A Time Series Regression Analysis of Future Climate

by

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Abstract

Current approaches to climate modeling, including environmental simulation, may not be able to generate actionable results for a few decades yet. Over the last 50 years, methods attempting to capture and predict states of the climate system have flourished and diversified. However, many such models are subject to errors and uncertainty arising from parameterization problems, the obligate characterization of poorly understood phenomena, and high capacity requirements stemming from the incredible computing power needed. As the window for meaningful actions towards altering the climate change trajectory closes, we should consider the use of simple methods that generally predict the conditions of the future climate. For my analysis, I developed a time-series regression analysis of land surface trends in precipitation and near-surface temperature. For each global 0.5° land surface grid, values for 1901-2009 baseline means were calculated, and 2050 values were predicted using time series regression models for each of four historical data subsets. Average predicted warming across the subsets range from 0.89 °C to 5.8 °C above the baseline, with high northern latitudes predicted to experience the most warming. Precipitation is predicted to follow the wet getting wetter, dry getting dryer paradigm, with average predicted changes across the subsets ranging from 3.2% to 26% above the baseline.
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All models of physical phenomena are predicated on dubious initial states, and therefore inevitably generate dubious forecasts\textsuperscript{1,2}. Yet, the climate system itself is a realization of its own internal model, which perfectly describes how the system is expressed in current and future states. Attempts to pin down this internal state of the climate system constitute one of the most growing endeavors in science, and vary widely in complexity, application, and uncertainty\textsuperscript{3}. Despite advances in scientific understanding, computing power, and research capacity over the last 30 years, and in spite of more finely-resolved observations, the range of predicted climate sensitivity remains quite wide\textsuperscript{4}. The specter of climate change has mobilized vast resources dedicated to describing and forecasting the climatic conditions that await us in the future, but are the results useful on a time scale meaningful to affecting the current trajectory of climate change? In the following, I propose that forecasts of climatic trends in key variables, such as temperature and precipitation, might be generated through simple linear time series analysis.
1.1 A Brief Survey of Forecasting Methods and the Task at Hand

Any meaningful model assessment must highlight variables of interest, decision-relevant temporal scales, and a set of information to be used in constructing forecasts. Over the last 50 years, methods attempting to capture and predict states of the climate system have flourished and diversified: the computational behemoth of these models, the Global Circulation Model (GCM), lies at the core of the IPCC’s endeavors to predict and describe changes in the climate system. Such models slice the ocean, earth surface, and atmosphere into 3-dimensional grids, perform differential equations describing wind speed, radiation loading, fluid dynamics, surface hydrology, atmospheric chemistry, and a host of other factors. Individual cells and blocks thereof are allowed to exchange information according to defined rules; for example, “coupled” models allow otherwise separate ocean and atmospheric subsets to periodically exchange information.

Complex numerical simulations such as GCMs have become the method of choice for predicting the future state of the climate. However, uncertainties in environmental simulations arise from a number of sources, including:

- **Initial Conditions:** Differential equations require boundary conditions and initial system states which must be set up at the beginning of the model run. While one can choose values within the expected range for the system, the choice is effectively arbitrary, and inevitably influences the result of the model.

- **Parameterization and Approximation:** Model parameterization is a means of reducing sub-grid processes (such as cloud cover and radiation loading) to generalized model inputs. Parameterization has become a hot topic as of recent, as these reductions are only effective tunings rather than true optimizations. The climateprediction.net experiment, which ran thousands instances...
of a GCM with perturbed, yet plausible parameterizations, yielded estimates of climate sensitivity ranging from less than 2 °C to 11 °C. Such variability demonstrates that the search for optimal parameterization is crucial to reliable simulation.

- **Evolving Understandings:** In contrast to parameterization, model misspecification arises from the routine generalization of poorly understood processes (e.g., water vapor formation, aerosol surface chemistry) within the model, and confers a higher degree of model error than may be accounted for by the model itself.

- **Randomness:** Stochastic models should be expected to accumulate localized error artifacts. Such uncertainty arises even in deterministic systems, resulting from insufficient precision rather than measurement error.

- **Uncertainty in the Data:** Quality control in measuring raw environmental data has always been serious concern when running models of high precision and complexity. While the well-known example of urban heat island effects may soon be put to rest, the choice of scale in some key variables is still of great question.

- **Coding errors:** Programmed systems of increasing complexity are subject to occasional bugs.

The core philosophical assumption of GCM models, that complex physical systems require complex calculi to describe, may lead environmental simulation to approach optimization as science and computing capacity progress in the near future. However, these same assumptions contribute to levels of uncertainty that accrete throughout model runs. If the goal of environmental simulation is to retrieve scientifically sound, politically actionable values for a prediction time period,
a reliable estimation of climate sensitivity may be decades away\textsuperscript{10}, how might we make useful decisions from the results?

At its heart, the future climate question is one of “when” and “what”; such a simple reduction is manifested in another set of climate models that, instead of attempting to describe the minutiae of stochastically interacting physical phenomena, take a parsimonious, statistical approach to a limited set of variables whose behaviors are fairly well-understood. In a 2010 letter, Mark Cane\textsuperscript{12} highlights the need for decadal-scale climate predictions. These predictions rely on the simple assumption that one could compress and account for interannual and seasonal variability through statistical methods in order to capture a general sense as to the climatic conditions in the next few decades. As the window for collective political and social action closes, it might be most useful to get the most general sense of a trend for crucial variables like precipitation, temperature, and effective moisture.

Notable among the statistical tools for climate prediction is a suite of time series analyses, whose utility in forecasting has been long known to economists in the form of ARIMA (Autoregressive Integrated Moving Average) and Holt-Winters predictions. Simpler yet, GLMs, GAMs, and univariate linear regression models are tried-and-true methods for estimating future conditions\textsuperscript{13} given the right tuning. Specifically, linear time series methods allow us to project the status quo into the future, such that we might extrapolate current trends and estimate their magnitude.

I highlight here these schools of thought in order to make a somewhat simplistic distinction: GCMs and the like aim to describe what the climate does, while descriptive and numeric forecast make their predictions by characterizing what the climate is doing. The distinction is a subtle one, and it begs a teleological question that would be better addressed by a much different paper; what is of import here is that we might use the advantages of numerical models to inquire as to the direction of the system, rather than examine discrete behaviors.
John Little, in his foundational discussion of models\textsuperscript{14} (or ‘decision calculus,’ as he deems them), notes that models need be, to name a few qualities:

- **Simple:** Parsimony allows for ease of interpretability and a certain elegance in asking fundamental questions.

- **Robust:** It should be difficult to get such a model to deliver bad answers (the definition thereof is its own important question). Robust models are discerningly sensitive.

- **Easy to Control:** Models should be easily adapted to new conditions, new datasets, and corrections as they are released, with minimal tinkering.

- **Complete on Important Issues/Dimensions:** Little notes that completeness “is in argument with simplicity,” but completeness may not necessarily translate to the description of all discrete phenomena that yield the emergent qualities of the system.

- **Interpretability:** For both policymakers and scientists, the outcomes of such a model should lend itself well to decision-making.

Time series methods enable us to cover each of these qualities, facilitate simplicity and completeness for a handful of variables, and avoid a few of the trappings of GCMs (chiefly, parameterization and the characterization of poorly understood phenomena).

1.2 Formal Assumptions

As I submit the linear method as an alternative solution to problems in numerical modeling, I should first explore the basis for applying such a technique. The application of linear regression needs to meet four statistical assumptions: Linearity, Independence, Homoscedasticity, and Normality.
1.2.1 Linearity

The core property that enables us to explain climate change is that the climate responds to forcings while exhibiting internal oscillations and feedbacks. For scientists and policymakers, first among these forcings are greenhouse gases. The nature of $CO_2$ increase over the last two centuries is exponential when compared to millennial timescales; thus, climate change is long understood to exhibit non-linear behavior. However, the temperature response to this forcing, when viewed on a centennial timescale, can be described as pseudo-linear; periods of warming are followed by plateaus, which are in turn followed by further periods of warming. Feedback loops, changes in GHG output, and unknowns in the aerosol budget are likely culprits.

In their 2004 paper, Seidel and Lanzante\textsuperscript{15} assessed alternatives to characterizing temperature increase as linear over the last 100 years using piecewise and “sloped steps” linear models. These models, while accounting for both seasonality and non-linear behavior, were able to reduce RMS error by only about 0.09 °K over a 102-year timespan with relation to linear models for characterizing overall temperature change. This analysis was performed on historical data with known outcomes; for predicting decades into the future with a linear model, stepwise and piecewise implements become problematic, and any projection would still need to rely on a linear term for future conditions. A linear characterization of temperature change thus is appropriate for centennial time scales, and satisfies the linear assumption of regression.

1.2.2 Independence

A linear regression model also assumes independence, and in this case, independence through time. We already know this not to be the case: seasonality is a fundamental component of precipitation and temperature, and as most available data are monthly averages, we would be safe in assuming serial correlation through time for environmental variables. Techniques such as ARIMA and Holt-Winters aim to smooth these
serial correlations by adjusting for a lag period of 12 months.

However, if we re-tool the regression question from one about the nature of trends through shorter periods of time, such as a year or decade, to one about centennial trends, we can view climatic covariates as stationary about the trend line. This behavior is defined as cyclo-stationarity\textsuperscript{16} (Figure 1.1). If we then apply a linear regression method to variables correlated in time as such, the ordinary least squares term becomes then a reflection of the central trend about which the variable varies. Smaller-scale time series may reflect low-frequency internal oscillations of the climate system, however, over centennial timescales we can effectively estimate the larger state of the system by acknowledging that regression will take a central tendency within the context of serial correlation.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Serial_Correlation_in_Temperature.png}
\caption{Serial Autocorrelation in Monthly Temperature}
\end{figure}
1.2.3 Homoscedasticity

Regression also requires homoscedasticity in our data. Violations of equal variance in the context of a time-series regression would imply that lower annual temperature and precipitation values change at a different rate than higher values. In a linear model that assumes equal variance when expressed through time, we assume that, for example, maximum (summer) temperatures do not change at a different rate than minimum (winter) temperatures, and vice versa.

1.2.4 Normality

Historical temperature data are classically gaussian, while precipitation data are somewhat more problematic; as precipitation indices are zero-bounded, they are usually best-characterized by a gamma distribution. In this case, a time-series GLM with gamma distribution may be more appropriate than simple time series regression, but a linear method can still generalize trends without transformation.

1.3 Qualitative Assumptions

Linear model predictions of temperature and precipitation implicitly assume the extension of the status quo in a number of factors that influence climate change, including development rates, deforestation, industrial GHG output, and international mitigation efforts. One might expect that a linear model could generalize the current state of feedback loops by accounting for them in the raw variable data, but such a model would not be able to account for tipping points, also known as catastrophic bifurcations, in which the state of the system precipitously shifts\textsuperscript{17}. In contrast to GCMs that are able to simulate these amplifying or attenuating phenomena, linear model prediction is fundamentally insensitive to such shifts. As such, we should highlight the role of GCMs in describing these events. Nevertheless, a linear model’s
predictions in the absence of tipping points can yield valuable insights into the current trajectory of the system.

1.4 Climate Change Characterization

In designing a linear method to capture the warming period, careful attention should be allotted to designating the proper 20th century climate change period. While there is evidence that, absent internal oscillations, the 20th century warming trend describes a monotonic increase\(^\text{18}\), a linear model will be particularly sensitive to the correct baseline. Using the CRU TS 3.1 dataset (see Methodology, section 2.1), we can make a preliminary visualization of global change. Figure 1.2 shows the raw historical change in global temperature:

![Historical Global Temperature](image)

**Figure 1.2:** Historical Global Temperature
Roughly, the warming period to be described could be viewed as beginning in 1960. Likewise, Figure 1.3 shows the raw trend in global precipitation since 1900.

![Historical Global Precipitation](image_url)

**Figure 1.3: Historical Global Precipitation**

Considering both of these figures, it becomes apparent that the period of time covered by the linear model will impact its ability to describe the trend. As such, multiple historical subsets of the data should be implemented and compared in order to establish an understanding sensitivity to the range of time covered by the data.

1.4.1 Spatial Patterns

Given the dynamic nature of the climate system with respect to geographic location, we should consider the use of fine-scale spatial data. Using many thousands of linear models to capture these discrete trends at the resolution of the data is a logical solution, and is entirely feasible given current computing capacity. Thus, given the
availability of historical data at fine-scale spatial resolutions, predictions could be
generated that both reflect highly localized trends and enable us to visualize regional
patterns of change.

1.5 Implementation

Having submitted that linear models are parsimonious solutions, highly interpretable,
relatively complete, and are able to avoid the pitfalls of stochastic calculation and
parameterization, it follows that we should build one for comparison against other
models in the field. In the following, I describe the development and implementation
of a linear model for predicting future climate conditions.
2.1 Background: CRU TS 3.1 Data

The Climate Research Unit Time Series (CRU TS) 3.1 dataset\textsuperscript{19,20,21} provides global, fine-scale, monthly land surface (excluding Antarctica) climatic data for the period 1901-2009 in Network Common Data Form (NetCDF). Developed by the Climate Research Unit at University of East Anglia, the CRU data represent a homogenization of seven repositories of historical station data. Using an iterative process, historical station data were checked for continuities to detect correlation, homogenize, and complete neighboring station time series data. The CRU team then interpolated the results onto a continuous 0.5° map surface, resulting in global, monthly best estimates of the variables shown in Table 2.1.

For the purposes of my analysis, the variables of interest are precipitation and monthly average near-surface temperature. For each variable, the CRU TS 3.1 dataset covers a time span of January 1901 to December 2009, yielding 1308 time periods (months). Values for each variable are stored in dimensions of 720 latitudes and 360 longitudes, yielding a global 0.5° grid for each time period.
Table 2.1: CRU TS 3.1 Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cloud Cover</td>
<td>Percentage</td>
</tr>
<tr>
<td>Diurnal Temperature Range</td>
<td>Degrees Celsius</td>
</tr>
<tr>
<td>Frost Day Frequency</td>
<td>Days</td>
</tr>
<tr>
<td>Precipitation</td>
<td>Millimeters</td>
</tr>
<tr>
<td>Monthly Mean Temperature</td>
<td>Degrees Celsius</td>
</tr>
<tr>
<td>Monthly Average Daily Minimum Temperature</td>
<td>Degrees Celsius</td>
</tr>
<tr>
<td>Monthly Average Daily Maximum Temperature</td>
<td>Degrees Celsius</td>
</tr>
<tr>
<td>Vapor Pressure</td>
<td>Hecta-Pascals</td>
</tr>
<tr>
<td>Wet Day Frequency</td>
<td>Days</td>
</tr>
<tr>
<td>Potential Evapotranspiration</td>
<td>Mm</td>
</tr>
</tbody>
</table>

2.2 NetCDF

CRU TS 3.1 data for precipitation and temperature were acquired from the British Atmospheric Data Centre in NetCDF format. NetCDF is a self-describing data format developed by the Unidata Program Centre in the late nineties for the purpose of efficiently storing multidimensional variables and their associated geographic information for analysis and display. Based on NASA’s Common Data Format, a NetCDF contains dimensions and variables, each with attributes for describing units, scaling, and transformations. Aside from providing a convenient package for describing more than one variable in space and time, NetCDF is fairly portable and highly compressible.

2.3 Data Preparation

Preparation of each dataset was performed in the R statistical computing environment using the ncdf library. NetCDFs for each variable contain three dimensions: longitude, latitude, and time. The NetCDF format is structured such that geographically-referenced information is most readily extracted in slices along the time dimension; thus, for a time series with length \( n \), we would need to extract vari-
able values in $n$ slices, each of dimension $\text{longitude} \times \text{latitude}$ and containing 360x720 (259200) values. For easy access within the R environment, each slice was then sequentially placed along the time axis in an array of dimensions $\text{latitude} \times \text{longitude}$ $\times$ $\text{time}$, resulting in an array of dimensions 360x720x1308. The time dimension was then extracted independently and stored as a vector of integer days after a reference date (I use 1900-01-01, for ease of analysis). Missing values, such as those over the ocean and Antarctica, were coded as NA. The full NetCDF extraction script is available in Appendix A.1.

### 2.4 Linear Model Prediction

Time series regression was iteratively performed on the values for each grid cell. Equation 2.1 describes the simple linear model, wherein $Y_t$ is the variable of interest ( precipitation or temperature) at time $t$, and $X_t$ is a value in the vector set $T$ of dates in days since 1900-01-01.

$$Y_t = \beta_0 + \beta_1 X_t + \epsilon, \quad X = \{X_t : t \in T\}$$  \hspace{1cm} (2.1)

A prediction set was generated consisting of estimated $Y$ values for all months in 2050; this set was then averaged and output to the corresponding grid cell in a geo-referenced Esri ASCII grid using the adehabitat library for R. For array $A$, having dimensions of $i$ (latitude), $j$ (longitude), and $t$ (time), the data preparation and linear model process is summarized in Figure 2.1, and the full script is available in Appendix A.2.

For both precipitation and temperature, four linear models were generated per grid cell to predict the 2050 value (Table 2.2). The year 2050 was chosen for ease of comparison with other existing models, along with its usefulness as a short-term benchmark for decision-makers. For precipitation, which is zero-bounded, predictions
For date \( t \), extract lat/lon grid

Assemble slice into R array at \( z=t \)

Extract all variable values through time for gridcell \( a_{ij} \)

Are they NA?

Perform Time Series Regression

Predict 2050 Annual Mean

Output to georeferenced ASCII

Figure 2.1: Model Flowchart

less than 0 mm/month were coded as \( 0 \). Each model uses a subset of the historical data, such that the prediction represents the linear trend present in that time period.

Table 2.2: Historical Subset Linear Models

<table>
<thead>
<tr>
<th>Model</th>
<th>Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Baseline</td>
<td>1901-2009</td>
</tr>
<tr>
<td>50-Year Subset</td>
<td>1959-2009</td>
</tr>
<tr>
<td>30-Year Subset</td>
<td>1979-2009</td>
</tr>
<tr>
<td>10-Year Subset</td>
<td>1999-2009</td>
</tr>
</tbody>
</table>
2.4.1 Baselines

The model also generates an ASCII grid representing the variable baseline from 1901-2009 for grid cell $a_{ij}$. For each cell, the mean of all values through time was calculated, representing an average value for the time period 1901-2009 (Equation 2.2).

\[
\frac{1}{T} \sum_{t=1}^{T} a_{ijt} \tag{2.2}
\]

2.5 Raster Calculations

ASCII grids were imported into a Geographic Information System (GIS), wherein a number of calculations were performed (script available in Appendix A.3). Grids were converted to raster datasets, projected, and rotated if necessary. To highlight high relative changes and downplay those of lower magnitude for the precipitation variable, percentage change from the baseline was calculated for the predicted value for each grid cell (Equation 2.3).

\[
\left( \frac{\text{Prediction}_{ij} - \frac{1}{T} \sum_{t=1}^{T} a_{ijt}}{\frac{1}{T} \sum_{t=1}^{T} a_{ijt}} \right) \times 100 \tag{2.3}
\]

Predicted 2050 temperature anomalies were calculated using a similar method, whereby baseline temperature averages were subtracted from the predicted values for each grid cell (Equation 2.4).

\[
\text{Prediction}_{ij} - \frac{1}{T} \sum_{t=1}^{T} a_{ijt} \tag{2.4}
\]
2.5.1 IPCC Model Comparison

Full baseline model results were compared to the A1B ensemble average model scenario (2040-2070) for both predicted 2050 precipitation and temperature. Multi-model ensembles were acquired from the Coupled Model Intercomparison Project Phase 3 source\textsuperscript{28}. Model results were compared using a difference map, whereby A1B values were subtracted from the linear regression 2050 prediction.

2.5.2 Evapotranspiration & Available Moisture

Theoretical reference-crop evapotranspiration and available moisture were calculated using the Blaney-Criddle method\textsuperscript{29,30}, provided by Equation 2.5:

\[ ET_o = p(0.46 \times T_{mean} + 8) \]  

where \( p \) is the mean daily percentage of daylight hours. A matrix of values for \( p \) by latitude were generated using a table provided by the FAO\textsuperscript{30}, after which evapotranspiration was calculated using the raster calculator in ArcGIS. Available moisture is given by the following equation:

\[ AM = P - ET_o \]  

where \( P \) is precipitation for a given raster cell. Thus, using overlain raster grids in ArcGIS, available moisture was calculated for the full subset 2050 precipitation prediction.

2.5.3 Summary Statistics

Global statistics for each variable were calculated in R for each of the four linear models, and zonal summary statistics were calculated in ArcGIS using a continent mask.
2.6 Latitudinal Averages

A number of latitudinal calculations were also performed on the datasets produced. The resulting baseline temperature, baseline precipitation, temperature anomaly, and precipitation percent change data were analyzed for south-north trends. For each result, a vector was produced of all non-NA values for each latitude, after which an average value for that latitude was produced using the length of its corresponding non-NA vector. Treating the geographic grid as a matrix, the calculation for all rows $i$ is described in Equation 2.7:

$$\frac{1}{J_{i}^{NA}} \sum_{j=1}^{J} a_{ij}$$ (2.7)

This calculation effectively normalizes changes by the amount of landmass present at each latitude.
3.1 Temperature

For each model result, the average anomaly by latitude is shown, accompanied by a map showing values for each grid cell.

3.1.1 Baseline

Temperatures for the baseline period 1901-2009 decrease predictably with distance from the equator and ITCZ (Figures 3.1 & 3.2), demonstrating local and regional variability with topography (see Himalayan and Andes formations) and latitude. The mean global temperature for the baseline period was 8.2 °C, with a maximum average temperature of 30.1 °C and a minimum temperature of -27.9 °C.
Figure 3.2: Average Baseline Temperature, 1901-2009
3.1.2 2050 Temperature Prediction, Full Baseline Subset

The full historical linear model yields an average global 2050 temperature increase of 0.87 °C from the 1901-2009 baseline (Figure 3.3), centered on 1954, which is consistent with the IPCC’s estimate of 0.74 °C ± 0.18°C per 100 years\textsuperscript{31}. High temperature deviations from the baseline are predicted in high latitudes. Anomalies between 0.15 and 0.5 °C are anticipated for the tropics, with notably higher values in Western and Southeastern Sahara (Figure 3.3). The Middle East, Northern Asia, Northern Canada, Southern Africa, and North America are predicted to experience anomalies of 1 to 2.7 °C. Notably, Madagascar, North-Central Australia, Regions in the Southeastern US, and regions of Peru, Bolivia, and Argentina are expected to cool by as much as 1.5 °C. Highest average North-South anomalies occur at approximately 50 °N, while average cooling is predicted near 50 °S (Figure 3.4). The maximum temperature anomaly increase is 2.65 °C, while the most decrease is -1.45 °C. Average global warming is predicted to be 0.879 °C over the baseline in 2050.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{average_temperature_anomaly_by_latitude.png}
\caption{Average Temperature Anomaly by Latitude, Full Baseline Subset}
\end{figure}
3.1.3 2050 Temperature Prediction, 50-Year Subset

The 50-year subset model shows a dampening of the local 30 °C maximum shown in the full baseline subset model, though this peak is still present, showing an anomaly of 1.2 °C (Figure 3.5). The maximum average warming by latitude occurs near 50° north, representing a 3 °C anomaly above the baseline. Likewise, the average anomaly by latitude does not show any cooling, with the minimum anomaly at 0.3 °C. The global average anomaly is 2.1 °C, with a maximum warming of 5.5 °C and a maximum cooling of 2.9 °C below the baseline (Figure 3.6).

![Average Temperature Anomaly by Latitude, 50-Year Subset](image)

**Figure 3.5:** Average Temperature Anomaly, 50-Year Subset
Figure 3.6: 2050 Temperature Anomaly, 50-Year Subset
3.1.4 2050 Temperature Prediction, 30-Year Subset

The 30-year subset model predicts trends that are similar to the 50-year subset, demonstrating more variability in extremes. Maximum average warming by latitude is predicted to be 4.4 °C, while the most cooling is observed around 40° South, at -0.14 °C (Figure 3.7). As with the 50-year and full model subset, warming increases with distance north from the equator, but there is more local and regional heterogeneity in the results than with the 10-year subset (Figure 3.8). The average global anomaly from the baseline is 2.7 °C, with a maximum warming of 8 °C above the baseline, and maximum cooling of 5 °C below the baseline. Coastal Australia and Oceania, the western coast of South America, and parts of North America show some degree of cooling, while the northern hemisphere shows moderate to extreme warming anomalies, increasing in magnitude northward.

Figure 3.7: Average Temperature Anomaly, 30-Year Subset
**Figure 3.8:** 2050 Temperature Anomaly, 30-Year Subset
3.1.5 2050 Temperature Prediction, 10-Year Subset

The 10-year subset shows more extreme warming anomalies, particularly in the northern hemisphere (Figure 3.9), where average warming up to 12.5 °C are predicted. Average cooling of up to -2.55 °C is also predicted for the southern hemisphere, near 40° South. The prediction map shows less regional variability than the full baseline model (Figure 3.10), with parts of Canada, South America, southern Africa, and coastal Australia cooling, while high northern latitudes in Alaska, Canada, Russia, and northern Europe show extreme warming relative to the baseline. The maximum temperature anomaly predicted is 22.5 °C, while the most cooling predicted is -11.3 °C. Global average anomaly is predicted to be 5.8 °C above the baseline.

**Figure 3.9: Average Temperature Anomaly, 10-Year Subset**
Figure 3.10: 2050 Temperature Anomaly, 10-Year Subset
3.1.6 2050 Temperature Prediction, Linear Model Comparisons

Figure 3.11 shows global summary statistics for each of the subset models:

![Boxplot of Global 2050 Temperature Anomaly](image)

**Figure 3.11: Global 2050 Temperature Anomaly**

The full baseline model shows a more conservative maximum and minimum anomaly, with each subsequent subset increasing in range as well as mean global temperature anomaly. The 10-year subset shows the widest spread, with maximum anomalies reaching above 20 °C and predicted cooling up to 10 °C.

Likewise, Figure 3.12 shows the minimum, maximum, and average anomaly by region. Regional anomalies show a similar pattern in subset model ranges, with the full baseline model expressing the most conservative range of anomalies while the 10-year subset model showing extremes. Average regional anomalies increase as the historical subset decreases from full baseline to 10 years for most regions, but Australia, Oceania, and South America show either modal or decreasing trends.
3.2 Precipitation

For each model result, the average percent change by latitude is shown, accompanied by a map showing values for each grid cell.

3.2.1 Baseline

The calculated baseline precipitation from 1901-2009 was found to conform to expected patterns, with high precipitation within the intertropical convergence zone and low precipitation in deserts and the horse latitudes (Figure 3.13). Rainfall also experiences a spike of 186 mm/month at approximately 45-50° from the equator, particularly in the southern hemisphere. Visually, we can see that the baseline average accurately maps areas with high annual rainfall (Figure 3.14), including the Amazon basin, southeast Asia, the northwest coast of North America, and west-central Africa. Likewise, extremely dry regions are also visually represented. The
mean baseline precipitation is 58.6 mm/month, with a maximum of 627 mm/month.

**Figure 3.13:** Baseline Precipitation Average, mm/month
Figure 3.14: Baseline Precipitation, 1901-2009
3.2.2 2050 Precipitation Prediction, Full Baseline Subset

Global annual precipitation for the full baseline period is predicted to be an average of 710.30 mm, while global change averages at 0.3%, with a maximum increase of 38.16% and a maximum decrease of -54.35%. Projected 2050 annual means are best expressed in percentage change from the baseline, such that dramatic changes might be highlighted while small relative changes are minimized.

These results indicate that precipitation changes from the baseline to 2050 express high spatial heterogeneity (Figure 3.16). The highly regionalized precipitation changes are expected, but my results are consistent with the IPCC’s trend analysis of precipitation change by latitude\(^{31}\). Generally, we can see that dry regions will tend to get dryer while wet regions will tend to get wetter, conforming to predictions made by Held and Soden\(^{32}\) regarding future precipitation trends. Specifically, precipitation in the southern hemisphere tropics is expected to increase by up to 5% above baseline. In contrast, dry, northern latitude regions between 0-40\(^{\circ}\), such as the Sahara and Taklamakan/Gobi, and Baja Peninsula, are expected to get drier by a factor of 1-5% below baselines (Figure 3.15 & Figure 3.16).

\[\text{Average Precipitation Change by Latitude}\]

**Figure 3.15:** Average Precipitation Change, Full Baseline

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33
Figure 3.16: 2050 Precipitation Change, Full Baseline
3.2.3 2050 Precipitation Prediction, 50-Year Subset

Precipitation change varies widely with latitude (Figure 3.17), with a maximum average percent change of 11% represented around 40° S, and a minimum of -14.4% represented near 50° S. Visually, the 50-year subset model is somewhat less patchy than the full baseline prediction, but distinct regions of change can still be observed (Figure 3.18): Africa, the Middle East, central Europe, western and eastern Australia, Asia, and eastern China show drying trends, while central Australia and parts of North America, northern Europe, and South America show increases in precipitation over the baseline period. The average global precipitation change is 3.2% above the baseline, with a maximum percent change of 94.2% and a minimum precipitation change of 100%.

![Average Precipitation Change by Latitude, 50-year subset](image)

**Figure 3.17:** Average Precipitation Change, 50-Year Subset
Figure 3.18: 2050 Precipitation Change, 50-Year Subset
3.2.4 2050 Precipitation Prediction, 30-Year Subset

The 30-year subset model shows more distinct regions of change with respect to the 50-year and full baseline subset models. By latitude (Figure 3.19), a maximum increase in precipitation of 37.5% is predicted around 20° N, with the greatest average decrease of -25.9% predicted near 35° S. Globally (Figure 3.20), the mean precipitation change is 7.8% above the baseline, with a maximum increase of 174.8%, while the most drying is predicted to be 100% below the baseline. The western US, south-central South America, Middle East, eastern Asia, and Southeast Australia are predicted to have the most extreme decreases in precipitation, while the northeast US, north-central and south-west Africa, and southern India are predicted to have large increases in precipitation over the baseline.

![Average Precipitation Change by Latitude, 30-year subset](image)

**Figure 3.19:** Average Precipitation Change, 30-Year Subset
Figure 3.20: 2050 Precipitation Change, 30-Year Subset
3.2.5 2050 Precipitation Prediction, 10-Year Subset

The 10-year subset model shows even more distinct regions of change, though the predictions show extreme maxima and minima across the globe. By latitude, the maximum average percent change is predicted to be 111.6% above the baseline, near 20° N, with a minimum average percent change of -88.5% near 40° S (Figure 3.21). Most southern hemisphere latitudes appear to be getting dryer, while all northern hemisphere latitudes are, on average, getting wetter. Global average precipitation change is 26% above the baseline, while the maximum predicted change is 942% above the baseline, with a minimum of 100% below the baseline. The 10-year subset map shows highly distinct regions of change (Figure 3.22), including extreme drying in central Australia, South Africa, southern South America, North Africa, and the Middle East. Regions of high precipitation increases are also predicted, including the southwest and central United States, north-central Africa, India, and north-eastern Russia.

**Figure 3.21: Average Precipitation Change, 10-Year Subset**
**Figure 3.22:** 2050 Precipitation Change, 10-Year Subset
Global precipitation change summary statistics for each subset model are shown in Figure 3.23:

![Global 2050 Precipitation Change](image)

**Figure 3.23: Global Precipitation Change**

As with temperature, the 10-year subset model shows extreme 2050 prediction changes relative to the baseline, while the full, 50-, and 30-year subset models are rather well-constrained. Likewise, Figure 3.24 shows minimum, maximum, and average precipitation change by region. As with temperature, the full baseline model is the most conservative in terms of range, with minima and maxima showing greater divergence as the subset period decreases. The 10-year subset shows the greatest maximum change in Africa, followed by Asia and North America. Average precipitation change increases with decreasing historical subsets for Asia, Africa, Oceania, and Europe, while the converse is true for Australia.
3.3 Secondary Analyses: A1B Model Comparisons

The A1B scenario, as defined by the IPCC Special Report on Emissions Scenarios\textsuperscript{33}, describes a set of conditions under which GCMs may run. Specifically, the A1B scenario describes a development pathway in which the world depends on a balance of both fossil- and non-fossil fuel sources, wherein global population peaks around mid-century, and rapid technological responses to global problems. This scenario was chosen for its relatively conservative estimate of our ability to curb global greenhouse gas emissions. Below, multimodel ensemble predictions under the A1B scenario are compared to the full subset linear model prediction for 2050 for each variable.

3.3.1 A1B Comparison with 2050 Temperature Prediction, Full Baseline Subset

Figure 3.25 shows the 2050 full baseline subset - A1B multimodel ensemble difference map. Positive numbers, shown in blue, are where the linear model over-predicts
relative to the A1B ensemble (or, more aptly, where the A1B ensemble is *cooler*). Negative numbers, in red, are where the full linear model under-predicts relative to the A1B ensemble (likewise, where the A1B ensemble is *warmer*). An initial scan reveals that these two models disagree on areas of extreme elevation: the Himalayan Plateau, Andes, Western US, Great Rift Valley of Africa, the Zagros and Hindu Kush mountain ranges, and the Alaska Range are areas of extreme disagreement. Elsewhere, the linear model tends to under-predict the A1B ensemble prediction, but otherwise there are few regions of extreme disagreement.
Figure 3.25: A1B Comparison, 2050 Temperature, Full Baseline Subset
3.3.2 A1B Comparison with 2050 Precipitation Prediction, Full Baseline Subset

Figure 3.26 shows the difference map between the precipitation full linear model and the A1B ensemble average monthly precipitation prediction. Generally, areas of extreme precipitation are found to be in disagreement; extremely wet regions, such as the Amazon, southeast Asia, and central Africa, are under-predicted by the linear model. Conversely, extremely dry regions such as the southern Sahara and Central America, are also regions of disagreement in which the linear model over-predicts precipitation. Given these regions of disagreement, however, the models agree for much of the globe.
Figure 3.26: A1B Comparison, 2050 Precipitation, Full Baseline Subset
3.4 Secondary Analysis: 2050 Available Moisture Prediction, Full Baseline Subset

Figure 3.27 shows the global predicted available moisture, given by both Equations 2.5 and 2.6. This prediction uses the full baseline precipitation subset, the equations above, and a raster of percent daylight hours by latitude in order to calculate $ET_o$, from which available moisture is derived. Regions with zero or near-zero predicted precipitation resulted in null values, giving us gaps in the map generated. The map conforms generally to the full model predicted 2050 precipitation detailed in Figure 3.16; regions that are predicted to experience increases in precipitation, such as central and southern South America, central Australia, North America, and northern Europe, are predicted to express higher available moisture. Likewise, north-central Africa, the Taklamankan/Gobi, and Baja Peninsula are predicted to show decreases in available moisture.
Figure 3.27: 2050 Available Moisture Change, Full Baseline
The linear model method is implicitly a null hypothesis, which asks: all things held equal with respect to trends in precipitation and temperature, how might the world look in 2050? My results bear the signals of a changing climate, and allow us to visualize patterns thereof at finely-resolved spatial scales. As highlighted in the introduction and the methodology, the linear model is simple, parsimonious, and interpretable, but not without pitfalls. I understand that are data are both serially correlated and, in the case of precipitation, most likely non-normal. Furthermore, I make fundamental assumptions as to non-shifting baselines with regard to equal variance. Nevertheless, this analysis yields a number of important findings in the absence of regarding predicted values as absolute: the magnitude of local, regional, and global change trends can be estimated using an extremely simple time series regression analysis. The linear method is thus useful for plumbing the nature of the trend and its magnitude.

Crucially, the prediction sets for both variables show that few regions are expected to remain climatologically similar to their baseline conditions. Across model subsets, latitudes above 30 °N show strong warming trends relative to the baseline, while
landmasses in the southern hemisphere are generally predicted to stay the same or
even cool. Precipitation patterns across all subsets are highly localized, with some
areas consistency between models.

Comparisons of the full baseline model to A1B predictions show predictions that
are surprisingly similar, despite the areas of disagreement indicated in sections 3.3.1
and 3.3.2. Further analysis is needed to fully explore the congruity between these
models, and would ideally involve all linear model subsets.

4.1 Historical Subset Sensitivity

Among the most interesting results is the variability between subset models. Average
predicted global temperature anomalies and precipitation change for each model
increase as the historical subset of the data is shortened (Table 4.1), suggesting that
the 20th century rate of change may have been increasing beyond 1950. The range
of predicted change from the baseline increases likewise for each variable (Figures
3.11 & 3.23).

Table 4.1: Average Global 2050 Change from Baseline

<table>
<thead>
<tr>
<th></th>
<th>Full</th>
<th>50-Year</th>
<th>30-Year</th>
<th>10-Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global Temperature Anomaly</td>
<td>0.87 °C</td>
<td>2.1 °C</td>
<td>2.7 °C</td>
<td>5.8 °C</td>
</tr>
<tr>
<td>Global Precipitation Change</td>
<td>0.3%</td>
<td>3.2%</td>
<td>7.8%</td>
<td>26%</td>
</tr>
</tbody>
</table>

That the predicted 2050 values are sensitive to different subsets of the historical
data is an important observation. Equally interesting is that the 10-Year subset
models for both precipitation and temperature predict extreme values, while the
other models produce more constrained predictions. A number of explanations exist:
first, the longer periods of time covered by the 30-year, 50-year, and full baseline
models may serve to capture internal oscillations in the climate system, only portions
of which are captured by the 10-year subset. Secondly, if the climate system response
to novel forcings is indeed piecewise or stepwise linear\textsuperscript{15}, the shorter subset may be capturing a period of rapid change, oblivious to antecedent and subsequent plateaus. Lastly, it is possible that the 10-year subset predictions reflect a view of extreme changes we might expect by 2050.

4.2 Avenues for Further Research & Validation

A number of additional analyses would be useful in characterizing patterns and trends in the predictions generated here. Delving further into the linear model predictions would yield important understandings of the data generated: Examining the subset model prediction maps for regions of both agreement and disagreement would bolster our understanding of this method’s sensitivity to historical subsets, and would enhance our confidence in the results. Furthermore, with the understanding that increased temperatures bring increased extreme precipitation\textsuperscript{34}, an examination of the degree to which predicted precipitation relates with predicted temperatures would be welcome.

A backward prediction of 2009 values using historical data would further enhance confidence in linear model results. This practice is common with GCMs, and would not only speak to the efficacy of the linear method, but would also aid in the selection of the proper historical subset.

As the resolution of the dataset permits, an analysis of regional and local heterogeneity would allow for the characterization of fine-scale patterns in the change maps; elevation, land form, vegetation type, and other variables could be used to characterize and interpret these predicted changes. Secondly, additional comparisons with other SRES multimodel ensembles, including those from both Assessment Reports 4 and 5 by the IPCC, would be very useful for estimating the goodness-of-fit with GCMs. Necessarily, the picture would be more complete with the inclusion of
sea surface temperature and precipitation, as well as a set of historical observations for Antarctica.

4.2.1 Alternate Models

Future efforts could perform a similar analysis with an ARIMA model in order to account for serial correlation. An alternative to this would be the construction of a model that just examines the mean temperature or precipitation by month, thus producing January, 2050 predictions, February 2050 predictions, and so forth. This would also yield insights as to whether winter temperatures are increasing faster than those in the summer, or vice versa.

Controlling for non-normality in precipitation with a gamma family GLM may also better describe the historical data and yield more accurate forecasts with respect to the trend. Other linear methods may also be useful, particularly those that are less sensitive to outliers, such as Thiel-Sen estimators.

4.2.2 Multiple Baselines

The 1901-2009 baseline average was chosen for this analysis because this period captures the medium- and short-term oscillations within the climate system. Furthermore, this baseline centers around the mid-20th Century, enabling an ease of comparison between the known mid-century averages and the predicted 2050 values. The use of alternate baselines would not change the model predictions, but rather would change how these predictions are visualized. Shorter, perhaps decadal, baseline averages might provide a more concise benchmark against which to compare the 2050 predictions.
Conclusions

If we accept the adage that “all models are wrong, but some are useful,” it follows that the behavior of complex systems can be generally characterized by simple models. Linear regression is among the most basic tools in the kit for describing such behavior through time. My results demonstrate that this technique can be used to project highly-resolved local and regional trends in climatological variables into the future.

The need for near-term, simple, and interpretable predictions of future climate cannot be overstated: in order to achieve a world worth living for in 2050, we need a decent sense of what lies ahead. While this application may not boast the sophistication or complexity of other methods relying discrete physical phenomena, it may prove equally useful for informing decision-makers and the public.
Bibliography


Acknowledgments

I wish to thank my adviser Dr. Paul Baker for nurturing this idea in spite of his more relaxing sabbatical obligations. My family, Jim, Patty, and Barratt Rudulph, and my partner, Kevin Robinson, deserve commendation for their patience and support throughout this process. Thank you to the outstanding faculty and staff at the Nicholas School for laying the intellectual groundwork and fostering an environment in which simple ideas can take root and grow.
Appendix A

Scripts

A.1 NetCDF Conversion: R Language

```r
require(ncdf)
require(forecast)
require(zyp)
require(adehabitat)
require(PerformanceAnalytics)
require(plotrix)
require(matlab)

#NETCDF Extraction: Temperature

tmp <- temp$var[[1]]  #the first and only variable of temp
time <- get.var.ncdf(temp,"time")
date <- as.Date(time, origin = "1900-01-01")  #Convert our dates here
lons <- get.var.ncdf(temp,"lon")  #get all longitudes into a vector
lats <- get.var.ncdf(temp,"lat")  #get all lats into a vector
lonlength <- length(lons)  #This is 720
latlength <- length(lats)  #This is 360
timelength <- length(time)  #1308 months between 1901 and 2009
tempvalues <- array(data=NA,dim=c(latlength,lonlength,timelength))
t <- 1
while (t <= 1308){  #We’ll start by looking at the first longitude
  start <- c(1,1,t)
```
`count <- c(720,360,1)`  #This takes the whole globe in slices and rearranges them in an R array.
`gridtemp <- get.var.ncdf(temp, varid="tmp", start, count)`
`tempvalues[, , t] <- rot90(gridtemp, k=1)`
`t <- t+1`
`counter <- c("timestep", t)`
`textplot(counter)`
`close.ncdf(temp)`
`save(tempvalues, file="/Users/Demos/Desktop/Duke/MP/NetCDFs/CRUTS3/temparray.R")`  #Export this new R array for later

```r
#NetCDF Extraction: Precipitation
`pre <- prec$var[[1]]`  #the first and only variable of prec
`time <- get.var.ncdf(prec,"time")`
`date <- as.Date(time, origin = "1900-01-01")`  #Convert our dates here
`lons <- get.var.ncdf(prec,"lon")`  #get all longitudes into a vector
`lats <- get.var.ncdf(prec,"lat")`  #get all lats into a vector
`lonlength <- length(lons)`
`latlength <- length(lats)`
`timelength <- length(time)`
`precvalues <- array(data=NA, dim=c(latlength,lonlength,timelength))`
`t <- 1`

```c
while (t <= 1308){
    #We’ll start by looking at the first longitude
    `start <- c(1,1,t)`
    `count <- c(720,360,1)`
    `gridprec <- get.var.ncdf(prec, varid="pre", start, count)`
    `precvalues[, , t] <- rot90(gridprec, k=1)`
    `t <- t+1`
    `counter <- c("timestep", t)`
    `textplot(counter)`
}
```
`close.ncdf(prec)`
A.2 Linear Models: R Language

```r
# The test for the array data

date <- get(file.path(path = ""/Users/Demos/Desktop/Duke/MP/NetCDFs/CRUTS3/date.R""))

test <- Sys.time()
t <- 1
i <- 1
j <- 1
tempascii <- matrix(nrow=latlength, ncol=lonlength) # Preallocate a few matrices in memory
tempmeans <- matrix(nrow=latlength, ncol=lonlength)
temp30y <- matrix(nrow=latlength, ncol=lonlength)
temp50y <- matrix(nrow=latlength, ncol=lonlength)
temp10y <- matrix(nrow=latlength, ncol=lonlength)
time50 <- time[708:1308] # This will give us the last 50 years (in months since 1901)
time30 <- time[948:1308] # The last 30
time10 <- time[1188:1308] # The last 10

newpredict = c(54802, 54832, 54861, 54892, 54922, 54953, 54983, 55014, 55045, 55075, 55106, 55136) # getting all twelve months of 2050, in days since 1901...
future = data.frame(time=newpredict) # an array of our dates to be predicted.
future50 = data.frame(time50=newpredict) # an array of our dates to be predicted.
future30 = data.frame(time30=newpredict) # an array of our dates to be predicted.
future10 = data.frame(time10=newpredict) # an array of our dates to be predicted.

while (i <= latlength) {
  # The while loop goes row by row, checking down each column and extracting values
  # for a linear model through time.
  while (j <= lonlength) {
    if (is.na(tempvalues[i, j, 1]) == TRUE) {
      j <- j + 1
      next
    } else {
      # An LM on all values through time
      grid.lm <- lm(tempvalues[i,j,] ~ time)
      grid.predict <- predict.lm(grid.lm, future, interval="prediction") # predict 2050.
    }
  }
}
```

60
tempascii[i,j] <- mean(grid.predict[,1])  #Save that prediction to the matrix

#last 50 years time period LM
grid.50y.lm <- lm(tempvalues[i,j,708:1308]~time50)
grid.predict <- predict.lm(grid.50y.lm,future50,
                          interval="prediction")
temp50y[i,j] <- mean(grid.predict[,1])

#last 30 years LM
grid.30y.lm <- lm(tempvalues[i,j,948:1308]~time30)
grid.predict <- predict.lm(grid.30y.lm,future30, 
                          interval="prediction")
temp30y[i,j] <- mean(grid.predict[,1])

grid.10y.lm <- lm(tempvalues[i,j,1188:1308]~time10)
grid.predict <- predict.lm(grid.10y.lm,future10,
                          interval="prediction")
temp10y[i,j] <- mean(grid.predict[,1])

tempmeans[i,j] <- mean(tempvalues[i,j,])  #Calculate the average for the whole baseline period

counter <- c("lon",(-1*(j/2)-180),"lat",(-1*(i/2)-90))  # A convenient counter while the script runs.
textplot(counter)
j <- j+1}

j <-1
i <- i+1

tempanom.full <- tempascii-tempmeans  #calculate the temperature anomaly for the full baseline
tempanom.50y <- temp50y-tempmeans  #Calculate last 50 year anomaly
tempanom.30y <- temp30y-tempmeans  ...
tempanom.10y <- temp10y-tempmeans

d endTime <- Sys.time()
eendTime<-begTime

color2D.matplot(tempascii)
color2D.matplot(tempmeans)
save(temp10y, file="/Users/Demos/Desktop/Duke/MP/grids/temp10y")
save(temp30y, file="/Users/Demos/Desktop/Duke/MP/grids/temp30y")
save(temp50y, file="/Users/Demos/Desktop/Duke/MP/grids/temp50y")
save(tempascii, file="/Users/Demos/Desktop/Duke/MP/grids/tempascii")
save(tempmeans, file="/Users/Demos/Desktop/Duke/MP/grids/tempmeans")
save(tempanom.full, file="/Users/Demos/Desktop/Duke/MP/grids/tempanom.full")
save (tempanom.50y, file="/Users/Demos/Desktop/Duke/MP/grids/tempanom.50y")
save (tempanom.30y, file="/Users/Demos/Desktop/Duke/MP/grids/tempanom.30y")
save (tempanom.10y, file="/Users/Demos/Desktop/Duke/MP/grids/tempanom.10y")

export.asc (as.asc (rot90 (tempasci,k=-1), xll = -179.75, yll = -89.75, cellsize = .5, type = "numeric"), "/Users/Demos/Desktop/Duke/MP/grids/tempESRIasciirotate")
export.asc (as.asc (rot90 (tempmeans,k=-1), xll = -179.75, yll = -89.75, cellsize = .5, type = "numeric"), "/Users/Demos/Desktop/Duke/MP/grids/tempESRImeansrotate")
export.asc (as.asc (rot90 (temp10y,k=-1), xll = -179.75, yll = -89.75, cellsize = .5, type = "numeric"), "/Users/Demos/Desktop/Duke/MP/grids/temp10y")
export.asc (as.asc (rot90 (temp30y,k=-1), xll = -179.75, yll = -89.75, cellsize = .5, type = "numeric"), "/Users/Demos/Desktop/Duke/MP/grids/temp30y")
export.asc (as.asc (rot90 (temp50y,k=-1), xll = -179.75, yll = -89.75, cellsize = .5, type = "numeric"), "/Users/Demos/Desktop/Duke/MP/grids/temp50y")

### This is the original monthly precipitation analysis with subsets added.


begTime <- Sys.time()
t <- 1
i <- 1
j <- 1
precMONTHLY2050 <- matrix (nrow=latlength, ncol=lonlength)
precMONTHLY50y <- matrix (nrow=latlength, ncol=lonlength)
precMONTHLY30y <- matrix (nrow=latlength, ncol=lonlength)
precMONTHLY10y <- matrix (nrow=latlength, ncol=lonlength)
precMONTHLYbaseline <- matrix (nrow=latlength, ncol=lonlength)
MONTHLYtime2050 <- time[708:1308]
MONTHLYtime30y <- time[948:1308]
MONTHLYtime10y <- time[1188:1308]
newpredict = c
(54802,54832,54861,54892,54922,54953,54983,55014,55045,55075,55106,55136)

# getting all twelve months of 2050, in days since 1901...
future50 = data.frame(MONTHLYtime50=newpredict) # an array of our dates to be predicted.
future30 = data.frame(MONTHLYtime30=newpredict) # an array of our dates to be predicted.
future10 = data.frame(MONTHLYtime10=newpredict) # an array of our dates to be predicted.
future = data.frame(MONTHLYtime=newpredict) # an array of our dates to be predicted.

while (i <= latlength){
  while (j <= lonlength){
    if (is.na(precvalues[i,j,1])==TRUE){# Checking for NAs would be great to have mask
      j<-j+1
    next}
    # full time period LM
    grid.lm <- lm(precvalues[i,j,]~time)
    grid.predict <- predict.lm(grid.lm,future,interval="prediction")
    mean2050 <- mean(grid.predict[,1])
    precMONTHLY2050[i,j] <- mean2050
    # last 50 years time period LM
    grid.50y.lm <- lm(precvalues[i,j,708:1308]~MONTHLYtime50)
    grid.predict <- predict.lm(grid.50y.lm,future50,
                               interval="prediction")
    mean2050.50 <- mean(grid.predict[,1])
    precMONTHLY50y[i,j] <- mean2050.50
    # last 30 years LM
    grid.30y.lm <- lm(precvalues[i,j,948:1308]~MONTHLYtime30)
    grid.predict <- predict.lm(grid.30y.lm,future30,
                                interval="prediction")
    mean2050.30 <- mean(grid.predict[,1])
    precMONTHLY30y[i,j] <- mean2050.30
    grid.10y.lm <- lm(precvalues[i,j,1188:1308]~MONTHLYtime10)
    grid.predict <- predict.lm(grid.10y.lm,future10,
                                interval="prediction")
    mean2050.10 <- mean(grid.predict[,1])
    precMONTHLY10y[i,j] <- mean2050.10

    counter <- c("lon",(j/2)-180,"lat",(i/2)-90)
    # means
    precMONTHLYbaseline[i,j] <- mean(precvalues[i,j,])
textplot(counter)
}

63
150  j <- j+1
151  }}
152  j <- 1
153  i <- i+1
154  }
155  precperc.monthly.full <- ((precMONTHLY2050-precMONTHLYbaseline)/
156                             precMONTHLYbaseline)*100
157  precperc.monthly.50 <- ((precMONTHLY50y-precMONTHLYbaseline)/
158                            precMONTHLYbaseline)*100
159  precperc.monthly.30 <- ((precMONTHLY30y-precMONTHLYbaseline)/
160                            precMONTHLYbaseline)*100
161  precperc.monthly.10 <- ((precMONTHLY10y-precMONTHLYbaseline)/
162                            precMONTHLYbaseline)*100
163  endTime <- Sys.time()
164  endTime <- begTime
165  color2D.matplot(precascii)
166  color2D.matplot(precmeans)
167  color2D.matplot(precMONTHLY10y)
169           precperc.monthly.full")
171            precperc.monthly.50")
173            precperc.monthly.30")
175            precperc.monthly.10")
176  save(precMONTHLY10y, file=" /Users/Demos/Desktop/Duke/MP/grids/
177            precMONTHLY10y")
178  save(precMONTHLY30y, file=" /Users/Demos/Desktop/Duke/MP/grids/
179            precMONTHLY30y")
180  save(precMONTHLY50y, file=" /Users/Demos/Desktop/Duke/MP/grids/
181            precMONTHLY50y")
183            precMONTHLY2050")
184  save(precMONTHLYbaseline, file=" /Users/Demos/Desktop/Duke/MP/grids/
185            precMONTHLYbaseline")
186  export.asc(as.asc(rot90(precMONTHLY2050,k=-1), xll = -179.75, yll =
187               -89.75, cellsize = .5, type = "numeric"), "/Users/Demos/Desktop/Duke
188               /MP/grids/precMONTHLY2050asc")
189  export.asc(as.asc(rot90(precMONTHLYbaseline,k=-1), xll = -179.75, yll =
190               -89.75, cellsize = .5, type = "numeric"), "/Users/Demos/Desktop/Duke
191               /MP/grids/precMONTHLYbaseline")
192  export.asc(as.asc(rot90(precMONTHLY10y,k=-1), xll = -179.75, yll =
193               -89.75, cellsize = .5, type = "numeric"), "/Users/Demos/Desktop/Duke
194               /MP/grids/precMONTHLY10y")
### A.3 ArcGIS Model: Python

```python
# Import arcpy module
import arcpy

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

# Load required toolboxes
arcpy.ImportToolbox("C:/Users/Phobos/Downloads/Sample_Tools/SampleTools.tbx")

# Local variables:
precperc_monthly_full_asc = "C:\Users\Phobos\Desktop\2050_MP\precperc_monthly.full.asc"
precperc_monthly_10_asc = "C:\Users\Phobos\Desktop\2050_MP\precperc_monthly.10.asc"
precperc_monthly_30_asc = "C:\Users\Phobos\Desktop\2050_MP\precperc_monthly.30.asc"
precperc_monthly_50_asc = "C:\Users\Phobos\Desktop\2050_MP\precperc_monthly.50.asc"
tempanom_10y_asc = "C:\Users\Phobos\Desktop\2050_MP\tempanom.10y.asc"
tempanom_30y_asc = "C:\Users\Phobos\Desktop\2050_MP\tempanom.30y.asc"
tempanom_50y_asc = "C:\Users\Phobos\Desktop\2050_MP\tempanom.50y.asc"
tempanom_full_asc = "C:\Users\Phobos\Desktop\2050_MP\tempanom.full.asc"
latpoints_shp = "C:\Users\Phobos\Desktop\2050_MP\latpoints.shp"
tempESRIascirotate_asc_2 = "C:\Users\Phobos\Desktop\2050_MP\tempESRIascirotate.asc"
precMONTHLY2050asc_asc = "C:\Users\Phobos\Desktop\2050_MP\precMONTHLY2050asc.asc"
tempESRImeansrotate_asc_2 = "C:\Users\Phobos\Desktop\2050_MP\tempESRImeansrotate.asc"
precMONTHLYbaseline_asc = "C:\Users\Phobos\Desktop\2050_MP\precMONTHLYbaseline.asc"
temp10y_asc = "C:\Users\Phobos\Desktop\2050_MP\temp10y.asc"
temp30y_asc = "C:\Users\Phobos\Desktop\2050_MP\temp30y.asc"
temp50y_asc = "C:\Users\Phobos\Desktop\2050_MP\temp50y.asc"
```

65
ET_50_img = "C:\Users\Phobos\Desktop\2050_MP\ET_50.img"
ET_10_img = "C:\Users\Phobos\Desktop\2050_MP\ET_10.img"
prec30_img = "C:\Users\Phobos\Desktop\2050_MP\raster\prec30.img"
prec10_img = "C:\Users\Phobos\Desktop\2050_MP\raster\prec10.img"
prec50_img = "C:\Users\Phobos\Desktop\2050_MP\raster\prec50.img"
availablem_50_img = "C:\Users\Phobos\Desktop\2050_MP\availablem_50.img"
availablem_30_img = "C:\Users\Phobos\Desktop\2050_MP\availablem_30.img"
availablem_10_img = "C:\Users\Phobos\Desktop\2050_MP\availablem_10.img"
available_perc50_img = "C:\Users\Phobos\Desktop\2050_MP\available_perc50.img"
available_perc30_img = "C:\Users\Phobos\Desktop\2050_MP\available_perc30.img"
available_percFull_img = "C:\Users\Phobos\Desktop\2050_MP\available_percFull.img"
available_perc10_img = "C:\Users\Phobos\Desktop\2050_MP\available_perc10.img"
tempanomfull = "C:\Users\Phobos\Desktop\2050_MP\Statistics\tempanomfull"
precpercfull = "C:\Users\Phobos\Desktop\2050_MP\Statistics\precpercfull"
available_percfull = "C:\Users\Phobos\Desktop\2050_MP\Statistics\available_percfull"
tempanom50 = "C:\Users\Phobos\Desktop\2050_MP\Statistics\tempanom50"
tempanom10 = "C:\Users\Phobos\Desktop\2050_MP\Statistics\tempanom10"
tempbaseline = "C:\Users\Phobos\Desktop\2050_MP\Statistics\tempbaseline"
precperc50 = "C:\Users\Phobos\Desktop\2050_MP\Statistics\precperc50"
precperc10 = "C:\Users\Phobos\Desktop\2050_MP\Statistics\precperc10"
precperc30 = "C:\Users\Phobos\Desktop\2050_MP\Statistics\precperc30"
precbaseline = "C:\Users\Phobos\Desktop\2050_MP\Statistics\precbaseline"
v40_70_alb_tmean_img = "C:\Users\Phobos\Desktop\2050_MP\40_70_alb_tmean.img"
tempfull_alb_diff_img = "C:\Users\Phobos\Desktop\2050_MP\tempfull_alb_diff.img"
v40_70_alb_precipmean_img = "C:\Users\Phobos\Desktop\2050_MP\40_70_alb_precipmean.img"
prefull_alb_diff_img = "C:\Users\Phobos\Desktop\2050_MP\prefull_alb_diff.img"

# Process: ASCII to Raster (3)
arcpy.ASCIIToRaster_conversion(tempanom_full_asc, tempanomfull_img, "FLOAT")

# Process: ASCII to Raster (5)
arcpy.ASCIIToRaster_conversion(tempanom_50y_asc, tempanom50_img, "FLOAT")

# Process: ASCII to Raster (7)
arcpy.ASCIIToRaster_conversion(tempanom_30y_asc, tempanom30_img, "FLOAT")

# Process: ASCII to Raster (9)
arcpy.ASCIIToRaster_conversion(tempanom_10y_asc, tempanom10_img, "FLOAT")

# Process: ASCII to Raster (8)
arcpy.ASCIIToRaster_conversion(precperc_monthly_50_asc, precperc50_img, "FLOAT")

# Process: ASCII to Raster (6)
arcpy.ASCIIToRaster_conversion(precperc_monthly_30_asc, precperc30_img, "FLOAT")

# Process: ASCII to Raster (4)
arcpy.ASCIIToRaster_conversion(precperc_monthly_10_asc, precperc10_img, "FLOAT")

# Process: ASCII to Raster (2)
arcpy.ASCIIToRaster_conversion(precperc_monthly_full_asc, precpercfull_img_2, "FLOAT")

# Process: ASCII to Raster (10)
arcpy.ASCIIToRaster_conversion(tempESRIascirotate_asc_2, temp_img, "FLOAT")

# Process: ASCII to Raster (11)
arcpy.ASCIIToRaster_conversion(precMONTHLY2050asc_asc, precfull_img, "FLOAT")

# Process: ASCII to Raster (12)
arcpy.ASCIIToRaster_conversion(tempESRImeansrotate_asc_2, tempbaseline_img, "FLOAT")

# Process: ASCII to Raster (13)
arcpy.ASCIIToRaster_conversion(precMONTHLYbaseline_asc, precbaseline_img, "FLOAT")

# Process: ASCII to Raster (14)
arcpy.ASCIIToRaster_conversion(temp10y_asc, temp10_img, "FLOAT")

# Process: ASCII to Raster (16)
arcpy.ASCIIToRaster_conversion(temp30y_asc, temp30_img, "FLOAT")

# Process: ASCII to Raster (15)
arcpy.ASCIIToRaster_conversion(temp50y_asc, temp50_img, "FLOAT")

# Process: ASCII to Raster (18)
arcpy.ASCIIToRaster_conversion(precMONTHLY10_asc, prec10_img, "FLOAT")

# Process: ASCII to Raster (17)
arcpy.ASCIIToRaster_conversion(precMONTHLY30_asc, prec30_img, "FLOAT")

# Process: ASCII to Raster (19)
arcpy.ASCIIToRaster_conversion(precMONTHLY50_asc, prec50_img, "FLOAT")

# Process: ASCII to Raster (20)
arcpy.ASCIIToRaster_conversion(map_mean_ensemble_50_AR4_Global_50k_a1b_tmean_14_2040_2069_asc, v40_70_a1b_tmean_img, "FLOAT")

# Process: ASCII to Raster (21)
arcpy.ASCIIToRaster_conversion(map_mean_ensemble_50_AR4_Global_50k_a1b_pptPct_16_2040_2069_asc, v40_70_a1b_precipmean_img, "FLOAT")

# Process: Batch Define Coordinate System
arcpy.BatchDefine_samples("C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\tempanomfull_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\tempanom50_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\tempanom30_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\tempanom10_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\precperc50_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\precperc30_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\precperc10_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\precpercfull_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\tempfull_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\tempbaseline_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\precfull_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\precbaseline_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\temp10_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\temp30_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\temp50_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\precl0_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\prec10_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\precl0y_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\prec50_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\40_70_alb_tmean_img:C:\\Users\\Phobos\\Desktop\\2050_MP\\raster\\40_70_alb_precipmean_img","GEOGCS["GCS_WGS_1984",DATUM["D_WGS_1984"],SPHEROID["WGS_1984",6378137.0,298.257223563]],PRIMEM["Greenwich",0.0],UNIT["Degree",0.0174532925199433]]", ")

# Process: Raster to Point
arcpy.RasterToPoint_conversion(tempanom30_img, point_tempanom30.shp, "Value")

# Process: Point to Raster
arcpy.PointToRaster_conversion(lat_points_shp, "LAT", lat_raster.img, 
"MOST_FREQUENT", "NONE", "0.5")

# Process: Raster Calculator
arcpy.gp.RasterCalculator_sa(“Con(Abs(\"%lat_raster.img\")<55,.,27.,.26)”, global_p_img)

# Process: Raster Calculator (8)
arcpy.gp.RasterCalculator_sa(“(\"%global_p.img\")*0.46*\"%temp50.img\")”, ET_50_img)

# Process: Raster Calculator (10)
arcpy.gp.RasterCalculator_sa(“Con((\"%prec50.img\")<ET_50.img%)”, availablem_50_img)

# Process: Raster Calculator (4)
arcpy.gp.RasterCalculator_sa(“\"%global_p.img\")*0.46*\"%tempbaseline.img\")”, ET_baseline_img)

# Process: Raster Calculator (5)
arcpy.gp.RasterCalculator_sa(“Con((\"%precbaseline.img\")<ET_baseline.img%)”, availablem_baseline_img)

# Process: Raster Calculator (13)
arcpy.gp.RasterCalculator_sa(“(\"%availablem_50.img\")/\"%availablem_baseline.img\")*100”, availablem_perc50_img)

# Process: Raster Calculator (7)
arcpy.gp.RasterCalculator_sa(“(\"%global_p.img\")*0.46*\"%temp30.img\")”, ET_30_img)

# Process: Raster Calculator (11)
arcpy.gp.RasterCalculator_sa(“Con((\"%prec30.img\")<ET_30.img%)”, availablem_30_img)

# Process: Raster Calculator (14)
arcpy.gp.RasterCalculator_sa(“(\"%availablem_30.img\")/\"%availablem_baseline.img\")*100”, availablem_perc30_img)

# Process: Raster Calculator (9)
arcpy.gp.RasterCalculator_sa(“(\"%global_p.img\")*0.46*\"%temp10.img\")”, ET_10_img)

# Process: Raster Calculator (12)
arcpy.gp.RasterCalculator_sa(“Con((\"%prec10.img\")<ET_10.img%)”, availablem_10_img)

# Process: Raster Calculator (16)
arcpy.gp.RasterCalculator_sa("("\"%availablem\_10.img\"\%\"%availablem\_baseline.img\"\)/\"%availablem\_baseline.img\"\)*100", available\_perc10\_img)

# Process: Zonal Statistics as Table
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", tempanomfull\_img, tempanomfull, "DATA", "ALL")

# Process: Zonal Statistics as Table (2)
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", prepercfull\_img\_2, prepercfull, "DATA", "ALL")

# Process: Raster Calculator (2)
arcpy.gp.RasterCalculator_sa("\"%\%global\_p.img\"\%\%(0.46\%\"%temp.img \%\"%\+\%\")\%\"", ET\_full\_img)

# Process: Raster Calculator (3)
arcpy.gp.RasterCalculator_sa("\"Con\%(\"%\$\%\"%ET\_full.img \%\"\%\"%\"%\"%\")\%\")\%\"<0,0,\"%\$\%\"%ET\_full.img \%\"\%\"%\"%\"%\")\%\", available\_full\_img)

# Process: Raster Calculator (15)
arcpy.gp.RasterCalculator_sa("\"%\%availablem\_full.img\"\%\%\"%availablem\_baseline.img\"\%\%\"%availablem\_baseline.img\"\%\""); available\_percFull\_img)

# Process: Zonal Statistics as Table (3)
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", available\_percFull, available\_percfull, "DATA", "ALL")

# Process: Zonal Statistics as Table (4)
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", tempanom50\_img, tempanom50, "DATA", "ALL")

# Process: Zonal Statistics as Table (5)
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", tempanom30\_img, tempanom30, "DATA", "ALL")

# Process: Zonal Statistics as Table (6)
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", tempanom10\_img, tempanom10, "DATA", "ALL")

# Process: Zonal Statistics as Table (7)
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", tempbaseline\_img, tempbaseline, "DATA", "ALL")

# Process: Zonal Statistics as Table (8)
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", preperc50\_img, preperc50, "DATA", "ALL")

# Process: Zonal Statistics as Table (9)
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", precperc10_img, precperc10, "DATA", "ALL")

# Process: Zonal Statistics as Table (10)
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", precperc30_img, precperc30, "DATA", "ALL")

# Process: Zonal Statistics as Table (11)
arcpy.gp.ZonalStatisticsAsTable_sa(continents, "CONTINENT", precbaseline_img, precbaseline, "DATA", "ALL")

# Process: Raster Calculator (6)
arcpy.gp.RasterCalculator_sa("\"%temp.img\" \"%40_70_alb_tmean.img\"", tempfull_alb_diff_img)

# Process: Calculate Statistics
arcpy.gp.CalculateStatistics_sa(tempfull_alb_diff_img, "1", "1", "")

# Process: Raster Calculator (17)
arcpy.gp.RasterCalculator_sa("\"%precfull.img\" \"%40_70_alb_precipmean.img\"/(3)\"", precbaseline_alb_diff_img)

# Process: Batch Calculate Statistics
arcpy.gp.BatchCalculateStatistics_management("C:\Users\Phobos\Desktop\2050_MP\raster\precpercfull.img;C:\Users\Phobos\Desktop\2050_MP\raster\precperc10.img;C:\Users\Phobos\Desktop\2050_MP\raster\precperc30.img;C:\Users\Phobos\Desktop\2050_MP\raster\precperc50.img;C:\Users\Phobos\Desktop\2050_MP\raster\tempanom10.img;C:\Users\Phobos\Desktop\2050_MP\raster\tempanomfull.img;C:\Users\Phobos\Desktop\2050_MP\raster\tempanom50.img;C:\Users\Phobos\Desktop\2050_MP\raster\tempanom30.img;C:\Users\Phobos\Desktop\2050_MP\raster\precbaseline.img;C:\Users\Phobos\Desktop\2050_MP\raster\tempbaseline.img", "1", "1", "")