Can Texas Grow Enough Food to Sustain Its Own Population?

An Agricultural Compatibility Analysis for the State of Texas

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Introduction

A large portion of food found on supermarket shelves is exported from all over the world. This not only has adverse effects on the economies we are sourcing our food from, but also the fossil fuels burned to transport the food are a large contributor to greenhouse gas emission. In order to attain a more sustainable society, optimally we would source all of our food locally. If you've ever been to a farmer's market, you can imagine how difficult it would be to feed our entire population of locally grown and harvested food. However, this analysis will be performed to see if, under ideal conditions, given the current land-use conditions, Texas could grow enough calories annually to feed its human population.

According to the United States Census Bureau, the population of Texas was estimated as of July 2016 to be 27,862,596 people. 50.4% of these humans is female, which means 49.6% is male (US Census Bureau 2017). A weighted average amount of calories that should be consumed by a moderately active male was calculated to be 2332 per day based on age percentages provided by census bureau and caloric intake provided by (USDA, 2002). The same calculation was made for that of a moderately active female and the calculation showed that she should consume 1886 calories per day. Averaging this based on the percent of male versus female population shows an average need of 2107 calories per day per Texan.

Given that there are 365.25 days per year, that makes an annual total of 769,790 calories required per year per human. This means that to sustain the entire population of Texas, the state would have to produce 2.14X10^13 calories per year. To determine if it is possible to do this, am ArcGIS raster analysis was performed that included current land-use restrictions, soil-agricultural compatibility, and precipitation. Four maps of farmable cropland were produced, one for each season. Then area of farmland was compared to amount of calories provided by various crops per kilometer squared per day. This yielded a final amount of potential calories that could ideally be produced by the state of Texas.

1. State the problem

Given ideal conditions, can Texas grow enough food to sustain it population?

2. Break the problem down

In order to address this issue, various factors have to be taken into account. To grow food, you need water, sun, and good soil. In terms of data, that comes down to precipitation, temperature and soil classification. Other than these three main factors, certain parts of the state have to be taken out. Crops can not be grown where there is existing development, water bodies or exposed rock. For this part of the problem, land-use data is fitting.

While land-use and soil type are relatively static over time, precipitation and temperature are temporally and, more specifically, seasonably variable. In order to properly address the problem, you have to consider these factors within seasonal variation. This will require temperature and precipitation data sets that show seasonal variation. Some crops may grow well in summer, while other may thrive in winter. This is a factor of temperature and amount of daylight hours. Other factors that would influence this are wind, relative humidity, and cloud cover. To simplify the problem, these factors are not included. Data is highly variable and these variations can be assumed

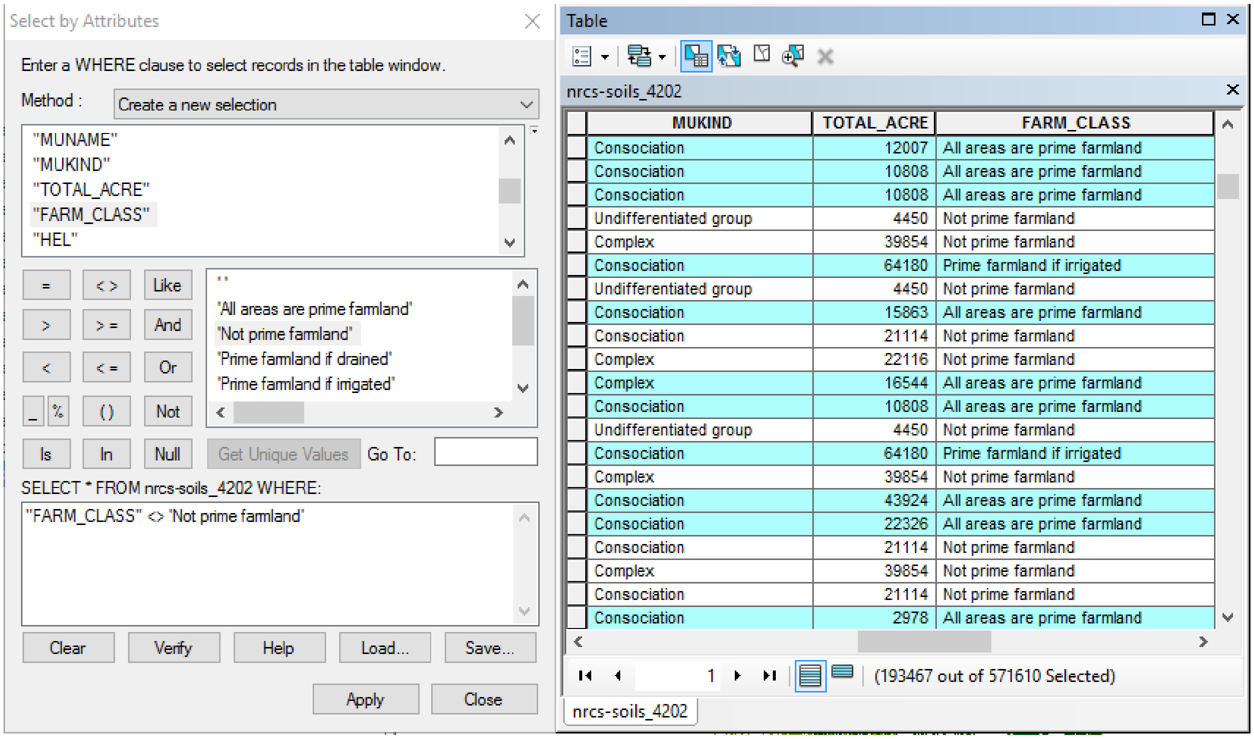
3. Explore input data

Soil Type:

There were multiple steps to pre-processing the soil data. This included querying, merging data sets, and reclassifying as a raster. This data was drawn from TNRIS.

STEP 1: Query

The data came in as a shapefile that divided the land into FARM_CLASS categories. This field classified polygons as either ‘prime farmland’ or ‘not prime farmland’ with some additional requirements such as ‘prime farmland if irrigated’ or ‘prime farmland if protected from flooding’. The only values that should not be considered in this analysis were ‘not prime farmland’, as the others could be included at different ranks. To take out the values that were not prime farmland, I performed a query on the attribute table of the soil data and selected all data not equal to ‘not prime farmland’ (Figure 1), then exported this selected data into a new file named: good_soil. This new file contained only areas in which the soil was compatible with agriculture.



MUKIND	TOTAL_ACRE	FARM_CLASS
Consociation	12007	All areas are prime farmland
Consociation	10808	All areas are prime farmland
Consociation	10808	All areas are prime farmland
Undifferentiated group	4450	Not prime farmland
Complex	39854	Not prime farmland
Consociation	64180	Prime farmland if irrigated
Undifferentiated group	4450	Not prime farmland
Consociation	15863	All areas are prime farmland
Consociation	21114	Not prime farmland
Complex	22116	Not prime farmland
Complex	16544	All areas are prime farmland
Consociation	10808	All areas are prime farmland
Undifferentiated group	4450	Not prime farmland
Consociation	64180	Prime farmland if irrigated
Complex	39854	Not prime farmland
Consociation	43924	All areas are prime farmland
Consociation	22326	All areas are prime farmland
Consociation	21114	Not prime farmland
Complex	39854	Not prime farmland
Consociation	21114	Not prime farmland
Consociation	2978	All areas are prime farmland

Figure 1: Selecting farmable land

STEP 2: Merge

The data came in as 5 different sections that were divided from North to South (Shown in figure 2).

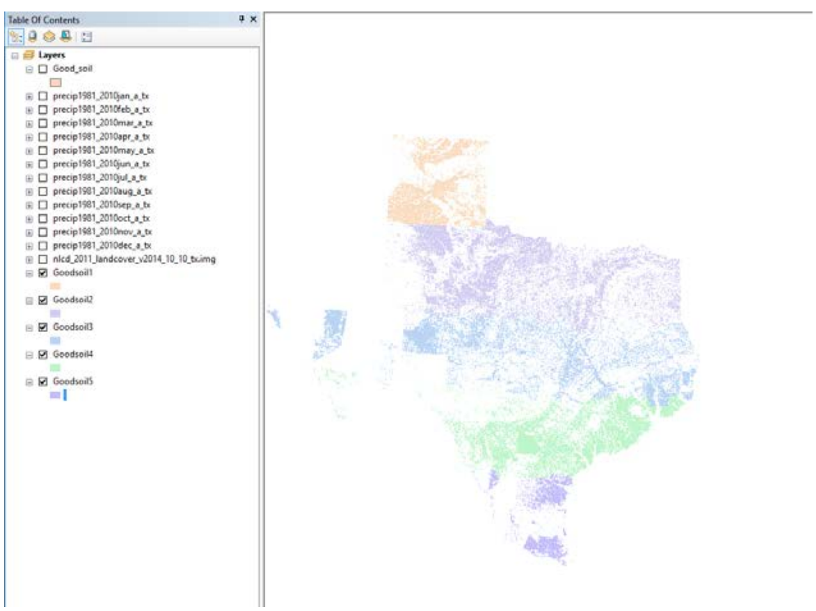


Figure 2: Soil Type Data in 5 different sections

Before converting the file into raster format, they were merged into one file in order to make reclassifying more efficient. This was done using the Merge tool within Data Management (Figure 3).

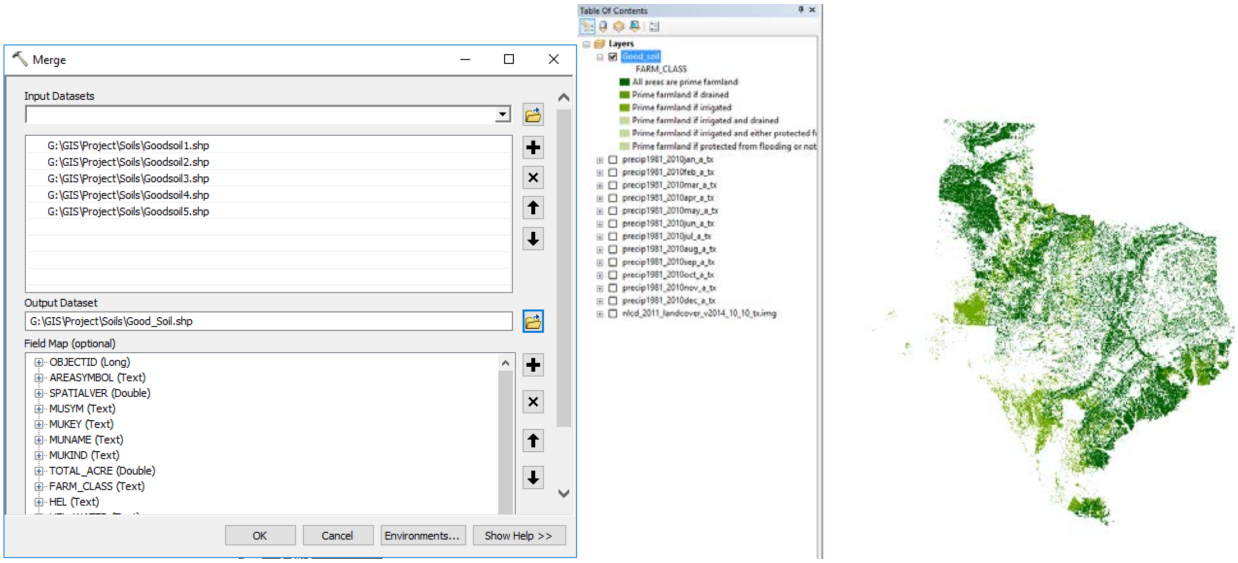


Figure 3: Merging soil sections into one

Figure 3 also shows the values symbolized with increasingly farmable soil type in darker green. This symbolization gave way to the ranks in which I classified the raster, which was the next step.

STEP 3: reclassify and convert to raster

The data was divided into varying levels of FARM_CLASS as mentioned previously. In order to convert these into an ordinal raster, first a new field had to be added to the existing data set. This field had to be only integers, so a ranking scheme was used. Field calculator (Figure 5) was used to rank the soils from 1-3 reflecting varying levels of agricultural compatibility. The rank of 3 was assigned to area of ‘all prime farmland’ classification. The rank of 2 was assigned to areas of 1 extra criteria: ‘if drained’, ‘if irrigated’, or ‘if protected from flooding or not frequently flooded during the growing season'. Rank 1 was assigned to areas that included two extra criteria from the above list. An example of the query used to select these features is shown in figure 5.

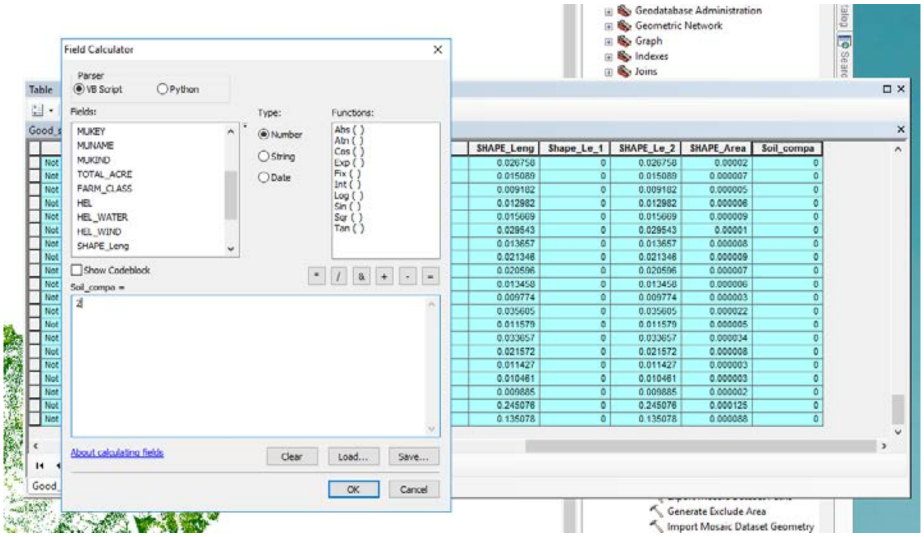


Figure 4: Field Calculator used to rank soils

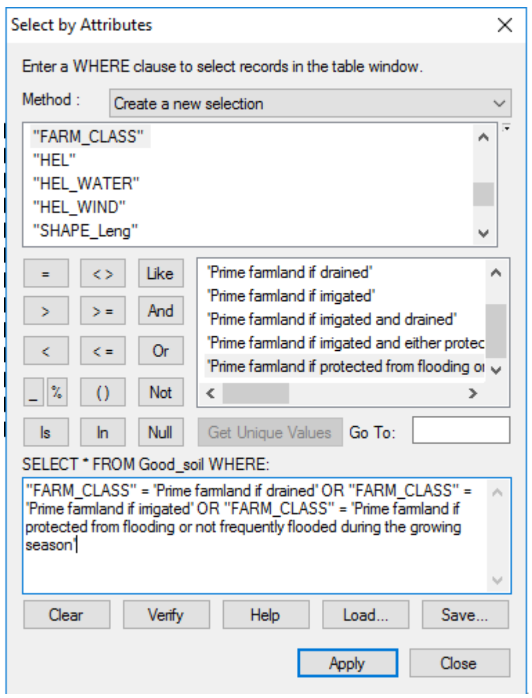


Figure 5: query used to select attributes for soil ranking

Once this field had been added, the shapefile could be converted into a simplified raster. This was done with the Polygon to Raster too (figure 6).

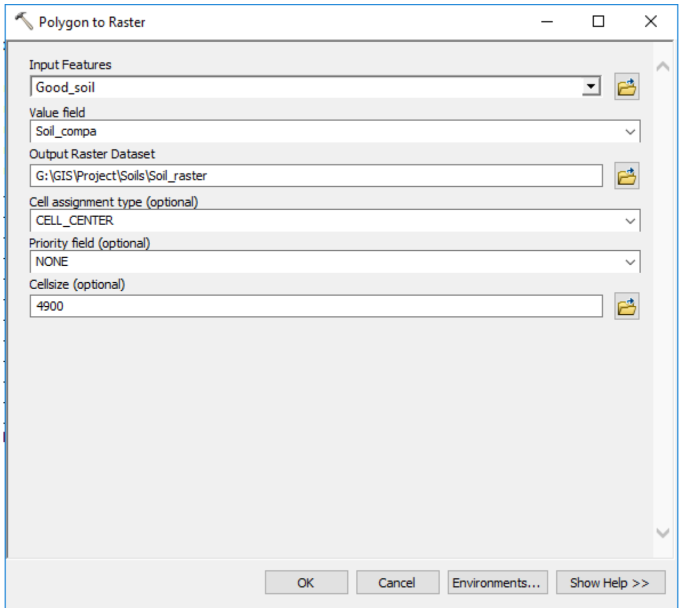


Figure 6: converting the soil shapefile into a raster

It was first attempted with a 4900 cell size, but upon seeing the extremely rough results, I decided to go with a 100 cell size. After many minutes of waiting...

Precipitation:

The precipitation data came in as 12 separate shapefiles of averaged monthly means. Each data set was contoured into 5-6 polygons depending on average total monthly precipitation. An example of this data, symbolized by inches of rainfall is shown below in figure 7. This data was pulled from TNRIS.

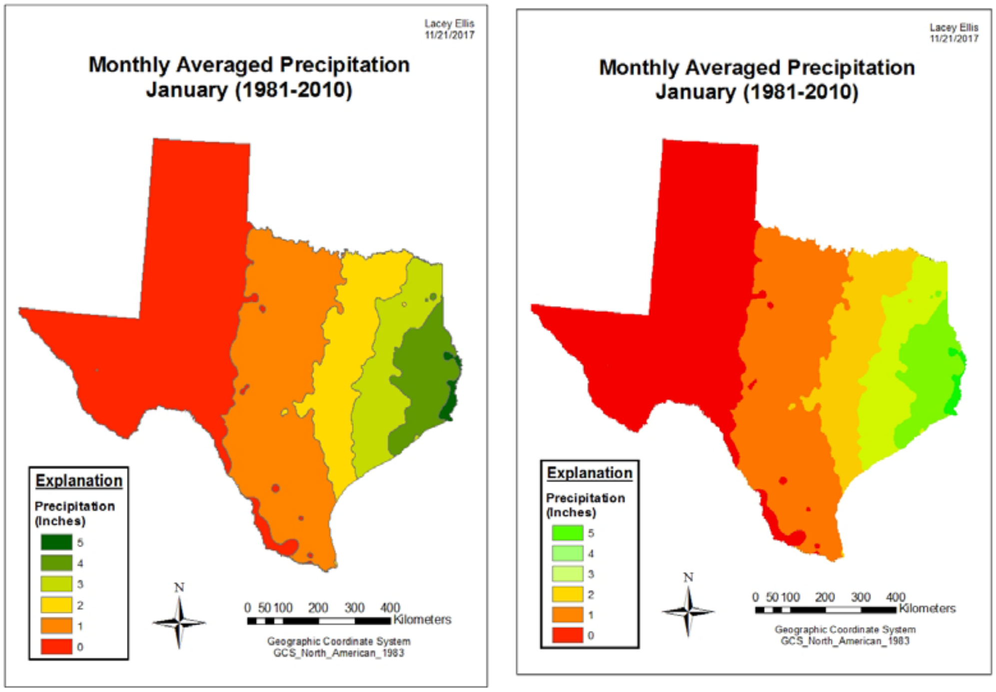


Figure 7: Monthly averaged precipitation shapefile (left) and raster (right)

In order to use this data in the overall ranking scheme, it requires conversion into raster, and then raster algebra to further average the precipitation by season. Each data set had to be converted into a raster. This was done with the polygon to raster tool as in the soil type section. Each monthly data set had to be converted, and they were all done so at a 100X100 cell size to match that of the soil type. (Figure 8)

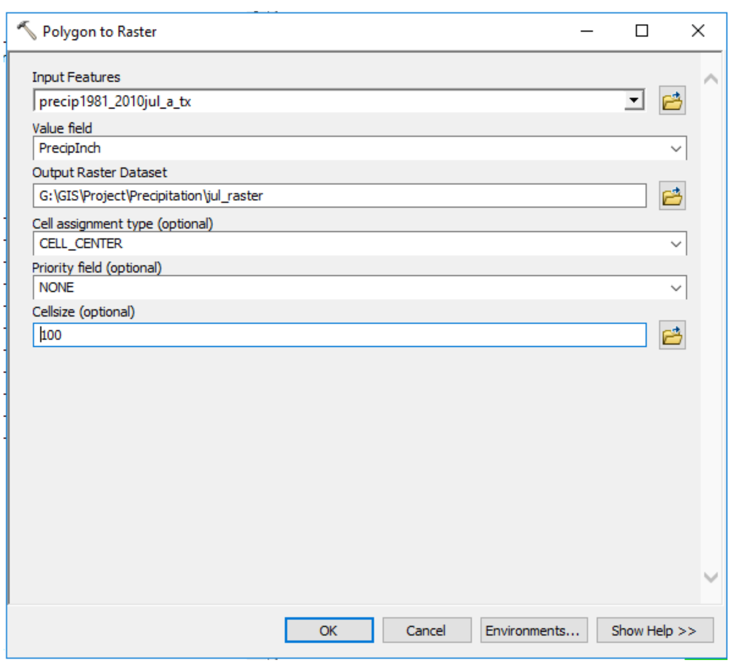


Figure 8: Shapefile of precipitation to raster

After the rasters were created for each individual month, I performed raster algebra to determine seasonally averaged rainfall, as this is a more concise way to display these maps. To determine the average, I simply added the months included in each season and divided by three (as seen in figure 9).

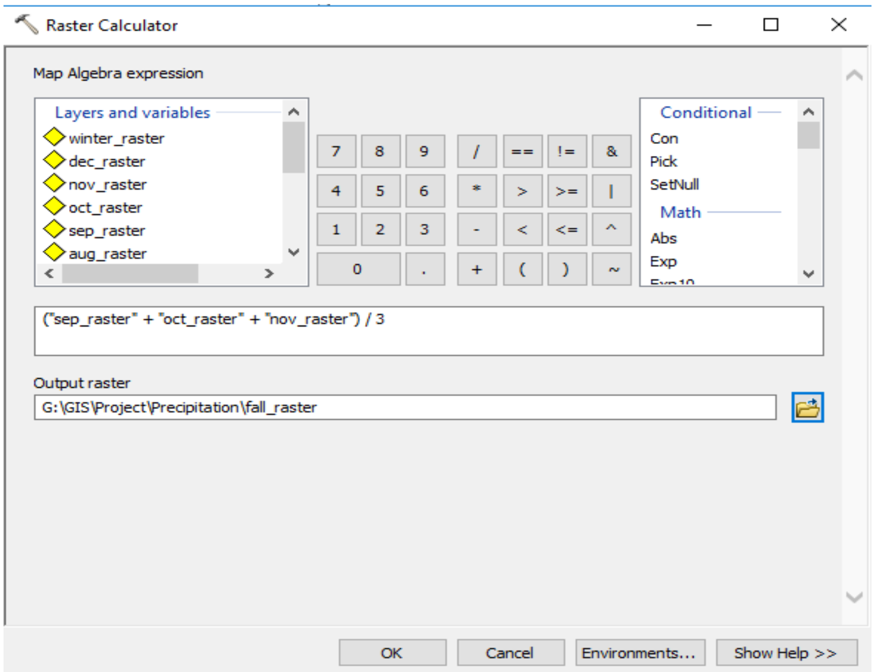


Figure 9: Raster Calculator to average rainfall seasonally

Temperature:

Temperature was not included due to a lack of applicable data available. Analyses of multiple data sources were attempted including: NOAA monthly averages from 1981-2010 (which would have been optimal), TNRIS averaged monthly maximum and minimum temperatures (sub-optimal), and NOAA Customs Monthly Normals Text data (also sub-optimal). The first attempt was unsuccessful due to problems with processing averaged monthly temperature data from NOAA. No spatial reference was present when downloaded and georeferencing was not a significant analysis due to inherent data display in RGB color code without any attribute table. The second attempt was to download monthly averaged highs and low, which would at least give and idea of extreme highs and lows for certain regions. This analysis, however, was also insignificant because since the data was averaged monthly, there were no values less than 32 or greater than 100 degrees Fahrenheit. The same problem occurred when the NOAA text data

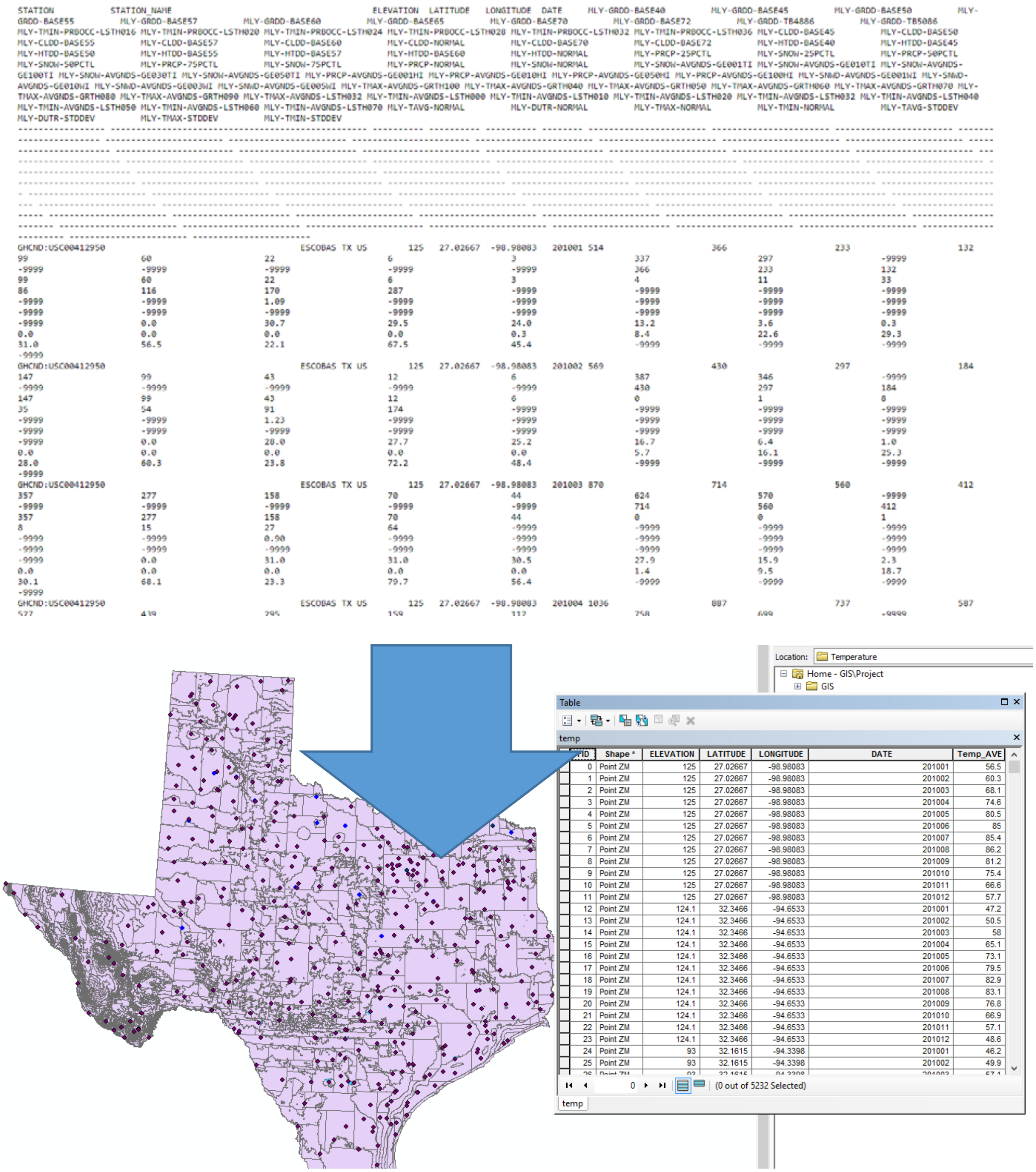


Figure 10: One of many attempts to include temperature. Excel to ArcMap

was imported. The data showed monthly averages for 2010 at 433 different locations around Texas. The plan was to perform an IDW on each month, convert these graphics to rasters, and then average them seasonally as was done with precipitation. The raw data was scrupulously edited in excel to only include latitude, longitude, date and temperature (Figure 10). Multiple queries were executed to edit data, dividing by month and removing null values. When looks at the coldest months, values still did not drop below 32 degrees Fahrenheit. When analyzing agricultural compatibility, these are essentially the only values that will effect success or failure. Due to the nature of Texas climate, temperature data was not included in raster analysis as the state generally does not have enough days of extreme cold (<32F) or heat (>100F) to show up in the data provided. A quantitative analysis is included in the discussion of results.

<u>Landuse / landcover:</u>

Landuse-landcover data came in as a raster from TNRIS, but it was bounded geographically, instead of to the outline of Texas. Additionally, it was broken into 17 groups based on different types of land-use, ranging from open water (11) to emergent herbaceous wetlands (95). This data had to be (1) clipped to the shape of texas and (2) reclassified to represent varying agricultural potential for the land based on current land use. Raw data is shown below in figure 11.

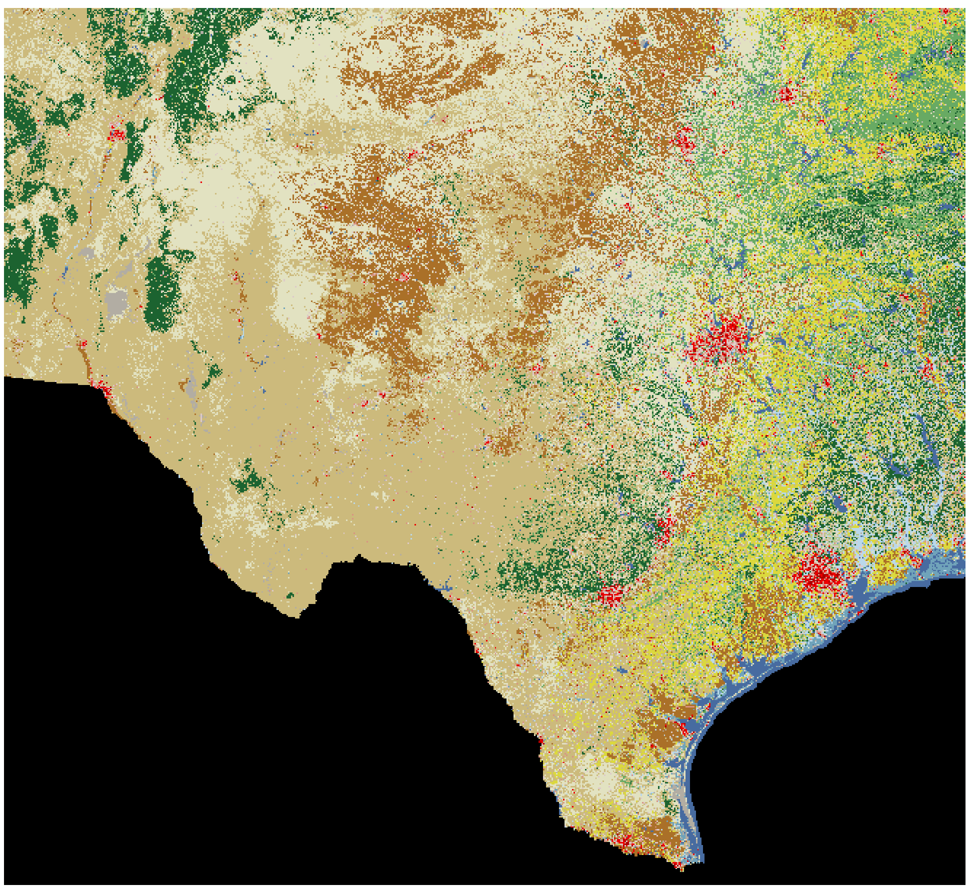


Figure 11: Raw Land-use Land-cover data

PART 1: Extract by Mask

The extract by mask tool was used to trim the data to the outline of Texas. This trimmed the raster to an uploaded polygon of the state of Texas in the same coordinate system (figure 12).

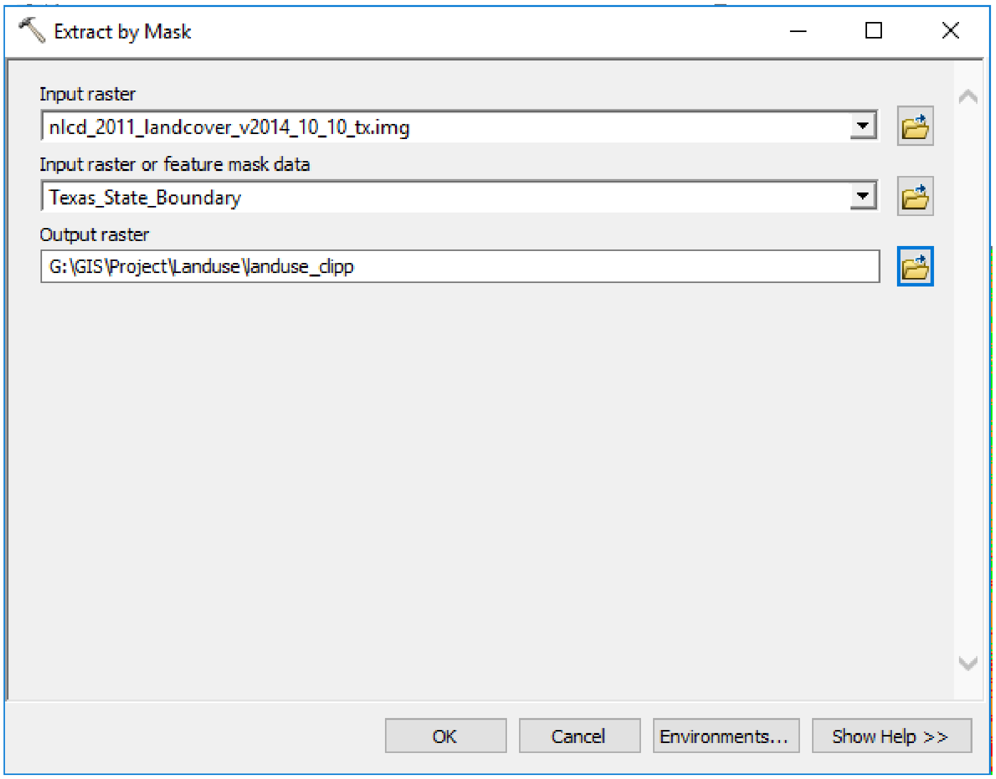


Figure 12: Extracting the land-use land-cover raster by mask

PART 2: Reclassify

The land-use data was also put into a ranking system based on qualitative reasoning. This part of the analysis was mostly executed to show what parts of the land are impossible to farm on (without major alteration to current landscape) i.e. high intensity development, open water, evergreen forest. In doing this, I realized that some of the categories, though not intentionally suited for farming (i.e. pasture/hay and cultivated crops) still had some sort of farming potential whether it be a backyard garden or mixed use land. This led me to choose a ranking scheme for this portion as well. This ranking scheme was enforced through raster reclassification. Table 1 (MRLC 2017) shows which land cover categories were included in the original data set as well as which rank was assigned to each. High rank (4) correlates to high potential for agriculture, while low rank (0) correlates to no potential for agriculture. This reclassification was done using the Reclassify tool as seen in figure 13.

Land Cover Number	Land Cover Classification	Raster Rank
11	Open Water	0
12	Perennial Ice/Snow	0
21	Developed, Open Space	4
22	Developed, Low Intensity	3
23	Developed, Medium Intensity	2
24	Developed, High Intensity	1
31	Barren Land	0
41	Deciduous Forest	0
42	Evergreen Forest	0
43	Mixed Forest	0
52	Shrub/Scrub	1
71	Grassland	4
81	Pasture/Hay	4
82	Cultivated Crops	4
90	Woody Wetlands	0
95	Emergent Herbaceous Wetlands	0
NoData	none	NoData
0	none	NoData

Table 1: Land-use Categories and Corresponding Raster Rank

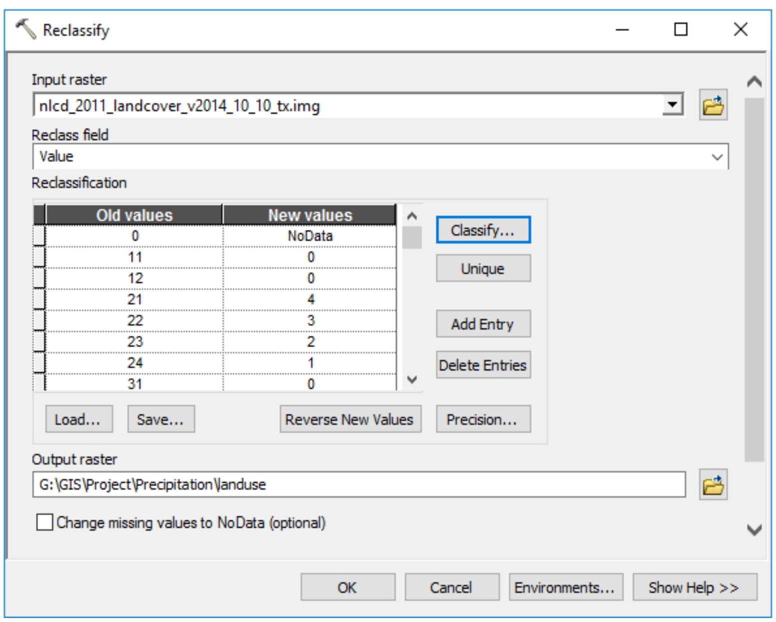


Figure 13: Land-cover raster was reclassified to attain ranks

The product of both of these steps is shown below in figure 14.

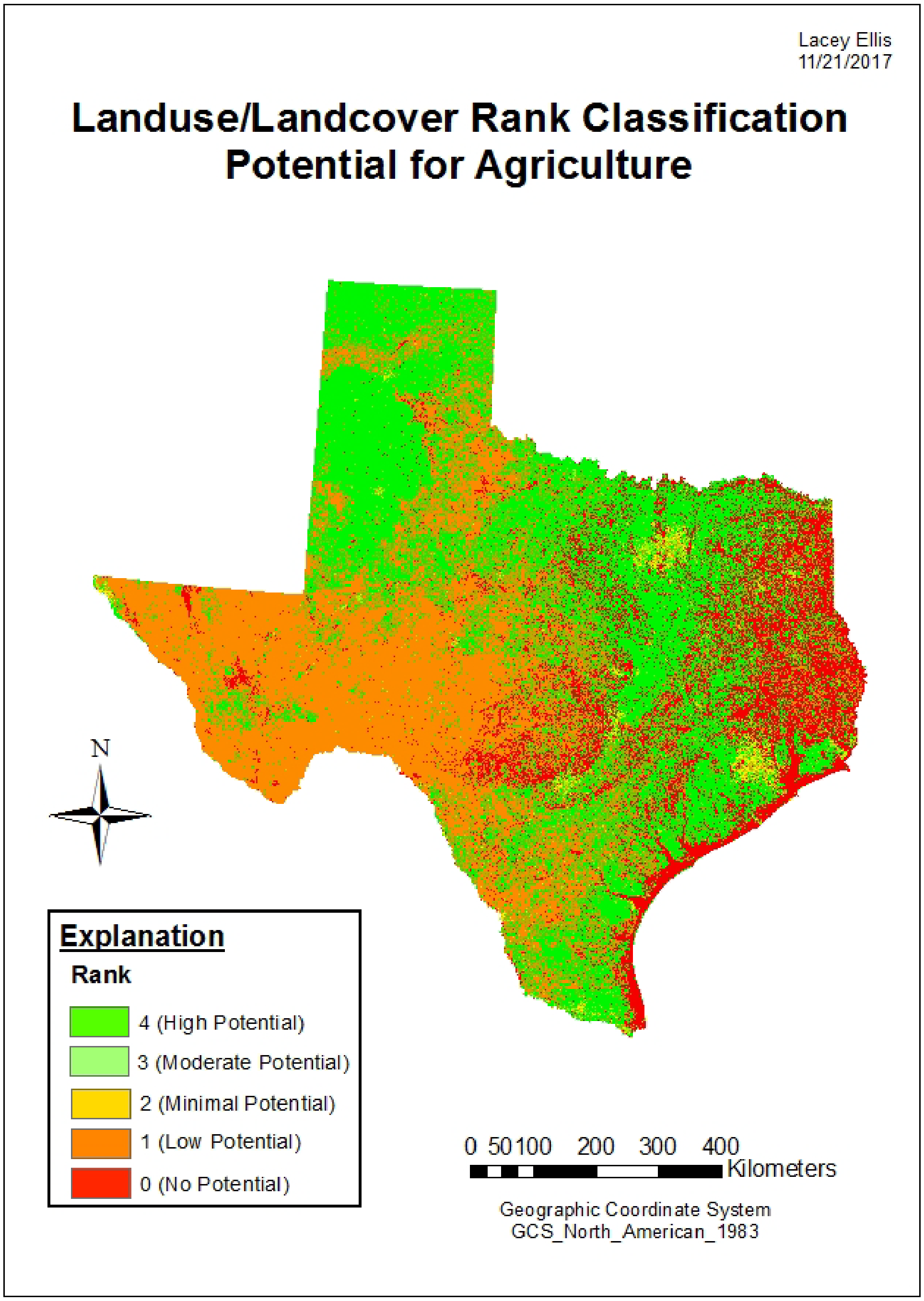


Figure 14: Reclassified Landuse/Landcover

4. Perform analysis

All of three rasters, land-use, soil type, and precipitation were combined with equal weights, as was intended when assigning initial ranks. This process is shown in figure 15.

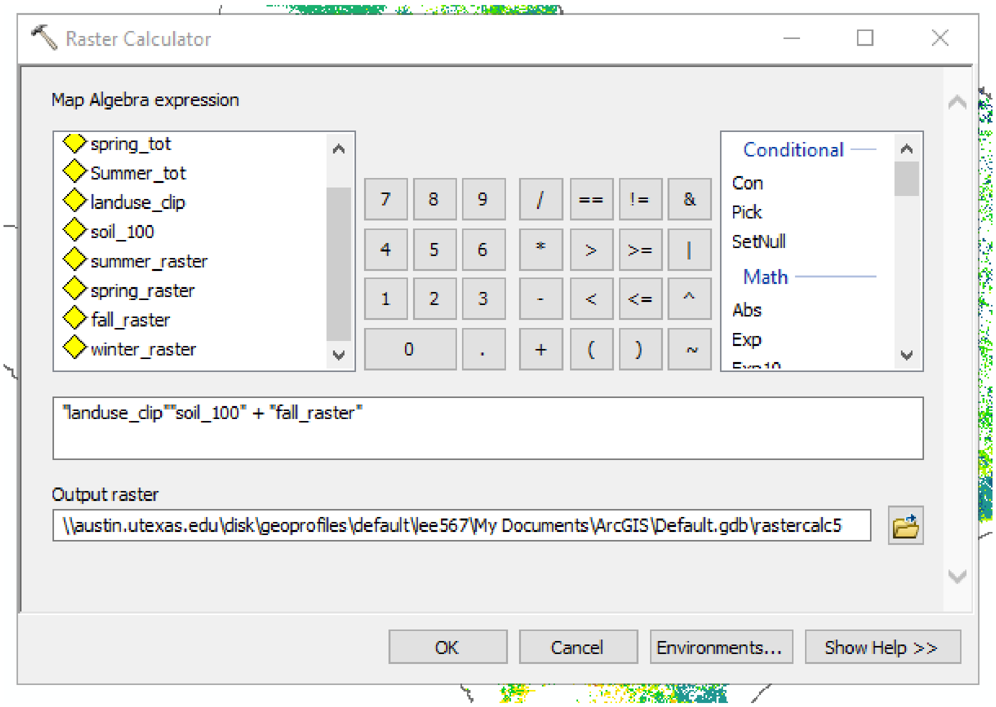


Figure 15: final combination of rasters

Since the raster cell size was 100x100, I used this to computer rough areas for each agricultural compatibility rank for each season. This was done by manually entering this data into excel and then calculating each area. (Table 2) This figure also shows the total amount of farmable area during each season. A weighted average was then performed on each of the seasons to determine the mean ranking of agricultural potential. For winter, spring, summer, and autumn, respectively, these were 5.55, 5.86, 6.82, and 6.08 out of maximum ranking of 12.

	Winter		Autumn		Spring		Summer	
Rank	Count	Farmable Area (km)	Count	Farmable Area (km)	Count	Farmable Area (km)	Count	Farmable Area (km)
0	14588	145.88	6605	66.05	11511	115.11	5759	57.59
1	629861	6298.61	170334	1703.34	609324	6093.24	67740	677.4
2	206206	2062.06	457623	4576.23	124211	1242.11	553257	5532.57
3	170709	1707.09	263595	2635.95	551033	5510.33	230712	2307.12
4	230418	2304.18	198338	1983.38	165796	1657.96	143825	1438.25
5	195316	1953.16	249678	2496.78	255871	2558.71	248869	2488.69
6	184941	1849.41	164052	1640.52	257661	2576.61	297760	2977.6
7	593891	5938.91	320184	3201.84	176370	1763.7	133299	1332.99
8	333164	3331.64	518022	5180.22	547318	5473.18	227107	2271.07
9	303122	3031.22	258673	2586.73	356204	3562.04	887532	8875.32
10	103336	1033.36	278726	2787.26	299445	2994.45	144465	1444.65
11	242681	2426.81	139060	1390.6	359738	3597.38	465146	4651.46
12	136	1.36	76934	769.34	0	0	91276	912.76
Total:	3208369	32083.69	3101824	31018.24	3714482	37144.82	3496747	34967.47
hted Averages of Ranks:		5.553422315		6.07902576		5.860813971		6.825458061

Table 2: Farmable area with rank and season

The final maps are below (Figures 16-19)

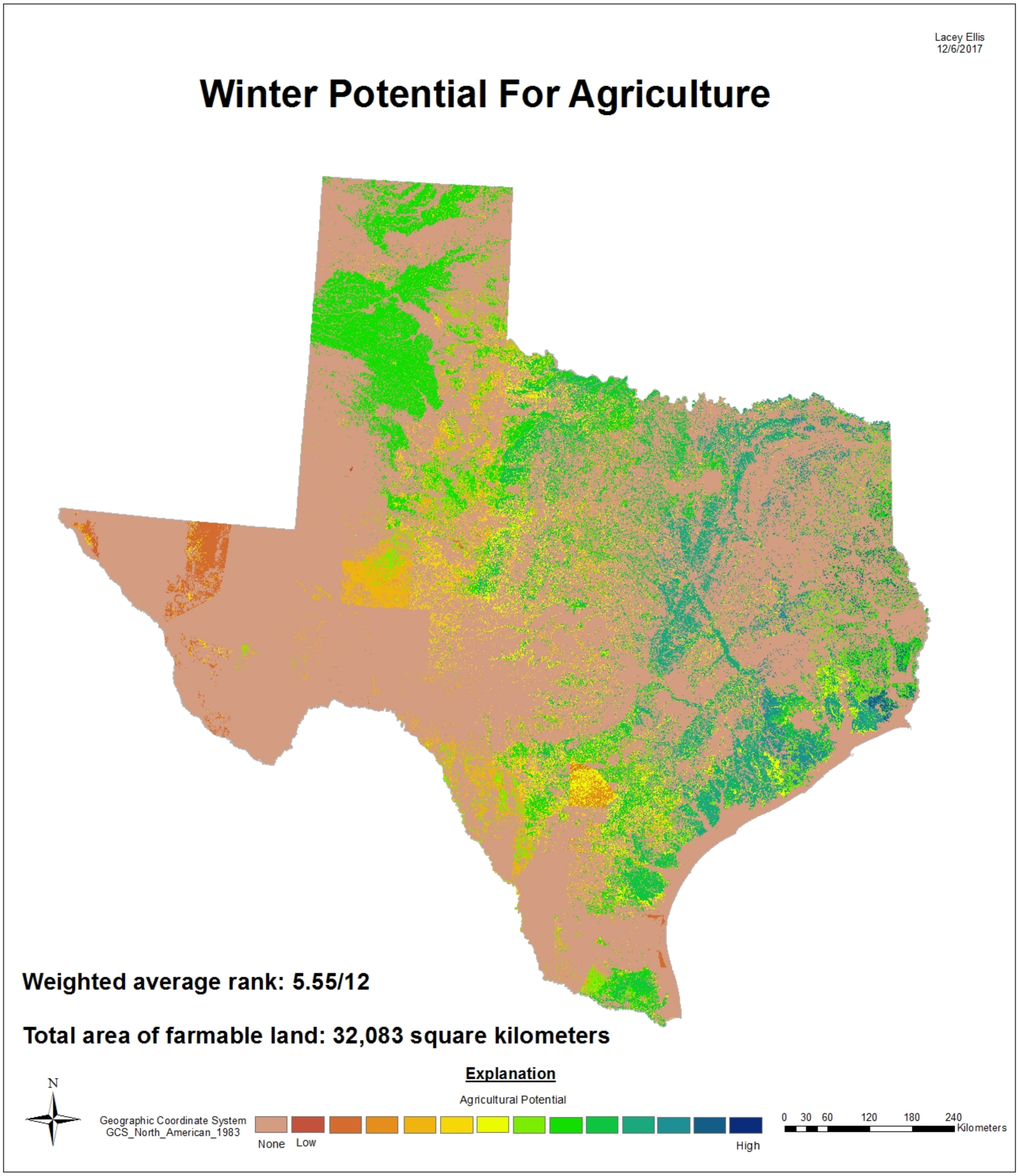


Figure 16: Winter Potential for Agriculture

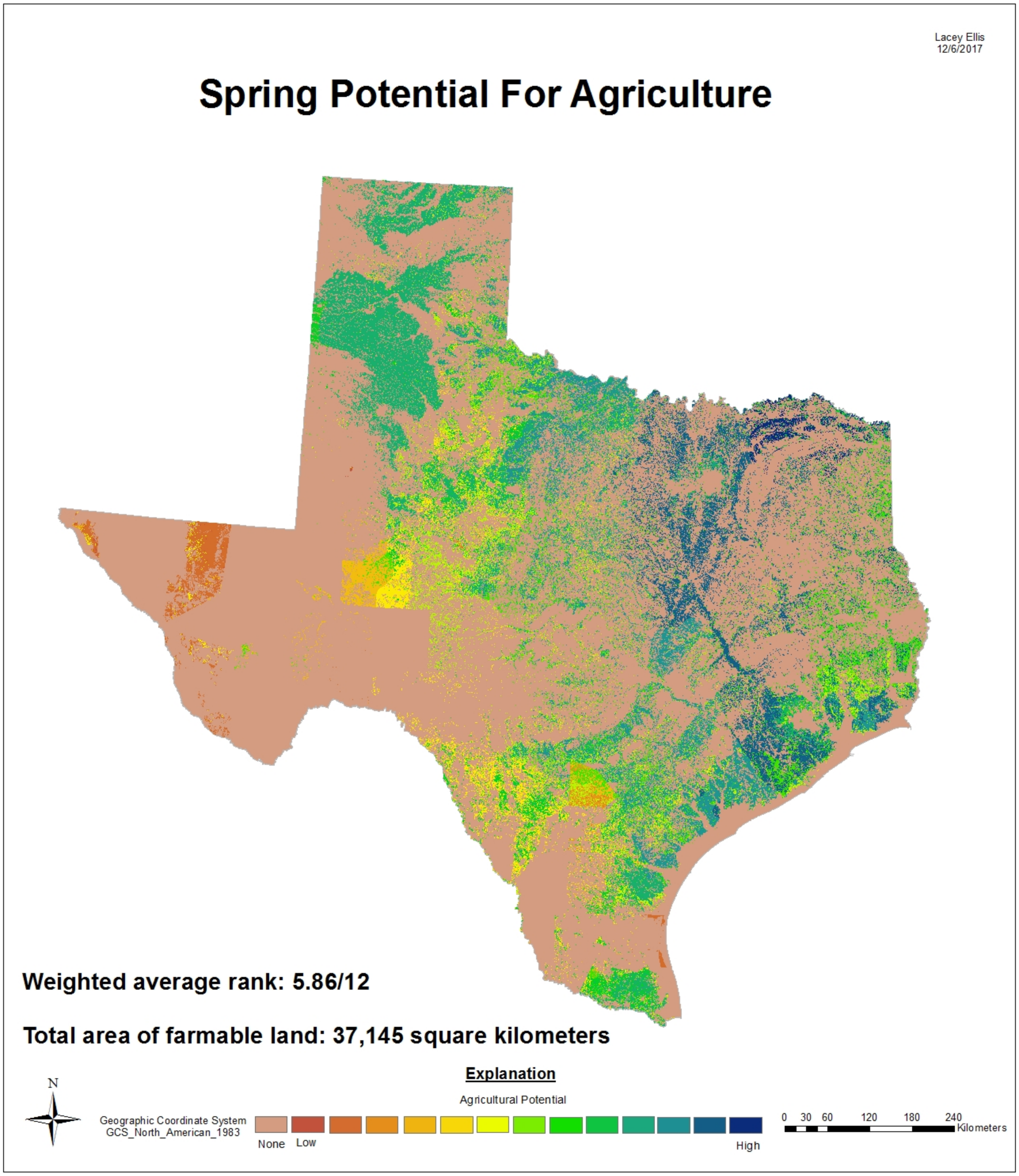


Figure 17: Spring Potential for Agriculture

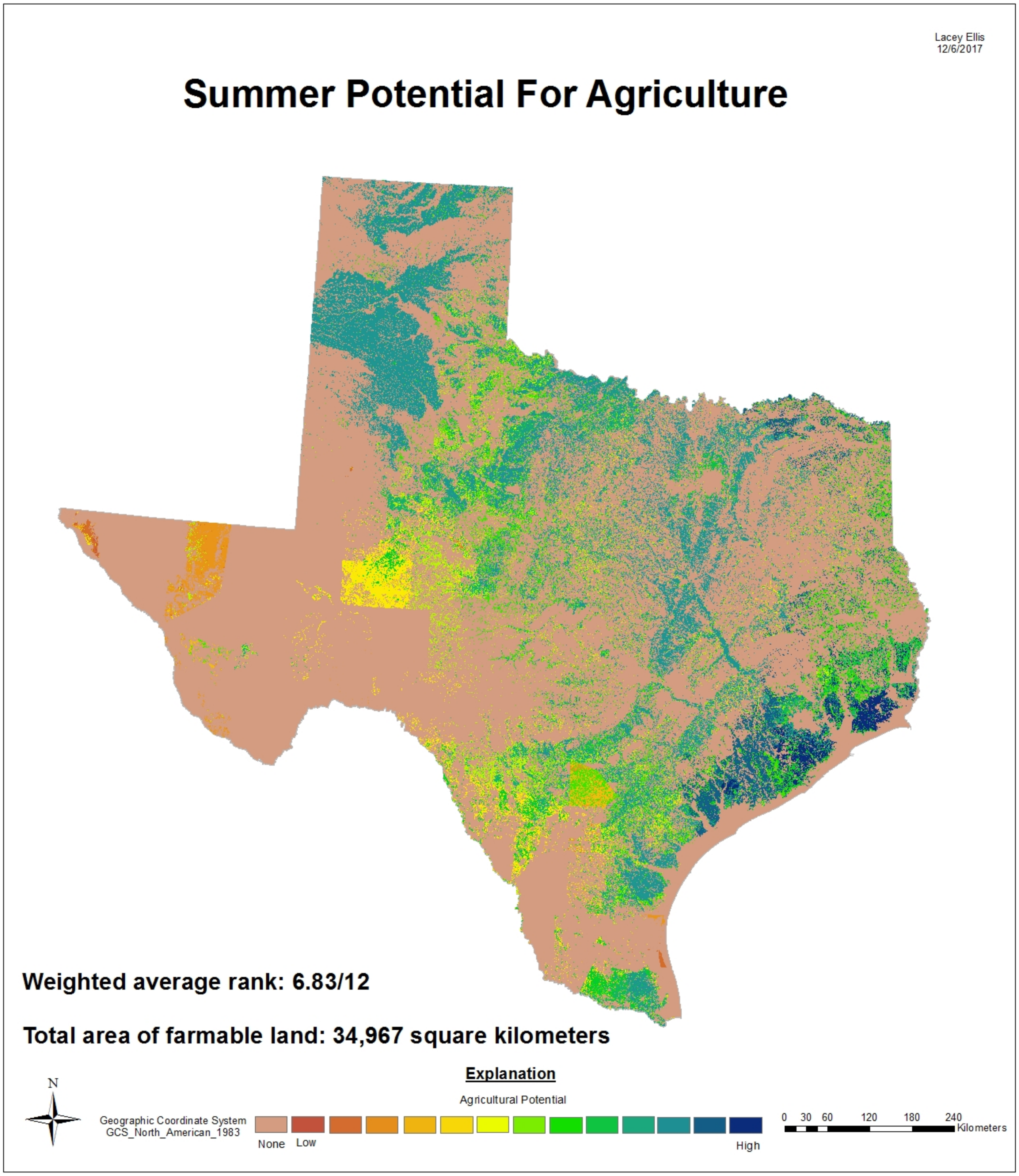


Figure 18: Summer Potential for Agriculture

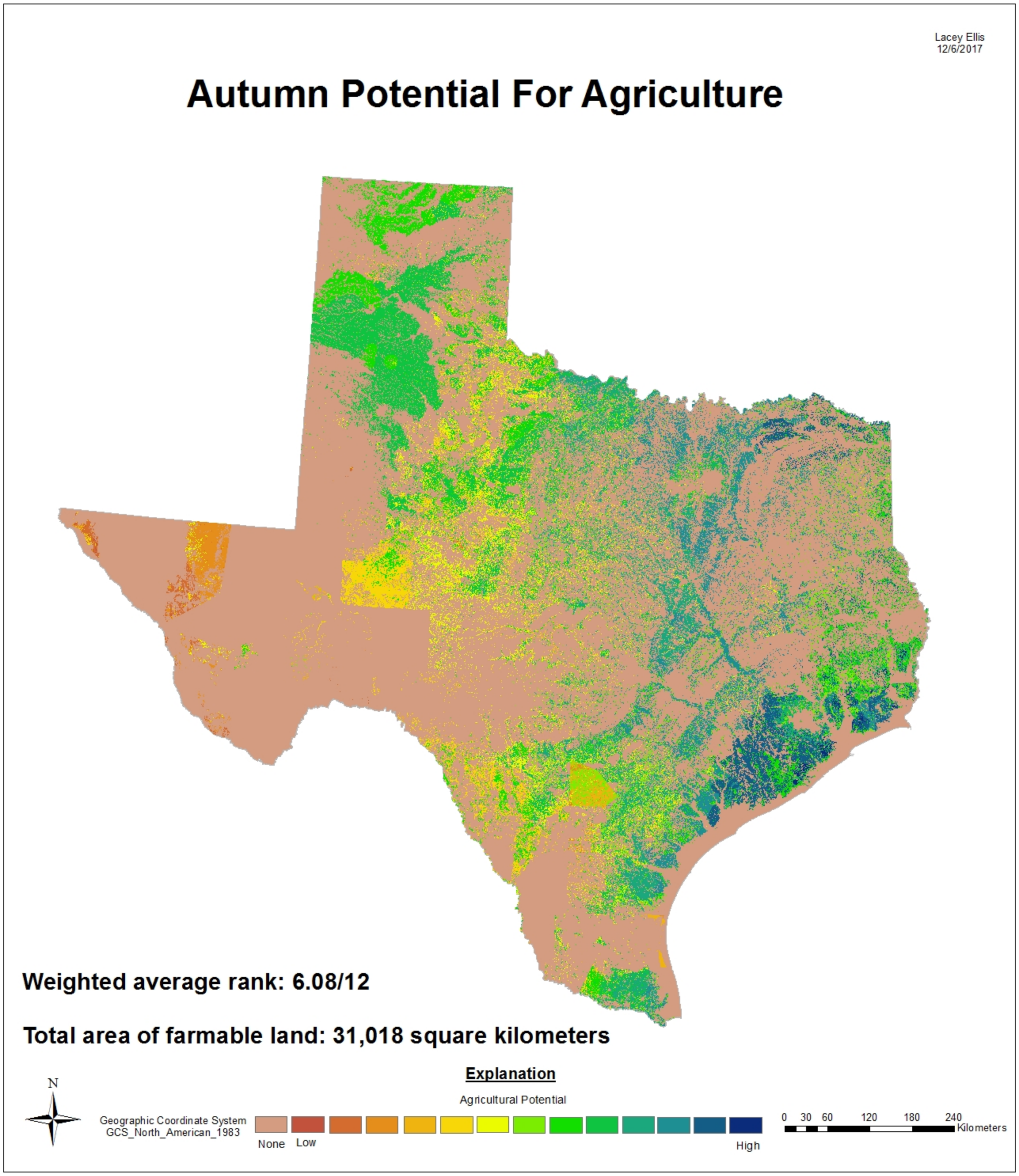


Figure 19: Autumn Potential for Agriculture

Different types of crops yield different amounts of calories per amount of area grown. Table 3 shows a range of these values (ACP 1981). These values were used to calculate various amount of calories produced per season. Days per season were based on the months included in these seasons (Winter = December +January+ February; Spring = March + April + May; Summer = June + July + August; and Autumn = September + October + November). These are shown in table 4.

Type of Food	Cal/ha/day	Cal/km^2/day
Sweet Potato	70000	700
Rice	49000	490
Wheat	40000	400
Lentil	23000	230

Table 3: Calories provided by different types of food

Food Type	Calories (Winter)	Calories (Spring)	Calories (Summer)	Calories (Autumn)	Calories per Year
Sweet Potato	2026887116	2392126408	2251905068	1975861888	8646780480
Rice	1418820981	1674488486	1576333548	1383103322	6052746336
Wheat	1158221209	1366929376	1286802896	1129063936	4941017417
Lentil	665977195.2	785984391.2	739911665.2	649211763.2	2841085015

Table 4: Calories potentially grown in Texas per season for various food

Given this very rough and approximate analysis, it is concluded that the state of Texas could produce much more than the necessary caloric intake. The necessary intake of calories per year, calculated in the introduction, is 21,400,000,000,000 (2.14x10^13) calories per year. The maximum yield that Texas could produce is 8,650,000,000 (8.65x10^9) calories per year. Sadly, this is not enough to sustain the population. Maybe if we partnered up with a friends in Mexico, we could. Urban, apartment, or roof-top gardens could also increase this yield. In the end, if each person grew enough for themselves, the problem would be solved.

5. Verify results (if possible)

Results cannot be validated with any existing data, as it is such a particular case study. There are many caveats that need to be mentioned. As discussed above, temperature was not included in this analysis, which also means that evapotranspiration was not included. If there is one day below freezing, it can alter crop yield to a large degree. Wind was not included, as it has less of an effect than the factors chosen. Additionally, this report does not evaluate the use of pesticides. The website that the calorie/day data was drawn did not indicate whether or not it included the use of pesticides or fertilizers. The seasonality of the crops was also not included. This is a very ideal analysis.

References

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