# Agriculture in a Changing Landscape

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***Modeling shifts in the geospatial distribution of crops in response to climate change***

By

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## Abstract

Altered patterns of temperature and precipitation associated with global climate change are expected to affect the productivity of agricultural regions around the world, with varying regional impacts. Since ideal environmental conditions vary depending on the physiological needs of specific plant types, the regions where we grow different crop varieties are likely to shift in response. This shift will have profound implications for rural landscapes and communities, as well as global food supply and international markets.

In this research I use Classification and Regression Tree (CART) modeling to investigate whether changes in climate over the past 50 years have contributed to shifts in the distribution of crops in Minnesota. I incorporate climate, soil, and agricultural management data to create a time series of regression tree models which predict the acreage of three different important commodity crops, corn, soy, and wheat, for each county.

The resulting models indicate that farmers' decisions to grow corn are positively associated with warmer winter temperatures, with the temperature threshold increasing over time. Soil quality is the primary predictor of soybean acreage, with a stable threshold over time. Wheat models produced inconsistent results, possibly due to displacement by conversion of wheat acreage to corn acreage. This suggests that farmers are already employing crop-switching strategies in response to climate changes. As the impacts of climate change increase in severity, additional research and investment will be needed to help agricultural producers continue to adapt.

## Contents

## Introduction

Altered patterns of temperature and precipitation linked to global climate change are already having an impact on many of the world' most productive agricultural regions (Gornall et al 2010, IPCC 2013). In the coming years, continued climate change may change the quality and availability of "habitat" for many commercially important crop species (Battisti 2009, Burton 2005, Gornall et al 2010). Since ideal environmental conditions vary depending on the physiological needs of specific plant types, the regions where we grow different crop varieties are likely to shift in response. This shift will have profound implications for rural landscapes and communities, as well as global food supply and international markets (Battisti 2009).

While the largest changes in the climate are yet to come, temperature and precipitation patterns have already begun to shift in many regions. Observed temperature shifts have been dramatically larger in high latitude areas than those closer to the equator (IPCC 2013). By looking at the changes in agricultural land use patterns that are beginning to emerge in the northern-most reaches of prime agricultural regions, such as the Midwestern United States, we may be able to better anticipate the impact of future climate changes on food supplies, agricultural markets, and rural communities. In this analysis I investigate the potential for shifts in the growing areas for wheat, corn, soybeans, and barley across the state of Minnesota using statistical analysis to model distributional changes over the past 50 years.

## Minnesota's agricultural landscape

Over its history, Minnesota's agricultural sector has undergone numerous dramatic shifts. From the mid- to late-1800s, the state was one of the nation's most important producers of wheat. Although the cold climate and hard spring wheat produced lower yields than the winter wheat grown further south, superior milling technology allowed the area to become an epicenter for the flour industry. Falling yields attributed to soil exhaustion and proliferation of damaging wheat rusts led the "wheat frontier" to move further west, and Minnesota's farmers to diversify. Until the mid-1900s, the state produced a mix of wheat, barley, oats, dairy, beef, and pork. As the livestock industries grew both locally and nationally, the demand for feed spurred the expansion of corn and later soybeans, which now account for a large portion of the state's total agricultural production (University of Minnesota Libraries 2013).

Agriculture continues to play a critical role in Minnesota's landscape and economy. Farmland makes up over half of the state's total land area, and is nearly evenly split between livestock and crop production. The vast majority of Minnesota farms are moderate in size (on average, 332 acres) and are owned and operated by individuals or families (nearly 90%) (USDA ERS 2014). Table 1 below shows the worth of the top 5 crops produced in Minnesota in 2012.

| Commodity | Gross Receipts ($bil) | % of MN Production | % of US Production |
|---|---|---|---|
| Corn | $6.97 | 33.9% | 10.1% |
| Soybeans | $3.72 | 18.1% | 9.1% |
| Sugar Beets | $0.84 | 4.1% | 34.3% |
| Wheat | $0.58 | 2.8% | 3.8% |
| Potatoes | $0.12 | 0.6% | 3.2% |

***Table 1.*** *Sales of top 5 commodity crops produced in Minnesota in 2012, in current dollars (USDA ERS 2014)*

Minnesota farmers clearly contribute significantly to domestic production of some of the most important food and fuel crops, contributing approximately 10% of national production of both corn and soy. Several seasons of poor production due to extreme weather events shortages in corn and soy during the past decade have caused spikes in food prices around the world. As one of the northern-most producers of corn and soy, Minnesotan farmers may play an increasingly important role in production of these key commodities as climate change threatens yields for farmers further south.

## Climate change in the Midwest

Air temperatures have been steadily rising, with an especially steep upward trend over the past 40 years. Figure 1 shows global annual average air temperatures at the land surface, expressed as anomalies from the 1961-1990 mean baseline (dotted line).

In addition to higher mean temperatures, the variability of temperature is increasing

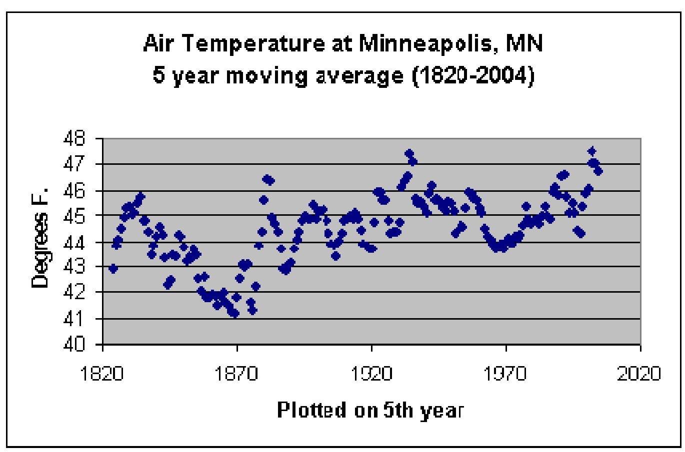



***Figure 1.*** *5-year mean land-surface air temperature trend in Minneapolis, Minnesota over the period of 1820 – 2005. Data from NOAA NCDC (Neuman 2005).*

around the world as well. Figure 2 to the right compares the distribution of summer temperature anomalies in the United States between two recent decades (1959-1969 and 2001-2011). The mean summer temperature has dramatically increased, while the left tail of the distribution (representing extreme cold temperatures) is becoming smaller in the 2001-2011 period, indicating that unusually cold temperatures are becoming increasingly rare. On the other hand, the right tail of the distribution (representing extreme hot temperatures) has become "fatter", meaning that unusually hot temperatures are becoming more common.

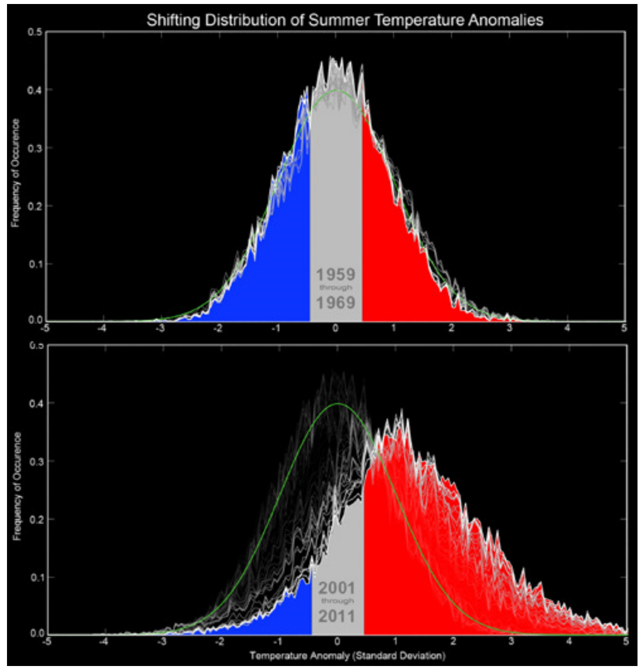



***Figure 2.*** *Comparison of summer temperatures in the US. Upper graph shows the mean-centered distribution of summer temperatures for 1959-1969, while the lower plots the distribution from 2001-2011 on the 1959-1969 mean centered axis (Hone 2012)*

## Vulnerabilities to climate extremes

All crops have a range of temperatures and moisture levels for which they are optimally adapted. Continued exposure to temperatures or moisture conditions outside of this optimal range may reduce yield. For most plants, this relationship is nonlinear- many species have critical thresholds beyond which yield drops dramatically. Crops are particularly sensitive to heat or drought stress during certain critical stages of development such as germination or anthesis (Challinor et al. 2005, Porter and Semenov 2005, Wolfram and Schlenker 2009). At the global scale, if farmers continue to grow the same crops in the same regions where they grow today, yields could drop by 30-45% in the most conservative scenario and over 80% in the most rapid climate warming scenario (Roberts and Schlenker 2011) .

The threshold temperatures at which yields start to decline dramatically are lower than one might think. The threshold for corn is around 29°C or 84°F, while soybeans' threshold is around 30°C or 86°F (Roberts and Schlenker 2011). Thresholds for wheat are significantly lower, 21°C or 69.8°F. Minnesota's climate is currently cool enough for most growing season weather to fall below the optimal growth temperature for staple crops, including corn, soybeans, and wheat. Warming trends are thus not necessarily detrimental for agriculture in this region, and could potentially benefit producers through lengthened growing seasons, decreased frequency of freezing temperatures during the early spring and late fall which interfere with planting, germination, and harvest, and increased crop vigor through carbon dioxide fertilization (Wuebbles and Hayhoe 2004). Combined, these positive impacts of climate change could give farmers in Minnesota and their neighbors throughout the upper Midwest a boost in production and an advantage over farmers in areas which may more frequently exceed the critical temperature thresholds of staple crops.

On the other hand, farmers trying to take advantage of these benefits may be hampered by less helpful climate changes which come along with rising temperatures. Warmer climates may cause a sizeable increase (up to 30%) in winter and spring precipitation during the planting season and decreased summer and autumn precipitation during the plant growing season, which could translate to lower crop yields (Wuebbles and Hayhoe 2004). Overall annual precipitation rates are expected to increase, with a higher frequency of heavy rainfall events followed by periods of little or no rainfall events (Wuebbles and Hayhoe 2004). In addition, some studies suggest that warmer temperatures could cause increases in flooding as ice melts earlier in the spring, adding to the already elevated amount of water in streams from the additional heavy rains and increased spring precipitation. These changes in precipitation and available water may force farmers to invest in drainage systems to mitigate water damage in the spring, while also investing in irrigation infrastructure to combat water shortage during the summer and autumn.

There is a tentative consensus in the field that warmer temperatures will have a net benefit in increasing agricultural yield in the United States, especially in the upper Midwest. These benefits will vanish, however, if the climate continues to warm past the critical thresholds for crop production, at which point increasing temperatures will lead to heat stress and lower agricultural production (Schlenker and Roberts 2009). The genetically modified crops that helped increase yields so dramatically over the past 50 years (and now account for over 90% of both corn and soybeans grown in the US) may increase the US agricultural sector's vulnerability to the effects of climate change due to the loss of diversity which may have helped crop species evolve greater heat tolerance in response to gradual temperature increases (Roberts and Schlenker 2011).

O'Neal, et al. (2005) predicted that farmers will adapt to changes in climate by altering which crops are planted and when during the season. The purpose of this study is to examine the changes that farmers have already made to their cropping choices over the past 50 years in response to climate change in counties throughout Minnesota, and compare the climatic drivers of change between several major commodity crops. A better understanding of the ways in which climate contributes to agricultural change is key to creating efficient and effective farm support programs through both state agricultural policy and the federal Farm Bill. Transitioning to a new type of crop requires investment in knowledge and infrastructure, and elevates farmers' risk and decreases the predictability of cash flow. Smaller family farms generally have limited cash flow and have the most difficulty making those kinds of investments. Programs intended to help stabilize and support the agricultural sector, such as crop insurance and agricultural extension support, should be structured to improve the adaptive capacity of American farms and help farmers make transitions between crops in an economically and environmentally sustainable way.

## Methods

In order to investigate whether climate change has impacted the distribution of crops grown in Minnesota, I built a series of Classification and Regression Tree (CART) models using 3 main types of data- climate, soil, and agricultural management. While the application of CART models is still relatively rare in the field of agronomy, I believe the approach is well suited for modeling the change in the geographic distribution different types of crops across a broad study area. Tree models are very different from other statistical modelling frameworks, and have not been adopted widely, although they are very frequently used in a variety of special research applications, including for actuarial prediction and for the formulation of clinical decision rules (Lewis 2010). The CART modeling has proven most effective in cases where researchers need to capture complex non-linear relationships, while the results need to be simple and straightforward enough to support a practical framework for decisionmaking.

The intended audiences of this research are primary agricultural producers, rural community leaders, and policy makers. A long history of poor communication between scientists and rural communities has created and perpetuated a level of skepticism and distrust in the scientific establishment. This barrier between the researcher and the decision makers has stymied the type of open conversation and collaboration that needs to happen in order to address the challenges of adapting to climate change.

In this context, the CART framework has 4 principal advantages over more conventional theory-based agronomic modeling approaches:

1. *Easily interpretable output.*
   CART results can be displayed geospatially as maps, or conceptually through hierarchical tree models. Both of these formats are intuitive and easily interpreted by lay audiences. Hierarchical models can be used as sort of "decision tree" which can help farmers predict

how changes in future environment and management conditions could affect their farm's viability.

2. *Reliance on observed trends rather than theoretical modeling.*
   The statistical approach of CART modeling, which bases projections solely on observed trends within the study area, is appealing to a broad range of audiences because it reduces potential for disagreement around the parameters and assumptions of the model, and reduces reliance on datasets with a high range of uncertainty (such as climate simulations).
3. *Ability to examine human behavioral responses to environmental changes.*
   Unlike theoretical models predicting plant responses to changing natural parameters, statistical habitat models, including CART, can examine human-induced habitat change. In contrast to wild plants, crops do not "select" their own habitat via propagation and natural selection. Therefore habitat models reflect human decision-making, in terms of what types of crops farmers decide to plant. CART models are well-suited to this type of behavioral analysis because they are able to identify non-linear relationships and complex interactions between variables which are common in human decision-making (Ariely 2008).
4. *Ability to function despite multicollinearity in the predictors.*
   Parametric statistical techniques can be confounded by multicollinearity- or a strong correlation between two or more independent variables in the model. Many climate variables, especially high and low temperatures, correlate strongly with each other, and thus pose a multicollinearity problem. If used together in a parametric model, will likely result in inflated standard errors and (erroneous) lack of significance. Although multicollinearity is still undesirable, non-parametric techniques such as CART are not as prone to distortion of the results due to multicollinearity.

However, CART modeling also has some considerable deficiencies when applied to this kind of data set, which may decrease the precision and accuracy of the final results:

1. *CART models are non-continuous*.
   CART produces a "step-function" result in which the predicted result (yhat) is the same for every observation within the same leaf or ending category on the tree. This means that CART models are bad at modelling linear relationships and produce predictions with coarser resolution than linear regression models.
2. *CART models are easy to "over-fit"*.
   Unrestricted CART specifications may fit the predictive model to the idiosyncrasies of the data set, producing lower branches which do not reflect real, generalizable trends. This

"over-fitting" of the model can be prevented by judicious pruning of the tree, which restricts the model to the number of splits in which relative error is minimized.

3. *CART models may be "unstable".*
   Rerunning a CART model using identical data does not produce the exact same results consistently over time. Datasets in which there are multiple possible splits producing the same goodness of fit may produce different model outcomes depending on the alternative splits, with the same statistical validity.

To examine the impact of these weaknesses of the CART modeling framework on the validity of my results, I will perform a comparative analysis on the corn data using Principal Components Analysis (PCA). PCA is a multivariate technique used to examine the relationships among variables and quantify the explanatory power of environmental gradients on the primary and secondary axes of variation. I will compare the PCA axes and factor loadings with the primary and secondary splits identified in the CART models and will use the PCA results to assess the potential for instability in the CART results.

## Data

Although I sought to base the models on a diverse, comprehensive data set including environmental and management data over a long-term time-series, the availability of sound agricultural management data limited the scope of the analysis. The first moderately consistent records of irrigation and application of chemical inputs such as fertilizers, pesticides, and herbicides began in the early 1990s. Even the most current records present many challenges due to poor data quality, which will be discussed in subsequent sections of this paper.

### *Historical Climate*

I used daily temperature and precipitation records from the United States Historical Climatology Network (USHCN) to calculate monthly mean climate indicators for each decade from 1960 through 2009. The data set included minimum temperature, maximum temperature, and total precipitation for each of 34 U.S. Cooperative Observing Network and National Weather Service weather stations in Minnesota. The period of record varies for each station; some stations may be missing from some years of the analysis. The weather stations do not cover the entire state at regular geospatial intervals. The USHCN was developed by the National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC) to provide a basis for regional climate change research. It has been widely used in climate research from the state to national levels (CDIAC 2013).

The USHCN data set includes an extensive system of flags that indicate potential issues with data quality. If all observations with quality flags were thrown out, insufficient data would be left to perform a robust analysis, therefore I systematically removed all data with quality issues that could significantly change the outcome of the analysis and included all data with issues that were very unlikely to affect the outcome. I excluded all records with logical consistency issues, including minimum temperature that exceeded maximum temperature, records with less than 4°F difference between high and low temperature for the day, and days with a low temperature higher than the previous day's high temperature or high temperature lower than the previous day's low temperature. I kept all data with quality flags that don't interfere significantly with the validity of the analysis, including observations that didn't have more than one duplicate record for corroboration, those with slight lags in collection time, and observations that were compiled from 2 or more subsets of daily data (for example, 2 12 hour precipitation totals were added to calculate to get total precipitation for the 24 hour period). All records of "Trace" precipitation (<0.01") were replaced with value of zero for this analysis.

I used the daily temperature data to compute the mean daily high temperature, mean daily low temperature, and total monthly precipitation. These monthly data were then divided into three groups depending on the period of plant development associated with the given month: winter (including November, December, January, February, and March), early growing season (including April, May, and June), and late growing season (including July, August, September, and October). Subdividing climate observations based on agronomically relevant periods allows the additional opportunity for the models to differentiate the impact of seasonally-specific climate trends on agricultural management decisions.

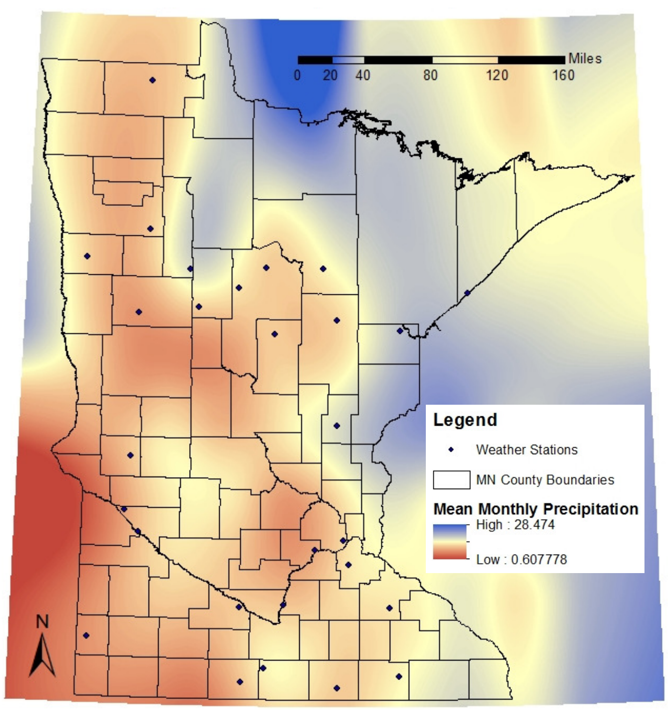



*Figure 3. Regularized spline interpolation of precipitation records from all MN weather stations during the period of 1960-1969. Spline weighting set to 0.1 using the 3 nearest weather stations to approximate the amount of precipitation for each raster cell.*

Because of the irregular placement of weather stations across the state, to compile climate data for each county I had to interpolate temperature or precipitation "surfaces" across the state to approximate local conditions for each month in the historical record. I interpolated the data using a regularized spline method, incorporating the 4 closest point observations. I then calculated mean temperature for each county using the zonal statistics function in ArcGIS, with the zone delineated by county boundaries. Figure 3 above shows an example of an interpolation used to calculate the county mean for each variable during each time period.

Certain areas of the state produce consistently skewed results due to insufficient coverage, meaning that the nearest weather stations are too far away to predict local conditions. Counties in the southeast corner of the state, including Houston, Fillmore, and Winona Counties show a moderate negative skew, while counties in the northeast corner of the state, including Cook and Lake Counties show a strong positive skew. I excluded Cook and Lake Counties from further analysis because of their minimal agricultural activity and large temperature skew, to mitigate the impact of error introduced by the interpolation process on the model results.

***Soil***

I used the Crop Productivity Index (CPI) ratings from the Natural Resources Conservation Service (NRCS) to approximate soil quality. The CPI is a ranked index that approximates the relative potential for intensive cultivation of crops on a particular parcel of land, with values ranging from 0 (no agricultural production potential) to 100 (highest production potential). I obtained the CPI values for the state of Minnesota at 10m resolution from the Gridded Soil Survey Geographic (gSSURGO) Database State-tile Package (National Cooperative Soil Survey 2013).

The gSSURGO data set is the most comprehensive and detailed soil geographic data set available based on the National Cooperative Soil Survey, however, several counties in Minnesota have declined to participate in the National Survey. Cook and Lake Counties are completely missing, while Pine and Crow Wing Counties are missing more than half of the spatial data. In order to convert the CPI values from 10x10m resolution to county-level resolution, I performed a zonal statistics operation in ArcGIS which calculates the county average CPI using values from each 10m grid cell within county boundaries.

### *Agricultural Management*

Records from the USDA's National Agricultural Statistics Service containing survey (annual or biannual) and census (every 5 years) datasets were used to calculate the net acres planted per growing season for each crop in each Minnesota county. I then calculated mean acreage for each time period in the analysis. Census data was augmented by extensive survey estimates for corn and soybeans, however for wheat and barley, survey data became sparser over time, and therefore mean acreage for wheat and barley are based on fewer data points (USDA NASS 2013).

Irrigation data was acquired from the Minnesota Department of Natural Resources (MN DNR). The department has tracked and regulated large withdrawals through a permit system since 1988. All users withdrawing more than 10,000 gallons of water per day or 1 million gallons per year are required to measure monthly water use to an accuracy of 10%. Because actual water use is not verified and is self-reported on an annual basis, there is significant potential for error in the data. However, since there are no verified records on a statewide basis, it is the most complete and robust record of irrigation available. I calculated irrigation use by county as the sum of reported actual use by all ground and surface water permit holders within the county classified as "Major Crop Irrigation" for each year from 1988-2011 (MN DNR 2013).

Unfortunately, the best available data sets pertaining to chemical inputs, including fertilizers, pesticides, and herbicides, are not of high enough quality to include in this analysis. State regulators track only the sale of such chemicals, not the location of application. Distributors often sell large amounts of these inputs to farmers who may use them in neighboring counties, resulting in a dataset which incorrectly shows agricultural chemical use concentrated in just a few counties. These data were therefore excluded due to the significant source of error they would introduce into the geospatial analysis.

## Analysis

Using the data described above, I created a series of CART models, which describe the primary drivers predicting crop prevalence in a given county. Because the dependent variable in this analysis (percentage of total cropland planted in the selected crop) is continuous, my models take the form of regression trees.

I performed the analysis using the statistical package R (R Core Team 2013) and the "rpart" program (Therneau et al 2014). I specified the models with a standard ANOVA regression, using the PARMS splitting technique to divide each branch by maximizing the similarity within each group and maximizing the dissimilarity between each group. Each model was specified using the same independent variables, as shown in the example of the wheat model for 2000-2009:

```
wheat.rpart.info <-
rpart(wheat~wintermin+wintermax+winterprecip+grow1min+grow1max+grow1precip+grow2min
+grow2max+grow2precip+cpi+irr, data=wheat.data,method="anova",
parms=list(split="information"))
```

This model specification produces a fully enumerated tree using the specified data, showing the splitting parameters for each branch from the root (the undivided sample) to the leaves (the ultimate categorical descriptors of the subgroups characterized by the model). Each leaf shows the predicted value (in this case the proportion of cropland predicted to be planted with the selected crop), the number of samples within the dataset which fall into the category, and the percentage of the total dataset which falls into the category. Figure 4 below shows the resulting wheat model for 2000-2009 as constructed using the code shown above, in unpruned form.

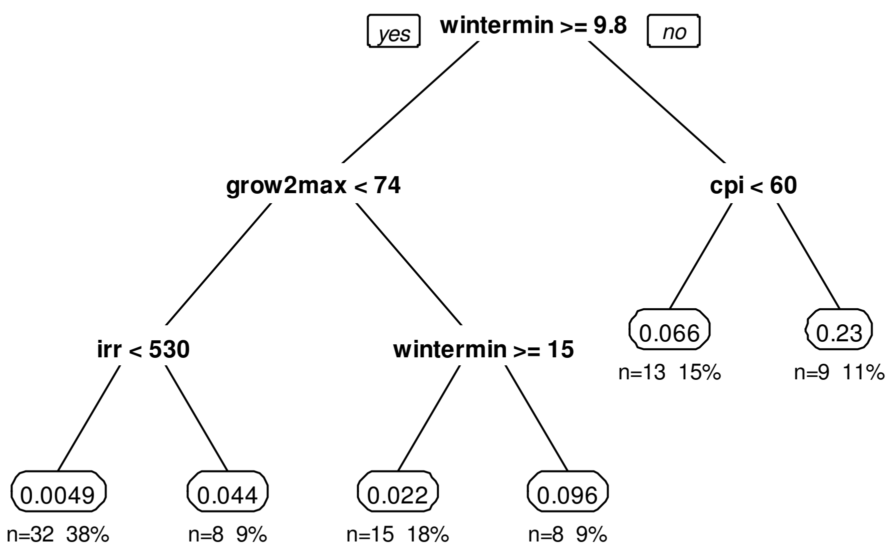



***Figure 4.*** *CART model of wheat planting decisions during the period 2000-2009, unpruned.*

### *Cross Validation and Pruning*

Each of the trees was then examined using 10-fold cross-validation. This process divides the data into 10 equal subsets; builds the tree using 9 of the 10 subsets (called the "training" data), then assesses error using the tenth subset which was not included in the training dataset (called the "testing" data). This process is repeated, leaving out each unique subset in turn and errors are then averaged and scaled to calculate the X-value relative error.

A cross validation table compares the X-value relative error depending on the size (number of branches within) the tree. It is important to select the tree size which minimizes relative error, in order to minimize over-fitting the model with weak (high relative error) terminal splits. Removing weak splits is called "pruning" the tree. In each case I created a cross-validation table and pruned the tree to minimize X-value relative error. It is important to note that cross-validation and pruning may produce different results when run multiple times, because the data are subset differently during each run. The cross validation plots included in the results section of this paper are only one of many possible outcomes for error assessment on the given model. Figure 5 below shows an example of the pruning process.

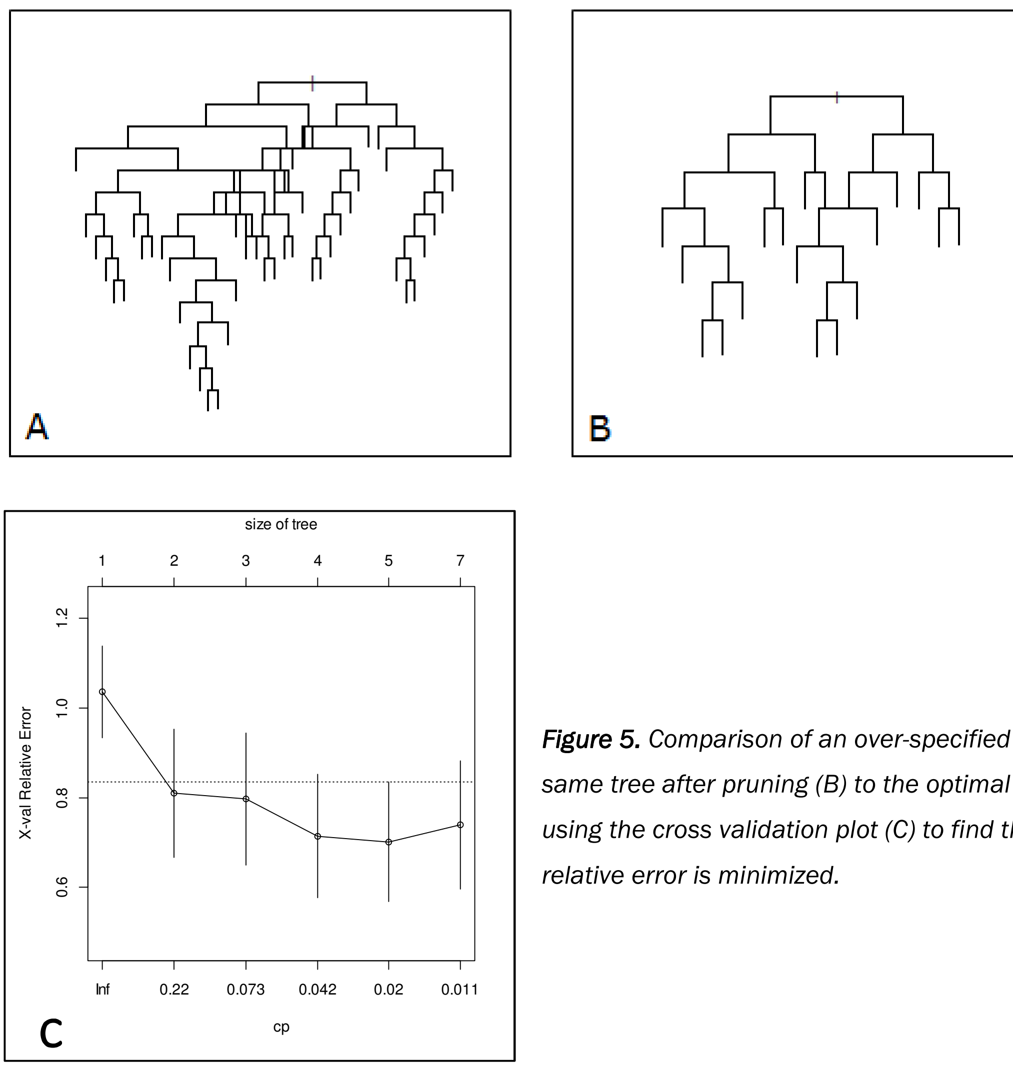



***Figure 5.*** *Comparison of an over-specified tree (A) and the same tree after pruning (B) to the optimal tree size indicated using the cross validation plot (C) to find the tree size at which relative error is minimized.*

### *Comparison Analysis*

I conducted the comparison analysis by running Principal Components Analysis on each decade of the corn dataset. I only ran the comparison analysis for one crop because corn was the only crop which exhibited strong, consistent CART model results dominated by climate factors (as I will explain in depth in the Results shortly). I constructed the PCA analysis using the basic statistical functions in R (R Core Team 2013) using the code below:

```
env2.pca <- princomp(env.data[,-1], cor=T, scores=T)
```

I specified correlation matrices to accommodate the environmental variables in various different units of measure. I compare the results from all components accounting for greater than 10% of the total variance in the model.

## Results

The CART analyses showed that changes in local climate conditions are predictive of changes in the types and quantities of corn and wheat being grown within MN counties. Increasing temperatures are especially strongly predictive of increases in corn acreage, while wheat acres show the opposite relationship (increasing in acreage with decreasing temperatures, possibly a reflection of the displacement of wheat by corn acreage in warmer temperatures). Soil quality is the strongest predictor of soybean acreage, while temperature and precipitation play relatively more minor roles in explaining the variance in acreage across the state.

### *Corn*

Winter weather conditions consistently have the strongest signal on predicting the prevalence of corn. Average daily minimum temperature during the winter months was the strongest predictor in 3 of the 5 decade models, including the 1970s, 1990s, and 2000s. The threshold temperature in each of these models differs, with higher temperature thresholds in the 1990s and 2000s (11.02° and 10.53°F, respectively) than the 1970s (5.775° F). The root factor in the 1960s was similarly a winter temperature threshold, this time the average daily maximum (29.75°), with corn-growers again favoring warmer winter temperatures.

While farmers consistently favor areas with warmer winter conditions (which indicate earlier thaw and thus longer growing season), the upward trend in threshold temperatures reflects the trend of winter weather getting warmer over time throughout the state, while corn production is not moving northward at a commensurate rate.

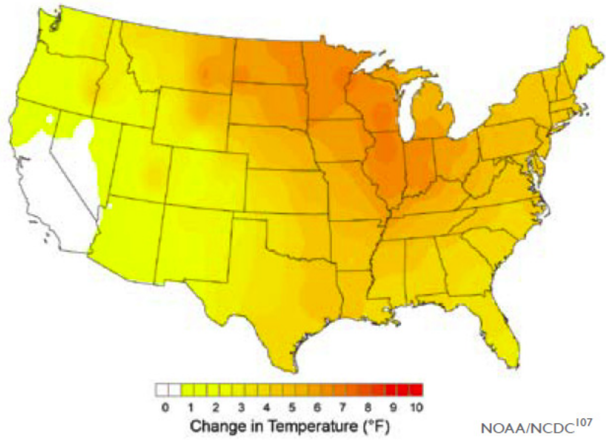



***Figure 6.*** *Winter temperature trends from 1975 to 2007. The warming trend is strongest in the north Midwest, especially Minnesota, Wisconsin, and Illinois (NOAA/NCDC, excerpted from USGCS Climate Change in the US Report 2009).*

In the secondary and tertiary nodes, interdecadal variation between models is much higher. Late growing season precipitation thresholds appear in the “warm winter” branches of the 1960s, 1970s, and 1980s, with early season precipitation and irrigation dominating lower branches of the 1990s model.

Overall the 1980s and 2000s models showed the greatest compositional variation when compared with the more stable and consistent 1960s, 1970s, and 1990s models. The 1980s was the only decade to depart from the trend of low winter temperatures as the primary driver of variation, with growing season precipitation as the secondary driver. During this decade the relationship appears to be flipped, with winter precipitation playing the driving role and winter temperatures dominating the lower branches of the tree model. This suggests that water stress may have been particularly influential factor in farmers’ decisions during the 1980s. The 2000s decade seems to be unique in that precipitation never appears in the model, while soil quality appears to be taking a larger role in determining corn cropping prevalence, suggesting that water stress was generally less critical during this period.

***Comparison to Principal Components Analysis***

The analysis of the corn data using Principal Components Analysis (PCA) shows that although temperature is again found to be the primary driver of variation within the data, the strong multicollinearity between maximum and minimum temperature variables could lead to some over-specificity in the CART models. Higher temperatures, not only in winter but year round, are associated with higher percentages of corn. Variation in precipitation is similarly collinear, although it is orthogonal to temperature variation. This suggests that additional experimentation is needed to determine whether the changes in winter temperature specifically (as opposed to an overall warming trend) are causally related to corn expansion. However, the PCA results support the overall conclusion that higher temperatures are associated with higher percentages of corn in Minnesota counties, while precipitation plays a secondary role.

Multicollinearity within temperature and precipitation variable groups similarly presents an issue for all statistical analyses of climate impacts on crops. While it appears overall trends are robust, interpretation of the specific thresholds in the following models should be with the caveat that the thresholds may be "soaking up" the explanatory power of collinear variables and indicative of the impacts of a more general warming trend.

***Soy***

Models of soybean prevalence consistently indicate soil quality to be the single strongest predictor of the prevalence of soybean acreage within a county. From the 1970s through the 2000s, the primary branch of every predictive model indicates that the threshold of soil quality lies between 65 and 67 points on the Crop Productivity Index, a remarkably narrow range of variation for a period of forty years. A threshold of 66.7 CPI is the secondary branch in the 1960s model, while early growing season minimum temperatures are the strongest predictor for this decade.

Secondary and tertiary splits show somewhat more variation, with the "high quality soil" branches of the models showing early growing season temperature and precipitation as a strong predictive factor during the 1970s through 1990s, while late growing season precipitation and maximum temperature appeared to have greater influence during the 2000s. All temperature predictors showed counties above the temperature threshold had higher prevalence of soybean acreage, indicating that farmers are taking advantage of higher temperatures to increase growth, and heat stress has not yet become a limiting factor for most soybean growers.

***Wheat***

Models of wheat prevalence showed inconsistency in the primary driver of variation between decades, although all related to winter climate conditions. Winter maximum temperatures dominated the 1960s and 1970s (with thresholds at 26.63° and 25.47° F average, respectively), with lower temperatures corresponding to greater prevalence of wheat. The 1980s and 1990s both show winter precipitation (threshold of 7.992 tenths and 8.506 tenths of an inch, respectively) as a stronger predictive split. The 2000s once again returned to winter temperature, with low average minimum temperature in winter predicting the greatest amount of variability (threshold of 9.82°F). The secondary and tertiary branches in wheat models were similarly dissimilar throughout, with a wide range of different factors appearing to hold sway during different decades.

The fact that wheat models lacked consistency except for a common shift towards colder temperatures may be indicative of a larger socio-economic shift in the agricultural sector which was driven by an omitted variable. The spread of corn and soy northward during the study period, which was driven by grain prices, technological advances, and public policy which increased demand for corn-based biofuels, may have caused wheat to retreat to colder and colder areas due to displacement. Unfortunately, data limitations prevented these socioeconomic factors from being included as predictors in this study, but it is an area where further investigation is needed.

***Barley***

Models of barley lacked statistical significance due to the relative scarcity of barley in Minnesota counties. The sample size of counties in which barley is grown and the small prevalence within those counties contributed to the failure of any model to produce adequate explanatory power for analysis.

## Conclusions

In order to adapt to changing climate conditions, farmers all over the world will need to make changes in what they grow and how they grow it. As my research shows, these changes have already started to happen at the edges of the ranges of major commodity crops in the United States. Farmers are reacting (consciously or unconsciously) to maximize their production in an environment that is drastically different than it was less than 25 years ago, as shown in Figure 7.

While farmers in places like Minnesota may be on average benefiting from the warmer weather, there are significant risks to agricultural production, especially in lower latitudes. Farmers in both low and high latitudes will need additional investment in the form of both research and capital resources in order to successfully adapt to the new challenges and demands placed upon them.

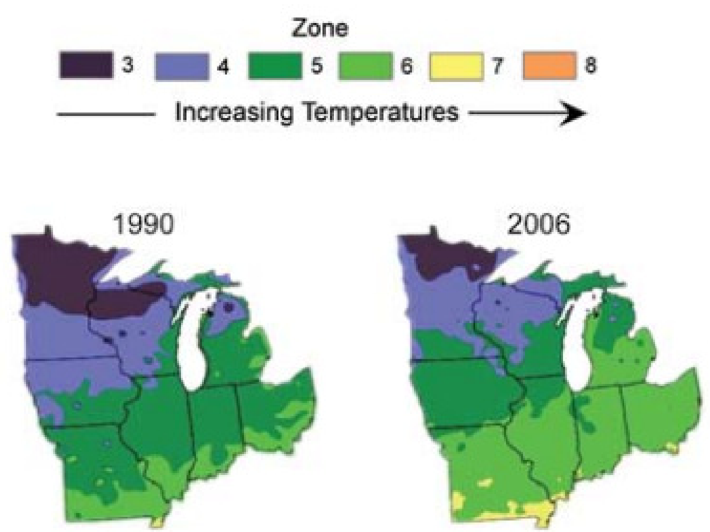



*Figure 7. Comparison of the US Dept. of Agriculture's hardiness zone classifications between 1990 and 2006, showing the northward movement of optimal growing regions for plants based on their temperature tolerances (Arbor Day Foundation 2006)*

Additional research is needed to learn more about the interaction between environmental, management, and economic factors in driving agricultural land use change and climate adaptation. The primary stumbling block preventing this type of research is data availability and quality. Even fairly fundamental agricultural practices are extremely difficult to analyze due to the lack of quality data over any significant time period.

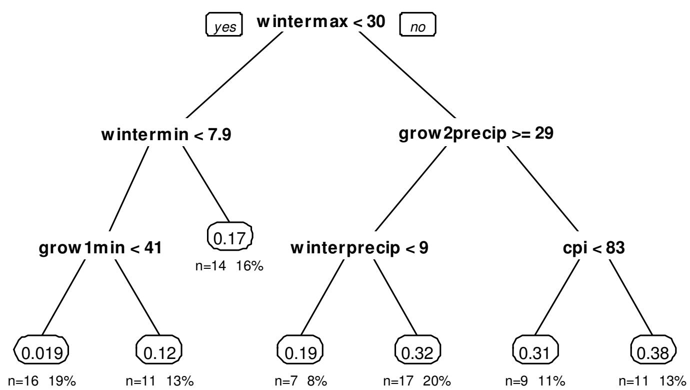
The national agricultural census and surveys conducted by the USDA National Agricultural Statistics Service (NASS) need sustained funding in order to establish a collection of data on management practices that is sufficient in geographic scope and temporal extent to allow integration of this incredibly important data into studies of agricultural adaptation in the United States. There is not (at this point in time) a sufficient proxy that can make up for the lack of comprehensive, consistently collected management data, especially regarding chemical inputs such as pesticides, herbicides, and fertilizers.

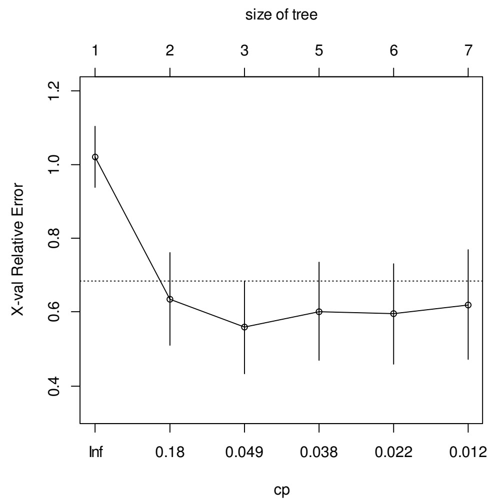
## Appendix A: Model Output

Model output from CART modelling and PCA comparison analyses.

### *Corn*

1960-1969

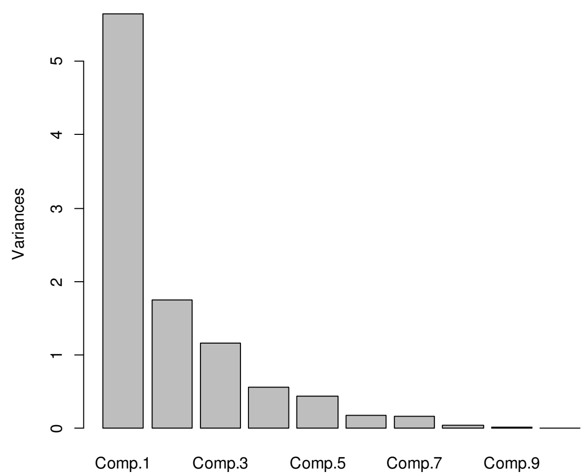


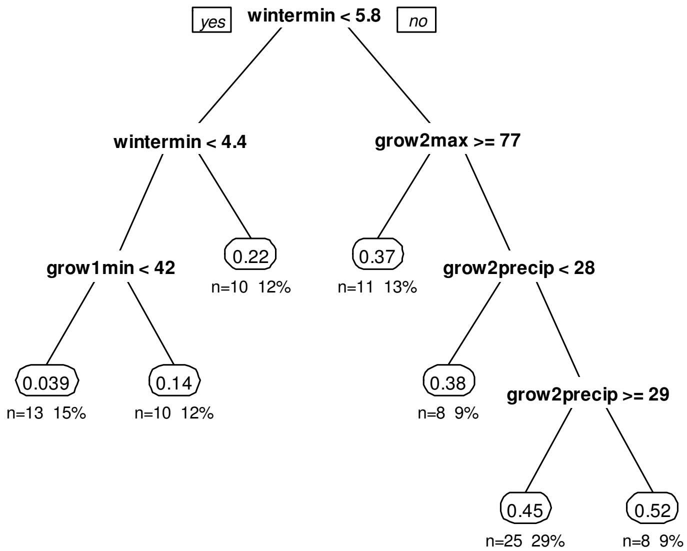

### *Comparison Principal Components Analysis*

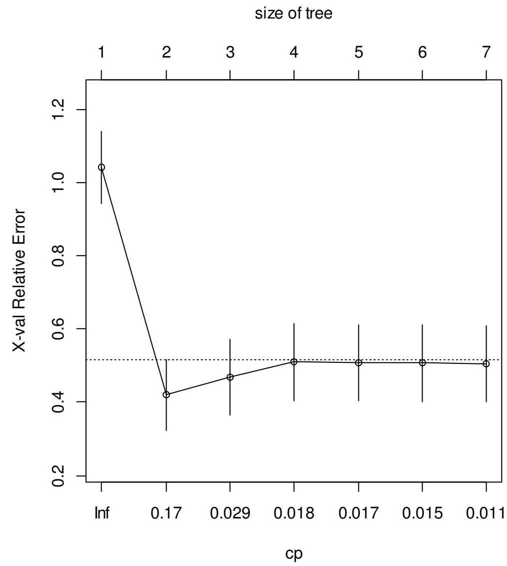
PCA Factor Loadings

| | Comp.1 | Comp.2 | Comp.3 |
|---|---|---|---|
| wintermin | -0.38489 | 0.1108 | -0.27201 |
| wintermax | -0.37697 | 0.1484 | -0.17838 |
| winterprecip | -0.00548 | 0.4245 | -0.71169 |
| grow1min | -0.39885 | -0.0911 | -0.02115 |
| grow1max | -0.36825 | -0.2263 | -0.01318 |
| grow1precip | -0.18008 | 0.5347 | 0.37634 |
| grow2min | -0.37994 | -0.0436 | -0.00453 |
| grow2max | -0.33771 | -0.3344 | -0.12905 |
| grow2precip | -0.22012 | 0.5231 | 0.35129 |
| cpi | -0.27522 | -0.2296 | 0.32459 |



1970-1979



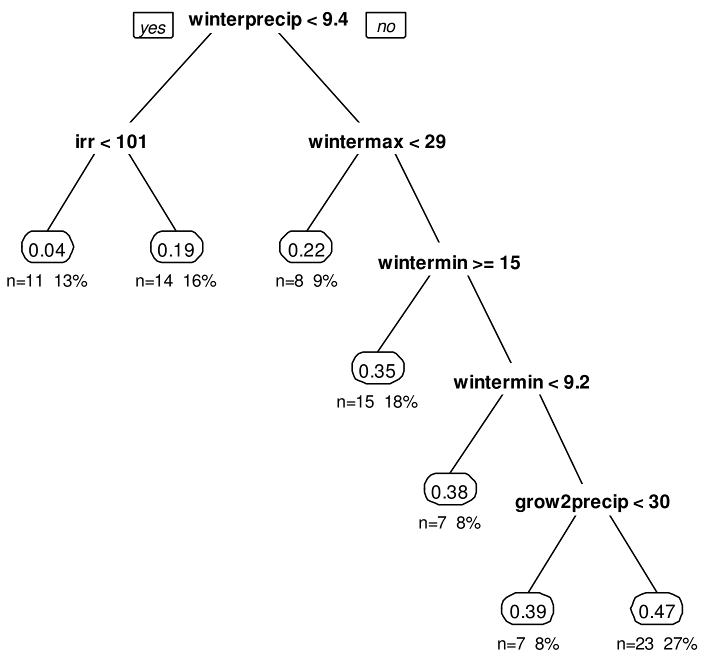



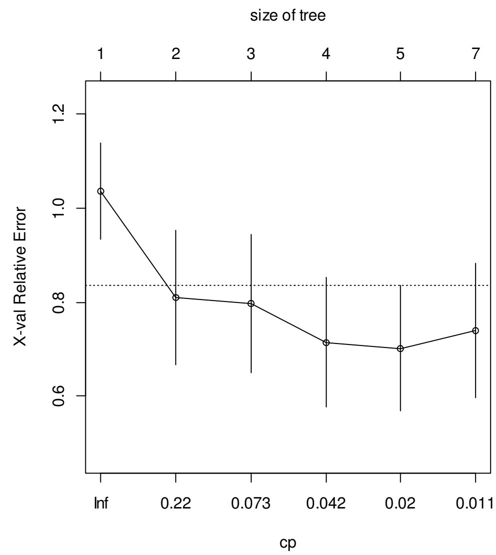

***Comparison to Principal Components Analysis***

PCA Factor Loadings

| | Comp.1 | Comp.2 |
|---|---|---|
| wintermin | -0.3803 | 0.1284 |
| wintermax | -0.3769 | 0.0313 |
| winterprecip | -0.3098 | 0.3675 |
| grow1min | -0.3622 | -0.1178 |
| grow1max | -0.3063 | -0.3216 |
| grow1precip | -0.3276 | 0.2971 |
| grow2min | -0.3443 | 0.0326 |
| grow2max | -0.3297 | -0.3475 |
| grow2precip | -0.0834 | 0.6283 |
| cpi | -0.2252 | -0.3541 |

1980-1989



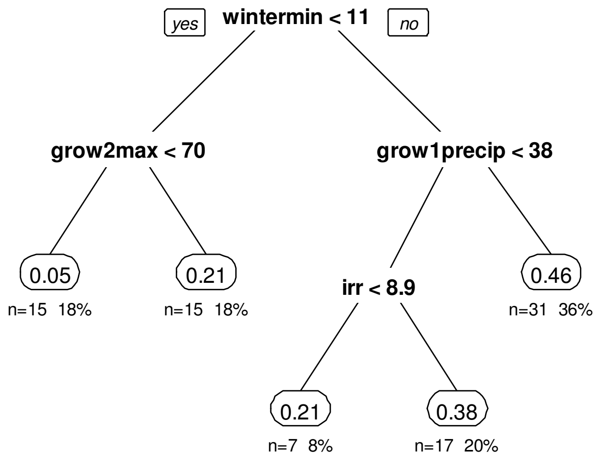



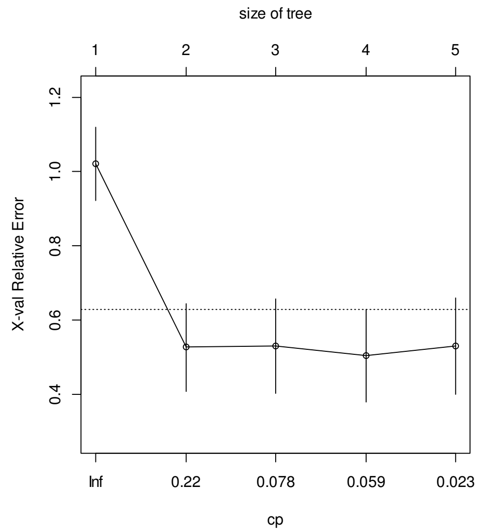

### *Comparison to Principal Components Analysis*

PCA Factor Loadings

| | Comp.1 | Comp.2 | Comp.3 |
|---|---|---|---|
| wintermin | -0.3892 | 0.12586 | -0.1933 |
| wintermax | -0.3464 | -0.08406 | 0.3895 |
| winterprecip | -0.2523 | 0.39956 | -0.3376 |
| grow1min | -0.3958 | 0.00821 | -0.2089 |
| grow1max | -0.3240 | -0.34472 | 0.3012 |
| grow1precip | -0.2646 | 0.38142 | 0.1966 |
| grow2min | -0.3513 | 0.19463 | -0.3495 |
| grow2max | -0.3750 | -0.25709 | 0.1723 |
| grow2precip | -0.0523 | 0.49762 | 0.5851 |
| cpi | -0.2575 | -0.43618 | -0.0609 |
| irr | -0.0112 | 0.10591 | 0.1611 |

1990-1999



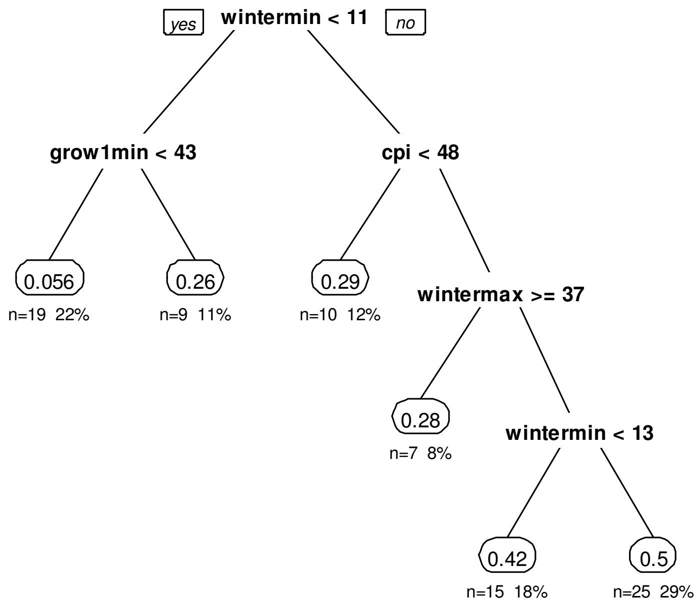



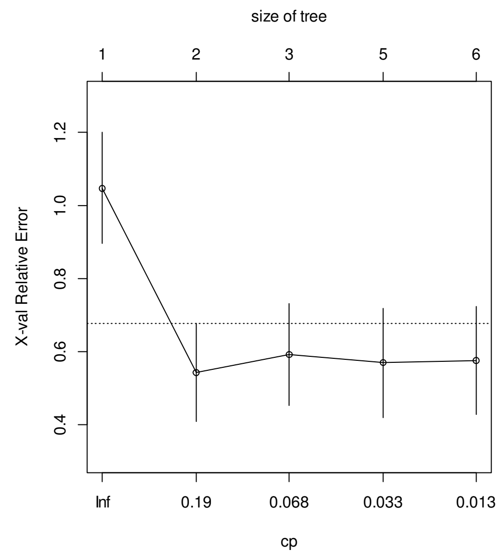

***Comparison Principal Components Analysis***

PCA Factor Loadings

| | Comp.1 | Comp.2 | Comp.3 |
|---|---|---|---|
| wintermin | -0.390644 | 0.0906 | -0.206 |
| wintermax | -0.369071 | 0.2329 | 0.224 |
| winterprecip | -0.189123 | 0.5775 | -0.167 |
| grow1min | -0.378328 | -0.2437 | -0.138 |
| grow1max | -0.297225 | -0.1321 | 0.541 |
| grow1precip | -0.314404 | 0.0658 | -0.431 |
| grow2min | -0.370637 | -0.1371 | -0.217 |
| grow2max | -0.341604 | -0.1617 | 0.405 |
| grow2precip | -0.150411 | 0.5571 | 0.269 |
| cpi | -0.261540 | -0.3731 | -0.162 |
| irr | 0.000113 | -0.1687 | 0.270 |

2000-2009



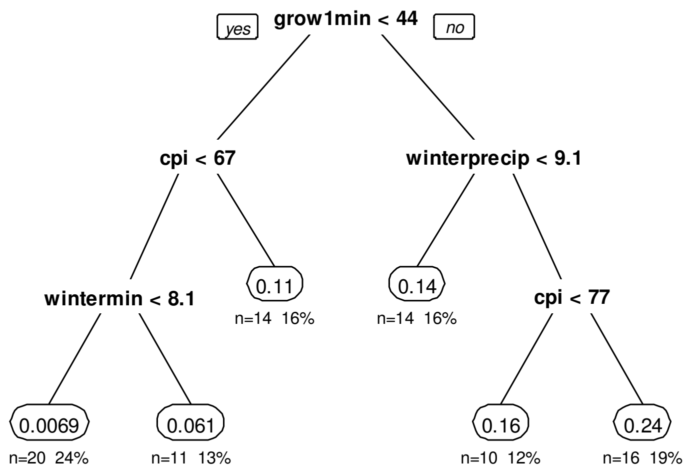



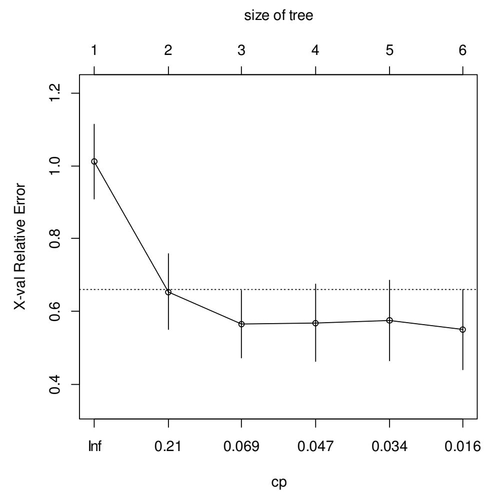

Comparison Principal Components Analysis:

| | Comp.1 | Comp.2 | Comp.3 |
|---|---|---|---|
| wintermin | -0.4150 | 0.0619 | -0.189 |
| wintermax | -0.3713 | 0.2745 | -0.314 |
| winterprecip | -0.0993 | -0.5175 | -0.275 |
| grow1min | -0.3463 | -0.2394 | 0.460 |
| grow1max | -0.4159 | 0.1000 | -0.144 |
| grow1precip | -0.1026 | -0.4523 | -0.359 |
| grow2min | -0.3602 | -0.2119 | 0.389 |
| grow2max | -0.4230 | 0.1450 | -0.129 |
| grow2precip | 0.0569 | -0.5440 | 0.059 |
| cpi | -0.2472 | 0.0154 | 0.393 |
| irr | 0.0600 | 0.1380 | 0.321 |

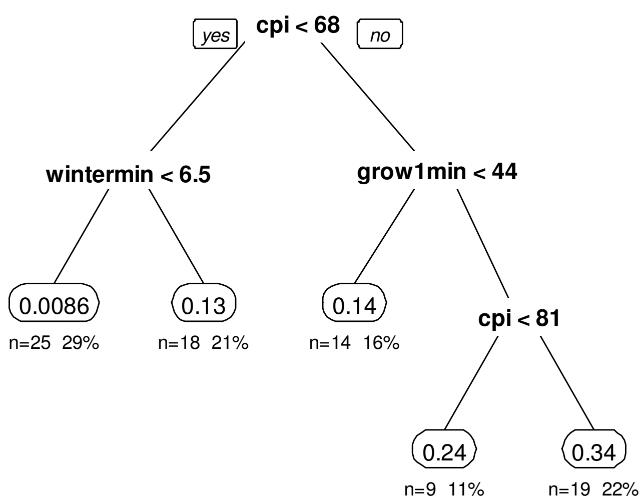
***Soybeans***

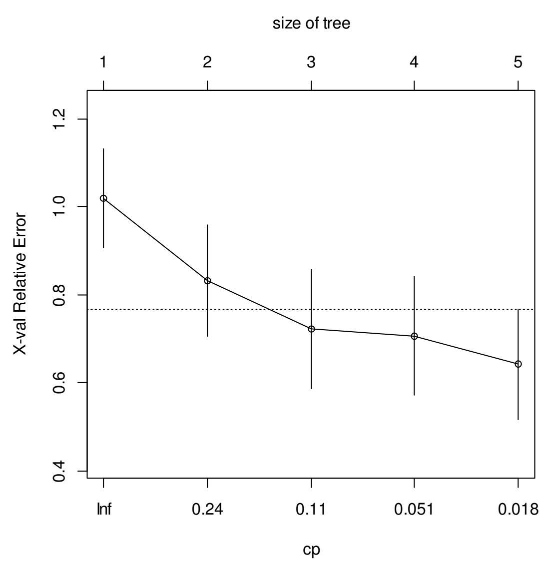
1960-1969



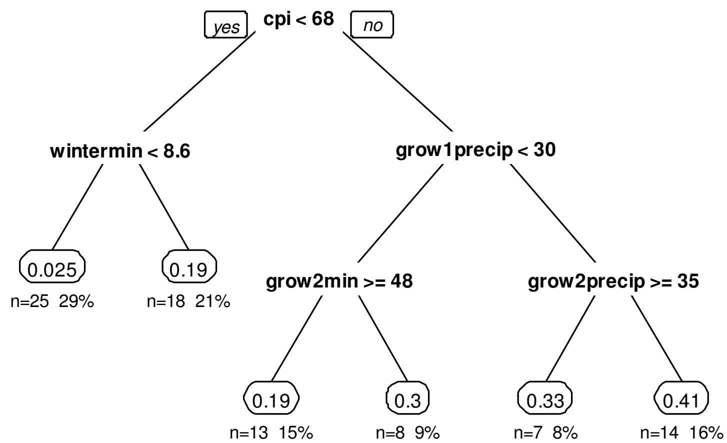



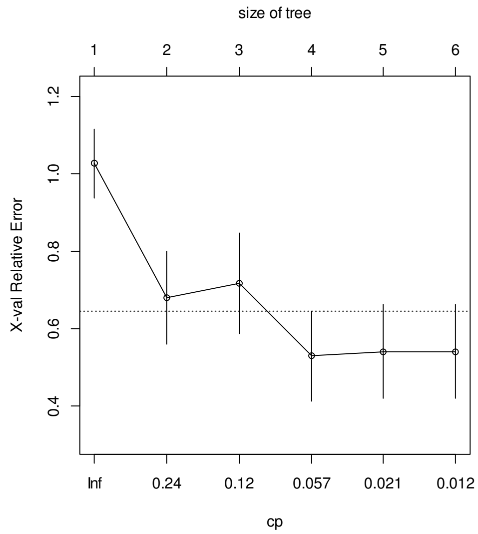

1970-1979



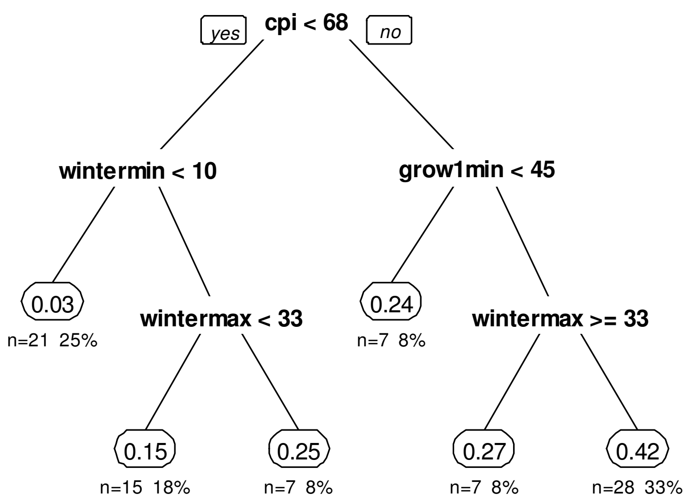



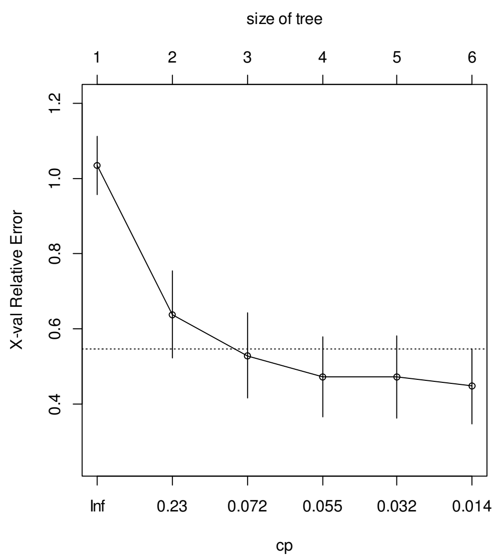
1980-1989



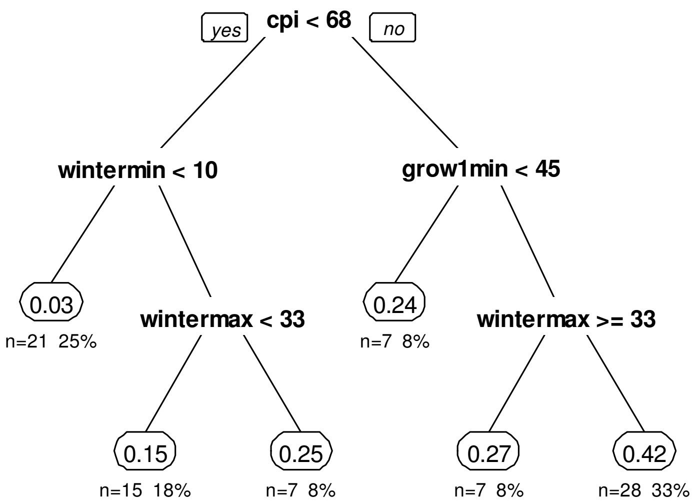



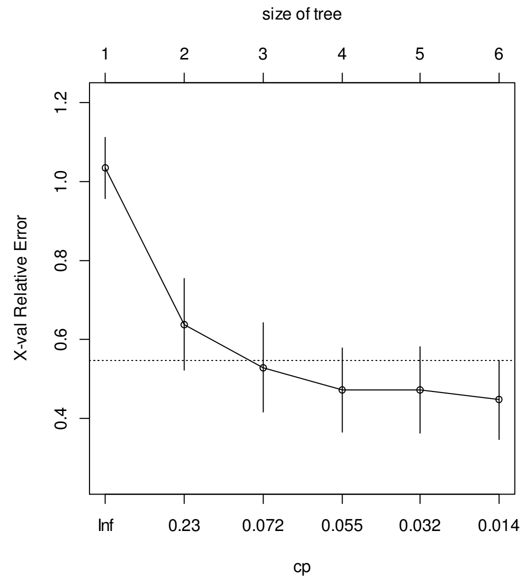

1990-1999



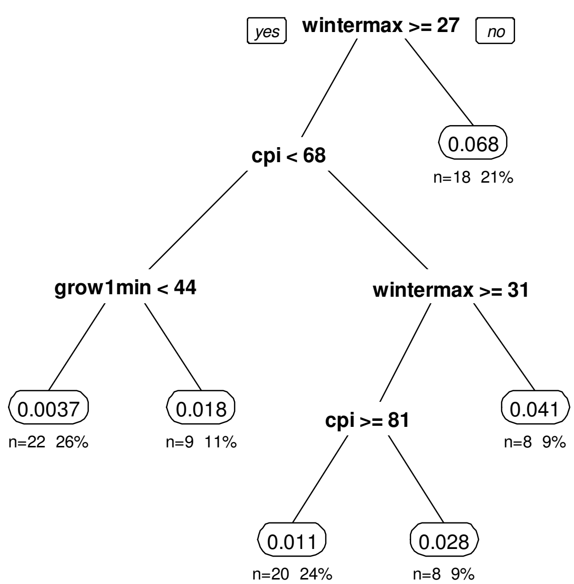



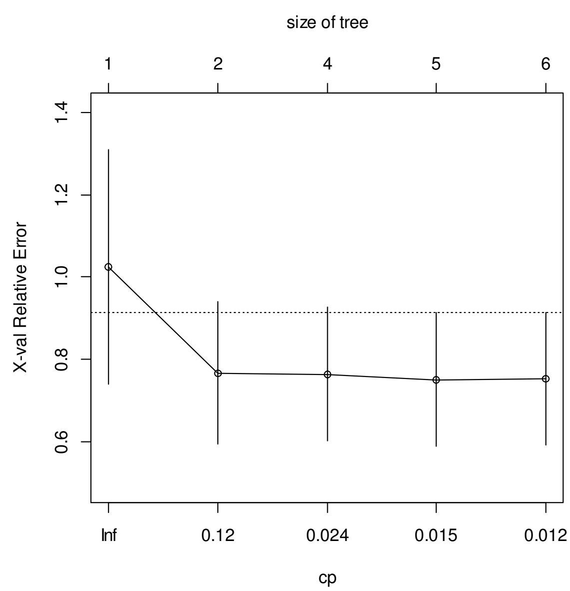
2000-2009



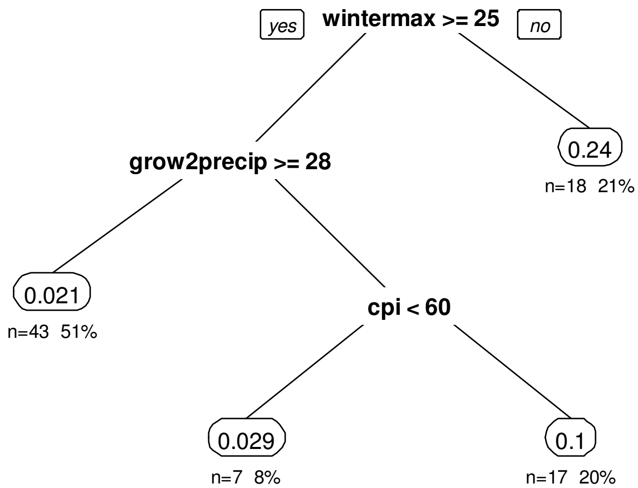



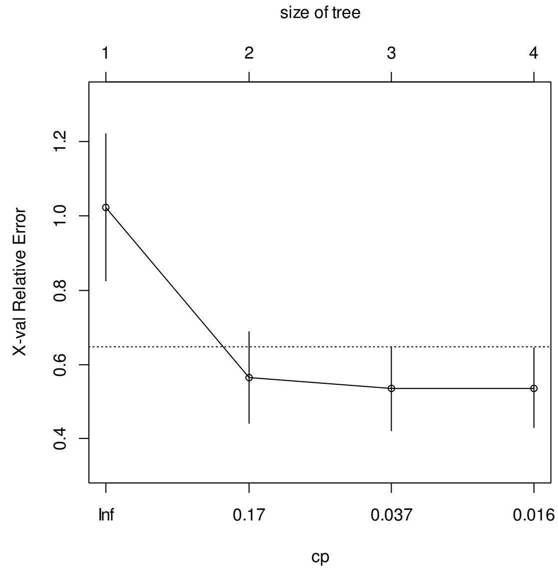

***Wheat***
1960-1969



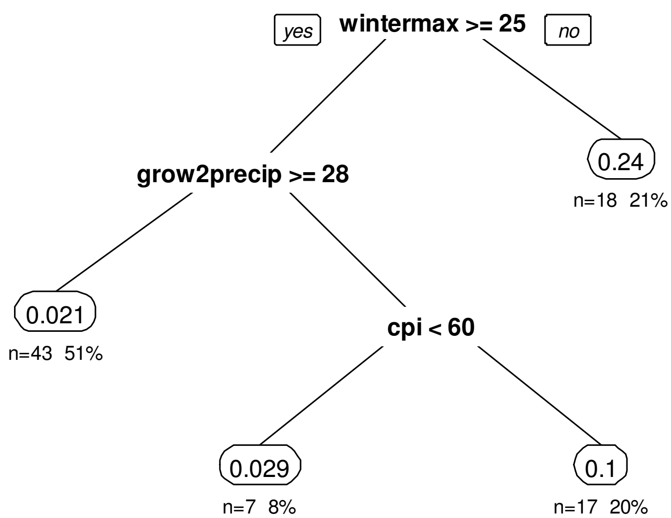



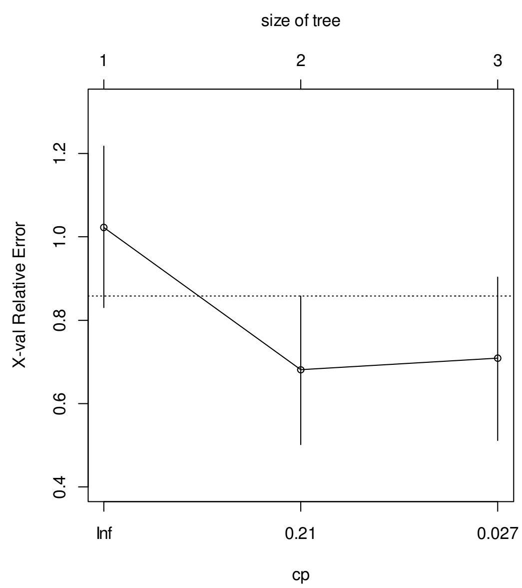
1970-1979



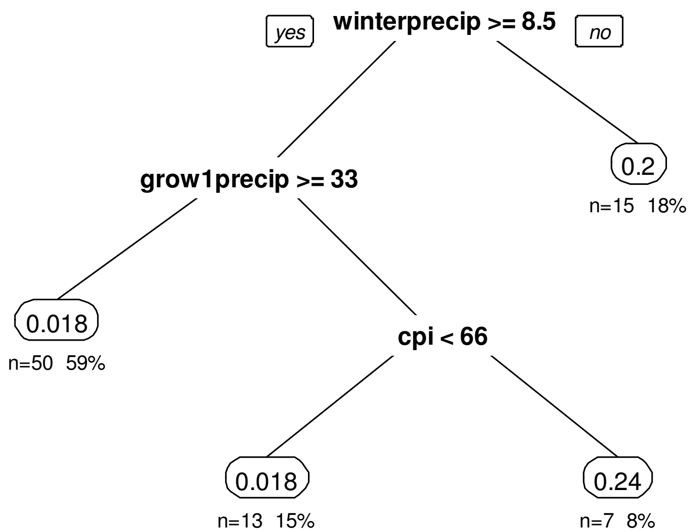



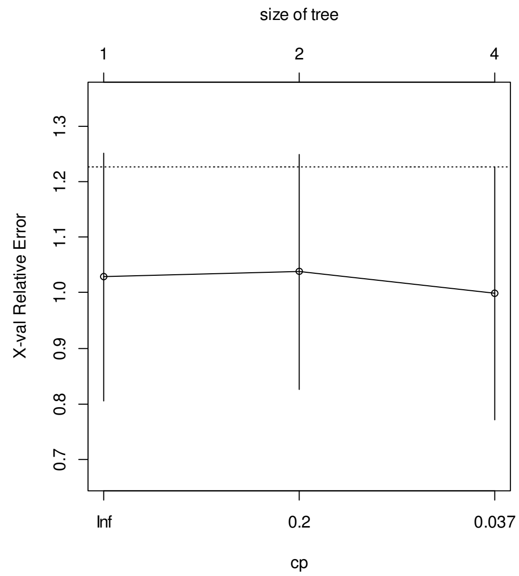

1980-1989



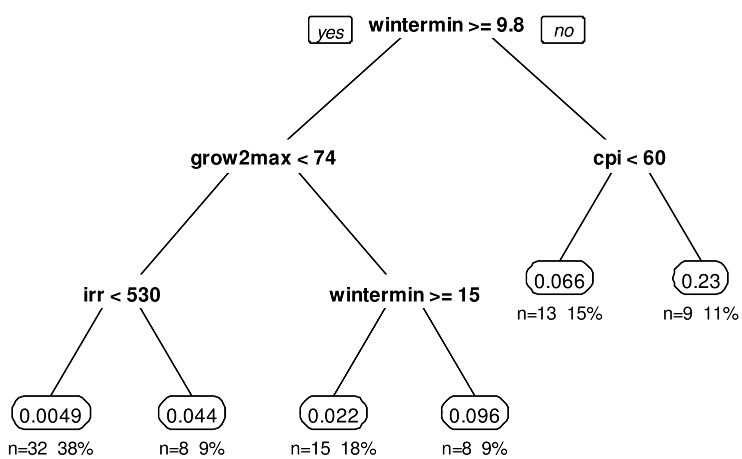



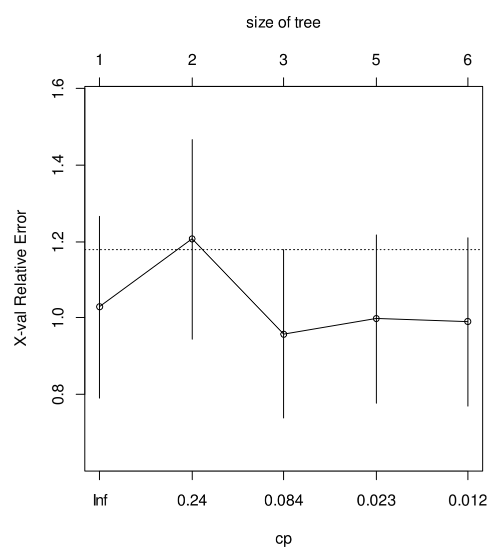
1990-1999




2000-2009



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