse behavior by planting rice instead of soybean and leaving fields fallow instead of planting onions (see subsection on "Trust heuristics").

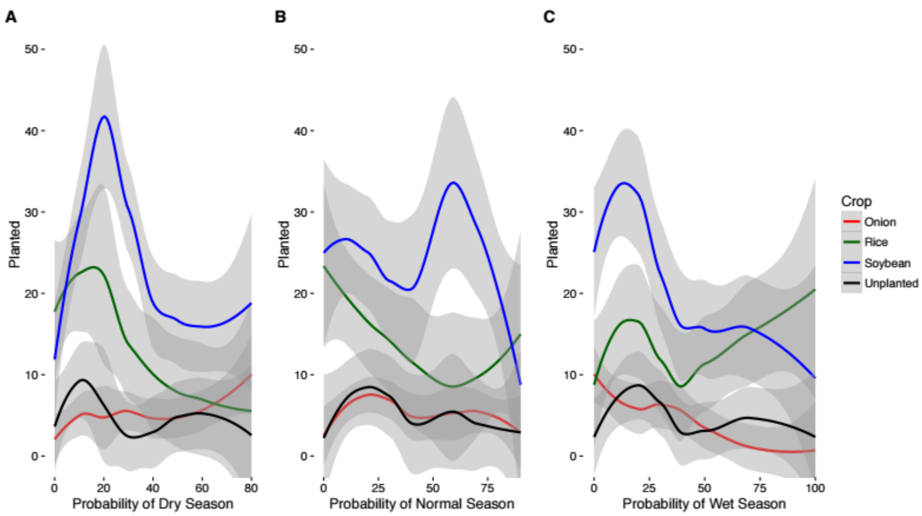


**Figure A5**. Planting decisions as a function of weather probabilities for A) dry season, B) normal season and, C) wet season. Lines represent average values while shaded regions represent 95% confidence interval for a LOESS fit to the data. Generally, farmers preferred to plant soybean except when the probability of wet or dry weather is high, in which case farmers opted to plant rice or onions over rice respectively.

**Crop yield**: Crop yields are binned into three categories: successful, normal, and poor. We assume that the farmer has the necessary knowledge to plant and maintain their crops and that the crop yields are not biophysically constrained (e.g., by soil type) on their hypothetical field. Therefore, the crop yields are purely a function of water availability. Both rice and soybean require more water for a bountiful crop while onions perform better in drier conditions due to root rot issues (Brouwer and Heibloem, 1986). So assuming that Huruluwewa is at average capacity, wet weather is needed for successful rice and soybean crops while dry weather is needed for a successful onion crop (Table A2).

**Table A2. Crop yields as a function of weather conditions.**

| | **Dry** | **Normal** | **Wet** |
|---|---|---|---|
| Rice | Poor | Normal | Successful |
| Soybean | Poor | Normal | Successful |
| Onion | Successful | Normal | Poor |
| Fallow | None | None | None |

**Education**: Our game results show that farmers with more education (i.e., greater than grade 9) moved more quickly towards planting rice under increasingly wet probabilities of weather (Figure A6). Therefore, we created a binary education variable that only impacts the implementation of the adaptive farmer's planting approach. If the farmer's education is less than grade 9, then there is some variability in their adaptive behavior; half of the time, the farmer makes a decision following the rationale outlined above and the other half of the time, the farmer chooses an option at random with a preference for planting rice 70% of the time and one of the other options (i.e., soybean, onion, or fallow) the remaining 30% of the time. This heavier weighting towards rice in the stochastic component reflects the positive association between education and predictability of rainfall in the ADAPT-SL survey data; our data shows that farmers who are less educated were less likely to state that they could predict rainfall; the ADAPT-SL survey data indicates that a farmer's predictability of rainfall is related to the likelihood the farmer is to plant OFCs (see subsection on "Trust heuristics").

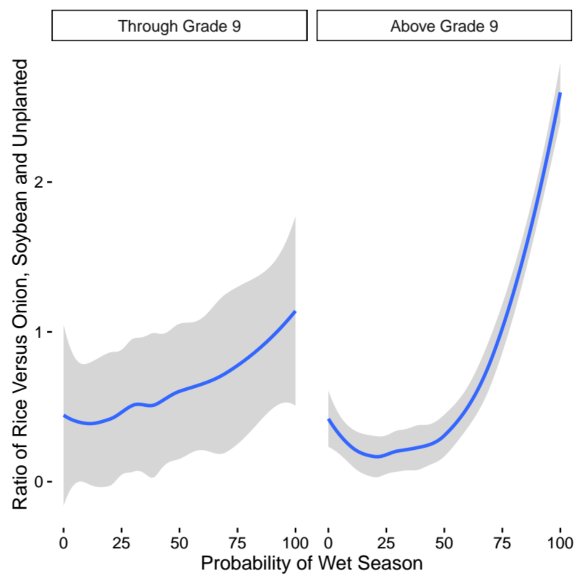


**Figure A6.** Impact of education on farmer crop selections. Lines represent average values while shaded regions represent 95% confidence interval for a LOESS fit to the data. Less educated farmers planted more rice at lower probabilities of wet season whereas more educated farmers moved more quickly towards planting rice as the probability of a wet season increased.

**Market return**: Market return is modeled as a function of crop yield and market conditions. Consistent with current Sri Lankan policies, we model rice with a fixed return while returns for soybean and onions are market-dependent; market returns for soybean are less variable than those for onions given the presence of futures contracts (whereby farmers enter agreements with businesses to buy the crop at an agreed price) in System MH. In the model, the returns for soybean and onions are randomly drawn from a uniform distribution of the ranges specified in Table A3. The market relationships in Table A3 were established based on aggregate data for costs (including both labor and materials) and returns from agricultural statistics books (Department of Agriculture, 2010-2011).

**Table A3. Crop costs and returns (x 30,000 Sri Lankan Rupees), normalized per acre (Source: Department of Agriculture, 2010-2011). Crop returns are a function of crop yield.**

| Crop planted | Cost | Returns | | |
|---|---|---|---|---|
| | | Successful | Normal | Poor |
| Rice | 1 | 3 | 2 | 1 |
| Soybean | 2 | 3-5 | 2-4 | 1-3 |
| Onion | 5 | 5-15 | 4-12 | 3-7 |
| Fallow | 0 | 0 | 0 | 0 |

**Trust heuristics***:* We use a cognitive model for trust in our simulation; specifically, trust is as an accumulation of experiences over time and can influence behavior in the future (Earle and Siegrist, 2008; Hoogendoorn et al., 2012). Trust heuristics are an important aspect of farmer behavior since the farmer's efficacy beliefs/perceived effectiveness of a particular behavior are strongly correlated with their intent to perform that behavior in the future (Esham and Garforth, 2013; Truelove et al., 2015). The rice-alone farmer is not influenced by heuristics in the model; for the climate and adaptive farmers, we assume that there is an immediate feedback at the end of each season for the next season's decisions.

Trust in the forecast and trust in the market are modeled as percentages bounded between 0 and 100 (Sutcliffe and Wang, 2012), with the specific trust level representing the probability that the farmer decides to rely on their rationale; this approach is similar to the concepts of graded trust and subjective probability discussed in Lorini and Demolombe (2008) and Castlefranchi et al. (2003) respectively. At the end of each season, the farmer's trust in the forecast is updated by their experiences using Eq. [1]:

$$Trust_{t+1} = Trust_t + I_t A_t, \qquad [1]$$

where $t$ is a season number, $I_t$ is the increment for trust change in forecast, and $A_t$ is the seasonal adjustment; recall that the farmer is initialized with 70% trust in the forecast. The increment for trust change is calculated each season as the minimum difference between the actual trust level and the boundary conditions (0% and 100%). By making the increment a function of the actual trust levels, our model captures the basic assumption that people with high trust are more likely to be tolerant of failures/bad experiences (Jonker and Truer, 1999; Sutcliffe and Wang, 2012).

The seasonal adjustment value, $A_t$, is based on prospect theory principles that people generally value losses more than gains (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981). Using the farmer's crop yields as the reference point for weather observations, the adjustments were defined as follows:

- If their crop has a successful yield: +6%
- If their crop has a poor yield: -10%

This approach is similar to the methodology employed by Ziervogel et al. (2005), where farmers lost trust in the forecast when their crop yields were poor. If the farmer's trust in the forecast drops below a threshold of 30%, then the farmer reverts to the risk averse behavior of planting rice. This model set-up is consistent with our ADAPT-SL survey findings that as a farmer's predictability of weather decreases, they are less likely to plant OFCs. The farmer continues to update their heuristics regarding weather predictability (relative to their crop planted) throughout the simulation.

The heuristics associated with market trust also follow Eq. [1]. Specifically, the next season's trust is influenced by the current season's actual returns and the increment of change is a function of the actual trust level and the minimum distance to the boundary conditions. Furthermore, the adjustments each seasons are based on the farmer's expected return for each crop (assumed to be 80% of the maximum return possible for soybeans and onions as the default):

$$A_t = \begin{cases} +6\% & if \dfrac{actual\ return}{expected\ return} \geq 0.8 \\ -10\% & if \dfrac{actual\ return}{expected\ return} < 0.8 \end{cases}$$

If the farmer's market trust falls below the threshold of 50%, then they lose trust in the market and opt to plant rice instead of soybean and leaving their field fallow instead of planting onion. Again, similar to forecast trust heuristics, the farmer continues to update their market heuristics regarding market predictability throughout the simulation.

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# Appendix B

## Game Overview and Instructions

# Game Overview and Instructions

## Background

Surveys and simple role play exercises have typically been used to understand how farmers would change their decision, for example, if forecast of below normal rainfall was expected (Hansen et al., 2004; Bharwani et al., 2005; Ziervogel et al., 2005; Roudier et al., 2014). While these approaches are critical first steps for understanding stakeholders' mental models (Elsawah et al., 2015), the lack of feedback and iterative components does not emulate the complex system in which farmers make their decisions. Games have been used to inform model development (Barreteau et al., 2001; Berger and Troost, 2014), but in forecast studies, such participatory approaches are usually limited to education and outreach contexts (Patt, 2001; Suarez and Patt, 2004; Patt et al., 2005; Roncoli, 2006; Roncoli et al., 2009; Ziervogel and Opere, 2010; Dilling and Lemos, 2011; Hansen et al., 2011) and have not been actively used for model development. By incorporating game findings, our simulation actively incorporates the role of cognition into adaptation behavior, a factor often neglected in studies (Grothmann and Patt, 2005).

We designed a contextualized, dynamic game to investigate how farmers respond to and interpret weather forecasts. Specifically, the farmers were provided with a randomly selected seasonal forecast and asked to select which crops they would plant for the season. To limit the impact of communication method on forecast interpretation, forecast information was presented through a mixture of effective methods (Suarez and Patt, 2004; Roncoli, 2006; Ash et al., 2007): orally, as numeric values in written form, and as a weather wheel (i.e., pie chart with spinner; similar to Suarez and Patt, 2004) (Figure 3A-B). After receiving the forecast, farmers made a decision about which crop(s) to plant. Farmers could choose between rice, soybean, onion, leaving their fields fallow, or a mix of these options on their 3 fields; each of the crops had specific planting costs (normalized by 30,000 Sri Lankan Rupees (LKR)) associated with them, based on actual government data about crop-specific costs and revenues (Department of Agriculture, 2010-2011). The farmers communicated their planting decisions by placing crop cards (similar to those developed by Hertzog et al., 2014) onto their game fields (Figure 3C-D).

Once the farmers' decisions were recorded by the game facilitators and planting costs collected (paid out of an equal, initial allocation of start-up capital), the weather wheel was spun to determine the actual weather for the season. Yields and corresponding economic returns were dependent on the weather; rice and soybean returns were fixed across rounds, but onion returns varied based on how many other fields of onion were planted each round. The relationships between crops, weather, and market returns were presented to the farmers on a yield return sheet (Figure 3E); the farmers were told to assume that Huruluwewa was at average capacity, the condition at which the relationships on the yield return sheet were derived. The wheel also had small slices representing rare extreme weather events such as droughts and floods, both of which would have a severe impact on returns.

After the returns for the crops were issued to the farmers for the first season, the wheel was configured to a new seasonal forecast and another round began. The same group of farmers participated in 6 rounds of the game to incorporate previous seasons' outcomes (similar to Hoekstra, 2012). We did not inform participants of the exact length of game (number of rounds) because "end-game" effects can alter game behaviors (Javaid and Falk, 2015). The field assistants informed the farmers to role play (similar to Joireman et al., 2009) as if they were planting on their own fields during the dry season; all game directions were presented in Sinhalese by the field assistants. We also played multiple practice rounds to ensure the farmers understood the rules prior to resetting the game and commencing data collection. A copy of the game instructions is provided below.

The game was played with 49 farmers in System MH in January 2016, in 4 groups of 12-13 players per group. Two versions of the game were played with each group: one where the farmers played without coordination amongst players and one where they were allowed to coordinate their planting decisions with their fellow players. At the end of each game, each farmer's profit was tabulated and the farmers with the most chips were awarded with a payout. These payouts encouraged friendly competition and incentivized participants to be invested in the game (Camerer, 2003). After the games, short post-surveys were conducted to collect demographic information (i.e., education and gender) about the farmers and a subsequent discussion was led by the field assistants to understand the general impressions and strategies employed by the farmers in the game.

Farmers expressed that the game was easy to understand and, generally, they opted to plant rice when the probability of a wet season was high. Most of the farmers also expressed that the weather forecast was a more relevant factor governing their crop selection decisions than market conditions; some said that having more specific information about market conditions would have helped inform their decision-making. Many of the farmers shared afterwards that they enjoyed playing the game and approached it as if the game was emulating reality and they were making decisions about crops on their own farm. After the discussion, all farmers were issued a small participation gift and the same payout as the winning farmer after the surveys.

## Instructions
### (To be read to farmers by facilitators)

***Note to facilitators: Pass out materials to each farmer:*** *plots, poker chips, crop cards, yield return sheets*

**Plots:** You should each have three plots of farm land and 5 poker chips in front of you [point to the structure each has in front of them]. Let us know if you don't. Each land plot represents 0.5 acres. You will individually choose what to plant for each of the three plots by placing one of the crop cards [point to crop cards in front of them]. If you want, you can plant nothing by placing no card on your plot for that season. You can plant the same crop on all 3 plots, or you can plant up to three different types of crop, or anything in between.

**Crop cards:** Now, look at these crop cards. To plant a crop, put its corresponding card on top of the plot of land you want to plant it in. The cards also show each crop's cost per plot per season. It costs 1 chip to plant rice in one field, 2 chips to plant soybean, and 5 chips to plant onions. To make that clear, there is one dot on the rice card, 2 dots on the soybean card, and 5 dots on the onion card.

**Money:** Costs to plant the crops and returns from selling them are measured in poker chips [point to poker chips and point to the number of poker chips indicated on each crop card]. You will receive a set amount of working capital for your cultivation decisions. To begin, you will receive 5 poker chips. At the end of this game, the farmer with the most poker chips will receive a cash prize. At the beginning of each season you need to pay for the crops you decide to plant. If you do not have enough poker chips, then plant fewer or different crops.

**Yield return sheet:** The return sheet in front of you shows the different crop yields under different weather conditions. Note that while the return for rice and soybean are fixed, the return for onions is a range of values; the specific return is dependent on how many of your fellow farmers also plant the same crop. For every additional farmer who plants onion, the return is reduced by one poker chip. For example, if you plant onion and 3 other farmers also plants onion and the weather is dry that season, then a maximum return of 12 poker chips would be reduced by 3 so each of the farmers would only receive 9 poker chips for each plot of onion.

**Weather:** As you can see on the return sheet, the number of poker chips you can earn at the end of a season depends on the weather. There are 3 main weather possibilities: dry – less rain than normal, normal, and wet – more rain than normal. Most seasons there will also be a small probability of drought or floods as well. Each of these weather possibilities is color coded to match the weather wheel and the yield return sheet: dry is orange, normal is yellow, and wet is green while flood is blue and drought is red. Some crops do better with high levels of rain, and some do better with less rain – the yield return sheet shows the relationship between the crops and weather. Game play is led by [INSERT NAME OF PERSON LEADING and point to them]. [INSERT NAME] will spin the Wheel of Rain [point at wheel] and it will spin many times like this [actually spin the wheel] and randomly land on a color. When more of a color is on the wheel, there is a higher chance it will land on that color. In this example, the forecast states there is a 70% chance of wet weather (more rain than normal), so 7 of the 10 slots on the wheel are colored green. When the wheel spins, the color it lands on determines the weather for that season. Let's spin the wheel a few times and see where it lands. (Assume Huruluwewa tank is at average dry season or "yala" levels.)

Now we will go through **rules of the game**:

1. Each round of the game represents one yala (or "dry") season.
2. The facilitator picks a random forecast card and reads it. It will state that the government forecast for the season ranges will be between 0 and 100% chance of it being dry, normal, or wet. An individual card could state, for example, that the season has a 0% chance of it being dry, 30% chance of it being normal, and 70% chance of it being wet. [Draw another card and talk through what that card means. Do this a couple times.]
3. You pay the bank the costs on the cards that you choose to plant for that season.
4. The facilitator spins the Wheel of Rain, which has been configured to accurately represent the forecast. The Wheel lands on a particular slot, which will dictate the amount of rain in the season. [Do this.]
5. The amount of rain indicated by the wheel will determine yields and profits. Your return sheet indicates the profit for each weather possibility. The facilitator pays you the appropriate amount of profit in poker chips and records your number of poker chips.
6. Another round starts. We will play multiple rounds.
7. The goal of the game is to accumulate as many poker chips as possible.

**Directions for facilitators:**

1. Bring together a maximum of 13 farmers in a room for a session.
2. Pass out all game materials:
    a. Farm land with 3 plots
    b. 5 poker chips
    c. Crop cards (3 of each crop)
    d. Yield return sheet
3. Read out game instructions ***Facilitator 1: Weatherman***
4. (Have group explain game back to us)
5. Play a practice game.
    a. Show weather wheel for season's forecast
    b. What are you going to plant in each of your plots?
    c. Invest some money into preparing your plots
    d. Banker goes and around and collects the cost while Recorder updates chart with farmers' planting choices ***Facilitator 2: Banker*** ***Facilitator 3: Recorder***

| Round: | No collaboration | | | | | |
|---|---|---|---|---|---|---|
| Seasonal Forecast: (F-W-N-D-Dr) | | | | | | |
| Actual Weather: | | | | | | |

| Farmer # | Field # | Yala 1 | Yala 2 | Yala 3 | Yala 4 | Yala 5 | Yala 6 | Ending Chips |
|---|---|---|---|---|---|---|---|---|
| | 1 | | | | | | | |
| 1 | 2 | | | | | | | |
| | 3 | | | | | | | |
| | 1 | | | | | | | |
| 2 | 2 | | | | | | | |
| | 3 | | | | | | | |
| | 1 | | | | | | | |
| 3 | 2 | | | | | | | |
| | 3 | | | | | | | |
| | 1 | | | | | | | |
| 4 | 2 | | | | | | | |
| | 3 | | | | | | | |
| | 1 | | | | | | | |
| 5 | 2 | | | | | | | |
| | 3 | | | | | | | |

    e. Spin wheel
    f. Banker goes around and returns profits ***F2*** ***F3 assists***
    g. Repeat steps a-f with changing forecast wheel a few more times as needed
6. Answer questions
7. Now we will play Version One, where you **<u>are not allowed</u> to** discuss your planting decisions with your neighbors
    a. Repeat a-g under Step 5
8. After 6 rounds, sum up farmers' profits and pay out winner
9. Now we will play Version Two, where you **<u>are allowed to</u>** discuss your planting decisions with your neighbors
    a. Repeat a-g under Step 5
10. After 6 rounds, sum up farmers' profits and pay out winner
11. Conduct post-game survey and discussion
12. Give non-winning farmers the participation prize (which is the same as the winner's prize)

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