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Burgundy Terroir: A Regional GIS Comparison Between the Burgundy and the Willamette Valley Wine Regions

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A Major Individual Project Report submitted in partial satisfaction of the requirements
for the degree Master of Science in Geographic Information Systems

by:
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The report of Anthony J. Hewitt is approved.

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October, 2011

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I would first like to thank my family, especially my wife for her patience and encouragement through this whole process.

I would like to thank Professor Kumler for rescuing my project and daring to become my third advisor.

I would also like acknowledge Cohort 8 as the best cohort ever!

And most importantly, I would like to thank God, the original Cartographer and creator of Geography. Without whom we would not be able to make sense of this world. *"For from him and through him and for him are all things. To him be the glory forever. Amen."* Romans 11:36

"I am the vine; you are the branches. If you remain in me and I in you, you will bear much fruit; apart from me you can do nothing." John 15:5

Foreword

This project was completed in 2006 while Anthony was a student in the University of Redlands MS GIS Program. Completion of this report and the defense of his work were delayed while Anthony supported the U.S. Government's intelligence efforts in Iraq and Afghanistan.

Most of the technical work was completed using software that was at the time, state-of-the-art (ArcGIS 9.1). Although there are some technical differences in how this work would be completed with the current version, ArcGIS 10, the significance of the project and its results are unchanged. That alone attests to its value. The advisory committee gave him the highest possible grade.

Mark Kumler, Ph.D.
Chair of the Advisory Committee
Professor of Geographic Information Sciences
October 17, 2011

Abstract

Burgundy Terroir:
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by
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This project examines the concept of Terroir as a wine varietal's physical habitat. The famous European wine regions were assumed to represent the mother habitat characteristics for optimum varietal growth. This project specifically examined the Burgundy region of France in order to determine the physical characteristics required to grow the Pinot Noir varietal. Once these characteristics were determined, they were used to rate the suitability of the Willamette Valley, Oregon, to grow similar quality Pinot Noir grapes. The test region was found to be suitable, although did not match the source region suitability one hundred percent. Finally, a logit regression model was explored to ascertain the viability of this approach to rate an area as a vineyard or non-vineyard, and to further define the influence of individual physical aspects in rating a varietal area. The results indicated the logit regression model as a viable approach for varietal rating given higher resolution data.

x

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1.0 INTRODUCTION

No other food or drink has played such a pivotal role in the history of humanity as wine. Wine is a symbol of life in many religions and cultures. The Romans and Greeks had Dionysus and Bacchus, the gods of wine, showing the important role wine had in those ancient civilizations. In the Judeo-Christian belief, wine is very symbolic and plays an important role. Jesus' first miracle was to turn water into wine, and later used wine as a symbol at the Last Supper, as an example. Human cultures also saw wine as an important dietary and medicinal substance. Romans perfected the mass production and trade of wine owing to the massive size of the empire. As the empire spread, so did the need for wine resulting in the diffusion of vineyards throughout Europe (see Figure 1). After the main grape varietals were established in Europe, western civilization spread throughout the globe, colonizing wild foreign lands and taking their vines with them. European settlers took vines with them for religious, medicinal, and culinary purposes. In those new locations, some of the cuttings succeeded while others failed, and in this way; the settlers incrementally created the new world wine regions.
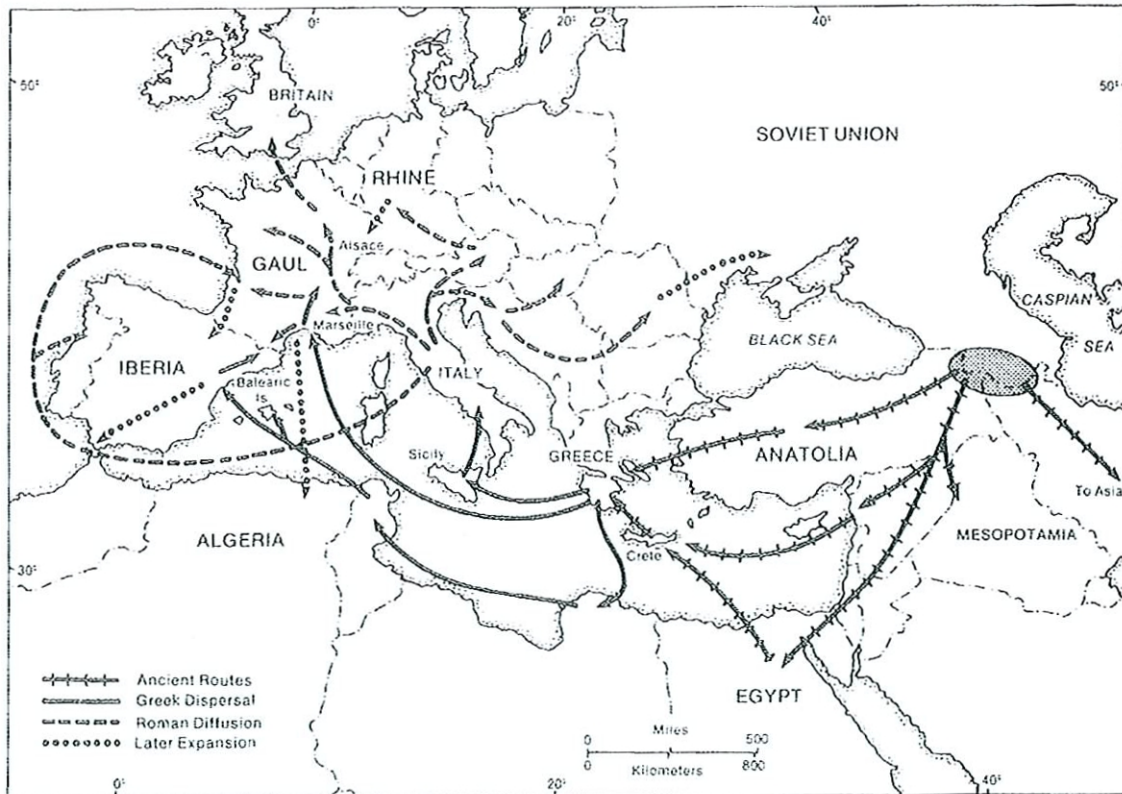
Figure 1 Expansion of Viticulture (de Blij, 1983, p. 115)

1.1. Terroir

The reason vines succeeded in certain areas is because those areas possessed the right terroir. No discussion of vineyards can be complete without addressing the concept of Terroir. Jacques Fanet defines terroir as the "Subtle interaction of natural factors and human skills that define the characteristics of each wine growing area"(Fanet, 2004). Put another way, it is the geographic thumbprint left on a wine

from a particular region which influences taste and quality. This study will define terroir as the physical or natural growing conditions of the wine region such as climate, soils, elevation, and latitude. This kind of definition more readily lends itself to GIS analysis, whereas the human factor is much more difficult to define and analyze. This project will look at Terroir in terms of natural habitat - where a particular varietal will thrive given the right natural conditions.

1.2. Client and Problem Statement
The classic wine regions of Europe are often seen as the ideal natural habitat for particular grape varietals: Burgundy, France for Pinot Noir, La Rioja, Spain for Tempranillo, and Rheingau, Germany for Riesling, are just three examples. As the Europeans spread and colonized the new world, they took their vines with them. The new world regions in which the varietals produced excellent wines closely match the terroir, or habitat, of the source varietals in mother Europe. This is the theory of the project client, Dr. Tim Krantz, an environmental sciences professor at the University of Redlands and a wine enthusiast. Dr. Krantz would like to explore his theory using Geographic Information Systems (GIS) analysis. The project's charge is to use GIS to analyze source varietals' terroir to model the critical geographic elements necessary to produce excellent wines, and to rate the suitability of new areas to grow similar quality wines. This study will analyze the pinot noir region of Burgundy, France, and apply it to the Willamette Valley of Oregon. To accomplish this, the project will produce a database to support analysis and cartography for the client's book.

1.3. Literature Review
Modern geographical studies of Terroir started in the 1930's, when Amerine and Winkler used degree days to distinguish ripening capacity areas in California (Amerine & Winkler, 1944). Their study initiated the modern era of varietal selection and growing based upon climate and geographic location ("Viticulture & Enology", 2007). In the 1950's, Olmstead created a U.S. scale inventory map of Orchards and Vineyards, using agricultural census data. He used the maps to explain current trends and factors influencing agricultural distribution (Olmstead, 1956). Tukey and Clove evolved grape suitability study farther with an early GIS-like analysis, using tables of attributes to determine grape suitability in Washington State. They used factors such as frost-free days, heat units, soil attributes, and precipitation in their study (Tukey & Clove, 1973). The published studies of the 1980's laid the groundwork for the application of GIS to viticulture. Geographic works, like de Blij's, summarized key viticultural geographic features, thereby inadvertently forecasting data needs for GIS analysis (de Blij, 1983). This time period also saw geographic factor refinement. Researchers determined latitude related variables as useful in regional separation of cultivars (Jackson & Cherry, 1988, p. 22). The use of GIS in the 1990's took viticulture studies to the next level. Practitioners started to use GIS in all aspects of oenology study: from site suitability analysis to micro vineyard disease and maintenance analysis. A pertinent example includes Watkins's work on 'Vineyard Site Suitability in Eastern California'. This study looked at the potential for GIS use in viticultural land suitability analysis for a Zinfandel growing area of California, by examining the significance of several vineyard and non-vineyard site variables (Watkins, 1997, p.

230). Watkins uses topographic, soil, and geology variables in his study, but did not include climate factors (Watkins, 1997, p. 234). Vineyard site suitability analysis continued to evolve into the present decade with Jones, Snead, and Nelson's GIS study of the Terroir Potential of the Umpqua Valley, Oregon, being a prime example (Jones, Snead, & Nelson, 2004, p. 170). This analysis incorporated factors from three important elements: topography, soil/geology, and climate. The authors filtered the data with accepted academic and local vintner expertise in determining potential vineyard sites in the Umpqua valley.

This study will draw on previous literature, but will differ in three significant ways. The study will use sample data from the 'mother' Pinot Noir terroir region, Burgundy France, to determine suitable characteristics for measuring against a test area, instead of expert opinion and accepted values. At the client's request, this study will examine soil-water balance as a suitability factor, an element which has been absent in previous research, except in irrigation calculation studies. Finally, this study will explore using logit regression in separating vineyard regions from non-vineyard regions, a somewhat novel approach in vineyard suitability studies.

2.0 DATA METHODOLOGY

Three factors influenced the project's data requirements analysis: literature review, the client's direction, and freely available data. The client specifically wanted to use the soil water balance as an important wine growing factor. The client believes that the vines must suffer during the latter part of the growing season to produce quality grapes. The soil water balance will show if and when the soil contains a surplus or deficit of water available for plant use. The client had no data for the execution of the project. Because of this, much of the time spent early on in the project focused on finding free data, and determining what analysis could be done with it. Finding free GIS data in Europe is a challenge, because most European national level mapping agencies charge for data access and licensing. Data discovery becomes even more of challenge with the language barrier. A few national level agencies may have limited English translations for a few of the basic introductory web pages, but the pages containing the data, deep within the websites, are usually in the native language. A very useful tool in the search for data is Google's Language tools which translate web pages and words to and from a number of languages. Free data covering the Oregon Willamette Valley area was much easier to find and access. The data discovered determined this study would be a regional analysis using the following important physical geographical terroir elements of climate, soil, soil water balance, and topography.

2.1 Climate Data
Climate plays an extremely important role in growing wine grapes, especially in France where irrigation is prohibited by the Institut National des Appellations d'Origine (INAO) (Gade, 2004, p. 852). The Bordeaux area, being on the coast, enjoys a temperate maritime influenced climate. Burgundy, however, experiences a slightly more extreme climate as it lies in a transition area between the continental and maritime climate zones. "Climatic factors are essential for the growth of the vine and the final ripening of the grapes, irrespective of other environmental factors" (Pomerol, 1986, p. 73). The sun (temperature and latitude) is vital to grape vine health and fruit maturation (Bohmrich, 1996). Precipitation provides the necessary water to sustain the vine (Van Leeuwen & Seguin, 2006, p. 7). Climate is an important factor of Terroir and should be incorporated into any regional wine study.

Raw climate data used in this study consisted of temperature and precipitation data collected at multiple weather stations and averaged over a period of 20 years. The intended use for the climate point data was to interpolate temperature and precipitation surfaces over the areas of study.

French climate data came from Meteo France, www.meteo.fr; France's national Weather and Climate service. The standard French climate product used for the project is entitled "Fiche Climatologique, Statistiques 1971 – 2000 et records". See Appendix D for an example fiche. The project digital data files will include all fiches acquired and used in the study. The French data came in either a PDF or text fiche style format and included the following common attributes: weather station name and coordinates;

precipitation in millimeters; maximum, minimum, and mean temperatures in Celsius. Other attributes which the fiche may include are: record temperature and precipitation events, degree days, solar radiation, potential evapotranspiration, wind speed and direction, and number of days with fog, hail, or snow. These other attributes were far less complete on the fiches, with only a few weather stations actually recording data for them. The temperature and precipitation data was by far the most complete, and the only data the study used because of the spatial extent needed to cover the wine growing regions. Normally Meteo France charges for the climatology fiches; however data was acquired at no charge for a student's academic project from Olivier Mestre, Olivier.Mestre@meteo.fr. Normally, Meteo charges €8.20 per station for an academic research license; commercial use is even more costly.

Climate data for the American test areas came from the Western Regional Climate Center (WRCC), http://www.wrcc.dri.edu/index.html. NOAA funds and administers these regional climate centers. The WRCC offers a plethora of daily and monthly data organized by station discovered through a clickable map interface for free. Even though an overabundance of data attributes exist per weather station, only monthly precipitation, and monthly mean, maximum, and minimum temperature data were used for the study in order to match the data layers collected and created for France.

2.1.1 Climate Data Preparation
The French data was copied straight from the electronic fiches and pasted into a master Excel document consisting of records of climate stations by rows, monthly attributes and coordinate information in columns (Table 2.1).

Table 2.1 Excerpt of Climate Data Spreadsheet

Station	P_Jan	P_Feb	P_Mar	P_Apr	P_May	P_Jun	P_Jul	P_Aug	P_Sep	P_Oct	P_Nov	P_Dec
BAZAS	79.60	76.80	70.60	76.60	84.00	62.20	54.30	56.80	69.50	75.00	86.60	87.30
LE BARP	99.10	81.30	71.40	84.90	79.10	69.90	53.60	53.20	89.10	104.70	119.80	121.70

Data were organized this way to facilitate the creation of interpolation surfaces for each month, using Geostatistical Analysis. The spreadsheet was saved as a database IV file (.dbf) to enable ingest by ArcGIS. Once the .dbf file was added to an ArcMap document, the table was converted to a feature class using the 'Add XY' event tool and exported to the appropriate feature dataset within the France Geodatabase.

The U.S. climate data was handled in much the same way as the French climate data, except that instead of copying the data from a fiche, the data were copied straight from the website and pasted into a spreadsheet.

2.1.2 Geostatistical Analysis for Climate Surfaces
To generate the climate surfaces, the ArcGIS Geostatistical Analysis extension tool was used. This tool was chosen because of its data exploration tools and wizard to assist in the process, as well as the tool's ability to produce error statistics, along with the results, to give a measure of confidence. Steve Lynch of ESRI, a product engineer who works with the Geostatistical Analyst extensions, recommended Kriging (Lynch, 2006) because of its sophistication and ability to produce smother surfaces than Inverse Distance Weighting (IDW). The study used the following surface fitting

methodology: Represent Data, Explore Data, Fit a Model, Perform Diagnostics, and Compare the Models (ESRI, 2004, p. 18). The following sections will show examples from each step in the surface fitting methodology

2.1.2.1 Represent Data: The data are initially represented as points, given the real-world phenomena are collected as points at each weather station location.

2.1.2.2 Exploring Data: Data is explored using the Geostatistical Analyst Data Exploration tool. The first step in data exploration is to check to see if the data are normally distributed. The Geostatistical Analysis extension gives two exploration techniques to determine the distribution: the Histogram and the QQ plot. The QQ plot (Figure 2.1) is a check to see how close the data are to a normal distribution. The closer the points fit the straight line, the more the data is normally distributed (ESRI, 2004, p. 20). As you can see from figure 2.1, the precipitation data example is nearly normally distributed. If the data are not normally distributed, then the analyst may perform a transformation on the data before generating the interpolated surface in order to get it closer to a normal distribution. This is accomplished as a step in the Geostatistical Analyst wizard.
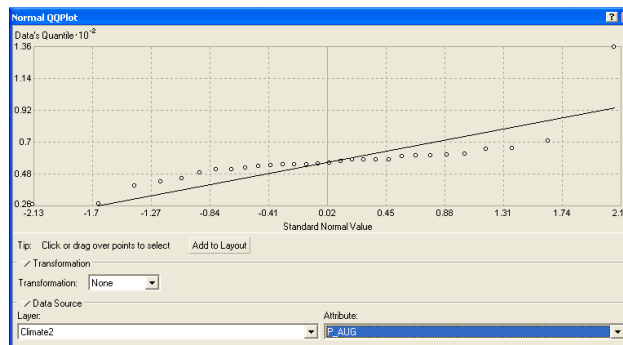
Figure 2.1 Normal QQ plot for Bordeaux Precipitation

Trend Analysis
Trend analysis is done to look for global trends which may dominate the distribution and over-ride or minimize the affect of spatial autocorrelation of local points. Using the Trend Analysis tool, one can look for global trends in two direction planes, North-South (Y) and East-West (X). The tool plots a best fit curve between the points. If the curve is relatively flat, then no trend exists. If there is a pattern, such as an upward trend, downward trend, or a curve, then a global trend may exist across the data set.

In the Burgundy Figure 2.2 below, we see a trend from the outlying data points in the four cardinal directions. This is most likely due to the outlying points being from a different data set. These points were brought in to stretch the interpolation outside the study area and should not affect the interpolation around the main data point core. This trend exists in all of the precipitation and temperature fields.
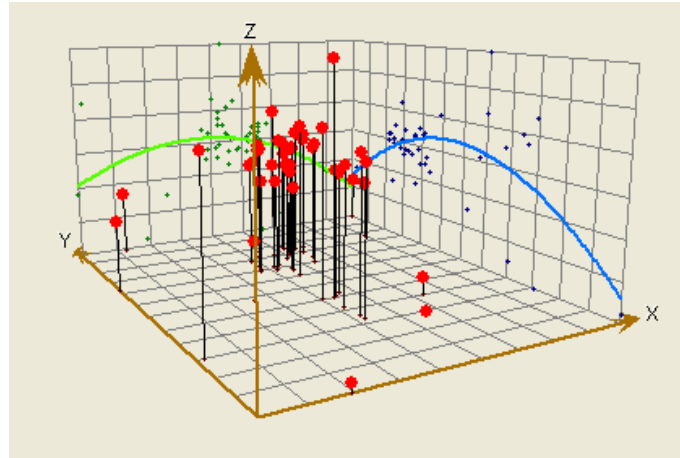
Figure 2.2 Trend analysis for Burgundy's precipitation

The Geostatistical Analysis tools provide the Semivariogram to look for outliers and anisotropy within the data. The Semivariogram depicts pairs of points with distance between them plotted on the X axis and value difference plotted on the Y. This pairing shows the spatial autocorrelation of the data. Global outliers would appear as a separate cluster strata of data points above the main point cloud. Local outliers would appear as just a couple of dots above the main cloud. Anisotropy is local directional variation in the data which cannot be explained by outside processes. Anisotropy is found by using the search direction function of the Semivariogram tool. The tool lets you look at the data in different directions on the semivariogram surface. If there is a rapid change in the variance (data cloud) in one direction versus another, then you have anisotropy. Figure 2.3 below shows an example of the tool's semivariogram exploration.
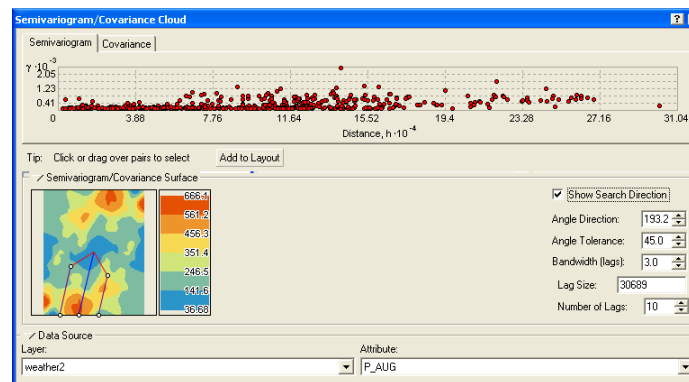
Figure 2.3 Burgundy August precipitation

No outliers were discovered in the data; however, some of the months did show anisotropy. The anisotropy was compensated for by checking the anisotropy box during the Geostatistical wizard process.

2.1.2.3 Fit a Model

Two models were fit initially to compare them. They were Inverse Distance Weighting (IDW) and Ordinary Kriging.

2.1.2.4. Perform Diagnostics

In performing Diagnostics, the goal is to get the most accurate surface. The Geostatistical Wizard's last page produces a measure of the accuracy of the surface and provides statistics and a chart upon which the accuracy is based. The goal is to get the Mean Error as close to 0 as possible and to get the Root Mean Square Standardized Error as close to 1 as possible. To achieve or improve accuracy, a number of parameters can be adjusted through-out the Geostatistical Wizard. One parameter is the Transformation parameter (Step 1 of the wizard), which transforms the data using a Log or a Box-Cox transformation to make the data more normally distributed. During data exploration, one would determine the need of this parameter. Another parameter used to improve accuracy was the Anistropy checkbox in the Semi-Variogram page of the wizard (Step 2 of the wizard). Checking this box removes any non-attributed directional trending of the data. Again, the need to do this comes from data exploration phase of Geostatistical Analysis. The last parameter adjusted was the size and shape of the searching neighborhood (Step 3 of the wizard) used to compare and estimate values. Dependant upon the data exploration and initial results, all, some, or none of these three parameters were adjusted to improve the accuracy of each surface generated.

2.1.2.5 Compare the Models

Both the Inverse Distance Weighting (IDW) and Ordinary Kriging models were generated using the Geostatistics wizard. IDW produced similar prediction results, but the surface was not as clean or smooth as the Kriging (Figure 2.4). Not only did Ordinary Kriging yield a more realistic surface, given that the data are continuous, but it also produces uncertainty statistics.
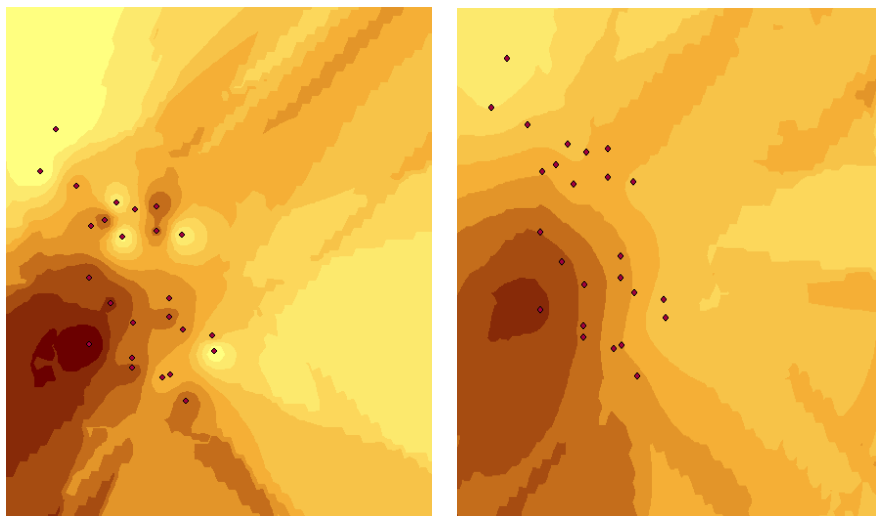
Figure 2.4 with IDW on the left and Ordinary Kriging on the right

Cross Validation Comparison

Compare: Inverse Distance Weighting   To: Ordinary Kriging

Predicted | Error

Predicted | Error | Standardized Error | QQPlot

Regression function: 0.212 * x + 57.421

Regression function: 0.191 * x + 58.956

Prediction Errors
Mean: 0.1118
Root-Mean-Square: 5.515

Samples: 24 of 24

Prediction Errors
Mean: 0.1368
Root-Mean-Square: 5.573
Average Standard Error: 5.579
Mean Standardized: 0.01969
Root-Mean-Square Standardized: 0.9955

Samples: 24 of 24

Close

2.1.2.6 Results

The result of the Geostatistical process was monthly surfaces generated for precipitation and mean average temperature using Ordinary Kriging. Separate surfaces were created for each area of study from the acquired weather station data. The precipitation surfaces were generated for each month of the growing season (April through October). The Potential Evapotranspiration model requires mean average temperature; therefore, mean temperature surfaces were generated for every month of the year. All months were required for the Potential Evapotranspiration model to generate the heat index used in equations. The following section explains Potential Evapotranspiration in further detail. The interpolation resulted in surfaces with a cell size of 818 meters for the Burgundy region of France and the cell size for the Oregon surfaces was approximately 1000 meters.

2.2 Soils

Soils are an important part of the Terroir concept (Gade, 2004, p. 849) and can influence vine health and wine flavor (Van Leeuwen & Seguin, 2006, pp. 5,6). The traditional wine grape growing countries, France, Italy, and Germany, all consider soil an "essential factor" in appellation boundary delineation (Berry, 1990).

2.2.1 European Soils Database

Soils Data for Europe came from the European Union's Joint Research Center's European Soils Database found at: http://eusoils.jrc.it/Data.html. The point of contact was Marc Van Liedekerke. The Soils database covers most of Europe (Figure 2.5) at 1km resolution.

Figure 2.5 European Soils Database Coverage

2.2.1.1 European Soils Database Organization
The database is in raster format with Soil Mapping Units (SMU) as the raster value. Multiple tables are related to the SMUs via Soil Typological Units (STU) (Figure 2.6) containing multiple attributes such as soil type, parent material, and obstacle to roots.
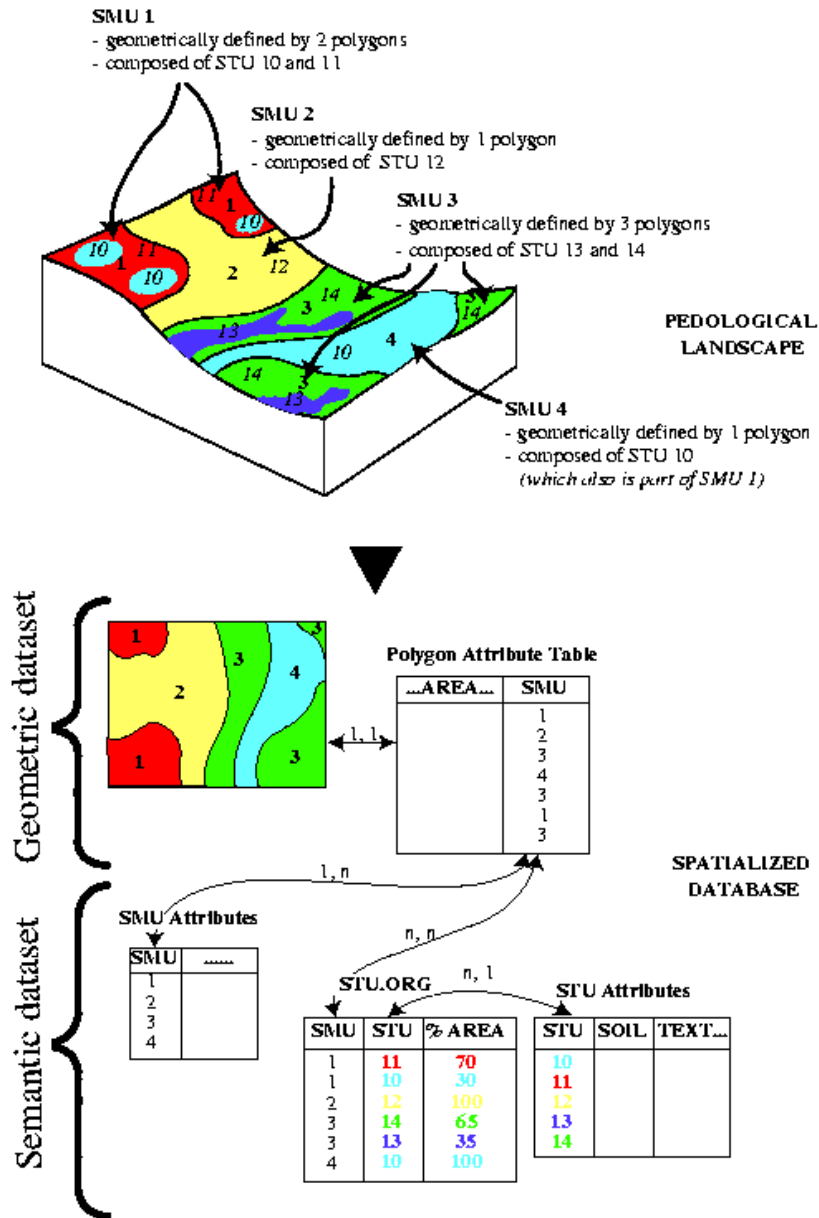
Figure 2.6 Soil Database Organization (Land Management & Natural Hazards Unit, 2006)

2.2.1.2 European Soil Data Extraction Methodology

The attributes extracted from the European Soils Database included Available Water Holding Capacity (AWC) in millimeters, Texture (TEXT1), Depth to Rock (DR) in millimeters, and Food and Agriculture Organization 1985 (FAO 85) soil type. Water holding capacity was chosen because of its importance to vine growth and fruit production affecting the quality and quantity of wine produced (Berry, 1990). Rice argues that "Texture is soil's most important physical property for grape growing, since it influences water holding capacity, root growth, and overall vine vigor" (Rice, 2002). Depth to Rock is a good attribute that captures a number of desirable soil qualities

including root depth and drainage (Tukey & Clove, 1973, p. 7). The study looked at soil type to see if it was important in growing similar grapes in other regions or if only the soil attributes matter. These attributes were chosen because of their importance in wine growing, as stated by the literature, and because these attributes also exist in the State Soil Geographic (STATSGO) database of the United States. The European Soil database raster of the Soil Mapping Units was first clipped to the France feature class using the Extract by Mask tool located in the Extraction toolbox of the Spatial Analyst Tools resulting in producing only the Soil Mapping Unit raster file of France. The soil attribute tables are linked to the soil raster file through the Soil Mapping Unit value given each raster cell. With vector data, one could easily perform a Join and then export the data as a new file. A relate is possible with raster data, but exporting the related table to a new data set is not. To get around this problem, a reclassification was done using the 'Reclass by Table' tool located in the 'Reclass toolbox' within the Spatial Analyst tools. The result was a separate raster data set for each desired attribute over the area of interest with 1000 m cell size. The Soil-Water balance equation used the soil Available Water Holding Capacity raster as an input. The remaining soil attribute raster surfaces were inputs into the Sample tool, the next step of the analysis, to determining the dominant terroir values of the Burgundy area.

Soil attributes and definitions followed the convention shown in Tables 2.2 and 2.3.

Table 2.2 Texture Attributes

Attribute	Attribute Definition
0	No Information
1	Very Fine
2	Fine
3	Medium Fine
4	Medium
5	Coarse
6	No Texture

Table 2.3 Depth to Bedrock Attributes

Attribute	Attribute Definition	Original Attribute
0	Null/NA	
1	0 – 40 cm	S
2	40 – 80 cm	M
3	80 – 120 cm	D
4	>120 cm	VD

The following table lists the possible attribute codes for the soil types found in the France subset of the European Soils Database, using the FAO 85 soil type coding and the value assigned in the raster (Table 2.4).

Table 2.4 FAO 85 Attribute codes for France

Value	Fao85_full		
1	Re	37	Jd
2	Dd	38	Poh
3	Je	39	Wd
4	Jcg	40	Plh
5	Lc	41	Gev
6	Be	42	Zg
7	Jc	44	444
8	111	45	Dg
9	Lo	46	Bv
10	Bk	47	Bh
11	Eo	48	De
12	Oe	49	Bcc
13	Jeg	50	Rd
14	Qc	51	Bkh
16	333	52	Ic
17	Gh	54	Ich
18	D	55	555
19	U	56	Bg
20	Bd	57	Hc
21	Po	58	Gd
22	Lg	59	Qcd
23	Ql	60	E
24	Bec	61	Id
25	Od	62	Th
26	Ge	63	I
27	Beg	64	La
28	Pg	65	To
29	Lgs	66	Jcf
30	Bkv	67	Ph
31	Bvc	68	Ie
32	Bc	69	Qld
33	Bev	70	Zo
34	Bgv		
35	Pl		
36	Vp		

A conversion table exists to convert the FAO soil types into the US STATSGO soil types (Deckers, Nachtergaele, & Spaargaren, 2003).

2.2.2. State Soil Geographic (STATSGO) database

The STATSGO GIS soil database of Oregon came from the United States Department of Agriculture's (USDA) Natural Resources Conservation Service (NRCS) website http://www.soils.usda.gov/survey/geography/. This website is a valuable resource for soil data of the continental United States. This website offers both the STATSGO GIS data and the Soil Survey Geographic (SSURGO) GIS data. The STATSGO GIS dataset was used because it is a regional scale (1:250,000 scale) dataset more in line with the scale of the European Soils. The STATSGO database covers the entire US and is broken up by state. All are available at the 1:250,000 scale, except Alaska which is at the 1:2,000,000 scale.

2.2.2.1 STATSGO Database Organization

The STATSGO database comes in ESRI Shapefile vector format from the NRCS website with several attribute tables. The tables are related to the spatial vector through the MUID (Map Unit ID) attribute, much like the SMU (Soil Mapping Unit) of the European Soils database (Figure 2.7). Some tables relate directly to the MUID, such as the Component table, because they describe the SMU as a whole.
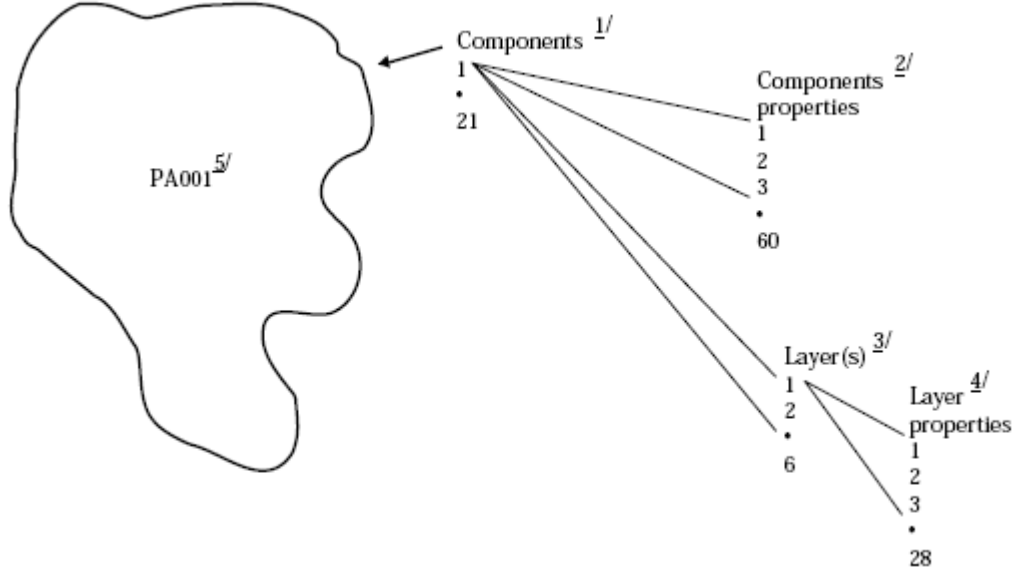
Figure 2.7 STATSGO Organization (USDA, 1995, p. 9)

Other attributes must be aggregated and then related to the MUID, such as the Component Properties or Layer Property tables, because they represent sub-strata (or layer) within the SMU. The layer tables represent the lowest level in the database schema, and must be aggregated in order to relate them to the map unit (MUID).

2.2.2.2 STATSGO Data Extraction Methodology

The attributes from the STATSGO tables which most closely approximated the European Soil Database attributes were the following: 'awcl/awch' (Available Water Capacity Low/High) from the Layer table, 'SURFTEX' (Surface Texture) from the Comp (Component) table, 'ROCKDEPL/ROCKDEPH' (Rock Depth Low/High) from the Comp (Component) table, and 'ORDER' (Soil Order) from the 'TAXCLASS' (Taxonomy) table.

To get an Available Water Holding Capacity for the whole map unit (muid), the 'awcl' and 'awch' had to be aggregated over the layer and then summed for each sequence of layers. To perform the calculations, the layer table was brought into MS Excel. First the weighted average for the soil layer is calculated using the following equation:

$$wtavg = (laydeph - laydepl) \times \frac{(awcl + awch)}{2}$$

Equation 2.1 Weighted Water Holding Capacity for Each Layer (USDA, 1995, p. 11)

Where laydepl and laydeph represent the lower and upper limit of the layer's depth, awcl and awch represent the low and high measure of the water holding capacity, and wtavg is the total inches of water available in each soil layer. Laydepl, laydeph, awcl, and awch are fields in the layer table, standard in STATSGO data. Once the wtavg is found, it is summed over each layer sequence to find the available water holding capacity for the map unit (muid) (USDA, 1995, p. 11 & 12). Since over 9000 records are involved and the sequence varies, a Visual Basic macro was written within the excel framework to calculate the sum (Equation 2.2).

```
Sub seq()
x = 2
i = 0
z = 0
y = Cells(x, 1).Value
Do While Cells(x, 1).Value <> ""
    If Cells(x, 1).Value = y Then
        i = i + 1
        z = z + Cells(x, 2).Value
    Else: Cells(x - 1, 3).Value = z
    y = Cells(x, 1).Value
    z = Cells(x, 2).Value
    End If
x = x + 1
Loop
Cells(x - 1, 3).Value = z
End Sub
```

Equation 2.2 VB code to sum soil layer sequences

Once the sum was calculated, it was converted to millimeters from inches and then brought into the comp table for relation to the MUID. The available water holding capacity was converted to millimeters to match the units of the European Soils data base. To create the available water holding capacity surface, the comp table was joined to the STATSGO shape using the 'MUID' field and then exported to the

geodatabase to retain all of the joined attributes. The actual water holding capacity raster surface was created by using the 'Feature to Raster' tool found in the 'Conversion' toolbox, nominating the 'AWHC_MM' field in the tool parameters. The soil water balance model required the available water holding capacity surface as an input to create surfaces for the suitability and logical regression analysis.

Surface texture represents the texture in the first horizon of the soil; from the surface down to the next horizon. Surface texture (SURFTEX) is an attribute which resides in the comp table and is directly related to the 'MUID'. However, surface texture in the STATSGO table is categorized differently than the surface texture of the European Soils database. Where the European Soils database classifies surface texture from 'Very Fine' to 'Coarse', the STATSGO database uses a material description following the 'clay-silt-loam-sand' texture categorization. For example, where the European database would have 'Coarse' as an attribute, STATSGO would have something like 'very stony loam' as a surface texture attribute.   One can use the USDA's texture triangle to equate the STATSGO surface texture to the European soils texture (Figure 2.8).

```
        100/\                                    100/\
       /    \                                   /    \
     90/     \10                              90/     \10
     /        \                               /        \
   80/         \20                          80/         \20
   /            \                           /            \
 / \  70/        \30                      / \  70/        \30
 |   /            \                       |   /            \
 |  60/     C      \40                    |  60/    FINE    \40
 |   /            /\                       |   /            \
Percent clay 50/\        / \50 Percent silt  Percent clay 50/            \50  Percent silt
 /    \        / SiC\                      /    \                        \
40/ SC \      /      \60   |            40/                      \60   |
/_____\  CL  \ SiCL  \    |            /-----------------------\    |
30/ SCL \      \       \70 \ /          30/                      \70 \ /
/_____\       \       \                /                        \
20/      \  L   /  SiL   \80            20/                        \80
/     SL  \    /          \            /-------                    \
10/\       \  /            \90         10/       \     MEDIUM       \10
/ S \ LS \  /      Si      \           /          \                  \
/_____\/_____\90          /  COARSE   \------------------\
100 90 80 70 60 50 40 30 20 10        100 90 80 70 60 50 40 30 20 10
      <--------------->                     <--------------->
        Percent sand                          Percent sand
```
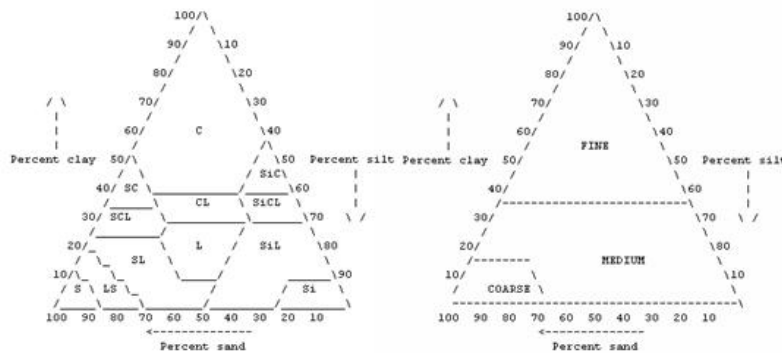
Figure 2.8 USDA soil texture triangles (USDA, 1951, p. 18)

In the USDA soil texture triangle, only three texture categories exist and they do not match the granularity of the European soil texture categorization of 'Very Fine', 'Fine', 'Medium Fine', 'Medium' 'Coarse', and 'No Texture'. The STATSGO database 'SURFTEX' attributes do contain descriptive modifier codes in conjunction with the texture class codes; Table 2.5 lists all of the possible modifiers and classes used in the 'SURFTEX' attribute field.

Table 2.5 Texture Modifies (USDA, 2005, pp. Exhibit 618-615)

Code	Modifier	Code	Texture	Code	Fragment
ASHY	Ashy	C	Clay	BR	Bedrock
BY	Bouldery	CL	Clay loam	BY	Boulders
BYV	Very bouldery	COS	Coarse sand	CB	Cobbles
BYX	Extremely bouldery	COSL	Coarse sandy loam	CN	Channers
CB	Cobbly			FL	Flagstones
CBV	Very cobbly	FS	Fine sand	G	Gravel
CBX	Extremely cobbly	FSL	Fine sandy loam	HPM	Highly decomposed plant material
CEM	Cemented	L	Loam	MAT	Material
CN	Channery	LCOS	Loamy coarse sand	MPM	Moderately decomposed plant material
CNV	Very channery	LFS	Loamy fine sand		
CNX	Extremely channery	LS	Loamy sand	MPT	Mucky peat
COP	Coprogenous	LVFS	Loamy very fine sand	MUCK	Muck
DIA	Diatomaceous			PBY	Paraboulders
FL	Flaggy	S	Sand	PCB	Paracobbles
FLV	Very flaggy	SC	Sandy clay	PCN	Parachanners
FLX	Extremely flaggy	SCL	Sandy clay loam	PEAT	Peat
GR	Gravelly	SI	Silt	PFL	Paraflagstones
GRC	Coarse gravelly	SIC	Silty clay	PG	Paragravel
GRF	Fine gravelly	SICL	Silty clay loam	PST	Parastones
GRM	Medium gravelly	SIL	Silt loam	SPM	Slightly decomposed plant material
GRV	Very gravelly	SL	Sandy loam	ST	Stones
GRX	Extremely gravelly	VFS	Very fine sand	W	Water
GS	Grassy	VFSL	Very fine sandy loam		
GYP	Gypsiferous				
HB	Herbaceous				
HYDR	Hydrous				
MEDL	Medial				
MK	Mucky				
MR	Marly				
MS	Mossy				
PBY	Parabouldery				
PBYV	Very Parabouldery				
PBYX	Extremely Parabouldery				
PCB	Paracobbly				
PCBV	Very Paracobbly				
PCBX	Extremely Paracobbly				
PCN	Parachannery				
PCNV	Very Parachannery				
PCNX	Extremely Parachannery				
PF	Permanently frozen				
PFL	Paraflaggy				
PFLV	Very Paraflaggy				
PFLX	Extremely Paraflaggy				
PGR	Paragravelly				
PGRV	Very Paragravelly				
PGRX	Extremely Paragravelly				
PST	Parastony				
PSTV	Very Parastony				
PSTX	Extremely Parastony				
PT	Peaty				
ST	Stony				
STV	Very stony				
STX	Extremely stony				
WD	Woody				

These modifier codes were used in conjunction with the soil triangles to equate and convert the STATSGO 'SURFTEX' attributes to the same semantic granularity as those of the European Soils Database. This is a potential source of error because the

semantic equivalent was based on one particular interpretation of the texture modifiers, and whether or not it further defined or changed the texture category. For example, looking at the triangles, a SL (Sandy Loam) falls in the 'Medium' texture category. However, if the SL is preceded by an STX (Extremely Stony) modifier, it may bump the texture equivalent to a 'Coarse' classification. Once the textures were equated, a new texture class field was created in the 'comp' table using the same classification as the European Soils database, Table 2.2. The texture surface was created by, again, using the 'Feature to Raster' tool, with the 'Text_Clas' field as the parameter from which to create the raster values. The Suitability Analysis and the logistic regression analysis both used the texture surface.

Depth to bedrock is the number of inches from the soil surface to the bedrock below. One can find this attribute in the 'comp' table of the STATSGO database, labeled as 'ROCKDEPL' and 'ROCKDEPH', denoting rock depth low and rock depth high respectively. Rock depth low, or 'ROCKDEPL', represents the minimum value for the range in depth to bedrock. Rock depth high, or 'ROCKDEPH', represents the maximum value for the range in depth to bedrock (USDA, 1995, p. 56). Using the 'ROCKDEPL' and ROCKDEPH' attributes, the average was calculated to find the depth to bedrock by adding each set of records together and dividing them by two. The results were converted to centimeters and then inserted into a new column field entitled 'AVGRCKDPTH' within the 'comp' table. The results were converted to centimeters to match the measurement units of the European Soils Database 'DR' (Depth to Rock) attribute. Once in centimeters, the values were classified into the same categories as those of the European Soils Database 'DR' attribute where each class represents a range of depths. These classes were inserted into a new field entitled 'RCKDPTH_cls'. The 'rockdepth' raster layer was created using the 'Feature to Raster' tool, and the 'RCKDPTH_cls' field as the parameter from which to create the raster values. Again, the suitability and logistic regression analysis used the rock depth surface as an input.

Without being a soil expert, Soil Type is hard to equate between FAO soil types and USDA soil type. The most understandable thing to do was to keep the soils at the most general soil order level. In Table 2.6 below, the possible general soil orders are listed from the STATSGO database.

Table 2.6 STATSGO Soil Order Attributes (USDA, 1995, p. 87)

Field	Attribute	Definition
order	A	Alfisols
order	C	Andisols
order	D	Aridisols
order	E	Entisols
order	H	Histosols
order	I	Inceptisols
order	M	Mollisols
order	O	Oxisols
order	S	Spodosols
order	U	Ultisols
order	V	Vertisols

The soil order attributes are found in the 'TAXCLASS' table of the STATSGO soils database. The STATSGO database gets very specific, going down to the sub-order and class level of soil classification, but the more specific the soil classification, the more difficult the translation to the FAO soil classification system. The analysis portion of this document will further explain the soil type translation process. The methodology to rasterize the soil order was the same as the previous attributes; the 'order' field was used as the parameter in the 'Feature to Raster' tool to provide the raster values. The resulting raster layer was used in the Suitability Analysis and logistical regression analysis.

2. 3 GEOLOGY

Closely related to soils, Geology is also recognized by experts as an important factor in growing quality wine grapes and can influence such factors as mineral intake and thermal conditions of the root zone (Courjault-Radé, Munoz, Maire, & Hirissou, 2007).

The geology data for both Europe and the United States came from the United States Geological Service (USGS). Both data sets depict the general lithology and geologic ages of the bedrock found in each area. This was the only common geologic data that could be found between the two regions.

The geologic data for Europe came from the USGS's Energy Resources Program website: http://certmapper.cr.usgs.gov/data/we/ofr97470i/spatial/shape/geo4_2l.zip. The scale of the European data is 1/5,000,000 and is in shapefile format. The data was clipped to the France shape using the France feature class and the 'Clip' tool found in the 'Analysis Tools' toolbox in order to obtain the geologic portion of just France to keep the file size small. The data was then imported into the France geodatabase as a feature class.

The geologic data for Oregon came from the USGS Western Region's website: http://wrgis.wr.usgs.gov/docs/geologic/or/oregon.html. The scale of the Oregon data is

1/500,000 and was in Arc/Info export (e00) format. This file was converted to a coverage file using the 'Import from Interchange' tool located in the 'Coverage Tools' toolbox. Once in coverage format, the data were imported into the Oregon geodatabase as a feature class.

Both data sets originally came from the sites with codes representing the age of each record. For example, Js represented the Jurassic age or TRPv stood for Triassic and Permian. Each dataset came with a chart which defined each code. These charts were converted to Database files and then joined with the shapefiles using the code as the common field between the two files. The file was then imported into the geodatabase so it would contain both the code and the code description for clarification and ease of use.

To make the data sets easier to use in analysis, a more generalized time period was applied to each record. The database, as is, describes the Epoch or Epochs the bedrocks were thought to have spanned. This led to several possible combinations of epochs, making any kind of comparison between regions very difficult. To simplify the data for easier comparison, the codes were generalized to Periods, one level higher than Epochs. For example, an epoch code of 'Qf' meaning 'Holocene, Pleistocene' would be re-categorized by the Period each Epoch belonged to into a new field as 'Quaternary'. This process was done using the 1999 Geologic Time Scale, Appendix B, as a guide (Palmer & Geissman, 1999).

Raster datasets were created from the geology feature classes using the 'Feature to Raster' tool. These datasets were used as inputs into the Suitability Analysis and the logistical regression analysis.

2.4 Soil-Water Balance

The soil-water balance is a measure of water surplus or deficit in the soil available for the plants to draw upon. "Growing a successful vintage requires a precarious balance between these two factors over the growing season, a balance which can determine the varietal grown" (Wilson, 1998, pp. 5, 10). The soil-water balance is an important factor because it incorporates essential elements for grape growing such as climate, potential evapotranspiration and soil properties (Milly, 1994, p. 2143). In France, irrigation is not allowed on appellation vineyards (Gade, 2004, p. 852), so calculating the soil-water balance truly captures the land and climate's ability to support the grape's water needs. Given that various regions within France grow distinct varietals, soil-water balance can be calculated for each region and therefore each distinct varietal grown in that region. In view of the fact that Meteo France provided monthly precipitation and temperature data, the Thornthwaite water balance model (McCabe & Markstrom, 2006) was used to accommodate the acquired data. Thornthwaite developed the Potential Evapotranspiration index used in this model, which some experts claim as "better than the degree days system since it includes the effect of Latitudinal day length differences" (Jackson & Cherry, 1988, p. 19) Seeing as the data was monthly, the growing season was assumed to be April through October; therefore, Soil-Water balance surfaces were created for each month of the growing season. It

was also assumed that Soil-Moisture capacity was at its maximum level in April. Growing season soil water balance surfaces were created for both the Burgundy and the Willamette Valley regions.

2.4.1 Soil-Water Balance Calculation

The soil-water balance is usually calculated in a simple bucket method where the soil is the bucket, precipitation as an addition to the bucket, and runoff and evapotranspiration (potential/actual) as subtractions from the bucket (Figure 2.9).
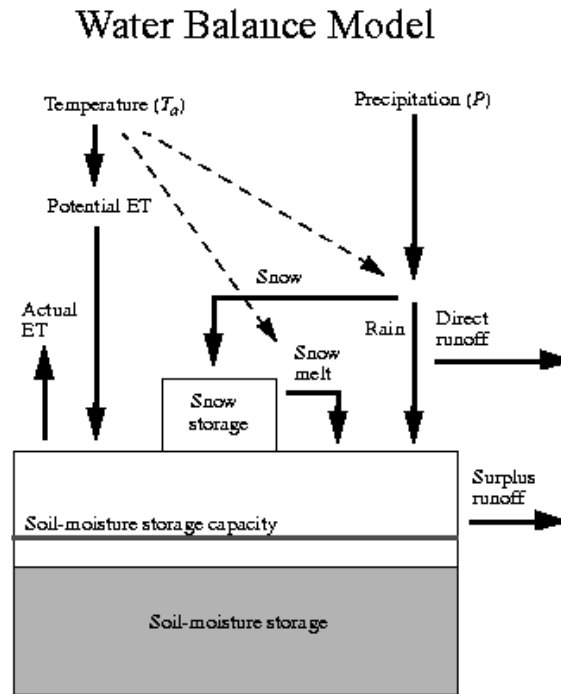
Figure 2.9 Water Balance Model (McCabe & Markstrom, 2006)

Any excess moisture above the soil-moisture capacity is surplus runoff, and any negative difference between the evapotranspiration and the soil-moisture storage is a deficit. The above model is outlined on the following USGS webpage: http://wwwbrr.cr.usgs.gov/mms/thorn/, and was adapted for GIS to calculate water balance surfaces. A Model Builder model (Figure 2.10) was developed to create the Soil Water balance surface for one month.

2.4.2 Water Balance Model

Figure 2.10 Soil Water Balance Model Builder Model for One Month

The following section will explain each part of the Soil Water balance model in detail in order to explain the equations and data used in calculating the Soil Water balance for each month of the growing season.

2.4.3 Water Input into the Bucket

The blue 'Precipitation' surface was simply the surface created as a result of the Geostatistical Analysis tool process using the raw climate 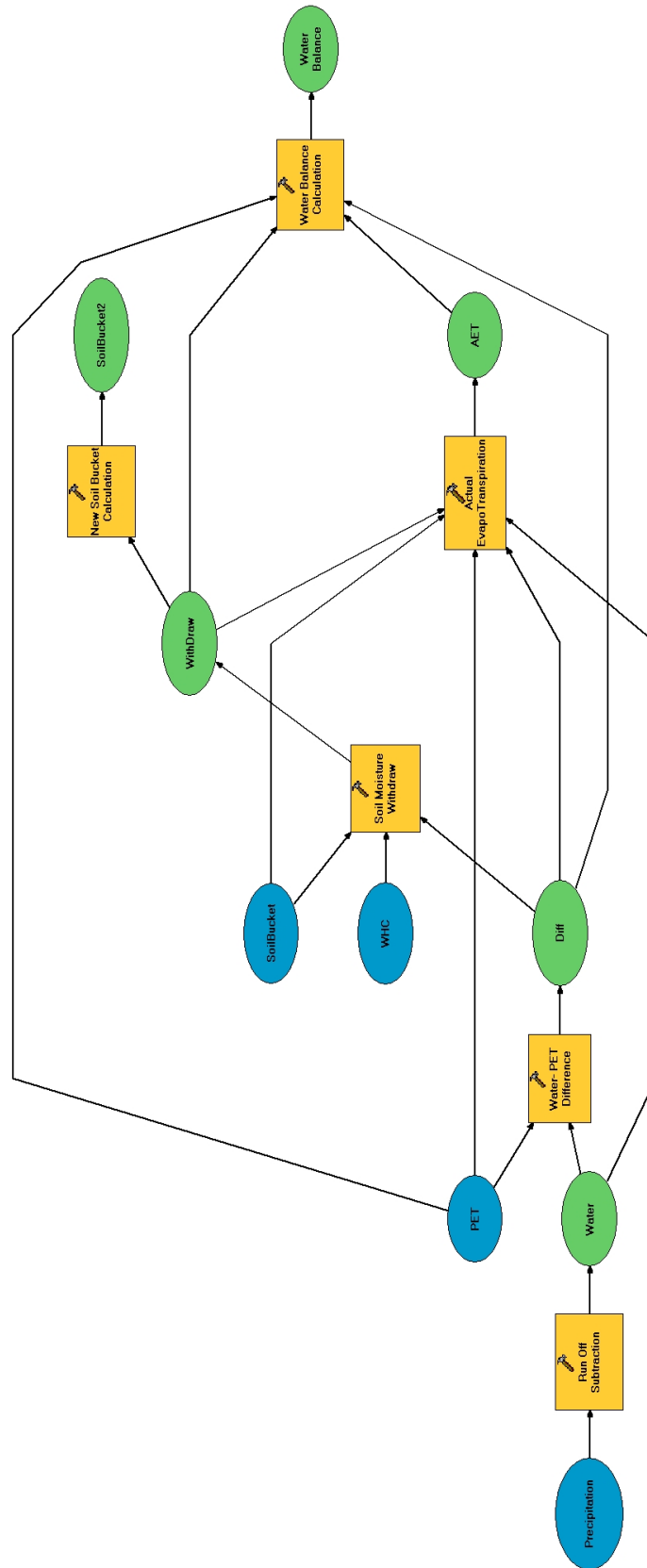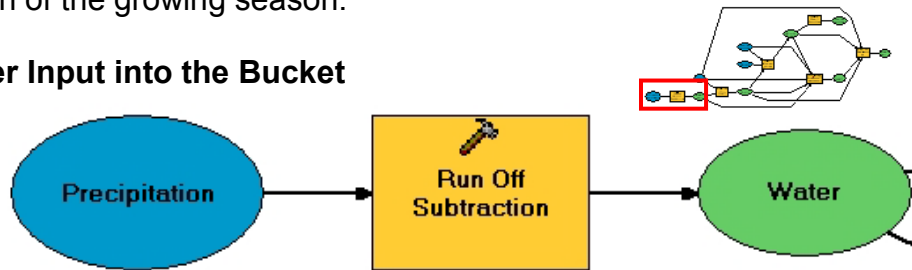station data, see the Climate section. The precipitation surface used matched the month of the Soil Water balance surface calculation. The "Run Off Subtraction" is a Single Output Map Algebra equation (SOMA):

$$Precipitation - (Precipitation * 0.05)$$

Equation 2.3 Run Off Subtraction

This equation adjusts the precipitation or water input and accounts for any initial run-off water loss caused by impervious surfaces and or rapid over-saturation from heavy rainstorms. The result was the green 'Water' surface. As a point of interest, if the Soil Water balance was being calculated for a winter month in an area which receives snow precipitation, a snow adjustment calculation would also have to be made. This snow adjustment is outlined in the procedure page of the mentioned USGS website. The unit of measurement of both the 'Precipitation' and 'Water' surfaces is millimeters.

2.4.4 Potential Evapotranspiration Calculation
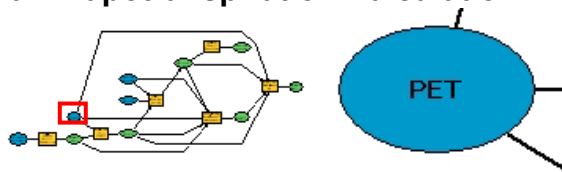
Pidwirny defines Potential evapotranspiration as "a measure of the ability of the atmosphere to remove water from the surface through the processes of evaporation and transpiration assuming no control on water supply" (Pidwirny, 2006, p. ch. 8). In the model terms, Potential Evapotranspiration is the atmosphere subtracting water from the 'bucket'. The blue 'PET', or Potential Evapotranspiration, surface was created using the Thornthwaite Potential Evapotranspiration calculation method. The Thornthwaite method was used for consistency (the Thornthwaite method was used for the Soil Water balance calculation), and because of the nature of the monthly data acquired from Meteo France. The Thornthwaite method is relatively simple, requiring only temperature data and the latitude of the study area. Other PET calculation methods require additional parameters such as radiation, as in the Priestley-Taylor

method (Priestley & Taylor, 1972, p. 90) or humidity and wind speed, such as in the FAO-24 method (Jensen, Burman, & Allen, 1990). Temperature and precipitation data points were the only consistent climate data parameters provided, so the Thornthwaite method was chosen to accommodate the available data. A separate Model Builder model was used to apply the Thornthwaite method and calculate the PET surfaces for each month.

Thornthwaite's PET equations:
Step One: Heat Index Calculation

$$i = \left(\frac{T}{5}\right)^{1.514} \quad \text{for } T > 0$$

$$i = 0 \quad \text{for } T \le 0$$

Equation 2.4 Heat Index Calculation

T is the average monthly temperature in Celsius

Step Two: Sum the Heat Index Over the Whole Year

$$I = i_{JAN} + i_{FEB} + i_{MAR} \cdots + i_{DEC}$$

Equation 2.5 Annual Heat Index

Step Three: Calculate the Exponent 'm'

$$m = (6.75 \times 10^{-7}) I^3 - (7.71 \times 10^{-5}) I^2 + (1.79 \times 10^{-2}) I + 0.492$$

Equation 2.6 Exponent m Calculation

Step Four: Calculate the Un-adjusted PE

$$0 \qquad T < 0°C$$

$$16\left(\frac{10T}{I}\right)^m \qquad T \le 0 \le 26.5°C$$

$$-415.85 + 32.24T - 0.43T^2 \qquad T > 26.5°C$$

Equation 2.7 Un-adjusted Potential Evaporation

Step Five: Adjust the PE with the Daylight Correction Table (2.7):

Table 2.7 Daylight Correction Table

Latitude	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0	1.04	0.94	1.04	1.01	1.04	1.01	1.04	1.04	1.01	1.04	1.01	1.04
10 N	1.00	0.91	1.03	1.03	1.08	1.06	1.08	1.07	1.02	1.02	0.98	0.99
20 N	0.95	0.90	1.03	1.05	1.13	1.11	1.14	1.11	1.02	1.00	0.93	0.94
30 N	0.90	0.87	1.03	1.08	1.18	1.17	1.20	1.14	1.03	0.98	0.89	0.88
40 N	0.84	0.83	1.03	1.11	1.24	1.25	1.27	1.18	1.04	0.96	0.83	0.81
>50 N	0.74	0.78	1.02	1.15	1.33	1.36	1.37	1.25	1.06	0.92	0.76	0.70
10 S	1.08	0.97	1.05	0.99	1.01	0.96	1.00	1.01	1.00	1.06	1.05	1.10
20 S	1.14	1.00	1.05	0.97	0.96	0.91	0.95	0.99	1.00	1.08	1.09	1.15
30 S	1.20	1.03	1.06	0.95	0.92	0.85	0.90	0.96	1.00	1.12	1.14	1.21
40 S	1.27	1.06	1.07	0.93	0.86	0.78	0.84	0.92	1.00	1.15	1.20	1.29
>50 S	1.37	1.12	1.08	0.89	0.77	0.67	0.74	0.88	0.99	1.19	1.29	1.41

To get PE Multiply the Un-adjusted PE by the correction factor relevant for your latitude (GLOBE, 2003, pp. 11-14; Xu & Chen, 2005, p. 3723).

Thornthwaite's Method Applied in a Model Builder Model

All of the Thornthwaite steps outlined in the previous section were executed using a model (**Figure 2.11**) to build PET surfaces for each month of the growing season (April – October).
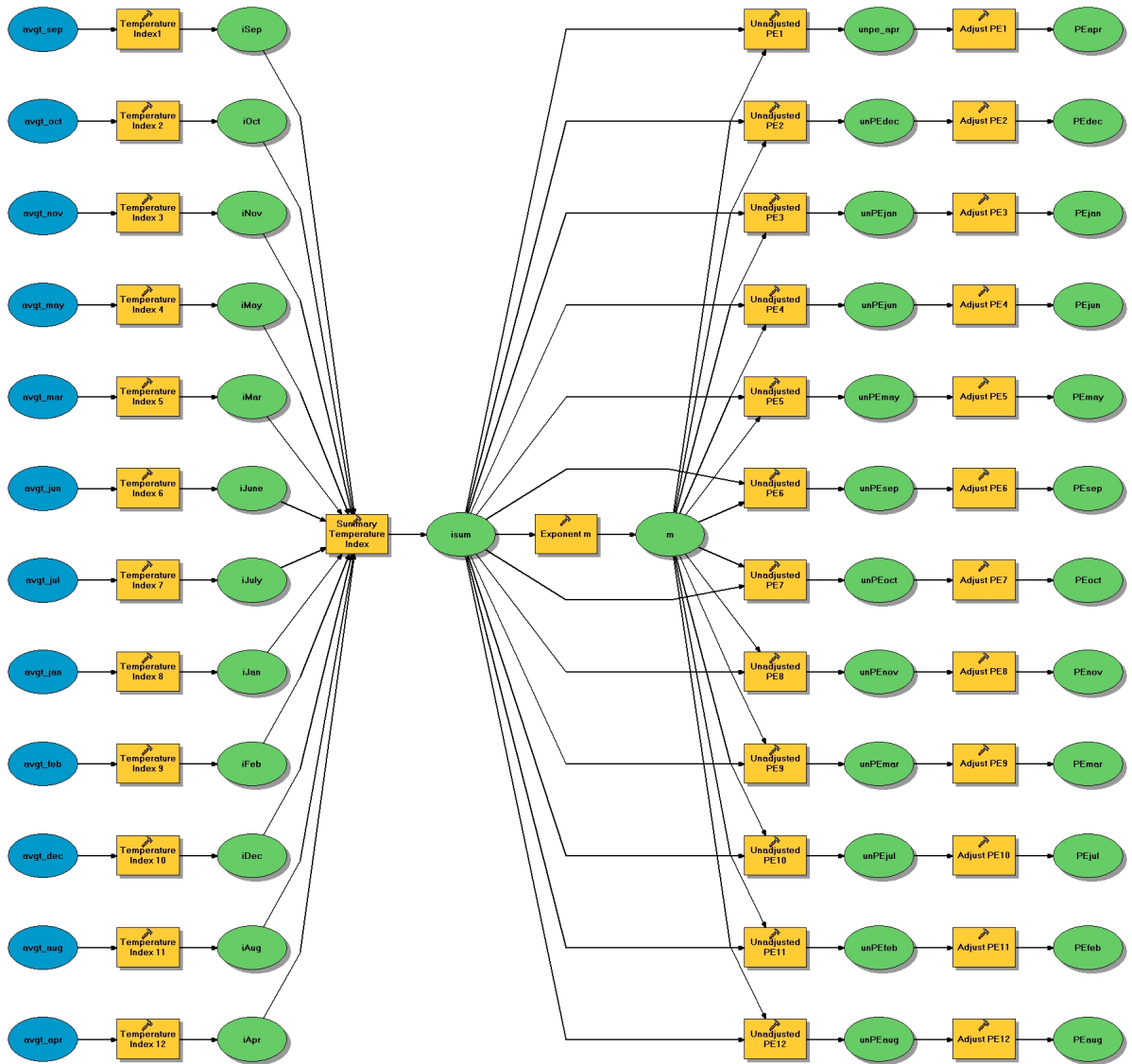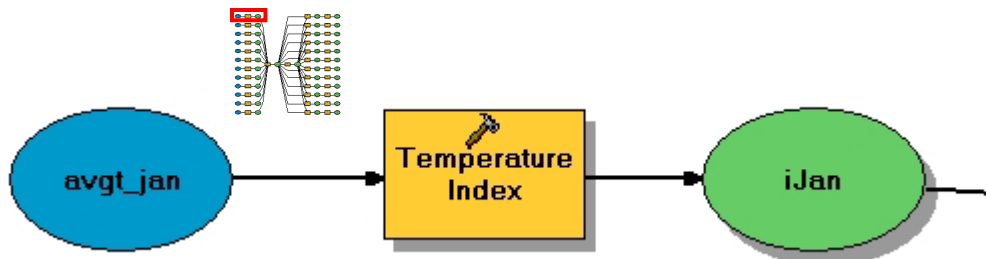
Figure 2.11 Model to Calculate Potential Evapotranspiration

Step 1: Heat Index Calculation

$$i = \left(\frac{T}{5}\right)^{1.514} \qquad \text{for } T > 0$$

$$i = 0 \qquad\qquad \text{for } T \leq 0$$

Heat Index Portion of the Model 1

27

Calculate the 'Temperature Index' or 'i' for each average monthly temperature surface ('avgt_jan') using the following SOMA equation:

$$POW((avgt\_apr\ div\ 5),\ 1.514)$$

The average monthly temperature surfaces were created using the raw station data. The model calculated a temperature index for each month. The Thornthwaite PET method requires the summary heat index for all months of the year.

Step Two: Sum the Heat Index Over the Whole Year

$$I = i_{JAN} + i_{FEB} + i_{MAR} \cdots + i_{DEC}$$

Sum all of the Heat Indexes Portion of the Model
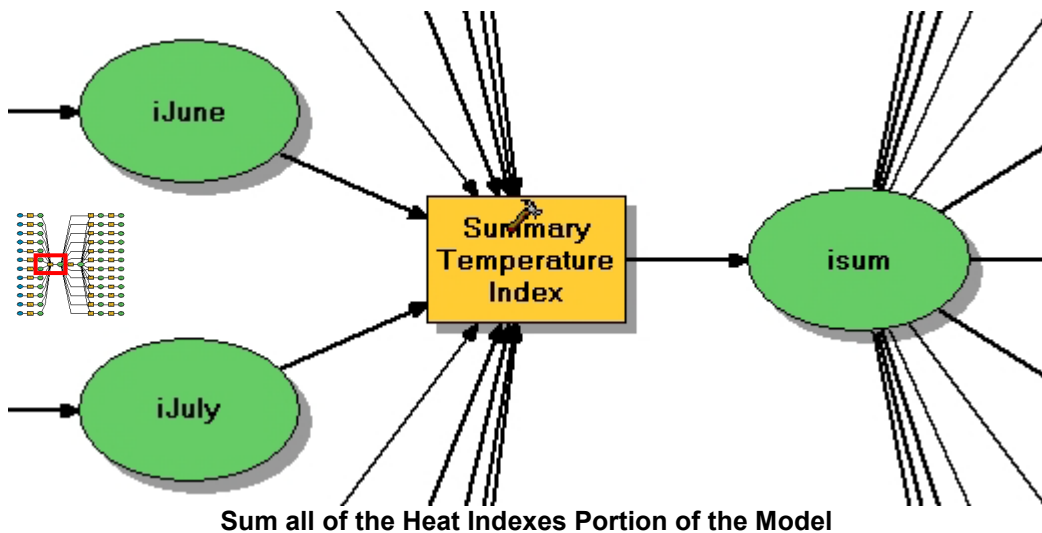
The 'Summary Temperature Index' simply sums all of the individual monthly index surfaces together using the following SOMA equation:

$$iJan + iFeb + iMar + iApr + iMay + iJune + iJuly + iAug + iSep + iOct + iNov + iDec$$

The result is the 'isum' total temperature index surface.

Step Three: Calculate the Exponent m

$$m = (6.75 \times 10^{-7})\ I^3 - (7.71 \times 10^{-5})\ I^2 + (1.79 \times 10^{-2})\ I + 0.492$$

Calculate Exponent 'm' Portion of the Model
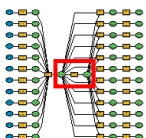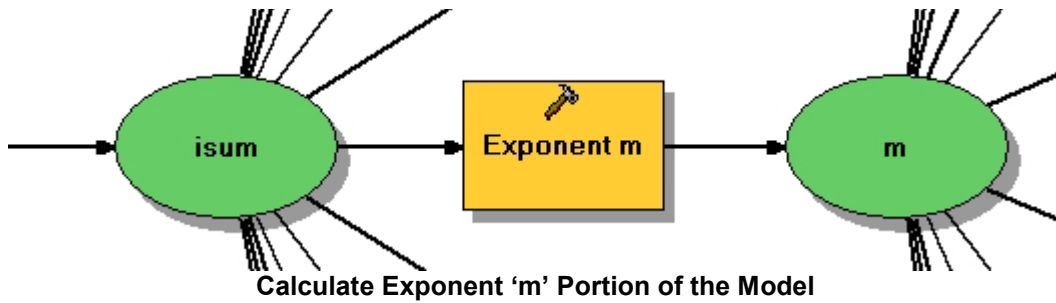
The 'Exponent m' was solved using the 'isum' surface and the following SOMA equation:

$$(6.75e\text{-}7) * POW(iSum, 3)) - ((7.71e\text{-}5) * POW(iSum, 2)) + (1.79e\text{-}2 * iSum) + 0.492$$

The result of this step is the 'a' surfaces which are the intermediate parameters needed to calculate the un-adjusted PE in the next part of the model.

Step Four: Calculate the Un-adjusted PE

$$0 \qquad T < 0°C$$

$$16\left(\frac{10T}{I}\right)^m \qquad T \leq 0 \leq 26.5°C$$

$$-415.85 + 32.24T - 0.43T^2 \qquad T > 26.5°C$$

Unadjusted PE Portion of the Model
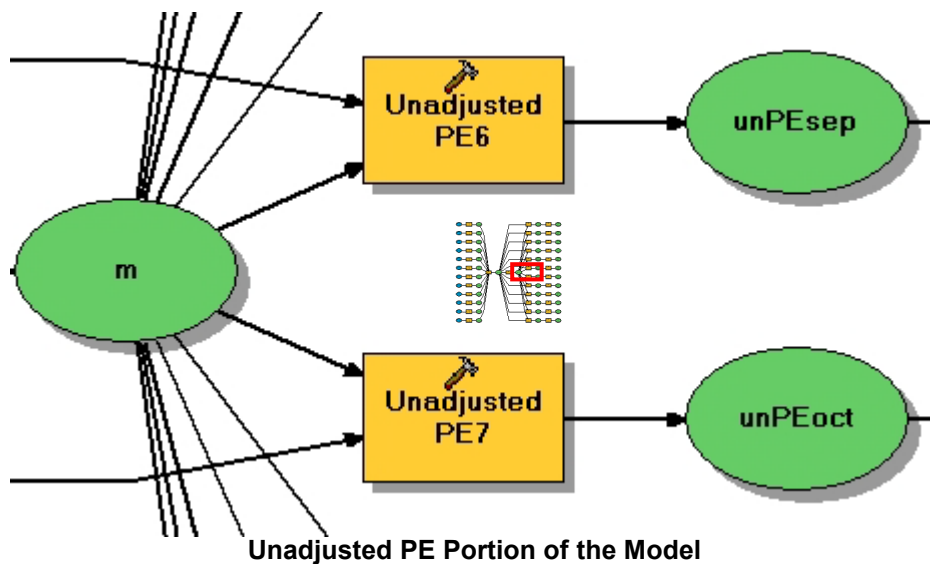
The 'Unadjusted PE' is calculated for each month using the average temperature surface ('avgt_apr'), the summary heat index ('isum') and the exponent 'm' in the following SOMA equation:

$$(POW(((10 * avgt\_apr) / isum), m)) * 16$$

The result is an un-adjusted PET surface for each month. Only the middle un-adjusted PET equation was used because no average temperature surface was below 0º Celsius or above 26.5º Celsius.

Step Five: Adjust the PET with the Daylight Correction Table:

Latitude	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
40 N	0.84	0.83	1.03	1.11	1.24	1.25	1.27	1.18	1.04	0.96	0.83	0.81

| 40 S | | 1.27 | 1.06 | 1.07 | 0.95 | 0.86 | 0.84 | 0.92 | 1.00 | 1.15 | 1.20 | 1.29 |
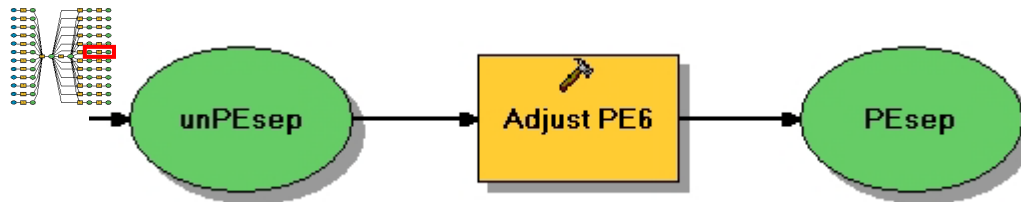
Adjust PE Portion of the Model

The correction factors for 40º N were chosen as the Burgundy and the Williamette Valley wine regions both reside in this latitude band. The un-adjusted PE surfaces for each month were multiplied by the corresponding daylight correction factor from the table. The result was the PET surface for each month. The unit of measurement for PET is millimeters. These PET surfaces were input parameters into the Soil Water balance model. Continuing with the Soil Water Balance model, PET becomes an important input into three functions.

2.4.5. Subtract the PET Outtake from the Water Input
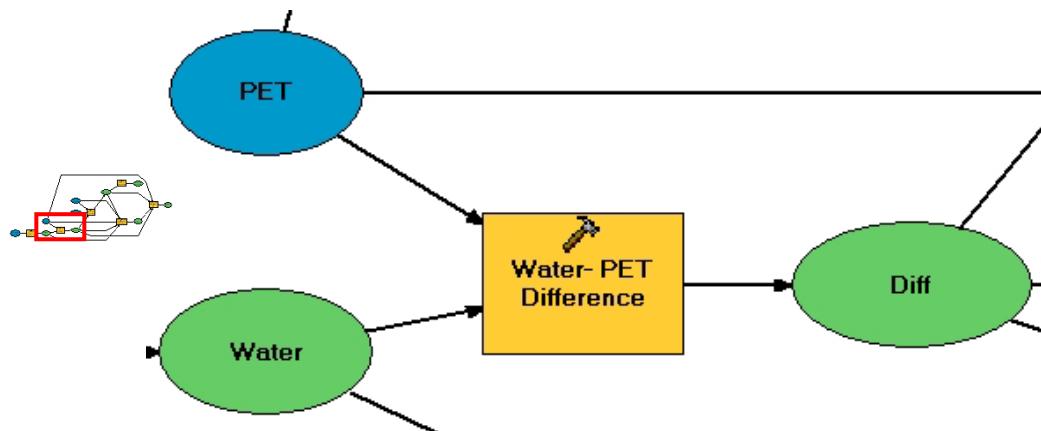
In this step, water loss which occurs from 'PET' is subtracted from the 'Water' input using the following SOMA:

Water – PET

Equation 2.8 Water loss from Potential Evapotranspiration

This calculation accounts for the real world potential of the sun to 'sweat' the water out of the plant and soil. The 'model uses the Diff' surface in the calculation of the Soil Moisture Withdraw, Actual Evapotranspiration, and the Water Balance surface itself.

2.4.6 Calculate the Soil Moisture Withdraw
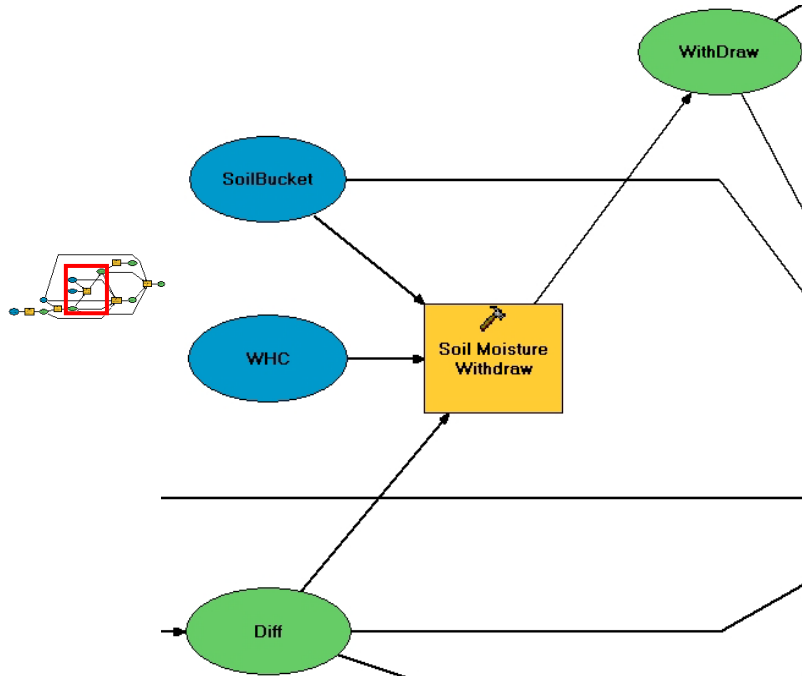
The 'Diff' surface was created in the previous step. The 'WHC' or Water Holding Capacity, was created from the attributes of the soil data (see Section 2) and represents the maximum amount of water the soil can hold in millimeters. The 'SoilBucket' is the soil's current amount of water it is holding in millimeters. For the first calculation of the Soil Water Balance for the month of April, it was assumed that the soil was at maximum water holding capacity. In model terms, 'SoilBucket' = 'WHC' for the month of April calculation. The 'Soil Moisture Withdraw' is calculated using the following SOMA equation:

CON(Diff < 0, (SoilBucket - (ABS(Diff) * (SoilBucket / WHC))), (SoilBucket + Diff))

Equation 2.9 Soil Moisture Withdraw Calculation

This equation basically states that if the 'PE' is greater than the 'Water' ('Diff' cell < 0) then the amount of 'Withdraw' for that cell is a percentage of the 'Diff' subtracted from the soil bucket ('Soilbkt'), otherwise there is no 'Withdraw' and the 'Withdraw' becomes positive, meaning extra water recharges the soil bucket for the next month's calculation.

2.4.7 Calculate the Actual Evapotranspiration (AET)
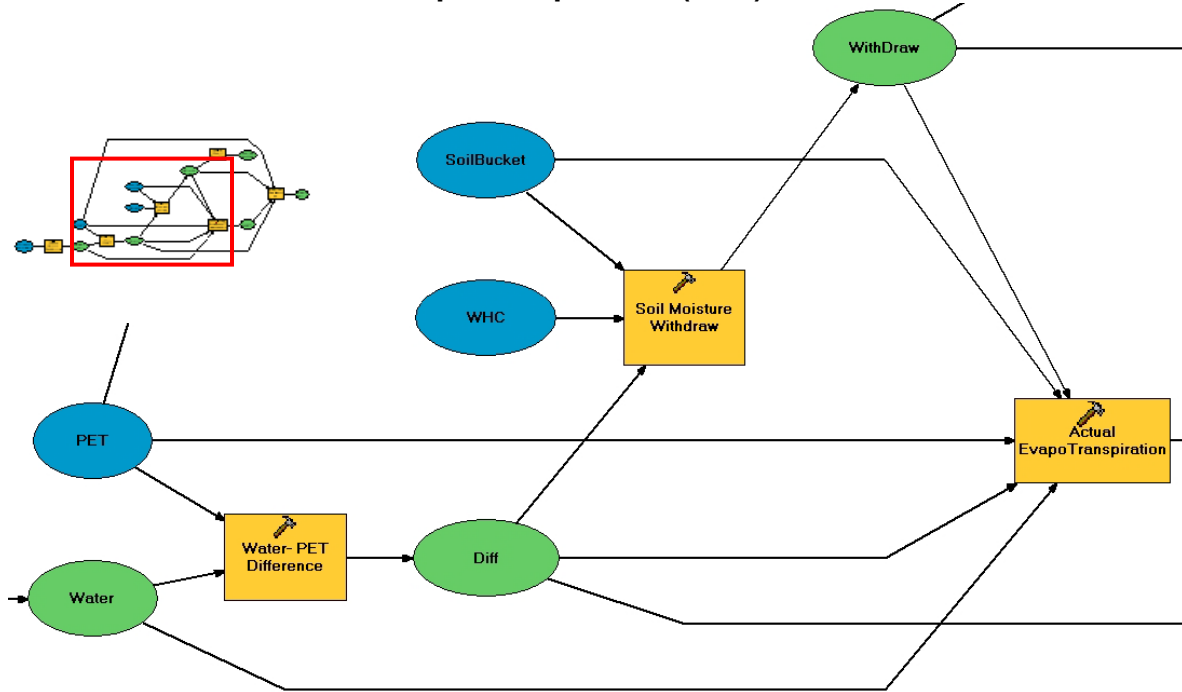
Actual Evapotransporation or AET, represents the actual amount of water removed through evapotranspiration (Pidwirny, 2006). AET is calculated using the following SOMA equation:

$$CON(Diff < 0, (Water + (-1 * (WithDraw - SoilBucket))), PET)$$

Equation 2.10 Actual Evapotranspiration Calculation

This equation states that for every cell if the 'PET' is greater than the 'Water', then AET is equal to the 'Water' plus the amount of moisture which can be withdrawn from the soil ('WithDraw' - 'SoilBucket'); otherwise if amount of 'Water' exceeds 'PET', then AET cell is equal to 'PET'(McCabe & Markstrom, 2006, p. 4).

2.4.8 Calculate the Soil Water Balance Surface
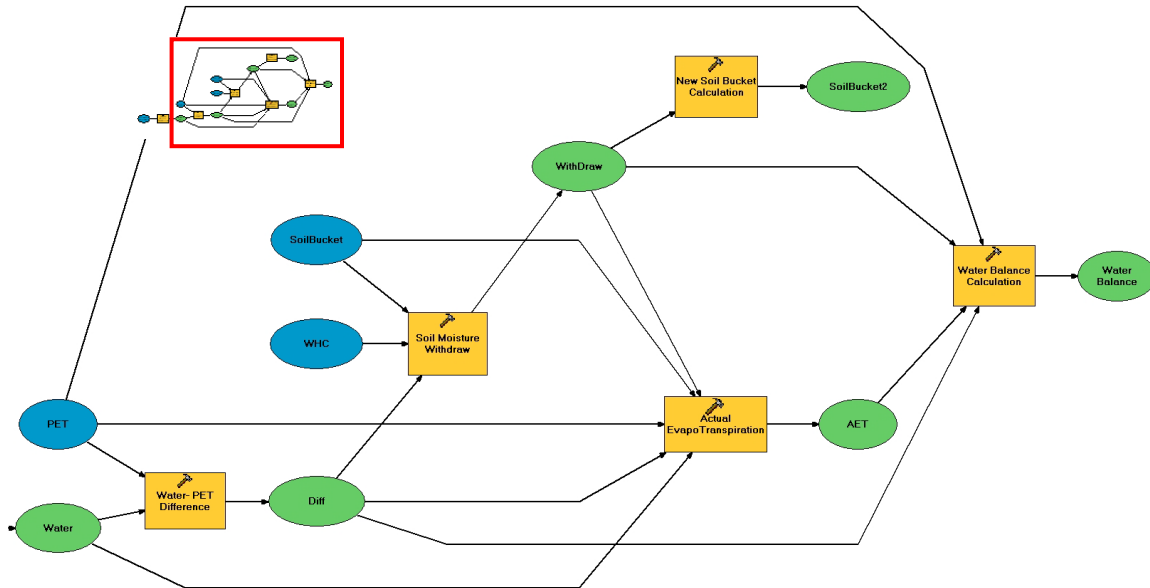
The 'Water Balance' is negative, or at a deficit when the 'PET' is greater than the AET. If there is a surplus of water then the excess goes to fill up the soil up to 'WHC', any excess after that results in a positive 'Water Balance' which can also be categorized as run-off. If there is not enough water to fill to WHC, then the 'Water Balance' goes to zero, because there is no run-off or deficit.   The 'Water Balance' was calculated using the following SOMA equation:

$$CON(Diff < 0, (AET - PET), CON(WithDraw > WHC, (WithDraw - WHC), 0))$$

Equation 2.11 Water Balance Calculation

  In Figure 2.12 below, we see an example surplus and an example deficit 'Water Balance' surface calculated for the months of April and August respectively.
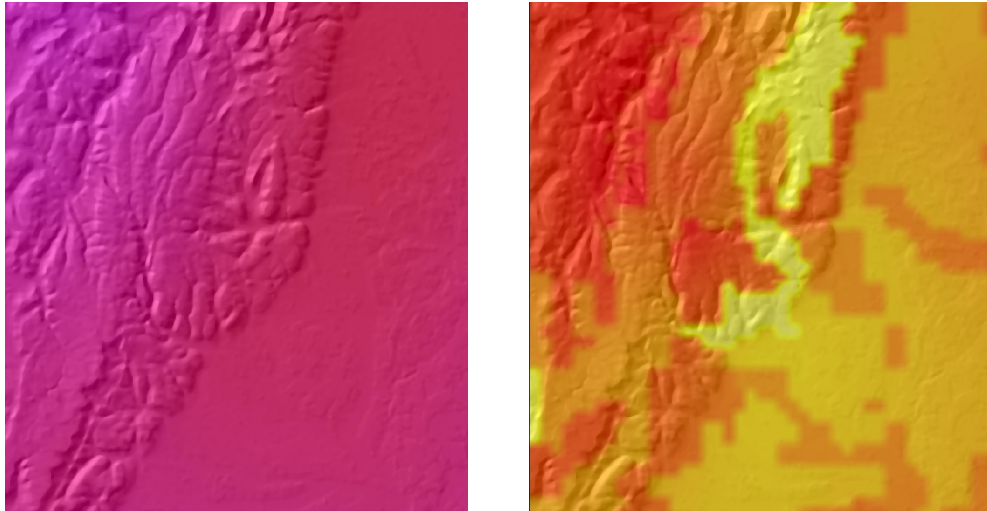
Figure 2.12 Water Balance Surface for April and August

The April surface is mainly affected by the climate input surfaces, because there is a surplus of water. In August, effects of the soil attributes upon the water balance process influence the soil water balance surface, because evapotranspiration is greater than the precipitation coming in, so the soil has to use its water holding capacity. Before moving on to the next month's calculation, the new soil bucket or 'SoilBucket2' must be calculated to use as next month's 'SoilBucket'.

2.4.9 Calculate the New Soil Bucket
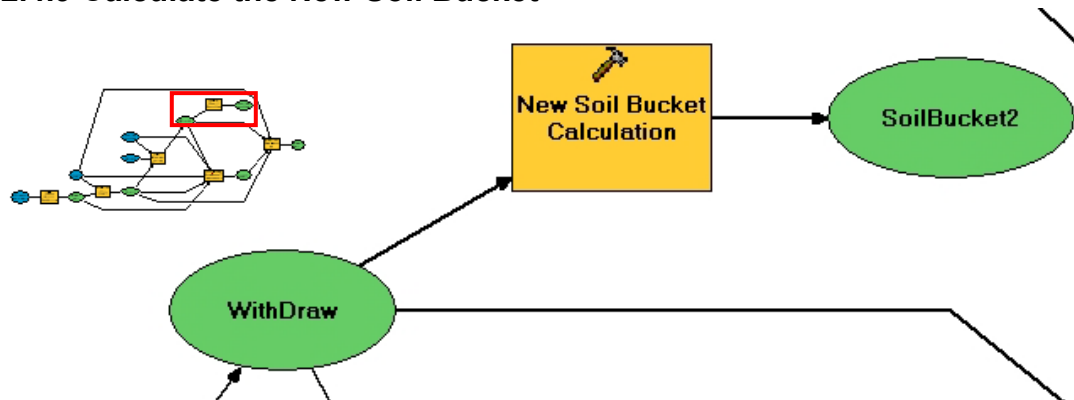
If the 'WithDraw' is negative then there is no soil moisture left and the 'SoilBucket2' cell is put at zero, otherwise the positive 'WithDraw' or excess water is used to fill up the 'SoilBucket2' cells up to water holding capacity (WHC). The following SOMA equation was used to calculate the 'SoilBucket2' surface:

$$CON(WithDraw < 0, 0, CON(WithDraw > WHC, WHC, WithDraw))$$

Equation 2.12 Soil Bucket Calculation for the Next Month

The 'SoilBucket2' surface is carried over to the next month to be used as the 'SoilBucket' surface for calculation of that month's soil water balance.

34
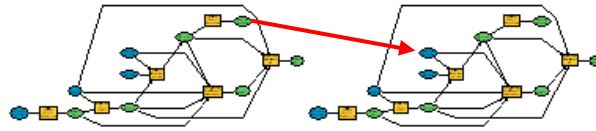
Using this model, 'Water Balance' surfaces were created for each month of the growing season. The Suitability Analysis and Logistical Regression Analysis both used the 'Water Balance' surfaces created.

2.5 Elevation Data

Two elevation characteristics are very important in grape growing, slope and aspect. Slope is important because a gentle slope allows for good drainage of both water and cold air. Good drainage of water keeps the roots from getting water logged. Good drainage of the cold air helps keep the grapes slightly warmer than the valley floor and helps protect from frost damage (Berry, 1990). In Burgundy it is said that the best vineyards, the Grand Cur, are located on gentle slopes (see Figure 2.13).

Figure 2.13 Slopes of Burgundy, France ("Fondvigne", 2001)

Aspect is the direction a slope faces and is important as it can impact the amount of sun the grapes receive (Jones, Snead, & Nelson, 2004, p. 170). Both factors work together to affect the microclimate of a viticulture area (Van Leeuwen & Seguin, 2006, p. 5).

A Digital Elevation Model (DEM) dataset was used to calculate the slope and aspect for each area of interest.

2.5.1 Elevation Data Source

The DEM data for this project came from the Shuttle Radar Topography Mission (SRTM) data sets. These raster data sets were obtained from the Consultative Group on International Agricultural Research-Consortium for Spatial Information (CGIAR-CSI) website: http://srtm.csi.cgiar.org/. The data sets were downloaded using a Google Earth interface, Figure 2.14.

Figure 2.14 CGIAR-CSI Google Earth Interface for Data Acquisition (Consultive Group on International Agricultural Research - Consortium for Spatial Information (CGIAR-CSI); Google)

CGIAR-CSI divided the SRTM data into 5º x 5º tiles, the extents of which are laid out on Google Earth as a grid. The user simply selects the hyperlink in the middle of the desired grid and a window pops up with information and a hyperlink to download the selected tile. The data are approximately 90m resolution and come in a geographic coordinate system, WGS84 datum. The data can be downloaded in GEOTIFF or ESRI ASCII file formats (Consultive Group on International Agricultural Research - Consortium for Spatial Information (CGIAR-CSI)). The elevation data for Burgundy, France and the Williamette Valley, Oregon were both obtained through this interface.

2.5.2 Slope and Aspect Data Methodology

To create the slope and aspect datasets, the DEM for each region was used as input into ESRI's 'Spatial Analyst' tools. Both the 'Aspect' and 'Slope' tools are found in the 'Surface' toolbox of the 'Spatial Analyst' tools (ESRI, 2005). The result of each tool is shown in Figure 2.15, overlaid onto a hillshade.
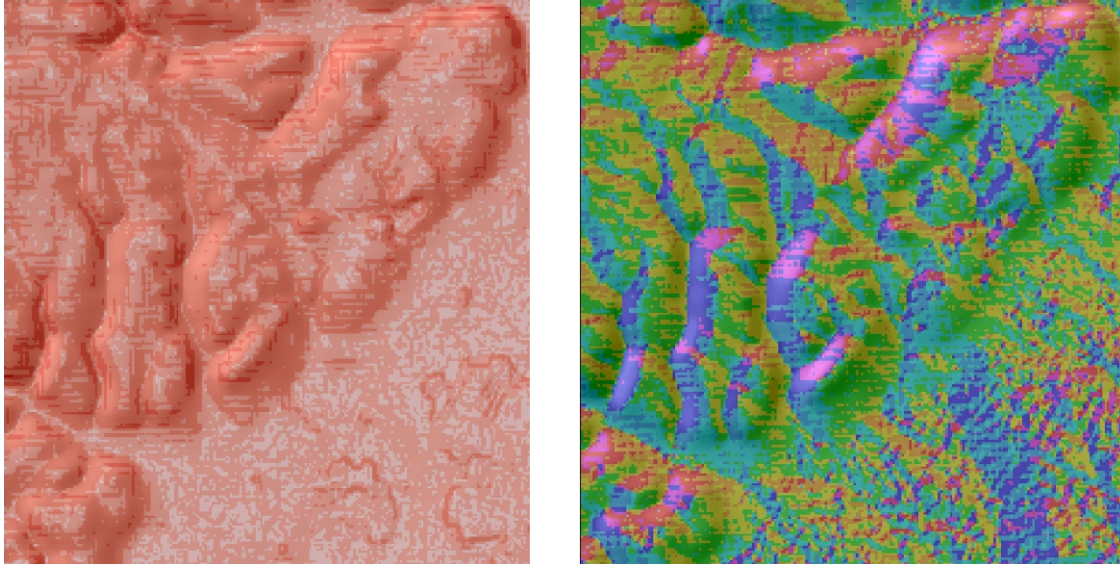
Figure 2.15 Slope and Aspect Example Products from the Burgundy Region

The slope surface shows different ranges of degree slopes, with the steepest slope range in dark red. The aspect model colors the compass directions; green represents the Southeast aspect. The analysis portion of the project used both the slope and aspect datasets.

The elevation data were also used for cartographic products, see section 2.7.

2.6 Vineyard Location Data

Vineyard Location data became quite important to obtain as it would provide the boundaries from within which sample data could be taken for analysis. It would also prove important to check the accuracy of the Suitability Analysis. Finally, the Vineyard location data was useful for cartographic products in the areas of interest.

2.6.1 French Vineyard Location Data

The French Vineyard delineation data proved very difficult to obtain. The Institut National des Appellations d'Origine (INAO), which manages the French Wine Law (Appellation d'Origine Controlee (AOC)), was the first place searched because the AOC system is based on 'distinct geographical locations'(Institut National de l'Origine et de la qualite (INAO), 2011). However, as mentioned before, the French national organizations charge for GIS data and the INAO was unwilling to give the data for academic purposes. After much searching, the data were discovered in the form of land cover, at the European level. The European Environment Agency (EEA) provides free environmental data for Europe, to include the Corine 2000 European Land Cover dataset available at EEA's website: http://dataservice.eea.europa.eu/dataservice/metadetails.asp?id=667. Once permission is

obtained from the EEA, both vector and raster versions are freely available. Table 2.7 gives us a sample of the land cover codes and categories, to include code 221 for Vineyards.

Table 2.8 Corine Land Cover Data Dictionary (The European Topic Centre on Terrestrial Environment, 2000)

Code Level 3	Label Level1	Label Level2	Label Level3
111	Artificial surfaces	Urban fabric	Continuous urban fabric
112	Artificial surfaces	Urban fabric	Discontinuous urban fabric
121	Artificial surfaces	Industrial, commercial and transport units	Industrial or commercial units
122	Artificial surfaces	Industrial, commercial and transport units	Road and rail networks and associated land
123	Artificial surfaces	Industrial, commercial and transport units	Port areas
124	Artificial surfaces	Industrial, commercial and transport units	Airports
131	Artificial surfaces	Mine, dump and construction sites	Mineral extraction sites
132	Artificial surfaces	Mine, dump and construction sites	Dump sites
133	Artificial surfaces	Mine, dump and construction sites	Construction sites
141	Artificial surfaces	Artificial, non-agricultural vegetated areas	Green urban areas
142	Artificial surfaces	Artificial, non-agricultural vegetated areas	Sport and leisure facilities
211	Agricultural areas	Arable land	Non-irrigated arable land
212	Agricultural areas	Arable land	Permanently irrigated land
213	Agricultural areas	Arable land	Rice fields
221	Agricultural areas	Permanent crops	Vineyards
222	Agricultural areas	Permanent crops	Fruit trees and berry plantations
223	Agricultural areas	Permanent crops	Olive groves
231	Agricultural areas	Pastures	Pastures

Figure 2.16 shows the whole Corine land cover dataset over France; Vineyards are colored red. The data's scale is 1:100,000.
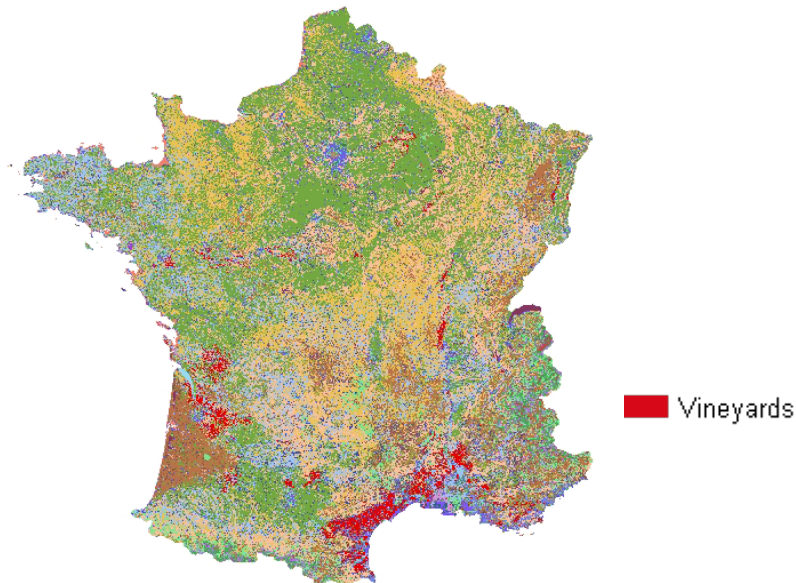
Figure 2.16 Corine Land Cover Data of France

The vineyard land cover data was extracted in ArcMap by selecting the code '221' attribute and then exporting the selected features as a separate shapefile (Figure

2.17). This was accomplished by using the 'Select by Attributes' and 'Data Export' functions within ArcMap. The data was then clipped to the areas of interest using the 'Clip' tool and another feature class as the outline (ESRI, 2005).
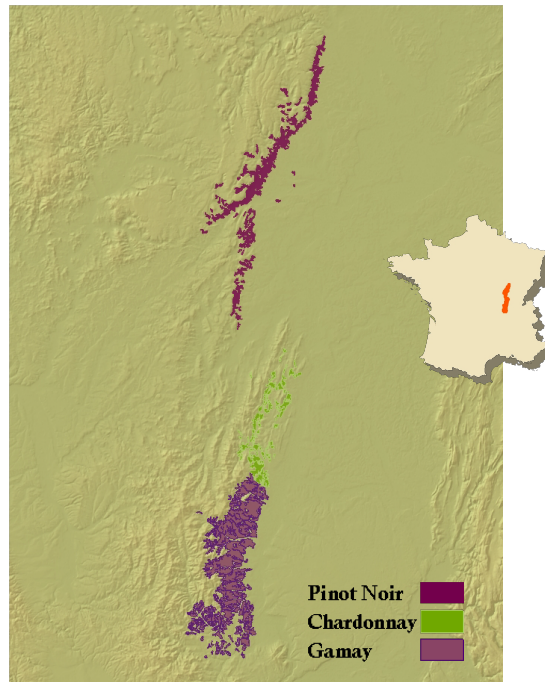
Figure 2.17 Burgundy Vineyard Land Cover with Hill shade

Ancillary data from *Wines of the World* (Dorling Kindersley Publishers, 2004) further categorized the vineyard land cover data by main grape varietal grown. This ancillary data was used to sub-type the feature in the geodatabase which allowed for color variation based upon subtype.

2.6.2 Oregon Vineyard Location Data

Oregon Vineyard location data was not as easy to obtain. Land Cover data over the Willamette Valley was obtained from the Pacific Northwest Ecosystem Research Consortium website: http://www.fsl.orst.edu/pnwerc/wrb/access.html. This data comes in ESRI GRID raster format at 30m resolution. This data only partially met the requirement as the category of interest was number 73, Berries & Vineyards Table 2.9, Figure 2.18.

Table 2.9 Williamette Valley Land Cover Categories

66	Hybrid Poplar
67	Grass Seed
68	Row Crops
71	Grains
72	Nursery Crops
73	Berries & Vineyards (Blueberries, caneberries, and wine grapes)
74	Double Cropping (grains in spring and row crops in late summer)
75	Hops
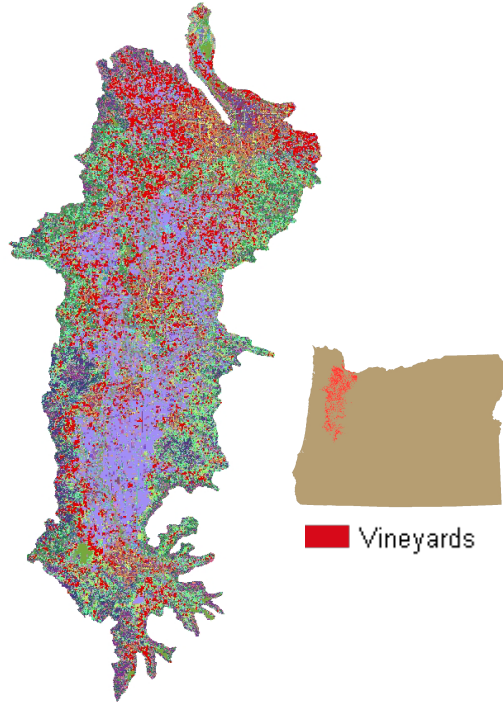
Figure 2.18 Willamette Valley Oregon Land Use Land Cover Data

There are quite a few Berry and Vineyard cells in the Willamette Valley region. In an effort to get better location data about the vineyards themselves, a list of Oregon wineries and addresses was obtained from the Oregon Wines website: http://www.oregonwines.com/. These addresses were then Geo-Coded using ESRI's Street Network data, Figure 2.19.
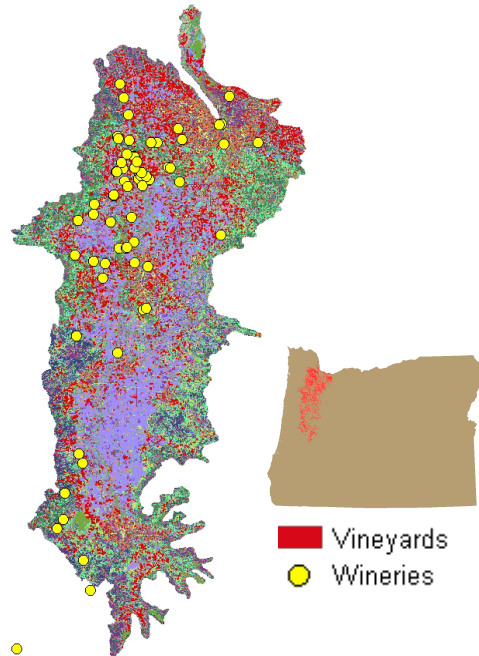
Figure 2.19 Winery Locations in Yellow

Two potential problems with the Winery data is that one, the list is probably not comprehensive, and two, the winery may not be physically collocated with the vineyard itself. Using both the Land Use/Land Cover and the Winery data, while still not a 100% solution, was considered sufficiently accurate to compare with the analysis results.

2.7. Base Map Data
Base Map Data was used for the creation of cartographic products and included things such as cities, roads, political boundaries and Hill Shades.

2.7.1 France Base Map Data
France Base Map data came from a variety of sources and was used to make cartographic products of the Burgundy region.

2.7.1.1 Transportation and Hydrological Data
Transportation and hydrological data for France came from the National Geospatial-Intelligence Agency's (NGA) Vmap level 0 data. This data was downloaded in shapefile format from the FAO's GeoNetwork website: http://www.fao.org/geonetwork/srv/en/main.home. Since the downloaded data is worldwide extent, the data was clipped to the outline of France using the ArcGIS Clip tool.

2.7.1.2 City Data
The point city data was obtained from the NGA's Geonames server at http://gnswww.nga.mil/geonames/GNS/index.jsp. The Geonames files contain names for numerous point features, separated by country, including populated places, administrative, hypsographic, vegetation, and hydrographic features. The country file was downloaded as a tab delimited text file. This file was saved as a dBase IV (.dbf) file using Microsoft Excel, because ArcGIS can read .dbf table files. The file was then brought into ArcMap and plotted using the 'Add XY data' tool. Once the data was displayed in ArcMap, it was saved in Shapefile format. The populated places features were extracted from the shapefile and saved as a separate feature class to use as city data.

The urban polygons for major cities were acquired from the European Environmental Agency's (EEA) website http://dataservice.eea.europa.eu/dataservice/metadetails.asp?id=720. The 'Urban Morphological Zones' are a derived dataset from the Corine Landcover dataset; the same one used to determine vineyard locations. This dataset covers all of Europe, and was clipped to France using the ArcGIS Clip tool.

2.7.1.3 Administrative Boundaries
The Administrative Boundaries were obtained from the French Institute Geographic National (IGN): http://www.ign.fr/rubrique.asp?lng_id=EN. The polygon shapefile contains the level one department boundaries. This shapefile was used to create a good country boundary for France from the ArcGIS 'Dissolve Tool'. The France boundary polygon was used to clip many data sets and also to display France itself.

2.7.2 Oregon Base Map Data

All of the Oregon base map data were collected from the State of Oregon's Geospatial Enterprise Office (GEO) website: http://www.oregon.gov/DAS/EISPD/GEO/alphalist.shtml. This data included the transportation, hydrologic, administrative, and city shapefiles. This base data was used to create cartographic products for the project.

2.7.3 Base Map Hill Shade

The SRTM DEMs, of both France and Oregon, were also used to make a 'Swiss Hill shade' effect for cartographic products. The Swiss Hill shade method (Buckley & Barnes, 2004) and model ("Hillshade Tools for Base Map Data Model", 2004), Figure 2.20, were obtained from the ESRI Knowledge Base: http://support.esri.com/index.cfm?fa=downloads.dataModels.filteredGateway&dmid=3. All of the model parameters were followed.
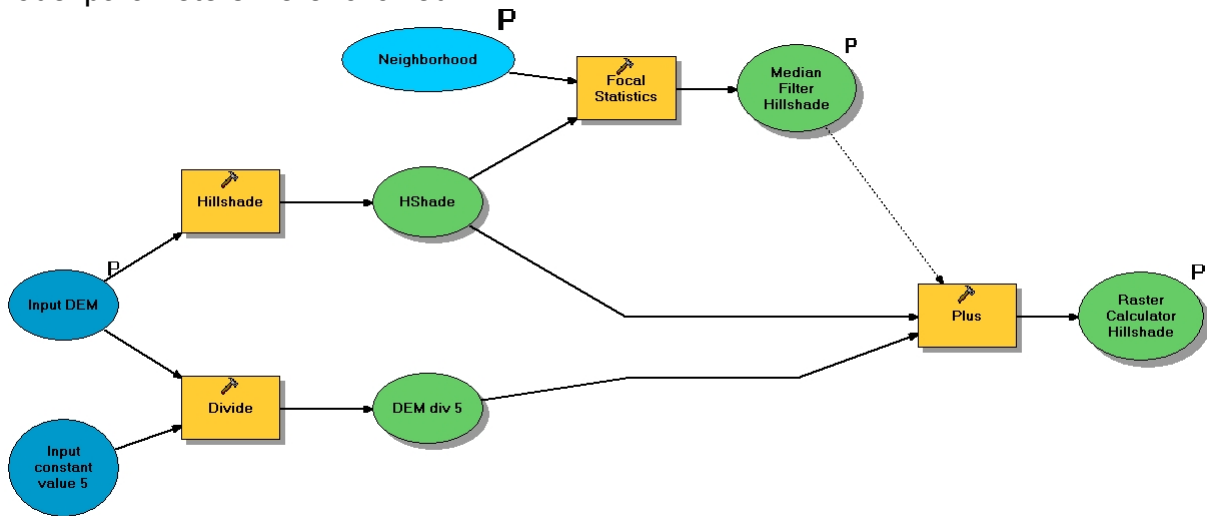

Figure 2.20 Swiss Hill Shade model

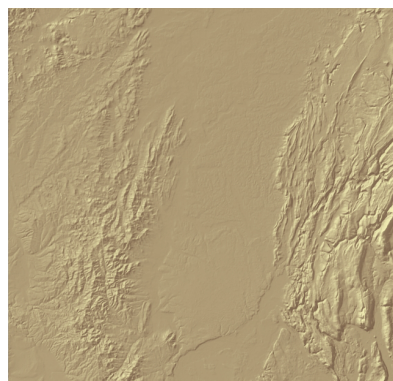Some custom color ramps were applied to achieve the final effect (Figure 2.21)

Figure 2.21 Swiss Hill Shade Result

Hill Shade products were used in cartographic products for both France and Oregon.

3.0 DATABASE IMPLEMENTATION

With so many files downloaded, extracted, and created, a database was needed to organize all of the data needed for each region. ESRI's Geodatabase format was used for the project to store and organize the vector data. The Geodatabase allows the creation of Feature datasets where like features can be stored and maintained in the same projection, providing greater efficiency and consistency when working with the data. The Geodatabase also stores any custom tools created for the project, making it easy to package the project and to share data and methodologies. Separate Geodatabases were created for France and Oregon, in order to avoid confusion and to allow space for any future data additions.

3.1 France Geodatabase

The France Geodatabase consists of four feature datasets: 'Burgundy', 'Climate_Burg', 'Dirt', and 'France'. 'Burgundy' contains a subset of France feature classes, clipped to regional size. 'Cities' for example was extracted from the 'GeoNames' feature class, and 'VineCover' was extracted from the 'LandCover' feature class. The 'Burgundy' feature dataset also contains the 'Pinot_ Smpl' point feature class which contains the sample points taken for the analysis. The regional boundary polygons, used for clipping and reference, are also located in the 'Burgundy' feature dataset. 'VineCover' takes advantage of the geodatabase subtypes ability, which uses codes to allow similar features to reside in the same feature class thereby saving space and allowing the features to be symbolized uniquely. 'VineCover' contains three different grape varietal subtypes: Pinot Noir, Gamay, and Chardonnay; all differentiated by codes in the database.

The 'Climate_Burg' feature dataset includes the 'Climate_stns' point feature class, which holds the location and climate data for the Burgundy weather stations. This feature class was used to generate the climate surfaces from the Geostatistical Analysis process. The contour line features generated from the Geostatistical procedures also reside in this feature dataset.

The 'Dirt' feature dataset contains the soil and geology polygon feature classes. The Domains function of the geodatabase was utilized for some of the soil attributes. Two of the auxiliary soil tables reside in the database for reference. The 'France' dataset holds all of the country wide feature classes, such as 'Roads', 'Rail' and 'LandCover'. It also contains the administrative boundaries for France and for surrounding countries. The 'Burg' raster catalog resides in the geodatabase point to all of the raster datasets used in the analysis or for cartographic purposes.

The 'France' Geodatabase includes the 'Model' toolbox which contains three tools used in the project: soil water balance model, potential evapotranspiration model, and a samples model. It may seem redundant, but the 'Burgundy' dataset was created specifically for efficient cartographic operations. The 'France' dataset exists in the geodatabase to hold the master country wide features, and as a contingency in case other wine regions of France were added to the study, Figure 3.1. Lambert Conformal Conic is the projection and Réseau Géodésique Français (RGF) 93 is the datum used

for all datasets. This projection and datum are the ones recommended by France's Institute Geographic National (IGN) (Institut Geographique National, 2005, p. 6) for the proper display of maps of France.
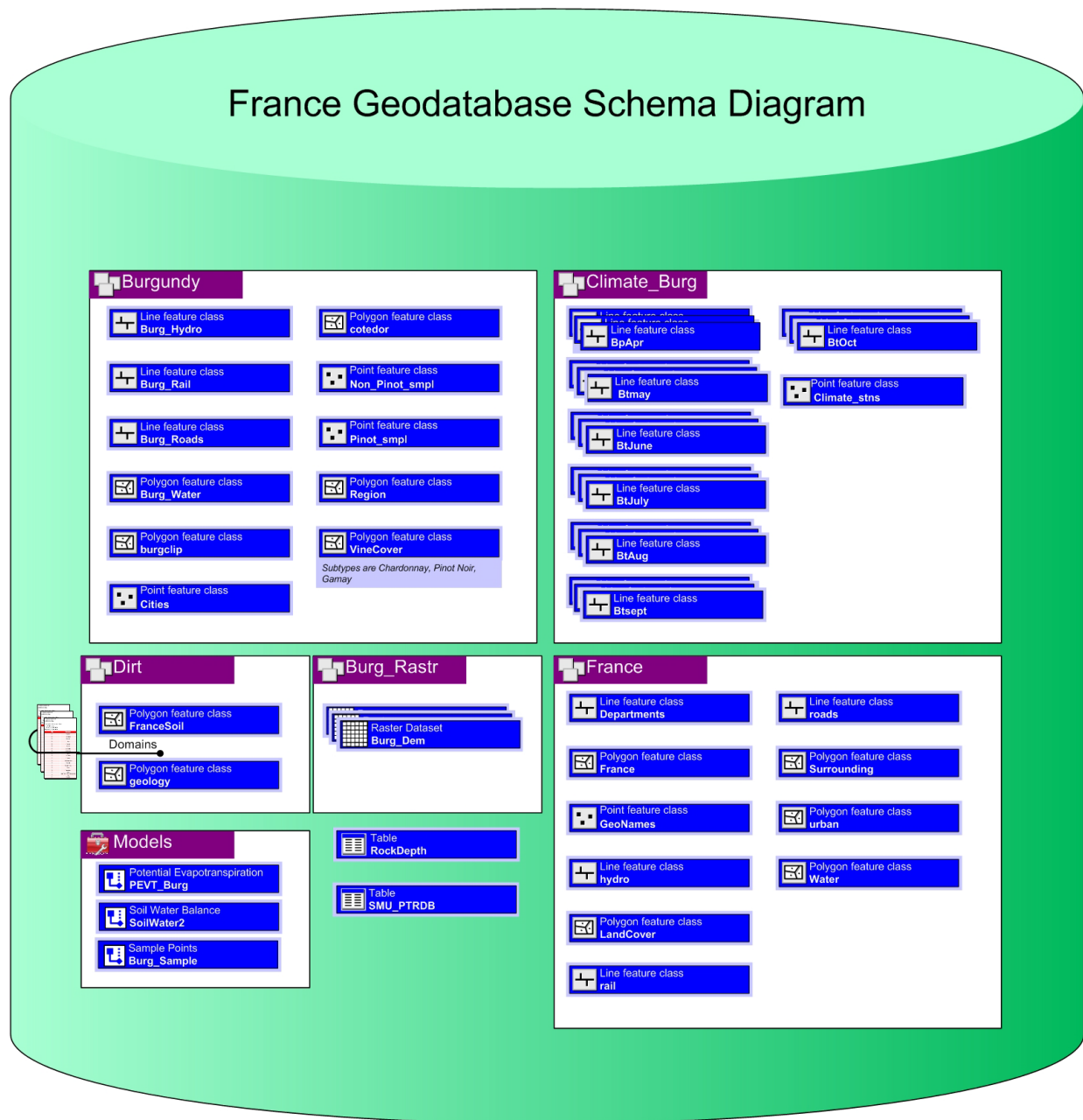
Figure 3.1 France Geodatabase

3.2 Oregon Geodatabase

The Oregon Geodatabase consists of three feature datasets: 'Base', 'Climate', and 'Soils'. The 'Base' feature dataset contains all of the base feature classes, such as 'State' boundary, 'Cities', and 'Rivers'. The 'Climate' dataset contains the 'climate_stn' point feature class which includes the location and climate attribute data for all of the

study area weather stations. This feature dataset also contains the contour lines generated from the Geostatistical Analyst process. The 'Soils' dataset contains the 'Soils', 'Geology', and 'LandUse' polygon feature classes used in the study. A raster catalog resides in the database to point to all of the Oregon raster sets used in the project. Attached to the geodatabase is the toolbox holding all of the models used in data preparation and analysis, including the Soil Water balance, Potential Evapotranspiration, and Overlay models, Figure 3.2. Lambert Conformal Conic is the projection, with the North American Datum 1983 (NAD 83) used for all three feature datasets. This is the projection and datum used by the state of Oregon for all of their data.
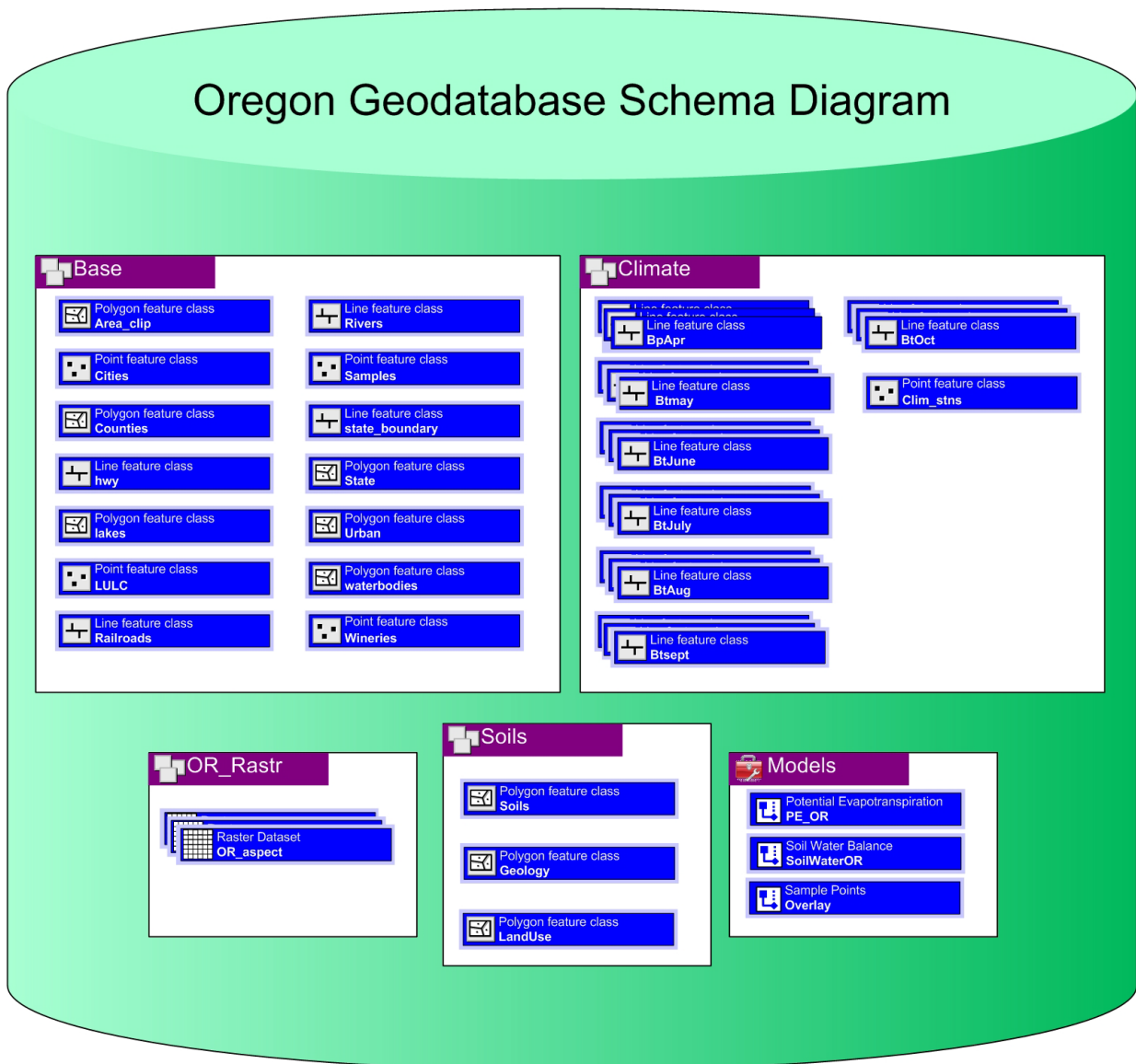
Figure 3.2 Oregon Geodatabase

4.0 ANALYSIS

The goal of the analysis was to determine the dominant physical characteristics of the Pinot Noir source region, the Cote D'Or and Cote Chalonnaise regions of Burgundy, and apply those values to rate another known Pinot Noir growing region, Willamette Valley, Oregon. The purpose was to determine if physical characteristics alone account for grape quality and to discover key Pinot Noir growing characteristics.

The first step in the analysis consisted of sampling the datasets to determine those dominant characteristics (Kleyer, 2002, p. 167). A suitability analysis applied the dominant values to a test area. Finally, a Logistical Regression was performed in order to determine key variables and to compare the results with that of the suitability analysis.

The analysis used the following derived raster layers: aspect, slope, temperature, precipitation, soil-water balance, soil type, soil texture, soil depth to rock, and underlying geologic age. The monthly climate and water balance raster surfaces were aggregated into three time periods, each representing a sub-section of the growing season in order to capture the unique characteristics of each period. The time periods are Budding, April through May; Growing, June through August; and Maturation, September through October (Wilson, 1998, p. 120). Budding represents the period where the new shoots of the vine are sprouting. The Growing period of the season models the plant growth. Finally, the Maturation period represents the grapes' cluster formation and maturation until ripe for picking.

4.1 Determine Dominant Characteristics

The first step of the analysis was to determine the dominant physical characteristics of the Pinot Noir source region, Burgundy, France. Once determined, these physical traits will reclassify the data layers over the Willamette Valley test area in a Suitability Analysis. This was achieved through the use of the Sample tool, found within the Extraction toolbox of the Spatial Analyst tools, Figure 4.1.
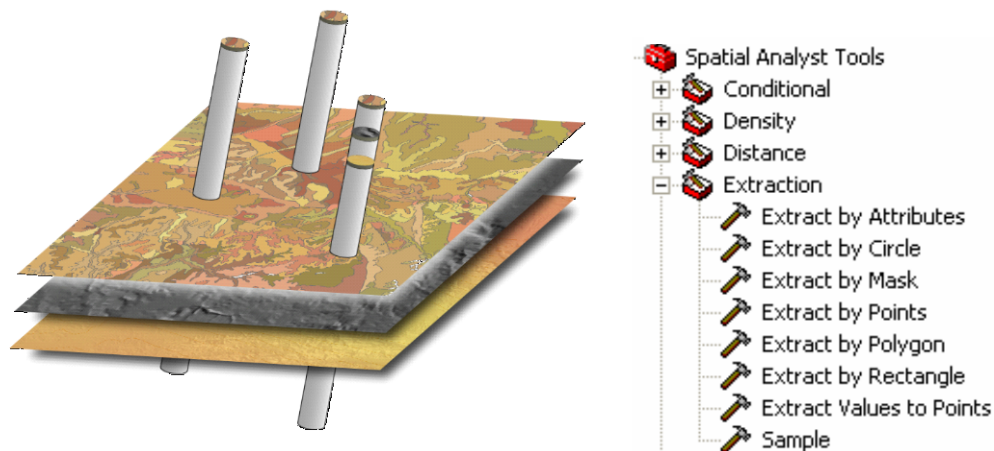
Figure 4.1 Sample Tool Illustration

To utilize the Sample tool, a feature class or shapefile of all sample points (X, Y locations) must exist over the study area. Sample points were placed randomly within the vineyard land cover polygon feature ('VineCover') Pinot Noir boundaries, Figure 4.2, to create the feature class.
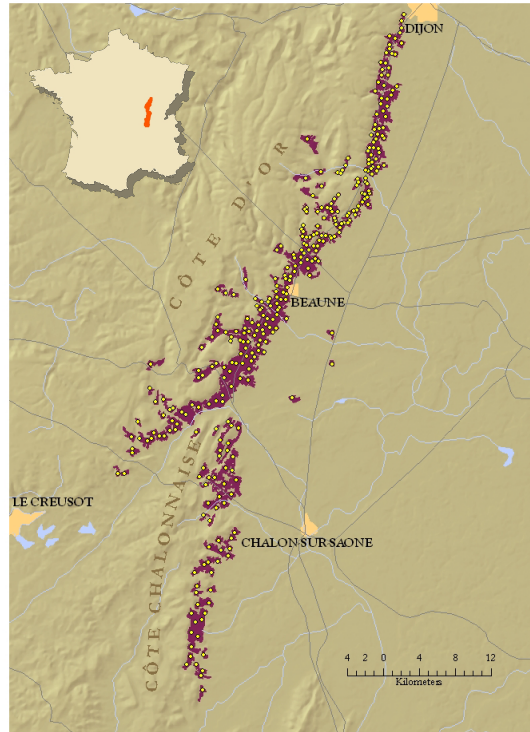
Figure 4.2 Pinot Noir Sample Points

This ensured the sample points were taken within vineyard boundaries. The Sample tool requires nomination of all the relevant raster datasets and the sample point file as parameters. As the tool runs, it takes data points from each raster layer pixel which coincides with the x,y location of the sample points. The Sample tool packages the sample point data values into a database table as an output, Table 4.1.

Table 4.1 Excerpt of Sample Tool Output

mask	x	y	bud_precip	grow_preci	mat_precip	total_prec	bud_avg_te	grow_avg_t	mat_avg
0	851477.120701	6691111.49217	140.63	183.55	143.57	467.75	23.38	56.56	26.74
0	851260.056486	6689592.04266	140.21	182.88	142.85	465.95	23.40	56.64	26.75
0	849926.662026	6688661.76746	140.82	182.80	143.52	467.14	23.39	56.56	26.74
0	851198.038139	6687886.53812	139.87	182.22	141.90	463.99	23.34	56.66	26.71
0	849895.652852	6687762.50143	140.53	182.32	143.09	465.94	23.38	56.59	26.72

The generated data table then can be brought into MS Excel where statistical tools are used to determine the dominant range of values for each raster dataset. A Frequency Distribution analysis was completed to determine the dominate data range of the sample points from each dataset. For numerical dataset types, such as temperature, the data must be binned into 'mutually exclusive sub-groupings' (Kaboudan, 2005, ch 2) before the Frequency Distribution can be done. These bins were determined using

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the 'power of two rule which states that one should select the number of classes as the first power of 2 that just equals or exceeds n' (Kaboudan, 2005, ch. 2), where n is the number of sample points. The number of samples taken from the Burgundy area is 327. The power of 2 which equals or exceeds 327 is 2^9, or 512; therefore, the number of classes to group the data into is 9. To determine the width of classes, the following formula is used: "Class Width = Range / c, where Range = Highest observed value - Lowest observed value, and c = number of classes. Class width is always an integer and any number that is not one must be rounded upwards" (Kaboudan, 2005, ch2). For example: if the range of the dataset was 89, and the class size taken from above is 9, the Class Width = 89/9 = 9.89, rounding up would be 10. Once the bins were determined, the MS Excel Histogram tool (Tools>Data Analysis>Histogram) was employed to determine the frequency of the bins and to plot the histogram graph, Figure 4.3.

Aspect	
Bin	Frequency
20	3
60	16
100	54
140	104
180	79
220	35
260	18
300	9
340	8
360	1
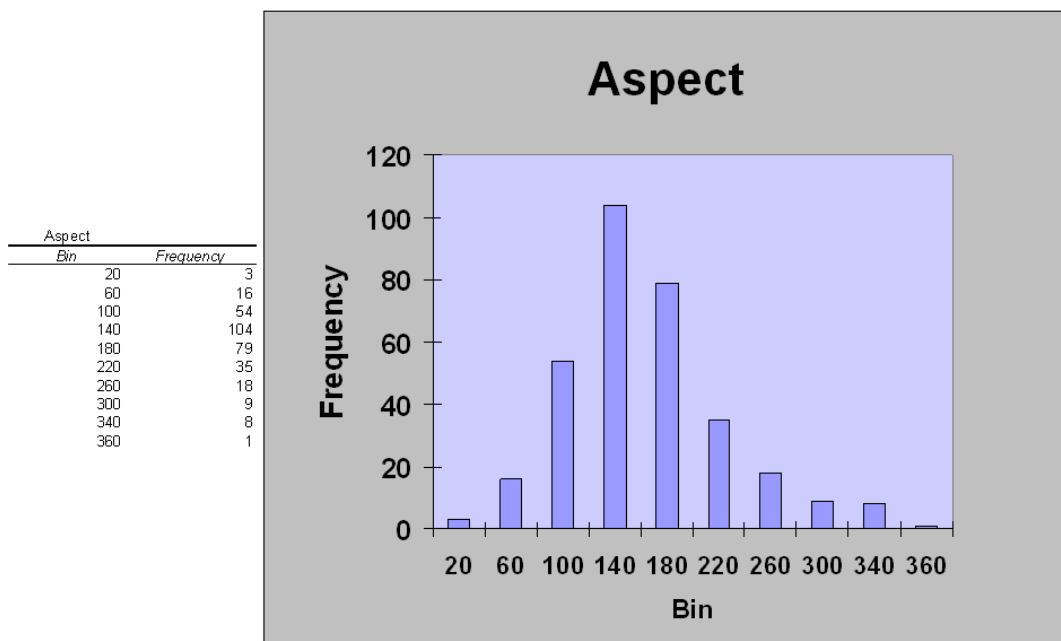
Figure 4.3 Histogram of Aspect Data Samples

Figure 4.3 is an example of Frequency Distribution of the Aspect sample data values. The 100 -140 degree (South East) Aspect data range is the most frequent, occurring 104 times in the Burgundy sample set.

For the Nominal data, such as Soil Type or Texture, the bins were determined by simply using each unique data value. This was done because the data was nominal, and therefore no data values would fall between ranges. The Excel Data Filter tool (Data>Filter>Advanced Filter) determined the unique data value from each sample. Once the bins were determined, again the histogram tool was used to chart and plot the Frequency Distribution, Figure 4.4.

Rock Depth

Rock Depth	
Bin	Frequency
1	86
2	196
3	24
4	21
More	0
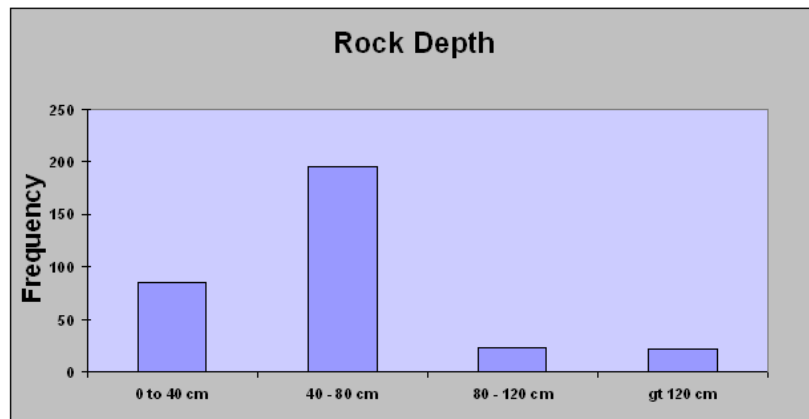
Figure 4.4 Rock Depth Frequency Distribution

In the Depth to Rock sample dataset, the 40-80 cm range bin is the most frequent value in the Burgundy sample set. All the datasets sampled were analyzed in this way; all resulting Frequency distributions can be found in Appendix C. Table 4.2 displays the approximate range of dominant values from the datasets.

Table 4.2 Approximate Burgundy Dataset Dominant Value Ranges

Dataset	Dominant Value Range	Frequency
Aspect (º)	100 - 140	104
Slope(º)	0 - 4	167
Budding Temperature (C)	23.1 - 24	327
Growing Temperature (C)	56.1 - 57	174
Maturation Temperature (C)	26.1 - 27	292
Total Temperature (C)	107.1 - 109	177
Budding Precipitation (mm)	139.1 - 149	283
Growing Precipitation (mm)	176.1 - 191	262
Maturation Precipitation (mm)	135 - 152	286
Total Precipitation (mm)	457.1 - 475	245
Budding Water Balance (mm)	9 - 19	271
Growing Water Balance (mm)	-51.9 - -34	170
Maturation Water Balance (mm)	-7.9 - -1	294
Total Water Balance (mm)	-36.9 - -25	113
Soil Type	Inceptisols	208
Geology	Mesozoic	148
Rock Depth	40 - 80 cm	196
Texture	Medium Fine	191

According to the samples, the most frequent Aspect is the South East facing range (100º -140º). These results agree with the experts that state "better Vineyards are placed on slopes which face south to south west" (Hancock, 1999, p. 76). A slight slope of 0 to four degrees seems to occur the most often among the vine covered lands of Burgundy. Budding Temperature, the first two months of the growing season, averages between 23º and 24º Celsius in all of the samples. Growing and Maturation also only vary a degree during their respective time periods. Of note, the warmest

50

period is during the Growing part of the season. The wetter months of the season, tends to be during the Budding and Maturation periods, with a majority of the samples receiving 135-152 mm of precipitation. As far as soil-water balance goes, a majority of the samples have a slight surplus of water during the Budding season, and large deficit of water during the summer growing season with up to -52 mm, and then only a slight deficit throughout the Maturation part of the season. The dominant sample Soil Type is Inceptisols. The most common Geologic age of the samples is the Mesozoic structure. The most common Rock depth is in the 40-80 cm range. Finally, the Medium Fine texture dominates the Burgundy samples. In Figure 4.5, both the most dominant range for each dataset is displayed.
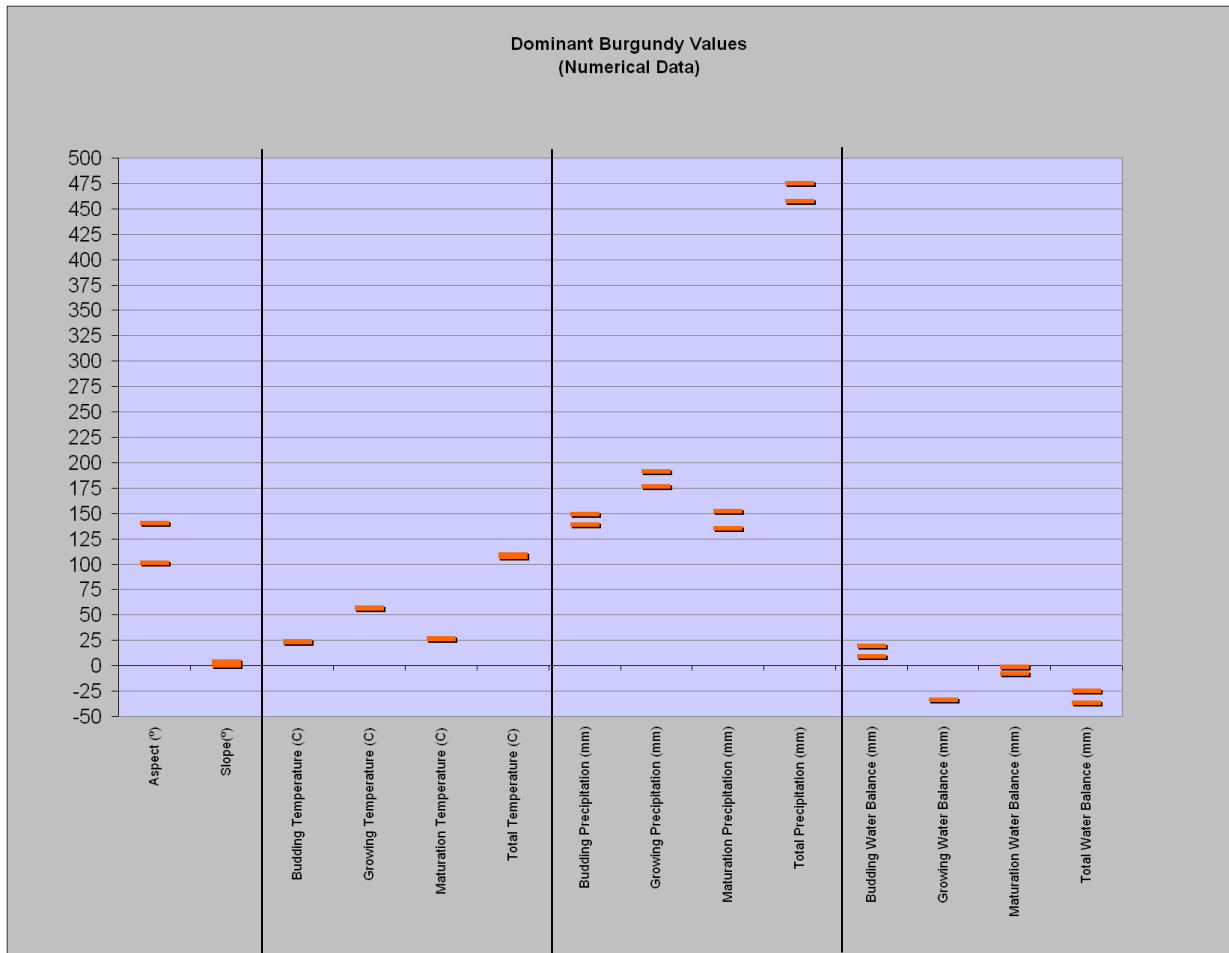
Figure 4.5 Graphic of the Burgundy area's most frequent data ranges

4.2 Suitability Analysis

4.2.1 Reclassify

The Burgundy data ranges were used to reclassify the Willamette Valley, Oregon data. The most frequent Burgundy data range was assigned a high number of 3, with subsequent data ranges given 2, 1 and 0. This was done to model levels of suitability,

assuming the most frequent data range represented the most suitable data range. Data availability forced this assumption and methodology. The preferred method would involve using some sort of spatially referenced vineyard quality data to guide the suitability rating. Since this kind of data was unattainable, the simpler 'dominant is best' approach was adopted. This system was used as a guideline to reclassify the Oregon datasets. For example, 23.1º – 24º C was the most frequent temperature range for the Burgundy Budding Season. The corresponding data range in the Willamette Valley Budding Temperature dataset, was reclassified to a 3, the most suitable. The Reclassify tool from the Spatial Analyst tools was used to reclassify the Oregon raster datasets. To account for the fact that the Burgundy samples did not capture the full data range, a suitability value of 1 was assigned to the Oregon data, which may not have fallen within the Burgundy sample range, but did fall within the Burgundy minimum/maximum data range of the original data.

4.2.2 Suitability Overlay and Results
Once all of the Oregon data layers were reclassified, they were added together, using the Single Output Map Algebra tool. This created a simple suitability surface from all of the reclassified data sets, with the higher numbers representing the most suitable areas. Fifteen data layers in total were added together, so the highest possible suitability was 45. In the actual result below, Figure 4.6, the highest suitability value observed in the overlay was 27 (dark red).
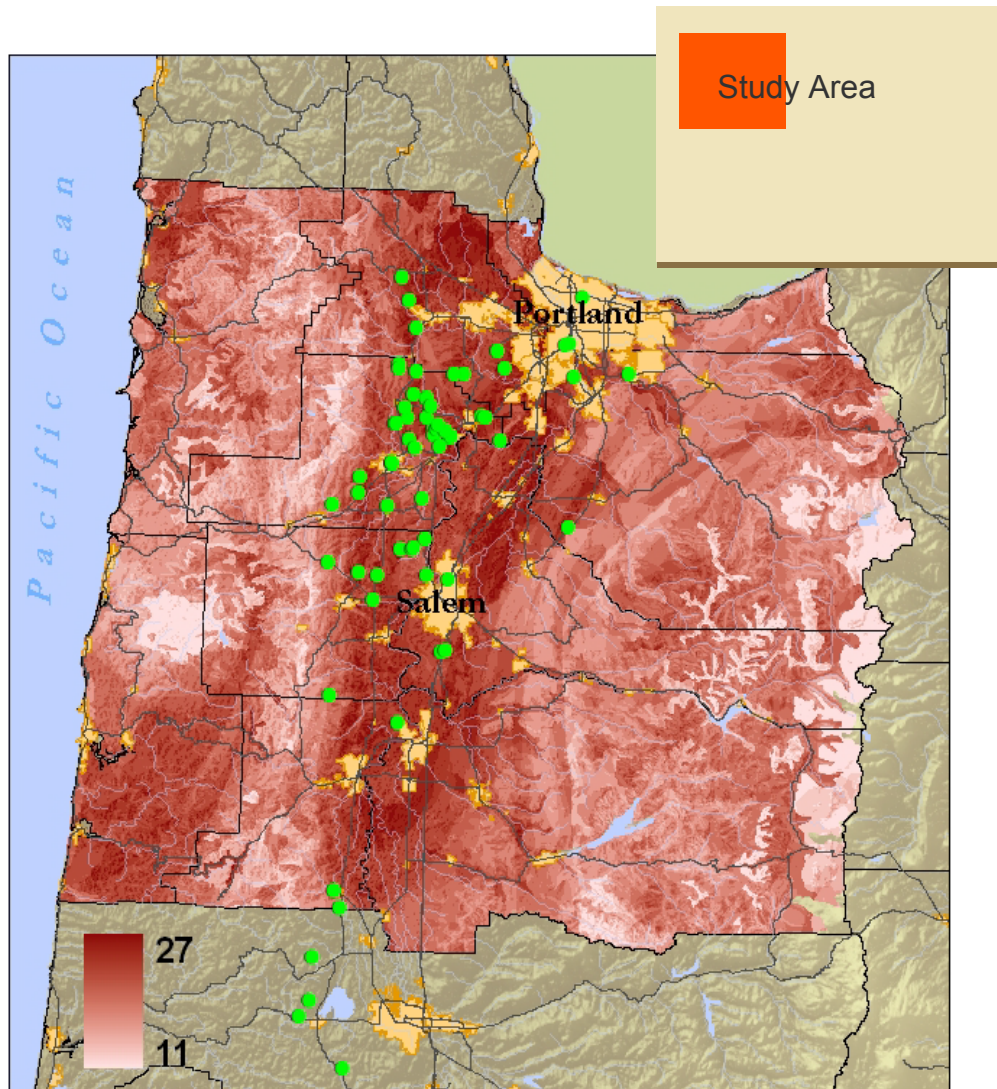
Figure 2 Suitability Analysis Results with Winery Locations

With the winery locations (green points) overlaid, we see that in fact the wineries are generally located in the most suitable areas of the Willamette Valley. Looking at the land use, Figure 4.7, 'berries and vineyards' category in green, one can observe that it lies within some of the most suitable parts of the Willamette Valley as well. However, 27 out of 45 is only 60% suitable. Sample points from both regions can be used to compare like datasets to determine similarities and differences. By observing the similarities, it may be possible to determine key physical elements common to both geographical locations; elements which could be important in indicating good pinot noir terroir in new regions.
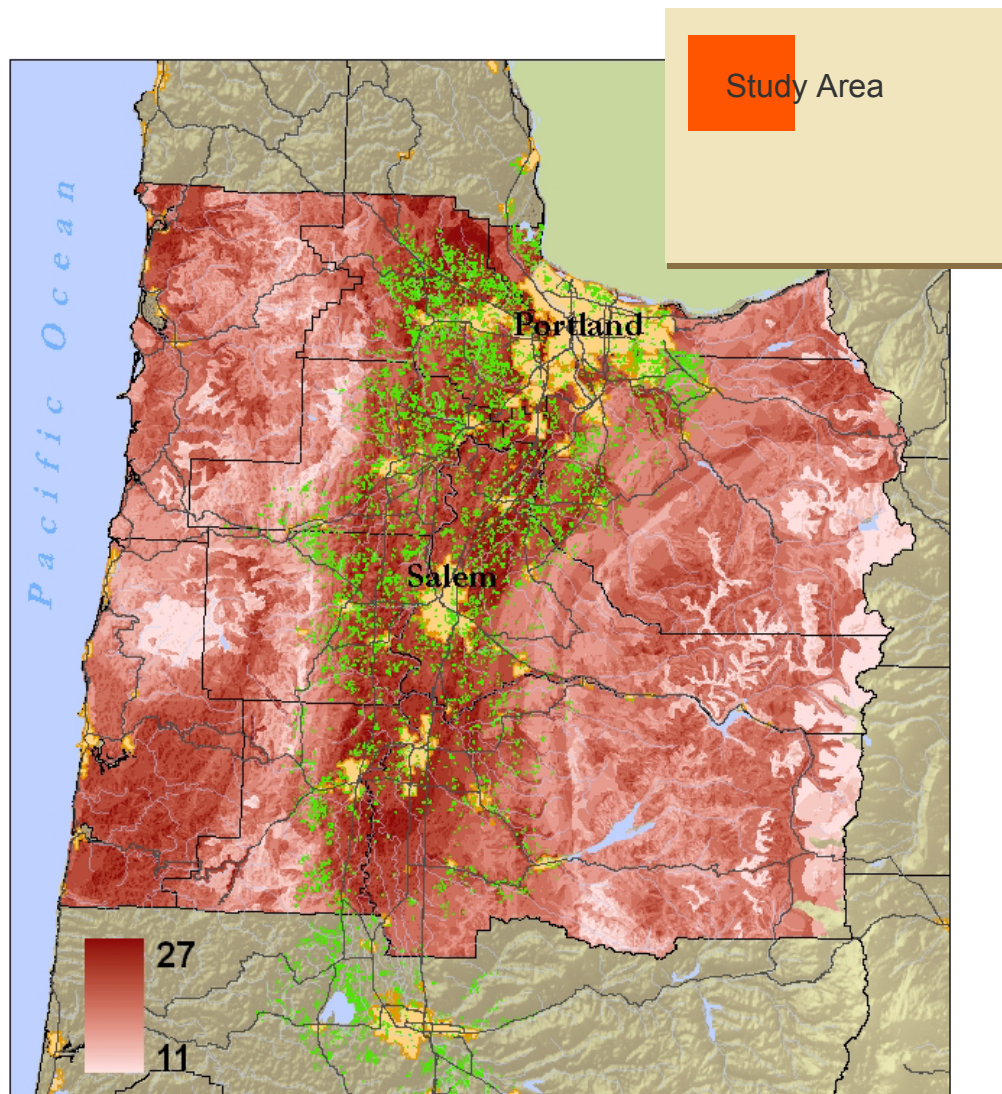
Figure 4.7 Land Use Overlaid on Suitability

Box-plots visually compare the numerical attributes. In Figure 4.8, Aspect and Slope are shown to be similar between the regions.
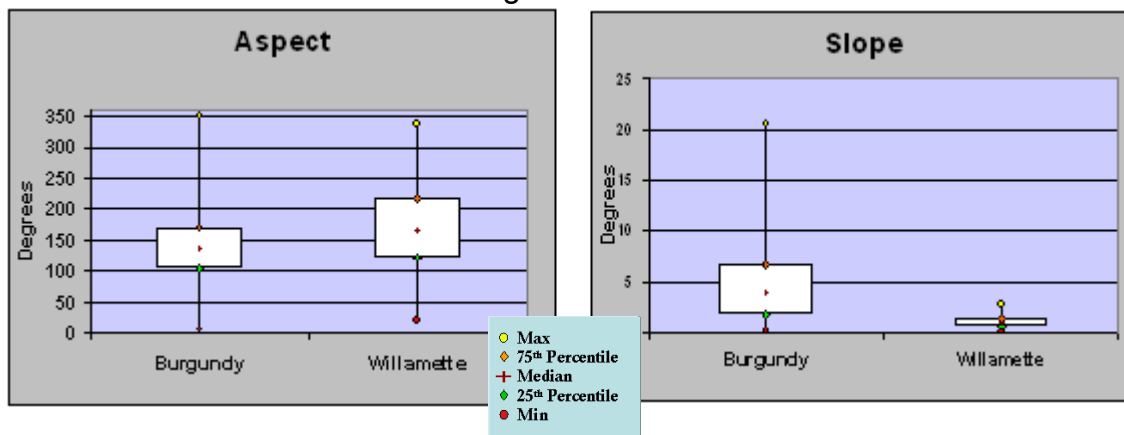
Figure 4.8 Aspect and Slope Comparison

Both Burgundy and the Willamette Valley have a dominant East to Southeast aspect, and both show a gentle slope in a majority of the vineyard locations sampled. In the precipitation box plots, Figure 4.9, the Budding and Maturation periods of the growing season are similar, with a large difference in the Growing period of the season.
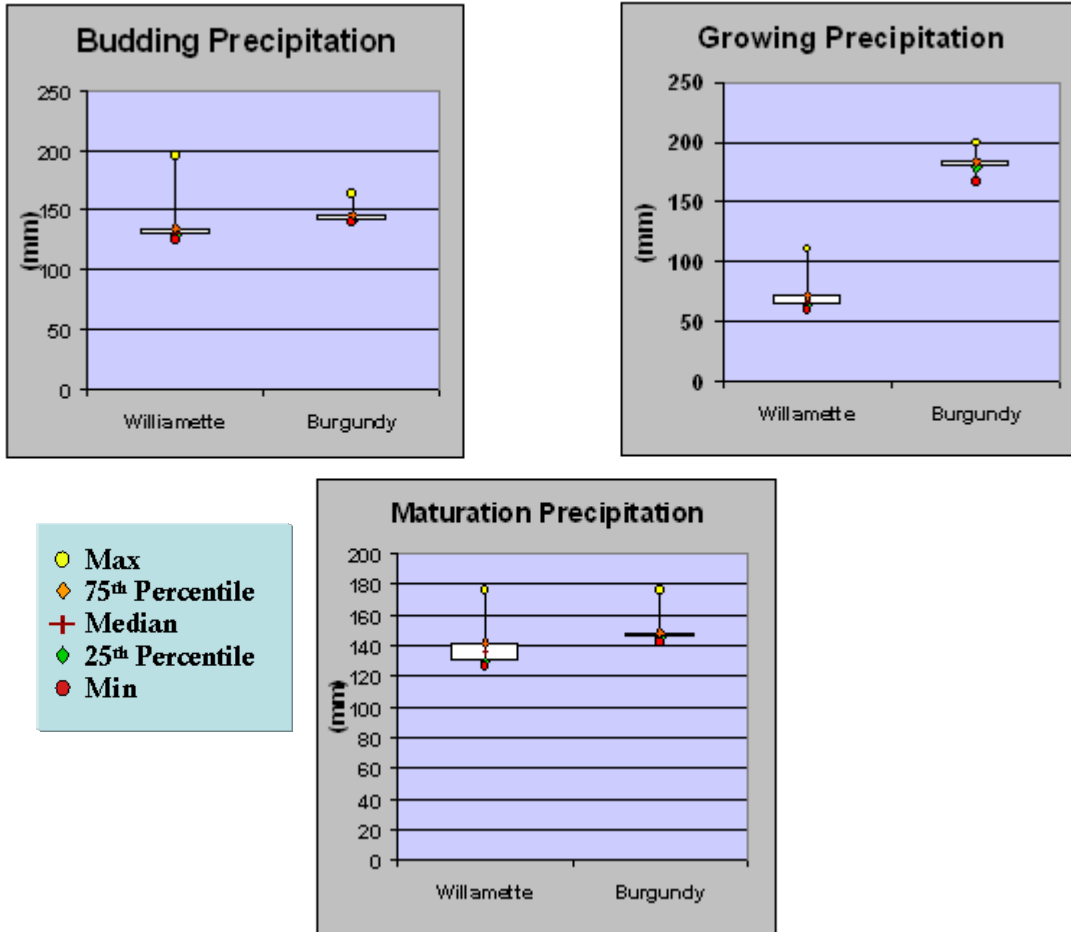
Figure 4.9 Precipitation Comparison

Although irrigation is not restricted in the Willamette Valley, as it is in France,   wine growers for the most part, do not irrigate (Bagnall, 2001). Median Temperature differs only about 3 degrees at most, Figure 4.10, so temperature appears to be another attribute the two regions share.
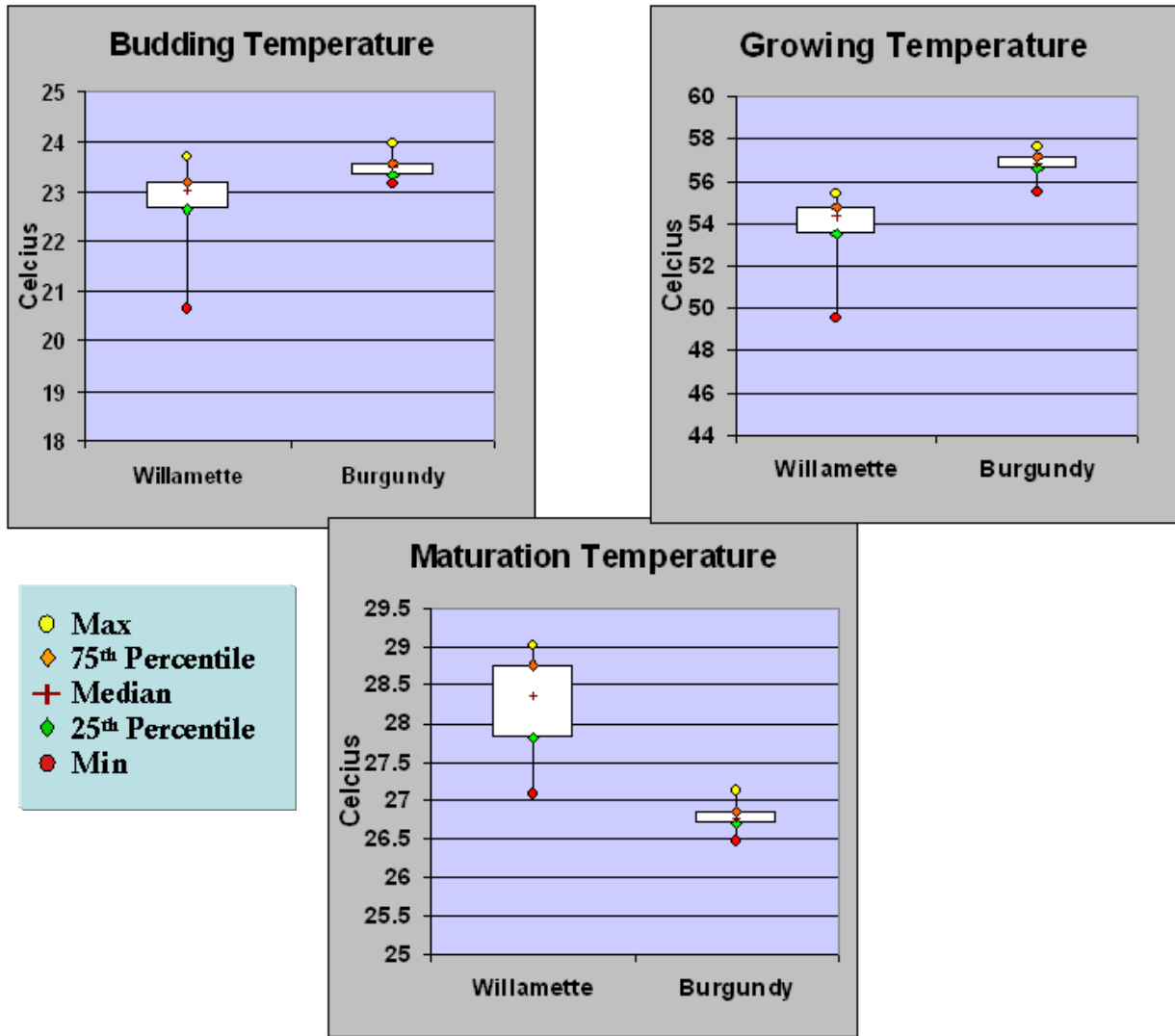
Figure 4.10 Temperature Comparison

The Willamette Valley and the Burgundy region soil-water balance differ greatly, especially during the last two parts of the growing season, Figure 4.11.
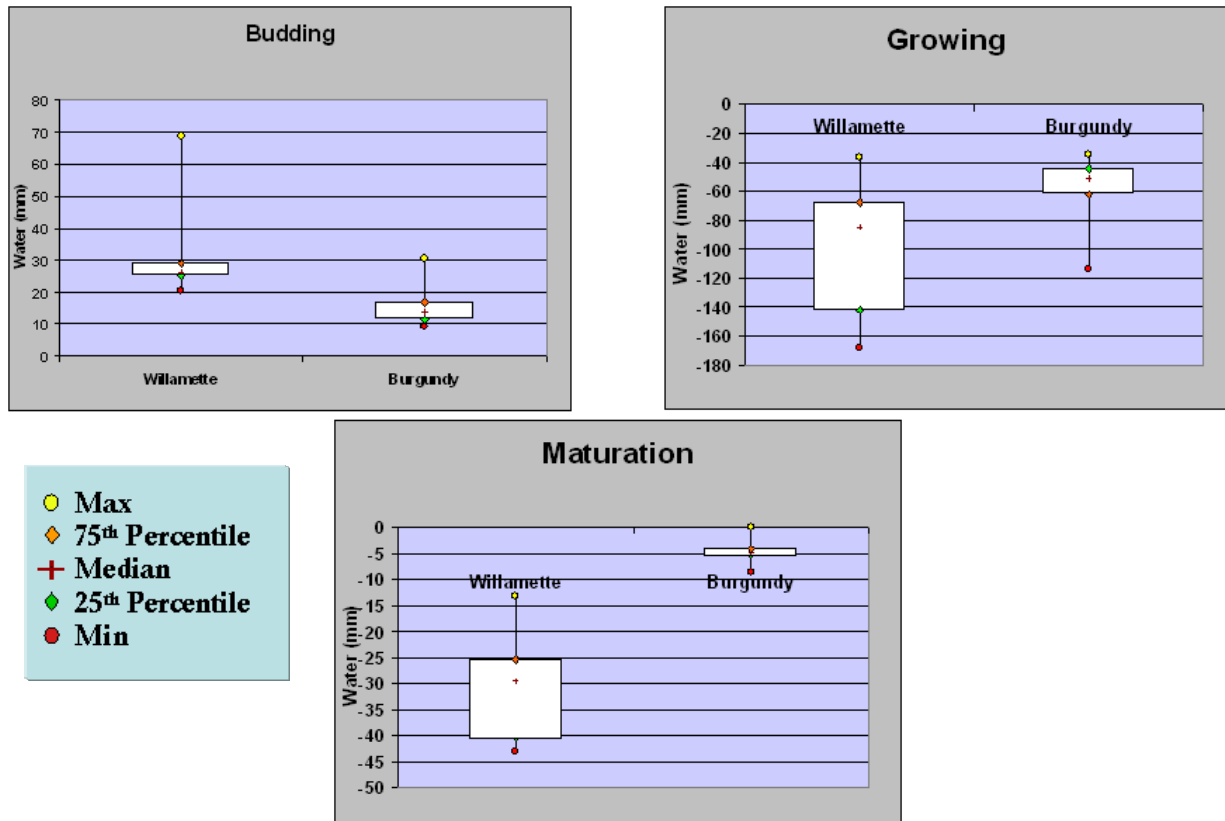
Figure 4.11 Soil - Water Balance Comparison

The water differences between the two regions come from the unique interplay of the water holding capacity of the soil, the temperature, and rainfall throughout each part of the season. The Willamette data depicts a drier soil during the last two parts of the growing season, explaining some of the differences between the regions.

The qualitative data demanded the use of histograms to compare the data between the wine regions of study, Figure 4.12.
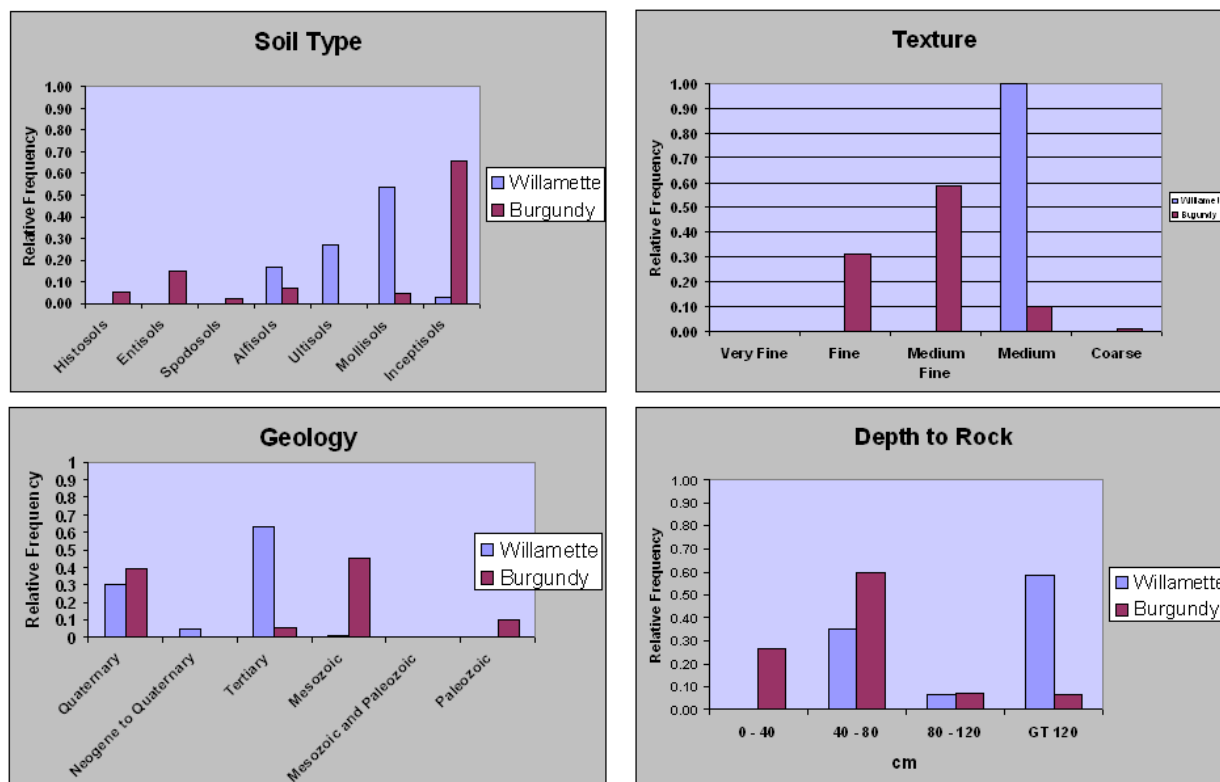
Figure 4.12 Soil and Geology Comparison

Inceptisols dominate the Burgundy samples, whereas Mollisols seem to dominate the Willamette samples. Inceptisols tend lack distinguishing features and are found in river valleys and forested slopes (Buol, Southard, Graham, & McDaniel, 2002, p. 293); whereas, Mollisols tend to be more fertile with organic matter and are generally located in such agricultural areas as the Great Plains of the United States (Tan, 1994, p. 13 & 14). Both regions tend toward the medium textured soil, with Burgundy's texture being finer. The Mesozoic age tends to be the most common geology era in Burgundy, whereas the Willamette is more dominated by the Tertiary age. It is interesting to note, however, that both share a secondary peak in the Quaternary epoch. The Depth to Rock attribute differs between the two with the Willamette Valley having a deeper soil profile before hitting bedrock.

By observing the comparison plots, conclusions can be drawn as to what makes the grape growing regions of the Willamette Valley the most suitable when compared to Burgundy, but also why the region does not reach the maximum suitability score. Elements which are similar between the regions and positively impact the suitability score include: aspect, slope, temperature, and precipitation. Elements which differ include the Soil Water balance, Soil Type, and Texture. Geology and the Depth to Rock attributes both contain some secondary similarities which would facilitate the suitability as well. Despite Willamette Valley scoring only a maximum of 60% on suitability, both wine regions produce award winning Pinot Noir. This apparent disconnect could stem from a number of possible reasons. As the Roman poet Ovid is

reported to have wrote in the 1ˢᵗ century A.D., "Good Wine comes from vines that are well tended". The human element could help account for quality wine grapes and quality wine, but is hard to measure and is not included in this study. It could indicate the amazing adaptability of the Pinot Noir varietal. Or it could be that Oregon found a genetic strain or clone of Pinot Noir which adapted well to the physical terroir of the Willamette Valley. Lack of strong suitability could also stem from the coarseness and lack of available data. Whatever the reasons for the suitability outcomes, the differences between the regions maybe a good thing, and could possibly indicate what contributes to the uniqueness and distinction of Willamette Valley wines, and may point toward further study into Pinot Noir geographic requirements. In the above analysis, no data set was weighted higher than the other, all had equal influence. A regression analysis can determine how much each data element impacts the Burgundy region in order to develop a predictive model for determining suitable Pinot Noir habitats in other areas.

4.3 Logistical Regression
A logistical, or logit, regression determines the importance of the independent variables and develops a predictive model (Sellars & Jolls, 2007, p. 1196). Results are in a binary form 1 or 0 and show the relative importance of each independent variable upon the dependant variable. This analysis explored a logistical regression to investigate the possibility of developing a predictive model for determining suitable Pinot Noir habitat locations in the Oregon study area. A model based on the Cote D'Or and Cote Chalonnaise Burgundy sample data. In this instance, a result of 1 would represent a Pinot Noir vineyard region, and a 0 result represents a non-Pinot Noir vineyard region. The resulting equation from the logit regression uses the spatial form of the data in GIS to determine the locations of the suitable Pinot Noir vineyard areas (Jennie & Ferrier, 2000, p. 128).

4.3.1 Logistic Methodology
The datasets used in the Suitability Analysis, were used as independent variables in the logit regression. The same sample data used to determine the dominant data values of the Burgundy Vineyard areas for the Suitability Analysis, became the independent variable values whose y or dependant value equaled 1, a vineyard location. The analysis required non-Vineyard samples of the data as well, for the logit regression to work. These dependant variables were given the value of 0, and their independent data variable values were included so that the logit could determine which independent variables really contribute to the Burgundy Vineyards being a vineyard, or a 1. The Non-Vineyard samples were taken in the same manner as before, using the 'Sample' tool in ArcGIS.

4.3.2 Logit Data Preparation
Data preparation included assigning dummy variables for each instance of an attribute, of independent variables whose values were nominal. Dummy variables allow statistical analysis of categorical data (Hardy, 1993, p. 2). In the example table excerpt below, Table 4.3, the nominal data set 'soil_rckd', or Soil Rock Depth, a dummy variable was assigned to each possible

Table 4.3 Soil Rock Depth Dummy Variables

soil_rckd	DVSR1	DVSR2	DVSR3	DVSR4	DVSR5
1	0	1	0	0	0
1	0	1	0	0	0
1	0	1	0	0	0
1	0	1	0	0	0
1	0	1	0	0	0
3	0	0	0	1	0
2	0	0	1	0	0
0	1	0	0	0	0

unique nominal value and then substituted for every occurrence of that unique value in the samples. The logit regression included a total of 503 vineyard and non-vineyard samples of the data. Dummy variables were assigned to represent each possible value of the Soil Rock Depth, Soil Texture, Soil Type, and Geology independent datasets.

Next, random numbers, generated in Excel, reordered all of the data samples in order to eliminate any bias inherent in the original data order. 23 of the 503 sample points, approximately 22%, were set aside for validation of the resulting model. The project data includes a copy of the original ordered dataset and a copy of the randomly ordered data.

4.3.3 Logit Regression Execution

Regression Analysis of Time Series (RATS) software performed the logit regression computations. The software mandates that all of the data inputs have a variable to replace the name. The following table 4.4 is a variable dictionary to understand the software's logit output.

Table 4.4 Logit Variable Definitions

Depth to Solid Rock	Soil Texture	FAO Soil Type	Geology
DVSR1	DVST1	DVFAO1	DVG1
DVSR2	DVST2	DVFAO2	DVG2
DVSR3	DVST3	DVFAO3	DVG3
DVSR4	DVST4	DVFAO4	DVG4
DVSR5	DVST5	DVFAO5	DVG5
	DVST6	DVFAO6	

Aspect	Slope	Budding Precip	Budding Avg Temp	Budding Soil Water Balance	Growing Precip	Growing Avg Temp	Growing Soil Water Balance	Maturation Precip	Maturation Avg Temp	Maturation Soil Water Balance
X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11

The RATS software ran a total of seven regression iterations; each time the variables were evaluated and sometimes removed, depending upon their influence in the results of the iteration. The final (seventh) iteration produced the following equation, 4.1:

$$Y = -164.70 + (26.58 \cdot DVSR2) + (26.89 \cdot DVSR3) + (25.63 \cdot DVSR4) + (25.77 \cdot DVSR5) + (1.60 \cdot DVST3) + (1.11 \cdot DVST4) +$$
$$(26.31 \cdot DVG1) + (25.60 \cdot DVG2) + (28.02 \cdot DVG3) + (27.59 \cdot DVG4) + (-0.0048 \cdot X1) + (0.18 \cdot X2) + (-2.57 \cdot X4) +$$
$$(-0.29 \cdot X5) + (2.92 \cdot X7) + (0.047 \cdot X8) + (0.081 \cdot X9) + (-0.28 \cdot X11)$$

Equation 4.1 Vineyard Logit Equation

It is interesting to note which variables fell out and which remained as a result of the logit process. Most of the depth to rock variables remained except for the first one, DVSR1. This makes since DVSR1 represents the values where there is no information. The logit process retained only the variables representing the "Fine" and "Medium-Fine" texture categories, DVST3 and DVST4, indicating their importance in indicating a Burgundy vineyard. The final iteration kept all of the Geology variables, except for the one representing the Precambrian age. Slope and Aspect both survived the iterations. Variables representing the average temperatures for the Budding and Growing segments of the growing season remained, as well as only the precipitation variable representing the Maturation segment of the growing season. It is interesting to note that all three seasonal variables representing the soil water balance stayed, which could indicate an importance in determining a Burgundy Pinot Noir type vineyard. It is just as intriguing that all soil type indicator variables dropped out of the equation. This fact could come from the samples indicating no difference between the vineyard and non-vineyard samples of the soil type, therefore making it useless to determine vineyard status.

Before applying the equation, it was tested using the original samples to see how well the equation worked in predicting vineyard or non-vineyard status, the dependant variable. To accomplish this, the data samples were entered into an equation in Excel, and then these results were run through the prediction equation, 4.2.

$$\text{Prediction} = \text{EXP(Equation Result)} / (1 + \text{EXP(Equation Result)})$$

Equation 4.2 Logit Prediction

EXP is the Microsoft Excel function used to raise the constant e, the base of the natural logarithm, to the power of the "Equation Result". The Prediction equation forces the results to be in a range between 0 and 1. This process was done for all 503 sample datasets, including the 23 test samples left out of the logit process. Once the Prediction values were determined from the logit equation results, they were rounded

to 1 or 0 based on whether or not they fell above or below 0.5. If above the 0.5 threshold, a 1 was assigned, indicating a vineyard. If the outcome was below 0.5, then a zero was assigned, indicating not a vineyard. The Predicted Y was compared to the Original Y, Table 4.5.

Table 4.5 Excerpt of Predicted Y versus Original Y

ENTRY	Original Y	Predicted Y	Categorized as Vineyard when not	Categorized as Not a Vineyard When it is
			41	12
1	0	0	0	0
2	1	1	0	0
3	1	1	0	0
4	1	1	0	0
5	0	1	1	0
6	0	1	1	0
7	1	1	0	0
8	1	1	0	0

From the table excerpt above, a total of 41 samples out of the 503 were predicted to be a vineyard, when in fact, not an actual vineyard. Only 12 samples were predicted to not be a vineyard when it actually was a vineyard. The prediction error is about 8% and 2% respectively. When observing just the 23 values kept out of the logical regression process, the results are similar, Table 4.6.

Table 4.6 Model Validation Values Comparison

ENTRY	Original Y	Predicted Y	Categorized as Vineyard when not	Categorized as Not a Vineyard When it is
			3	0
481	0	1	1	0
482	0	0	0	0
483	1	1	0	0
484	0	0	0	0
485	1	1	0	0
486	0	0	0	0
487	0	0	0	0
488	0	0	0	0
489	0	1	1	0
490	1	1	0	0
491	0	0	0	0
492	1	1	0	0
493	0	1	1	0
494	0	0	0	0
495	1	1	0	0
496	0	0	0	0
497	1	1	0	0
498	1	1	0	0
499	1	1	0	0
500	0	0	0	0
501	0	0	0	0
502	0	0	0	0
503	1	1	0	0

Only 3, or 13%, of the 23 validation sub-set were mis-categorized as vineyard and none were mis-categorized as a non-vineyard. With the logit equation determined and validated, it can now be applied to test the logit model.

4.3.4 Logistic Model Applied to Burgundy

The resulting logistic equation was applied to the Cote D'Or and Cote Chalonnaise Burgundy regions to further validate the Pinot Noir logit model. Before the Burgundy raster datasets can be fed through the logit equation, the nominal raster data sets must be converted to variable indicator grids; grids which represent the presence or absence of each unique attribute of the nominal data grid (Warmerdam, 2003, p. 49). This action matches the logit regression dummy variable methodology so that the unique attributes can be used in the resulting logit equation. Figure 4.13, represents the indicator raster dataset of a nominal Depth to Rock attribute.

Figure 4.13 Indicator Raster for a Depth to Rock Attribute

Once the indicator raster sets were prepared, the logit model (Equation 4.1) was applied using the Burgundy raster datasets and the Single Output Map Algebra (SOMA) tool found in the ArcGIS Spatial Analyst tools. The resulting surface is then fed into the prediction equation (Equation 4.2) using the SOMA tool, and then the resulting surface was rounded to 1's or 0's, again using the SOMA tool. The resulting grid is an indicator surface where 1 means a vineyard area and 0 means not a vineyard area. Figure 4.14 depicts the logit result, where we see the 1's, or Vineyards, depicted in orange.

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Figure 4.14 Logit Equation Results Indicating a Burgundy Vineyard

With the Vineyard landcover overlaid, Figure 4.15 below, we see that the model prediction matches the observed map quite well.
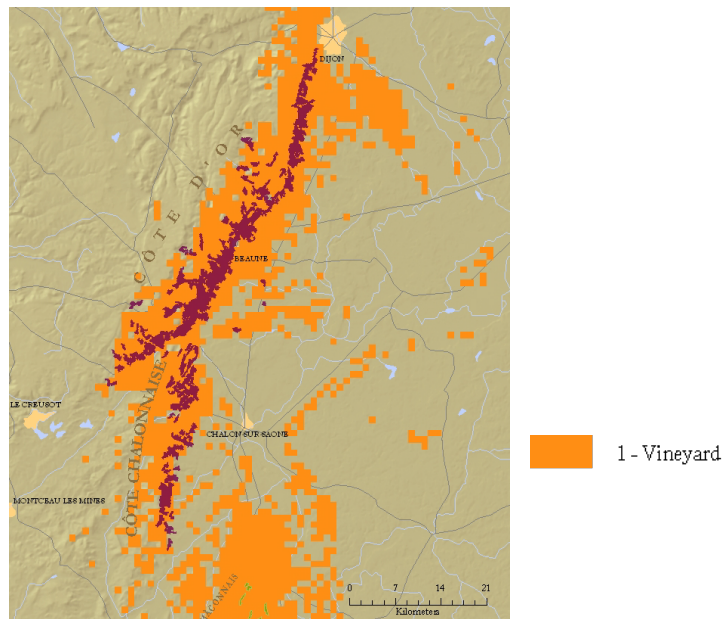
Figure 4.15 Logit Results with Vineyard Landcover Overlaid

When observing the whole region, the logit model also captures the other varietals growing in the region, as Figure 4.16 depicts.
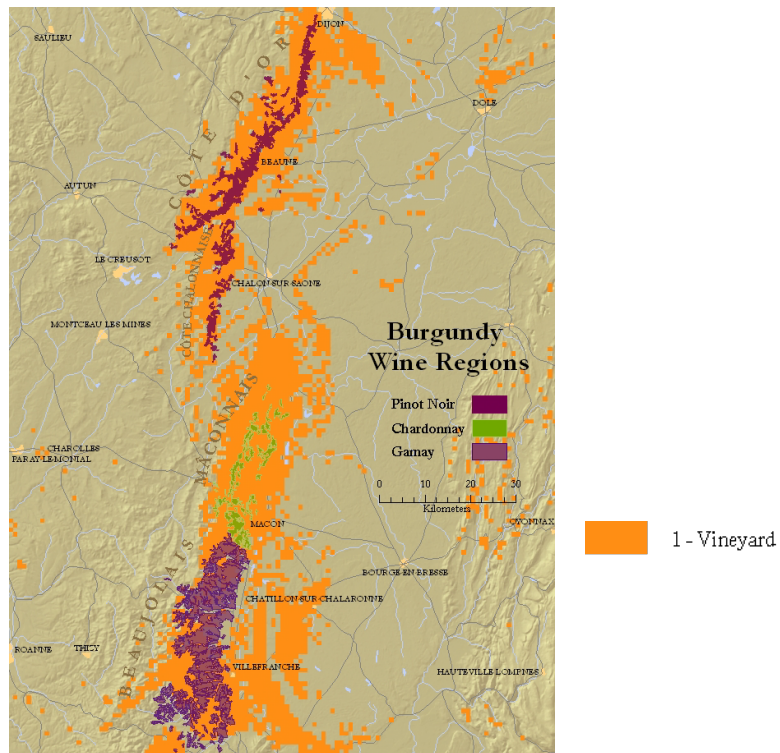
Figure 4.16 Logit Results for the Entire Burgundy Region

The results indicate the logit model predicts whether it is a Burgundy varietal growing region, not just Pinot Noir. This is probably due to the coarseness of the regional data which these results indicate that they may not have the resolution necessary to isolate the Pinot Noir varietal from the other Burgundy varietals. The varietal data shown in Figure 4.16 above only shows the dominant varietal grown in each region, but in reality, a mix of the other local varietals grow as well. Chardonnay and Gamay, are grown in the region as well, just in smaller numbers. At a regional scale, the results may also indicate that Pinot Noir, Chardonnay, and Gamay varietals all share the same growing habitat requirements. Regardless of the results, it is still an interesting exercise to apply the logit equation to the Willamette Valley in Oregon to at least see if that region contains the same potential to grow Burgundy varietals.

4.3.5 Logistic Model Applied to Willamette Valley
In order to apply the logistic equation to the Willamette Valley datasets, the nominal data grids first must be separated out into variable indicator grids; grids which represent the presence or absence of each unique attribute of the nominal data (Warmerdam, 2003, p. 49). Figure 4.17 depicts the presence or absence of a unique nominal attribute of the Depth to Rock dataset.
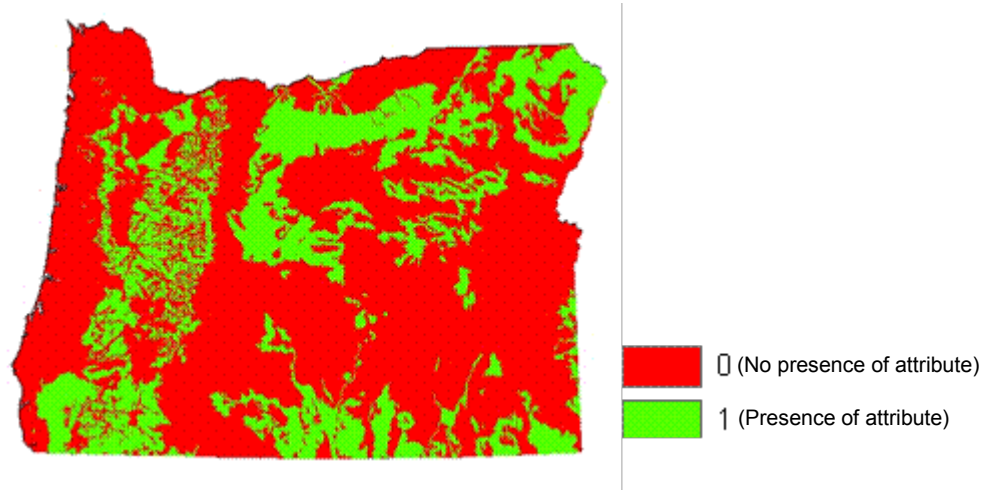
Figure 4.17 Indicator Grid for a Depth to Rock Dummy Variables

This step is necessary because of the dummy variable process produces a coefficient for each unique value of the nominal dataset in the resulting logit equation. Once this step is completed for all of the dummy variables, the indicator grids, along with the numerical data grids, are fed through the determined logit equation (Equation 4.1) using the ArcGIS SOMA tool. The resulting surface is then fed into the prediction equation (Equation 4.2) using the SOMA tool, and then that surface is rounded to 1's or 0's, again using the SOMA tool. The resulting grid is an indicator surface where 1 means a vineyard and 0 means not a vineyard. Figure 4.18 depicts the predicted 1's, vineyards, in green, overlaid on the Suitability Analysis surface created earlier in the study.
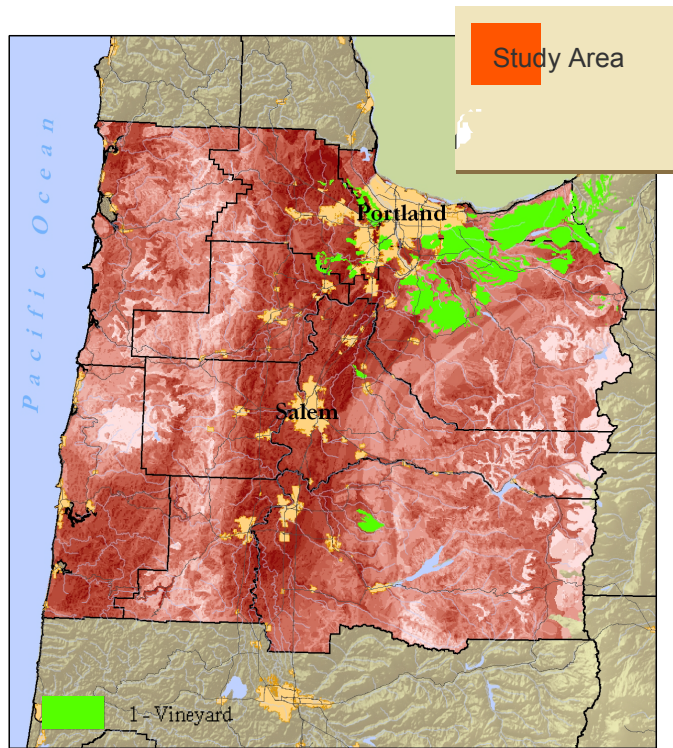
Figure 4.18 Logit Results Overlaid Suitability Results

The figure shows very interesting results; the predicted vineyard areas, in green, actually being located within the Willamette Valley high suitability area, darker red. Overlaying the Vines and Berries category from the Land Use/Land Cover dataset in Figure 4.19 gives a little more validation to the results.
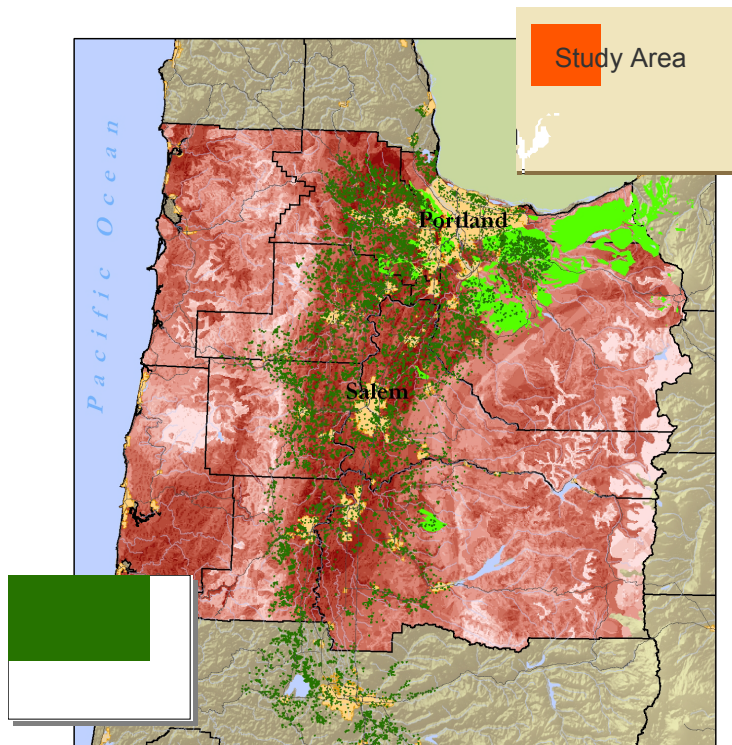
Figure 4.19 Logit Results with Land Cover Overlaid

To explain why the logit vineyard results do not line up with a majority of the suitability results or the Oregon vines/berries land cover, one must examine the data sets used in the model. Figure 4.20 shows the difference of data set values between a 'Vineyard' classified area, and a 'Non-Vineyard' classified area in the Willamette Valley.
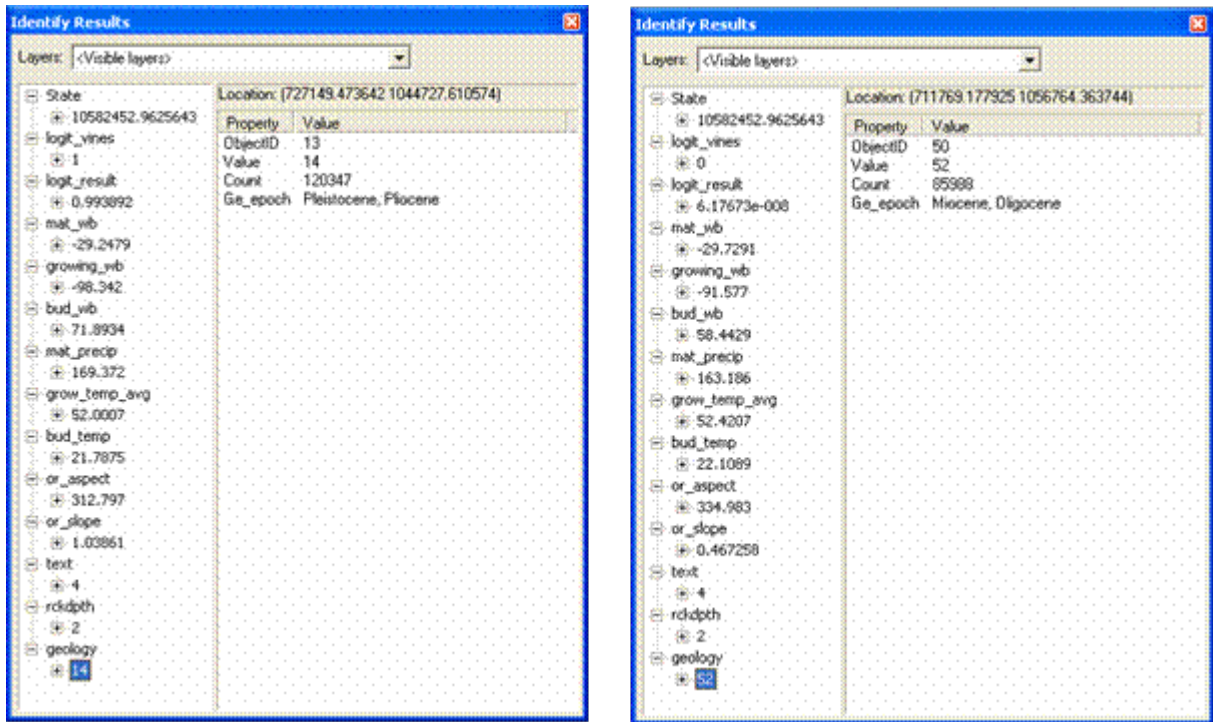
Figure 4.20 Data Values Comparison, a Vineyard on the Left and Non-Vineyard on the Right

It looks as though Geology is the only major difference between two data points, which are located near each other, but classified differently. This difference occurred, because the coefficients for Geology and Rock Depth are weighted the highest in the logit equation (Equation 4.1). This is where the Suitability Analysis may be more forgiving than the logit regression. The above geology differences are only an epoch off, but still would be given some weight in a Suitability Analysis; whereas, the logit model is pretty rigid.

5.0 Summary and Conclusion

This analysis attempted to test the client's terroir habitat concept using a traditional GIS Suitability Analysis and logit regression approach. The results of the Suitability Analysis proved it is a viable approach to locate areas capable of growing certain varietals based on ideal habitat parameters. Better data and data refinement may further improve the suitability results. Results showing less than perfect suitability may indicate adaptability of varietal to non-ideal conditions. The logit regression approach showed promise, but did not quite give the desired results. Again, data refinement might lead to superior results. The logit approach warrants further investigation.

Next steps in this analysis might be to re-run the logit regression without the nominal data. The nominal data turned out to have very high coefficients compared to those of the numerical data. It would be interesting to separate the nominal data from the numerical data and run the logit regression again to compare the results. The logit regression results may reflect the suitability results if run separately. As more data become freely available, a future step could be to acquire higher resolution data over the parent and test sites and run the analysis again for specific varietal site selection. Once the approach is verified, it could be tested further over areas not currently growing grapes followed by field test growing. Another research tangent may include gathering suitable characteristics from all known Pinot Noir growing areas to further refine suitability requirements.

Other direction options one could pursue would include examining Co-Kriging to see if more accurate results could be obtained for the climate data interpolation. Co-Kriging with the SRTM 90 elevation data set was initially tried, but this data set is too dense for the Geostatistical Analyst. In the future, a 1km resolution DEM may be more appropriate to use. Co-Kriging with a distance from the coast raster as a secondary dataset was tried, but it seemed to have no effect on the outcome of the prediction. The reason for this is probably due to the fact that the area covered by the weather station points for each area is relatively small and varies little. Distance from the coast may be more appropriate at a much smaller scale where the stations vary greatly. For future work in generating climate surfaces, Co-kriging could be utilized with other potential influencing data sets, such as wind speed and direction, or a coarse elevation data set.

Given good data, these approaches may be useful in determining naturally occurring sustainable viticulture areas, where irrigation is not required. Scientists could also use this methodology for climate change studies modeling impacts in current viticulture areas. Finally, given higher resolution data, these methodologies could be used by prospective vineyard buyers to select prime locations for specific varietals. Just as in the days of old, the hunt for great vineyard sites continues.

APPENDIX A

The full attribute description for all possible Food and Agriculture Organization (FAO) 85 attributes.

FAO85-FULL

Attribute	Full Description
	No information
A	Acrisol
Af	Ferric Acrisol
Ag	Gleyic Acrisol
Ah	Humic Acrisol
Ao	Orthic Acrisol
Ap	Plinthic Acrisol
B	Cambisol
Ba	Calcaric Cambisol
Bc	Chromic Cambisol
Bcc	Calcaro-Chromic Cambisol
Bch	Humo-Chromic Cambisol
Bck	Calci-Chromic Cambisol
Bcr	Rhodo-Chromic Cambisol
Bd	Dystric Cambisol
Bda	Ando-Dystric Cambisol
Bdg	Gleyo-Dystric Cambisol
Bds	Spodo-Dystric Cambisol
Be	Eutric Cambisol
Bea	Ando-Eutric Cambisol
Bec	Calcaro-Eutric Cambisol
Bef	Fluvi-Eutric Cambisol
Beg	Gleyo-Eutric Cambisol
Bev	Verti-Eutric Cambisol
Bf	Ferralic Cambisol
Bg	Gleyic Cambisol
Bgc	Calcaro-Gleyic Cambisol
Bge	Eutri-Gleyic Cambisol
Bgg	Stagno-Gleyic Cambisol
Bgs	Spodo-Gleyic Cambisol
Bgv	Verti-Gleyic Cambisol (?)
Bh	Humic Cambisol
Bhc	Calcaro-Humic Cambisol
Bk	Calcic Cambisol
Bkf	Fluvi-Calcic Cambisol
Bkh	Humo-Calcic Cambisol
Bkv	Verti-Calcic Cambisol

Bm	Mollic Cambisol
Bv	Vertic Cambisol
Bvc	Calcaro-Vertic Cambisol
Bvg	Gleyo-Vertic Cambisol
Bvk	Calci-Vertic Cambisol
Bx	Gelic Cambisol
Bxs	Spodo-Gelic Cambisol
C	Chernozem
Cg	Gleyic Chernozem
Ch	Haplic Chernozem
Chp	Pachi-Haplic Chernozem
Chv	Verti-Haplic Chernozem
Ck	Calcic Chernozem
Ckb	Vermi-Calcic Chernozem
Ckc	Calcaro-Calcic Chernozem
Ckcb	Vermi-Calcaro-Calcic Chernozem
Ckp	Pachi-Calcic Chernozem
Cl	Luvic Chernozem
D	Podzoluvisol
Dd	Dystric Podzoluvisol
De	Eutric Podzoluvisol
Dg	Gleyic Podzoluvisol
Dgd	Dystric Gleyic Podzoluvisol
Dge	Eutric Gleyic Podzoluvisol
Dgs	Stagno-Gleyic Podzoluvisol
E	Rendzina
Ec	Cambic Rendzina
Eh	Histic Rendzina
Eo	Orthic Rendzina
F	Ferralsol
Fo	Orthic Ferralsol
G	Gleysol
Gc	Calcaric Gleysol
Gcf	Fluvi-Calcaric Gleysol
Gcs	Stagno-Calcaric Gleysol
Gd	Dystric Gleysol
Gdf	Fluvi-Dystric Gleysol
Gds	Stagno-Dystric Gleysol
Ge	Eutric Gleysol
Gef	Fluvi-Eutric Gleysol
Ges	Stagno-Eutric Gleysol
Gev	Verti-Eutric Gleysol
Gf	Fluvic Gleysol

Gfm	Molli-Fluvic Gleysol
Gh	Humic Gleysol
Ghf	Fluvi-Humic Gleysol
Ghh	Histo-Humic Gleysol
Ght	Thioni-Humic Gleysol
Gi	Histic Gleysol
Gih	Humo-Histic Gleysol
Gl	Luvic Gleysol
Gls	Stagno-Luvic Gleysol
Gm	Mollic Gleysol
Gmc	Calcaro-Mollic Gleysol
Gmf	Fluvi-Mollic Gleysol
Gmv	Verti-Mollic Gleysol
Gs	Stagnic Gleysol
Gt	Thionic Gleysol
Gtz	Undefined code
Gx	Gelic Gleysol
H	Phaeozem
Hc	Calcaric Phaeozem
Hcb	Vermi-Calcaric Phaeozem
Hcf	Fluvi-Calcaric Phaeozem
Hcn	Alkalino-Calcaric Phaeozem
Hcs	Saline-Calcaric Phaeozem
Hg	Gleyic Phaeozem
Hgc	Calcaro-Gleyic Phaeozem
Hgf	Fluvi-Gleyic Phaeozem
Hgs	Stagno-Gleyic Phaeozem
Hgv	Verti-Gleyic Phaeozem
Hh	Haplic Phaeozem
Hhv	Verti-Haplic Phaeozem
Hl	Luvic Phaeozem
Hlv	Verti-Luvic Phaeozem
Ho	Orthic Phaeozem
I	Lithosol
Ic	Calcaric Lithosol
Ich	Humo-Calcaric Lithosol
Id	Dystric Lithosol
Ie	Eutric Lithosol
J	Fluvisol
Jc	Calcaric Fluvisol
Jcf	Fluvi-Calcaric Fluvisol
Jcg	Gleyo-Calcaric Fluvisol
Jd	Dystric Fluvisol

Jdf	Fluvi-Dystric Fluvisol
Jdg	Gleyo-Dystric Fluvisol
Je	Eutric Fluvisol
Jef	Fluvi-Eutric Fluvisol
Jeg	Gleyo-Eutric Fluvisol
Jm	Mollic Fluvisol
Jmg	Gleyo-Mollic Fluvisol
Jmv	Verti-Mollic Fluvisol
Jt	Thionic Fluvisol
K	Kastanozem
Kh	Haplic Kastanozem
Khb	Vermi-Haplic Kastanozem
Kk	Calcic Kastanozem
Kkb	Vermi-Calcic Kastanozem
Kkv	Verti-Calcic Kastanozem
Kl	Luvic Kastanozem
Ko	Orthic Kastanozem
L	Luvisol
La	Albic Luvisol
Lap	Plano-Albic Luvisol
Lc	Chromic Luvisol
Lcp	Plano-Chromic Luvisol
Lcr	Rhodo-Chromic Luvisol
Lcv	Verti-Chromic Luvisol
Ld	Dystric Luvisol
Ldg	Gleyo-Dystric Luvisol
Lf	Ferric Luvisol
Lg	Gleyic Luvisol
Lga	Albo-Gleyic Luvisol
Lgp	Plano-Gleyic Luvisol
Lgs	Stagno-Gleyic Luvisol
Lh	Humic Luvisol
Lk	Calcic Luvisol
Lkc	Chromo-Calcic Luvisol
Lkcr	Rhodo-Chromo-Calcic Luvisol
Lkv	Verti-Calcic Luvisol
Lo	Orthic Luvisol
Lop	Plano-Orthic Luvisol
Lp	Plinthic Luvisol
Ls	Spodic Luvisol
Lv	Vertic Luvisol
Lvc	Chromo-Vertic Luvisol
Lvcr	Rhodo-Chromo-Vertic Luvisol

Lvk	Calci-Vertic Luvisol
M	Greyzem
Mo	Orthic Greyzem
Nc	Cambic Nitosol
O	Histosol
Od	Dystric Histosol
Odp	Placi-Dystric Histosol
Oe	Eutric Histosol
Ox	Gelic Histosol
P	Podzol
Pf	Ferric Podzol
Pg	Gleyic Podzol
Pgh	Histo-Gleyic Podzol
Pgs	Stagno-Gleyic Podzol
Ph	Humic Podzol
Phf	Ferro-Humic Podzol
Pl	Leptic Podzol
Plh	Humo-Leptic Podzol
Po	Orthic Podzol
Pof	Ferro-Orthic Podzol
Poh	Humo-Orthic Podzol
Pol	Lepto-Orthic Podzol
Pp	Placic Podzol
Pph	Humo-Placic Podzol
Q	Arenosol
Qa	Albic Arenosol
Qc	Cambic Arenosol
Qcc	Calcaro-Cambic Arenosol
Qcd	Dystri-Cambic Arenosol
Qcg	Gleyo-Cambic Arenosol
Qcs	Spodo-Cambic Arenosol
Qh	Humic Arenosol
Ql	Luvic Arenosol
Qld	Dystri-Luvic Arenosol
Qlg	Gleyo-Luvic Arenosol
R	Regosol
Rc	Calcaric Regosol
Rd	Dystric Regosol
Rds	Undefined code
Re	Eutric Regosol
Rx	Gelic Regosol
S	Solonetz
Sg	Gleyic Solonetz

Sm	Mollic Solonetz
So	Orthic Solonetz
Sof	Fluvi-Orthic Solonetz
T	Andosol
Th	Humic Andosol
Tm	Mollic Andosol
To	Ochric Andosol
Tv	Vitric Andosol
U	Ranker
Ud	Dystric Ranker
Ul	Luvic Ranker
V	Vertisol
Vc	Chromic Vertisol
Vcc	Calcaro-Chromic Vertisol
Vg	Gleyic Vertisol
Vgs	Undefined code
Vp	Pellic Vertisol
Vpc	Calcaro-Pellic Vertisol
Vpg	Gleyo-Pellic Vertisol
Vpn	Sodi-Pellic Vertisol
W	Planosol
Wd	Dystric Planosol
Wdv	Verti-Dystric Planosol
We	Eutric Planosol
Wev	Verti-Eutric Planosol
Wh	Humic Planosol
Wm	Mollic Planosol
Ws	Solodic Planosol
X	Xerosol
Xk	Calcic Xerosol
Xl	Luvic Xerosol
Xy	Gypsic Xerosol
Z	Solonchak
Zg	Gleyic Solonchak
Zgf	Fluvi-Gleyic Solonchak
Zo	Orthic Solonchak
Zt	Takyric Solonchak
p	Plaggensol
111	Town
222	Soil disturbed by man
333	Water body
444	Marsh

555   Glacier
666   Rock outcrops

1999 GEOLOGIC TIME SCALE
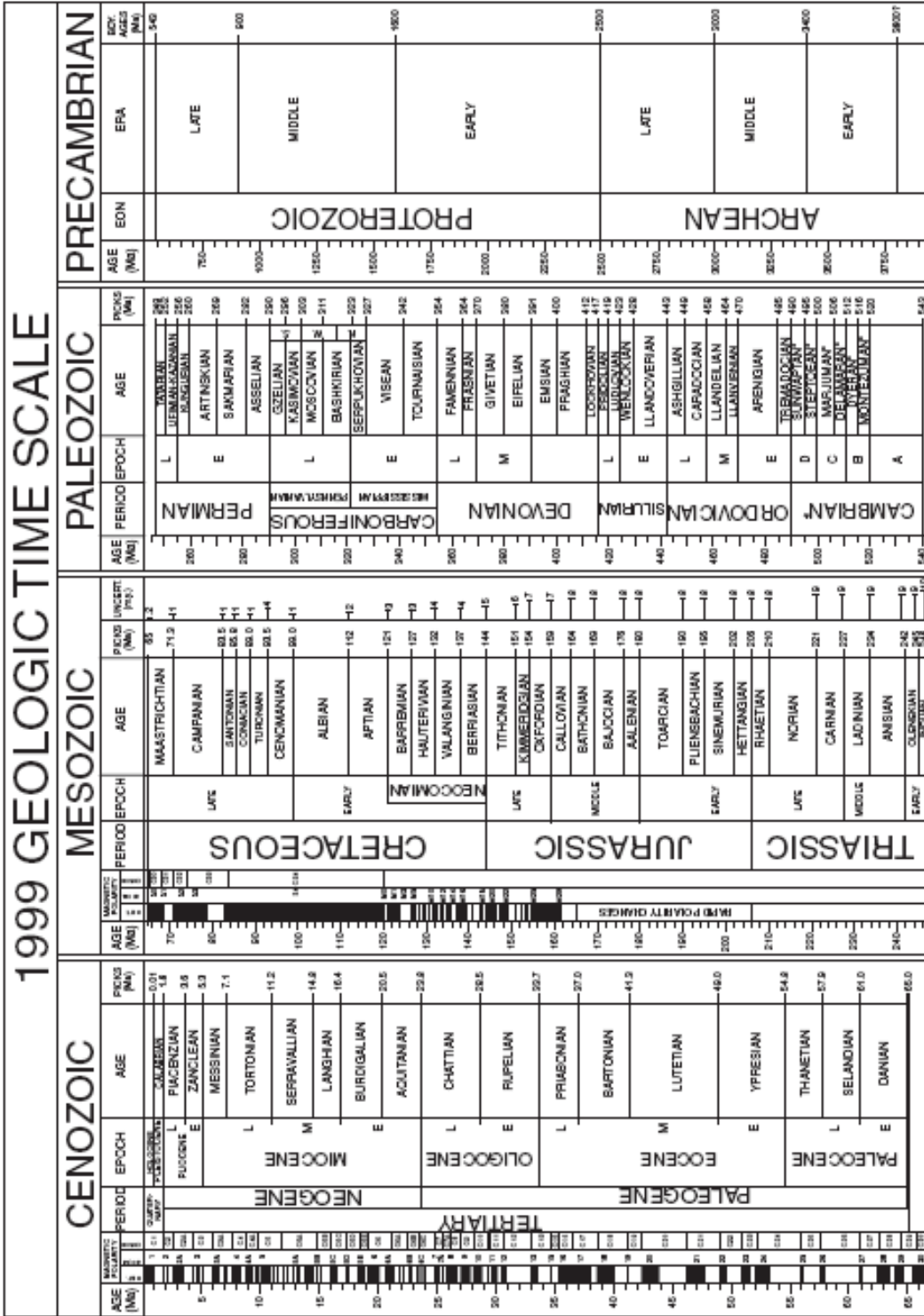
© 1999, The Geological Society of America. Product code CTS004. Compilers: A. R. Palmer, John Geissman.

*International ages have not been established. These are regional (Laurentian) only. Boundary Picks were based on dating techniques and fossil records as of 1999. Paleomagnetic attributions have errors, Please ignore the paleomagnetic scale.

Sources for nomenclature and ages: Primarily from Gradstein, F., and Ogg, J., 1996, *Episodes*, v. 19, nos. 1 & 2; Gradstein, F., et al., 1995, SEPM Special Pub. 54, p. 95–129; Berggren, W. A., et al., 1995, SEPM Special Pub. 54, p. 129–212; Cambrian and basal Ordovician ages adapted from Landing, E., 1998, *Canadian Journal of Earth Sciences*, v.35, p. 329–338; and Davidek, K., et al., 1998, *Geological Magazine*, v. 135, p. 305–309. Cambrian age names from Palmer, A. R., 1998, *Canadian Journal of Earth Sciences*, v. 35, p. 323–328.
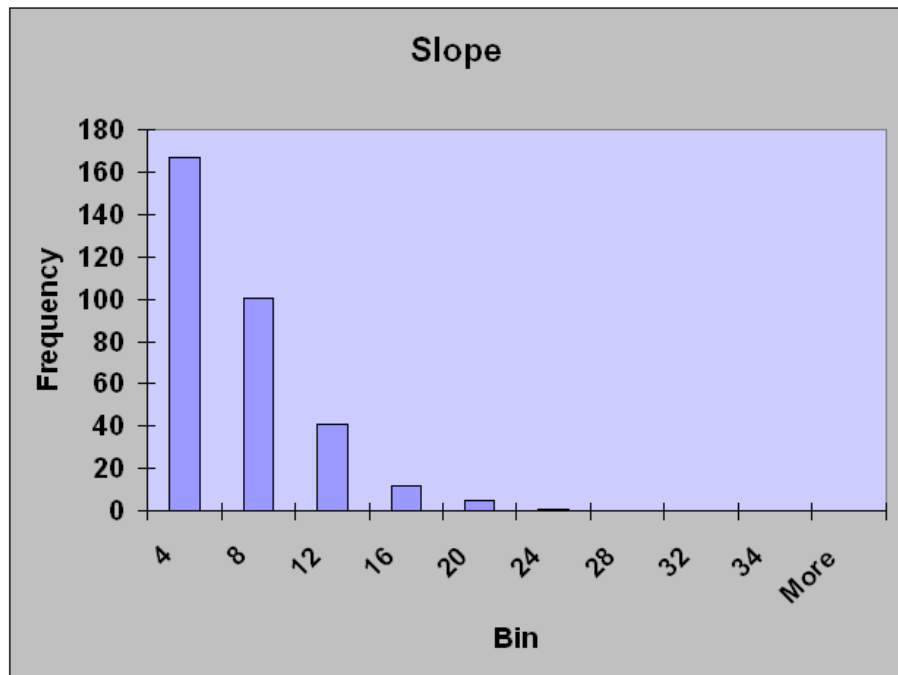
GEOLOGICAL SOCIETY OF AMERICA

Appendix C
Dominant Data Values of Burgundy France

Aspect

Bin	Frequency
20	3
60	16
100	54
140	104
180	79
220	35
260	18
300	9
340	8
360	1
More	0
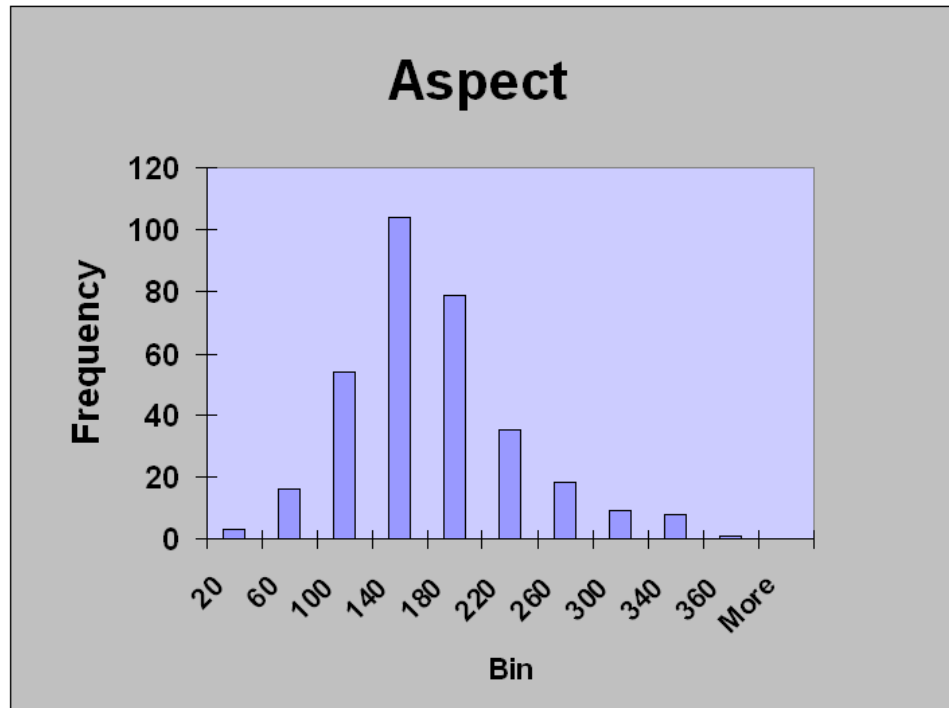
Slope

Bin	Frequency
4	167
8	101
12	41
16	12
20	5
24	1
28	0
32	0
34	0
More	0

83

Budding Average Temperature

bud temp

Bin	Frequency
22.00	0
23.00	0
24.00	327
25.00	0

Growing Average Temperature
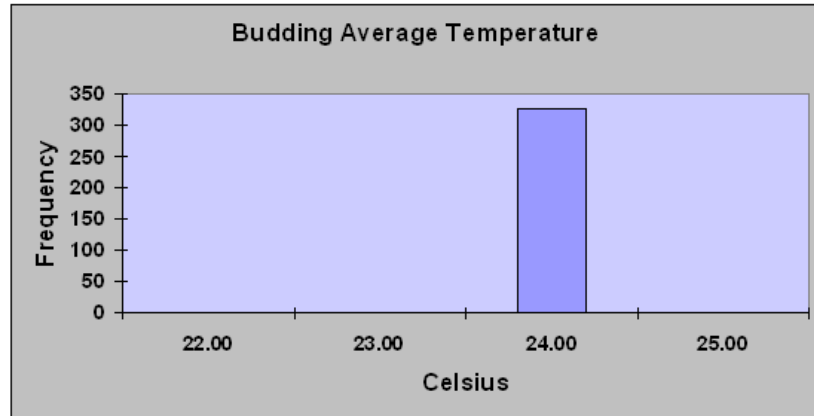
grow temp

Bin	Frequency
55	0
56	13
57	174
58	140
59	0
60	0
61	0
62	0
63	0
64	0

Maturation Average Temperature
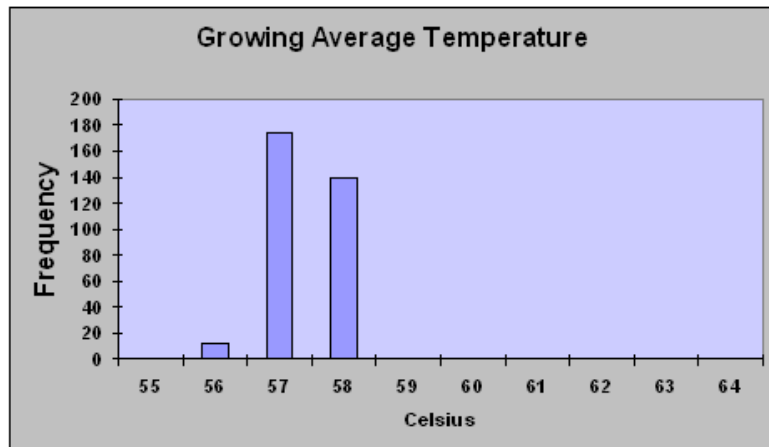
mat temp

Bin	Frequency
25	0
26	0
27	292
28	35
29	0
30	0

84
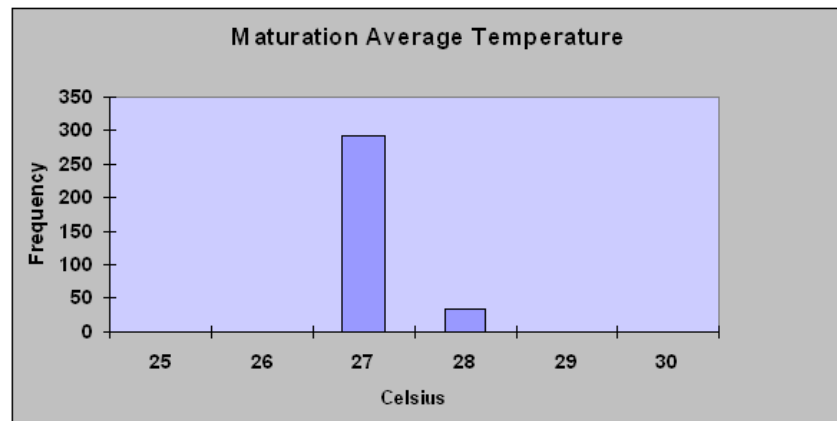
total T

Bin	Frequency
103	0
105	0
107	150
109	177
111	0
113	0
115	0

Total Average Temperature
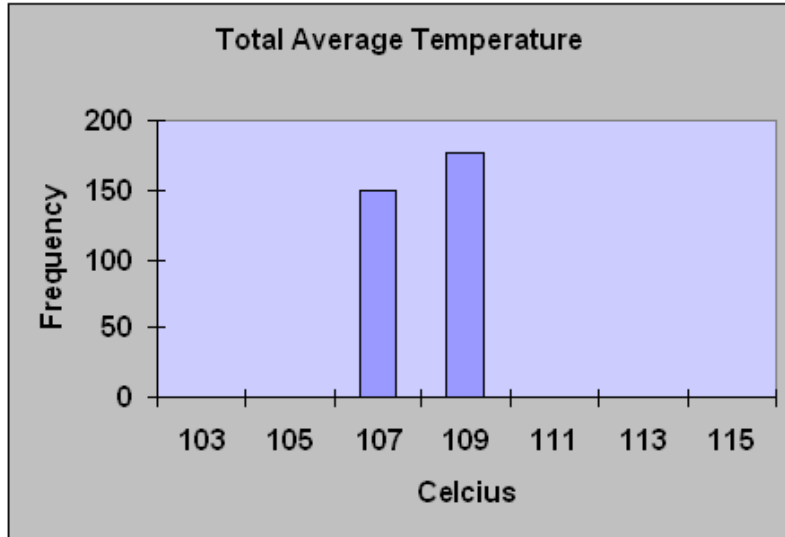
budding_precip

Bin	Frequency
149	283
159	27
169	17
179	0
189	0
199	0
209	0
219	0
225	0

Budding Precipitation
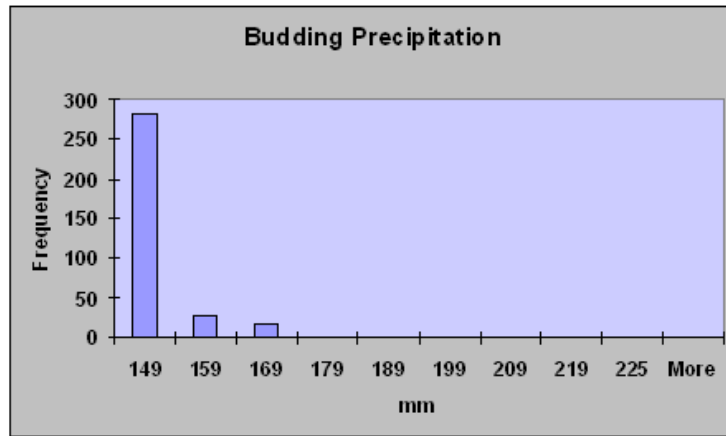
Growing Precip

Bin	Frequency
116	0
131	0
146	0
161	0
176	44
191	262
206	21
221	0
236	0

Growing Precipitation

85

Maturation Precipiataion
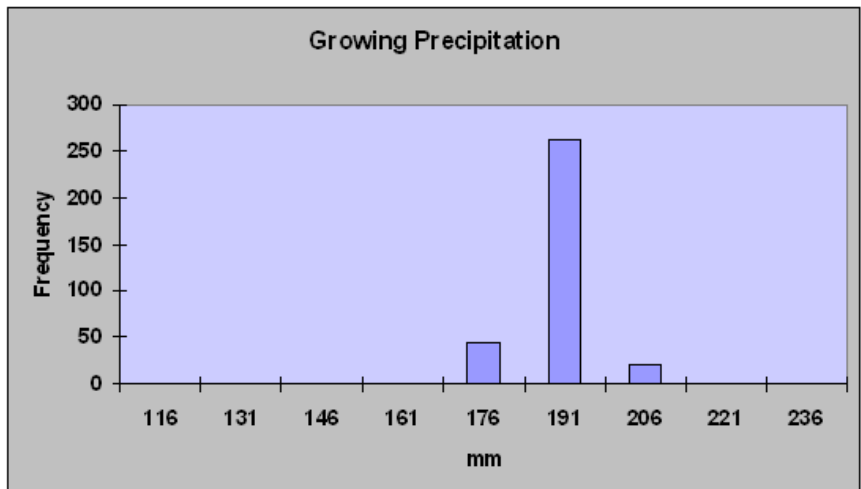
Mat_precip

Bin	Frequency
152	286
169	24
186	17
203	0
220	0
237	0
254	0
271	0
283	0

Total Precipitation
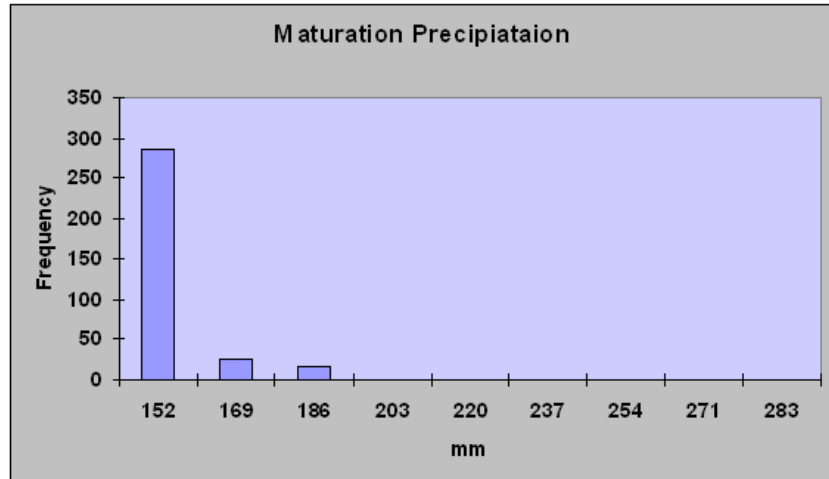
total P

Bin	Frequency
457	0
475	245
493	52
511	10
529	7
547	13
565	0
583	0
601	0
616	0

Budding Water Balance
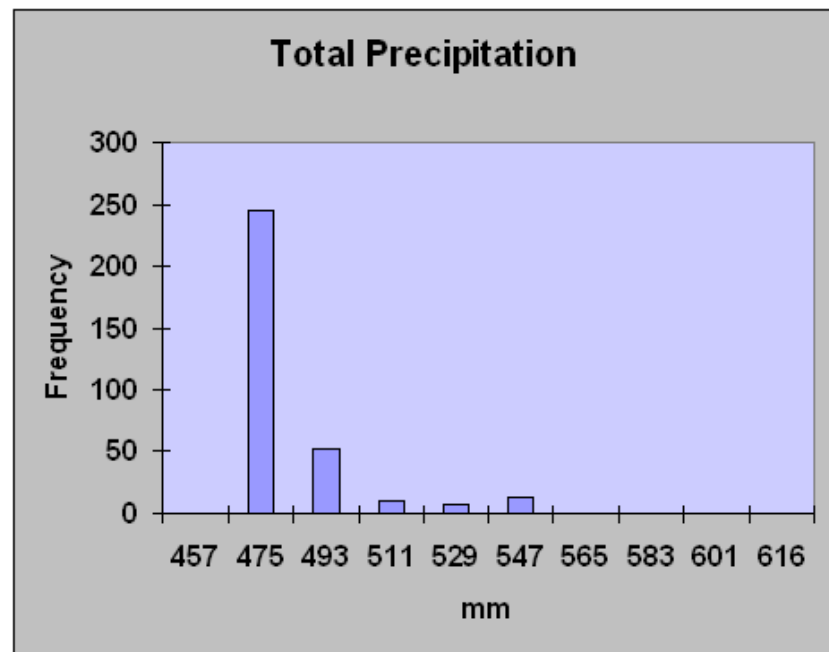
Budding Water Balance

Bin	Frequency
19	271
29	48
39	8
49	0
59	0
69	0
79	0
89	0
99	0

86
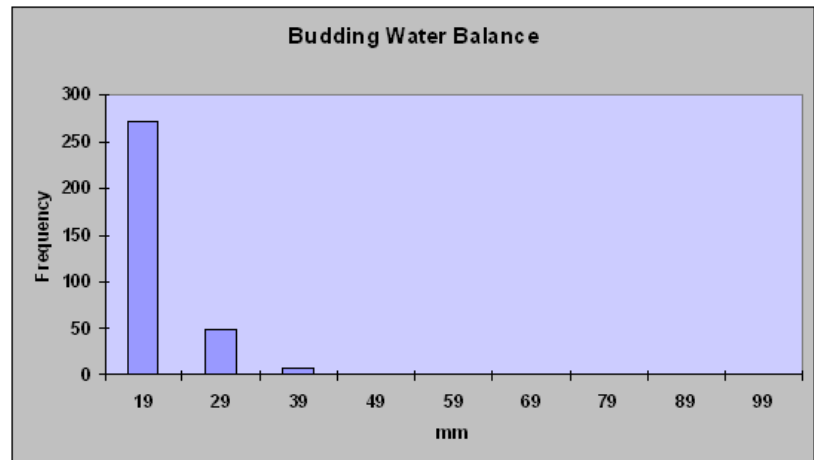
Growing Water Balance

Bin	Frequency
-160.00	0
-142.00	0
-124.00	0
-106.00	18
-88.00	12
-70.00	11
-52.00	116
-34.00	170
-20.00	0
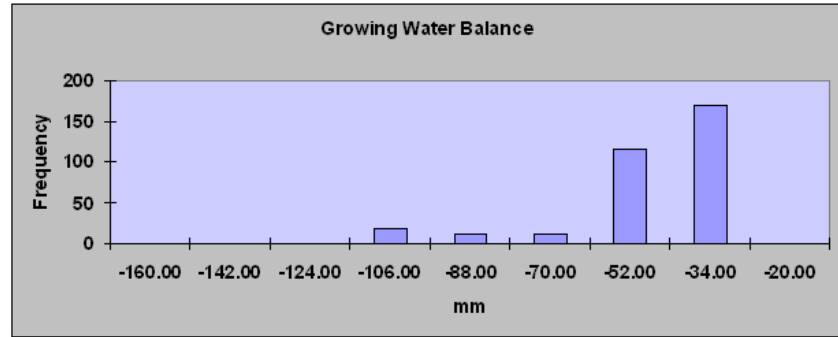
Maturation Water Balance

Bin	Frequency
-8	2
-1	294
6	31
13	0
20	0
27	0
34	0
41	0
47	0
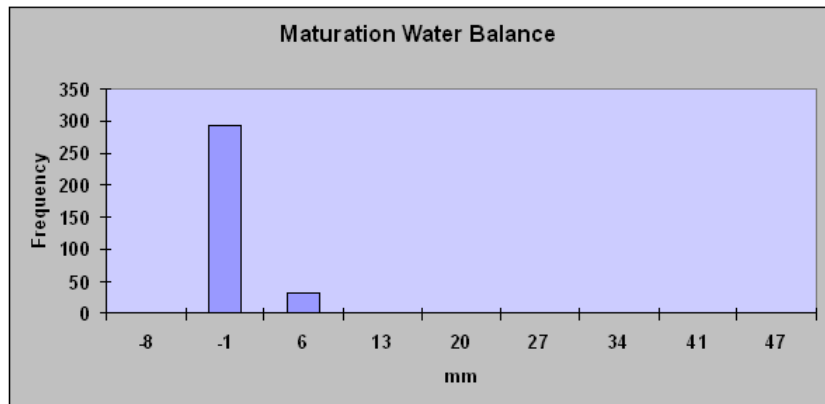
Total WB

Bin	Frequency
-97	19
-85	8
-73	8
-61	14
-49	64
-37	82
-25	113
-13	6
-4	13

Total Water Balance
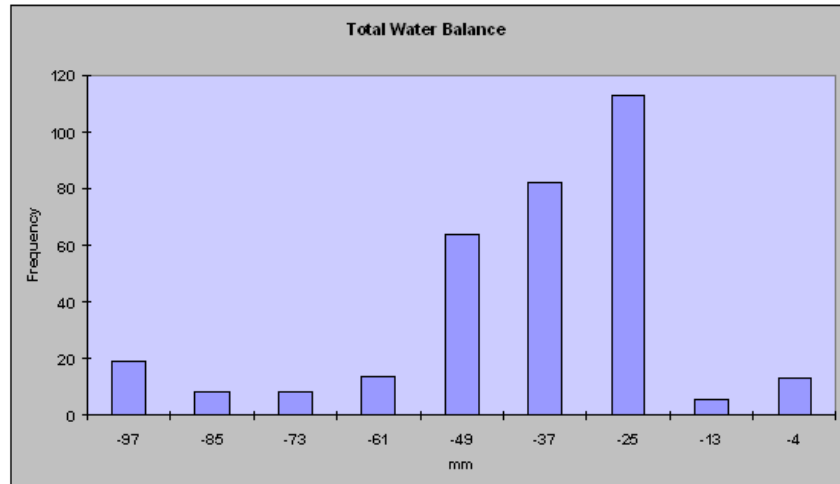
Rock Depth

Bin	Frequency
0 to 40 cm	86
40 - 80 cm	196
80 - 120 cm	24
gt 120 cm	21

Rock Depth
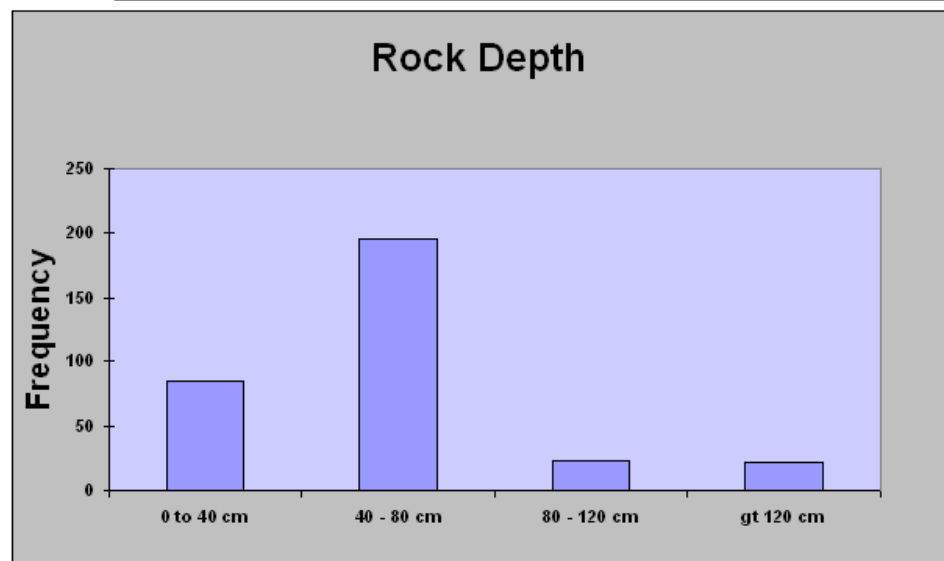
geology

Bin	Frequency
Quaternary	127
Tertiary	18
Mesozoic	148
Paleozoic	32

Geology
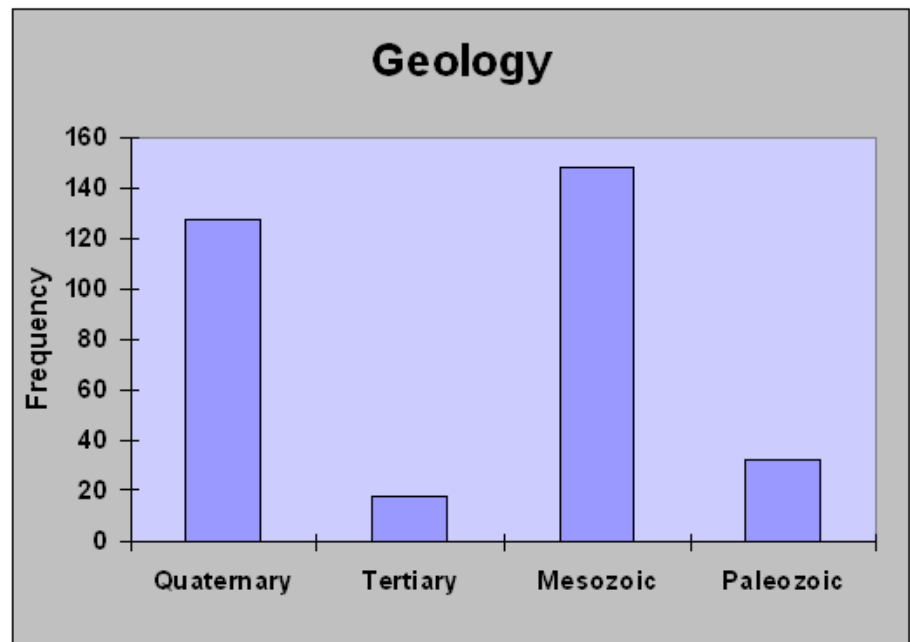
Soil Type

Soil Type

Bin	Frequency
Inceptisols	238
Entisols	26
Alfisols	107
Histosols	16
Mollisols	26
Spodosols	6
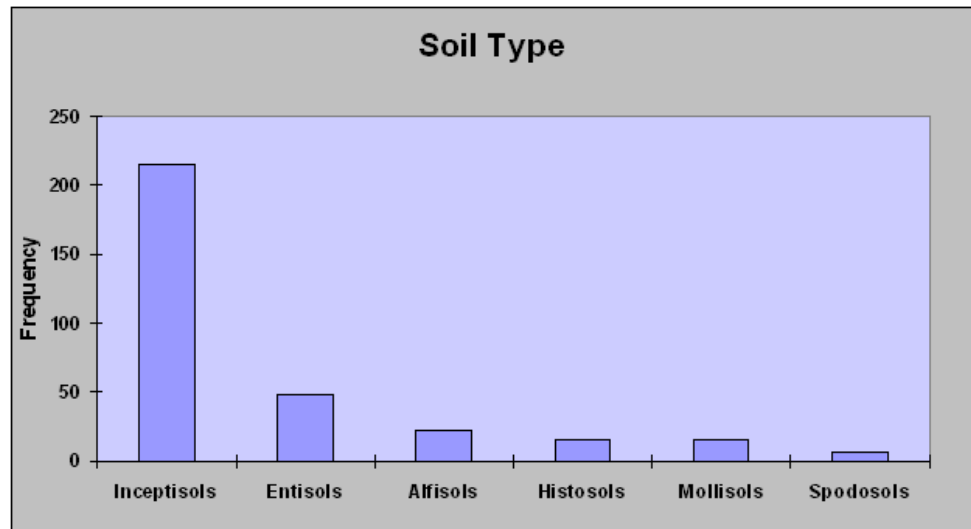
Texture

Soil Texture

Bin	Frequency
Fine	191
Medium Fine	101
Medium	33
Coarse	2

89

APPENDIX D

METEO FRANCE
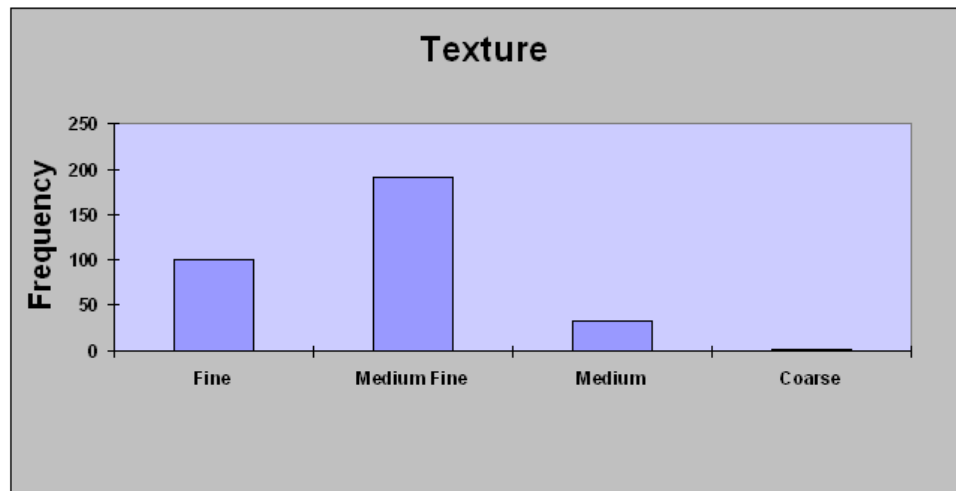
STATISTIQUES INTER-ANNUELLES

De 1971 à 2000

BULLY (69)

Indicatif : 69032001, alt : 300 m., lat : 45°50'42"N, lon : 04°35'06"E

Eléments météorologiques	Janv.	Févr.	Mars	Avril	Mai	Juin	Juill.	Août	Sept.	Oct.	Nov.	Déc.	Année
Températures													
moyenne des températures :													
minimales quotidiennes : Tn	-1.0	-0.5	1.2	3.5	7.5	10.5	12.8	12.5	9.3	6.0	1.9	-0.2	5.3
maximales quotidiennes : Tx	6.6	8.5	12.7	15.4	20.1	23.6	26.9	26.7	22.4	16.7	10.4	7.1	16.4
moyennes quotidiennes : (Tn+Tx)/2	2.8	4.0	7.0	9.4	13.8	17.1	19.9	19.6	15.9	11.4	6.2	3.5	10.9
minimale la plus basse	-23.0	-12.9	-12.0	-5.2	-3.2	1.0	4.2	2.1	-1.0	-7.2	-11.4	-13.5	-23.0
date	2/1971	10/1986	8/1971	5/1975	1/1976	5/1975	1/1972	30/1998	27/1972	31/1997	23/1998	9/1980	2/1/1971
maximale la plus élevée	19.0	21.7	25.8	28.5	32.0	34.8	39.9	39.3	33.0	29.0	23.8	21.5	39.9
date	16/1974	24/1990	21/1990	26/1992	14/1992	28/1986	22/1983	16/1974	14/1987	2/1985	3/1977	16/1989	22/7/1983
nombre moyen de jours :													
de fortes gelées (Tn <= -5°C)	5.1	4.2	2.0	0.1	.	.	.	.	.	0.2	2.1	4.2	17.9
de gel (Tn <= 0°C)	18.2	15.3	12.5	6.0	0.6	.	.	.	0.3	2.6	10.3	16.8	82.6
sans dégel (Tx <= 0°C)	2.7	1.4	0.2	.	.	.	.	.	.	.	0.5	2.4	7.2
chauds (Tx >= 25°C)	.	.	0.1	0.3	4.8	11.8	20.4	20.1	9.0	0.9	.	.	67.4
très chauds (Tx >= 30°C)	.	.	.	.	0.2	2.7	8.0	8.0	1.1	.	.	.	20.0
Précipitations													
hauteur moyenne mensuelle	44.5	38.7	41.8	53.8	80.8	74.3	61.1	66.4	73.0	68.8	62.4	47.5	713.1
hauteur maximale quotidienne	27.0	32.6	30.3	74.2	62.0	130.5	62.5	94.4	85.5	39.0	92.0	40.7	130.5
date	28/1990	13/1990	21/1991	25/1989	2/1984	10/2000	7/1996	26/1980	22/1993	16/1972	12/1996	6/1982	10/6/2000
nombre moyen de jours :													
avec hauteur quotidienne >= 1 mm	9.0	8.0	8.0	8.5	10.2	8.1	6.4	7.1	7.0	8.9	8.7	8.6	98.5
avec hauteur quotidienne >= 10 mm	1.0	0.8	1.0	1.4	2.5	2.5	2.1	2.3	2.6	2.6	1.7	0.9	21.4
ETP (non mesurée)													
moyenne des ETP mensuelles													
Insolation (non mesurée)													
durée moyenne mensuelle													
Rayonnement (non mesuré)													
moyenne mensuelle													
Vent (non mesuré)													
moyenne du vent moyen													
maximum du vent instantané quotidien													
date													
nombre moyen de jours :													
avec rafales > 16 m/s (soit 58 km/h)													
avec rafales > 28 m/s (soit 100 km/h)													
Occurrences													
nombre moyen de jours :													
de neige	-	-	-	-	-	-	-	-	-	-	-	-	-
de grêle	-	-	-	-	-	-	-	-	-	-	-	-	-

- : donnée manquante ; lorsqu'un paramètre n'est pas mesuré il n'y a pas de valeur associée (colonne ou case vide) ;   . : donnée égale à 0
Unités : les températures sont exprimées en degrés Celsius (°C), les précipitations et l'évapotranspiration potentielle (ETP) en millimètres (mm), les durées d'insolation en heures, le rayonnement en Joules/cm², le vent en km/h et les occurrences en nombre de jours.
Lorsque la période de mesure d'un paramètre diffère de la période globale, la période de mesure de ce paramètre est précisée entre parenthèses.

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