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A Programmatic Geographic Information Systems Analysis of Plant Hardiness Zones

A thesis
presented to
the faculty of the Department of Computing
East Tennessee State University

In partial fulfillment
of the requirements for the degree
Master of Science in Information Systems

by
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May 2023

Dr. Brian Bennett, Chair
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ABSTRACT

A Programmatic Geographic Information Systems Analysis of Plant Hardiness Zones

by

Andrew Bowen

The Plant Hardiness Zone Map consists of thirteen geographical zones that describe whether a plant can survive based on average annual minimal temperatures. As climate change progresses, minimum temperatures in all regions are expected to change. This work programmatically evaluates predicted future climate projection data and converts it to United States Department of Agriculture-defined hardiness zones. Through the next 80 years, hardiness zones are projected to move poleward; in effect, colder zones will lose area and warmer zones will gain area globally. Some implications include changes in crop growing degree days, which could alter crop productivity, migration and settlement of invasive species over native species in shifted zones, and the interruption of plant vernalization, which is an important factor in establishing dormancy. The programmatic evaluation and analysis of hardiness zone change is a strategic lens for viewing the effects and rate of climate change using an easy-to-grasp metric.

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CHAPTER 1. INTRODUCTION

Climate change is a global anthropogenic force caused by rising atmospheric levels of gases that trap heat and raise ambient temperatures. In 2007, the Intergovernmental Panel on Climate Change (IPCC) projected in their Assessment Report 4 (AR4) a worst-case scenario global temperature rise of 3.5 degrees Celsius (C) by the year 2100 [1]. Each successive report has projected a higher worst-case scenario global temperature rise, with AR5 (published in 2014) projecting 4.1 degrees C [2] and AR6 (published in 2021) projecting 4.8 degrees C by the year 2100 [3]. According to the AR5, the IPCC reported high confidence in presently occurring shifts of aquatic species habitat distribution, migration patterns, and species interactions [2]. Moreover, the negative effects of climate change on crops reportedly outweigh the positive effects [2], despite higher temperatures and supposedly longer growing seasons. The AR6 predicts high confidence of mountain and polar glacial melting, permafrost thaw, ocean acidification, and ocean deoxygenation [3]. The Southeastern United States is also projected to be impacted by climate change; minimum temperature deviation from the climate normal in the Southeast U.S. has increased up to seven percent, days per year with a temperature higher than 95 degrees Fahrenheit increase by at least 30 days, and many areas see 5 to 15% economic damage due to climate change [4].

The United States Department of Agriculture (USDA) maintains a Plant Hardiness Zone Map (PHZM) that depicts zones in which certain perennial plants are “hardy,” or whether they are likely to survive the seasonal changes in that location. The primary determinant in seasonal change of zones is the average annual minimum temperature, while maximum temperature can also be a factor. As such, the PHZM zones are based on the yearly average minimum temperature an area experiences [5]. The PHZM is primarily used as a recommendation for where a farmer and/or

gardener should grow which plants. As climate change progresses and temperatures rise, minimum temperatures, too, will rise and plant hardiness zones will shift, affecting the global ecosystem that all depend upon.

Background

Two botanists from Harvard University's Arnold Arboretum, Dr. Donald Wyman and Dr. Alfred Rehder, contributed to the creation of the first plant hardiness zone map for the U.S. [6]. Rehder detailed a system in 1927 in which the U.S. and Canada are divided into ten zones based on differences of about 5-6 degrees C in minimum temperatures. In 1940, Wyman used this same system, but based on nationwide data collected over a 40 year period (1895 to 1935) by the Weather Bureau and published by the USDA in 1936 [6]. Wyman quantitatively divided regions of the U.S. into hardiness zones accordingly (Figure 1) [6].

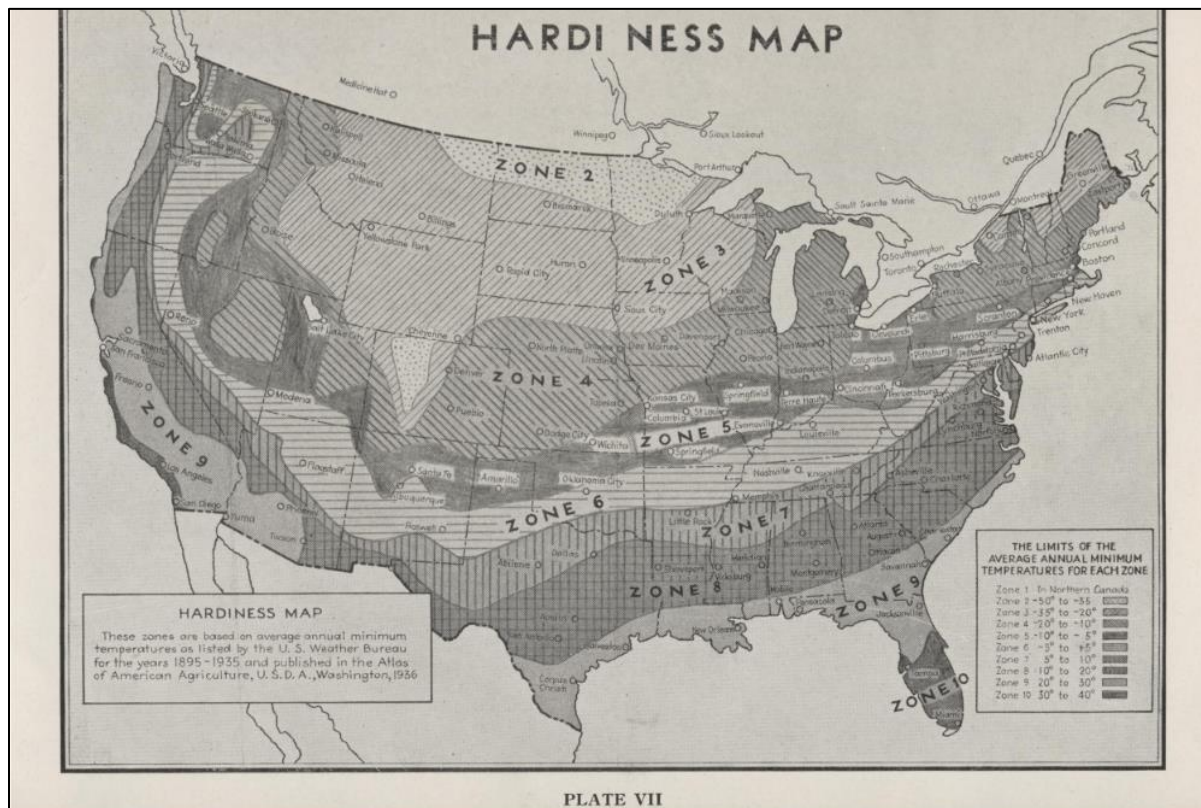


Figure 1. Dr. Donald Wyman's first Plant Hardiness Zone Map of the United States.

Since then, the USDA's PHZM has been expanded from ten zones to thirteen, each with an "a" and "b" subdivision; each subdivision covers a range of roughly 3 degrees C. The USDA most recently updated the map in 2012, while the previous update was in 1990 [7]. This work presents examples of what the PHZM could look like if it were updated today (ten years past the most recent update) and many years into the future, accounting for the accelerative nature of climate change by employing custom ArcGIS script tools that make use of complex climate prediction models. Climate and precipitation normals are recomputed every 10 and 5 years, respectively [8], [9]; the methodology presented may be repeated regularly as normals are updated.

CHAPTER 2. DATA ACQUISITION

Two primary data sources were used in this work: PaleoClim [10], which provides paleo-climate GeoTIFF data dating back to 3.3 million years ago, and WorldClim [11], which provides downloadable GeoTIFF image files of recent historical and future projections of climate data. These GeoTIFF image files are images that “know where they’re at” in regards to a world map. The resolution of the data used in this project for both data sources is 2.5 arc-minutes (around 5 square kilometers per pixel) and was downloaded to and accessed via an East Tennessee State University (ETSU) Microsoft OneDrive account. File size ranged from 9 megabytes to 450 megabytes per GeoTIFF file (the larger file size characterized by WorldClim data containing 19 different raster bands—one for each bioclimatic variable—inside one GeoTIFF file). PaleoClim and WorldClim data were kept separate with respectively named file folders. In WorldClim, up to 25 different global climate models (GCMs) are available for use over four time ranges: 2021-2040, 2041-2060, 2061-2080, and 2081-2100.

Table 1. PaleoClim

PaleoClim Time Periods	
1979 - 2013	Current (Observed)
4.2-0.3 ka	Pleistocene: late-Holocene
8.326-4.2 ka	Pleistocene: mid-Holocene
11.7-8.326 ka	Pleistocene: early-Holocene
12.9-11.7 ka	Pleistocene: Younger Dryas Stadial
14.7-12.9 ka	Pleistocene: Bølling-Allerød
17.0-14.7 ka	Pleistocene: Heinrich Stadial 1
130 ka	Pleistocene: Last Interglacial
787 ka	Pleistocene: MIS19
3.205 Ma	Pliocene: mid-Pliocene warm period
3.3 Ma	Pliocene: M2

Table 2. WorldClim

WorldClim Time Periods
1970 – 2000 (Observed)
2021-2040
2041-2060
2061-2080
2081-2100

Both sources use bioclimatic variables, which use monthly temperature and precipitation measurements to create “more biologically meaningful variables” [11]. Bioclimatic variables are coded 1 through 19 and each holds a data type that means something different than the next. BIO_1 is annual mean temperature, BIO_2 is mean diurnal range, and so on. This work uses BIO_6 for its analyses, which contains the minimum temperature of the coldest month. As plant hardiness zones are classified by the USDA based on the extreme minimum temperature a plant can endure, this is the most meaningful bioclimatic variable to use.

While many global climate models (GCM) are supplied by WorldClim, this work employs the EC-Earth3-Veg model. This model, one of eight created by the EC-Earth Consortium in preparation for the 6th edition of the Coupled Model Intercomparison Project (CMIP6), considers many variables: oceanic chemistry, atmospheric dynamics, river runoff, and dynamic vegetative guesses, are all used as variables in estimating future climate outcomes [12]. The EC-Earth3-Veg model falls to the middle of the pack in climate sensitivity, a metric used by Carbon Brief of which a higher score corresponds to a higher projection of global warming [13].

CHAPTER 3. METHODS

This work utilized various systems and tool including, but not limited to, the Windows 10 operating system, ArcGIS Pro 3, Python 3.9.9, and several Python programming libraries such as arcpy, os, NumPy, and Pandas. The ArcGIS Pro 3 license was acquired courtesy of the ETSU Department of Geosciences.

The project began visualizing estimated paleolithic climate data over ranges of thousands of years ago (ka). As mentioned in Data Used, the BIO_6 bioclimatic variable is applied in all datasets, which represents minimum temperature. The ranges of paleolithic minimum temperatures across the globe vary; PaleoClim present-day minimum temperatures cover a range from -67.8°C to 27.1°C , while PaleoClim estimations of minimum temperatures 130 ka range from -54.6°C to 26.4°C .

With the Python programming language and the arcpy library, written by Environmental Systems Resource Institute (ESRI), various scripts were written to convert these minimum temperature values to plant hardiness zones as they currently exist according to the USDA and symbolize the results in an intuitive manner. All the scripts share various features that do the following:

- Use the ESRI Reclassify tool in the Spatial Analyst toolbox to take the initial BIO_6 raster or raster band and reclassify ranges of temperatures to plant hardiness zones
- Check the input data for a format of degrees C or degrees C times 10, as the latter format is used by some older datasets like PaleoClim to utilize the integer data type to make math faster

- Provide informative messages to the user about the status of the script and whether datasets will or will not be used depending on their contents (principally, whether they contain a BIO_6 TIF image file)
- Take an optional “Colormap” parameter for faster, appropriate coloration of the resulting hardiness map

The scripts differ some in the way that the data directories are structured. For scripts that target “Nested Directory”, the data for each time period were compiled each in their own folder depending on the time range with each folder typically containing multiple TIF files—one for each bioclimatic variable (this is the PaleoClim directory structure). Scripts targeting “Raster Bands” look for data in a folder representing the climate scenario, containing one TIF file per time range which in turn contained raster bands representing bioclimatic variables (this is the WorldClim directory structure).

Arcpy Reclassify Tool

The arcpy Reclassify tool requires three input parameters: the input raster to be reclassified, the raster field that is to be used to perform the reclassification, and “remap,” which can be an object of either “RemapRange”—the object used in this study—or “RemapValue.” This object provides the logic for which temperature ranges should fall into which hardiness zones. The script checks each data source for a format of either degrees Celsius or degrees Celsius times 10 and then creates a custom formatted RemapRange object depending on the result.

The script then activates the Reclassify tool with the following parameters: the input raster provided by looping through the file list, the raster field of “Value”, and the RemapRange. An additional, optional input parameter, “missing values” is provided with a value of “NODATA” to ensure the script does not misrepresent missing temperature values as having a higher or lower

hardiness zone than what currently exists (for instance, 0 or 14) according to the USDA. The script then saves the result of the Reclassify tool, assigned to a variable, in a newly created output folder inside the directory given to the tool as a parameter and added to the current open map in ArcGIS Pro.

PaleoClim Script

The script used for reclassifying the PaleoClim data (`reclassify_nested_directory.py`) takes one required parameter: the directory that holds subdirectories having TIF raster files. Each subdirectory is a time-period, ranging from 130 ka to present day. Data from the PaleoClim organization includes a ZIP file containing one TIF file for each bioclimatic variable depending on whichever time range one chose. This work collected eight time ranges in total, from 130 ka to present day. Older time (787 ka, 3.2 Ma, and 3.3 Ma) data is available from PaleoClim, but they unfortunately lack the BIO_6 variable required to investigate extreme minimum temperatures. Each ZIP file was extracted to its own folder with the same name into a directory called “paleoclim,” resulting in eight folders with bioclimatic variable TIF files in each. This nested directory structure saves time and effort in extracting each BIO_6 TIF file into a single directory, changing each file’s name to match its source, and then creating a script based on that structure.

I instead scripted a recursive folder and file search using the Python ‘os’ library that finds the BIO_6.tif image file in each subdirectory and adds that subdirectory to a list of folders. The script then uses the list to iterate through each folder’s BIO_6.tif image file for reclassification. If the script does not find a BIO_6.tif image file in the subdirectory, an informative message—“[item] may not contain bio_6.”—is returned to the user in the ArcGIS Pro process window, that subdirectory is not appended to the list of folders to use, and the script moves to the next subdirectory.

WorldClim Script

The script used for reclassifying WorldClim data (`reclassify_tif_bands.py` for running through all files in a scenario directory at once, or `reclassify_layers.py` for choosing individual layers from the ArcGIS Pro window), like the PaleoClim script, takes one similar parameter: a directory. This directory, however, should have no nested directories and instead contain only TIF image files. These image files consequently contain raster bands, one for each bioclimatic variable. The climate data acquired from WorldClim is derived from the IPCC 6th Assessment Report and includes projected future temperatures based on four Shared Socioeconomic Pathways (SSPs) over four broad time ranges: 2021-2040, 2041-2060, 2061-2080, and 2081-2100. As such, folders for each SSP are created and include the corresponding time ranges in those folders.

As in the PaleoClim script, the Python ‘os’ library scans through the parameterized directory and searches for files (consequential directories are ignored). The script then attempts to use the “Describe” `arcpy` method to search for the file’s “children” or raster bands and verifies that the bands contain the text “_6”, indicative of the BIO_6 bioclimatic variable. If found, a path is made to the raster band and the path is added to the list of files to iterate for reclassification. If a valid file type is not found or the raster does not contain a band that matches the description of bioclimatic variable 6, the script returns a message to the user about which file is invalid and continues its search through the given directory until its contents have been exhausted.

AutoClip Scripts

An extra custom toolbox with replicated scripts is used in an additional effort to simplify the data output for users. This project primarily focuses on the contiguous U.S., where the USDA Plant Hardiness Zones are principally applicable. As such, these scripts contain an additional `arcpy` processing tool from the `arcpy` Management toolbox called “Clip” that aids in providing visual

results only for that land which is contained within the contiguous U.S. This tool takes three parameters: the input shapefile or layer to be clipped, the clip layer (or what to clip by), and a location for the output file. This work obtained a polygon shapefile from ESRI's Living Atlas called "United States Country Boundary 2021" [14] to use as the clip layer. This shapefile included the states of Alaska and Hawaii, so it was edited to exclude these two states before using it with the AutoClip scripts.

Hardiness Zone Change Analysis

This work makes use of a custom analytical script tool in ArcGIS Pro to export the resulting raster data numerically as the number of pixels for each zone. The tool takes multiple map layers as inputs (for WorldClim future data, ideally no more than four as there are four time ranges available for future climate data) and produces a Comma Separated Values (CSV) file. The script uses the Pandas Python library to build a data frame that contains pixels in each zone for each layer analyzed. This data helps to analytically visualize the change in each zone's land area over time.

Another script tool like the one described above was written that instead makes use of the `arcpy RasterToPolygon` method to convert a raster image file to a polygon with interlaid divisions for the new hardiness zones. This method enables the use of another `arcpy` tool, `CalculateGeometryAttributes`, which is used to find the area in square kilometers of each hardiness zone. This tool provides more meaningful insights into the change of each hardiness zone by storing results as square kilometers instead of asking the user to conceptualize "pixels" as a unit of area in the real world. Both above scripts save the results as a CSV file whose path is specified by the user.

In a final standalone script, `Matplotlib` helps create and save plots depicting the change in the hardiness zone area over time, where the x-axis is time in years (the specifics of which are

provided by the user), and the y-axis is area in square kilometers (only if the user is using data from the latter script tool, which outputs data in square kilometers). The ‘pearsonr’ function in SciPy’s stats class is used to perform a Pearson’s correlation test to uncover the correlation between the area gained or lost by each zone and time passed for future and past climate data. Also used are the ‘polyfit’ and ‘poly1d’ NumPy functions to discover the characteristics (namely slope and y-intercept) of the data trendline. The correlation and trendline data enable the visualization of analytical information like the correlation coefficient and p-value in the plot area. It should be noted that a plot for the hardiness zone is not created if the values for each zone are empty—this occurs primarily in AutoClip scripts where extreme zones like 1 and 13 are often excluded from the contiguous U.S.

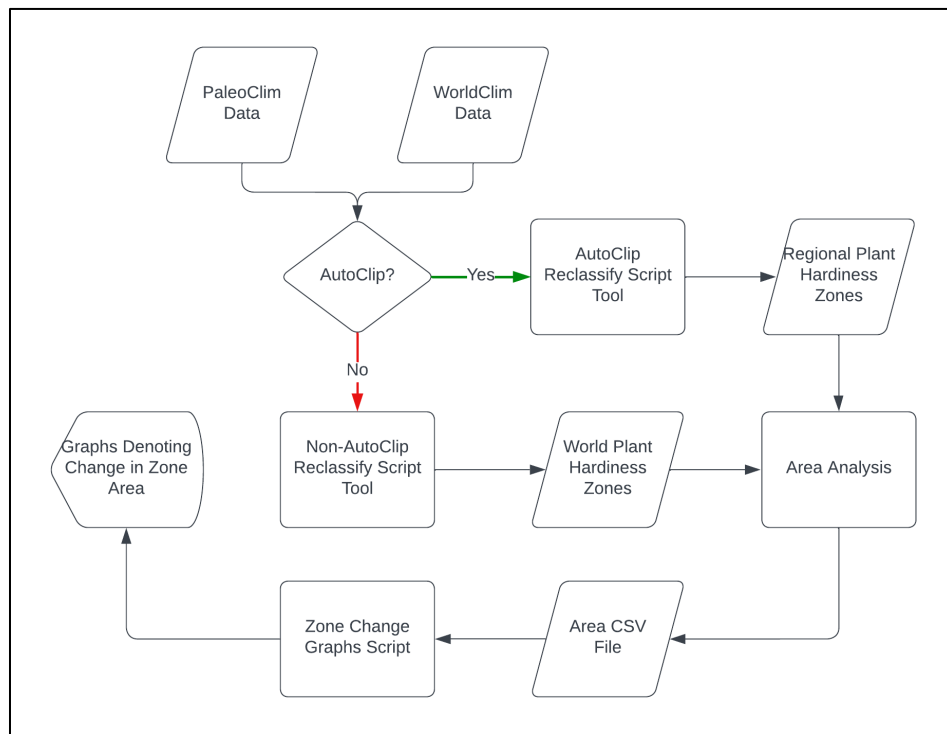


Figure 2. Workflow of thesis project.

CHAPTER 4. RESULTS

The visual outputs of this work are plentiful due to the abundance of data sources and the visual nature of ArcGIS Pro and GIS work in general. The raw GeoTIFF files from either PaleoClim or WorldClim plugged into ArcGIS Pro are visualized as a white-black gradient with white representing warmer temperature values and black representing colder temperature values. Running this layer data through the appropriate script results in an output of classified PHZs (see Figure 3). Application of the reclassification scripts to unclipped, raw PaleoClim or WorldClim data results in a land world map with plant hardiness zones visualized by a color map (Figure 4); high temperature zones take on a red shade while lower temperature zones take on a blue shade, with moderate temperature zones ranging from yellows to greens. Areas that contain values from source data and that experience extreme temperatures, such as northern South America and many parts of Oceania and Antarctica are purposefully missing colorization. This signifies a minimum temperature value outside the range of provided remap values as the USDA hardiness zone classification only covers -51.1°C to 21.1°C .

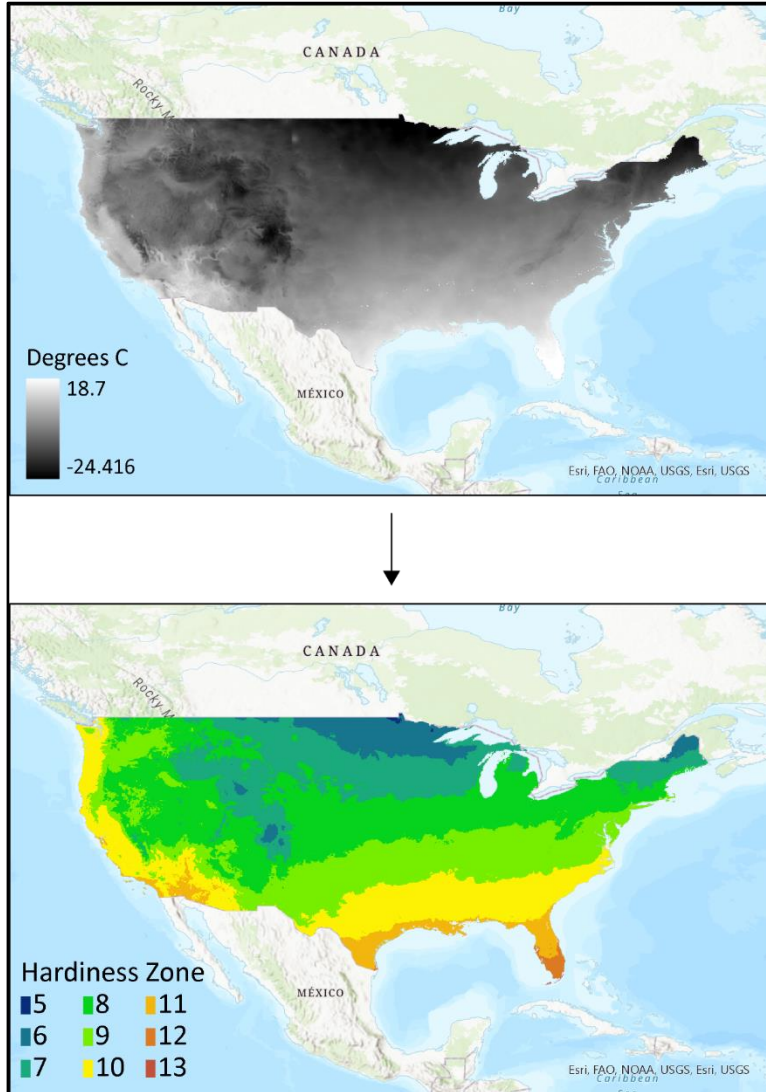


Figure 3. Before and after AutoClip script

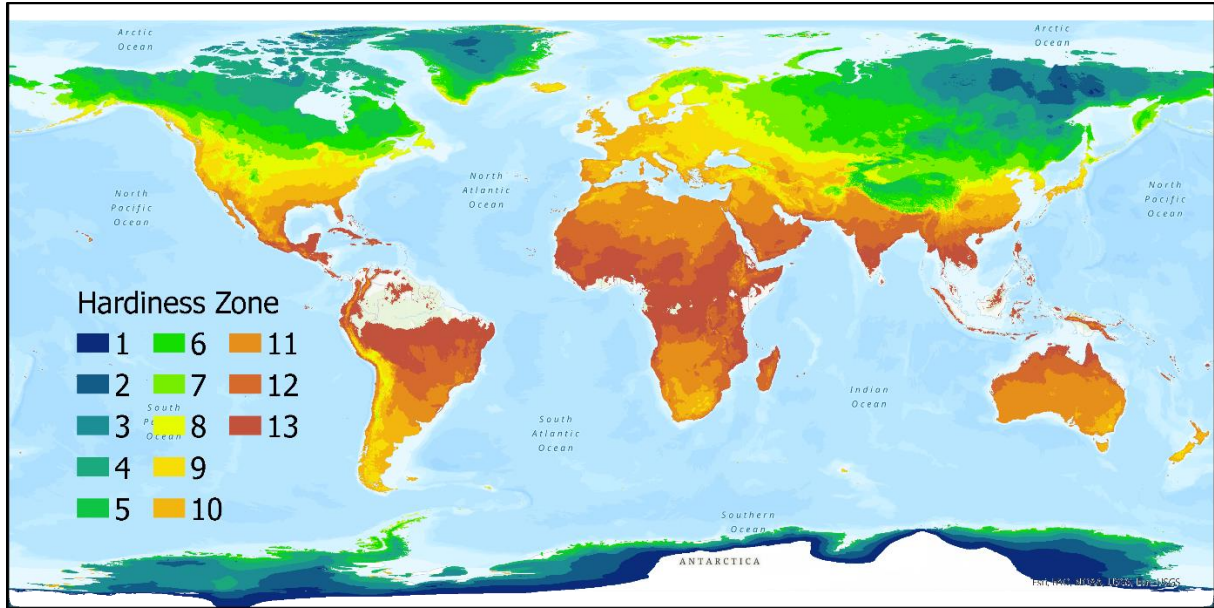


Figure 4. Global hardiness zones based on SSP126 for 2021-2040.

A non-visual output includes CSV data frame results generated by the analytical script tools. Column names referring to each of the time frame layers from ArcGIS Pro characterize the former, with each row representing a zone, starting with the index of 1. The final row in the data frame refers to the median year that characterizes the time frame of the layer; this value is an integer provided by the user so that 1), the user may change the representation of the time frame and 2), the integer can be used as the x axis in visual representations of the data, as wide time frames cannot. A modified example of this file can be seen in Table 3.

Plant Hardiness Zone Area over Time					
Zone	1970	2021-2040	2041-2060	2061-2080	2081-2100
1	-	-	-	-	-
2	-	-	-	-	-
3	-	-	-	-	-
4	-	-	-	-	-
5	4,021	-	-	-	-
6	410,113	122,730	69,060	8,341	-
7	1,386,054	861,636	729,427	409,127	153,374
8	2,403,925	1,920,243	1,786,212	1,532,842	1,179,266
9	1,820,813	2,416,716	2,510,897	2,518,932	2,159,175
10	1,407,968	1,773,127	1,846,932	2,075,083	2,573,001
11	326,344	621,250	749,552	1,085,458	1,472,926
12	43,526	85,401	105,783	160,202	245,313
13	1,631	3,292	6,532	14,410	21,185

Table 3. Area in square kilometers that each hardiness zone covers in the contiguous U.S.

The final output of this work represents the analysis of the ArcGIS Pro map and CSV results. Matplotlib scatter plots illustrate a trendline to visualize the change in the surface area of each hardiness zone over the time frame of each resulting hardiness zone layer. Included in the plots in Figure 5 show the equation for the slope, the correlation coefficient (r), and the p-value for each trendline. In Figure 5, one can see an observed downward trend of lower hardiness zones (such as 7 and 8) and an observed upward trend of higher zones (such as 10). The decision to include data from zones 7-10 is supported by the observation of Northeast Tennessee (the location of East Tennessee State University) being in zone 7 according to the USDA and zone 9 according to current time period BIO 6 variable calculations. Notably, zones 7, 8, and 10 in this visualization possess correlation coefficients (R^2) at or above 0.9, indicating a strong positive relationship between the progression of time and a respective gain or loss of zone area. This is further supported by the p-value calculation of 0.015 or lower—a value of lower than 0.05 is considered scientifically significant (the results were unlikely to have been obtained by chance or mistake).

The general trend of hardiness zone area in the contiguous United States is a loss of area at low zones and a gain of area for higher zones. This occurs as zones shift poleward (northward

in the northern hemisphere) and the colder, more northern zones leave the bounds of the U.S. while the warmer, more southern zones enter the U.S.

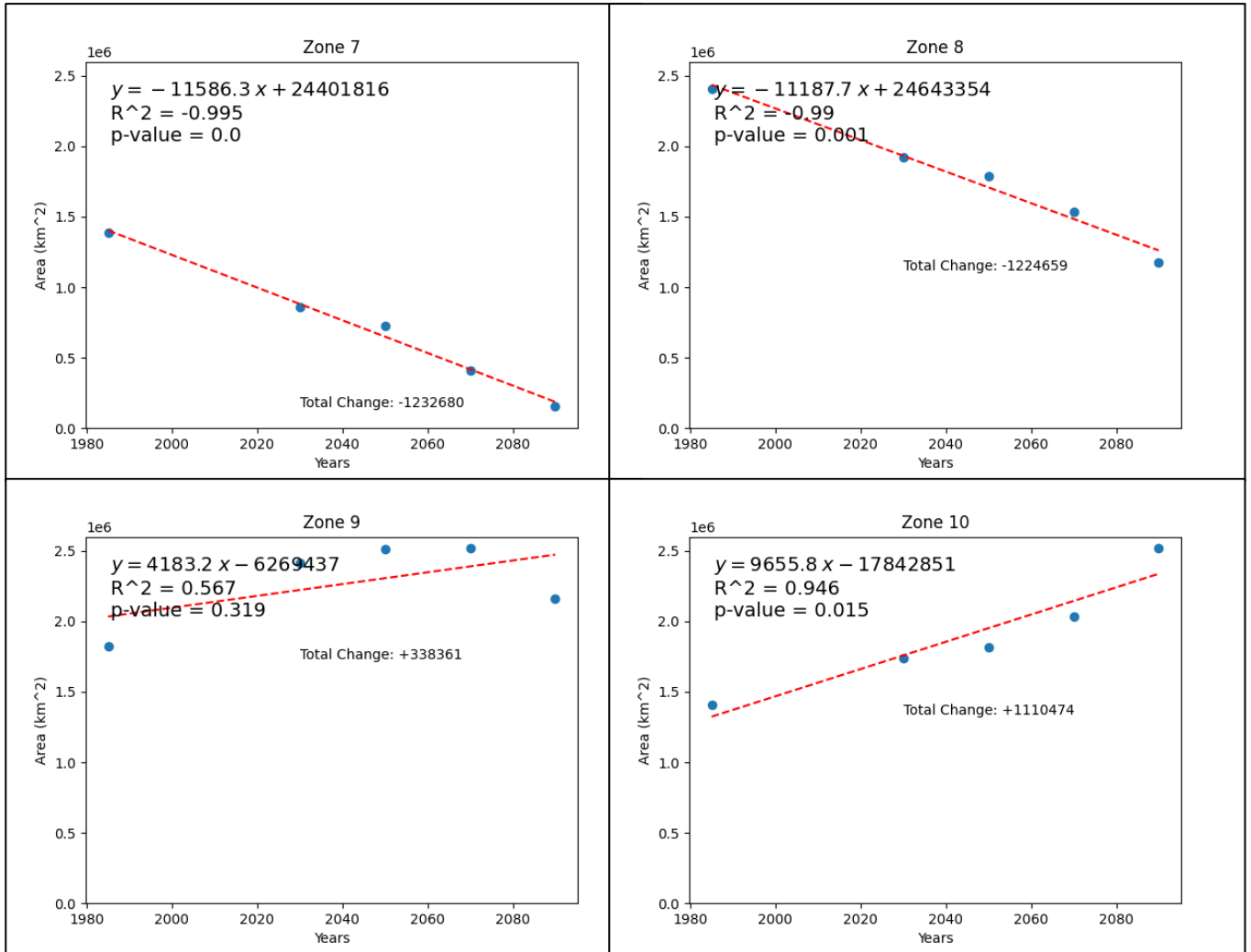


Figure 5. Graphs denoting change in area over time for zones 7-10, SSP 370 from 1970-2100.

CHAPTER 5. DISCUSSION

Discussion will take place primarily around the results of the AutoClip scripts that display results narrowed down to the contiguous United States and using WorldClim future data with SSP 370 unless stated otherwise. Additionally, the USDA's PHZM was originally created for use only with the United States, so to extend the scope beyond its originally intended use may not be a valid direction for this project.

In viewing each product raster of the Reclassify scripts—the first visible output when using these script tools in ArcGIS Pro—one can partially see the movement of the hardiness zones poleward as time progresses. This phenomenon occurs as expected, since generally rising temperatures results in increasing minimum temperatures in all regions; as minimum temperatures increase, they may then fall outside the definition of the zone they were previously classified as. For example, areas that previously held the title of Zone 6 may now fall under Zone 7 if an average annual minimum temperature increase of at maximum 10 degrees F occurs.

Change of hardiness zone area in the U.S. and its climate-driven nature are two of the primary foci of this work. The contiguous United States holds around 4,000 square kilometers of hardiness zone 5 in the present-day dataset that uses data from 1970-2000. Each subsequent future time range model contains no minimum temperatures that, according to USDA plant hardiness definitions, would be indicative of zone 5. This means that in between present-day and the 2021-2040 range, the contiguous U.S. will have lost about 4,000 square kilometers of zone 5 coverage under the SSP 370 prediction (otherwise stated, zone 5 will have been lost from the United States). Table 3 provides comprehensive data of hardiness zone area change from 1970 to 2100.

Other hardiness zones that do not completely disappear require a more complex analysis. For instance, zone 8—currently characterized by most of the Midwest and on into the Great

Plains—experiences a steady, regular decline in surface area in the U.S. over 130 years (Figure 5)—present and future estimations included. Pearson’s statistical correlation function determines the correlation coefficient for this trend to be -0.99 and the p-value to be 0.001. In other words, there is a clear, significant relationship between time moving forward (under SSP 370) and hardiness zone 8 losing area in the contiguous U.S. In another case, the state of Tennessee at present is almost entirely characterized by zone 9. As time continues, zone 9 steadily gains area; then in between 2081-2100, it loses some area (Figure 5). The general trend of the movement of this zone is still poleward, but the change in zone area is no longer linear; this analysis results in a correlation coefficient of 0.567—a moderate positive correlation—and a p-value of 0.319, so these results are more likely to have been obtained through error and are generally unreliable.

Zone 13, like zone 5, is another notable anomaly in this analysis. Based on current climate data, no area in the contiguous U.S. is occupied by zone 13. However, its distribution rises seemingly exponentially (more complex analyses required for further insights) over time under SSP 370 (Figure 6). The correlation coefficient for the analysis of this hardiness zone area change is 0.905 and the p-value is 0.034, which indicates a statistically significant change. Table 4 details more statistical information for each hardiness zone area change.

WorldClim SSP 370 1970-2100 Zone Stats		
Zone	Correlation Coefficient	P-Value
5	-0.832	0.081
6	-0.953	0.012
7	-0.995	0.0001
8	-0.99	0.001
9	0.567	0.319
10	0.95	0.013
11	0.959	0.01
12	0.93	0.022
13	0.905	0.034

Table 4. Correlation statistics, zone are over time.

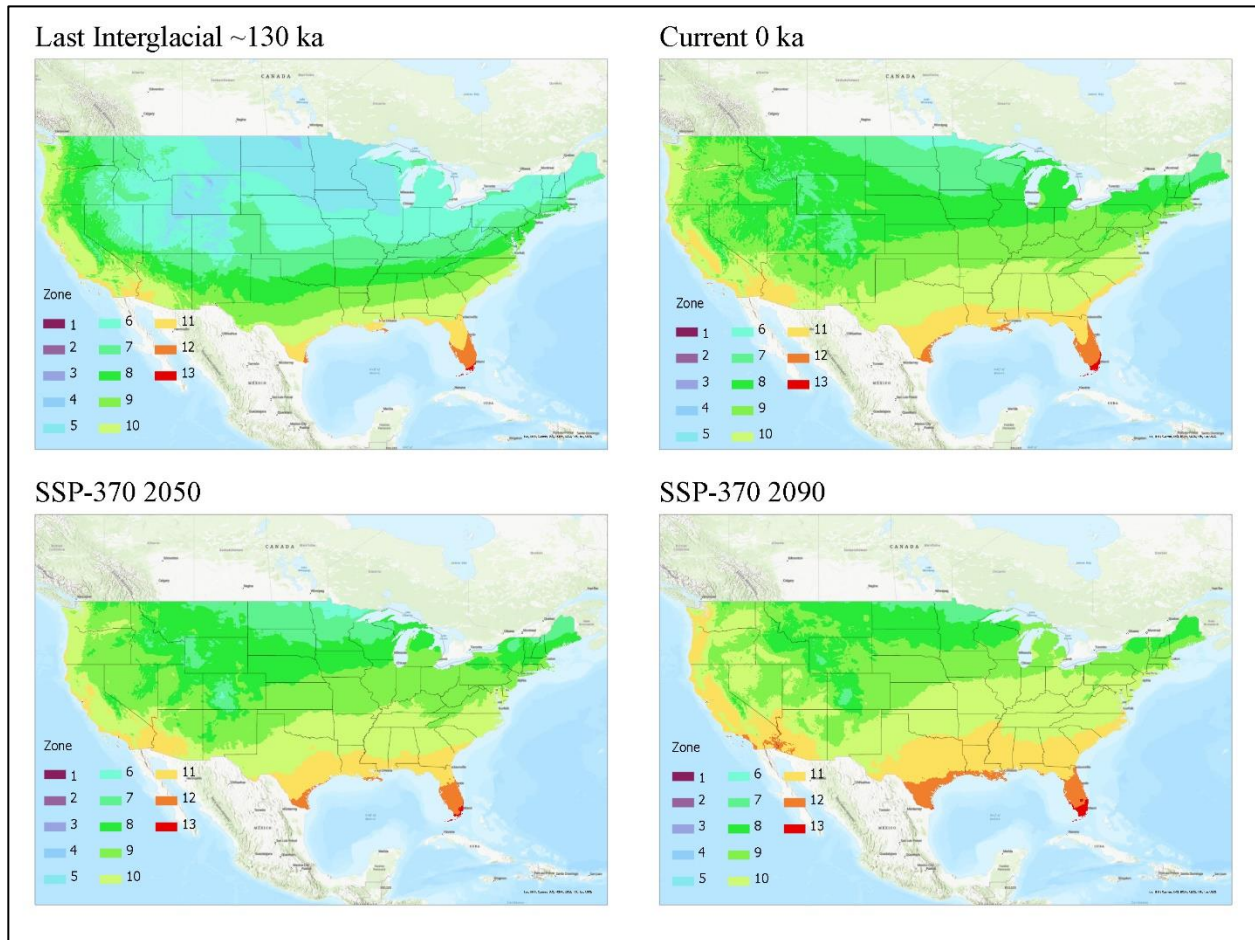


Figure 6. Hardiness zone comparison between 4 time periods.

Implications of Zone Shift

Realistically, plants are not affected by what zone they live in, but rather by the temperatures that categorize each zone. Especially important for agricultural crops is growing degree days (GDDs). The measure of GDDs helps growers to understand how quickly a plant is expected to reach maturity, grow, or produce fruit in a season. According to the Baskerville-Emin method of calculating GDDs, the growing degrees counter—which determines the “amount” of growth accumulated—begins to climb when this temperature is reached and stops when the temperature falls below it. The more growing degrees accumulated, the more opportunity a plant is given to grow, provided other conditions are optimal [15]. At first glance, it could be assumed

that since hardiness zones are moving poleward and minimum temperatures are rising, plants will experience more growing degree units and be more productive overall. However, higher temperatures and increased sunlight may inflict a number of conditions on plants such as sunscald or wilting of leaves, blossom or fruit drop, and bolting, which is the premature flowering of plants before they are ready to harvest [16]. Depending on region and plant species, the poleward shift of hardiness zones could improve or worsen the plant's productivity or ability to survive in that zone.

This poleward movement in zones implies an expected shift in plant species' distributions. Moser et al. performed an experiment in 2011 to determine whether a Northward shift in two United Kingdom grass species would result in a viable habitat for the grasses [17]. The result is dependent on several factors, including resistance of present biotic communities to the invader (which is largely determined by the identity of the invader species and all native species in the invaded environment), the ability of the extant species to adapt or outcompete the invading species in response to climate changes (like drought, high temperatures, or seasonal changes), and more. Differences in plants from differing habitats would benefit from further studies on out-competition and habitat adaptability, especially as climate change encourages poleward migration of many species.

Although summer and warm temperatures are often seen as indicative of plant growth and dispersal, many plants require colder temperature periods to activate flowering and seed production. This process is known as vernalization [18], and for many plants, it is necessary for the continuation of the species. Rinne et al. [19] investigated the effects of “decoupling of photo- and thermoperiod”—or the loss of the day-hot night-cold dichotomy which is important in establishing dormancy for many plants. They discovered that a warmer temperature scheme (24 degrees C during both the day and night) prevented hybrid aspen trees (*Populus* genus) from

establishing dormancy, and subsequently, undergoing vernalization [19]. Although climate change and shifting hardiness zones may not particularly result in a decoupling of photo- and thermoperiods, the rising of minimum temperatures do threaten to interrupt the vernalization and dormancy cycles of many deciduous plants soon.

Warmer temperatures can be detrimental to agricultural crop production for another reason. In a case study of Northern Japan's rice production, researcher Hiroyuki Shimono used a simple growth model based on cooling degree days (CDD), which characterize the duration and strength of cold over a given season, to estimate rice crop losses due to climate change. Two important stages of rice crops are booting, which is defined by the length of the developing "panicle", and heading, which is when the panicle can be seen growing out of the stem [20]. Shimono found that, from 1961 to 2010, rice crop heading dates came earlier (at about 0.7-1.9 days earlier every 10 years) due to climate change. Despite a general increasing trend in air temperatures, temperatures in the study area and duration during the booting period of the crop have decreased at a rate of 0.18 degrees C per 10 years. The drop in temperature during the booting stage combined with the earlier heading dates results in cold damage to the crop and an average yield loss of about 15% for a heading date of July 19th compared to an average loss of 2.5% for a heading date of August 28th [21]. These findings could be cause for concern, as rice is an extremely important crop to the global food supply. As explained by the Food and Agriculture Organization of the United Nations, "over 50 percent of the world population depends on rice for about 80 percent of its food requirements" [22]. Although shifting hardiness zones may indicate warmer conditions for crops, these conditions may be unexpectedly detrimental to more complicated growing requirements, like the sensitive maturity schedule of the rice crop.

Implications of Toolbox

The toolbox demonstrated in this work has many implications for the GIS scientific community and the general population. Firstly, it allows for a new visualization of a important topic: the progression of climate change. Other visualizations of climate change are often difficult to follow, especially those that use more complicated metrics such as parts per million (ppm) of carbon dioxide (CO₂) in the atmosphere. Those who are not familiar with these metrics may be quick to dismiss results of studies that use them. The PHZ metric is easier to understand because 1) it is more well known in the general population, especially among gardeners and outdoorspeople and 2) the customizable and visually indicative nature of PHZs as they progress from colder to warmer zones, and then how those zones change over time.

The toolbox is also unique in its methods of transferring data (numbers, temperatures as provided by climate data sources) to information (a classification of the data that then takes on an inferred meaning). This idea is easily transferrable to other disciplines that seek to convert data to some sort of classification of information. Finally, this toolbox provides access to specific ESRI geoprocessing tools without requiring the end user to know which tools they need to accomplish their purposes. In a distribution of this toolbox, its purpose would be explicitly and thoroughly stated with keywords that allow users to find it easily and leave the technical aspects to the tool.

CHAPTER 6. CONCLUSION

The systematic evaluation and analysis of plant hardiness zone change is a strategic lens for viewing the effects and rate of climate change using an easy-to-grasp metric. As climate change lowers the amount of cool and cold days in a year, hardiness zones move poleward, as changing annual minimum temperatures cause a change of zone territory. This work presents a workflow for converting extreme minimum temperatures to hardiness zones to gain an insight into how zones have changed in the past 100,000 years and how they may change in the future based on current climate projection models.

Limitations

Some limitations exist in the current work. To begin, the bioclimatic variable used—BIO 6—is not the exact same definition of the USDA Plant Hardiness Zones. BIO 6 is defined as the minimum temperature of the coldest month, while the USDA definition is “the average annual minimum winter temperature”. These definitions are marginally different and likely contributed to discrepancies between the current USDA PHZM and ones constructed using the toolbox and current data from both PaleoClim and WorldClim. In addition, there is another bioclimatic variable that could be used in further iterations of this project that could more closely match the USDA definitions. BIO 11, which is “mean temperature of coldest quarter” [11] could also provide meaningful results about future plant hardiness zones when applied to the tools in this work.

Many future climate models exist in the scientific climate change community. This work focuses only on EC-Earth3-Veg, while seven other models exist from the Earth Consortium alone and numerous others by other organizations that all use their own set of variables to estimate climate trends. Using any of the other future climate models may result in different map estimates.

A couple final limitations relate to the software used in this work. Python is a relatively slower language compared to its parent languages such as C, C++, C#, etc. An integration with one of these faster languages may help in performance, as well as a possible integration with ArcMap instead of ArcGIS Pro. End users will also require a license to use ArcGIS Pro and this toolbox.

Additional Applications

As stated above, the EC-Earth3-Veg GCM used in this work is not the only applicable model; many other models available through WorldClim may be used to attain different estimates of hardiness zone change, as each one considers different variables or use different processes than the last [13]. Standardization between models that use different variables could also yield more scientifically meaningful results. Additionally, more models are created with each iteration of CMIP, so the work presented here can continue onto CMIP7, and so on.

The script tools presented may find other applications in other areas of GIS study. The remap values may be adjusted inside the script and altered to create zones based on different data, such as maximum temperature, average precipitation, etc., as well as allowing for specification of one geographic area, such as within a state, province, or county.

Future Work

All visual GIS work was completed using ArcGIS Pro. ESRI maintains a suite of applications, including those that aid in the creation of web applications that encourage end-user interaction. Future endeavors related to this work could include creating a web app that pulls future climate projections automatically and, based on user input, displays which hardiness zone their residence or region may reside in 80 years into the future. Conversely, the same can be applied with PaleoClim data: end-users may be interested in what the climate was like at their residence

130,000 years ago. The work to make this information discoverable has already been done, and a web app could speed up the process and allow for enhanced end-user customization.

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