Development of a dryland corn productivity index for Kansas

by

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B.S., Kansas State University, 2016

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Agronomy
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2019

Approved by:

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Abstract

For many decades, researchers have created indices to rate soil on its ability to produce vegetative growth. The Soil Rating for Plant Growth (SRPG) model was developed by USDA-Natural Resources Conservation Service (NRCS) in 1992 to array soil mapping units relative to their potential to produce dryland commodity crops independent of management. A few years later, the Kansas Department of Revenue (KDR) Property Valuation Division (PVD) began using the SRPG model for land valuation. Since then, the SRPG was updated to a Kansas-specific model, KS-SRPG, later renamed and modified to PRGM-General Crop Production Index (GCPI), and stored in the National Soil Information System (NASIS). In 2003, modifications were made to the GCPI model to develop an irrigated index for Kansas and was termed the Kansas Irrigated Productivity Index (KIPI). KS-SRPG and KIPI are still used by the PVD, but are no longer updated, are not available to the public, and are difficult to understand. Therefore, it is necessary to construct a new model to predict dryland corn productivity for Kansas soil mapping units. This thesis calibrated and validated a new dryland corn index, which is termed the Kansas Commodity Crop Productivity Index (KCCPI) corn submodel. The KCCPI model was built in NASIS with the goal of being available to the public on Web Soil Survey. Corn yield data in NASIS were used to calibrate the model during development. Dryland corn yield data were obtained from Risk Management Agency (RMA) by Common Land Unit (CLU) and regressed against KCCPI for validation. Results during calibration were promising, but KCCPI was not as successful during validation. This suggests that more work needs to be done to the model with more sets of yield data.

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List of Acronyms

Acronym	Full Name
AWC	Available Water Capacity
CCE	Calcium Carbonate Equivalent
CEC	Cation Exchange Capacity
CLU	Common Land Unit
CRP	Conservation Reserve Program
EC	Electrical Conductivity
FIPS	Federal Information Processing Standard county code
FSA	Farm Service Agency
GCPI	General Crop Productivity Index
KBWSI	Kansas Black Walnut Suitability Index
KCCPI	Kansas Commodity Crop Productivity Index
KDR	Kansas Department of Revenue
KIPI	Kansas Irrigated Productivity Index
LCC	Land Capability Class
MAAT	Mean Annual Air Temperature
MAP	Mean Annual Precipitation
MUKEY	Map Unit Key
NASIS	National Soil Information System
NASS	National Agriculture Statistics Service
NCCPI	National Commodity Crop Productivity Index
NCSS	National Cooperative Soil Survey
NRCS	Natural Resources Conservation Service
OM	Organic Matter
PGI(TX)	Plant Growth Index (Texas)
PVD	Property Valuation Division of Kansas Department of Revenue
RMA	Risk Management Agency
RV	Relative Value
SAR	Sodium Adsorption Ratio
SOC	Soil Organic Carbon
SQL	Structured Query Language
SRPG	Soil Rating for Plant Growth
SSURGO	Soil Survey data collected by National Cooperative Soil Survey
TNCCPI	Tennessee Commodity Crop Productivity Index
USDA	United States Department of Agriculture
WICCPI	Wisconsin Commodity Crop Productivity Index

Acknowledgements

My time at Kansas State University has been a treasure, especially due to my major professor, Dr. Michel (Mickey) Ransom. Thank you, Mickey, for endless opportunities in soil judging, expanding my knowledge while learning and teaching in the classroom, sending me to several professional meetings, and being one of my strongest supporters during my time in Manhattan. Thank you to my committee, Dr. Arnaud Temme, Dr. Skye Wills, and Dr. Kraig Roozeboom for their help throughout the process. I would also like to thank Dr. Colby Moorberg, Dr. Kevin Donnelly, and Dr. Gerard Kluitenberg for encouraging me to teach and for professional and scientific advice.

A special thanks is extended to Robert Dobos and Jeffery Hellerich of USDA-NRCS for their expert knowledge, time, and willingness to help me better understand soil interpretations, NASIS, and for their career advice.

Thank you to my family and friends, near and far, for the laughter, guidance, and support over the years. To my mom and dad, Nancie and Devin, to whom my thesis is dedicated to, for the constant love and being my biggest fans through everything that I have decided to do in my life. To my grandpa and grandma, Robert and Joyce, and uncle Rick, I wouldn't be studying soil science if it weren't for our family's roots and appreciation of agriculture. Finally, to my fiancé Garrison, thank you for always giving me every bit of knowledge that you could to help me out and for loving me each day through it all.

Chapter 1 - Literature Review

Productivity Indices

For decades, scientists have collected physical and chemical data about soils across the globe to gain a better understanding of soil genesis, soil chemistry, productivity, and much more. With this information, soil scientists are able to develop interpretations about the use of soils and quantify soil function parameters (Soil Science Division Staff, 2017). Productivity ratings, which are suitability interpretations, were the primary reason for the initiation of soil surveys in the United States (Huddleston, 1984). Most interpretations, especially those built within the United States Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS), are built upon the soil survey structure. This means that interpretations are mostly based on physical and chemical properties that are inherent to the soil. Using inherent properties allows the interpretation to be used for several years, even decades, due to it being based on soil properties that do not change over a short period of time. Interpretations can then be used as a pathway to understand soil processes, habitat suitability, and land use limitations. More specifically, soil productivity ratings, which rate soil on its capacity to produce plant growth, can help determine best crop management practices and land value for taxation.

In a thorough review of productivity ratings by Huddleston (1984), it is clear that there is no "best way" to predict soil productivity. Models can be expressed qualitatively, such as a narrative statement or grouping soils into classes, or quantitatively, such as a numerical ranking procedure that is inductive or deductive (Ableiter, 1937; Huddleston, 1984). Inductive ratings are based entirely on soil properties, but deductive ratings are based on crop yield records. Huddleston (1984) observed that the combination of inductive and deductive procedures are often used to develop or calibrate the ratings. Simonson & Englehorn (1938) stated that the knowledge of the soils is not enough to develop ratings purely on an inductive basis, saying that the use of crop yields is critical in development. Many productivity ratings are built in a subjective manor that is based on expert judgement about soil properties, soil series, or crop yields. This can be beneficial for the developer because they often know which soils are better or worse. However, if the goal is to obtain an accurate rating of the quantity and quality of land, systems must be objective and comparable on large and small scales (Aldrich, 1967). The use of yield data removes the need for subjective interpretations of soil productivity (Ableiter, 1937). The main limitation with yield data is that there isn't enough of it consistently over time, over many soils, and over similar or different management systems that is accessible and of high quality (Huddleston, 1982). This is why productivity rating systems are so important.

On top of the differences in procedure, there are also differences in which soil properties, soil qualities, or environmental factors are included in a soil productivity model (Table 1-1). Typically, soil properties that are important to rooting depth and water holding capacity are chosen, as well as pH and bulk density (Soil Science Division Staff, 2017). Because soils vary from county to county and state to state, the predictors for modeling vary too. A corn model in the northwest United States is likely to differ from a corn model in the southeast. This can be due to differences in pH of parent materials, management strategy differences, and the climate where the soils formed. Many productivity ratings, especially those for crop production, include climate data because temperature and rainfall are undoubtedly major factors of dryland crop success.

Table 1-1. Properties used, by state, for determining productivity rating, modified from Sassman and Burras (2016)**.**

	States in North Central Area of United States												
Soil Factors	**IL**	**IN**	**IA**	**KS**	**MI**	**MN**	**MO**	**NE**	**ND**	**OH**	**SD**	**WI**	**Count**
<u>Soil Properties</u>													
Taxonomy			X						X				2
Parent Material		X	X							X			3
Physical		X		X		X	X	X	X	X		X	8
Chemical		X		X		X						X	4
Profile Characteristics	X	X		X			X	X	X			X	7
Restrictive Zone		X		X			X		X			X	5
<u>Landscape Properties</u>													
Slope	X	X	X	X		X	X	X	X	X	X	X	11
Erosion Phase	X	X	X	X			X	X		X	X	X	9
Flooding/Ponding	X		X	X		X	X	X				X	7
Drainage Class		X					X		X	X	X		5
Available Water Capacity (AWC)			X	X		X	X					X	5
Water Table				X				X			X		3
USDA Land Capability Class (LCC)											X	X	2
Climate				X		X	X	X			X		5
Yield	X				X					X	X	X	5
<u>Management</u>													
Management Groups	X				X								2
Current Practices							X	X					2

Mathematical Methods

Over the course of their development, productivity ratings and indices have been developed using several different mathematical methods. Soil scientists in Wisconsin (Berger et al., 1952; USDA Natural Resources Conservation Service, 2016a), Iowa (Fenton et al., 1971), Indiana (Walker, 1976), and Oregon (Huddleston, 1982) have calculated productivity ratings from additive systems. Soil properties are assigned numerical values according to their inferred impact on plant growth and summed or subtracted from a maximum rating of 100 for a final rating. Other models, such as the National Commodity Crop Productivity Index (NCCPI), SRPG, and KIPI, use either multiplication or division to reach a final rating. These systems assign factors to each property that is multiplied together to receive a final rating of either 0-1 or 0-100. Additive, multiplicative, or ratings with a combination of the two are usually a combination of inductive and deductive approaches by using crop yields for validation or calibration (USDA Natural Resources Conservation Service, 2016a).

According to Huddleston (1984), additive systems are more suited for state-level indices. They have the advantage of being able to incorporate information from more soil properties compared to multiplicative systems because in multiplicative systems, ratings become very low with the addition of more properties (USDA Natural Resources Conservation Service, 2016a). It is generally easier to determine which factors pull the rating down in additive systems, and a single factor does not have the power to severely influence the final rating. However, this is a disadvantage if there is a soil that has every characteristic that is considered highly productive except for one. For example, in Kansas, the Flint Hills region is extremely productive, but not for field crops. In this scenario, soils are high in organic matter, have high nutrient and water holding capacity, optimal pH, low bulk density, but have bedrock often within one meter or less of the soil surface. In an additive system, the soil receives high ratings for all factors except depth, and the final summed up rating could still be considered as "productive" for dryland corn.

Crop Productivity Indices in Kansas

The Soil Rating for Plant Growth (SRPG) model was developed by USDA-Natural Resources Conservation Service (NRCS) to array soil mapping units relative to their potential to produce dryland commodity crops independent of management across the nation (Sinclair et al., 1999). A few years after it was developed, the Kansas Department of Revenue (KDR) Property Valuation Division (PVD) began using the SRPG model for land valuation. Since then, the SRPG has been updated to a Kansas-specific model, KS-SRPG, later renamed and modified to PRGM-General Crop Production Index (GCPI), and stored in the National Soil Information System (NASIS). In 2003, modifications were made to the GCPI model to develop an irrigated index for Kansas and was termed the Kansas Irrigated Productivity Index (KIPI). KS-SRPG and KIPI are still used by the PVD for dryland and irrigated lands, respectively, but are no longer updated, are not crop specific, are not available to the public, and are difficult to work with.

SRPG is based on more than twenty-five soil properties and landscape features, including physical, chemical, and biological features (Table 1-2). The model recognizes extreme cases where a soil characteristic can severely affect the productivity of the soil. KIPI is a modification of SRPG and contains many of the same soil properties, but eliminated all factors except the Landscape Features component and the soil property values for sodium adsorption ratio (SAR) and electrical conductivity (EC) (Powers et al., 2001).

Table 1-2. Soil factors and subfactors included in the SRPG and KS-SRPG models (Scheyer et al., 1992)**.**

Soil factors	Soil subfactors
Surface characteristics	organic matter, bulk density, clay content, available water capacity, pH, sodium, adsorption ratio, calcium carbonate equivalent, gypsum, cation exchange capacity, shrink-swell, rock content
Water features	depth to water table, permeability, available water capacity
Soil chemistry	sodium adsorption ratio, electrical conductivity, salinity, cation exchange capacity, pH
Soil climatic factors	moisture regime, temperature regime, moisture & temperature interaction
Physical profile	physical root zone limitation, root zone available water, calcium carbonate equivalent
Landscape features	most restrictive feature used as rating, slope, ponded, eroded, flooded, gullied/channeled/stony/gravelly/cobbly/cherty

Applications of Productivity Indices

According to the U.S. Department of Agriculture National Agricultural Statistics Service in 2017, Kansas is the #7 producer of corn in the United States, producing 174 million kilograms of corn over 2.23 million hectares. Approximately 104 million kilograms were planted into dryland systems (USDA-NASS, 2017). Therefore, one can conclude that corn is an important crop in Kansas, and producers should be able to use as many tools as possible to manage their corn production systems. Productivity indices are excellent tools to use both by the producer and by land evaluators. Since the late 1800s, scientists have been working to develop these models, mostly for land valuation and management purposes (Huddleston, 1984). Simonson and Englehorn (1938) stated that productivity ratings and indices are primarily useful for assessment and appraisal of land, as well as how land is classified.

Land Valuation

Inequities in tax assessment led to efforts to develop objective ways of determining land value. Soil interpretations, specifically productivity ratings and indices, are used for farmland taxation and equalization, appraising land for loans, and guiding land buyers (USDA Natural Resources Conservation Service, 2016b). In Kansas, a use-value system is used to protect farmers and ranchers from inflationary land prices. This system is based on an eight-year average of yields, income, costs, and soil productivity capacity for four different agricultural land types: dryland, irrigated, native pasture, and improved pasture (Schlageck, 2001). The KDR PVD has used the KS-SRPG and KIPI for determination of dryland and irrigated land productivity capabilities, respectively, in assigning use-values.

Land Use and Management

Soil productivity is the single most important evaluation for farming (Soil Science Division Staff, 2017). Knowing a soil's productive capacities can help producers make land use and management decisions (Pine, 1961; USDA Natural Resources Conservation Service, 2016a). These decisions include cropping systems, tillage, seeding rates, and more. Ratings can also aid in developing conservation planning to compare costs and benefits of incorporating buffer strips, terraces, and cover crops. Moderate dryland productivity ratings can guide a producer to installing irrigation if necessary, or choose a crop that is less reliant on water, such as grain sorghum. Moreover, productivity ratings can tell a landowner whether farming is recommended or not. Soils that receive low ratings may be more useful as rangeland or put into programs that preserve environmentally-sensitive agricultural land such as the Conservation Reserve Program (CRP) with the USDA Farm Service Agency.

Soil Characteristics in Productivity Indices

Not all soils are efficient at producing commodity crops. Each plant species has optimal conditions to thrive, mainly due to how they have evolved in different climates and on diverse soils (Foth and Ellis, 1997). Therefore, some soils create a habitat best for rangeland, some are best for forestry, and some are not successful at producing much at all. Understanding this variability of soil properties and their effect on crop yield is a critical component of land use planning (Juhos et al., 2015). Although there is a complex relationship between crop yields and soil properties (Sys et al., 1991), scientists are still able to measure physical and chemical properties of soil, as well as natural external factors to make crop yield predictions. Commonly measured soil properties by soil testing labs and soil surveyors are often considered in soil productivity indices to predict production capacity of soils. These include but are not limited to chemical properties, such as pH, cation exchange capacity (CEC), organic matter; physical properties, such as texture, soil depth, bulk density; and landscape properties, such as slope and landform position.

Soil properties that influence corn growth specifically are also common for soybeans, wheat, etc., but there are differences. For example, usually legumes respond to lime better than grasses because grasses are able to receive their calcium needs from low pH soil (Troeh and Thompson, 1993). Many scientists have studied corn growth on different soils to determine factors affecting productivity. Juhos et al. (2015) reported pH, organic carbon, and topography as indicators for productivity and noted that in droughty years, salts, soil texture, and nutrient content determined yields. However, in humid years, topographic position, organic matter, and nutrients were limiting factors. Bruce et al. (1998), (Kosmas et al., 2001), Sparovek and Schnug (2001), Johnson et al. (2002), Cox et al. (2003), Kravchenko et al. (2003) and Papiernik et al.

(2005) documented that variability of soil characteristics including soil depth, available soil water, nutrients, pH, soil OM, and clay content affect yield. Due to the large number of soil and environmental variables, it is difficult to find which properties are most impactful in an open system. This is one of the main reasons behind differences in productivity ratings between states, as shown in table Table 1-1.

Chemical Properties

pH

pH is defined as the negative common logarithm of the hydrogen ion activity and is a master chemical variable because it controls many chemical processes in the soil (Essington, 2004). Although spatially and temporally variable, pH is one of the key components of a soil that determines nutrient availability, as shown in Figure 1-1. Excessive soil acidity, which is indicated by solution pH values less than 5.0 to 5.5, can be limiting to plant growth. This environment restricts availability of essential macro- and micronutrients and increased levels of soluble aluminum and heavy metals are observed (Essington, 2004). High levels of soluble aluminum decreases uptake of phosphorus in plants, and corn has a very low aluminum tolerance (Foth and Ellis, 1997). On the other hand, high pH values also restrict micronutrient availability, specifically iron, and pH values greater than 8.5 indicate the presence of sodium (Troeh and Thompson, 1993; Foth and Ellis, 1997). Nitrogen availability is greatest at pH values 6-8 because mineralization of N is maximum in this range (Foth and Ellis, 1997).

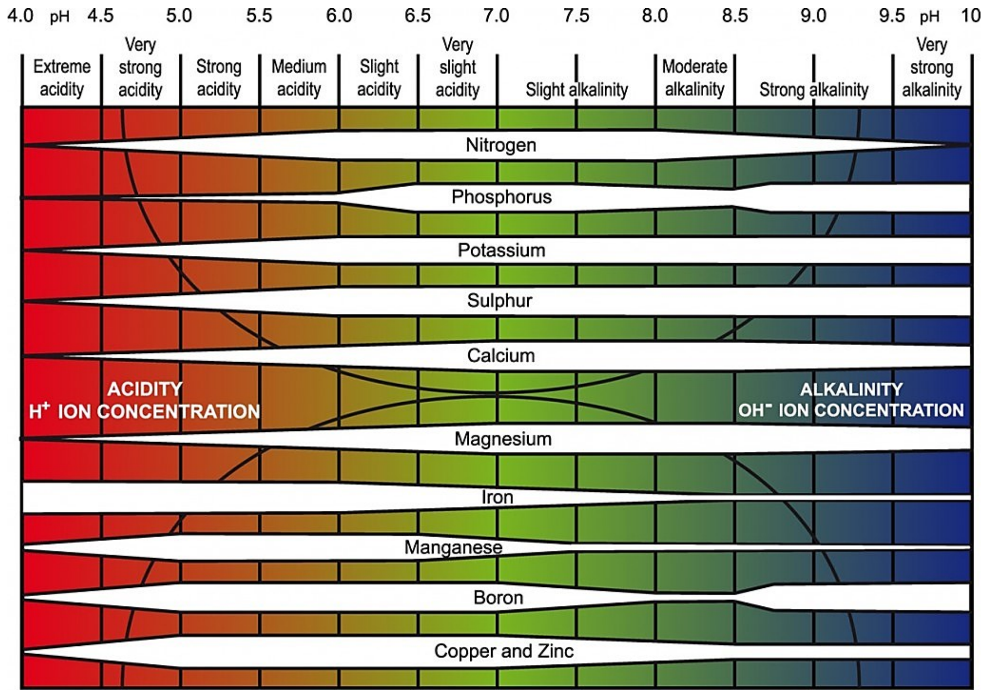

Figure 1-1. Nutrient availability at different pH levels (Truog, 1946; Potash Development Association, 2011)**.**

Extensive research has been done to find the optimal pH levels for corn productivity, which concludes that a pH range of 6.0-6.5 is favorable. For soils with low pH in the surface and subsoil, it is important to lime to a higher pH (6.5) to mitigate problems (Department of Agronomy, 2013). In most of Kansas, liming at pHs above 5.5 shows little corn yield response because of high pHs in the subsoil. Therefore, lime is only recommended on soils with a pH of 6.0 or less and a subsoil pH of less than 6.4 (Leikam and Mengel, 2007).

Cation Exchange Capacity

As defined by Essington (2004), cation exchange capacity (CEC) is the moles of adsorbed cation charge that can be displaced by an index ion per unit mass of soil at a specific pH. When measured, the CEC of a soil refers to the maximum negative surface charge and indicates the potential CEC of the soil. A higher CEC means more opportunity to hold nutrients for plant growth. CEC is primarily dictated by the abundance and types of phyllosilicates that are present, but also organic matter (Essington, 2004). Soils with higher CEC have a system that is more highly buffered, resulting in less change in pH with additions of materials that tend to either increase or decrease pH (Mengel, 2016).

Soil Organic Matter

Soil organic matter (OM) is a continuum of decomposing organic compounds (Lehmann and Kleber, 2015), which play important roles in the environment, affecting the biochemical, physical, and chemical properties of soil. Soil OM contains approximately 58% soil organic carbon (SOC), which serves as the main source of metabolic energy for soil microorganisms (USDA Natural Resources Conservation Service, 2009). Soil OM is also a source of macronutrients (nitrogen, phosphorus, sulfur) for plants and improves dissolution of soil minerals, complexes, and chelates metal cations and retains toxic compounds. soil OM, as well as water, temperature, pH, and salts, determine the ability of a soil to provide nitrogen to plants through mineralization (Foth and Ellis, 1997). Soil OM is extremely important for the maintenance of aggregate stability in farming systems, which can increase water retention and infiltration and provide aeration to roots (Mosier, 1919; Troeh and Thompson, 1993; Essington, 2004). It is also responsible for a fraction of CEC and buffers soil solution pH. Because of that, high organic matter soils typically only need to be limed to a pH 5.5 rather than 6.0-6.5 because high concentrations of soil organic carbon minimize the phytotoxic effects of aluminum and manganese in acidic soils (Essington, 2004). Although characterization analyses performed in scientific laboratories use SOC to determine taxonomic classifications, soil OM is used in soil interpretations because there are many benefits to soil OM as a whole structure (as stated above), not just the nutrient content.

Calcium Carbonate

Soils with high amounts of calcium carbonate commonly have high pH values. This high pH limits micronutrient availability and reduces the productivity of the soil. Calcium carbonate is usually found deeper into soil profiles, but in loess deposits on eroded landscapes in Kansas, it is common to find calcium carbonate near the surface. Calcareous soils have reduced solubility of forms of phosphorus associated with calcium because of increased activity of Ca^{2+} and adsorption on calcium carbonate (Foth and Ellis, 1997). Corn tends to suffer from potassium deficiency in high-calcium carbonate soils, so it is often recommended to apply potash (KCl) to supply a source of potassium to the corn (Troeh and Thompson, 1993). Kansas soils, however, tend to be high in potassium, so the threat of potassium deficiency in common high-calcium carbonate soils is low. More emphasis is often placed on pH effects from high-calcium carbonate soils.

Salts

The impact that excess salts have on a soil's physical and chemical properties depends on the type of salt present in soil or irrigation water. Saline soils are those with a high amount of salts in soil solution, which leads to increased osmotic pressure and can cause physiological drought. When salts are present, the osmotic potential of the soil solution is stronger (more negative) than the gravitational and capillary potentials, making the water unavailable for plant uptake (Troeh and Thompson, 1993). To determine if a soil is saline, scientists measure the electrical conductivity (EC) because the ability of a solution to conduct electricity is directly related to the concentration of dissolved salts (Essington, 2004).

Sodic soils are those with excessive concentrations of sodium, which is toxic to most commodity crops. Sodium promotes high soil pH, slaking of aggregates, and swelling and dispersion of soil clays, which decreases hydraulic conductivity, degrades soil structure, and impedes water and root penetration (Foth and Ellis, 1997; Soil Science Division Staff, 2017). To determine if a soil is sodic, scientists measure the sodium adsorption ratio (SAR).

Physical Properties and Qualities

Texture

Three mineral fractions, sand (2.0-0.05mm), silt (0.05-0.002mm), and clay (<0.002mm), are used to determine one of 12 texture classes on the texture triangle (Soil Science Division Staff, 2017). These texture classes are used in Soil Taxonomy (Soil Survey Staff, 1999a), by soil testing labs across the United States, farmers, contractors, and more to classify the soil or determine limitations that a particular soil may carry. Texture composition of a soil can be different spatially, both laterally and with depth, but does not change temporally within lifetimes.

Each particle class behaves differently in the soil depending on size and mineralogy. Clay tends to be sticky when wet and hard when dry (Mosier, 1919). Because it has a higher surface area and a negative electrical charge, clay works with organic matter to store water and plant nutrients (Troeh and Thompson, 1993). The two also help bind soil particles together into structural aggregates. Although clayey soils have a higher porosity, there are more micro- and mesopores than macropores. In this case, it is difficult for plant roots to access the tightly bound water in the smaller pores. At high water contents, a high-clay soil can be problematic due to a lack of aeration for plant roots.

Sand size particles serve as support help to make the soil permeable and are usually able to support heavy loads without causing compaction. However, they have relatively low water-holding capacities and are poor at storing nutrients. Therefore, they need frequent additions of water and nutrients to stay productive. This can cause leaching problems, especially on irrigated land, if the rate of application is higher than what is being taken up by plants.

Loam and silt loam are textures that are most desirable for several reasons (Troeh and Thompson, 1993). There is enough clay to hold water and nutrients, but also enough sand to encourage larger pores for aeration. Medium textured soils contain enough silt to gradually form more clay (to replace that lost by eluviation and erosion) and release fresh plant nutrients by weathering (Troeh and Thompson, 1993).

It is important to consider texture variations within a soil profile, not just the top horizon, when determining management strategies. B horizons with high clay can be restrictive to air, water, and root penetration. If the texture change is shallow in the profile, abrupt texture change can be so water restrictive that the soil is prone to flooding.

Bulk Density

Bulk density is the weight of solids per unit volume of total soil. The A horizons of mineral soils tend to have bulk densities between 1.0 and 1.6 Mg/m^3 depending on their texture and organic matter content (Troeh and Thompson, 1993). Organic matter decreases bulk density because it is lighter weight than sand, silt, and clay, and more importantly, it gives aggregate stability to the soil. Fine-textured soils have more pore space and lower bulk density than sandy soils, but it depends on the degree of compaction. In compacted layers, roots do not penetrate because of increased soil strength, reduced oxygen supply (Schumacher and Smucker, 1981). Water and roots are usually unable to infiltrate into soils with bulk densities that range from 1.4 Mg/m^3 for soils high in clay and 1.8 Mg/m^3 for soils low in clay (Jones, 1983; Troeh and Thompson, 1993).

Soil Depth

Depth of a soil refers to the thickness of soil material to a root restrictive layer (Soil Science Division Staff, 2017). Restrictive properties include physical properties, such as bedrock, densic horizons, fragipans, etc., are classified as root restrictive. A very deep soil is considered to have 150cm or more of soil material. Deep soils provide more root zone and have greater capacity to store water and nutrients than shallow soils, making them more productive and less prone stress (Troeh and Thompson, 1993).

Thickness of the A Horizon

An A horizon is defined as a mineral horizon that has formed at the soil surface or below an O horizon (Soil Survey Staff, 2014). A horizons must have accumulation of organic matter, and/or properties resulting from cultivation/pasturing, and/or a morphology that is distinctly different from underlying horizons (Soil Survey Staff, 2014). A horizons are often the most fertile of the horizons, have a lower bulk density, and more optimal permeability than underlying horizons, making it favorable for crop production. Experiments by Mielke and Schepers (1986) showed that where the A horizon is thickest, there was significantly more corn grain yield.

Coarse Rock Fragments

Rock fragments are those particles in the soil that are greater than 2mm in size that are pieces of geologic or pedogenic material with a strongly cemented or more cemented rupture-resistance class (Soil Science Division Staff, 2017). Rocks in the soil, particularly in surface horizons or at the surface, will slow soil erosion and increase steady-state infiltration (Cerdà, 2001). However, high rock contents at the surface reduce the rooting volume of soil and make it difficult to plow and plant. Therefore, it is best to have low coarse fragment content near the surface on farmland.

Available Water Capacity

Available water capacity (AWC) is the amount of water that a soil can store in a form available for plant use (Troeh and Thompson, 1993). Soil water is equally available throughout a range of soil wetness with an upper limit being “field capacity” and a lower limit “permanent wilting point”, which are both constant for a given soil, but are different for individual soils (Hillel, 2004). Texture plays a large role in determining AWC, with silt loams and loams having the most available water for crops. As Mosier (1919) stated, seeds will not germinate in a dry soil, so a productive soil must have the ability to hold moisture for several days to be productive. It is important to consider AWC for corn because it is less tolerant to a water deficit than grain sorghum due to a less dense and less prolific root system (Irmak and Rudnick, 2014). Plants can endure a longer drought when soils have a higher AWC because water will stay in the root zone during dry periods (Troeh and Thompson, 1993).

Landscape in Productivity Indices

The topography of an area can control how a soil develops and therefore can control the productive capacity of a soil. In a catena situation, the lowlands usually have higher productivity compared to shoulder/eroded positions due to increased organic matter contents, deeper A horizons from accumulation of eroded sediments from higher areas, more favorable pH, and typically more available water (Kravchenko and Bullock, 2000). However, some of these lower landscape positions are more susceptible to flooding. The duration of the flood depends on the rainfall event, depth to water table, and distance to a floodable water source.

Soils higher in the landscape, depending on parent material, can be quite high in calcium carbonate. This increases pH and reduces phosphorus availability, which can be detrimental to corn development. Shoulder positions are often eroded of their rich A horizons and lack organic matter, which limit the ability for crops to retrieve nutrients. Highly erodible land, which is often steeply sloping, is less likely to be used for crop production and can be difficult to farm with machinery (Miranowski and Hammes, 1984).

Climate in Productivity Indices

Incorporating climate into productivity indices and ratings is often controversial. Inherent indices do not include climate factors due to the variability both annually and spatially among soil series, but some do consider them as stable elements (Storie, 1933). Climate is an extremely limiting factor for corn growth, especially in dryland production because soil moisture and temperature regulate biological activity. In a study by Assefa et al. (2012), a significant positive correlation was found between March and July rainfall and dryland corn yields, as well as a significant positive correlation between March minimum and maximum temperatures and May through July minimum temperatures and dryland yields. These findings have to do with the optimal conditions for seed germination and emergence, as well as pollination and grain fill. Because dryland production relies heavily on rainfall, Mosier (1919) suggested that an area that receives less than 20 inches of rain annually is usually where producers draw the line on dryland and irrigated corn. Although no-tillage systems may be able to make up for little rainfall, not enough or too much rain is a factor in acid or alkaline soil development (Klages and Hubbs, 1942). Therefore, mean annual precipitation and mean annual temperature are common climatic factors in productivity indices. If included, climatic factors can allow the index or rating to be used on more than a local level, such as regional or nation-wide (Aldrich, 1967).

Conclusion

Productivity indices provide an interpretation about soil types that allows the user to make applicable decisions with soils. These can be used for land use planning, such as understanding cropping system dynamics and management systems for a broad area. Productivity indices also serve the purpose of providing an objectively determined equalization of land values. Due to the Kansas Department of Revenue Property Valuation Division using dated rating/index systems for land valuation, it is important to develop an index that is Kansas-specific, crop-specific, and understandable by producers, landowners, future landowners, assessors, and even researchers to properly array Kansas soils on their productive capacity. More land is being planted into dryland corn systems in Kansas each year, and a dryland corn specific rating can be an excellent tool to make further property decisions each year.

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Chapter 2 - Development of a Dryland Corn Productivity Index for Kansas

Introduction

For decades, soil scientists have developed interpretations about the use of soils and to quantify soil function parameters (Soil Science Division Staff, 2017). Productivity ratings, which are suitability interpretations, rate soil on its capacity to produce plant growth and were the primary reason for the initiation of soil surveys in the United States (Huddleston, 1984). Since then, most interpretations, especially those built within the United States Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS), are built upon the soil survey structure. This means that interpretations are mostly based on physical and chemical properties that are inherent to the soil. Using inherent properties in soil productivity ratings allows the rating to be used for several years, even decades, because it is based on soil properties that do not suddenly change over a short period (Storie, 1933).

The Kansas Soil Rating for Plant Growth (KS-SRPG) and the Kansas Irrigated Productivity Index (KIPI) models are still used by the Kansas Department of Revenue (KDR) Property Valuation Division (PVD) for dryland and irrigated lands respectively, but are no longer updated, are not crop specific, are not available to the public, and are difficult to work with. An updated dryland corn productivity rating that is consistent over time specifically for Kansas is needed for many uses, such as rental payments and assisting management decisions.

This thesis presents the Kansas Commodity Crop Productivity Index (KCCPI), which is generated in the National Soil Information System (NASIS) using the interpretations module. At present, the KCCPI arrays soils according to their inherent capacity to produce dryland corn and avoids inequities that are possible when only yield data is used to rate soils. The model was built using inherent soil properties, which vary little over time and location for a specific soil (map unit component) identified by the National Cooperative Soil Survey (NCSS) (Dobos et al., 2012). This thesis has completed and validated the dryland corn submodel for the KCCPI.

Methods

National Soil Information System (NASIS)

The Kansas Commodity Crop Productivity Index (KCCPI) was built inside the National Soil Information System (NASIS). This program is maintained by the USDA-NRCS and access to the database is limited to NRCS personnel or by special permission. NASIS stores soil survey information for the United States (Table 2-1), such as soil properties, landscape features, soil climate, parent material, and taxonomic classes using Soil Taxonomy. This information is routinely maintained and uniformly available throughout the nation. The information within NASIS is detailed enough to represent highly variable soils (Dobos et al., 2012). NASIS not only allows for data storage and organization of soil information, but also the development of interpretations that transforms data into information to help make land-use decisions.

Within the database, a phase or type of soil series or higher taxonomic unit is a map unit component. Values of each map unit component are typical for that component across the soil survey area and may differ from place to place due to geographic variability of the soils within the series (Dobos et al., 2012). In the development of interpretations, map unit components are used to complete their calculation, which means that the interpretation could show different results for a certain soil series.

Interpretations

Soil survey interpretations are traditionally built following these steps: 1) study an array of soils with known performance, 2) construct relationships to predict performance, 3) generate predictions for a wider array of soils using soil survey data, 4) test predictions against knowledge base or other performance measurement, such as yield (Soil Survey Staff, 1999b). NASIS supports these steps by providing soil survey data that can be queried to analyze information, the interpretations module where mathematical and conceptual relationships can be constructed, and some yield data that can be used to calibrate the model before validation. Manual calibration is used for soil interpretations because expert and logistical knowledge is often needed. Automatic calibration, such as using statistical analytics to find mathematical equations, would allow for the user to quickly find best fit, but possibly would not make agronomic or pedologic sense (Ndiritu, 2009).

The interpretations module in NASIS consists of properties, evaluations, and rules (Figure 2-1). A property is the soil data retrieved from the soil database of a specified soil property (USDA Natural Resources Conservation Service, 2010a). Each property has its own script of Structured Query Language (SQL) to extract information from the database to be used in the interpretation. Properties must include variables named Low, High, or Relative Value (RV) in order for the evaluation process to search the property's symbol table for the correct entries. They then also must contain a choice list field that states what the expected return values will be: high-low, high-low-rv, or just rv (USDA Natural Resources Conservation Service, 2010a). The scripts specify the data type, such as character or numeric, and default value for results that indicate how to interpret null values.

Properties are put into evaluations (Figure 2-1), which are tests that will be applied to the data returned from properties to determine the truth of propositions (USDA Natural Resources Conservation Service, 2010a). NASIS implements fuzzy logic in evaluations, which allows the use of continuous limits where a complete gradation of the truth (or false) of an interpretive statement can be represented (USDA Natural Resources Conservation Service, 2010b). The evaluation transforms the data returned from the property into a domain of numbers from 0 to 1, where 0 means completely false and 1 means completely true. The numbers in between represent the degree of truth. Fuzzy logic is often preferred in soil interpretations because when developing mathematical models for soil interpretations, “crisp limits” restrict the outputs to defined classes or groups. In NASIS, all of the following evaluation types can be used with numeric data: crisp curve, sigmoid curve, linear curve, arbitrary curve, arbitrary linear, PI curve, beta curve, Gaussian curve, triangle, trapezoidal, or is null. Character data can only be used by a crisp evaluation.

Evaluations and subrules (Figure 2-1) are used by the interpretation (the primary rule) to derive interpretive values. The interpretation simply states the land use, limiting features, and the relationship among features. A subrule is a limiting statement about one limiting feature and are considered the building blocks of an interpretation (USDA Natural Resources Conservation Service, 2010a). Subrules have at least one evaluation linked to them.

Along with the informational and data-extracting components of interpretations in NASIS, there are also components that are required to build the interpretation, which are the following: start state, operators, and hedges. Every rule begins with a start state (triangle in Figure 2-2). Operators define the interactions between the subrules and include *OR, SUM, AVERAGE, and PRODUCT*. The symbols “+,” “-,” and “*” are used for the membership values between subrules. Hedges can change the meaning of an evaluation depending on which type is used. Options for hedges include: *not, extremely, very, somewhat, slightly, positively, generally, add, subtract, multiply, divide, power, alpha, limit, weight, not null and, null or, null not rated*. Hedges are placed after the operators and before the subrule or evaluation in a subrule (USDA Natural Resources Conservation Service, 2010a).

Model Development

The KCCPI was developed in the traditional way that arrays soils according to their relative performance of producing a commodity crop. The structure of the Kansas Commodity Crop Productivity Index (KCCPI) model currently consists of one submodel, which is the dryland corn submodel. Other submodels may be developed for wheat, soybean, grain sorghum, etc. in the future.

Properties that were previously written in NASIS were chosen for this project. Hundreds of properties have been developed for each soil property/quality and are stored in NASIS. The process of choosing which properties to use involved knowing which interpretations they were developed for, the goal/purpose of the property, and what type of information it designed to return. The properties that were chosen for the dryland corn submodel of the KCCPI were mostly chosen from other productivity rating interpretations, such as the National Commodity Crop Productivity Index (NCCPI) and the Commodity Crop Productivity Index for Wisconsin (WICCPI). The properties that were used are in Appendix A.

After selecting a property for the interpretation, an evaluation was developed for that property. The selection of the evaluation type depended on the property and largely was chosen by 1) analyzing other evaluations in the database that were made by USDA-NRCS personnel, and 2) using fundamental knowledge of the interaction between the property and crop growth.

Subrules for each soil property evaluation were made to develop the primary rule. The KCCPI is set up as a summation equation modeled after the WICCPI (USDA Natural Resources Conservation Service, 2016a). Each subrule's evaluation(s) is multiplied by a decimal factor between 0 and 1, then the results of the subrules are summed to produce a final rating. To do this, hedges were used, as shown in Appendix C, which manipulated the fuzzy numbers being produced by the evaluation. Figure 2-3 shows the hedge factors for each subrule in the KCCPI model that are added to 1. Using hedge factors in this way provides two things: 1) it allows certain soil properties to have a greater weight in the equation than others and 2) keeps the final index value from producing a number greater than 1. The Interpretable Component Subrule is not included in the equation, but ensures that soil components that should not be rated are not included in the rating analysis, such as miscellaneous soils (gravelly land, water, etc.). Table D-1 and Table D-2 demonstrate the calculation of the KCCPI and the climate-included KCCPI. One soil component out of 21,242 Kansas components (Table 2-1) were used to illustrate the calculation.

Properties Considered

Soil properties that are important to consider when growing corn were used as parameters in the Kansas Commodity Crop Productivity Index (KCCPI) model to array the soils of Kansas based on their capacity to grow corn. The properties included in the KCCPI, as well as their respective hedge factors, were selected during manual calibration. Properties selected in the beginning of model development were chosen by 1) finding the most common soil properties that are used for corn productivity indices across the United States 2) based on their foundational connections to plant growth. Soil properties that have been found to have a significant effect on yield were added. Temporary fluctuations in productivity caused by management and annual variations in weather were not addressed in the non-climate KCCPI. A KCCPI corn submodel with climate included was created to test for a possible climate-included KCCPI. The climate properties chosen are presented in the criteria table in Table 2-2.

Calibration Method

Yield data from NASIS were used to analyze the success of the model as properties were added, removed, and as hedge factors were adjusted during manual calibration. Yield data versus KCCPI values and KCCPI subrule values were plotted. The correlation graphs and correlation values of the relationships were used to determine the success of the model and subrules. If results showed a poor relationship, the hedge factors or evaluation curves were changed, or the property was no longer considered for the model to predict dryland corn productivity. Final selection of the properties was made during the calibration of the model. Manual calibration was used because, unlike automatic calibration, it permits expert judgement and is logistical. Most soil productivity ratings require manual rather than automatic calibration because of the need for expert and practiced knowledge to array soils with different phases of soil properties.

The yield data in NASIS is the responsibility of the NRCS State Office staff, including an agronomist. It involves making expert estimates from records, reports, and/or knowledge of the soil's performance. These records are maintained relatively well in agricultural states, but not as much emphasis is placed on them now as in the past. Although the magnitude of the yields may not represent current yield trends, yields still reflect relative productivity and can be used effectively to rank soil productivity (R.R. Dobos, personal communication, 2019). In some scenarios, as advised by NRCS personnel, some soil components were removed that show inaccurate data. This was only the case for a few soil series that are known to disrupt data analysis due to inconsistency across political boundaries of soil survey areas.

Results and Discussion

Calibration

AWC

The soil properties with the highest weight in the KCCPI were AWC and pH. The KCCPI used the AWC sufficiency property in its evaluation, which considers water at a depth of 10 cm more valuable than water stored at 150 cm and is thus rated higher. AWC reflects several different soil properties that affect the amount of water a soil can hold and supply to roots, such as texture and porosity. In Kansas, it is common to go through a period of drought at some point in the growing season, so if a soil is able to hold water, then the corn roots are more likely to withstand high temperatures and dry spells. As shown in Figure 2-4, AWC sufficiency property shows a moderate positive relationship with corn yield, as well as the KCCPI AWC sufficiency subrule in Figure 2-5.

pH

Although pH is not always considered to be an “inherent” soil property, it is extremely important to consider when predicting corn growth. Soil pH creates an environment that governs nutrient availability and is optimal near neutral for most plants. The evaluation used for pH (Figure 2-4) was fitted to Kansas soil data with a steep Gaussian bell curve. This gave the KCCPI a larger spread in ratings from 0-1.

Soil Depth

Much of Kansas is covered in deep soils, but since there are some large areas in Kansas with shallow soils, soil depth is a factor that strongly limits soil arability. Therefore, soil depth was given the second highest weight factor (Figure 2-3). Two properties were used for soil depth: depth to bedrock and depth to retarding layer. Even if a soil is deep to a solid bedrock, there may be other soil properties that minimize rooting depth, such as fragipans or high clay content. The soil depth subrule (Figure 2-5) was successful in modeling a similar correlation as that shown by the depth to bedrock and depth to retarding properties (Figure 2-4).

CEC

Similar to AWC, CEC is a measurement that helps scientists interpret other properties of a soil, such as clay content and the ability to hold nutrients. If a soil has a low CEC, it can be predicted that the soil has a low clay content and therefore would not hold water or nutrients well. As shown in Figure 2-4, yield begins to decrease at high CEC. This could mean that the clay content is too high, and roots cannot easily penetrate the soil to receive nutrients, water, and stability. For these reasons, the evaluation curve for surface and subsoil CEC was changed from a sigmoid shape to an arbitrary bell curve (Figure B-6 & Figure B-7). This change increased the correlation between the KCCPI CEC subrule and dryland corn yield from 0.2503 to 0.2727.

OM

Over the past 20 years in the agricultural community, a strong push for soil health has increased the number and types of practices that producers can implement to conserve and even build up organic matter, which encourages microbial diversity and can improve overall plant health. Therefore, organic matter data in the current soil survey database (NASIS) may be slightly out of date because organic matter is a soil property that can change easily under different management systems. However, NASIS is still a significant source of organic matter data. It is commonly known that low organic matter produces low yields, and high organic matter produces high yields. When organic matter content is too high, it is not easily farmable. This relationship is shown in Figure 2-4, but was not a reason to change an evaluation curve. Kansas does not have many soils with greater than 5-6% organic matter, especially in agricultural production. A bell-shaped evaluation curve that gives a lower rating to high organic matter soils would be important in states with more organic soils, such as Minnesota.

CCE

Many soils in Kansas have moderate to high accumulation of calcium carbonate. Most occurrences are in high pH soils and/or those that are weathering from limestone bedrock. Figure 2-7 shows the relationship between CCE and pH from 0-20cm and 20-100cm in Kansas. For this index, CCE could be thought of as an extra dockage for those soils that have high pH and CCE. Figure 2-6 shows the relationship between dryland corn yield and CCE in the surface and subsoil. Soils with a very high CCE did not have yield data available, most likely because corn is not suitable and therefore, yield data was never collected at those locations. This situation also occurred with several other soil properties.

Bulk Density

Bulk density is a difficult property to model, so it was given a low hedge factor rating (Figure 2-6). Fortunately, there is not a large range in bulk density values in Kansas because loess, residuum, alluvium, and colluvium are the dominant parent materials. This allowed the bulk density evaluation curve (Figure B-12 & Figure B-13) to have a narrow range. The properties used for the bulk density subrules were derived from a Texas plant growth index in which an evaluation curve for low clay soils (<60% clay) was separate from the evaluation curve for soils with high clay (>=60% clay). The depth to high bulk density rule was also included to limit those soils that could have a dense horizon, such as a hard plow pan. The bulk density subrule was somewhat successful and indeed contributed to the overall model, but will need further refinement before the index is put to use. For example, the 60% cutoff for distinguishing "low clay" from "high" clay may need to be decreased to better represent Kansas soils.

Coarse Fragments

Coarse fragments are often also difficult to include in productivity models because they have both positive and negative indirect effects on landscapes. To a producer, coarse fragments are unwanted so that implements can easily move through the soil to prepare a seed bed and plant seed. However, coarse fragments contribute to soil stability, minimizing erosion of surface soil and in some systems, stabilizing roots. For these reasons, a sigmoid evaluation was given to the surface fragments < 25 cm property instead of linear. This keeps fuzzy membership close to one, even at 10% coarse fragments. However, “surface fragments > 25 cm” was evaluated with a linear membership line because a small percentage of large stones can have a much more dramatic effect on whether a soil is arable.

Slope

The one soil landscape rule that was chosen for the KCCPI was percent slope. Although slope does not directly impact corn growth, it is important for preventing soils with steep slopes (15-20%) from receiving high ratings. Steeply sloped soils are much more likely to erode, are more difficult to farm, and often do not have a deep surface horizon with high organic matter or nutrients. Figure 2-6 shows the negative relationship between slope and yield. The slope subrule was not very successful for predicting which soils are most suitable for corn, but it is important to include because it explains farmable land.

Overall Model

The ability of the KCCPI to predict dryland corn yield is presented in Figure 2-8. There is a moderate positive relationship between Kansas dryland corn yield and the KCCPI. This is considered very successful for productivity indices, especially when using soil survey data.

Calibrating the model to fit poor soils was difficult because of limited dryland corn yield data for soil across the productivity spectrum.

Climate Subrule

After working only with non-climatic factors, MAP and MAAT were included to test for a KCCPI corn climate submodel. These two climatic parameters were summed together and formed the KCCPI climate subrule. The climate subrule was then multiplied by the KCCPI (Figure C-2). The MAP property was used to represent the large gradient in precipitation from east to west across the state (Figure 2-9), which dramatically changes a soil's ability to produce dryland corn. The MAAT property captures the effects of southern Kansas that is close to the thermic temperature regime, which could become more suitable to growing cotton. MAP showed a moderate, positive correlation with dryland corn yield, but MAAT was more difficult to correlate (Figure 2-10). The climate subrule showed a moderate positive correlation with dryland corn yield (Figure 2-11), and adding the climate subrule improved the KCCPI (Figure 2-12).

Properties Not Included

Several soil properties and qualities that are used in other indices were tested for the KCCPI model but were not selected. EC and SAR were considered for estimating salt and sodium content, respectively, which can easily keep a soil out of production at high concentrations. However, not many soils in Kansas are affected by high salt or sodium. Also, there is minimal dryland corn yield data on salt- and sodium-affected soils, and therefore it was difficult to determine a relationship. It can be predicted that EC and SAR would more likely be considered in an irrigated index rather than a dryland index.

Water table was also considered but is a difficult property to evaluate. A shallow water table can be beneficial during droughty years, but can be extremely problematic in the spring during planting. If the soil is too wet, producers cannot take equipment to the field and the soil is poorly aerated for plant roots. This can cause excessive water stress, denitrification, and reduce yields (Kanwar et al., 1998). Due to this variability, water table was not included.

Ponding and flooding frequency/duration were considered, but not included in the KCCPI. NCCPI and WICCPI both use ponding and flooding characteristics in their ratings, but it can be quite controversial, especially for Kansas. Ponding and flooding terms were estimated for soils as they were surveyed but are determined by annual weather variations. Because Kansas commonly has droughty years and less rainfall compared to the eastern Corn Belt, soils next to rivers often have some of the highest productivity. Indeed, it is important to consider ponding and flooding for management decisions but was too inconsistent to include in the KCCPI.

Soil texture is used in several soil interpretations but was not included in the KCCPI. Soil texture is a difficult soil property to assign "good" or "bad" classes. For example, some texture classes are productive in no-tillage systems, but would not be productive in conventional tillage systems. Soil texture is captured in both AWC and CEC, so the KCCPI did not include soil texture.

Other Crops

The KCCPI corn submodel was tested against Kansas NASIS yield of grain sorghum, soybean, and wheat (Figure 2-13). All three crops showed a moderate positive correlation with the current KCCPI, which suggests that the KCCPI corn submodel could be an overall commodity crop index rather than being crop-specific. However, further testing, such as the calibration methods presented in this thesis, is needed.

The KCCPI corn submodel with climate was also tested against Kansas NASIS yields of grain sorghum, soybean, and wheat (Figure 2-14). Grain sorghum and wheat showed stronger correlations with the climate submodel compared to the non-climate KCCPI. Wheat showed a weaker correlation with the climate submodel compared to the non-climate KCCPI. This could be because wheat has a different growing season than the other crops that were tested. The results reaffirm the usefulness of including climate factors in productivity models, especially for Kansas.

Validation

A different set of yield data was used to test the ability of the KCCPI to predict corn productivity in Kansas as validation. Actual, measured, 10-year average of dryland corn yield by Common Land Unit (CLU) is managed by the Risk Management Agency and the Farm Service Agency. A CLU is the "smallest unit of land that has a permanent, contiguous boundary, a common land cover and land management, a common owner, and a common producer in agricultural land associated with USDA farm programs" (USDA Farm Service Agency). With this information, it is easy to visually see where corn is commonly grown in Kansas (Figure 2-15). The CLU data was averaged over the 10 years to attempt to eliminate climate variations from year to year.

With NRCS assistance, the CLU data was matched with gridded SURRGO data in ArcGIS. This eliminated sensitive geographic information of field locations and added the map unit key (MUKEY) to yield. Then, MUKEY was used to join the CLU yield data to the NASIS export that contained soil information and KCCPI. However, repeats of the same MUKEY were deleted to join the soil/KCCPI data from NASIS with the yield data. Only the major components of soil map units remained after repeated MUKEYs were deleted. Although this deleted some yield and soils data, it kept only the dominant soils in a CLU.

When the KCCPI was tested against the CLU yield data, a very weak positive relationship was found (Figure 2-16). This relationship is compared to the NCCPI Corn and Soybeans Submodel (II) (Figure 2-16) that showed a weak positive relationship with dryland corn yield by CLU. The KCCPI did not perform as well as the NCCPI Corn and Soybeans Submodel (II). However, the climate-included KCCPI performed similarly to the NCCPI (Figure 2-16), suggesting that the climate subrule is of value when predicting Kansas dryland corn yields. When ran against the Kansas CLU yields, the current KS-SRPG did not show a better or worse relationship than KCCPI (Figure 2-16). But once again, the climate-included KCCPI outperformed the KS-SRPG. This could suggest that with more calibration of hedge weight factors and evaluation curves, the climate-included KCCPI could potentially function as the new index used by the Kansas Department of Revenue, especially because it is easier to update and access.

To show examples of the KCCPI's performance on some Kansas soils, a random selection of 20 soils and their index values and yields by CLU are presented in Table 2-3. The subrules and KCCPI for Brownell return low values (Table 2-4), which can be explained by Brownell's soil property data in Table 2-5, Table 2-6, and Table 2-7. Brownell has high pH, high CCE, is somewhat shallow in depth, contains surface gravels, and has moderate bulk density and AWC. On the other hand, Muscotah displays almost ideal properties according to the KCCPI criteria table (Table 2-2) and therefore returns a high index value and almost maximum subrule fuzzy numbers (Table 2-4). For those soils with high MAP (Table 2-7), the climate-included KCCPI and non-climate KCCPI returned the same values. Soils in western Kansas, such as Richfield, received a lower climate-included KCCPI than non-climate KCCPI. The KCCPI was not successful for all soils, though. The Morrill soil component in Pottawatomie County received a high KCCPI and climate-included KCCPI (Table 2-3), but low/moderate KS-SRPG and NCCPI values. This is a disadvantage of an additive system. This Morrill soil has almost ideal attributes except for rock fragment content and slope (Table 2-6). Because these two factors have low weight in the KCCPI calculation, and because KCCPI is an additive system, the final rating was not as low as it should be. This Morrill component is certainly not as suitable to produce high yields as the KCCPI predicted.

Conclusion

The results produced by the KCCPI are similar to other crop productivity models, which produce a weak to moderate correlation depending on how much yield data is available over a certain number of soil types (Kiniry et al., 1983; Powers et al., 2001; Schaetzl et al., 2012). Some models use farm income and land price or tax rate as a method to check index/rating results (Fenton, 1975). Others use estimated yields as calibration, and expressing those yields as percentages of maximums so that the calibration data is on a 0 to 100 scale (Huddleston, 1982). This process has an advantage over using actual yield data because, as was found out while building the KCCPI, it is difficult to obtain quality yield datasets. This could be done for the KCCPI in the future, but it could be argued that the numbers are no longer relevant and therefore not an accurate test for a state-level index. Also, differences between the calibration yield (NASIS) and validation yield (CLU) datasets certainly are reasons why calibration and validation results were so different. In calibration, out of the 2,292 soils available, only 266 soils were attached to yield. In validation, out of 3,651 soils listed, 2,943 soils were attached to yield. The main reason why calibration had so few points is due to the NRCS cleaning up old data in NASIS. The NRCS focuses more on arraying soils relative to each other rather than using yield for verification.

The current KCCPI with the KCCPI corn submodel for dryland corn is not ready to be used for land appraisal. More calibration is needed to refine the subrules, evaluations, and properties that are used in the model to continue development for a Kansas-specific, crop-specific model. Manual calibration is a tedious method, because there are many combinations of hedge factors, evaluation types and ranges, and soil properties to be used in a crop productivity index. Expert knowledge is essential to do this, especially when using soil data.

The climate-included KCCPI has more promise for a dryland corn productivity index for Kansas than the non-climate KCCPI. This indeed is logical, as precipitation and ideal temperature is critical to consider for dryland corn production. However, the climate subrule does need some modification. It would be wise to use "growing season" precipitation and air temperature rather than an annual mean if the index is crop specific. This change would allow the user to more accurately create a climate subrule for a particular crop. For example, wheat is planted in the fall rather than the spring, so light rainfall is necessary after planting and at spring green-up. The KCCPI model was built with a separated climate model to ensure that in the future, a model would be available that does not change as much over time because including climate factors can make a model obsolete over a short time period even when using NASIS. Also, if a user does not want to rate soil with climate factors, they are able to do so. But for crop land appraisal, it would be wise to use the climate-included KCCPI to receive more accurate predictions of land potential. As stated by Dobos et al. (2012), new information will be added to refine the KCCPI as more relationships between soils and crop growth are understood.

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Table 2-1. Kansas soil survey database (NASIS) facts.

Field	Count	Note
Map units	5,793	The number of map units identified by the database element "muiid."
Total components	21,242	Major and minor components.
Major components	7,069	A major component is greater than 10% of a map unit.
Minor components	14,173	A minor component is less than 10% of a map unit.
Soil survey areas	105	
Individual soil polygons	595,072	Soil boundaries across Kansas.
Component horizons in NASIS	86,652	
Pedon descriptions in NASIS	38,303	

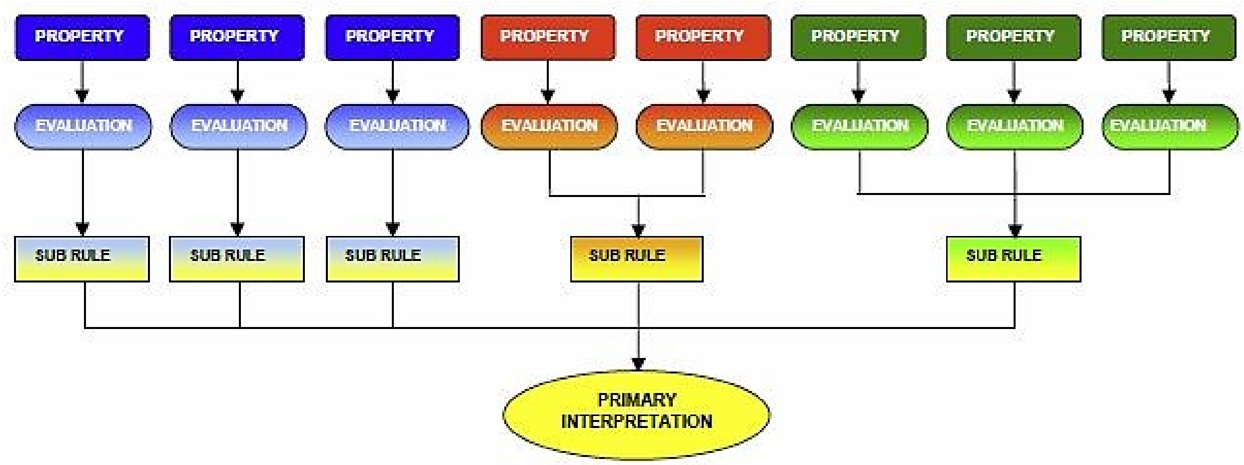


Figure 2-1. Example of the three-component concept of an interpretation (USDA Natural Resources Conservation Service, 2010a)**.**

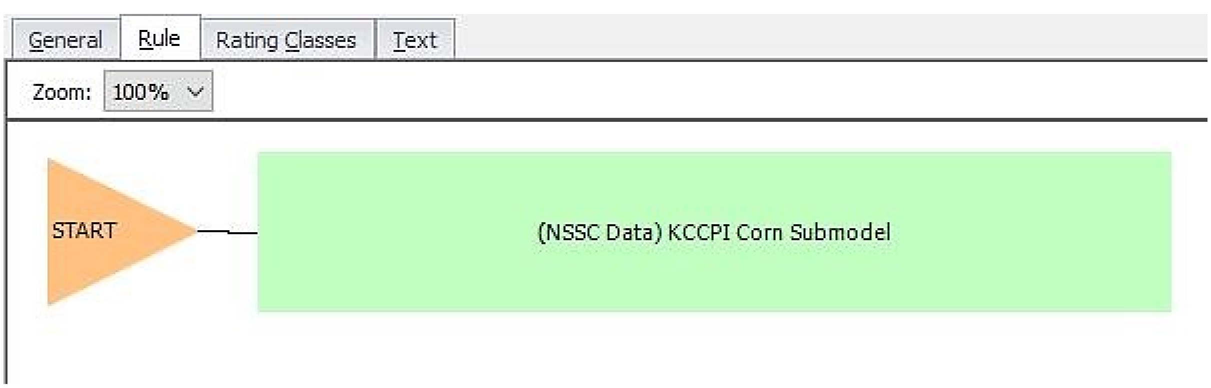


Figure 2-2. Beginning of an interpretation in the National Soil Information System (NASIS).

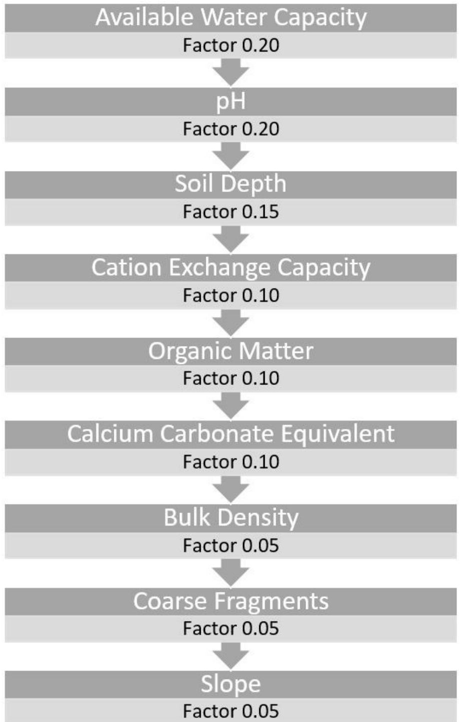


Figure 2-3. Additive system of the KCCPI model is summed to 1.

Table 2-2. Criteria table for KCCPI.

Property	Criteria (Ideal for Kansas)	Explanation
Available water capacity sufficiency	> 0.9 cm	Rooting depth ability to hold water for several days
pH	6.0-6.6	pH near neutral
Soil depth	>150 cm	No rooting barriers
Cation exchange capacity	25 meq/100g	High surface and subsurface CEC
Organic matter	> 2.5%	Provides nutrients, encourages microbial community, buffers pH
Calcium carbonate equivalent	< 5%	Low calcium carbonate content
Bulk density	1.2-1.3 Mg/m^3	No rooting barriers, ease for water movement
Coarse fragments	< 15%	Ease for implements in the field
Slope	< 3%	Low slope minimizes erosion, ease for implements in the field
Mean annual precipitation†	800-1100mm	Precipitation for dryland corn is critical.
Mean annual air temperature†	9-14ºC	Air temperature should not be freezing, but not be thermic for corn production.

†Used only in the climate-included KCCPI

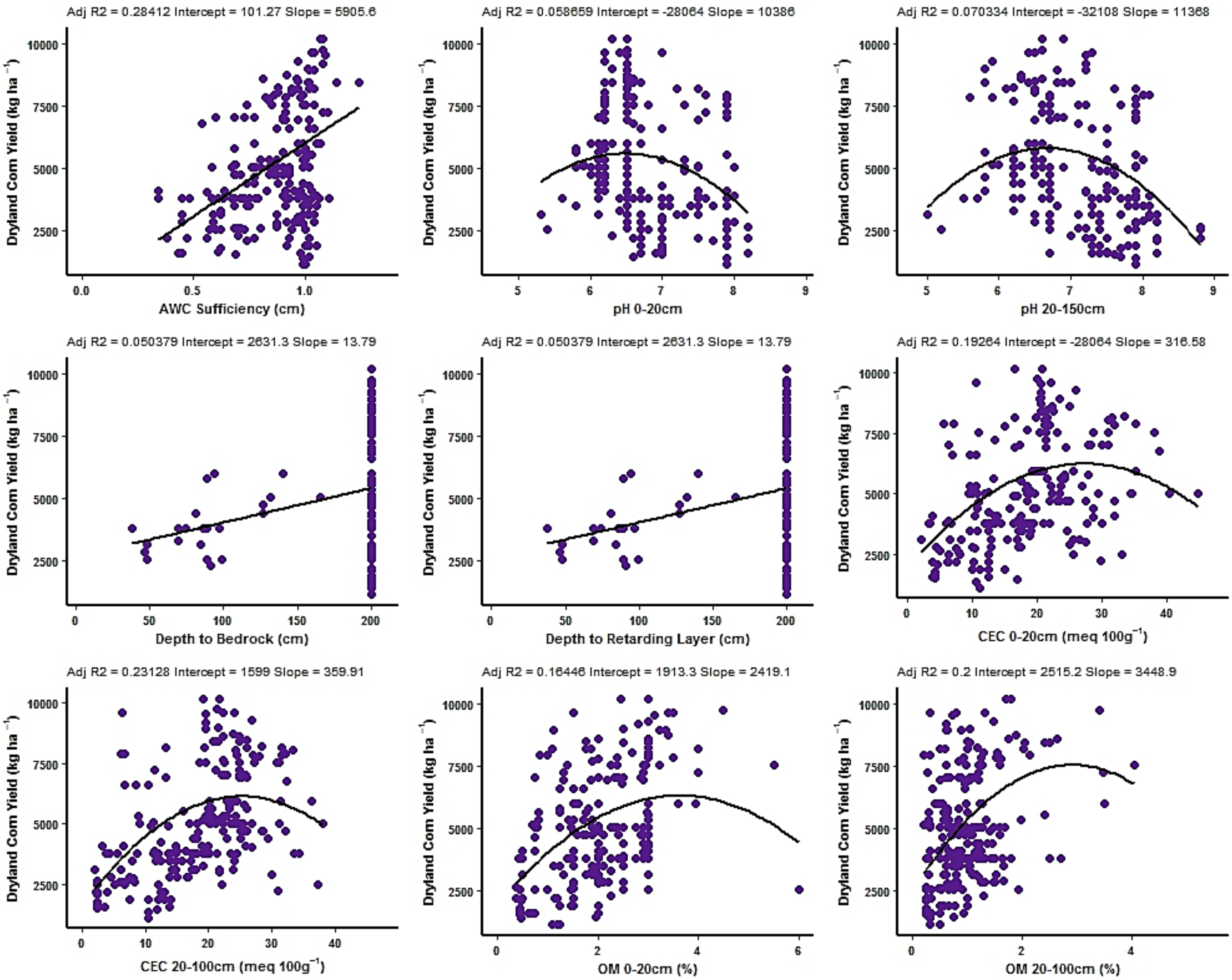


Figure 2-4. National soil information system (NASIS) dryland corn yield (kg ha^{-1}) vs NASIS soil property data of Kansas soils. Soil properties displayed are those included in the KCCPI (continued in Figure 2-6).

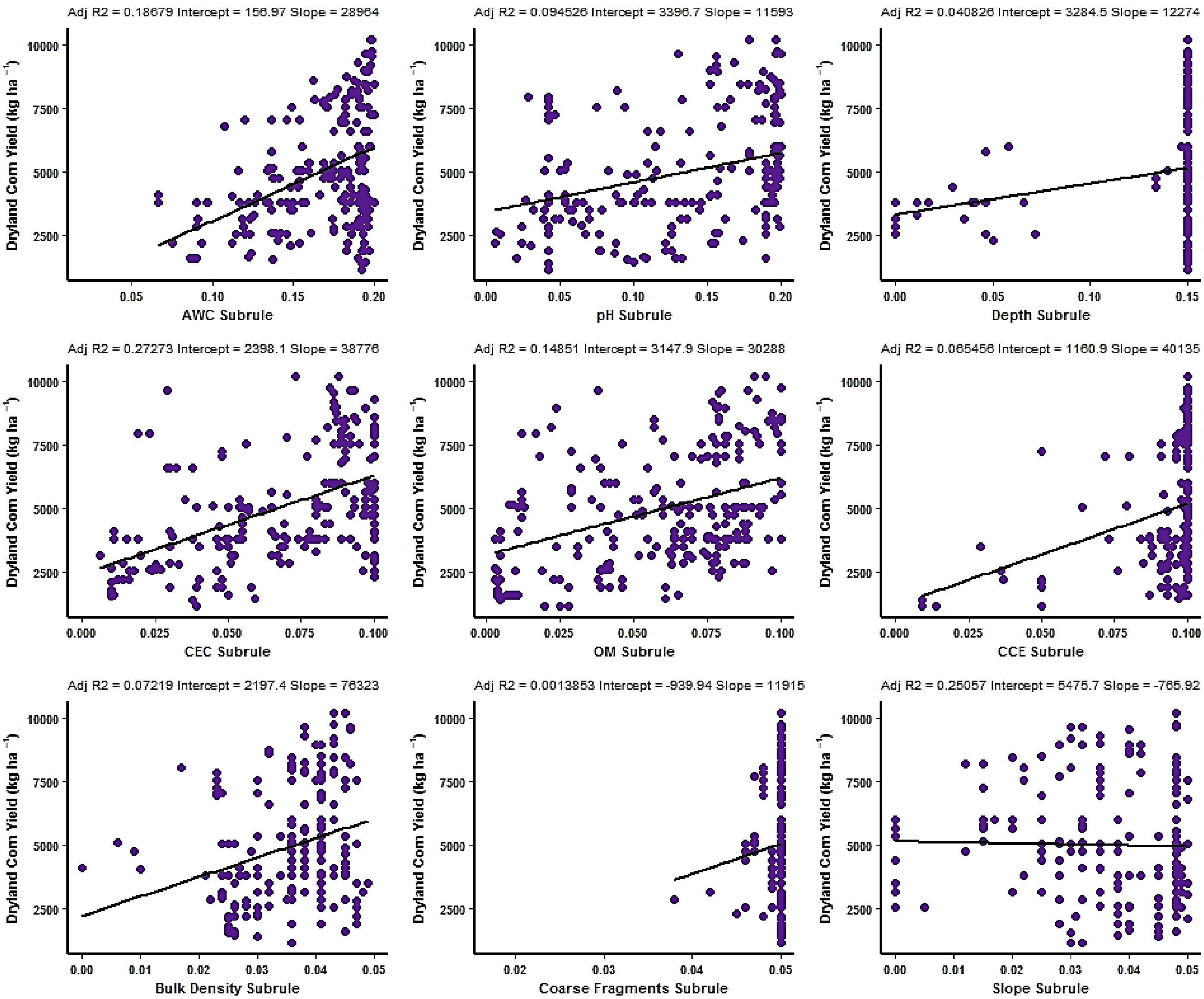


Figure 2-5. National soil information system (NASIS) dryland corn yield (kg ha^{-1}) vs KCCPI subrules fuzzy outputs for Kansas soils.

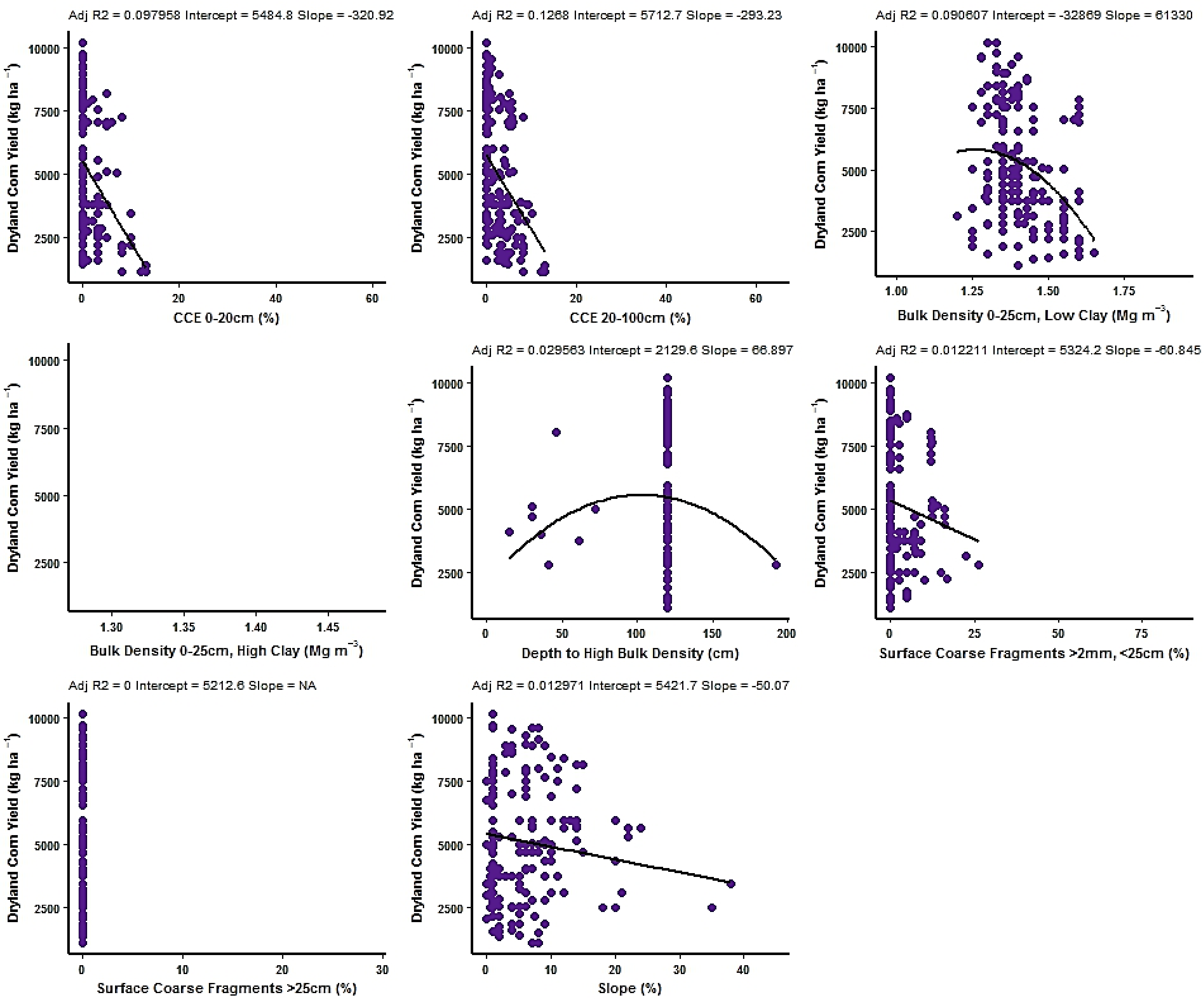


Figure 2-6. National soil information system (NASIS) dryland corn yield (kg ha^{-1}) vs NASIS soil property data of Kansas soils. Soil properties displayed are those included in the KCCPI (continued from Figure 2-4).

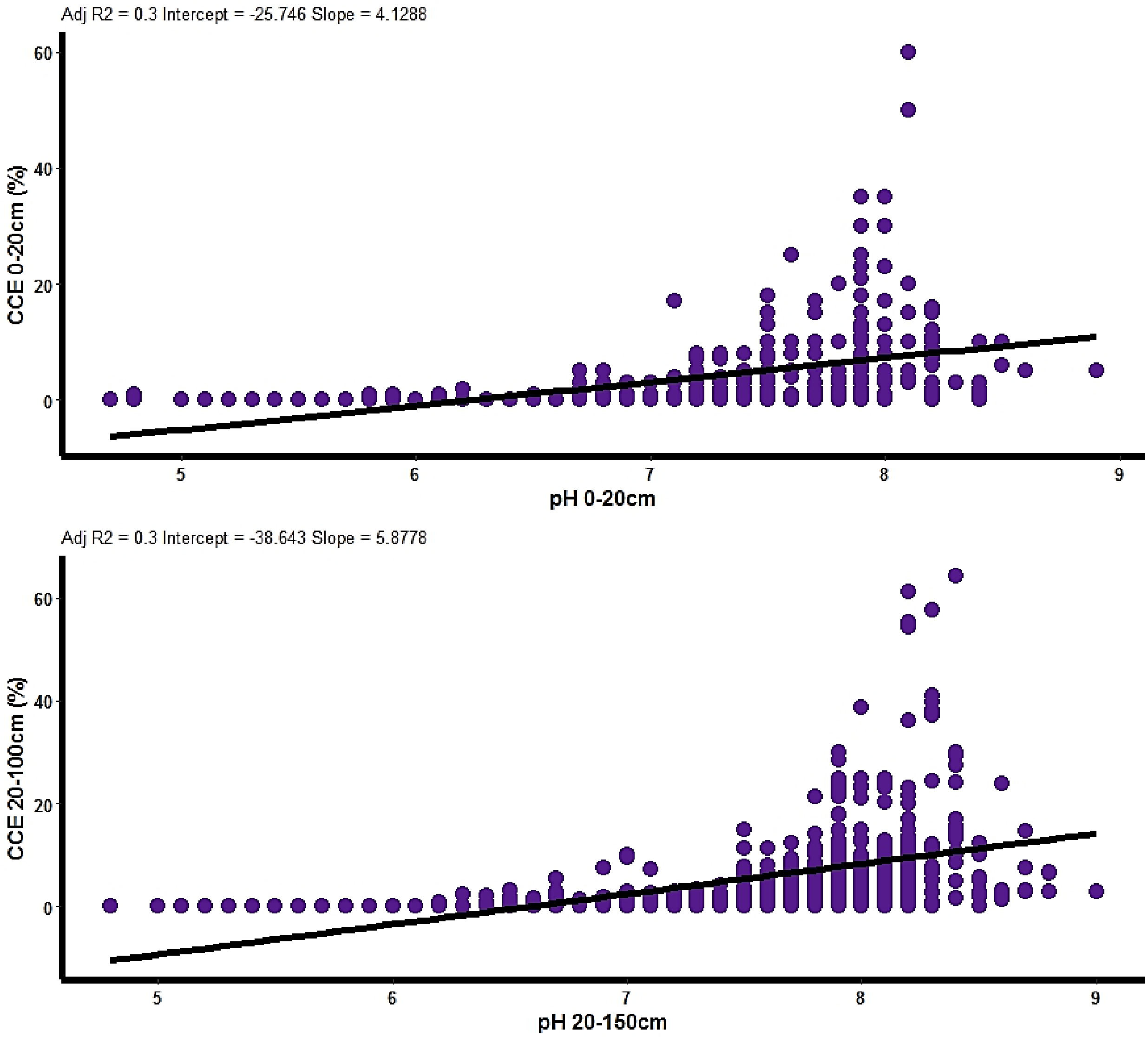


Figure 2-7. Weighted average calcium carbonate equivalent (CCE) (%) and pH from the national soil information system (NASIS) from two different depths for Kansas soils.

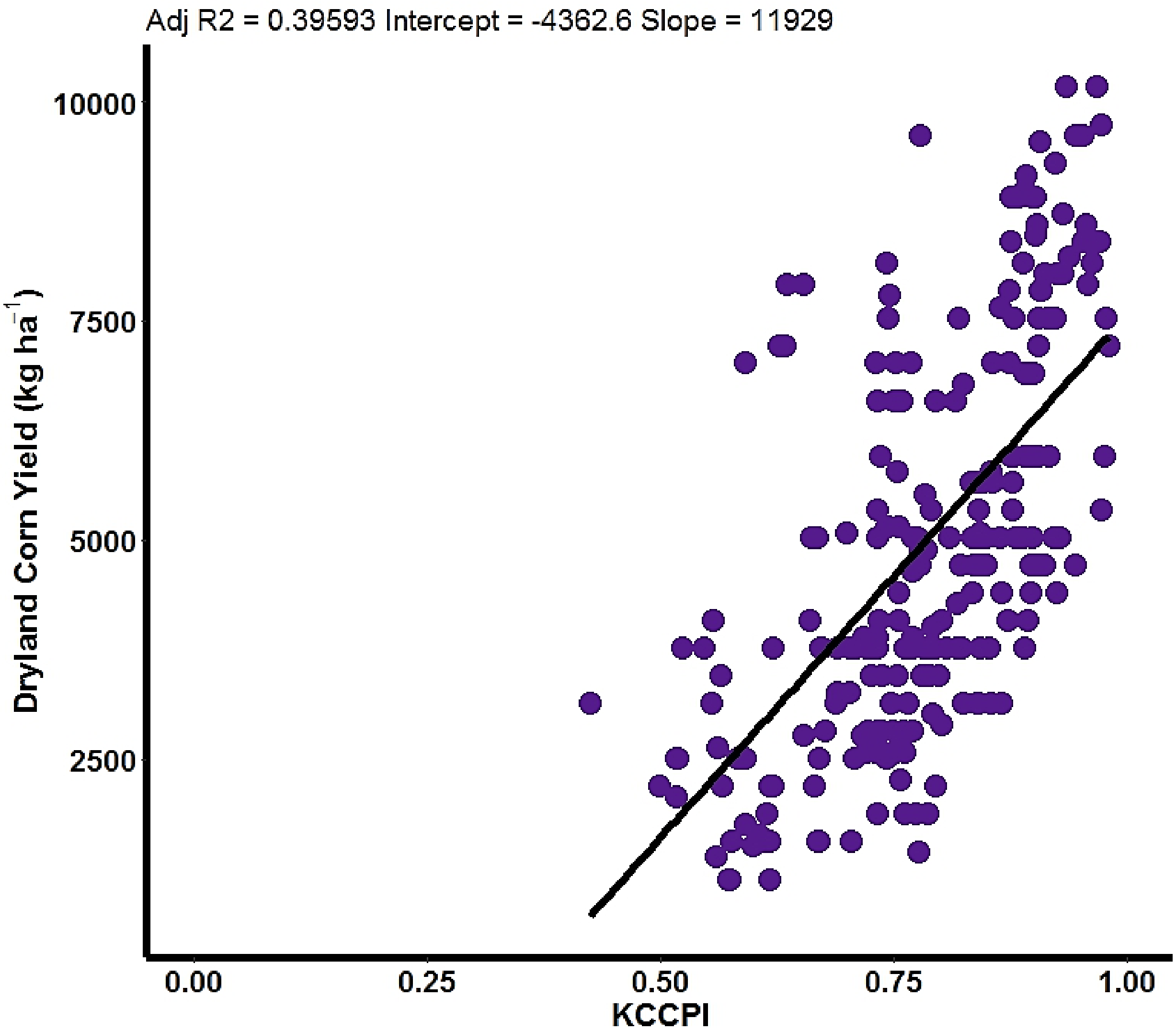
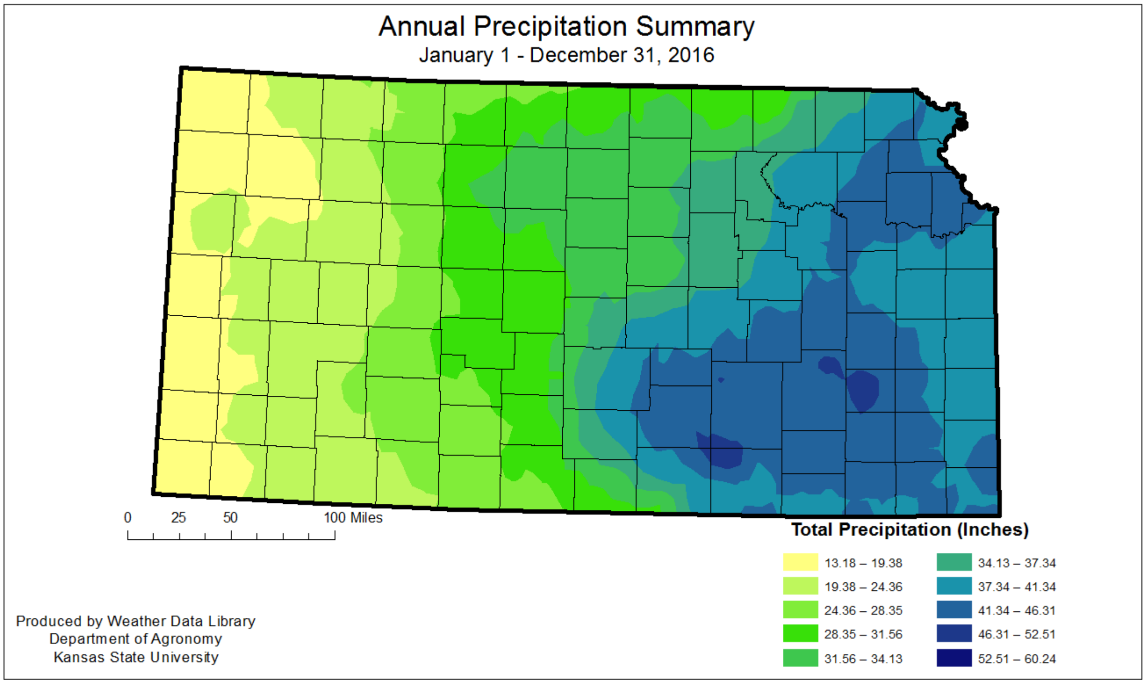


Figure 2-8. National soil information system (NASIS) dryland corn yield (kg ha^{-1}) vs non-climate KCCPI.



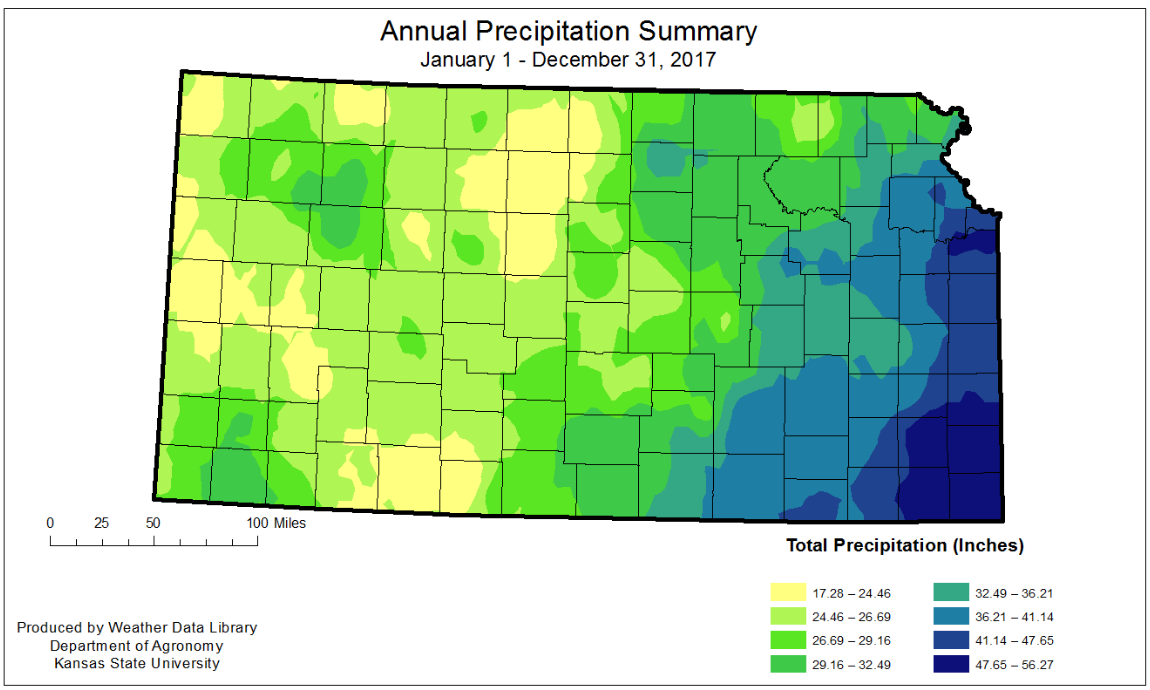


Figure 2-9. Annual precipitation in Kansas in 2016 and 2017.

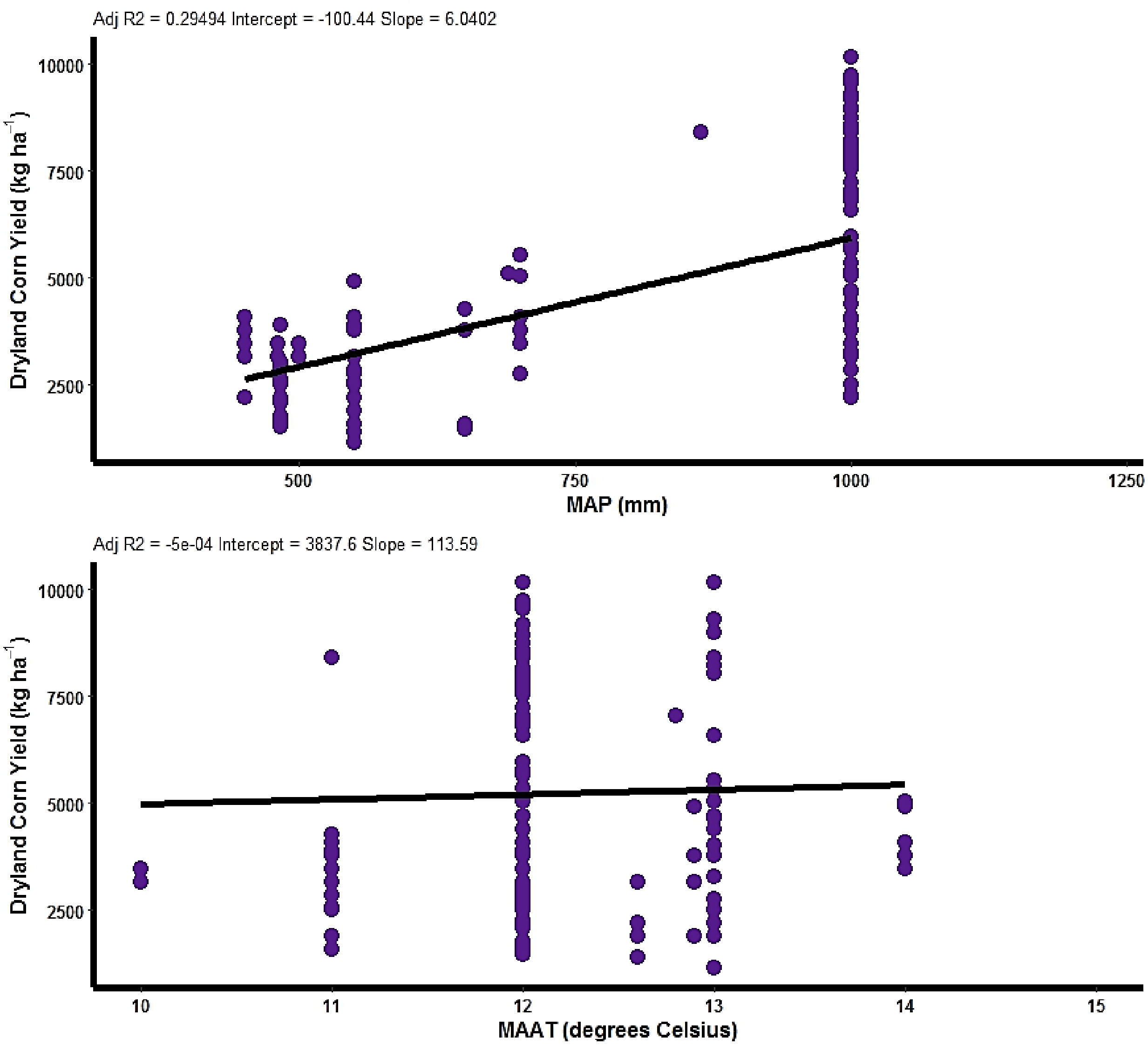


Figure 2-10. National soil information system (NASIS) dryland corn yield (kg ha^{-1}) vs NASIS soil property data of Kansas soils. Mean annual precipitation (MAP) and mean annual air temperature (MAAT) are included in the KCCPI climate subrule.

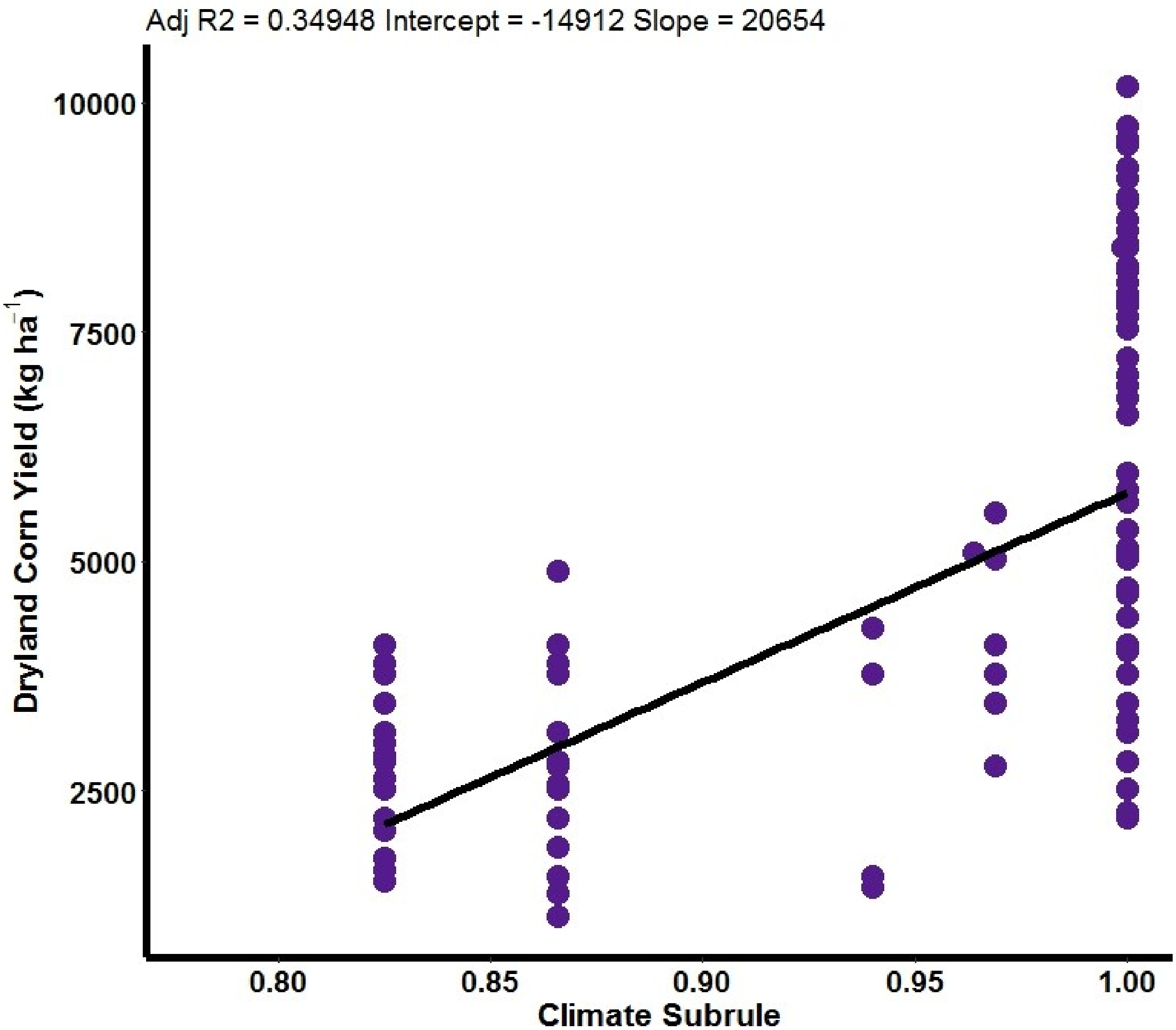


Figure 2-11. National soil information system (NASIS) dryland corn yield (kg ha^{-1}) vs the fuzzy outputs of the KCCPI climate subrule for Kansas soils.

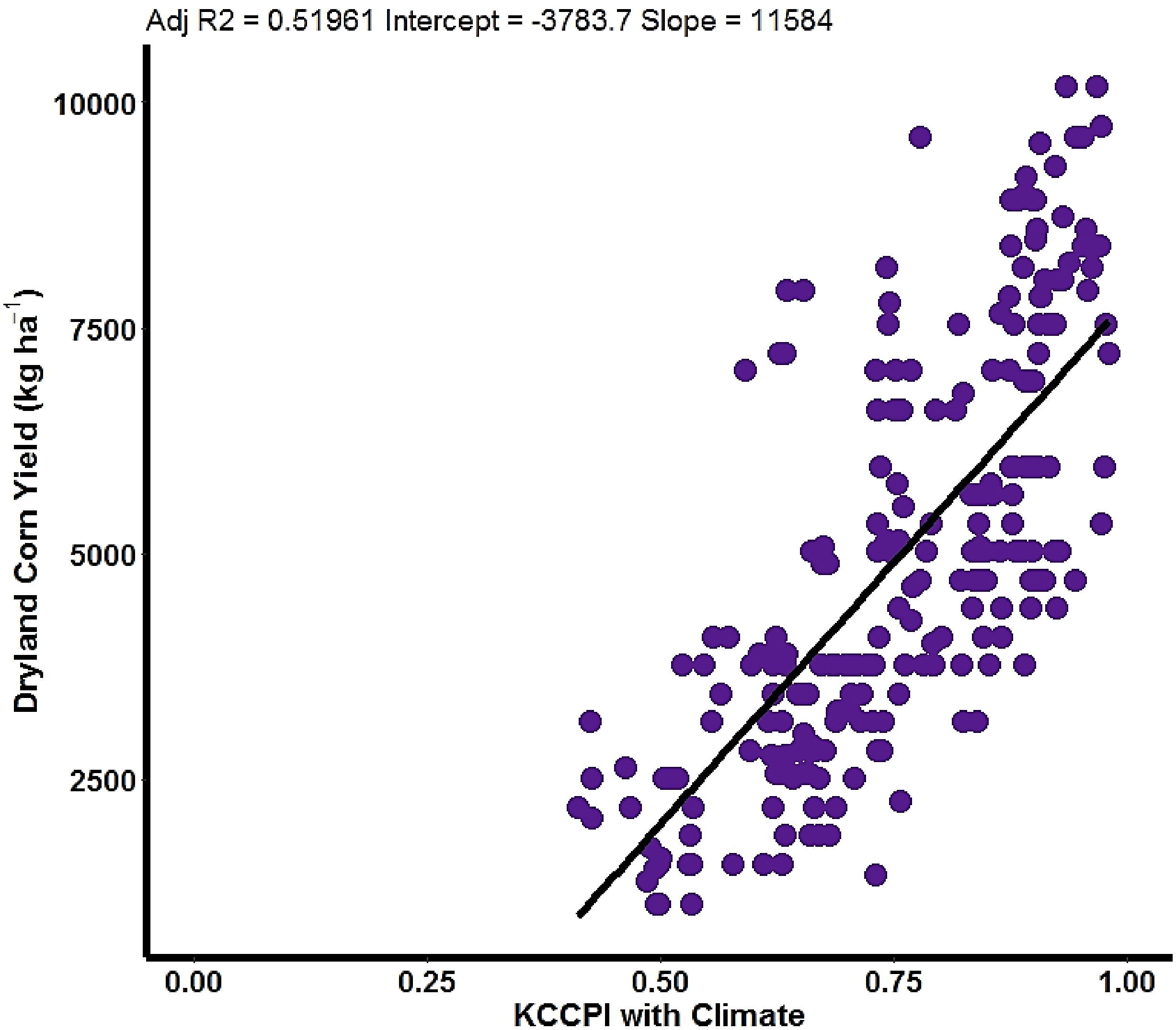


Figure 2-12. National soil information system (NASIS) dryland corn yield (kg ha^{-1}) vs climate-included KCCPI.

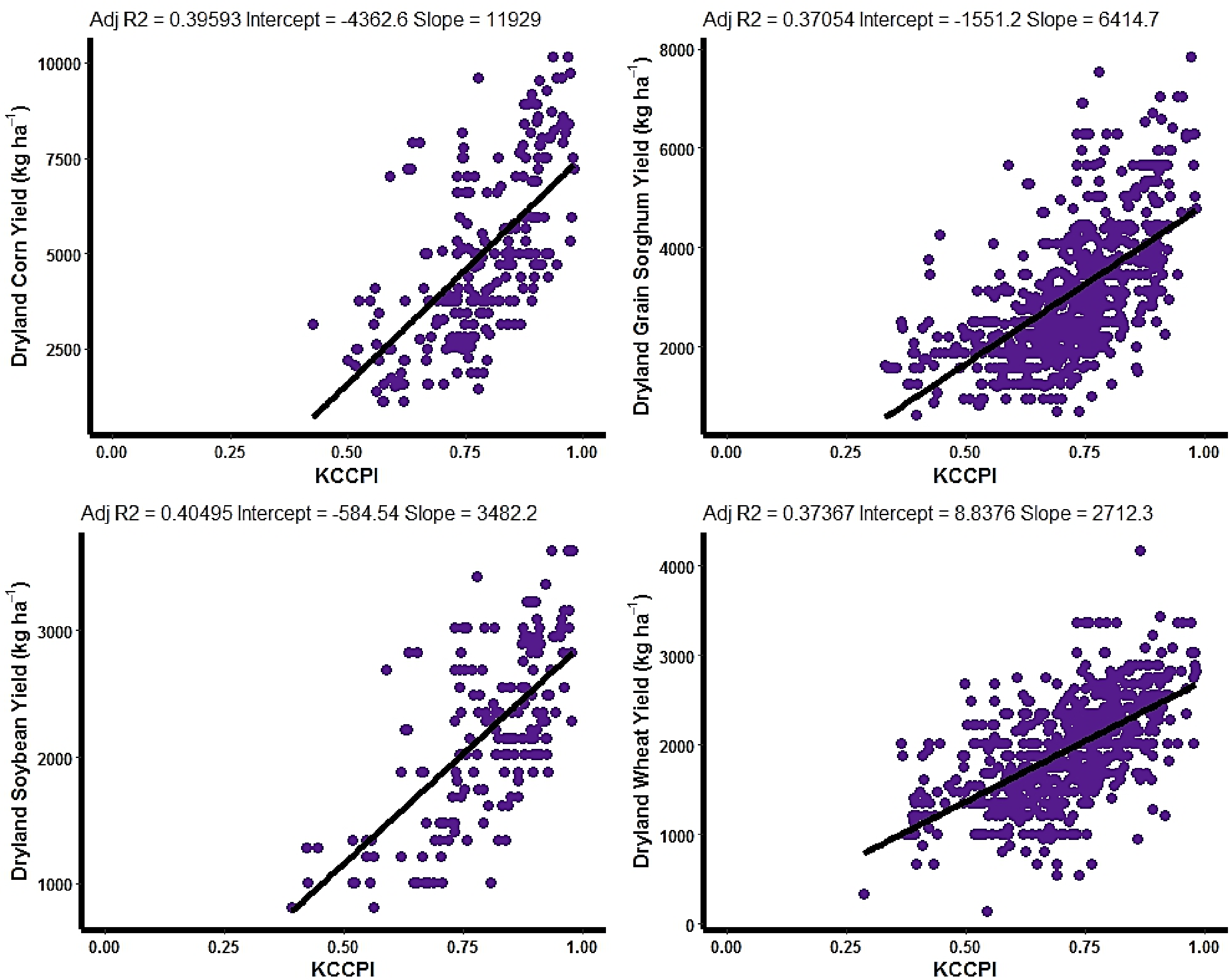


Figure 2-13. National soil information system (NASIS) dryland yields (kg ha^{-1}) for corn, grain sorghum, soybean, and wheat vs non-climate KCCPI.

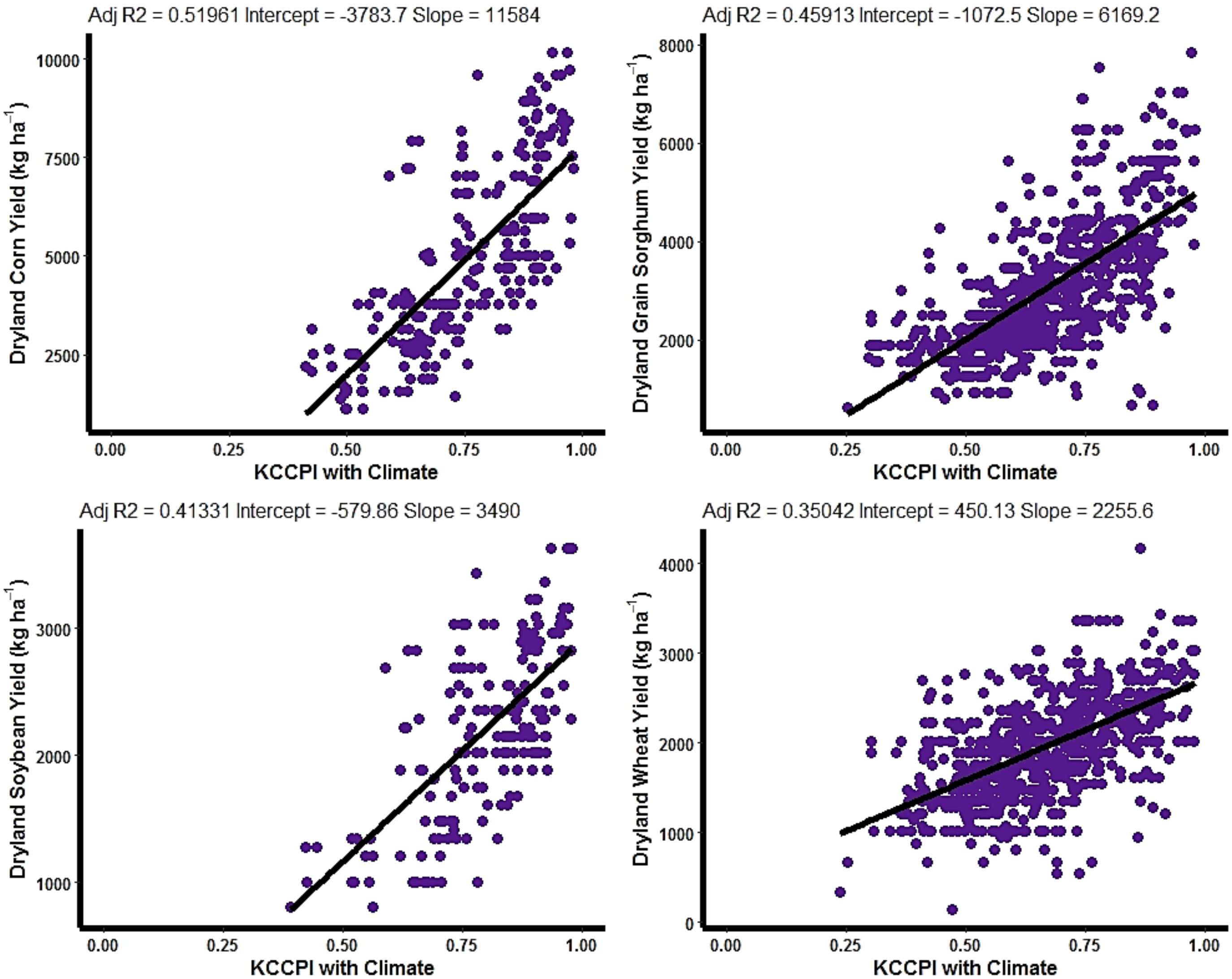


Figure 2-14. National soil information system (NASIS) dryland yields (kg ha^{-1}) for corn, grain sorghum, soybean, and wheat vs climate-included KCCPI.

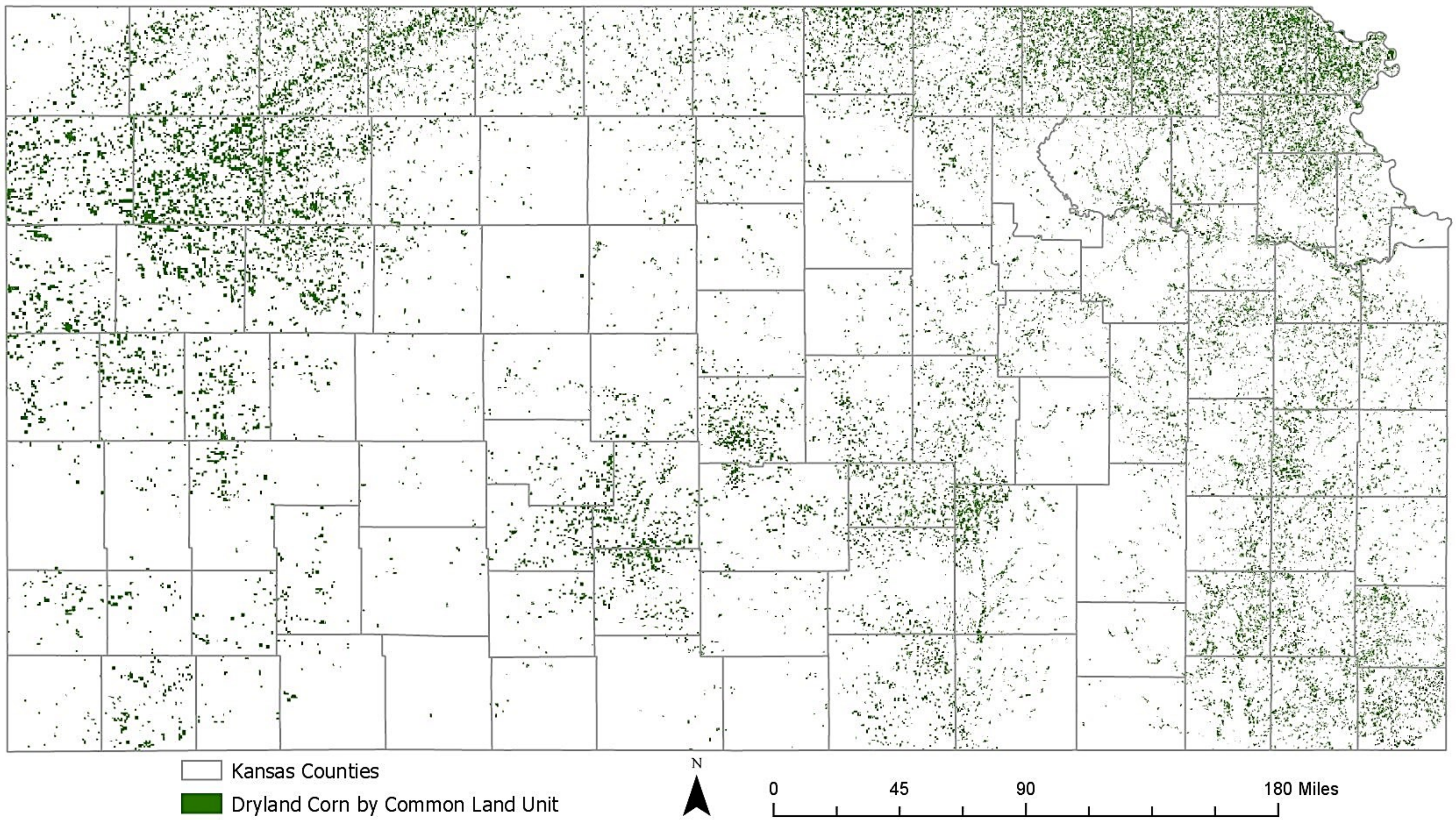


Figure 2-15. Dryland corn in Kansas by Common Land Unit (CLU).

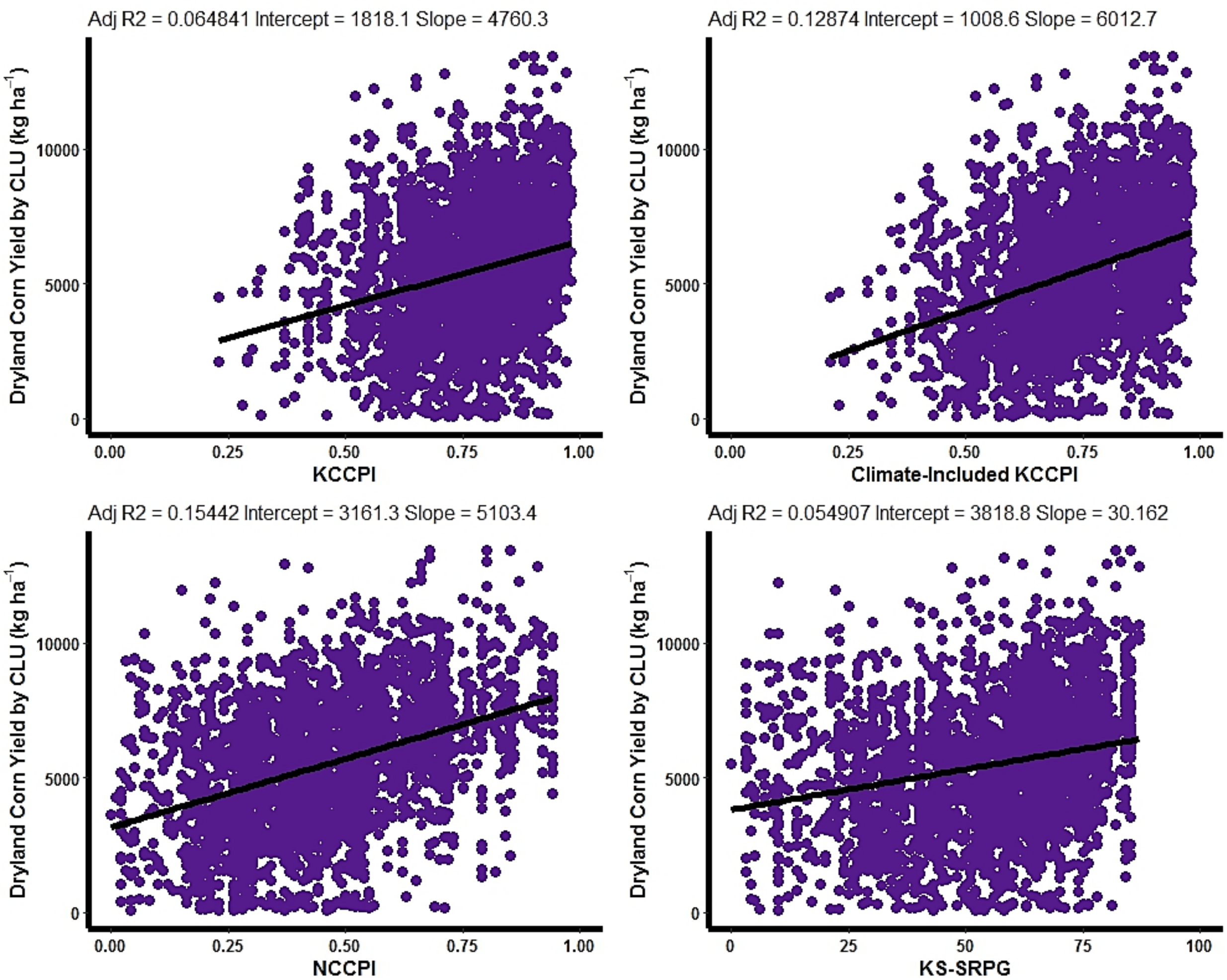


Figure 2-16. Dryland corn yield (kg ha^{-1}) by Common Land Unit vs Kansas indices and NCCPI corn and soybean submodel (II).

Table 2-3. Productivity index values and dryland corn yield by Common Land Unit (CLU) for 20 randomly selected Kansas soils.

Component	FIPS	MUSYM	KCCPI†	KCCPI with climate†	SRPG‡	KIPI‡	NCCPI†	Yield (kg ha^{-1})
Armster	KS103	7907	0.84	0.84	68	-	0.54	5030
Bridgeport	KS165	2310	0.74	0.68	60	98	0.76	4547
Brownell	KS183	2546	0.32	0.30	6	56	0.24	128
Campus	KS071	2562	0.42	0.38	14	60	0.35	3303
Case	KS033	5417	0.53	0.5	39	84	0.48	5338
Clime	KS073	4570	0.57	0.57	27	-	0.37	4755
Crisfield	KS077	6234	0.63	0.62	30	98	0.29	3436
Eram	KS003	8749	0.67	0.67	32	-	0.22	6479
Holdrege	KS089	2664	0.79	0.73	66	88	0.55	3456
Kenoma	KS133	8775	0.89	0.89	75	-	0.58	7369
Kuma	KS181	1655	0.76	0.63	59	94	0.48	2079
Labette	KS015	4740	0.78	0.78	66	72	0.47	2710
Mason	KS011	8501	0.91	0.91	85	-	0.72	9126
Morrill	KS149	7438	0.86	0.86	14	-	0.65	5520
Muscotah	KS161	7209	0.92	0.92	77	90	0.54	4107
Osage	KS205	8201	0.92	0.92	62	-	0.41	8068
Pratt	KS173	5928	0.69	0.68	40	96	0.29	3665
Richfield	KS069	1765	0.68	0.59	53	98	0.44	3485
Woodson	KS111	8961	0.89	0.89	78	-	0.49	6515
Zellmont	KS155	6490	0.65	0.64	45	47	0.33	5561

†KCCPI and NCCPI are on a 0-1 scale.
‡SRPG and KIPI are on a 0-100 scale.

Table 2-4. KCCPI, KCCPI with climate, and KCCPI subrule fuzzy outputs from the national soil information system (NASIS) for 20 randomly selected Kansas soils.

Component	MUSYM	KCCPI	KCCPI with climate	KCCPI subrules									
				AWC	pH	Depth	CEC	OM	CCE	Bulk density	Coarse fragments	Slope	Climate
Armster	7907	0.84	0.84	0.137	0.198	0.150	0.096	0.051	0.100	0.029	0.050	0.025	1.000
Bridgeport†	2310	0.74	0.63	0.196	0.037	0.150	0.063	0.076	0.081	0.035	0.050	0.048	0.860
Brownell	2546	0.32	0.30	0.081	0.023	0.020	0.052	0.042	0.000	0.030	0.038	0.035	0.920
Campus†	2562	0.42	0.35	0.129	0.032	0.024	0.062	0.046	0.000	0.039	0.050	0.028	0.856
Case†	5417	0.53	0.48	0.174	0.042	0.150	0.060	0.023	0.003	0.002	0.050	0.022	0.903
Clime†	4570	0.57	0.57	0.108	0.050	0.024	0.097	0.089	0.082	0.040	0.048	0.038	0.997
Crisfield	6234	0.63	0.62	0.084	0.151	0.150	0.013	0.005	0.100	0.034	0.050	0.048	0.969
Eram	8749	0.67	0.67	0.125	0.151	0.043	0.080	0.070	0.100	0.026	0.049	0.025	1.000
Holdrege†	2664	0.79	0.76	0.196	0.116	0.150	0.096	0.053	0.099	0.039	0.050	0.028	0.920
Kenoma	8775	0.89	0.89	0.155	0.179	0.150	0.076	0.094	0.100	0.037	0.050	0.045	1.000
Kuma	1655	0.76	0.63	0.174	0.048	0.150	0.070	0.075	0.097	0.048	0.050	0.048	0.825
Labette	4740	0.78	0.78	0.132	0.186	0.050	0.094	0.081	0.100	0.042	0.050	0.045	0.999
Mason	8501	0.91	0.91	0.191	0.190	0.150	0.051	0.096	0.100	0.036	0.050	0.048	1.000
Morrill	7438	0.86	0.86	0.169	0.186	0.150	0.081	0.086	0.100	0.036	0.036	0.017	1.000
Muscotah	7209	0.92	0.92	0.170	0.162	0.150	0.092	0.093	0.100	0.047	0.050	0.050	1.000
Osage	8201	0.92	0.92	0.156	0.190	0.150	0.100	0.091	0.100	0.030	0.050	0.048	1.000
Pratt	5928	0.69	0.68	0.108	0.191	0.150	0.012	0.008	0.100	0.028	0.050	0.042	0.987
Richfield†	1765	0.68	0.59	0.181	0.040	0.150	0.068	0.033	0.088	0.030	0.050	0.043	0.866
Woodson	8961	0.89	0.89	0.144	0.194	0.150	0.083	0.086	0.100	0.036	0.050	0.048	1.000
Zellmont†	6490	0.65	0.64	0.117	0.175	0.078	0.040	0.016	0.100	0.028	0.050	0.048	0.987
Maximum value		**1.000**	**1.000**	**0.200**	**0.200**	**0.150**	**0.100**	**0.100**	**0.100**	**0.050**	**0.050**	**0.050**	**1.000**

†Averaged over similar map units

Table 2-5. KCCPI soil property data obtained from the national soil information system (NASIS) for 20 randomly selected Kansas soils (continued in Table 2-6).

Component	Soil properties included in the KCCPI								
	AWC	pH 0-20cm	pH 20-150cm	Depth to bedrock	Depth retarding	CEC 0-20cm	CEC 20-100cm	OM 0-20cm	OM 20-100cm
	cm			——cm——		——meq $100g^{-1}$——		——%——	
Armster	0.69	6	6.5	200	200	23.41	28.6	1.7	0.7
Bridgeport	1.07	7.9	8.1	200	200	17.24	17.2	2.8	0.89
Brownell	0.41	7.9	8.2	76	76	14.25	12.2	1.48	0.83
Campus	0.41	7.8	8.1	33	33	10.67	7.7	0.86	0.5
Case	0.87	7.9	7.9	200	200	16	14	1.25	0.3
Clime	0.54	7.5	7.9	78	78	23.7	23.7	3	1.31
Crisfield	0.42	5.2	6.1	200	200	5.1	3.9	0.5	0.28
Eram	0.35	5.6	5.6	36	36	11.57	11.3	1.92	1.2
Holdrege	1.06	6.8	7.9	200	200	23.52	19.8	1.83	0.63
Kenoma	0.78	6.4	6.9	175	175	18.7	37.6	3.25	1.61
Kuma	0.87	7.2	8.1	200	200	17.5	16.2	2.15	1.25
Labette	0.66	6.1	6.8	91	91	28.87	38.2	2.9	0.86
Mason	0.98	6.2	6.2	200	200	12.05	15.3	3	1.8
Morrill	0.84	6	6.2	200	200	18.9	22.9	3	1.18
Muscotah	0.85	6.6	7.1	200	200	38.13	31.1	2.94	1.59
Osage	0.78	6.7	6.3	200	200	29.34	31.8	3.4	1.47
Pratt	0.54	6.5	6.2	200	200	4	3.7	0.7	0.2
Richfield	0.89	7.3	8.3	200	200	16.88	15.9	1.33	0.48
Woodson	0.72	5.9	6.5	200	200	19.3	33.7	2.5	1.37
Zellmont	0.63	5.9	6.6	81	81	10.5	20.1	1	0.46

Table 2-6. (Table 2-5 continued) KCCPI soil property data obtained from the national soil information system (NASIS) for 20 randomly selected Kansas soils.

Component	Soil properties included in the KCCPI							
	CCE 0-20cm	CCE 20-100cm	Bulk density, low clay†	Bulk density, high clay†	Depth to high bulk density	Coarse fragments 2mm-25cm	Coarse fragments >25cm	Slope
	%		Mg m^{-3}		cm	%		
Armster	0	0	1.46	-	120	0	0	10
Bridgeport	5	8	1.38	-	120	0	0	1
Brownell	35	55.4	1.45	-	120	27	0	6
Campus	10	10	1.46	-	-	8	0	13
Case	15	15	1.53	-	20	5	0	11
Clime	4	7.5	1.36	-	120	11.9	0	5
Crisfield	0	0	1.43	-	-	3.5	0	1
Eram	0	0	1.55	-	-	16.5	0	10
Holdrege	0	3.5	1.35	-	120	0	0	9
Kenoma	0	0.3	1.39	-	120	2	0	2
Kuma	0	4.7	1.23	-	120	0	0	1
Labette	0	0.2	1.34	-	120	0	0	2
Mason	0	0	1.4	-	120	0	0	1
Morrill	0	0	1.4	-	120	18.5	2	13
Muscotah	0	0	1.25	-	120	0	0	0
Osage	0	0	1.45	-	120	0	0	1
Pratt	0	0	1.5	-	-	0	0	3
Richfield	3	6.9	1.45	-	120	0	0	2
Woodson	0	0	1.4	-	120	0	0	1
Zellmont	0	0	1.48	-	120	7	0	1

†Bulk density from 0-25cm.

Table 2-7. National soil information system (NASIS) soil property data for 20 randomly selected soils in Kansas. Mean annual precipitation (MAP) and mean annual air temperature (MAAT) are included in the climate-included KCCPI.

Component	Soil properties included in the KCCPI climate subrule	
	MAP	**MAAT**
	mm	(^{o}C)
Armster	1000	12
Bridgeport	620	12
Brownell	620	12
Campus	620	12
Case	650	14
Clime	870	13
Crisfield	700	14
Eram	1000	14
Holdrege	620	12
Kenoma	1016	14
Kuma	406	10
Labette	870	13
Mason	1000	13.9
Morrill	1000	13.1
Muscotah	1000	12
Osage	1000	14
Pratt	740	13
Richfield	550	13
Woodson	1041	14
Zellmont	740	13

Appendix A- KCCPI Properties

This appendix contains the NASIS properties for the Kansas Commodity Crop Productivity Index (KCCPI) Corn Submodel and climate-included KCCPI Corn Submodel.

Available Water Capacity:

Property: "NSSC Data: AWC*Root Sufficiency (NCCPI)"
Used in evaluation: "NSSC Data: KCCPI – AWC* Root Sufficiency 0-200cm"
Used in subrule: "NSSC Data: KCCPI – AWC Subrule"
Originally developed for: NCCPI

```
BASE TABLE component.

EXEC SQL SELECT
     awc_r, hzdept_r, hzdepb_r
  FROM component, chorizon
  WHERE JOIN component TO chorizon;
sort by hzdept_r asc
AGGREGATE COLUMN awc_r NONE, hzdept_r NONE, hzdepb_r NONE.

# use a lower limit to emulate Fred's PI
#ASSIGN awc_r  ISNULL(awc_r) ? 0 : awc_r < 0.08 ? 0 : awc_r - 0.08.

# use an upper limit of 0.14 (0.22-0.08) for awc
#ASSIGN awc_r  awc_r > 0.14 ? 0.14 : awc_r.

# calculate the sufficiency using an ideal root equation for each cm increment
# each value, if in range, is added to the previous value (200 summations)
DEFINE suff 0.
ASSIGN suff hzdept_r < 1 AND hzdepb_r >= 1 ? suff + (awc_r/0.20 * (-0.0511789 * logn(1) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 2 AND hzdepb_r >= 2 ? suff + (awc_r/0.20 * (-0.0511789 * logn(2) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 3 AND hzdepb_r >= 3 ? suff + (awc_r/0.20 * (-0.0511789 * logn(3) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 4 AND hzdepb_r >= 4 ? suff + (awc_r/0.20 * (-0.0511789 * logn(4) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 5 AND hzdepb_r >= 5 ? suff + (awc_r/0.20 * (-0.0511789 * logn(5) + 0.270865)/10) : suff.
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ASSIGN suff hzdept_r < 6 AND hzdepb_r >= 6 ? suff + (awc_r/0.20 * (-0.0511789 * logn(6) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 7 AND hzdepb_r >= 7 ? suff + (awc_r/0.20 * (-0.0511789 * logn(7) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 8 AND hzdepb_r >= 8 ? suff + (awc_r/0.20 * (-0.0511789 * logn(8) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 9 AND hzdepb_r >= 9 ? suff + (awc_r/0.20 * (-0.0511789 * logn(9) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 10 AND hzdepb_r >= 10 ? suff + (awc_r/0.20 * (-0.0511789 * logn(10) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 11 AND hzdepb_r >= 11 ? suff + (awc_r/0.20 * (-0.0511789 * logn(11) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 12 AND hzdepb_r >= 12 ? suff + (awc_r/0.20 * (-0.0511789 * logn(12) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 13 AND hzdepb_r >= 13 ? suff + (awc_r/0.20 * (-0.0511789 * logn(13) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 14 AND hzdepb_r >= 14 ? suff + (awc_r/0.20 * (-0.0511789 * logn(14) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 15 AND hzdepb_r >= 15 ? suff + (awc_r/0.20 * (-0.0511789 * logn(15) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 16 AND hzdepb_r >= 16 ? suff + (awc_r/0.20 * (-0.0511789 * logn(16) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 17 AND hzdepb_r >= 17 ? suff + (awc_r/0.20 * (-0.0511789 * logn(17) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 18 AND hzdepb_r >= 18 ? suff + (awc_r/0.20 * (-0.0511789 * logn(18) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 19 AND hzdepb_r >= 19 ? suff + (awc_r/0.20 * (-0.0511789 * logn(19) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 20 AND hzdepb_r >= 20 ? suff + (awc_r/0.20 * (-0.0511789 * logn(20) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 21 AND hzdepb_r >= 21 ? suff + (awc_r/0.20 * (-0.0511789 * logn(21) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 22 AND hzdepb_r >= 22 ? suff + (awc_r/0.20 * (-0.0511789 * logn(22) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 23 AND hzdepb_r >= 23 ? suff + (awc_r/0.20 * (-0.0511789 * logn(23) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 24 AND hzdepb_r >= 24 ? suff + (awc_r/0.20 * (-0.0511789 * logn(24) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 25 AND hzdepb_r >= 25 ? suff + (awc_r/0.20 * (-0.0511789 * logn(25) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 26 AND hzdepb_r >= 26 ? suff + (awc_r/0.20 * (-0.0511789 * logn(26) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 27 AND hzdepb_r >= 27 ? suff + (awc_r/0.20 * (-0.0511789 * logn(27) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 28 AND hzdepb_r >= 28 ? suff + (awc_r/0.20 * (-0.0511789 * logn(28) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 29 AND hzdepb_r >= 29 ? suff + (awc_r/0.20 * (-0.0511789 * logn(29) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 30 AND hzdepb_r >= 30 ? suff + (awc_r/0.20 * (-0.0511789 * logn(30) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 31 AND hzdepb_r >= 31 ? suff + (awc_r/0.20 * (-0.0511789 * logn(31) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 32 AND hzdepb_r >= 32 ? suff + (awc_r/0.20 * (-0.0511789 * logn(32) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 33 AND hzdepb_r >= 33 ? suff + (awc_r/0.20 * (-0.0511789 * logn(33) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 34 AND hzdepb_r >= 34 ? suff + (awc_r/0.20 * (-0.0511789 * logn(34) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 35 AND hzdepb_r >= 35 ? suff + (awc_r/0.20 * (-0.0511789 * logn(35) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 36 AND hzdepb_r >= 36 ? suff + (awc_r/0.20 * (-0.0511789 * logn(36) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 37 AND hzdepb_r >= 37 ? suff + (awc_r/0.20 * (-0.0511789 * logn(37) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 38 AND hzdepb_r >= 38 ? suff + (awc_r/0.20 * (-0.0511789 * logn(38) + 0.270865)/10) : suff.
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ASSIGN suff hzdept_r < 39 AND hzdepb_r >= 39 ? suff + (awc_r/0.20 * (-0.0511789 * logn(39) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 40 AND hzdepb_r >= 40 ? suff + (awc_r/0.20 * (-0.0511789 * logn(40) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 41 AND hzdepb_r >= 41 ? suff + (awc_r/0.20 * (-0.0511789 * logn(41) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 42 AND hzdepb_r >= 42 ? suff + (awc_r/0.20 * (-0.0511789 * logn(42) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 43 AND hzdepb_r >= 43 ? suff + (awc_r/0.20 * (-0.0511789 * logn(43) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 44 AND hzdepb_r >= 44 ? suff + (awc_r/0.20 * (-0.0511789 * logn(44) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 45 AND hzdepb_r >= 45 ? suff + (awc_r/0.20 * (-0.0511789 * logn(45) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 46 AND hzdepb_r >= 46 ? suff + (awc_r/0.20 * (-0.0511789 * logn(46) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 47 AND hzdepb_r >= 47 ? suff + (awc_r/0.20 * (-0.0511789 * logn(47) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 48 AND hzdepb_r >= 48 ? suff + (awc_r/0.20 * (-0.0511789 * logn(48) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 49 AND hzdepb_r >= 49 ? suff + (awc_r/0.20 * (-0.0511789 * logn(49) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 50 AND hzdepb_r >= 50 ? suff + (awc_r/0.20 * (-0.0511789 * logn(50) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 51 AND hzdepb_r >= 51 ? suff + (awc_r/0.20 * (-0.0511789 * logn(51) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 52 AND hzdepb_r >= 52 ? suff + (awc_r/0.20 * (-0.0511789 * logn(52) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 53 AND hzdepb_r >= 53 ? suff + (awc_r/0.20 * (-0.0511789 * logn(53) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 54 AND hzdepb_r >= 54 ? suff + (awc_r/0.20 * (-0.0511789 * logn(54) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 55 AND hzdepb_r >= 55 ? suff + (awc_r/0.20 * (-0.0511789 * logn(55) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 56 AND hzdepb_r >= 56 ? suff + (awc_r/0.20 * (-0.0511789 * logn(56) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 57 AND hzdepb_r >= 57 ? suff + (awc_r/0.20 * (-0.0511789 * logn(57) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 58 AND hzdepb_r >= 58 ? suff + (awc_r/0.20 * (-0.0511789 * logn(58) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 59 AND hzdepb_r >= 59 ? suff + (awc_r/0.20 * (-0.0511789 * logn(59) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 60 AND hzdepb_r >= 60 ? suff + (awc_r/0.20 * (-0.0511789 * logn(60) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 61 AND hzdepb_r >= 61 ? suff + (awc_r/0.20 * (-0.0511789 * logn(61) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 62 AND hzdepb_r >= 62 ? suff + (awc_r/0.20 * (-0.0511789 * logn(62) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 63 AND hzdepb_r >= 63 ? suff + (awc_r/0.20 * (-0.0511789 * logn(63) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 64 AND hzdepb_r >= 64 ? suff + (awc_r/0.20 * (-0.0511789 * logn(64) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 65 AND hzdepb_r >= 65 ? suff + (awc_r/0.20 * (-0.0511789 * logn(65) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 66 AND hzdepb_r >= 66 ? suff + (awc_r/0.20 * (-0.0511789 * logn(66) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 67 AND hzdepb_r >= 67 ? suff + (awc_r/0.20 * (-0.0511789 * logn(67) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 68 AND hzdepb_r >= 68 ? suff + (awc_r/0.20 * (-0.0511789 * logn(68) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 69 AND hzdepb_r >= 69 ? suff + (awc_r/0.20 * (-0.0511789 * logn(69) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 70 AND hzdepb_r >= 70 ? suff + (awc_r/0.20 * (-0.0511789 * logn(70) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 71 AND hzdepb_r >= 71 ? suff + (awc_r/0.20 * (-0.0511789 * logn(71) + 0.270865)/10) : suff.
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ASSIGN suff hzdept_r < 72 AND hzdepb_r >= 72 ? suff + (awc_r/0.20 * (-0.0511789 * logn(72) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 73 AND hzdepb_r >= 73 ? suff + (awc_r/0.20 * (-0.0511789 * logn(73) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 74 AND hzdepb_r >= 74 ? suff + (awc_r/0.20 * (-0.0511789 * logn(74) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 75 AND hzdepb_r >= 75 ? suff + (awc_r/0.20 * (-0.0511789 * logn(75) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 76 AND hzdepb_r >= 76 ? suff + (awc_r/0.20 * (-0.0511789 * logn(76) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 77 AND hzdepb_r >= 77 ? suff + (awc_r/0.20 * (-0.0511789 * logn(77) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 78 AND hzdepb_r >= 78 ? suff + (awc_r/0.20 * (-0.0511789 * logn(78) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 79 AND hzdepb_r >= 79 ? suff + (awc_r/0.20 * (-0.0511789 * logn(79) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 80 AND hzdepb_r >= 80 ? suff + (awc_r/0.20 * (-0.0511789 * logn(80) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 81 AND hzdepb_r >= 81 ? suff + (awc_r/0.20 * (-0.0511789 * logn(81) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 82 AND hzdepb_r >= 82 ? suff + (awc_r/0.20 * (-0.0511789 * logn(82) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 83 AND hzdepb_r >= 83 ? suff + (awc_r/0.20 * (-0.0511789 * logn(83) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 84 AND hzdepb_r >= 84 ? suff + (awc_r/0.20 * (-0.0511789 * logn(84) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 85 AND hzdepb_r >= 85 ? suff + (awc_r/0.20 * (-0.0511789 * logn(85) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 86 AND hzdepb_r >= 86 ? suff + (awc_r/0.20 * (-0.0511789 * logn(86) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 87 AND hzdepb_r >= 87 ? suff + (awc_r/0.20 * (-0.0511789 * logn(87) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 88 AND hzdepb_r >= 88 ? suff + (awc_r/0.20 * (-0.0511789 * logn(88) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 89 AND hzdepb_r >= 89 ? suff + (awc_r/0.20 * (-0.0511789 * logn(89) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 90 AND hzdepb_r >= 90 ? suff + (awc_r/0.20 * (-0.0511789 * logn(90) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 91 AND hzdepb_r >= 91 ? suff + (awc_r/0.20 * (-0.0511789 * logn(91) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 92 AND hzdepb_r >= 92 ? suff + (awc_r/0.20 * (-0.0511789 * logn(92) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 93 AND hzdepb_r >= 93 ? suff + (awc_r/0.20 * (-0.0511789 * logn(93) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 94 AND hzdepb_r >= 94 ? suff + (awc_r/0.20 * (-0.0511789 * logn(94) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 95 AND hzdepb_r >= 95 ? suff + (awc_r/0.20 * (-0.0511789 * logn(95) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 96 AND hzdepb_r >= 96 ? suff + (awc_r/0.20 * (-0.0511789 * logn(96) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 97 AND hzdepb_r >= 97 ? suff + (awc_r/0.20 * (-0.0511789 * logn(97) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 98 AND hzdepb_r >= 98 ? suff + (awc_r/0.20 * (-0.0511789 * logn(98) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 99 AND hzdepb_r >= 99 ? suff + (awc_r/0.20 * (-0.0511789 * logn(99) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 100 AND hzdepb_r >= 100 ? suff + (awc_r/0.20 * (-0.0511789 * logn(100) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 101 AND hzdepb_r >= 101 ? suff + (awc_r/0.20 * (-0.0511789 * logn(101) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 102 AND hzdepb_r >= 102 ? suff + (awc_r/0.20 * (-0.0511789 * logn(102) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 103 AND hzdepb_r >= 103 ? suff + (awc_r/0.20 * (-0.0511789 * logn(103) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 104 AND hzdepb_r >= 104 ? suff + (awc_r/0.20 * (-0.0511789 * logn(104) + 0.270865)/10) : suff.
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ASSIGN suff hzdept_r < 105 AND hzdepb_r >= 105 ? suff + (awc_r/0.20 * (-0.0511789 * logn(105) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 106 AND hzdepb_r >= 106 ? suff + (awc_r/0.20 * (-0.0511789 * logn(106) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 107 AND hzdepb_r >= 107 ? suff + (awc_r/0.20 * (-0.0511789 * logn(107) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 108 AND hzdepb_r >= 108 ? suff + (awc_r/0.20 * (-0.0511789 * logn(108) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 109 AND hzdepb_r >= 109 ? suff + (awc_r/0.20 * (-0.0511789 * logn(109) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 110 AND hzdepb_r >= 110 ? suff + (awc_r/0.20 * (-0.0511789 * logn(110) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 111 AND hzdepb_r >= 111 ? suff + (awc_r/0.20 * (-0.0511789 * logn(111) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 112 AND hzdepb_r >= 112 ? suff + (awc_r/0.20 * (-0.0511789 * logn(112) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 113 AND hzdepb_r >= 113 ? suff + (awc_r/0.20 * (-0.0511789 * logn(113) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 114 AND hzdepb_r >= 114 ? suff + (awc_r/0.20 * (-0.0511789 * logn(114) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 115 AND hzdepb_r >= 115 ? suff + (awc_r/0.20 * (-0.0511789 * logn(115) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 116 AND hzdepb_r >= 116 ? suff + (awc_r/0.20 * (-0.0511789 * logn(116) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 117 AND hzdepb_r >= 117 ? suff + (awc_r/0.20 * (-0.0511789 * logn(117) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 118 AND hzdepb_r >= 118 ? suff + (awc_r/0.20 * (-0.0511789 * logn(118) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 119 AND hzdepb_r >= 119 ? suff + (awc_r/0.20 * (-0.0511789 * logn(119) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 120 AND hzdepb_r >= 120 ? suff + (awc_r/0.20 * (-0.0511789 * logn(120) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 121 AND hzdepb_r >= 121 ? suff + (awc_r/0.20 * (-0.0511789 * logn(121) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 122 AND hzdepb_r >= 122 ? suff + (awc_r/0.20 * (-0.0511789 * logn(122) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 123 AND hzdepb_r >= 123 ? suff + (awc_r/0.20 * (-0.0511789 * logn(123) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 124 AND hzdepb_r >= 124 ? suff + (awc_r/0.20 * (-0.0511789 * logn(124) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 125 AND hzdepb_r >= 125 ? suff + (awc_r/0.20 * (-0.0511789 * logn(125) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 126 AND hzdepb_r >= 126 ? suff + (awc_r/0.20 * (-0.0511789 * logn(126) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 127 AND hzdepb_r >= 127 ? suff + (awc_r/0.20 * (-0.0511789 * logn(127) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 128 AND hzdepb_r >= 128 ? suff + (awc_r/0.20 * (-0.0511789 * logn(128) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 129 AND hzdepb_r >= 129 ? suff + (awc_r/0.20 * (-0.0511789 * logn(129) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 130 AND hzdepb_r >= 130 ? suff + (awc_r/0.20 * (-0.0511789 * logn(130) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 131 AND hzdepb_r >= 131 ? suff + (awc_r/0.20 * (-0.0511789 * logn(131) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 132 AND hzdepb_r >= 132 ? suff + (awc_r/0.20 * (-0.0511789 * logn(132) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 133 AND hzdepb_r >= 133 ? suff + (awc_r/0.20 * (-0.0511789 * logn(133) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 134 AND hzdepb_r >= 134 ? suff + (awc_r/0.20 * (-0.0511789 * logn(134) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 135 AND hzdepb_r >= 135 ? suff + (awc_r/0.20 * (-0.0511789 * logn(135) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 136 AND hzdepb_r >= 136 ? suff + (awc_r/0.20 * (-0.0511789 * logn(136) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 137 AND hzdepb_r >= 137 ? suff + (awc_r/0.20 * (-0.0511789 * logn(137) + 0.270865)/10) : suff.
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ASSIGN suff hzdept_r < 138 AND hzdepb_r >= 138 ? suff + (awc_r/0.20 * (-0.0511789 * logn(138) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 139 AND hzdepb_r >= 139 ? suff + (awc_r/0.20 * (-0.0511789 * logn(139) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 140 AND hzdepb_r >= 140 ? suff + (awc_r/0.20 * (-0.0511789 * logn(140) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 141 AND hzdepb_r >= 141 ? suff + (awc_r/0.20 * (-0.0511789 * logn(141) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 142 AND hzdepb_r >= 142 ? suff + (awc_r/0.20 * (-0.0511789 * logn(142) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 143 AND hzdepb_r >= 143 ? suff + (awc_r/0.20 * (-0.0511789 * logn(143) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 144 AND hzdepb_r >= 144 ? suff + (awc_r/0.20 * (-0.0511789 * logn(144) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 145 AND hzdepb_r >= 145 ? suff + (awc_r/0.20 * (-0.0511789 * logn(145) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 146 AND hzdepb_r >= 146 ? suff + (awc_r/0.20 * (-0.0511789 * logn(146) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 147 AND hzdepb_r >= 147 ? suff + (awc_r/0.20 * (-0.0511789 * logn(147) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 148 AND hzdepb_r >= 148 ? suff + (awc_r/0.20 * (-0.0511789 * logn(148) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 149 AND hzdepb_r >= 149 ? suff + (awc_r/0.20 * (-0.0511789 * logn(149) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 150 AND hzdepb_r >= 150 ? suff + (awc_r/0.20 * (-0.0511789 * logn(150) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 151 AND hzdepb_r >= 151 ? suff + (awc_r/0.20 * (-0.0511789 * logn(151) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 152 AND hzdepb_r >= 152 ? suff + (awc_r/0.20 * (-0.0511789 * logn(152) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 153 AND hzdepb_r >= 153 ? suff + (awc_r/0.20 * (-0.0511789 * logn(153) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 154 AND hzdepb_r >= 154 ? suff + (awc_r/0.20 * (-0.0511789 * logn(154) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 155 AND hzdepb_r >= 155 ? suff + (awc_r/0.20 * (-0.0511789 * logn(155) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 156 AND hzdepb_r >= 156 ? suff + (awc_r/0.20 * (-0.0511789 * logn(156) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 157 AND hzdepb_r >= 157 ? suff + (awc_r/0.20 * (-0.0511789 * logn(157) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 158 AND hzdepb_r >= 158 ? suff + (awc_r/0.20 * (-0.0511789 * logn(158) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 159 AND hzdepb_r >= 159 ? suff + (awc_r/0.20 * (-0.0511789 * logn(159) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 160 AND hzdepb_r >= 160 ? suff + (awc_r/0.20 * (-0.0511789 * logn(160) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 161 AND hzdepb_r >= 161 ? suff + (awc_r/0.20 * (-0.0511789 * logn(161) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 162 AND hzdepb_r >= 162 ? suff + (awc_r/0.20 * (-0.0511789 * logn(162) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 163 AND hzdepb_r >= 163 ? suff + (awc_r/0.20 * (-0.0511789 * logn(163) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 164 AND hzdepb_r >= 164 ? suff + (awc_r/0.20 * (-0.0511789 * logn(164) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 165 AND hzdepb_r >= 165 ? suff + (awc_r/0.20 * (-0.0511789 * logn(165) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 166 AND hzdepb_r >= 166 ? suff + (awc_r/0.20 * (-0.0511789 * logn(166) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 167 AND hzdepb_r >= 167 ? suff + (awc_r/0.20 * (-0.0511789 * logn(167) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 168 AND hzdepb_r >= 168 ? suff + (awc_r/0.20 * (-0.0511789 * logn(168) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 169 AND hzdepb_r >= 169 ? suff + (awc_r/0.20 * (-0.0511789 * logn(169) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 170 AND hzdepb_r >= 170 ? suff + (awc_r/0.20 * (-0.0511789 * logn(170) + 0.270865)/10) : suff.

```
ASSIGN suff hzdept_r < 171 AND hzdepb_r >= 171 ? suff + (awc_r/0.20 * (-0.0511789 * logn(171) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 172 AND hzdepb_r >= 172 ? suff + (awc_r/0.20 * (-0.0511789 * logn(172) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 173 AND hzdepb_r >= 173 ? suff + (awc_r/0.20 * (-0.0511789 * logn(173) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 174 AND hzdepb_r >= 174 ? suff + (awc_r/0.20 * (-0.0511789 * logn(174) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 175 AND hzdepb_r >= 175 ? suff + (awc_r/0.20 * (-0.0511789 * logn(175) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 176 AND hzdepb_r >= 176 ? suff + (awc_r/0.20 * (-0.0511789 * logn(176) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 177 AND hzdepb_r >= 177 ? suff + (awc_r/0.20 * (-0.0511789 * logn(177) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 178 AND hzdepb_r >= 178 ? suff + (awc_r/0.20 * (-0.0511789 * logn(178) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 179 AND hzdepb_r >= 179 ? suff + (awc_r/0.20 * (-0.0511789 * logn(179) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 180 AND hzdepb_r >= 180 ? suff + (awc_r/0.20 * (-0.0511789 * logn(180) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 181 AND hzdepb_r >= 181 ? suff + (awc_r/0.20 * (-0.0511789 * logn(181) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 182 AND hzdepb_r >= 182 ? suff + (awc_r/0.20 * (-0.0511789 * logn(182) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 183 AND hzdepb_r >= 183 ? suff + (awc_r/0.20 * (-0.0511789 * logn(183) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 184 AND hzdepb_r >= 184 ? suff + (awc_r/0.20 * (-0.0511789 * logn(184) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 185 AND hzdepb_r >= 185 ? suff + (awc_r/0.20 * (-0.0511789 * logn(185) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 186 AND hzdepb_r >= 186 ? suff + (awc_r/0.20 * (-0.0511789 * logn(186) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 187 AND hzdepb_r >= 187 ? suff + (awc_r/0.20 * (-0.0511789 * logn(187) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 188 AND hzdepb_r >= 188 ? suff + (awc_r/0.20 * (-0.0511789 * logn(188) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 189 AND hzdepb_r >= 189 ? suff + (awc_r/0.20 * (-0.0511789 * logn(189) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 190 AND hzdepb_r >= 190 ? suff + (awc_r/0.20 * (-0.0511789 * logn(190) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 191 AND hzdepb_r >= 191 ? suff + (awc_r/0.20 * (-0.0511789 * logn(191) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 192 AND hzdepb_r >= 192 ? suff + (awc_r/0.20 * (-0.0511789 * logn(192) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 193 AND hzdepb_r >= 193 ? suff + (awc_r/0.20 * (-0.0511789 * logn(193) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 194 AND hzdepb_r >= 194 ? suff + (awc_r/0.20 * (-0.0511789 * logn(194) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 195 AND hzdepb_r >= 195 ? suff + (awc_r/0.20 * (-0.0511789 * logn(195) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 196 AND hzdepb_r >= 196 ? suff + (awc_r/0.20 * (-0.0511789 * logn(196) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 197 AND hzdepb_r >= 197 ? suff + (awc_r/0.20 * (-0.0511789 * logn(197) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 198 AND hzdepb_r >= 198 ? suff + (awc_r/0.20 * (-0.0511789 * logn(198) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 199 AND hzdepb_r >= 199 ? suff + (awc_r/0.20 * (-0.0511789 * logn(199) + 0.270865)/10) : suff.
ASSIGN suff hzdept_r < 200 AND hzdepb_r >= 200 ? suff + (awc_r/0.20 * (-0.0511789 * logn(200) + 0.270865)/10) : suff.
# return rv value for component as the sum of the horizons
DEFINE rv ARRAYSUM(suff).
```

pH

Property: “NSSC Data: pH IN DEPTH 0-20CM, WTD AVE”
Used in evaluation: “NSSC Data: KCCPI – pH 0-20cm”
Used in subrule: “NSSC Data: KCCPI – pH Subrule”
Originally developed for: NCCPI

base table component.

Retrieves the weighted average of pH 0cm to bedrock, or to 20 cm. The weighted average pH portion of each horizon in the depth range.

```
EXEC SQL select hzdept_r, hzdepb_r, ph1to1h2o_r, ph01mcacl2_r
   from component, chorizon
   where join component to chorizon and hzdepb_r > hzdept_r;
   SORT BY hzdept_r, hzdepb_r
   AGGREGATE column ph1to1h2o_r none, ph01mcacl2_r none.

# Determine the LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER.
DERIVE  layer_thickness from  rv using "NSSC Pangaea":"LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER"
(0,20).


define reph      isnull(ph1to1h2o_r) then ph01mcacl2_r else ph1to1h2o_r.

define low       wtavg(reph, layer_thickness).
define rv        wtavg(reph, layer_thickness).
define high      wtavg(reph, layer_thickness).
```

Property: “NSSC Data: pH IN DEPTH 20-150CM, WTD AVE”
Used in evaluation: “NSSC Data: KCCPI – pH 20-150cm”
Used in subrule: “NSSC Data: KCCPI – pH Subrule”
Originally developed for: NCCPI

base table component.

Retrieves the weighted average of pH 20cm to bedrock, or to 150 cm. The weighted average pH portion of each horizon in the depth range.

```
EXEC SQL select compname, hzdept_r, hzdepb_r, ph1to1h2o_r, ph1to1h2o_l, ph1to1h2o_h, ph01mcacl2_l, ph01mcacl2_h,
ph01mcacl2_r
    from component, chorizon
    where join component to chorizon and hzdepb_r > hzdept_r;
    SORT BY hzdept_r, hzdepb_r
    AGGREGATE column hzdept_r none, hzdepb_r none, ph1to1h2o_r none, ph1to1h2o_l none, ph1to1h2o_h none, ph01mcacl2_l
none, ph01mcacl2_h none, ph01mcacl2_r none.


# Determine the depth to RESTRICTIVE LAYER.
# Determine the LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER.
DERIVE  layer_thickness from  rv using "NSSC Data":"LAYER THICKNESS IN RANGE; ABOVE ROOT RESTRICT BELOW O"
(20,150).
DERIVE depth from rv using "NSSC Data":"DEPTH TO FIRST STR/VSTR CEMENTED BELOW ORGANIC LAYER".
DERIVE o_thickness from rv using "NSSC Pangaea":"THICKNESS OF SURFACE ORGANIC HORIZON".

assign hzdepb_r if depth ==0 then 0 else hzdepb_r.

# Find minimum of restriction depth and 200cm
DEFINE min_depth  depth < 250 and not isnull(depth) ? depth : 250.
DEFINE in_range   isnull (hzdepb_r) then hzdepb_r else
                        if (hzdepb_r - o_thickness <= min_depth) then 1 else
                        if (hzdepb_r-hzdept_r > 200) then 1 else 0.
#When the restriction is at the surface, in_range is never 1, so the weighted average
#calculation fails due to unequal dimensions.  If the restriction is at the surface,
#we make depth hzdept_r.  We do not want to always make in_range 1, only when the restriction
#depth is 0.  Default needs to be dimension 0.
```

```
assign layer_thickness          depth == 0 ? hzdept_r : layer_thickness.
assign in_range                 layer_thickness < 0 ? 1 : in_range.
DEFINE default                  0*layer_thickness.


# Find the weighted average clay content in the depth 30-200cm.

define lowph   isnull(ph1to1h2o_l) then ph01mcacl2_l else ph1to1h2o_l.
define reph    isnull(ph1to1h2o_r) then ph01mcacl2_r else ph1to1h2o_r.
define highph  isnull(ph1to1h2o_h) then ph01mcacl2_h else ph1to1h2o_h.

define low     wtavg((if hzdepb_r - o_thickness <=20 THEN default ELSE lookup(1, in_range, lowph)), layer_thickness).
define rv      wtavg((if hzdepb_r - o_thickness <=20 THEN default ELSE lookup(1, in_range, reph)), layer_thickness).
define high    wtavg((if hzdepb_r - o_thickness <=20 THEN default ELSE lookup(1, in_range, highph)), layer_thickness).

#define rv lookup(1, in_range, reph).
```

Soil Depth

Property: "MLRA05_Salina: BW Depth to bedrock or pan restrictive layer (KS)"
Used in evaluation: "MLRA05_Salina: BW: depth restricting (KS)"
Used in subrule: "NSSC Data: KCCPI – Depth Subrule"
Originally developed for: Kansas Black Walnut suitability interpretation

```
base table component.
# Get RV depths to the first restriction, based on RV depth.
exec sql select resdept_r
from component, corestrictions
where join component to corestrictions and reskind in ("fragipan", "densic material", "bedrock, lithic", "bedrock, paralithic", "bedrock, densic");
sort by resdept_r asc
aggregate column  resdept_r first.
DEFINE  rv  not isnull (resdept_r) ? resdept_r :200.
```

Property: "MLRA05_Salina: BW Depth to restrictive layer, any kind (KS)"
Used in evaluation: "MLRA05_Salina: BW: depth restarding (KS)"
Used in subrule: "NSSC Data: KCCPI – Depth Subrule"
Originally developed for: Kansas Black Walnut suitability interpretation

```
base table component.

# Get RV depths to the first restriction of any kind, based on RV depth.

exec sql select resdept_r
from component, corestrictions
where join component to corestrictions;
sort by resdept_r
aggregate column  resdept_r first.


DEFINE  rv  not isnull (resdept_r) ? resdept_r : 200.
```

Cation Exchange Capacity

Property: "MLRA06_Morgantown: CEC WEIGHTED AVG 0-20 CM ABOVE RESTRICTION"
Used in evaluation: "NSSC Data: KCCPI – CEC 0-20cm or Restriction"
Used in subrule: "NSSC Data: KCCPI – CEC Subrule"
Originally developed for: TNCCPI and WICCPI

```
base table component.

# Retrieves the weighted average cec from 0 to 20 cm or to a restrictive layer.  The weighted average cec is for that portion of each
horizon in the depth range.

EXEC SQL select hzdept_r, hzdepb_r,  cec7_r,  ecec_r
    from component,  chorizon
    where join component to chorizon and
    hzdepb_r > hzdept_r;
    SORT BY hzdept_r
    AGGREGATE column  hzdept_r none,  cec7_r none,   ecec_r none.

#Find the cec7 or ecec.
DEFINE cats_r   isnull(cec7_r) then ecec_r else cec7_r.

# Find thickness of each horizon in 0-10" (0-10 cm) range
derive layer_thickness  using "LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER" (0,20).

# Sum cec7 by horizon and compute weighted average.

DEFINE cec_rv          IF ISNULL(cec7_r) THEN ecec_r ELSE cec7_r.

define rv   wtavg(cec_rv, layer_thickness).
```

Property: "MLRA06_Morgantown: CEC WEIGHTED AVG 20-100CM ABOVE RESTRICTION"
Used in evaluation: "NSSC Data: KCCPI – CEC 20-100cm or Restriction"
Used in subrule: "NSSC Data: KCCPI – CEC Subrule"

Originally developed for: TNCCPI and WICCPI

base table component.

```
# Retrieves the weighted average cec from 20 to 100cm or to a restrictive layer.  The weighted average cec is for that portion of each
horizon in the depth range.

EXEC SQL select hzdept_r, hzdepb_r, cec7_r, ecec_r, hzname
    from component,  chorizon
    where join component to chorizon and
    hzdepb_r > hzdept_r;
    SORT BY hzdept_r
    AGGREGATE column  hzdept_r none, cec7_r none,  ecec_r none.

#Find the cec7 or ecec.
DEFINE cats_r   isnull(cec7_r) then ecec_r else cec7_r.

# Find thickness of each horizon in 0-10" (0-10 cm) range
Derive layer_thickness  using "LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER" (20,100).

# Sum cec7 by horizon and compute weighted average.

DEFINE cec_rv          IF ISNULL(cec7_r) THEN ecec_r ELSE cec7_r.

define rv   wtavg(cec_rv, layer_thickness).
```

Organic Matter
Property: "NSSC Data: ORGANIC MATTER IN DEPTH 0-20CM, WTD AVE"
Used in evaluation: "NSSC Data: KCCPI – OM 0-20cm"
Used in subrule: "NSSC Data: KCCPI – Organic Matter Subrule"
Originally developed for: NCCPI

```
base table component.

# Retrieves the weighted average of pH 0cm to bedrock, or to 20 cm.  The weighted average pH portion of each horizon in the depth range.

EXEC SQL select compname, hzdept_r, hzdepb_r, om_r
   from component, chorizon
   where join component to chorizon and hzdepb_r > hzdept_r;
   SORT BY hzdept_r, hzdepb_r
   AGGREGATE column om_r none, hzdept_r none, hzdepb_r none.

# Determine the LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER.
DERIVE  layer_thickness from  rv using "NSSC Pangaea":"LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER" (0,20).
# Determine the LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER.
DERIVE o_thickness from rv using "NSSC Pangaea":"THICKNESS OF SURFACE ORGANIC HORIZON".
DERIVE depth from rv using "NSSC Data":"DEPTH TO FIRST STR/VSTR CEMENTED BELOW ORGANIC LAYER".

#define repom isnull(om_r) then 0 else om_r.
define repom    om_r.

DEFINE min_depth    depth < 250 and not isnull(depth) ? depth : 250.
DEFINE in_range             isnull (hzdepb_r) ? hzdepb_r : (hzdepb_r - o_thickness <= min_depth ? 1 :
                                   hzdepb_r - hzdept_r >= min_depth ? 1 : 0).

#When the restriction is at the surface, in_range is never 1, so the weighted average
#calculation fails due to unequal dimensions.  If the restriction is at the surface,
```

```
#we make depth hzdept_r.  We do not want to always make in_range 1, only when the restriction
#depth is 0.  Default needs to be dimension 0.
assign layer_thickness          depth == 0 ? hzdept_r : layer_thickness.
assign in_range                 layer_thickness < 0 ? 1 : in_range.
DEFINE default                  0*layer_thickness.

define intval     lookup(1, in_range, repom).

# Sum the #200 sieve by horizon and compute weighted average for the layer and parts of layers within the range.

define rv    wtavg((if hzdepb_r - o_thickness <=0 THEN default ELSE lookup(1, in_range, repom)), layer_thickness).
#define rv       arrayavg(repom).
```

Property: "NSSC Data: ORGANIC MATTER IN DEPTH 0-20CM, WGT AVG"
Used in evaluation: "NSSC Data: KCCPI – OM 20-100cm"
Used in subrule: "NSSC Data: KCCPI – Organic Matter Subrule"
Originally developed for: NCCPI

```
base table component.

EXEC SQL SELECT hzdept_r, hzdepb_r, om_r
FROM component
INNER JOIN chorizon BY default AND hzdept_r < hzdepb_r
ORDER BY hzdept_r, hzdepb_r;
AGGREGATE COLUMN hzdept_r NONE, hzdepb_r NONE, om_r NONE.

#EXEC SQL select hzdept_r, hzdepb_r, om_r
 #   from component, chorizon
 #   where join component to chorizon and hzdept_r < hzdepb_r;
 #   SORT BY hzdept_r, hzdepb_r
 #   AGGREGATE column hzdept_r none, hzdepb_r none,
 #     om_r none.
```

```
# Find thickness of each horizon in (20-100 cm) range
derive layer_thickness  using "LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER" (20,100).

# Sum om by horizon and compute weighted average.
# Nulls in clay columns are assumed to mean 0.

define om_rv om_r ? om_r : 0.

define rv   wtavg(om_rv, layer_thickness).
```

<u>Calcium Carbonate Equivalent</u>
Property: "NSSC Data: CALCIUM CARBONATE FROM 0 to 20cm"
Used in evaluation: "NSSC Data: KCCPI – Calcium Carbonate Equivalent 0-20cm"
Used in subrule: "NSSC Data: KCCPI – Calcium Carbonate Equivalent Subrule"
Originally developed for: N/A

```
base table component.

# Get CaCO3 values from 0 to 20 cm.

exec sql select caco3_l, caco3_h, caco3_r
   from  component, chorizon
   where join component to chorizon
   and hzdept_r <= 20;
   aggregate column caco3_l max, caco3_h max, caco3_r max.

define rv        isnull(caco3_r) then 0 else caco3_r.
define high      isnull(caco3_h) then 0 else caco3_h.
define low       isnull(caco3_l) then 0 else caco3_l.
```

Property: "NSSC Data: CALCIUM CARBONATE FROM 20-150cm"
Used in evaluation: "NSSC Data: KCCPI – Calcium Carbonate Equivalent 20-150cm"
Used in subrule: "NSSC Data: KCCPI – Calcium Carbonate Equivalent Subrule"
Originally developed for: N/A

```
base table component.

# Retrieves the weighted average of CaCO3 20cm to bedrock, or to 150 cm.  The weighted average CaCO3 portion of each horizon in the depth range.

EXEC SQL select hzdept_r, hzdepb_r, caco3_r
   from component, chorizon
   where join component to chorizon and hzdepb_r > hzdept_r;
```

```
    SORT BY hzdept_r, hzdepb_r
    AGGREGATE column caco3_r none.

# Determine the LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER.
DERIVE  layer_thickness from  rv using "NSSC Pangaea":"LAYER THICKNESS IN RANGE; ABOVE A RESTRICTIVE LAYER"
(20,150).

define cacarbonate      wtavg(caco3_r, layer_thickness).
```

Bulk Density
Property: "MLRA09_Temple: BULK DENSITY 0 TO 25CM < 60% CLAY (TX)"
Used in evaluation: "NSSC Data: KCCPI Bulk Density < 60% Clay 0 to 25cm"
Used in subrule: "NSSC Data: KCCPI – Bulk Density Subrule"
Originally developed for: PGI(TX)

base table component.

Get bulk density where clay content is less than 60 percent

exec sql select dbthirdbar_l low, dbthirdbar_h high, dbthirdbar_r rv
from component, chorizon where
join component to chorizon
and claytotal_r < 60 and hzdept_r < 26;
aggregate column low max, high max, rv max.

Property: "MLRA09_Temple: BULK DENSITY 0 TO 25CM => 60% CLAY (TX)"
Used in evaluation: "NSSC Data: KCCPI Bulk Density => 60% Clay 0 to 25cm"
Used in subrule: "NSSC Data: KCCPI – Bulk Density Subrule"
Originally developed for: PGI(TX)

base table component.

Get surface bulk density where surface clay content is less than 60 percent

exec sql select dbthirdbar_l low, dbthirdbar_h high, dbthirdbar_r rv
from component, chorizon where
join component to chorizon
and (claytotal_r = 60 or claytotal_r > 60) and hzdept_r < 26;
aggregate column low max, high max, rv max.

Property: "MLRA09_Temple: DEPTH TO BULK DENSITY > 1.7 G/CC (TX)"
Used in evaluation: "NSSC Data: KCCPI Depth to Bulk Density > 1.7 (G/CC) 25 to 120cm"

Used in subrule: "NSSC Data: KCCPI – Bulk Density Subrule"
Originally developed for: PGI(TX)

base table component.

```
exec sql select hzdept_l, hzdept_h, hzdept_r, dbthirdbar_h
   from  component, chorizon
   where join component to chorizon and hzdepb_r > 25 and claytotal_r > 17;
   sort by hzdept_r
   aggregate column hzdept_l none, hzdept_h none, hzdept_r none.

define rv arraymin (NOT ISNULL (dbthirdbar_h) and dbthirdbar_h > 1.69 ? hzdept_r : (NOT ISNULL (dbthirdbar_h) and
dbthirdbar_h <= 1.69 ? 120 : 1/0)).
```

Coarse Fragments
Property: “NSSC Pangaea: GCPI Surface Fragments > 2mm and < 25cm”
Used in evaluation: “NSSC Data: KCCPI Surface Fragments 2mm-25cm”
Used in subrule: “NSSC Data: KCCPI – Surface Coarse Fragment Subrule”
Originally developed for: GCPI

```
base table component.

# Get fragments > 2mm for the surface horizon

exec sql select sieveno10_l, sieveno10_h, sieveno10_r,
   frag3to10_l, frag3to10_h, frag3to10_r
   from  component
INNER JOIN chorizon ON chorizon.coiidref=component.coiid and hzdept_r = 0;.

# Nulls in fragments columns are assumed to mean 0.
define frag3_l  frag3to10_l ? frag3to10_l : 0.
define frag3_h  frag3to10_h ? frag3to10_h : 0.
define frag3_r  frag3to10_r ? frag3to10_r : 0.

# Compute the percent 2mm - 3" by adjusting the percent retained on
# sieveno10, to account for fragments > 3".
# Note the low percent is derived from the high sieve and fragment percents.
define pct_l  (100 - sieveno10_h) * (100 - frag3_h) / 100.
define pct_h  (100 - sieveno10_l) * (100 - frag3_l) / 100.
define pct_r  (100 - sieveno10_r) * (100 - frag3_r) / 100.

# Add the > 3" percentages to the > 2mm percents.
define low  arraymax (pct_l + frag3_l).
define high arraymax (pct_h + frag3_h).
define rv   arraymax (pct_r + frag3_r).
```

Property: “NSSC Pangaea: GCPI FRAGMENTS > 250mm SURFACE LAYER”

Used in evaluation: "NSSC Data: KCCPI Surface Fragments > 25cm"
Used in subrule: "NSSC Data: KCCPI – Surface Coarse Fragment Subrule"
Originally developed for: GCPI

```
base table component.

# Get fragments >10" for the surface layer

exec sql select fraggt10_l low, fraggt10_h high, fraggt10_r rv
    from  component
INNER JOIN chorizon ON chorizon.coiidref=component.coiid and hzdept_r=0;
   aggregate column low max, high max, rv max.
```

<u>**Slope**</u>
Property: "NSSC Data: SLOPE"
Used in evaluation: "NSSC Data: KCCPI - Slope"
Used in subrule: "NSSC Data: KCCPI – Slope Subrule"
Originally developed for: Military Trafficability

```
base table component.

exec sql select slope_l low, slope_h high, slope_r rv from component;.
```

Appendix B- KCCPI Evaluations

The following figures are evaluations used in the Kansas commodity crop productivity index (KCCPI) Corn Submodel and climate-included KCCPI Corn Submodel.

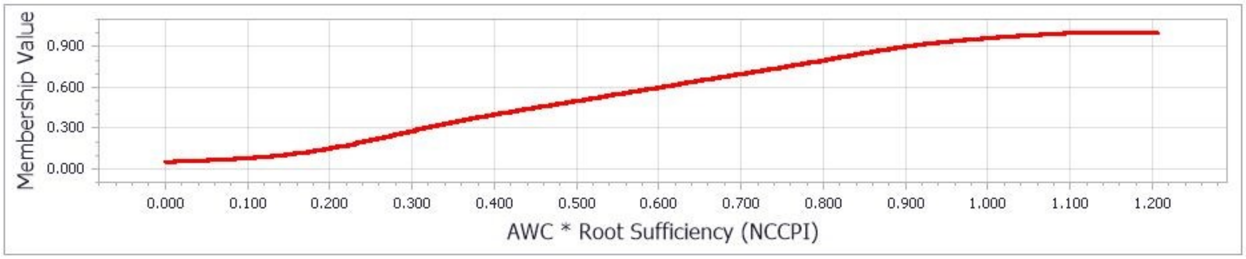

Figure B-1. KCCPI available water capacity 0-200cm evaluation (cm). Modeled after the NCCPI AWC evaluation.

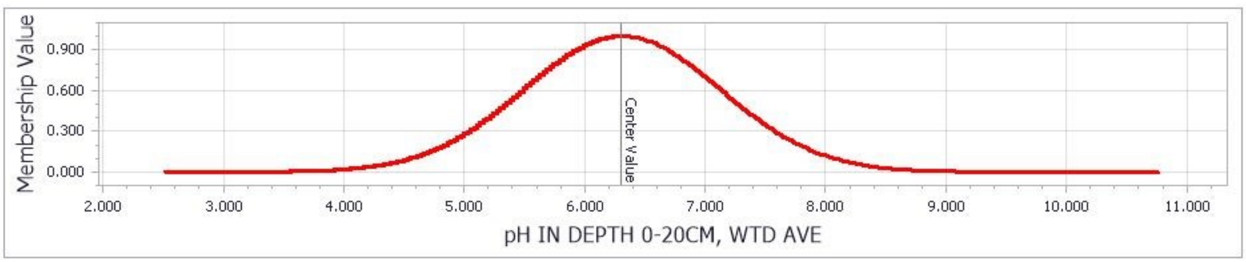

Figure B-2. KCCPI pH 0-20cm evaluation.

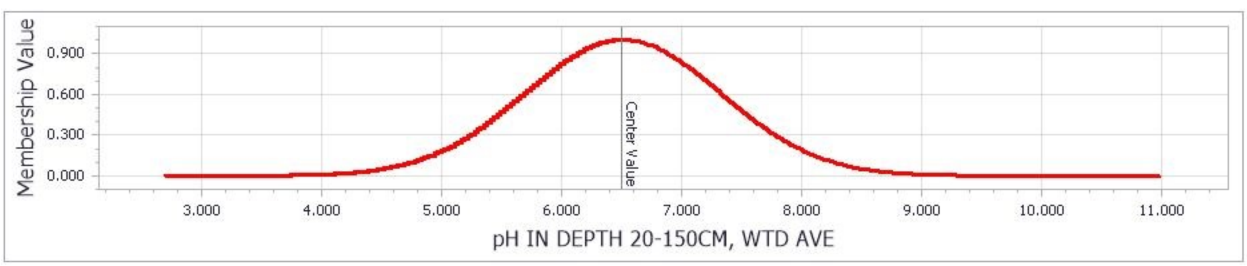

Figure B-3. KCCPI pH 20-150cm evaluation.

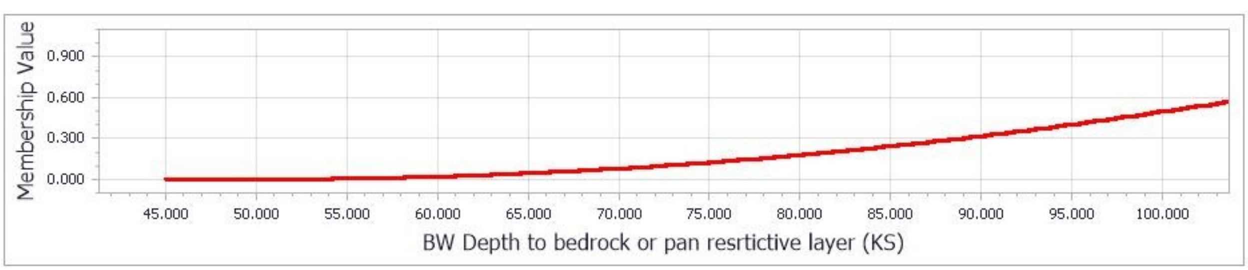

Figure B-4. Kansas Black Walnut depth to bedrock evaluation (cm).

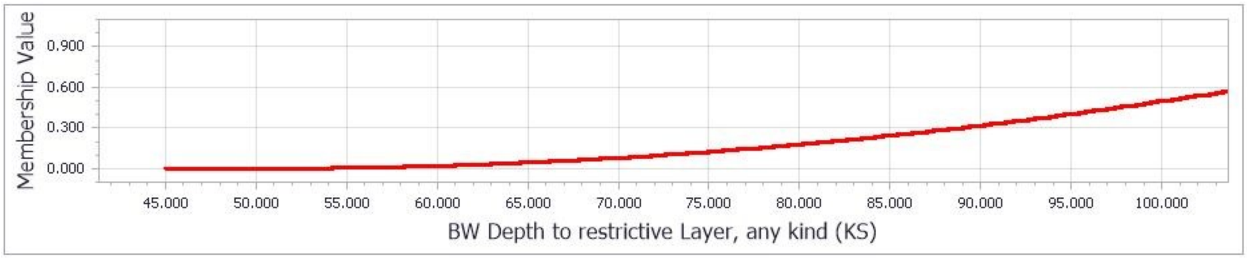

Figure B-5. Kansas Black Walnut depth to any restrictive layer evaluation (cm).

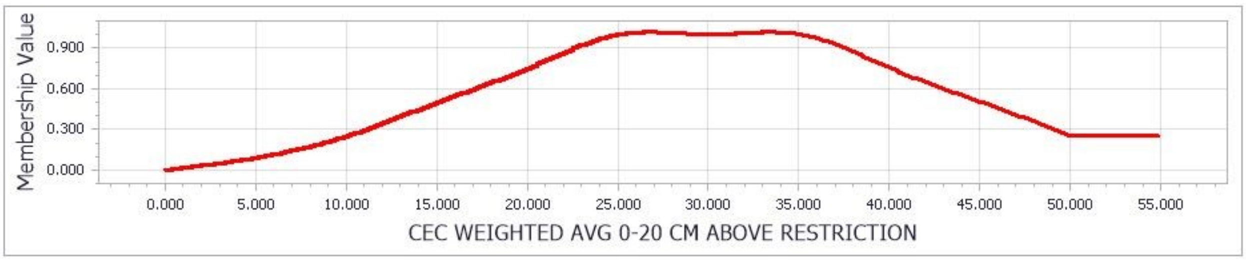

Figure B-6. KCCPI cation exchange capacity 0-20cm evaluation (meq $100g^{-1}$). Modeled after the WICCPI CEC evaluation.

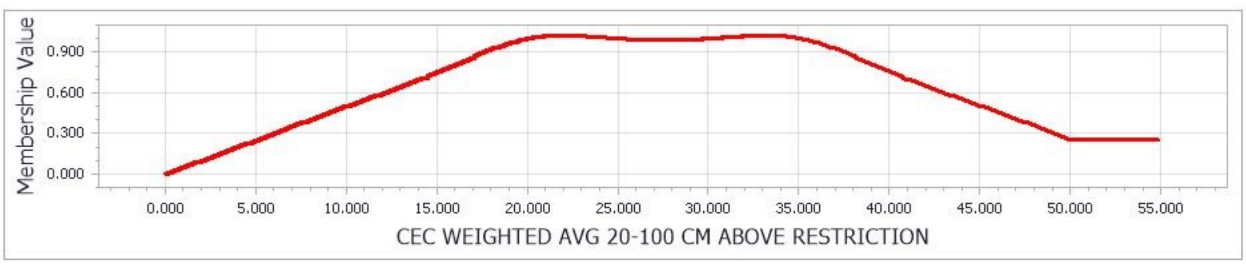

Figure B-7. KCCPI cation exchange capacity 20-100cm evaluation (meq $100g^{-1}$). Modeled after the WICCPI CEC evaluation.

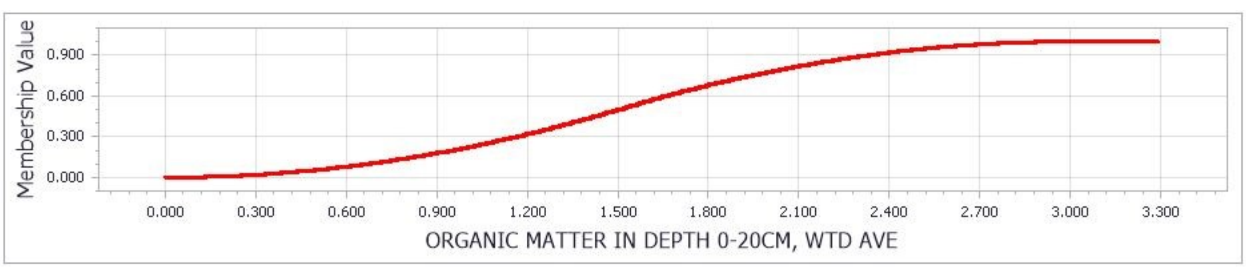

Figure B-8. KCCPI organic matter 0-20cm evaluation (%). Modeled after the NCCPI organic matter evaluation.

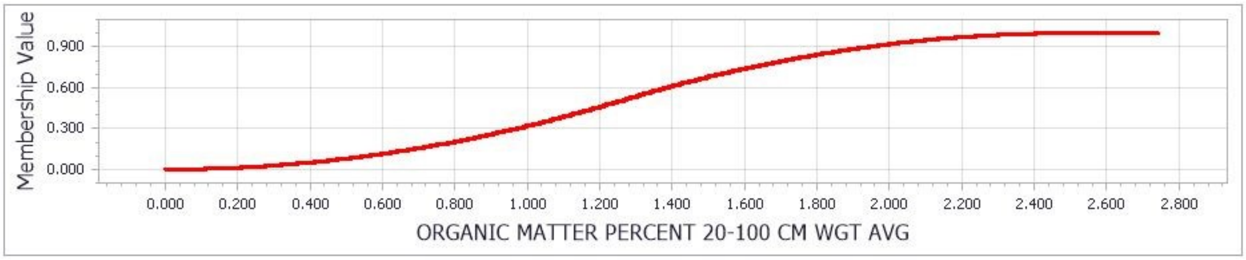

Figure B-9. KCCPI organic matter 20-100cm evaluation (%). Modeled after the NCCPI organic matter evaluation.

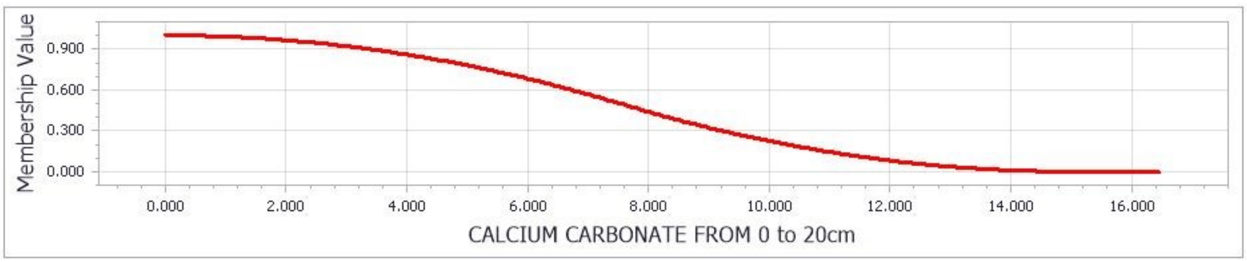

Figure B-10. KCCPI calcium carbonate equivalent 0-20cm evaluation (%).

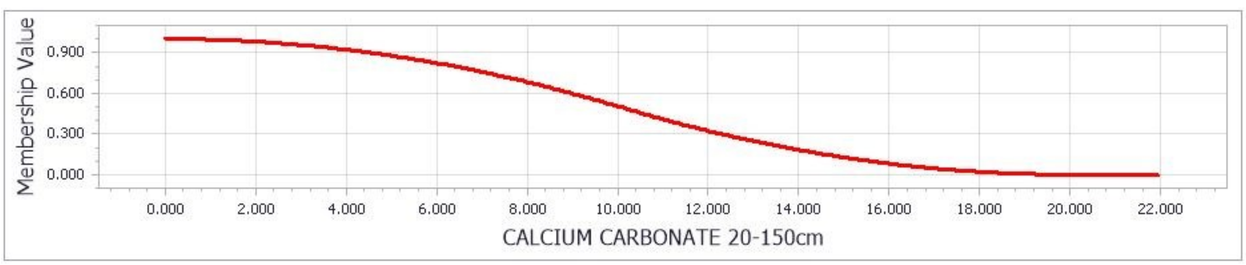

Figure B-11. KCCPI calcium carbonate equivalent 20-100cm evaluation (%).

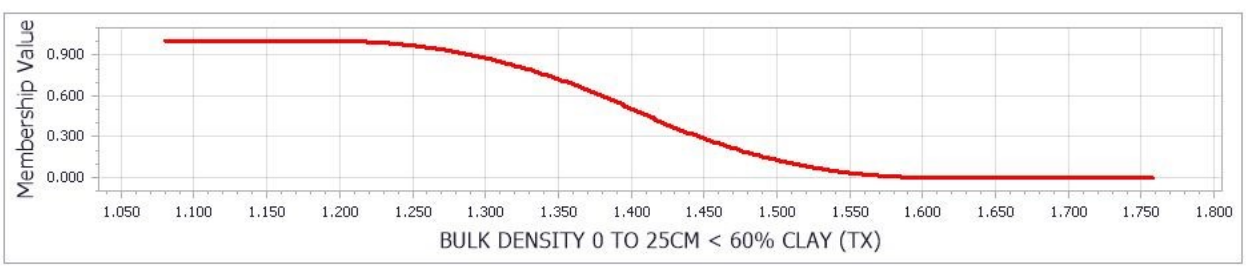

Figure B-12. KCCPI bulk density low clay 0-25cm evaluation (g cm^{-3}). Modeled after the PGI(TX) bulk density evaluation.

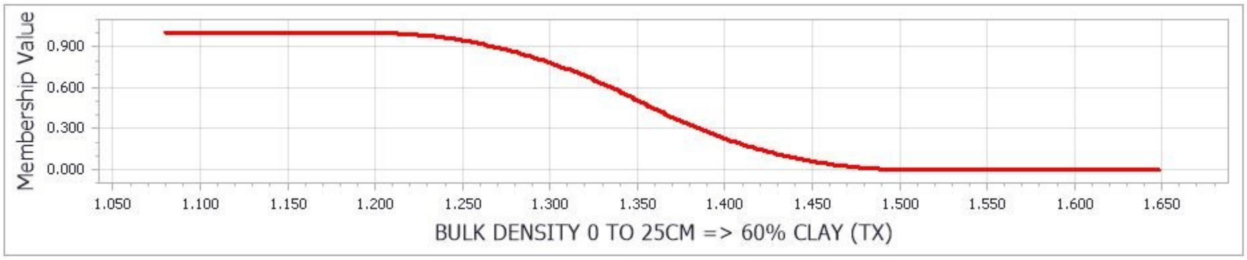

Figure B-13. KCCPI bulk density high clay 0-25cm evaluation (g cm^{-3}). Modeled after the PGI(TX) bulk density evaluation.

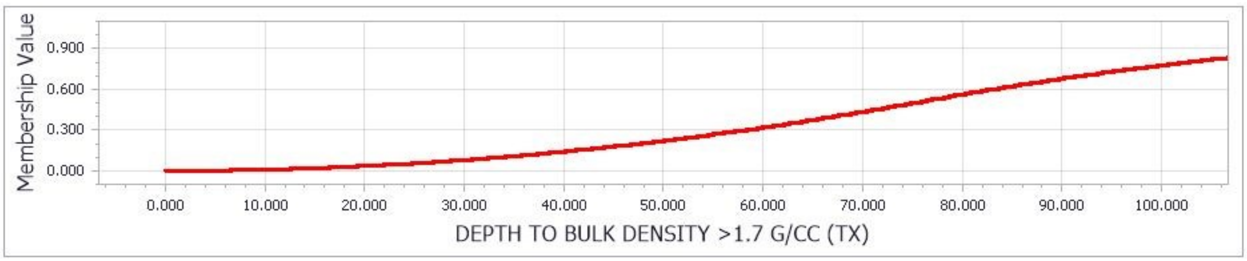

Figure B-14. KCCPI depth to high bulk density evaluation (cm). Modeled after the PGI(TX) depth to high bulk density evaluation.

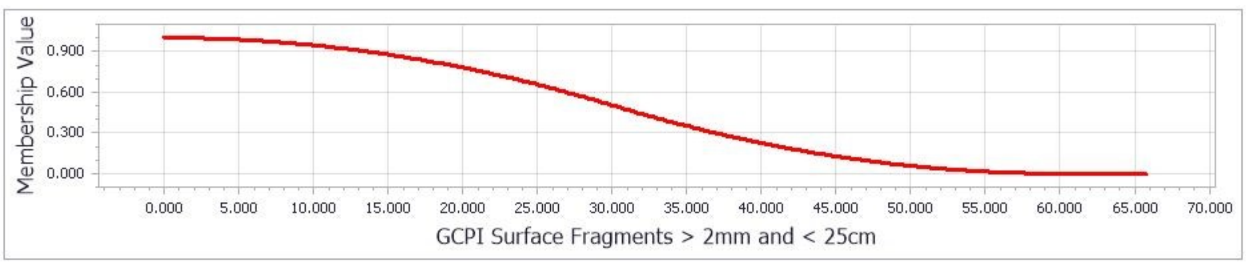

Figure B-15. KCCPI surface coarse fragments < 25cm evaluation (%). Modeled after the GCPI coarse fragment evaluation.

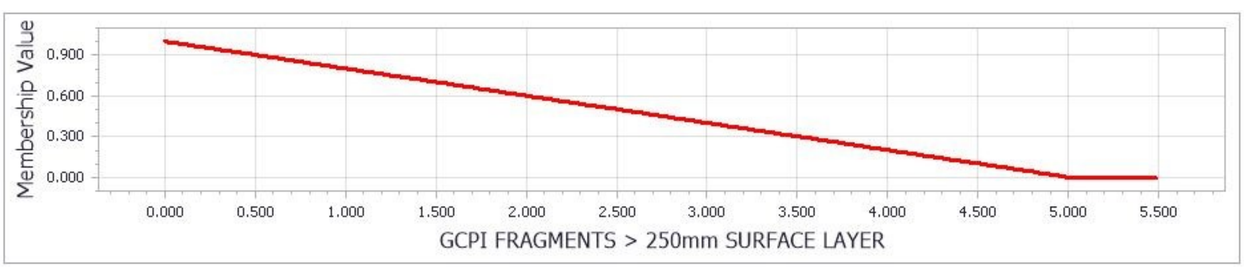

Figure B-16. KCCPI surface coarse fragments > 250mm evaluation (%). Modeled after the GCPI coarse fragment evaluation.

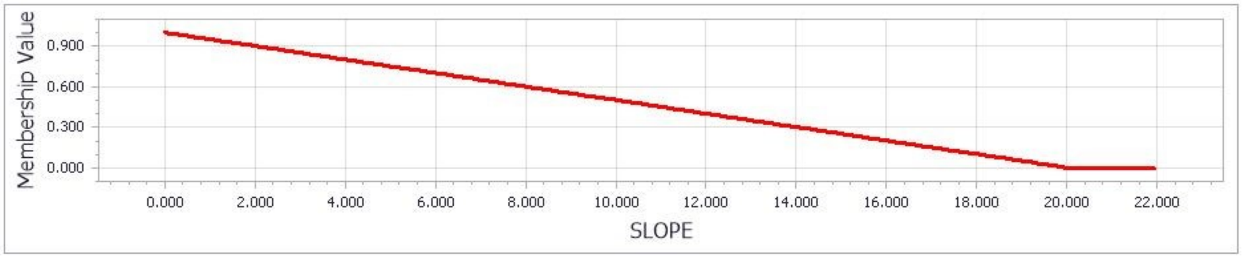

Figure B-17. KCCPI slope evaluation (%). Modeled after several different slope evaluations.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
X Value	501	800	850	1150	1000	1100	1300	1500	2000																
Y Value	0.65	1	1	0.97	1	1	0.88	0.86	0.85																

Membership Graph

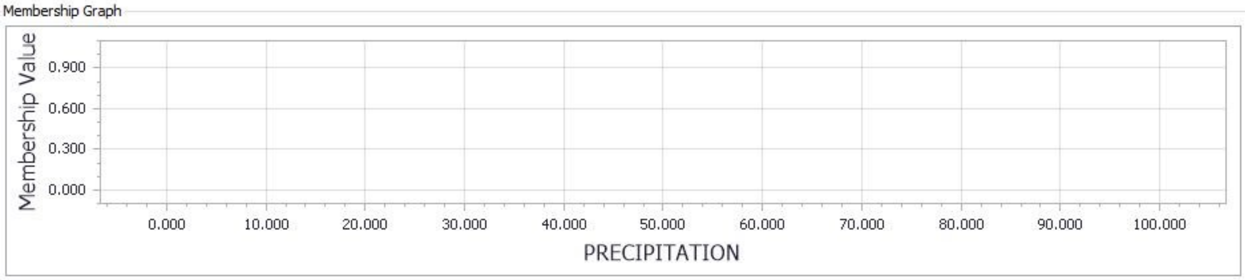

Figure B-18. SRPG Mean Annual Precipitation evaluation (mm).

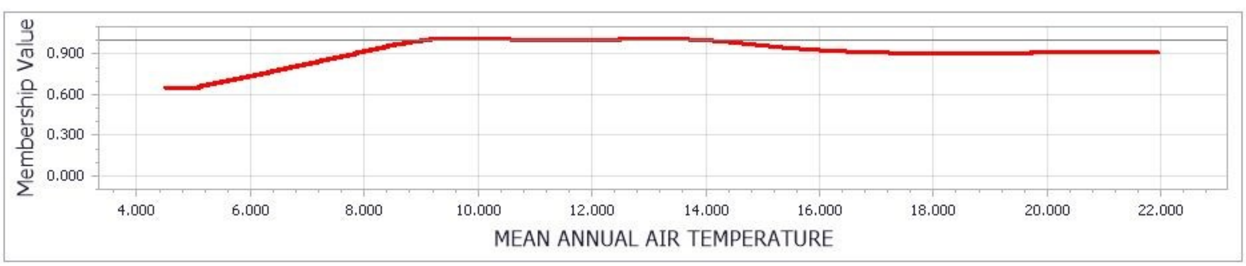

Figure B-19. KCCPI mean annual air temperature evaluation (⁰C). Modeled after the SRPG MAAT corn evaluation.

Appendix C - KCCPI Subrules

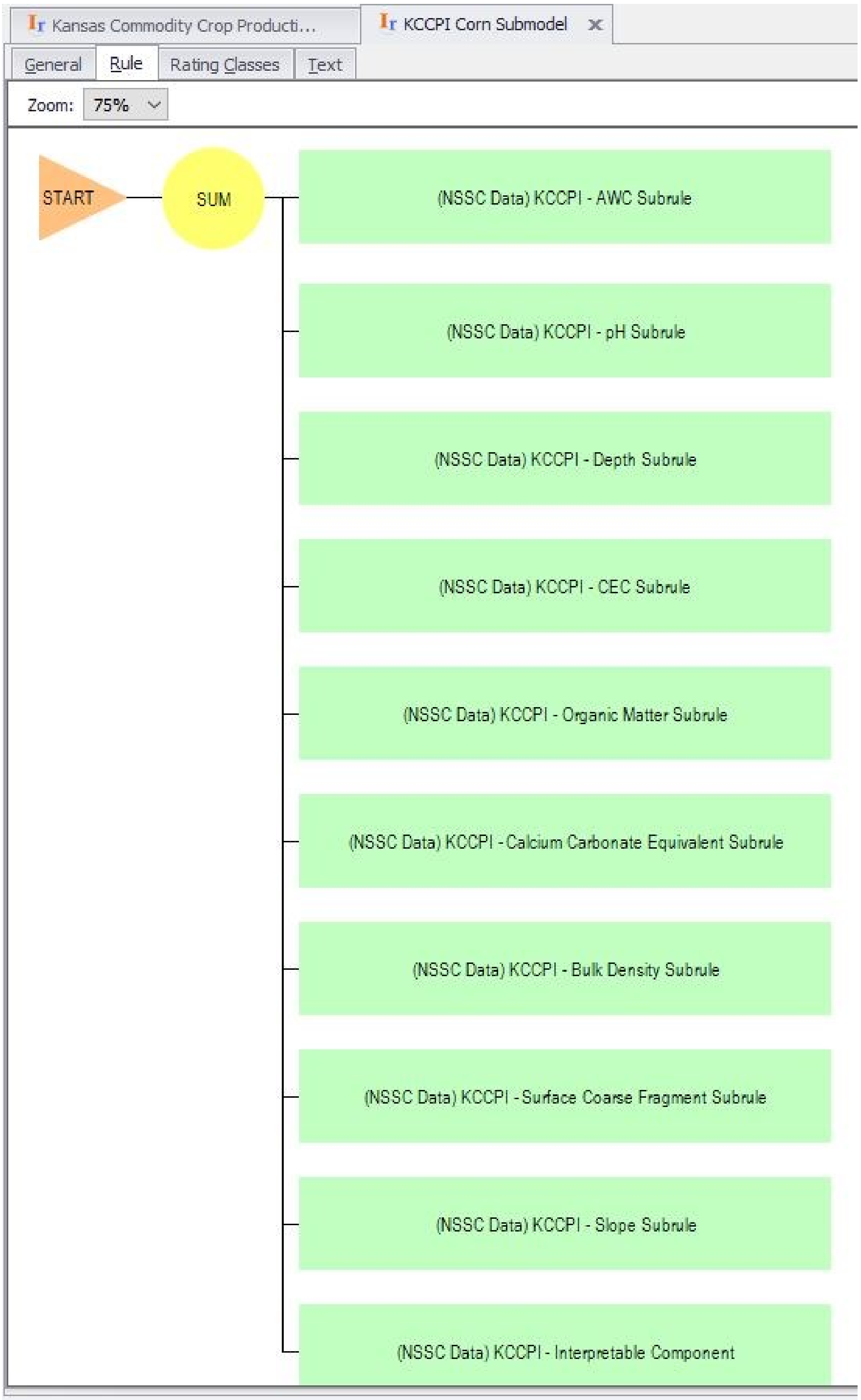

Figure C-1. The KCCPI corn submodel.

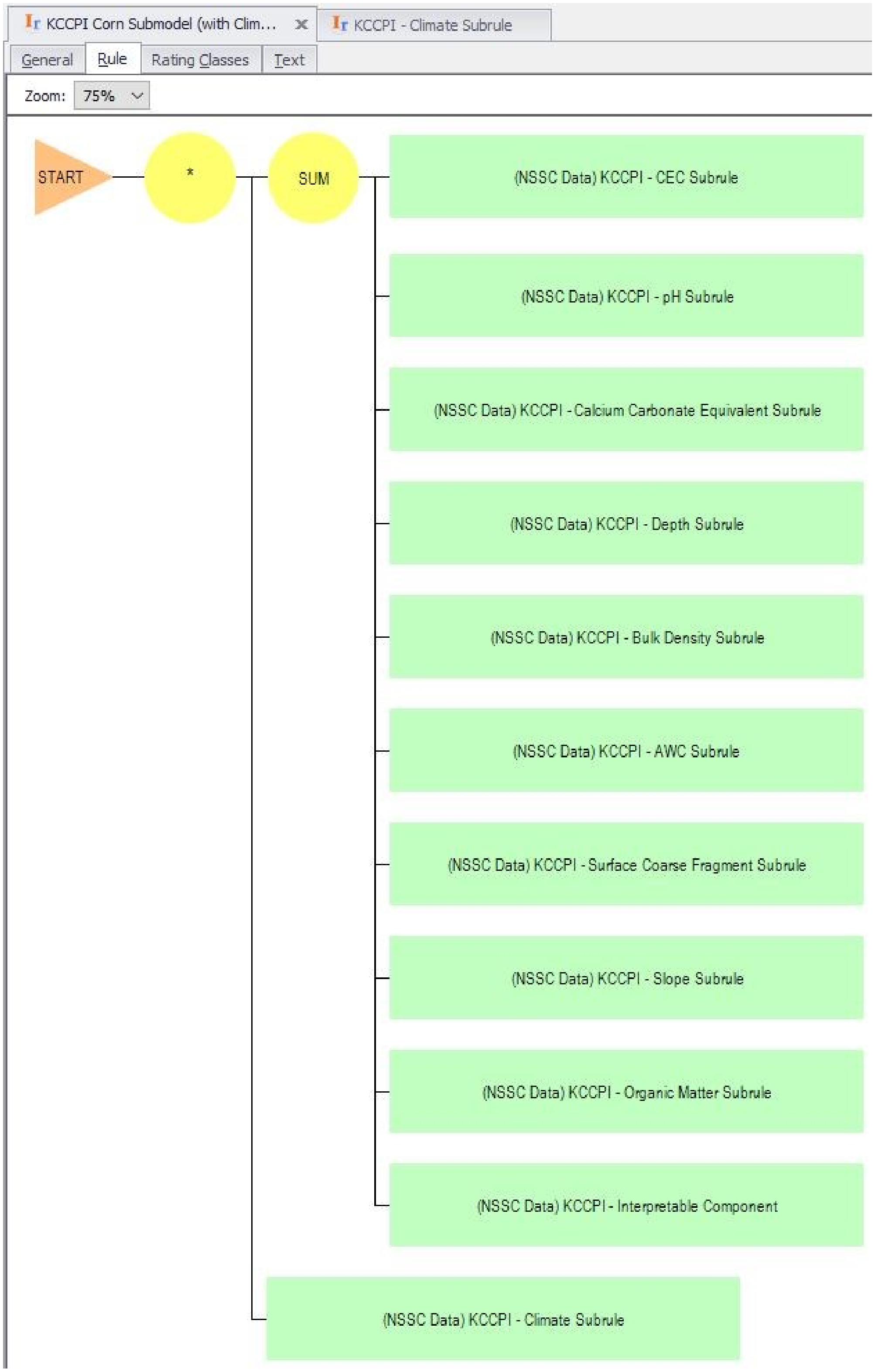

Figure C-2. Climate-included KCCPI corn submodel.

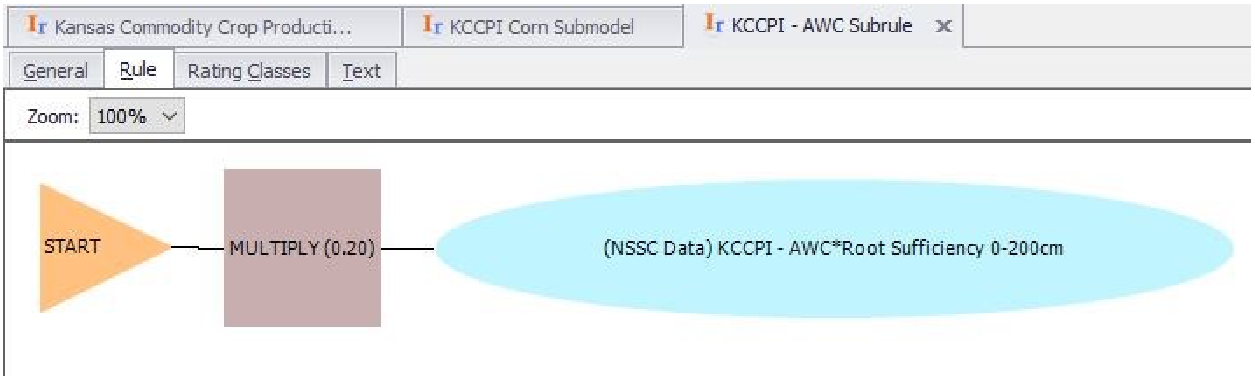

Figure C-3. KCCPI available water capacity subrule.

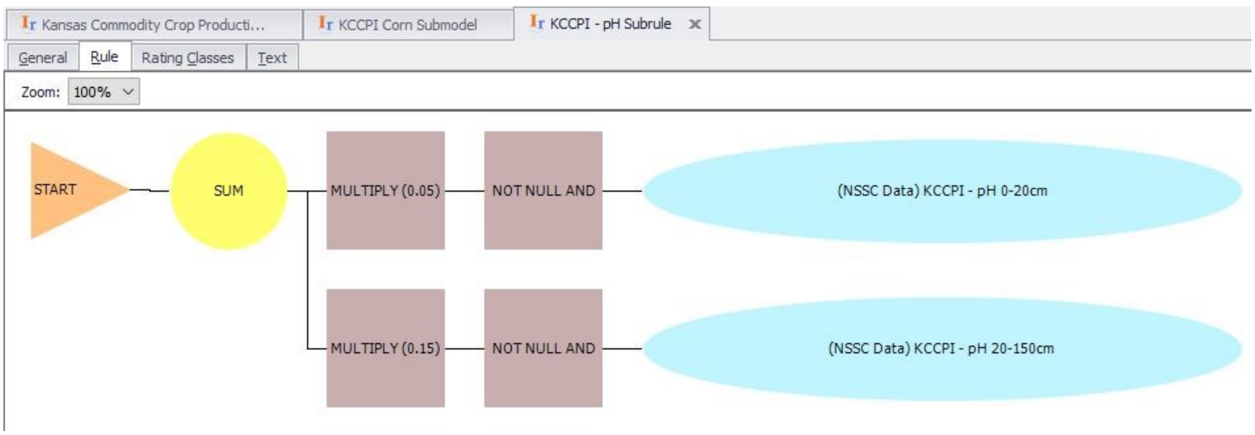

Figure C-4. KCCPI pH subrule.

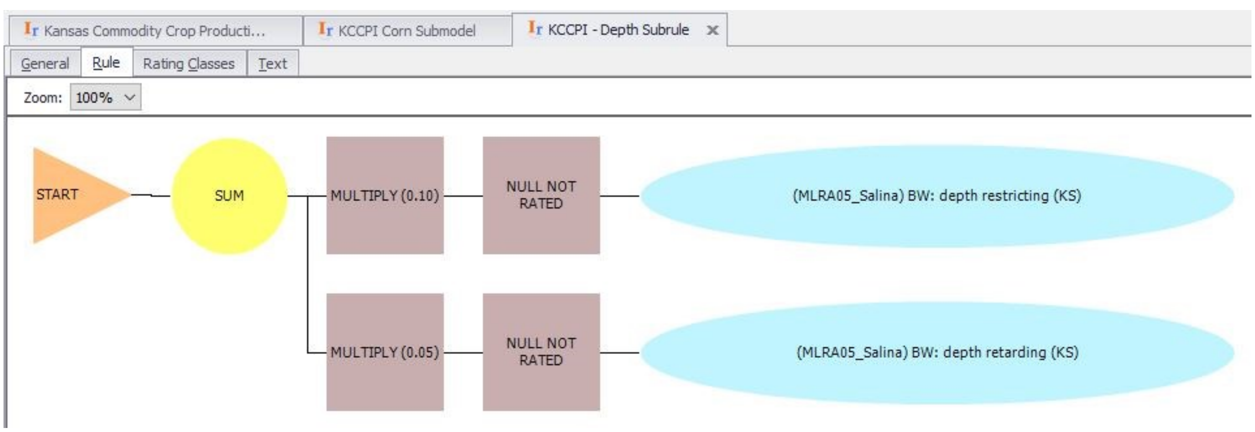

Figure C-5. KCCPI soil depth subrule.

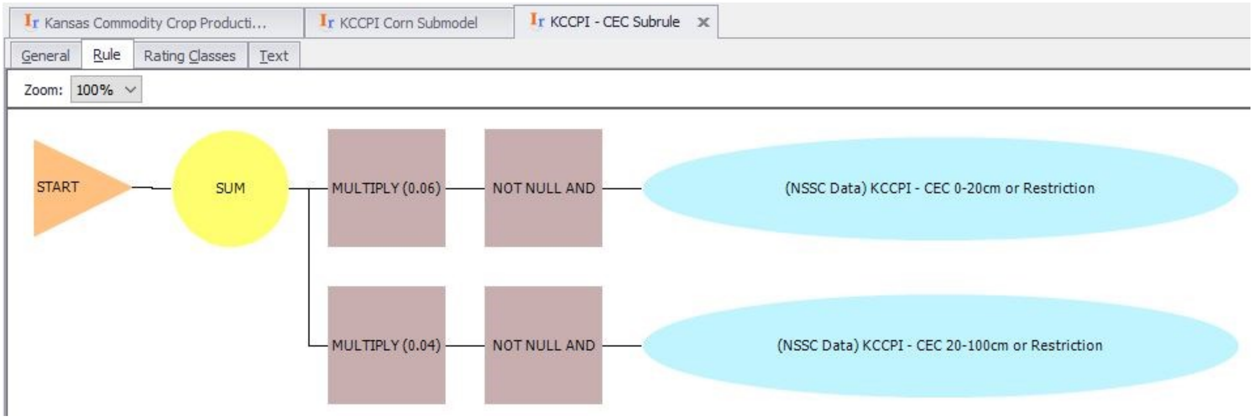

Figure C-6. KCCPI cation exchange capacity subrule.

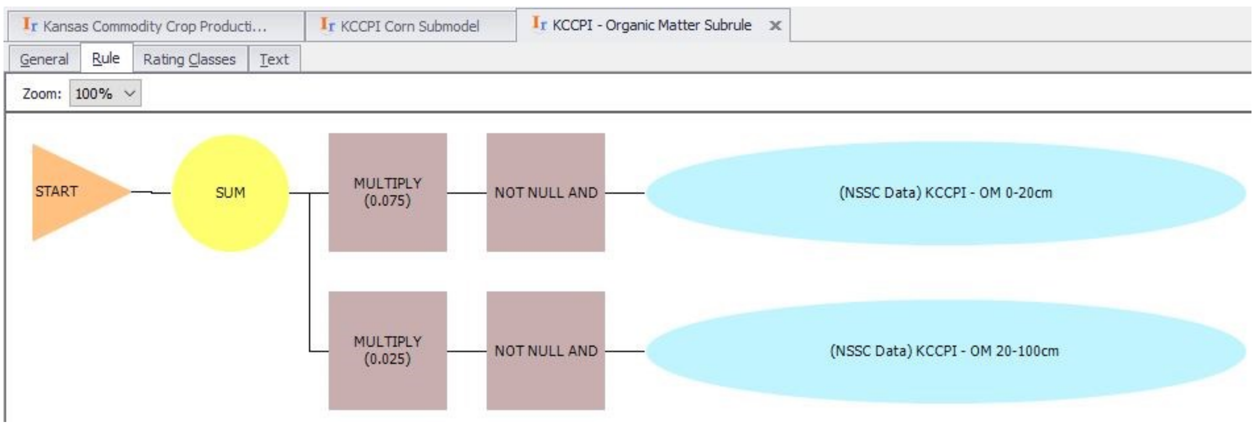

Figure C-7. KCCPI organic matter subrule.

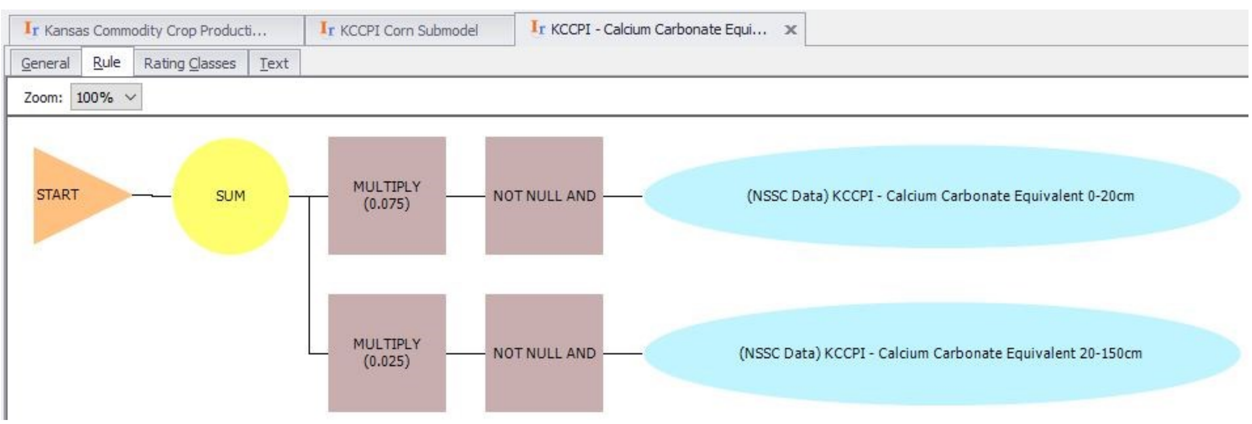

Figure C-8. KCCPI calcium carbonate equivalent subrule.

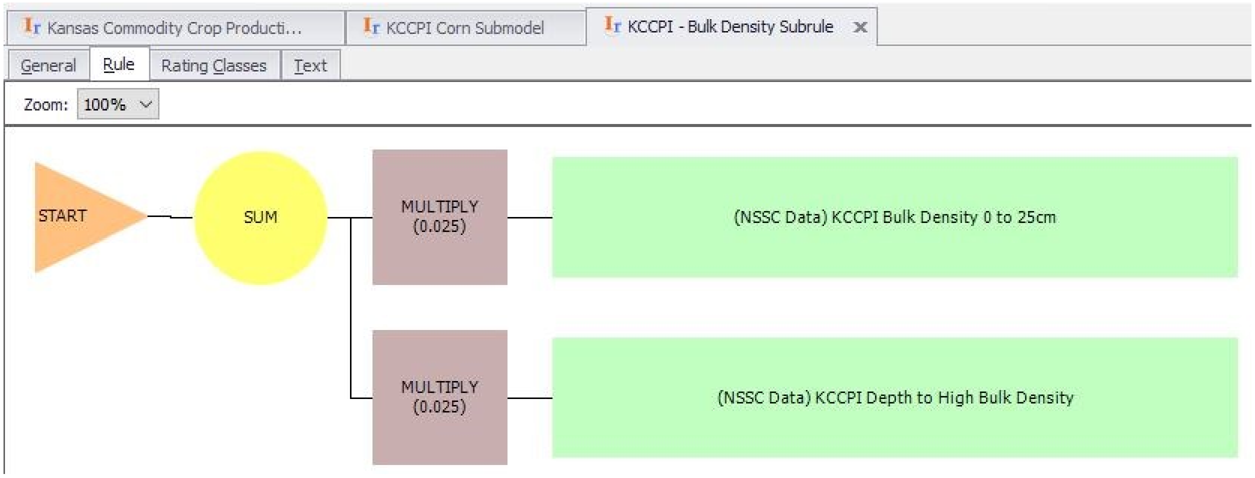

Figure C-9. KCCPI bulk density subrule.

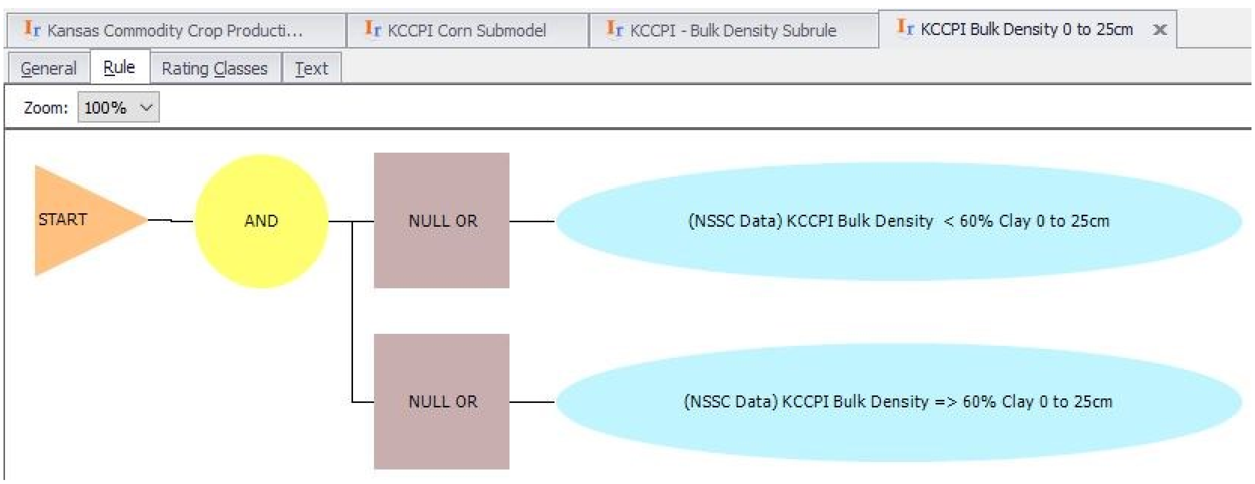

Figure C-10. KCCPI bulk density 0-25cm subrule.

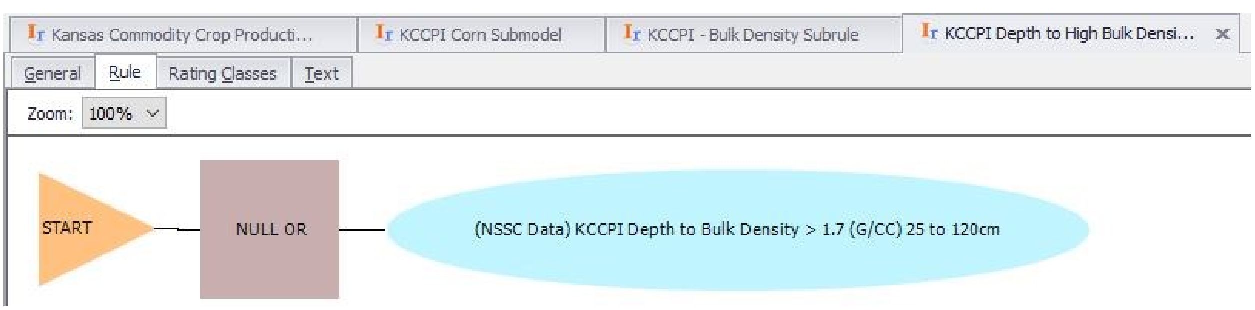

Figure C-11. KCCPI depth to high bulk density subrule.

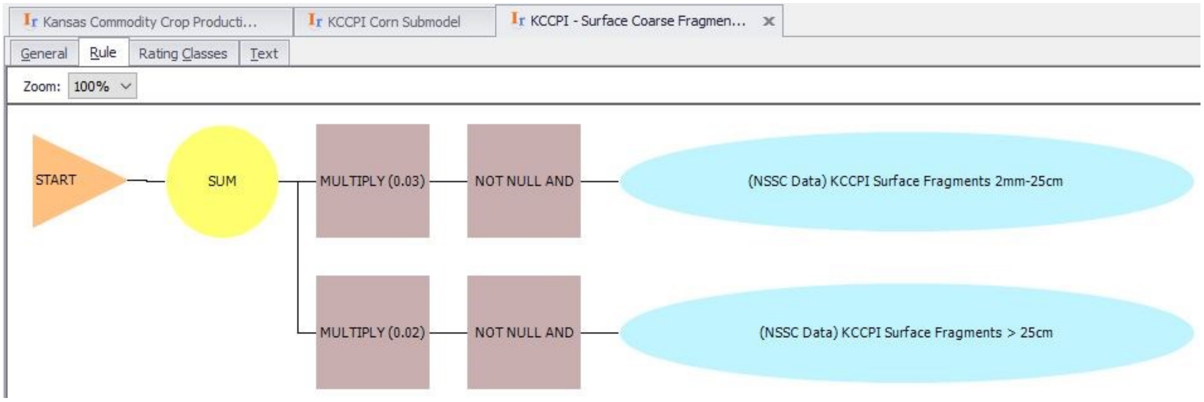

Figure C-12. KCCPI surface coarse fragment subrule.

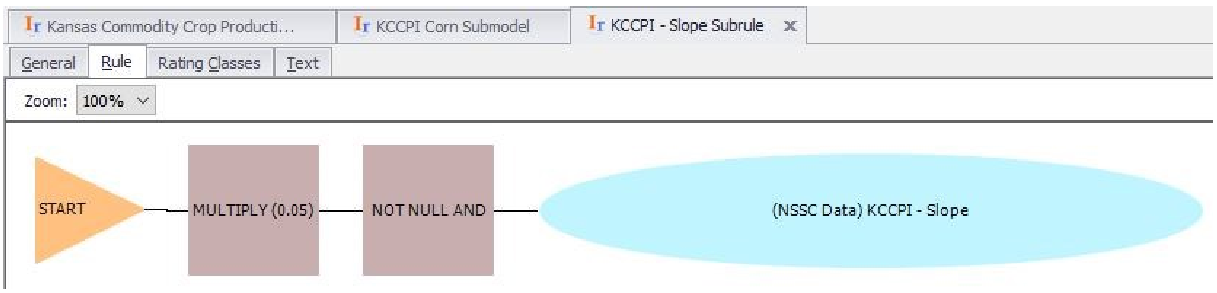

Figure C-13. KCCPI slope subrule.

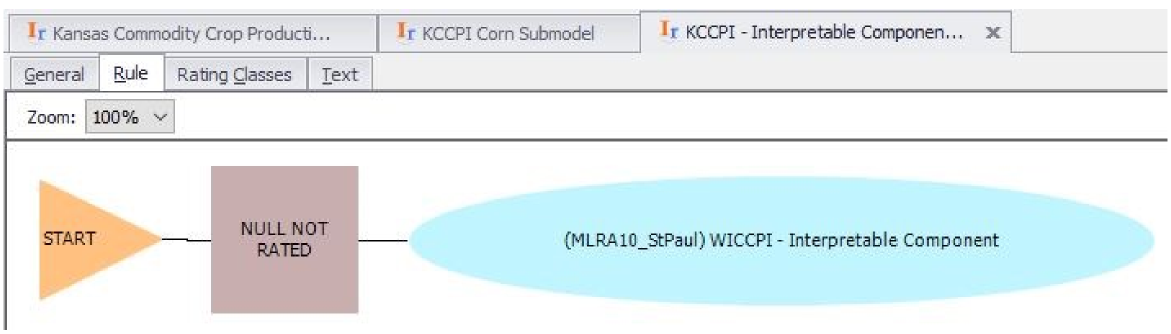

Figure C-14. KCCPI interpretable component.

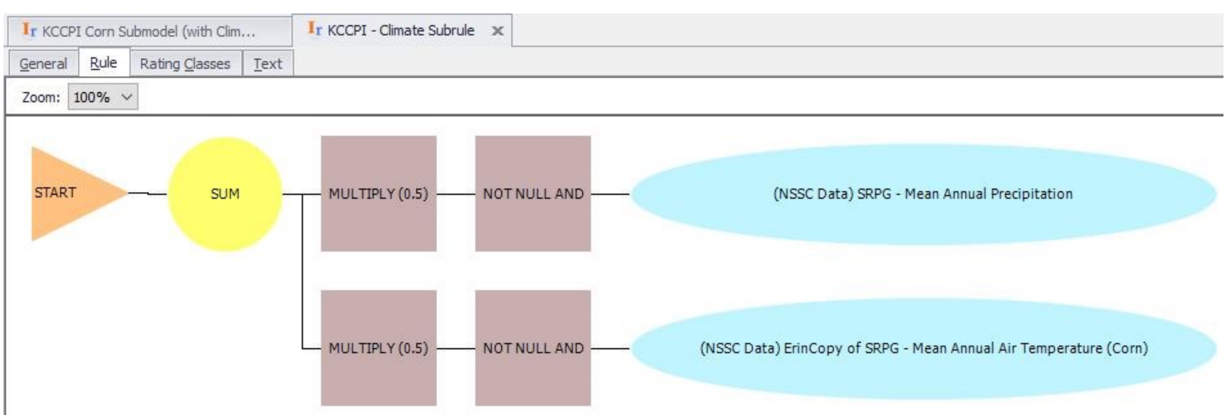

Figure C-15. KCCPI climate subrule.

Appendix D- Example Calculation

Table D-1. Example calculation of the KCCPI for the Brownell soil series reported in Tables 2-3, 2-4, 2-5, 2-6, 2-7. Values reported in columns B and C are high rv values.

A	B	C	D	E	F	G
Property in KCCPI	**Property value**	**Value returned from evaluation**	**Hedge weight factor in subrule**	**C*D**	**Sum of evaluation(s) in subrule (subrule output)**	**Final KCCPI rating (sum of F)**
AWC Sufficiency	0.69 cm	0.407	0.20	0.081	0.081	0.321
pH 0-20cm	7.9	0.140	0.05	0.007	0.023	
pH 20-150cm	8.2	0.104	0.15	0.016		
Depth to bedrock	76 cm	0.135	0.10	0.014	0.020	
Depth to retarding layer	76 cm	0.135	0.05	0.007		
CEC 0-20cm	14.25 meq $100g^{-1}$	0.462	0.06	0.028	0.052	
CEC 20-100cm	12.19 meq $100g^{-1}$	0.605	0.04	0.024		
OM 0-20cm	1.48%	0.487	0.075	0.037	0.042	
OM 20-100cm	0.83%	0.218	0.025	0.005		
CCE 0-20cm	35%	0	0.075	0	0	
CCE 20-100cm	55.4%	0	0.025	0		
Bulk density 0-25cm, low clay	1.45 Mg/m^3	0.281	0.025	0.007	0.030	
Bulk density 0-25cm, high clay	-	1.000				
Depth to high bulk density	120 cm	0.920	0.025	0.023		
Surface coarse fragments >2mm, <25cm	27%	0.595	0.03	0.018	0.038	
Surface coarse fragments >25cm	0%	1.000	0.02	0.02		
Slope	6%	0.700	0.05	0.035	0.035	

Table D-2. Example calculation of the climate-included KCCPI for the Brownell soil series reported in Tables 2-3, 2-4, 2-5, 2-6, 2-7. Values reported in columns B and C are high rv values.

A	B	C	D	E	F	G
Property	**Property value**	**Value returned from evaluation**	**Hedge weight factor in subrule**	**C*D**	**Sum of evaluation(s) in subrule (subrule output)**	**Final climate-included KCCPI rating (F*Table D-1 G)**
MAP	620 mm	0.84	0.5	0.42	0.92	0.30
MAAT	12 ºC	1.00	0.5	0.5		