Temporal Analysis of Soil Degradation in San Joaquin County, California:

A Close Examination of Soil Erosion Using RUSLE

by

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Dedicated to Ray, his family, and my own, for all their love and support.

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Abbreviations

AGNPS	Agricultural Non-Point Source Pollution Model
CA	California
CLU	Common Land Unit
CMIP5	Coupled Model Intercomparison Project Phase 5
C3S	Copernicus Climate Change Service
DEM	Digital elevation model
FAO	Food and Agriculture Organization
GCMs	Global circulation models
GIS	Geographic information system
gNATSGO	Gridded National Soil Survey Geographic Database
IPCC	Intergovernmental Panel on Climate Change
LANDUM	Land use and management
NASS	National Agricultural Statistics Service
NCSL	Non-cumulative slope length
NRCS	Natural Resources Conservation Service
RUSLE	Revised Universal Soil Loss Equation
SLR	Soil-loss ratio
SWAT	Soil and Water Assessment Tool
UN	United Nations
US	United States
USDA	United States Department of Agriculture
USGS	United States Geological Survey

USLE	Universal Soil Loss Equation
Watem/Sedem	Water and Tillage Erosion and Sediment Model
WEPP	Water Erosion Prediction Project
3DEM	3D Elevation Program

Abstract

Critical topsoil is eroding at an alarming rate due to climate change and abrasive farming practices, with the United Nations predicting a catastrophic loss within the next 60 years. Losing nutritious topsoil, also known as soil (or land) degradation, will exasperate climate change and threaten global food security for a growing population that is expected to number at 9.7 billion by the year 2050. The greatest contributor to soil degradation is soil erosion, which is responsible for about 84% of the global extent of degraded land. Within the United States, soil erosion is heavily overlooked in the agricultural sector of Central Valley of California (CA), which is the nation's largest food producing and exporting state. Despite its' importance, the Central Valley has not been seriously evaluated for soil erosion, even though it has been intensely cultivated for agriculture production for more than 70 years.

This project's aim is to understand how differing land management practices in agriculture, combined with climate change factors, can alter processes of soil erosion severity in an agricultural area. Evaluating the county of San Joaquin, CA, future estimates of soil erosion by water are investigating using the Revised Universal Soil Loss Equation (RUSLE) in R and ArcGIS Pro (v.2.8). RUSLE was calculated for the year 2021 for a present-day point of reference and future predictions were calculated for years 2030, 2050, 2070 and 2100. For each year, the RUSLE equation was calculated using three different types of support practices, including: strip cropping, contour cropping and terrace cropping. Results show that when including future precipitation patterns, the practice of strip cropping generates the most severe soil erosion for each study year, with terrace cropping generating the least. Overall, the findings demonstrate that if farmers continue to employ strip cropping as opposed to other conservation-based cropping practices, they will lose necessary nutritious topsoil in just one to two generations.

Chapter 1 Introduction

Soil is one of the most underrated wonders of the planet. In one single gram of soil, there could be as many as 50,000 species cohesively working together to expel and absorb various chemicals, bacteria, and toxins; together, this combination forms a nutritious environment for all life to grow (London 2020). Within this vast microbial ecosystem are cures to insalubrious foods, diseases, climate change, and ample clean drinking water. Many of the major problems threatening society today can truly be resolved by healthier, fully operative soils. However, with a multitude of issues at the forefront of individuals' minds such as social-related causes, water shortages, inflation, etc., soil conditions often go unnoticed or are simply ignored.

Despite its importance, the daunting fact is that soil is dying. Although there are several natural occurrences that contribute to soil degradation such as flooding and wind, the rate of topsoil loss has increased dramatically in the last 200 years (Cho 2012). In recent estimates, it has been suggested that soil has been lost at seventeen times the rate at which it is formed, much of which can be pinned to the intensive cultivation practices and monocropping in industrial agriculture. Considering California's historic role in implementing many of these aggressive farming practices to become the top agricultural producer in the United States (US) (as well as one of the top producers globally), there is a question about the health status of its soils (Desai 2018). Specifically, is soil degradation occurring amongst California's agriculture land and if so, at what rate?

According to Ronald Vargas, the Secretary of the Global Soil Partnership and Land as well as the Water Officer at the Food and Agriculture Organization (FAO) of the United Nations (UN), one of the major factors contributing to soil degradation is erosion, which is exasperated by intensive cultivation practices (UN 2022). Furthermore, the rate of which soil degradation has occurred at other locations (where critical topsoil has already been completely lost), indicates that this process is accelerating faster than what human intervention can potentially mitigate (Handelsman 2021). The combination of soil erosion contributing to soil degradation, the accelerated rate of which such processes are occurring elsewhere, and the contribution of California's agriculture production to the US and the world, makes evaluation of California's agriculture land more imperative than ever for conservation and prevention. This is why critical evaluation of San Joaquin County, which is predominantly agriculture, is an ideal case study for understanding how differing land management practices such as strip cropping, contour cropping and terrace cropping, combined with changing precipitation patterns, can alter processes of soil erosion severity in a relatively flat (little to no slope) area.

1.1. Motivation

Although most people are familiar with the basics of agriculture production, few are aware that ninety-five percent of all food produced today uses soil as its medium (FAO 2015). To date, there are no large-scale, sustainable alternatives to soil and the few that are in production are expensive, energy intensive, and limited in what they can grow. Although many would not consider this a large enough concern to worry, there are many global changes that may require alternative methods for food production. This includes the growth of the global population, which is projected to grow from its current number of 7.7 billion to 9.7 billion people by the year 2050 (FAO 2015). Worsening and more erratic weather conditions/patterns that are turning productive land into arid deserts. A steady increasing of water scarcity. Lastly, a diminishing number of *farmers to population* ratio that is further stressing the few nutrient-leeched farmlands remaining. Considering all of these possibilities, global food security is arguably going to become more dire and severe (Breene 2016).

1.1.1. Securing Soils for Global Food Security

In 1950, the world's population was estimated to be around 2.6 billion people. In 1987, the world's population reached 5 billion and then 6 billion people in 1999 (UN 2022). By 2022, the population was reported to be at 7.7. billion people. As the population has grown, increased demand in yields and food quality have put the worlds' soils under detrimental pressure (FAO 2015). Intensive crop production was required in order to supply the ever larger global population, depleting soil nutrients over time. Certain practices such as annual monocropping – the practice of growing the same crop on the same plot of land, simple crop rotation – the practice of rotating two crops over a period of one year or longer, synthetic fertilizers, pesticide use, factory farm waste (e.g., animal waste from concentrated animal feeding operations that is spread on agricultural fields), tillage – using heavy mechanical farm machinery to tear apart the top layer of soil for seeding, have over the course of decades and in some places, centuries, introduced harmful microbes, antibiotics and other pharmaceutical residues while also altering the microbial landscape of soil (Foodprint 2018). These harmful agriculture practices have decreased beneficial microbes, causing poor plant growth in present day and jeopardizing soils productive capacity to meet the needs of future generations (Foodprint 2018). In the year 2020 alone, nearly one in three people in the world (or 2.37 billion people) did not have access to adequate food, an increase of almost 320 million people from the previous year (UN 2022). At current rates, the amount of food growing today will feed only half of the population by 2050, with demand for food estimated to be 60% greater than what it is now (Breene 2016).

Industrial agriculture's effects on soils are further exasperated by competition for land, as climate change is heating the earth and desiccating nutrient-rich soils. Currently, 40% of the world's landmass is arid and rising temperatures will turn more of it into desert, reducing the amount of available productive soils (Breene 2016). This is magnified by the fact that coastlines around the world are being lost to rising sea levels, further reducing the amount of land available for food production. In addition to this, erratic weather patterns such as stronger and more destructive storms caused by warming temperatures (that cause more water to evaporate from the oceans, transferring energy and water vapor to the atmosphere), are resulting in heavier rains and snows that lead to worsening erosion and landslides (AMNH). By 2050, it is expected that soil erosion specifically may reduce up to 10% of crop yields (FAO 2021), which is roughly the equivalent of removing millions of acres of farmland that could total $23 trillion (UN 2022). It has also been reported that roughly 40% of soil used for agriculture around the world is already classed as either degraded or seriously degraded (the latter meaning that 70% of the nutritious topsoil is already gone), suggesting the current efforts to mitigate soil degradation are failing or simply too late (Crawford 2012). Overall, it is evident that degrading soil conditions are already impacting global food security, creating a state of emergency in many countries around the world.

The availability and accessibility of clean water is also affecting global food security in that 28% of agriculture lies in water-stressed regions (Breene 2016). Currently, it takes 1,500 liters (396 gallons) of water to produce a kilogram (2.2. pounds) of wheat, and about 16,000 liters (4,226 gallons) to produce a kilogram of beef (Breene 2016). As demands for food quantity increase along with higher temperatures, it is estimated that by the year 2050, twice as much water will be needed to sustain agriculture production for the global population (Breene 2016).

Lastly, in industrialized countries, less than 2% of the population grow crops or breed animals for food (Breene 2016). With fewer people entering farming as a profession, there are increased demands on a small group of people to secure enough food annually for the entire population. This pressure, combined with increased production costs and unreliable weather patterns, many farmers are choosing to leave the profession. This is devastating because farmers can play a central role in mitigating global food shortages in that they typically possess generations of agriculture knowledge that are now being loss (FAO 2015). Numerous and diverse farming approaches promote the sustainable management of soils that can improve productivity. However, as the agriculture community shrinks, the use of industrial equipment and chemicals will escalate in efforts to manufacture enough nutritious food to meet a population's caloric needs (FAO 2015).

1.1.2. Soil is Slow Growing and Irreplaceable

Soil is predominately dirt and dirt is everywhere: a large misconception that the planet's soils are an abundant byproduct of weathering processes that are reliable, regenerative and in excess. In simple language, *dirt* and *soil* are two very different things; the former is incapable of sustaining plant life, because it is void of minerals, nutrients, or living organisms. The latter however, contains decayed natural organic materials from leaves, grasses, weeds and tree bark that are essential for plant growth and development. Overall, what is ill-understood in the general population is not just this differentiation but more importantly, how soil is formed, how time-intensive that process is, and how critical the top layer of soil is for food production.

The early phase of soil formation starts with the decomposition of rocks by processes of weathering, including sun exposure, wind and rain. When these processes are combined and reoccurring, they break down the outer elements of the rock over millions and sometimes billions of years. When processes of weathering are aided by consistent temperature fluctuations, cracks and fissures will begin to form throughout allowing water to be captured in the rocks' cavities. As this water undergoes cycles of freezing and thawing, these cracks will slowly widen, allowing for more water to pool and larger surface exposure to wind, rain, and temperature fluctuations.

Pioneer vegetation such as lichens - a complex life form consisting of a fungus and an alga – are then able to settle in the rocks' cavities, allowing their root system to develop and create enough pressure to exasperate disintegration (ISRIC 2022). As the pioneer vegetation undergoes natural processes of growth and decay, the plants' debris will further dissolve the properties of rocks via the production of organic acids from decomposing plant matter. Over time, rock minerals will dissolve (or transform) and release various minerals like iron, which will oxidize and give soil a reddish or yellowish-brownish color (ISRIC 2022). In addition to this, soil flora (such as bacteria, fungi and algae) and fauna (such as protozoa, nematodes, Collembola and acarids) will settle and mix (i.e. homogenize) the soil (ISRIC 2022). It is this combination of mineral and soil flora/fauna accumulation that over the course of centuries and millennia, evolves into an expansive microecosystem teeming with life and nutrients.

In general, it takes about two thousand years to generate around ten centimeters of fertile topsoil (FAO 2015). This rate varies across the globe depending on the climate and topography of the land but overall, soil development is a startingly slow process. To put this into perspective, for farmers to successfully grow and produce the most common varieties of vegetables, they require a soil depth between 30-61 centimeters (11-24 inches) (Larum 2020). Therefore, it takes at a minimum six thousand years for the planet to naturally produce and accumulate enough fertile topsoil for humans to grow basic commodities, such as leafy greens. As a result of soil's slow development, fertile soil is considered to be finite in nature and irreplaceable once it has eroded.

Soil also possesses high amounts of carbon and is the largest terrestrial carbon store, stockpiling collectively three thousand billion tons (Quinton 2014). This has important implications for mitigating climate change (of which will be addressed later in this section) but also is a vital element for all soil functions (Quinton 2014). This is because carbon holds onto and supplies nutrients to all plant life by providing energy (i.e., food) for soil organisms like bacteria and fungi, that in return, produce a glue-like substance that aggregates the different components of soil to make it a stable structure for plant growth (Quinton 2014). In addition to this, carbon acts to increase the soil's available water holding capacity that steadily supplies water to crops (as well as prevent flooding), reducing the amount of irrigation needed for agriculture production (Quinton 2014). Overall, healthy soils supply the essential nutrients, water, oxygen and root support that food-producing plants need to grow and flourish.

1.1.3. Insufficient Technological Alternatives to Farming in Soil

Although there have been some technical advancements such as vertical farming – farming conducted in warehouses with nutrient-rich, soil-free material to grow and sustain agricultural production year-round – such forms of agriculture production require significant upfront investment, higher urban rents (majority of vertical farms are only financial viable near urban centers where farmland is in short supply), and the use of extensive lighting and ventilation systems that are energy intensive, which does not make them a viable alternative to traditional farming (UN 2022). In addition to this, vertical farming is limited in the variety of crops it can grow. Currently, only leafy greens are being produced in vertical farms like Bowery Farming Inc., with some limited exploration into growing sustainable strawberries. However, despite vertical farming advancements, they currently make up a very small portion of the overall agriculture industry (UN 2022). To date, soil is and will continue to be, the foundation for 90-95% of all food production (FAO 2021).

1.1.4. Importance of California's Soils; San Joaquin County Case Study

California is ideally suited for agriculture production. It has a moderate, sunny climate year-round with one of the most notable structural depressions between the Cascade Range to the north, the Sierra Nevada to the east, the Tehachapi Mountains to the south, and the Coast Ranges and San Francisco Bay to the west (USGS n.d.). This natural depression used to be a twenty thousand square mile inland sea that was drained by the Sacramento and San Joaquin Rivers (USGS n.d.). The geological development of this area created exceptionally fertile soils, which when combined with its Mediterranean-like climate and aquifers, made food production profitable, relatively easy, and reliable.

As a result of California's unique geomorphology, more than 250 different crops are grown in the Central Valley with California's farms and ranches receiving over forty-nine billion dollars in cash receipts for their output in 2020 alone (CDFA 2022). In addition to this, California contains fewer than one percent of US farmland but supplies eight percent of US agricultural output (by value). It is the leading agricultural production state in the nation in terms of both value and crop diversity (Desai 2018). Overall, California's agricultural abundance includes more than four hundred commodities and is responsible for the production of one third of the country's vegetables and two thirds of the country's fruits and nuts (USGS n.d.). It is understood that the counties within the San Joaquin Valley specifically, produce more food than any other comparably sized region in the world (Desai 2018). Overall, no other part of the world matches California's productivity per hectare (Desai 2018).

1.2. Study Area

San Joaquin County is the state's seventh largest agriculture producer (see Figure 1) (CDFA 2022). It is smaller than California's other top agriculture producers at 1,426 square miles where, for comparison, Fresno County, which is the top agriculture producer for California, is 6,011 mi². San Joaquin County's smaller size makes a county-wide soil erosion assessment more feasible by geographic information systems (GIS) (US Census Bureau 2022).

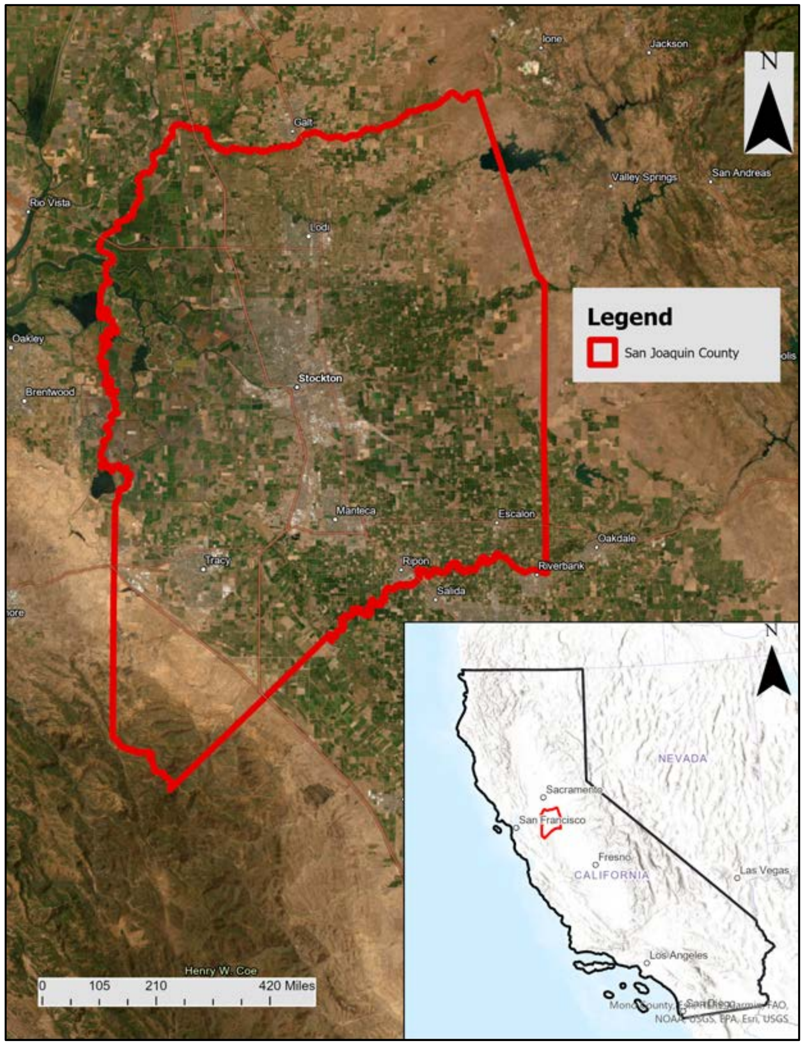

Figure 1. Study area, San Joaquin County in California, USA.

Its location at the northern part of the Valley between the Diablo Range and the Sierra Nevada Mountain ranges provides a unique low inland elevation that creates a very levelled drainage basin for the San Joaquin River and its numerous tributaries (see Figure 2 for an aerial view of the network of levees throughout San Joaquin County) (WEF 2000). This creates an exceptionally high water table that results in a marshy and swampy delta (WEF 2000). This delta has a tendency to flood in the spring as a result from melting snow runoff in the Sierra Mountains (WEF 2000). In addition to this, San Joaquin County is a uniquely flat area that has been used for agriculture production for more than one hundred and twenty years (see Figure 3).

Figure 2. San Joaquin County, CA 2019. (Source: aerialarchives.com)

This makes soil erosion by water an important consideration as it can lead to increased pollution, such as sedimentation in streams and rivers, as well as cause more extreme flooding due to degraded lands inability to hold onto water (see Figure 4) (WWF 2018).

Figure 3. Stockton, CA 2022. (Source: PMZ Real Estate)

Figure 4. The Dos Rios Ranch Preserve on the San Joaquin River, San Joaquin County. (Source: River Partners)

1.3. Project Overview

This project's aim is to understand how differing land management practices in agriculture, combined with climate change factors, can alter processes of soil erosion severity in areas with little to no slope. The approach for this project was incorporating RUSLE to calculate for erosion by water using R and ArcGIS Pro (v.2.8) software. This equation is presented in more detail in Chapter 2.

1.3.1. Project Goal

In conversations with the Natural Resources Conservation Service Office (NRCS) in Stockton, CA on November 4, 2022, Phil Smith, Area Resource Soil Scientist, expressed the difficulty of working with new and generational farmers throughout San Joaquin County, CA, about the importance of soil degradation and employing efforts to mitigate soil erosion. Admittedly, the slope gradient throughout San Joaquin County's agriculture fields typically measures between 1-2%, making soil erosion of little concern to agriculturists and farmers (Smith 2022). As a result, soil erosion by water (or wind) are not heavily evaluated at present-day nor in future climate change scenarios (Smith 2022). This approach is arguably an oversight in that climate change may have unforeseen effects on agriculture lands, even those areas that have traditionally not been highly affected by erosion. Therefore, investigation of agriculture lands is needed for proper evaluation to determine severity of future erosion and to test the influence of mitigation strategies.

1.3.2. Project Methodology

The Revised Universal Soil Loss Equation (RUSLE) is an easily applicable equation that estimates rates of soil erosion caused by rainfall and associated overland flow (USDA 2016). RUSLE uses a particular set of inputs, including: rainfall erosivity (R), soil erodibility (K), Slope length and steepness (LS), crop cover (C), and land management practices (P) (USDA 2016). The RUSLE equation was selected for this thesis as it is one of the most well-researched and most widely used calculations for soil erosion by water (USDA 2016). However, it must be clarified that the NRCS no longer maintains RUSLE factors for public use since they adopted

RUSLE2 in 2004 (Ferruzzi 2022). RUSLE, also known as RUSLE 1 or RUSLE 1.05, required the entry of factors like its predecessor, the Universal Soil Loss Equation (USLE). With RUSLE2, the user inputs the management information (along with other site information like soil map component, slope length, slope steepness, etc.) and the program calculates for all factors (R, K, LS, C, and P) on a daily basis and reports average annual values (Ferruzzi 2022). Despite the advantageous of this software, many researchers still use the basic RUSLE model for its ease of use over spatial environments (Ferruzzi 2022).

Processes of data selection and implementation of RUSLE calculations are conducted in both RStudio and ArcGIS Pro software programs. RUSLE was calculated for the year 2021 for a present-day point of reference and future predictions were calculated for years 2030, 2050, 2060 and 2100. For each year, the RUSLE equation was calculated using three different types of support practices (P factor), including: strip cropping (e.g., traditional lined cropping), contour cropping (e.g., tilling sloped land along lines of consistent elevation) and terrace cropping (e.g., growing crops on sides of hills or mountains by planting on graduated terraces built into the slope). All factors' values were inputted into the RUSLE equation in R and calculated together using all three scenarios to generate soil erosion rates by tons per acre annually. Raster outputs were evaluated and analyzed to determine future soil erosion conditions considering climate changes.

1.4. Remainder of Thesis Document

In Chapter 2 of this work, various publications and studies on RUSLE are presented and evaluated considering how to implement the RUSLE equation and its overall effectiveness. In Chapter 3, the methodology is presented specifying the application and implementation of the RUSLE equation, along with a link to Github, that provides free viewing access to all R code utilized in this project. The results from the calculations are presented in Chapter 4 with maps for viewing and comparison. The conclusion of this project in Chapter 5 provides a discussion about the results and future parameters that could potentially be beneficial for future soil degradation research and prevention.

Chapter 2 Related Work

The UN's Food and Agriculture Organization (FAO) has repeatedly stated that soil erosion by water and wind comprise the two most significant threats to soils (FAO 2017). Soil erosion studies have been conducted around the world using a multitude of calculations and models since the 1950s. There is sparse research and literature which employ GIS-based soil erosion evaluations of agriculture lands in the Central Valley of California, specifically San Joaquin County. Below are synopses of some of these works and their contributions to this paper's research approach and methodology implementation. Specifically, this includes: understanding how land management, climate change and soil erosion affect one another; the different ways to model soil erosion; and lastly, a breakdown of the RUSLE equation and how each input is calculated.

2.1. Modeling Soil Erosion

Soil is the essential resource for human security, including climate and food security, in the 21st century (Amundson et al. 2015). The present-day condition of most of the world's soils is fair, poor, or very poor (FAO 2015). Soils have only recently been given critical attention towards the end of the 19th century, with few tools to properly analyze and calculate for processes of its condition and erosion (Alewell 2019). Beginning in the mid-20th century, the possibility to model and predict soil erosion on large scales became more feasible, with first studies published in international journals more than seven decades ago using North American data sets (Alewell 2019). The majority of these models are categorized as empirical (based on experiments and observations), conceptual (soil erosion estimates derived from plot-based evaluations), physically-based or process-oriented (based on the region and topography of the study area) and are capable of measuring soil erosion at different spatial and temporal scales (Alewell 2019).

Many erosion models possess a combination of these categories. Within the soil science and GIS fields, researchers and analysts have been attempting to improve the applicability of complicated, process-oriented models. Such models include: the Water Erosion Prediction Project (WEPP), which estimates soi erosion on hillslopes and watersheds by taking into account climate, land use, site disturbances, vegetation, and soil properties (Morgan & Nearing 2011); the European Soil Erosion Model, a dynamic distributed model for simulating erosion, transport and deposition of sediment over the land surface by interrill and rill processes (Morgan et al. 1998); and the Universal Soil Loss Equation (USLE), which predicts the long-term average annual rate of erosion on a field slope based on rainfall pattern, soil type, topography, crop system and management practices (Di Stefano et al. 2017).

Of the proposed models, USLE and the revised USLE (referred to as RUSLE), are by far the most widely and universally-applied soil erosion prediction models that have been, and continue to be, utilized for a variety of purposes and under various conditions mainly because it meets the needs of researchers more effectively than any other tool (Risse et al. 1993). The details of the RUSLE are explained in section 2.2. The RUSLE Model.

2.2. The RUSLE Model

USLE/RUSLE models were originally developed in the US to assist researchers, urban developers, conservationists, etc. in management decision by creating a support tool (Alewell 2019). The USLE/RUSLE tool was at its origin, based on thousands of controlled studies that took place in small watersheds and on field plots and beginning in 1930 (Wischmeier & Smith, 1965). The model concept is based on understanding the process of soil erosion by incorporating measurable parameters that can accurately simulate this process using a mathematical algorithm that can generate a measured result (Alewell 2019).

As stated previously, the RUSLE is defined as:

$$A = R * K * L * S * C * P \quad (1)$$

where: A (A in $t \cdot ha^{-1} \cdot yr^{-1}$) is the annual average soil erosion, R ($MJ \cdot mm \cdot ha^{-1} \cdot h^{-1} \cdot yr^{-1}$) is the rainfall-runoff erosivity factor, K ($t \cdot ha \cdot h \cdot ha^{-1} \cdot MJ^{-1} \cdot mm^{-1}$) is the soil erodibility factor, L (dimensionless) is the slope length factor, S (dimensionless) is the slope steepness factor, C (dimensionless) is the coverage of the soil by plants, P (dimensionless) is the conservation practices factor (Renard et al., 1997).

The R-factor is included as one of the inputs in the USLE model using a logarithmic function between Kinetic Energy (KE) and Intensity (I) plus a constant value for intensities exceeding 76mm h^{-1} (Wischmeier & Smith, 1978). In general, RUSLE uses the proposed exponential relationship for estimating the unit rainfall energy (er) based on rainfall intensity (ir) (Alewell 2019):

$$E_r = 0.29\left[1 - 0.72e^{(-0.05ir)}\right] \quad (2)$$

There are additional equations that can be utilized for calculating rainfall erosivity such as erosivity (EI_{30}) of a single event (Renard et al., 1997). However, for the purposes of this project, the relationship of Moore is utilized as it does not differentiate between broad regions such as coastal zones, low lands and the plateaus but maintains a more generalized approach to rainfall erosivity and is driven by long-term precipitation amounts (Schuerz and Herrnegger 2019). The equation of Moore includes the same calculations are explained in Chapter 3, section 3.1.2. for how it was implemented in R.

The K-factor, soil erodibility, is regarded as the amount of soil loss per unit erosive force with K equal to A/R (Renard et al., 1997). The variable K was originally an empirical value based on 20 years of data that took place on experimental plots using 23 major soil types within the US, that were kept fallow for at least two years and all other factors kept constant (Wischmeier & Smith, 1965). Since the direct measurement of the K-value required such extensive observation periods at numerous locations, calculating the K-factor was simplified (Alewell 2019). Instead, the newer K variable includes only the most crucial parameters: particle-size, percent organic matter, soil structure and soil permeability (Wischmeier et al., 1971). The approximation equation for calculating the K-factor is as follows (Wischmeier & Smith, 1978):

$$K = 2.77 \times 10^5 \times M^{1,14} \times (12 - a) + 0.043\,(b - 2) + 0.033\,(4 - c) \qquad (3)$$

where M is the particle-size parameter, multiplied by the quantity (with the quantity defined as what percentage of the soil is clay), a is the percent organic matter, b is the soil-structure code used in soil classification, and c is the profile-permeability class (Wischmeier and Smith 1978). Again, there are other versions of this equation that include other considerations, such as: the effect of surface stones, the seasonality effects of freezing and thawing of the land, or life stock trampling (Alewell 2019). However, for the purposes of this project, soil erodibility layer was downloaded from the US Soil Survey Geographic database which utilizes the traditional USLE equation (Esri 2022).

The LS-factor represents the effect of topography of soil erosion, which is usually considered by the factors slope length (L) and slope steepness (S) (Alewell 2019). Soil loss is easily affected by slope steepness and much less affected by slope length, (McCool et al. 1987).

Slope steepness (S) is derived empirically where S = slope gradient in percent, using the following calculation (Esri 2022):

$$slope_{degrees} = ATAN\left(\sqrt{\left(\left[\frac{dz}{dx}\right]2 + \left[\frac{dz}{dy}\right]2\right)}\right) * 57.29578 \qquad (4)$$

where “slope is computed as the rate of change (delta) of the surface in the horizontal (dz/dx) and vertical (dz/dy) directions from the center cell to each adjacent cell and the value 57.29578 is a truncated version of the result from 180/pi” (Esri 2022). Slope length (L) is defined as the point where the surface flow travels to a point where the slop gradient (S) decreases enough for deposition (of water, soil, etc.) to become measurable or to the point where the flow becomes concentrated in a specific channel (Wischmeier and Smith 1978).

Calculating slope length is more complicated. Originally, a method was developed in the original USLE dividing irregular slope into a number of uniform segments and accounting for the effect of the shape of the slope on soil loss (Foster and Wischmeier 1974). This resulted in the L-factor as the ratio of field soil loss from a 22 meter slope, expressed as:

$$L = \left(\frac{\lambda}{22.1}\right)m \qquad (5)$$

where λ is field slope length in meters and m is a factor that varies with slope gradient in the ratio of rill (the number of small channels that form as a result of the rate of runoff) to interrill (the regions between the rills/channels) erosion in the RUSLE (Wischmeier and Smith 1978). This method however, is extremely time consuming and impractical when working with multiple slopes or over a large spatial scale (Alewell 2019). Instead, a multiple flow algorithm is implemented by RUSLE which improves the overall method however, it still does not account for variability the flow path and is incapable of being able to provide a deposition site (Karydas et al., 2014). To resolve this, there have been multiple algorithms implemented to calculate up or down various slopes to derive slope lengths (Alewell 2019). For this project, the single-direction flow algorithm is utilized, which calculates the upstream or downstream distance along the flow path for each cell (O'Callaghan and Mark 1984). This tool is applicable because it can be used to "create distance-area diagrams of potential rainfall and/or runoff events, using the weight raster as an impedance to movement downslope" (Esri 2022). The combination of slope steepness and slope length can be combined in the Flow Accumulation tool, which has been used to identify stream channels (that can also represent soil channels) by calculating cells with a high flow accumulation areas and concentrations of flow (Esri 2022).

The C-factor, cover or crop management, in the RUSLE equation measures the effects of biomass cover and soil-disturbing activities by specifically measuring the combined effects of the different types of soil cover and management actions on soil erosion (Wischmeier and Smith, 1965). It is expressed as the ratio of land managed under certain conditions to the loss of soil from clean-tilled, continuous fallow land, over a certain period of time, calculated as (Alewell 2019):

$$SLR = R \times K \times L \times S \qquad (6)$$

It should be noted that the C-factor calculations can vary in that C-factor values, or measurements, highly depend on the specific stage of vegetation growth (how rooted they are) and how the vegetation cover was implemented at the time the rain event (Alewell 2019). As of today, current tables of SLR values are no longer provided in the State of California (Alewell 2019). The combination of the arduous nature of obtaining accurate C-factor values (requiring numerous field samples, across long periods of time, from multiple storm events), along with the fact that government agencies are no longer proving such information, required this project to find alternative resources for C-values. It was recommended by Giulio Ferruzzi, FPAC of the NRCS, Portland, OR office to utilize results from the Land Use and Management (LANDUM) model that estimated the soil erosion cover-management factor at the European scale (Panagos et al. 2015). This model differentiated between arable lands and all other *land uses* as well as excluding artificial areas, wetlands, water bodies, bare rocks, beaches and glaciers (Panagos et al. 2015). The C-factor for the LANDUM model is calculated as:

$$C_{arable} = C_{crop} \times C_{management} \quad (7)$$

where C_{crop} is the crop composition of an agricultural area and $C_{management}$ calculates the influence of management practices such as on soil erosion reduction (Panagos et al. 2015).

Lastly, the P-factor, supporting conservation practices, are an important factor in mitigating soil erosion by redirecting runoff around the slope, generating less erosivity (or slowing down soil runoff) (Renard et al., 1997). It is arguably the most critical factor because it is the one factor that farmers and government policies have the most control over (Johnson 2017). The major factors considered in estimating the P-factor value are: erosivity and transport capacity of the runoff, runoff rate (based on location), slope steepness, hydraulic roughness of the surface and sediment size and density (Renard et al. 1997). Based on studies evaluating the effectiveness of various kinds of cropping or cultivation systems, it has been found that cultivation practices such as contour cropping (cultivation done on or near the contour of the field) or terrace cropping (cultivating by cutting a series of flat platforms into a sloped plane), are the better method for erosion control than traditional strip cropping (where the planting of different crops are sown in alternate strips to prevent soil erosion) (Johnson 2017). Terracing was found to be the ideal method based on not only its ability to better improve erosion control but also, in the yield potential of the crops cultivated, which increases in terrace farming (Johnson 2017). For the purposes of this project, these three cultivation practices are assigned decreasing values in subsequent order based on the severity of their impact on agricultural lands. This follows as:

Table 2. Cultivation Practices Assigned Values.

Type of Cropping System	Value Assigned
Strip	1
Contour	0.35
Terrace	0.25

These values are inputted into the RUSLE calculation as the last factor to generate RUSLE values of soil erosion in tons/per acre/per year.

2.3. Reason for Selecting RUSLE

It should be addressed that there are other, well-known models based on USLE/RUSLE equation that have been utilized in other soil erosion research. One is the Soil and Water Assessment Tool (SWAT), which is a free and open source hydrology model that is sponsored by the USDA. It is known for its small watershed-to-river basin scale modeling by simulating the quality and quantity of surface and ground water and predicts the environmental impact of land use, land management practices, and climate change on soil erosion totals (Arnold et al. 1998). Another USLE/RUSLE-based model is the AGricultural Non-Point Source Pollution Model (AGNPS), which is a joint USDA-Agricultural Research Service and Natural Resources Conservation Service system of computer models developed to predict the diffused contamination of water-source pollutants within agricultural watersheds (Bosch et al. 1998). In addition to these models is the Water and Tillage Erosion and Sediment Model (Watem/Sedem), that explores the spatial pattern of sediment sources, erosion hotspot areas, and annual sediment delivery (Van Rompaey et al. 2001). Lastly, is the Chinese Soil Loss Equation, which calculates the loss of soil for each spatial unit in a ten by ten meter grid using GIS (Liu et al. 2002).

Although there are numerous RUSLE-based models that could have been employed for this research (such as those previously listed), the basic RUSLE model was the best choice for the research conducted in this thesis. The predominant reasons for this are because of RUSLE's world-wide applicability due to its' overall flexibility: specifically, it can be utilized on a larger area and not limited to a small area consisting of one slope, for example. The RUSLE possesses extensive data accessibility that is generally from authoritative sources and publicly available. The equation maintains limited parametrization, so an excess amount of data is not required to gain a general understanding of soil erosion possibilities for the study area. Lastly, there are already considerable scientific literature available for this equation and because of the amount of literature available, it is easy to compare multiple results across a wide-range of studies (Alewell 2019). Collectively, these reasons have made the model immensely adaptable to a multitude of regions around the world and under varying conditions (Alewell 2019).

Despite its advantageous and wide-use applications, the USLE/RUSLE approach is an empirical modelling approach that still possesses limitations, such as the lack of simulation of soil deposition (e.g., sedimentation) and measured data to better determine the USLE/RUSLE factors for all specific situations and scenarios (Wischmeier and Smith 1978). Lastly, it is unknown if the research and development from 1965 to present-day has truly resolved or even improve these limitations enough to be able to apply the model algorithm to large scales, under which conditions and at what resolution (Alewell 2019).

2.4. Land Management, Climate Change and Soil Erosion

The relationship between land use and climate change is notable and highly intricate. In regards to the potential for soil erosion by water, when combined with climate change factors and standard industrial agriculture practices, the models display substantial increases in total global soil erosion (Borrelli et al. 2020). Notably, the models also display conservative decreases in soil erosion when models account for climate change factors combined with mitigating land management strategies (Borrelli et al. 2020). Today, Earth's land surface is comprised of around thirty-eight percent agriculture lands, an anthropogenic activity that serves as the predominant driver of soil erosion globally (Borrelli et al. 2020). Contemporary society continues to rely on traditional soil-based agriculture practices in the midst of growing and transformative weather patterns, with future climate projections suggesting a trend towards a more robust hydrological cycle, potentially increasing global water erosion by thirty to sixty-six percent (Borrelli et al. 2020). Modeling soil erosion at any scale is challenging because physical models are highly data intensive and unfortunately sparse, forcing many researchers to adopt a semiempirical approach to understand contemporary conditions and create a pragmatic approach to altering any anthropogenic impacts (Borrelli et al. 2020). Despite these difficulties however, researchers have found after testing for alternative scenarios (different weather patterns in concert with various kinds of land management practices), soil erosion can be mitigated using sustainable land management techniques along with policy changes (that accommodate for climate change) in order to prevent excessive future erosion (Borrelli et al. 2020).

To date, only a small percentage of all global arable land is categorized as "conservation agriculture" at around eleven percent to fourteen percent or roughly 1.42 billon hectares (FAOSTAT 2019). If traditional practices in soil treatment were to continue without any selfinitiated conservation efforts from the agriculture community or via government policy incentives, recent models estimate that the total annual global cumulative soil erosion is around forty-three picograms (Pg) annually (yr^{-1}) (Borrelli et al. 2020). This is arguably a conservative estimate in that other scientific research have found higher assessments for annual global soil erosion using similar modeling approaches, including: fifty Pg yr^{-1} (UN FAO 2015), one hundred and thirty-two Pg yr^{-1} (Yang et al. 2003) and one hundred and seventy-two Pg yr^{-1} (Ito 2007). Annual crops alone (e.g., watermelon, corn), which account for only sixteen percent of agricultural land cover around the globe in 2015, were estimated to be responsible for forty-one percent of that year's annual soil erosion (Borrelli et al. 2020). Altogether, agricultural lands that produce annual crops, permanent crops (e.g., fruit trees) and managed pastures are responsible for roughly fifty-four percent (or roughly twenty-three Pg yr^{-1}) of all global soil erosion (Borrelli et al. 2020). To mitigate these current projections, the models currently suggest that more resilient agricultural systems comprised of conservation agriculture practices would have to increase to sixty percent of all global arable land (Borrelli et al. 2020).

Many of these models stress the importance of land use but overall, current modelling projections indicate that climate change is likely to be the predominant driver of change in global soil erosion totals (Borrelli et al. 2020). For example, the REMIND-MAGPIE and the SSP1-RCP 2.6 models simulate future agricultural land use to decrease globally, demonstrating that this scenario combined with climate change projections will increase soil erosion by more than thirty (Borrelli et al. 2020). In the SSP2-RCP 4.5 model, which simulates future agricultural land use to increase (as a result of population growth), the projected outcome of soil erosion is likely to increase by more than fifty-one percent (Borrelli et al. 2020). Most alarming is the SSP5- RCP 8.5 model, which also simulates future agricultural land use to increase as well as higher greenhouse gas emissions, demonstrating global soil erosion increases by more than sixty-six percent or around seventy-one Pg yr^{-1} (Borrelli et al. 2020). The reasoning for the different predicted global soil erosion totals are due to considering the effects or results of variation in human/societal development (Borrelli et al. 2020). The SSP1-RCP2.6 for example (mentioned above), is a scenario in which humanity successfully prevents global mean temperature increase to a maximum of two degrees Celsius by the year 2100, as well as a global reorganization of land use, converting current agricultural lands to forests or semi-natural vegetative areas (Borrelli et al. 2020).

In addition to this, the models also address uncertainties in regards to how abrasive rainfall erosivity is likely to be in the future and in what areas of the world. For example, rainfall is likely to be more destructive in areas around the equator and less severe in areas located in the northern hemisphere. Although future land use will arguably affect soil erosion via the expansion or contraction of croplands, preliminary climate analyses from these models are predicting stronger hydrological cycles in the future (Borelli et al. 2020). Research has revealed that global warming will intensify hydrological cycles by “altering the rate of water fluxes to and from the terrestrial surface”, which will result in an increase in the size, velocity and frequency of raindrops and longer dry spells (Flickin et al. 2022, 1). Global rainfall surplus events will increase between eleven percent and eighteen percent for moderate and high emission scenarios and the duration between such events will become notably longer, between five percent and nine percent, by the end of the century (Flickin et al. 2022). In addition to this, the greatest change will occur in the northern latitudes and that between the years 2070-2100, more than one-third of those years will be “hydrologically intense... tripling that of the historical baseline” (Flickin et al. 2022, 1).

The climate models and land use scenarios findings are further supported by current research by the UN Convention to Combat Desertification's Intergovernmental Panel on Climate Change (IPCC), which is the UN's body for assessing the science related to climate change. The IPCC was created to provide policymakers with necessary information to determine implications and potential future risks, as well as to create adaptation and mitigation models for climate-change preparation and prevention (IPCC 2019). According to their findings, drylands currently cover around forty-six percent of the planet and by 2015, desertification "hotspots" had extended into new drylands by nine percent (Mirzabaev 2019). Specifically, they found that desertification, specifically land degradation by soil erosion, is exasperating the disintegration of all ecosystems across the globe and contributing to a particularly brutal cycle where, as ecosystems break down, the broken ecosystem both contributes to and is simultaneously affected by climate change. The IPCC state's that this process is fueling the overarching destabilization of the climate (IPCC 2019). The report also cites that agriculture is the dominant sector contributing to land degradation via soil erosion and that soil erosion from conventionally tilled land exceeds the rate of soil formation by more than two orders of magnitude, with soil loss outpacing the earth's ability to replace or regenerate it (IPCC 2019). The IPCC confirms that global soil erosion is occurring as a result of agricultural practices and based on the majority of models, will become worse. This makes modeling soil erosion on a larger scale and for future climate-change scenarios more critical than ever in allowing time for societal changes. Specifically, it allows government agencies time to create and implement land use policies/changes that can mitigate soil loss, preventing subsequent problems such as complete land degradation, food shortages and pressure on city/state infrastructures.

Chapter 3 Methodology

This chapter outlines the methods used in this study to determine future estimates of soil erosion from water in San Joaquin County, CA, using the RUSLE equation (see Chapter 2 for more information). Specifically, this chapter details the data acquisition, processing, RUSLE calculation, and future projections of RUSLE as well as how data was processed and analyzed in ArcGIS Pro (v2.8) and R (v2022.02) (see Figure 5 for methodological workflow and Table 2 for all data sources). RUSLE was calculated for 2021 for a present-day point of reference, and future predictions were calculated for years 2030, 2050, 2070 and 2100. For each year, the RUSLE equation was calculated using three different types of support practices (P factor), including strip cropping (e.g., traditional lined cropping; see Figure 3 for visualization), contour cropping (e.g., tilling sloped land along the lines of consistent elevation) and terrace cropping (e.g., growing crops on sides of hills or mountains by planting on graduated terraces built into the slope). The purpose of adding different support practices is to determine the severity of soil erosion by water due to agricultural practices combined with climate change in a flat (little to no slope) area. All data maintained its original resolution during processing and resampled to 30 meters before inputted into the RUSLE calculations. In addition to this, all data were computed using that data's original projection to ensure accuracy and then reprojected into NAD83/California zone 3 (ft US) after the completion of the RUSLE equations. The data and code created and utilized for this project can be accessed from this GitHub repository: (https://github.com/staceyj3088/soil-erosion-in-san-Joaquin). The results are further described in Chapter 4 Results and further discussion of the topic is conducted in Chapter 5 Discussion.

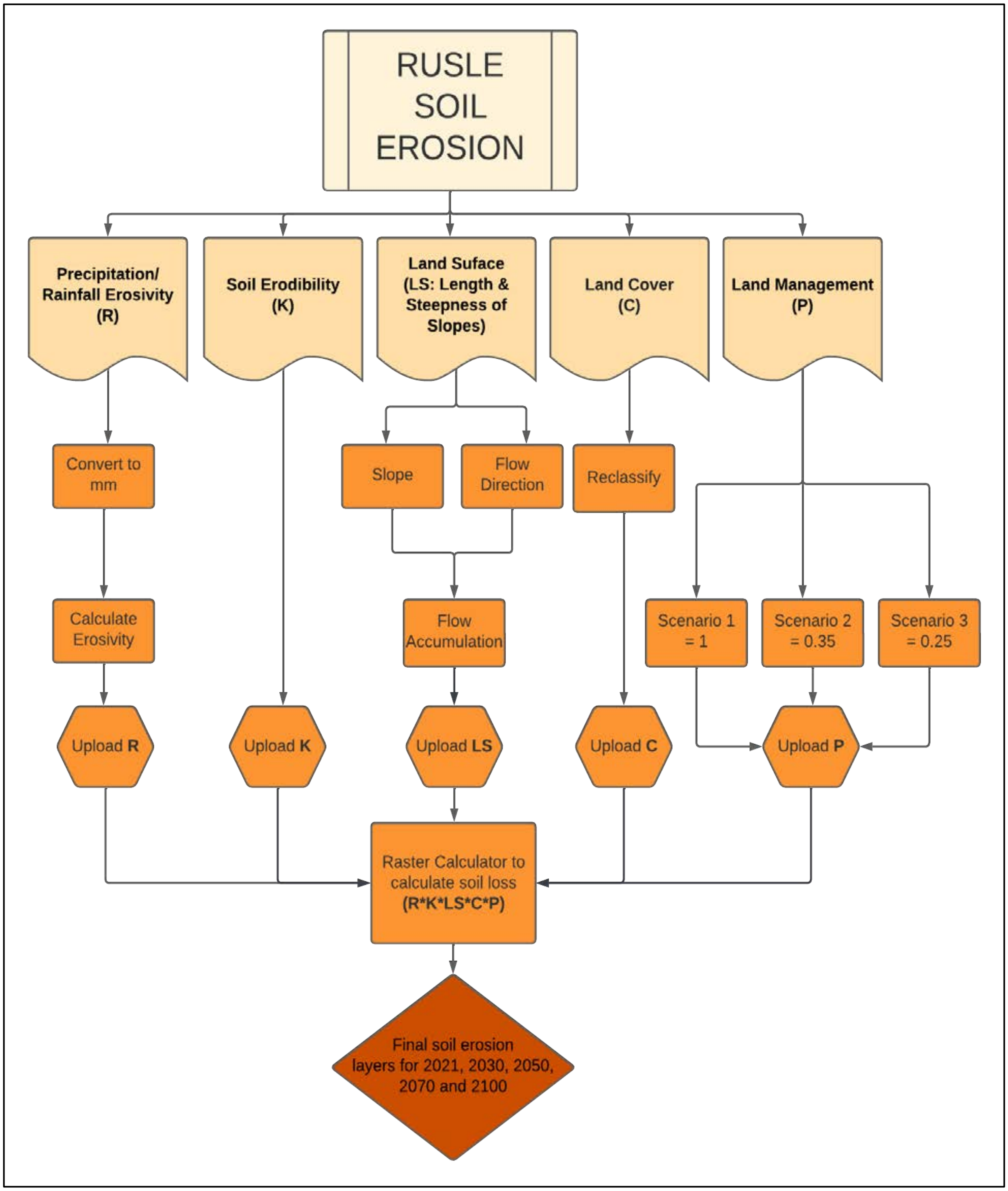

Figure 5. RUSLE soil erosion methodological workflow.

Table 3. Data table for RUSLE calculations.

Purpose	Dataset Name	Format	Source	Temporal Scale	Spatial Scale	Spatial Resolution
Rainfall for Erosivity (R-factor)	Global Bioclimatic Indicators from 1950 to 2100 Derived from Climate Projections	geoTIFF	Copernicus Climate Change Service (C3S)	2021, 2030, 2050, 2070, 2100	California, USA	4 km
Soil Erodibility (K-factor)	USA SSURGO Erodibility Data	shapefile	Gridded National Soil Survey Geographic Database	2017	California, USA	30 m
Topographic Steepness (LS-factor)	1/3rd arc-second Digital Elevation Models (DEMs) - USGS National Map 3DEP Downloadable Data Collection	geoTIFF	U.S. Geological Survey (USGS) National Geospatial Program	2022	San Joaquin County, USA	10 m
Crop/land Cover (C-factor)	2021 California Cropland Data Layer | NASS/USDA	geoTIFF	*U.S.D.A. National Agricultural Statistics Service CropScape Data*	2021	San Joaquin County, USA	30 meters

3.1. Rainfall Erosivity (*R* Factor)

The R-factor is one of the parameters used by RUSLE to estimate annual rates of erosion by calculating rainfall-runoff erosivity.

3.1.1. Copernicus Data

Precipitation data were collected from the *Copernicus Climate Change Service (C3S)*, which is one of six thematic information services provided by the *Copernicus Earth Observation Programme of the European Union* (Wouters et al. 2021). C3S is an operational program that builds on existing authoritative global research about the past, present and future climate (Wouters et al. 2021). The dataset utilized is titled *Global Bioclimatic Indicators from 1950 to 2100 Derived from Climate Projections*, which provides a complete set of global bioclimatic indicators derived from *Coupled Model Intercomparison Project Phase 5 (CMIP5)* climate projections at a resolution of 0.5° x 0.5° (i.e., 4 km) on a latitude-longitude grid (Wouters et al. 2021). The data utilizes the average rainfall measured in meters per second (converted into mean millimeters per year) (Vanuytrecht et al. 2021).

The data has been calculated based on daily CMIP5 climate projections from 10 different global circulation models (GCMs), including access1-0 (r1i1p1), bcc-csm1-1-m (r1i1p1), csiro-mk3-6-0 (r1i1p1), gfdl-esm2m (r1i1p1), hadgem2-cc (r1i1p1), hadgem2-es (r2i1p1), ipsl-cm5a-lr (r1i1p1), ipsl-cm5a-mr (r1i1p1), ipsl-cm5b-lr (r1i1p1) and noresm1-m (r1i1p1) (Vanuytrecht et al. 2021). The data has been additionally bias-corrected against ERA5 reanalysis data (ERA5 is a fifth-generation *European Centre for Medium-Range Weather Forecasts* reanalysis for the global climate; an independent intergovernmental organization supported by most of the nations of Europe) (Vanuytrecht et al. 2021).

The primary variable utilized from this dataset is the *Annual Precipitation (BIO12)*, which includes the annual mean of the daily mean precipitation rate (both liquid and solid phases) (Vanuytrecht et al. 2021). See Figure 6 for a visualization of original Copernicus rainfall data.

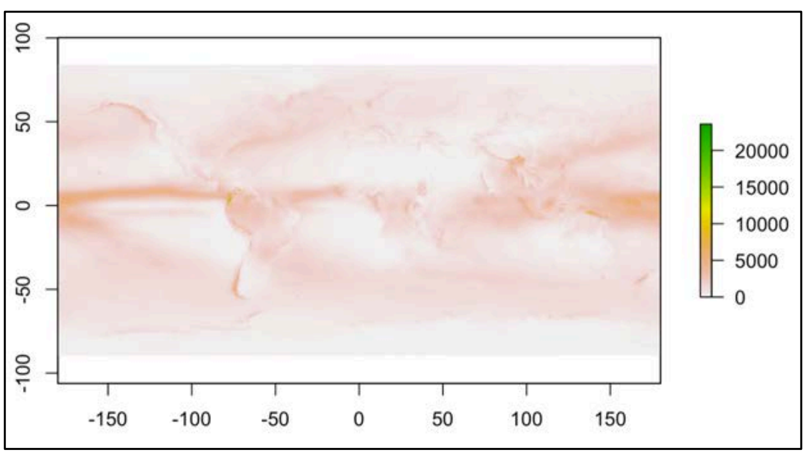

Figure 6. Copernicus Climate Change Service Precipitation data before processing.

3.1.2. Data Processing

Precipitation rasters were processed in *R* using the *raster* package (Hijmans et al. 2022). First, to compute total annual precipitation (mm year^{-1}), a conversion factor of 3600 x 24 x 365 x 1000 was applied. After that, the precipitation raster was cropped and masked to the state of California, using the *crop* and *mask* functions in the raster package (Hijmans et al. 2022). The masked raster was then resampled from 4 km to 30 m using the *resample* function (Hijmans et al. 2022). After resampling, the rasters were further cropped and masked to the boundary of San Joaquin County for subsequent processing.

Rainfall erosivity (R factor) was calculated using the Moore method. The R factor is an index of rainfall erosivity that calculates the potential capacity of rain to cause erosion by factors such as amount, intensity, velocity, drop size, and its distribution (Renard et al. 1997). This method was implemented here because the equation does not differentiate between Coastal zones, lowlands and plateaus regions, allowing for flexibility in various kinds of precipitation datasets, especially those containing future predictions (Schuerz and Herrnegger 2019). The method/equation of Moore in R code is as follows:

$$ke < -11.46 \times p - 2226$$

$$r < -0.029 \times ke - 26 \qquad (9)$$

$$r_{si} < -17.02 \times r$$

where *ke* is the kinetic energy, p is annual precipitation, *r* is annual rainfall erosivity and r_{si} is the conversion from imperial units to the International System of Units (see Figure 7) (Moore 1979). The resulting rainfall erosivity layer was then masked to agriculture-only designated land in San Joaquin County using the CropScape data layer (see section 3.4). This was done as the last step in processing to ensure data accuracy throughout the processing, especially when calculating for continuous data such as rainfall. Lastly, the agriculture-only masked rainfall erosivity layer was then inputted into the RUSLE calculations.

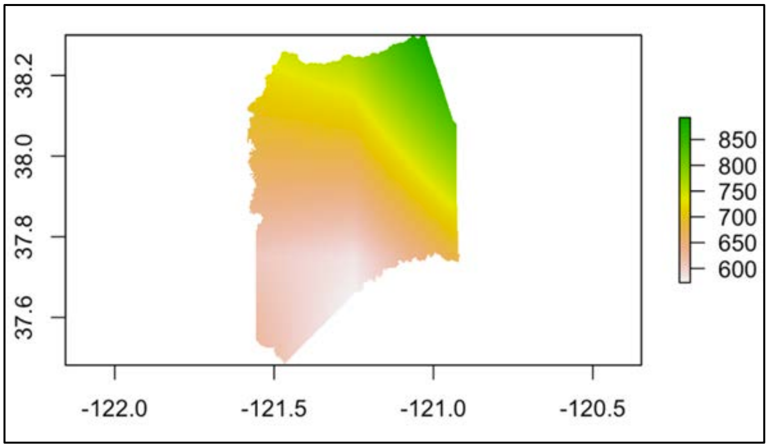

Figure 7. Precipitation raster in R, after rainfall erosivity calculation and before agriculture-only masking.

3.2. Soil Erodibility (*K* Factor)

The K-factor is one of the parameters used by RUSLE to estimate annual rates of soil erodibility by calculating the predisposition of soil particles to detachment and conveyance by rainfall and surface runoff.

3.2.1. USA SSURGO Erodibility Data

Soil erodibility data was collected from Esri's ArcGIS Pro portal, which provides free publicly-available data for download. Data to produce the erodibility layer was derived from the *Gridded National Soil Survey Geographic Database (gNATSGO)*, which is a USDA NRCS Soil & Plant Science Division composite ESRI file geodatabase that provides complete coverage of the best available soils information for all areas of the US and Island Territories (Soil Survey Staff 2022). This layer is derived from the 30 m (contiguous U.S.) and 10 m rasters (all other regions) produced by the NRCS and the final raster is in 30 m resolution (Esri 2022). This layer was published in 2017 and was last updated in February 2022 (Esri 2022).

According to the ArcGIS Living Atlas explanation, the soil erodibility factor (K factor) values (t ha h ha^{-1} MJ^{-1} mm^{-1}) for San Joaquin were computed by choosing the least transmissive horizon (Esri 2022), which is any soil horizon that transmits water at a slower rate relative to those horizons above or below it, of each map unit's dominant component (Mockus et al. 2007). This generated calculation is based on the saturated hydraulic conductivity equation and is measured in units of micrometers per second (Esri 2022). The raster layer consists of values ranging from 2 to 53 micrometers per second (μm/s), signifying the average long-term soil response to the erosive influence of rainstorms (Esri 2022).

3.2.2. Data Processing

The *USA SSURGO Erodibility Data* was exported from ArcGIS Pro to R, where it was *cropped* and *masked* to the county boundary of San Joaquin, CA (see Figure 8) (Hijmans et al. 2022). Spatial resolution was left at 30 m to match the precipitation data that was resampled from 4 km to 30 m. Since the calculations for soil erodibility were already completed and updated regularly by Esri, no other calculations were necessary. Lastly, the erodibility layer was masked to agriculture-only designated land in San Joaquin County using the CropScape data layer (see section 3.4) and inputted into the RUSLE calculation.

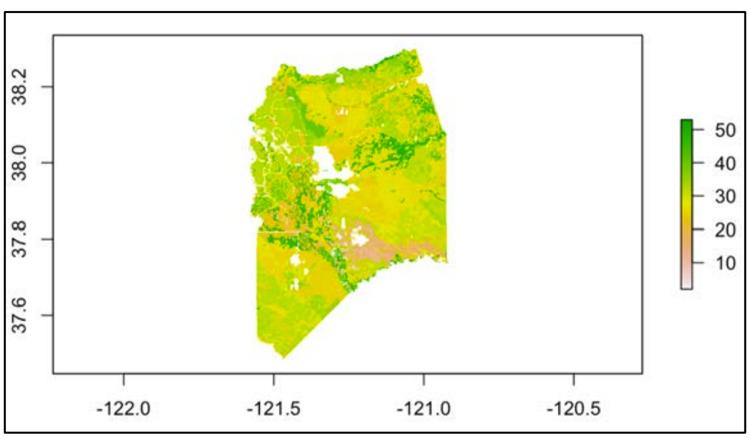

Figure 8. USA SSURGO Erodibility data raster layer before agriculture-only masking.

3.3. Topographic Steepness (*LS* Factor)

The LS-factor is one of the parameters used by RUSLE to compute the effect of slope length and steepness on erosion.

3.3.1. U.S. Geological Survey Digital Elevation Data

The digital elevation model (DEM) data were obtained from the U.S. Geological Survey (USGS) National Geospatial Program database. The dataset is titled *1/3rd arc-second Digital Elevation Models* from the *USGS National Map 3DEP Downloadable Data Collection* consisting of a tiled collection (USGS 2022). The 3D Elevation Program (3DEP) data provides high-quality topographic data and other three-dimensional representations of the US's natural and constructed features (USGS 2022). Within this 3DEP's collection, four tiles/DEMs were selected covering San Joaquin County in 1/3 arc-second (approximately 10 m) resolution (USGS 2022). Each tile/DEM utilized was collected between 2020 and 2021 and published in 2022 (USGS 2022).

3.3.2. Data Processing

The four DEM tiles covering the area of San Joaquin County were individually uploaded into R. The DEM tiles were mosaicked into a single raster using the *mosaic* function in the raster package, followed by cropping and masking to the boundary of San Joaquin County (see Figure 9) (Hijmans et al. 2022). The masked rasters were then used to calculate the slope using the *terrain* function in the raster package (Hijmans et al. 2022), which applies the Horn algorithm using 8 neighbors when calculating slope and is considered the best approach for rough surfaces (Hijmans et al. 2022). The slope rasters were then processed in ArcGIS Pro for LS factor calculation.

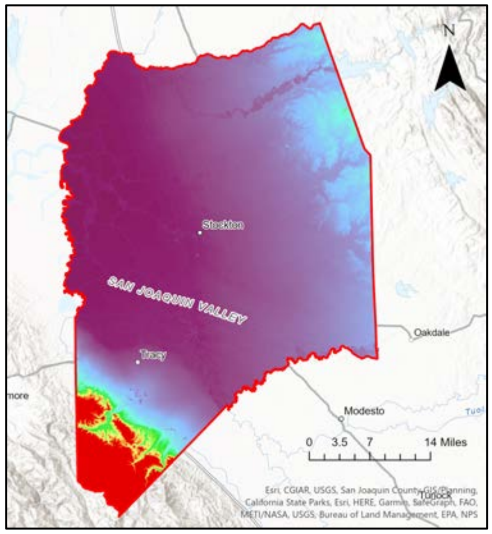

Figure 9. US Geological Survey DEM in ArcGIS Pro before agriculture-only masking.

To calculate flow accumulation for LS calculation, the *Flow Direction* tool was first utilized using the seamless DEM as the raster input and D8 as the flow direction type input. The resulting raster was inputted into the *Flow Accumulation* tool as the *Input Flow Direction Raster*, selecting *Float* for the *Output Data Type* and *D8* for the *Input Flow Direction Type*. Lastly, after calculating flow accumulation and slope in degrees, both raster layers were used to calculate the LS factor using the following non-cumulative slope length (NCSL) equation in the *Raster Calculator*:

$$\left(\frac{Flow\ accumulation\ \times\ Cell\ resolution}{22.1}\right)^{0.4} \times \left(\frac{Sin(Slope\ \times 0.01745)}{0.09}\right)^{1.4} \times 1.4 \qquad (10)$$

where *flow accumulation* is the calculated Flow Accumulation raster, *cell resolution* is exactly 9.28 m (roughly 10 meters) and the *slope* is the calculated Slope raster in degrees (Moore and Burch 1986). This calculation resulted in a final LS layer (see Figure 10) that was exported from ArcGIS Pro to R. In R, the resulting layer was then masked to only agriculture-designated land in San Joaquin County using the CropScape data layer (see section 3.4). This was done as the last step in processing to ensure data accuracy throughout the processing, especially when calculating for continuous data such as in the LS factor. Lastly, the agriculture-only masked LS layer was then inputted into the RUSLE calculations.

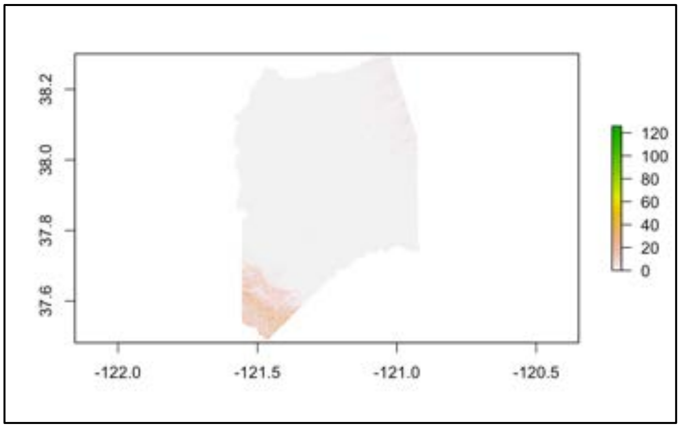

Figure 10. LS raster layer after processing and before agriculture-only masking.

3.4. Land Cover (*C* Factor)

The C-factor is one of the parameters used by RUSLE to account for the effects of cropping and management practices on erosion rates.

3.4.1. U.S.D.A. National Agricultural Statistics Service CropScape Data

CropScape Cropland data was collected from the U.S.D.A.'s National Agricultural Statistics Service (NASS), which conducts several surveys annually and publishes reports covering every aspect of U.S. agriculture by providing valuable statistics on crop production, including identifying crop types, specific GIS-based location, and the frequency of agricultural crops throughout the US (USDA 2022). The dataset utilized is titled *2021 California Cropland Data Layer*, which provides geo-referenced, crop-specific land cover data throughout San Joaquin County for the year 2021 (USDA 2022). The data is provided at 30 m resolution and was produced by satellite imagery from the Landsat 8 OLI/TIRS sensor, the ISRO ResourceSat-2 LISS-3, and the ESA SENTINEL-2 sensors collected during the 2021 growing season (USDA 2022). In addition to this, additional agricultural training and validation data are utilized from the

Farm Service Agency (FSA) Common Land Unit (CLU) program to supplement and improve the crop classification of CropScape layers (USDA 2022).

Traditionally, the calculation of C factor values for the USLE/RUSLE equations is conducted by government agencies that are then published to the public. This is because calculating C-factor values for croplands are based on field experiments which are very time consuming and expensive (see Chapter 2 for more information) (Panagos et al. 2015). According to the Stockton, CA NRCS office, San Joaquin County no longer possesses current C values available for use due to the advent of RUSLE2, a software program that contains all necessary formulas and databases for calculating the latest version of RUSLE. Instead, the NRCS office suggested utilizing the European methodology for determining C values for this project.

3.4.2. Data Processing

The 2021 CropScape data for San Joaquin County was first reclassified in ArcGIS Pro using the *Reclassify* tool. Reclassification values were assigned based on the works of Panos Panagos et al. (2015) who utilized the *LANDUM* model for C-factor estimation, which is based on literature review, remote sensing data at high spatial resolution, and statistical data on agricultural and management practices (ESDAC 2022). For this project and the recommendation from the NRCS, the C-factor values assigned to the various crops in San Joaquin County are derived from the calculations for arable agricultural lands in Europe, using the European scale (Panagos et al. 2015). The C-factor calculation follows:

$$C_{arable} = C_{crop} \times C_{management} \qquad (11)$$

where C_{crop} is the C-factor based on the crop composition of an agricultural area and $C_{management}$ typically quantifies the influence of management practices that can include factors such as reduced tillage, cover crop or crop residues, on soil erosion reduction (Panagos et al. 2015). To generate the C values for arable land, the LANDUM model utilized by Panagos (2015) finds the value for C_{crop}, calculated as:

$$C_{crop} = \sum_{n=1}^{17} C_{cropn} \times \%NUTS2_{cropn} \qquad (12)$$

where C_{crop} is the C-factor of the *n-crop* (type of crop), *%NUTS2crop* is the share of this crop in the agricultural land area of a region, where each region has a different C_{crop} according to its crop composition (regions with crops susceptible to erosion will have higher C_{crop} factors) (Panagos et al. 2015). $C_{management}$ is then calculated as:

$$C_{management} = C_{tillage} \times C_{residues} \times C_{cover} \qquad (13)$$

where $C_{management}$ is the quantification of the effects of management practices, $C_{tillage}$ are different tillage practices, $C_{residues}$ are different plant residues that are left on the land and C_{cover} are cover crops (Panagos et al. 2015).

Based on Panagos et al. (2015) research and analysis, their resulting C-factor values were assigned to the crops available in the CropScape layer for San Joaquin County. Unfortunately, the Panagos study did not provide a comprehensive list of crops that directly matched all crops presently grown in San Joaquin County. Therefore, crops that were not explicitly identified but are in the same genus or family of an identified crop in the Panagos' study were given similar values. In addition, areas with non-natural features such as pavement or buildings were given a value of *No Data*. After correcting this, the new C-factor layer was exported to R for RUSLE calculations (see Figure 11).

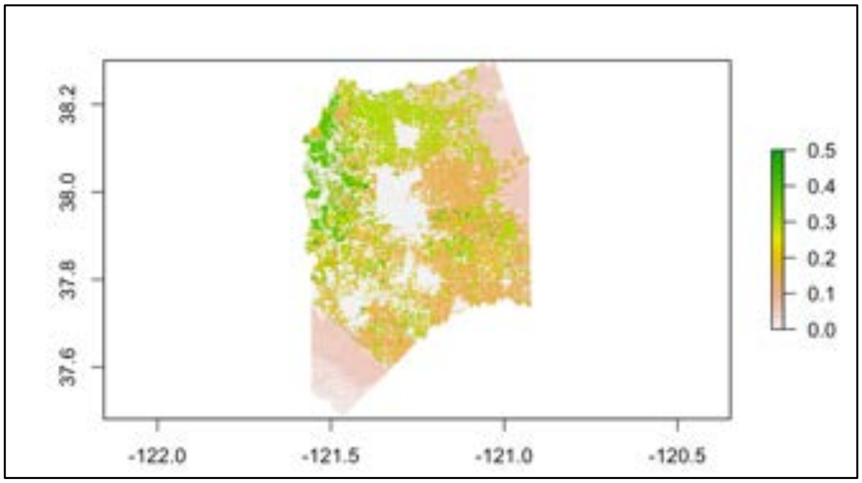

Figure 11. CropScape cropland raster layer after processing.

3.5. Land Management Practices (*P* Factor)

The P-factor is one of the parameters used by RUSLE to account for the impact of support practices on the average annual erosion rate.

3.5.1. Scenario Variables in R and RUSLE Calculations

Erosion control management practices (*P* factor) are not based on a particular dataset in RUSLE calculations (nor within the framework of this project) but instead, are different types of land management practices that, if applied, could improve or worsen soil erosion (Panagos et al. 2015). The P factor is included in the RUSLE equation to overall, compare the soil losses from various types of farming *styles* or *applications* regarding how the crops are planted and maintained beyond tillage, cover crops and residues (Panagos et al. 2015). The support practices of interest in this project are conventional strip cropping (the predominant method in San Joaquin County), contour farming and terrace farming.

This project aims to understand how different land management practices in agriculture, combined with climate change factors, can alter processes of soil erosion severity in a relatively flat (little to no slope) area. To accomplish this, a P-factor in R was created and titled Land Management (lm) Scenarios, specifying:

$$Plm = 1 \, for \, convention \, strip \, cropping$$
$$Plm = 0.35 \, for \, conservation \, contour \, cropping \qquad (14)$$
$$Plm = 0.25 \, for \, terrace \, cropping$$

The values selected are arbitrarily assigned to represent severity rates; 1 being the most severe, 0.35 for moderate severity, and 0.25 for the least severity. These values were then inputted into the RUSLE equation holding all other layer inputs constant. This generates three different scenarios for each future projection to understand the long-term effects of different land management practices combined with changing precipitation erosivity rates.

The first scenario, titled $RUSLE_1$, was thus calculated as:

$$RUSLE_1 = r_{moore} \times e_{factor} \times ls_{factor} \times c_{factor} \times 1 \qquad (15)$$

where r_{moore} is rainfall erosivity, e_{factor} is the erodibility factor, ls_{factor} is the calculated slope lengths and steepness throughout the study area, c_{factor} is crop effects on soil and *1* is the most severe scenario consisting of employing strip cropping (see Figure 12).

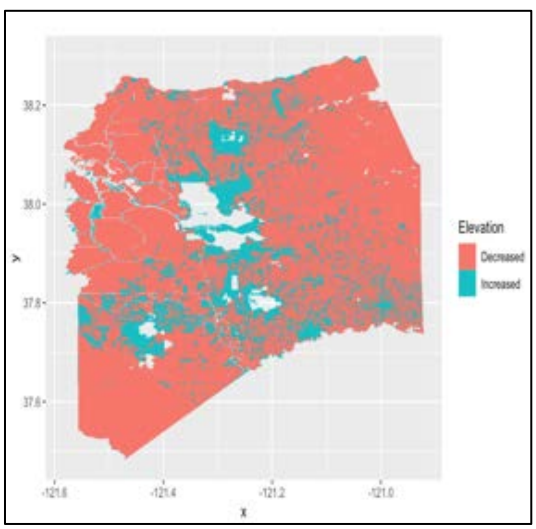

Figure 12. RUSLE calculation using the first scenario before agriculture-only masking.

The second scenario, titled $RUSLE_2$ is calculated as:

$$RUSLE_2 = r_{moore} \times e_{factor} \times ls_{factor} \times c_{factor} \times 0.35 \qquad (16)$$

where *0.35* is the moderately severe scenario consisting of employing contour cropping (see Figure 13).

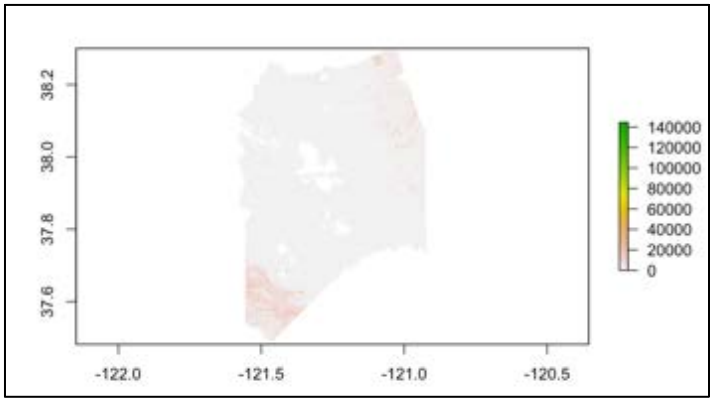

Figure 13. RUSLE calculation using second scenario before agriculture-only masking.

The third scenario, titled $RUSLE_3$ is calculated as:

$$RUSLE_3 = r_{moore} \times e_{factor} \times ls_{factor} \times c_{factor} \times 0.25 \qquad (17)$$

where *0.25* is the least severe scenario consisting of employing terrace cropping (see Figure 14).

Figure 14. RUSLE calculation using third scenario before agriculture-only masking.

All calculated RUSLE rasters were then exported to ArcGIS Pro for the chosen years and for the three scenario calculations to create final visualizations. All results are visualized and presented in Chapter 4 Results.

Chapter 4 Results

This chapter outlines the results in calculating soil erosion from rainfall and runoff for agriculture-designated land in San Joaquin County, CA using RUSLE. The results reveal that the majority of water erosion is likely to occur in the hillsides to the east and west sides of the county, while there appears to be mild measured amounts of soil erosion along the canal/irrigation channels and the depressed land between rows of crops throughout the agricultural-farmed lands. The empty (white) space in the center of the maps are the major urban centers for San Joaquin County and not identified or included in the results produced. Other white space visualized throughout San Joaquin County is land that was not designated as agriculture land by the CropScape data layer (see section 3.4 for more details). The results reveal that strip cropping generates higher levels of erosion than contour or terrace cultivation/cropping methods. It should be noted that the results visualize how much soil could hypothetically be lost but are not exact or determined soil erosion totals for future erosion events. The results produced also do not account for where eroded soil would be redeposited. Redeposition is a typical, geological process that occurs in soil erosion events but it is not the focus of this work.

4.1. Results for 2021 for Three Land Management Practices

The results for the year 2021 utilizing three different cultivation practices, strip cropping, contour cropping and terrace cropping (see Figure 15) reveal varying values for each land management practice. The amounts of erosion are identified by the colors blue (0 or no erosion) to red (most severe amounts of soil erosion of at least 10,000+ tons), with colors green and yellow indicating smaller levels but processes of soil erosion still occurring. Under strip cropping, water erosion totals 552,730 tons and occurs most noticeably in the hillsides to the east and among the channels and depressions associated with agriculture production (created from farming in straight lines) in the west-side of the county. Under contour cropping, water erosion totals 193,456 tons (359,274 tons less than strip cropping), again most noticeably in the rills and gullies associated with cropping mechanisms employed in the far west and eastern parts of San Joaquin County. The amount of erosion clearly eases throughout the flat, agriculture regions of the county with the number of yellow and green lines decreasing in the west-side of the county. Under terrace cropping, water erosion totals the least amount at 138,183 tons (414,547 tons less than strip cropping) with very little *severe* erosion occurring, as can be seen in the decrease amount of red in the hillsides. The agriculture lands between the hillsides in the west and east also reveals minimal amounts of erosion, as the center of county displays an almost uniform blue.

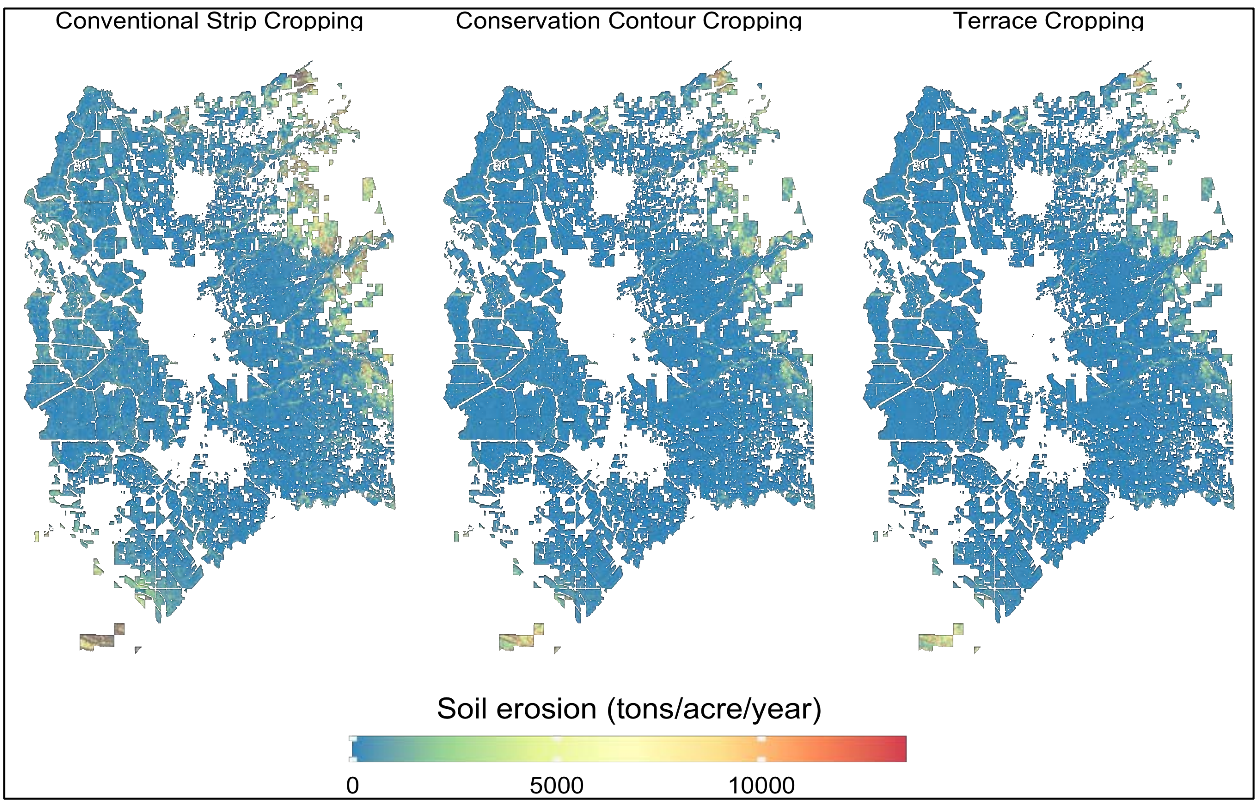

Figure 15. RUSLE-generated soil erosion values (tons per acre per year) for San Joaquin County for the year 2021 for three different cultivation practices.

4.2. Results for 2030, 2050, 2070 and 2100 for Strip Cropping

The results generated after calculating RUSLE for the year 2021 and future predictions for the years 2030, 2050, 2070 and 2100 employing the specific land management practice *strip cropping* (see Figure 16) reveal varying values for each year. Again, the amounts of erosion are identified by the colors blue (0 or no erosion) to red (most severe amounts of soil erosion of at least 10,000+ tons), with gradual increasing levels represented by colors green to yellow, indicating smaller levels of soil erosion overall. It is evident that as precipitation and storm events change as a result of climate change, water-generated soil erosion values will be affected. The years 2021 and 2070 appear to be the most severely affected with the total soil erosion amounts for 2021 equal to 552,730 tons and 2070 equal to 974,850 tons. The years 2030 and 2100 appear to be the least affected with the total soil erosion amounts for 2030 equal to 154,416 tons and 2100 equal to 197,542 tons. The year 2050 appears to be in the middle with soil erosion amounts totaling 300,552 tons. Again, the bulk of erosion appears in the hillsides in the east and the rills and gullies associated with agriculture land practices in the county. The eastern mountainous ranges in the county appear to have erosion rates that when more severe, branch further out into the agricultural lands and retreat when erosion is less. In the year 1970 specifically, erosion appears to be most severe across all agriculture lands between the west and east hillsides demonstrating erosion is occurring across even minimal 1-2% levelled slope lands.

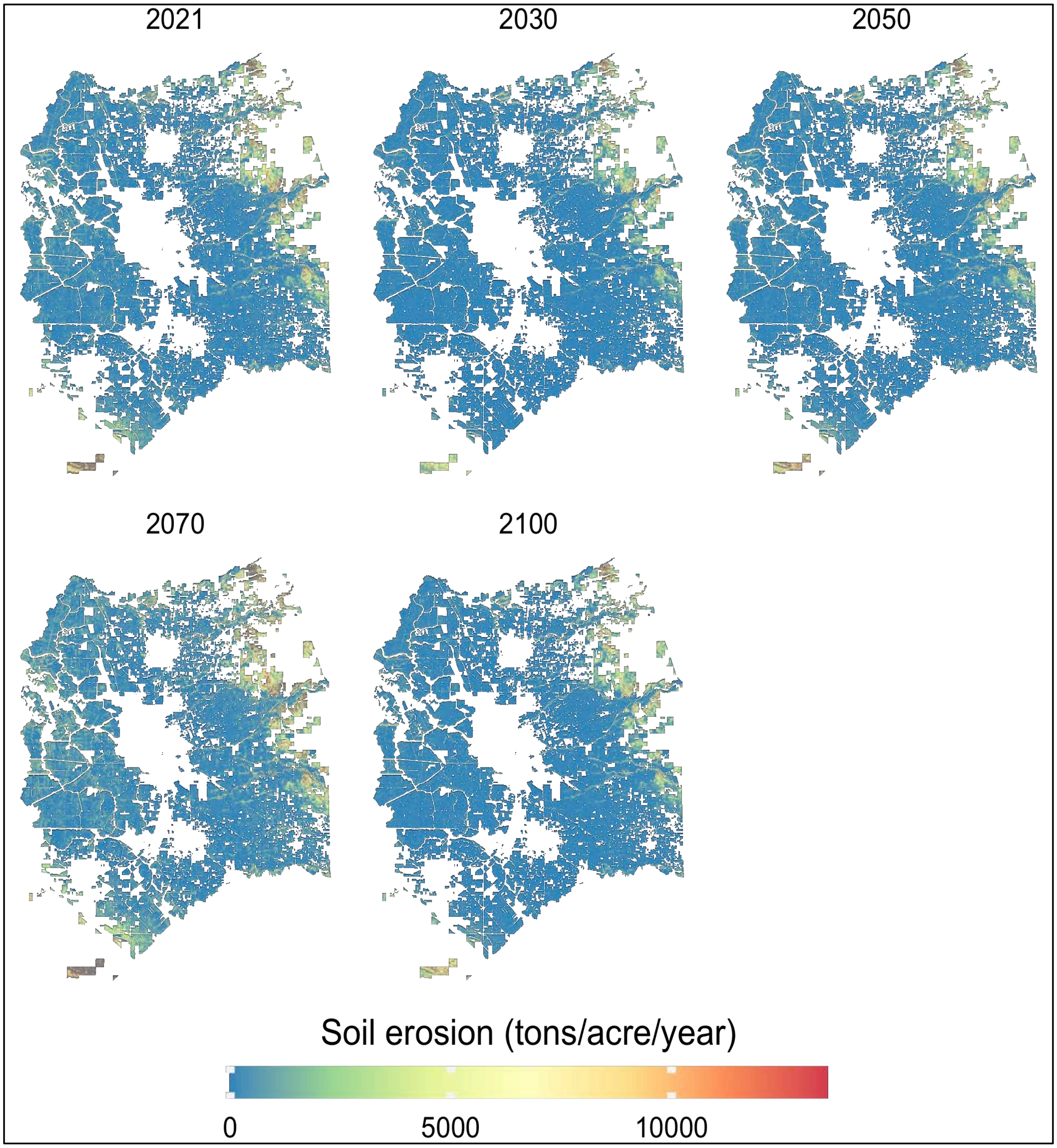

Figure 16. RUSLE-generated soil erosion values (tons per acre per year) for San Joaquin County for the years 2021, 2030, 2050, 2070 and 2100 under strip cropping practices.

4.3. Results for All Years and Land Management Practices

The results generated after calculating RUSLE for the year 2021 and future predictions for the years 2030, 2050, 2070 and 2100 investigating all three types of land management practices, strip, contour and terrace cropping (see Figure 17) reveal varying values for each year and cultivation practice. Again, the amounts of erosion are identified by the colors blue (0 or no erosion) to red (most sever amounts of soil erosion of at least 7,500+ tons), with gradual increasing levels represented by colors green to yellow to orange, indicating smaller levels of soil erosion overall. It is evident that for each year, terrace cropping has the least effect on soil erosion, mitigating its severity and preserving soil more effectively, as indicated by higher amounts of blue and green coloring for each map for each year, with the exception of 2070. Even under terrace cropping, the year 2070 appears to have green, yellow, and orange coloring demonstrating that levels of erosion will be predominant throughout the entire county. Overall, terrace cropping RUSLE values range between 38,604 (year 2030) and 243,713 tons (year 2070) of soil loss. Contour cropping is clearly in-between both land management practices strip and terrace, with values ranging between 54,046 tons (year 2030) and 341,198 tons (year 2070) of soil loss. Strip cropping is evidently the most sever with RUSLE values ranging from 154,416 tons (year 2030) and 974,850 tons (year 2070), with maps displaying higher levels of green, yellow, and orange coloring than any other maps under different land management practices.

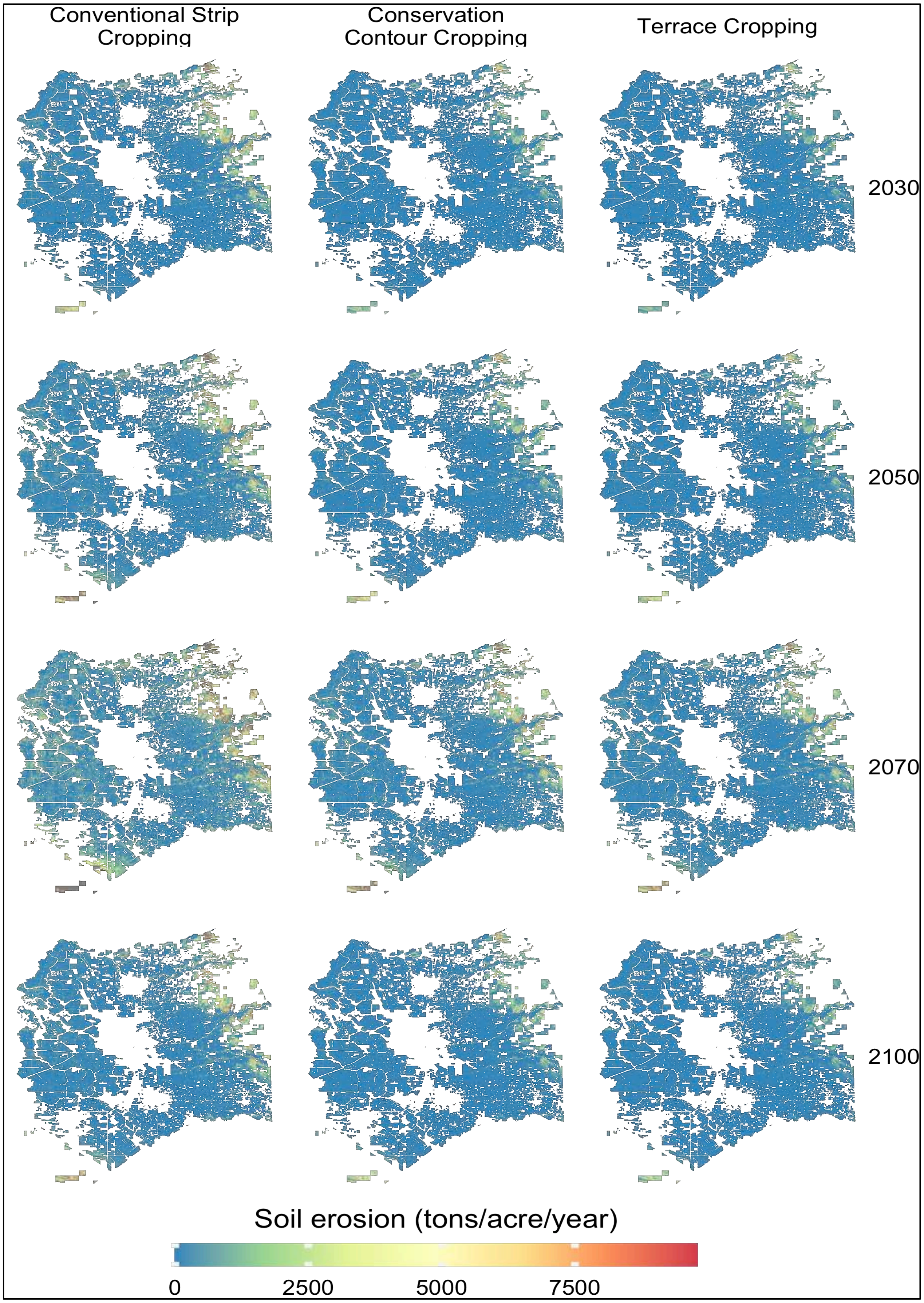

Figure 17. RUSLE-generated soil erosion values (tons per acre per year) for San Joaquin County for the years 2021, 2030, 2050, 2070 and 2100.

4.4. Results from Terrace Cropping and Strip Cropping Practices

The results generated after subtracting RUSLE results between strip cropping practices and terrace cropping practices for future predictions for the years 2030, 2050, 2070 and 2100, reveal the amount of soil that can be preserved if terrace cropping were enacted for future management practices as opposed to the continuing of strip cropping in San Joaquin County (see Figure 18). The amounts of erosion are identified by the colors dark red (0 or no erosion) to light yellow (amounts of soil preservation), with colors red to orange to dark yellow indicating gradual increasing amounts of soil conservation. The least affected year is 2030, ranging from 0 to 115,812 tons, the year 2050 ranging from 0 to 225,414 tons, the most sever year 2070 ranging from 0 to 731,138 tons and lastly, the year 2100 ranging from 0 to 148,157 tons of soil preservation. The results from this basic calculation indicate that terrace cropping can reduce the amount of soil erosion experienced by water, especially in highly vulnerable areas such as the hillsides in the east and west parts of Sam Joaquin County. There is evidence that even in the flat agricultural regions of the county, terrace cropping, although less than in the hillsides, will have mitigating effects on soil erosion as is indicated by the yellow coloring following the irrigation channels.

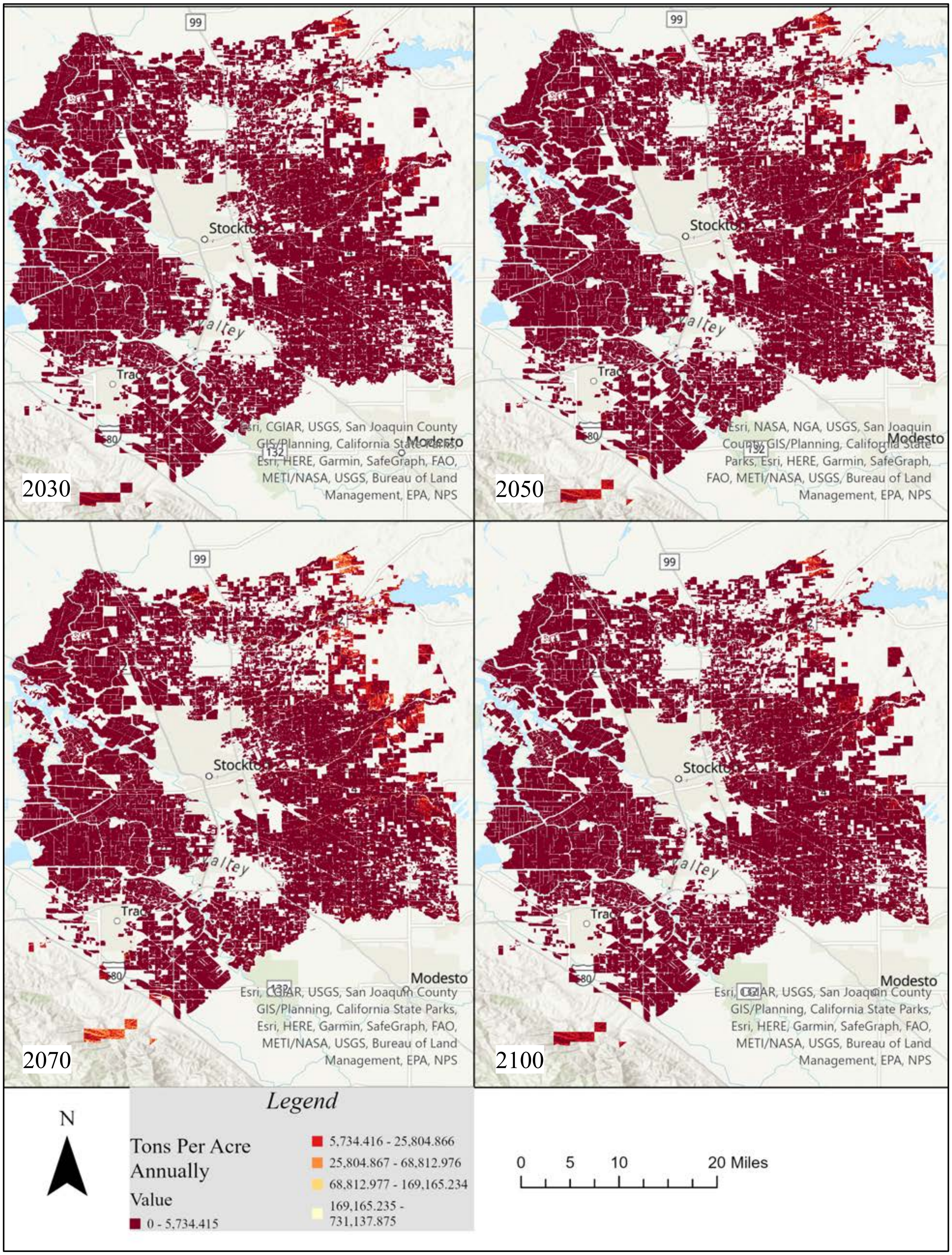

Figure 18. Total amount of soil that could be preserved for the years 2030, 2050, 2070 and 2100.

In Figure 19 (below), the same aerial view of San Joaquin County's network of levees that was originally presented in Figure 2, is visualized again with a side-by-side comparison of soil erosion from the year 2070 (the most severe year for soil erosion in this study). The results display the subtle difference between strip cropping and terrace cropping in agriculture land. The image on the left displays strip cropping and the image to the right displays terrace cropping: visually terrace cropping produced a slighter shad of yellow throughout the rills and gullies of the agriculture land, as well as along all the levees and waterways in San Joaquin County.

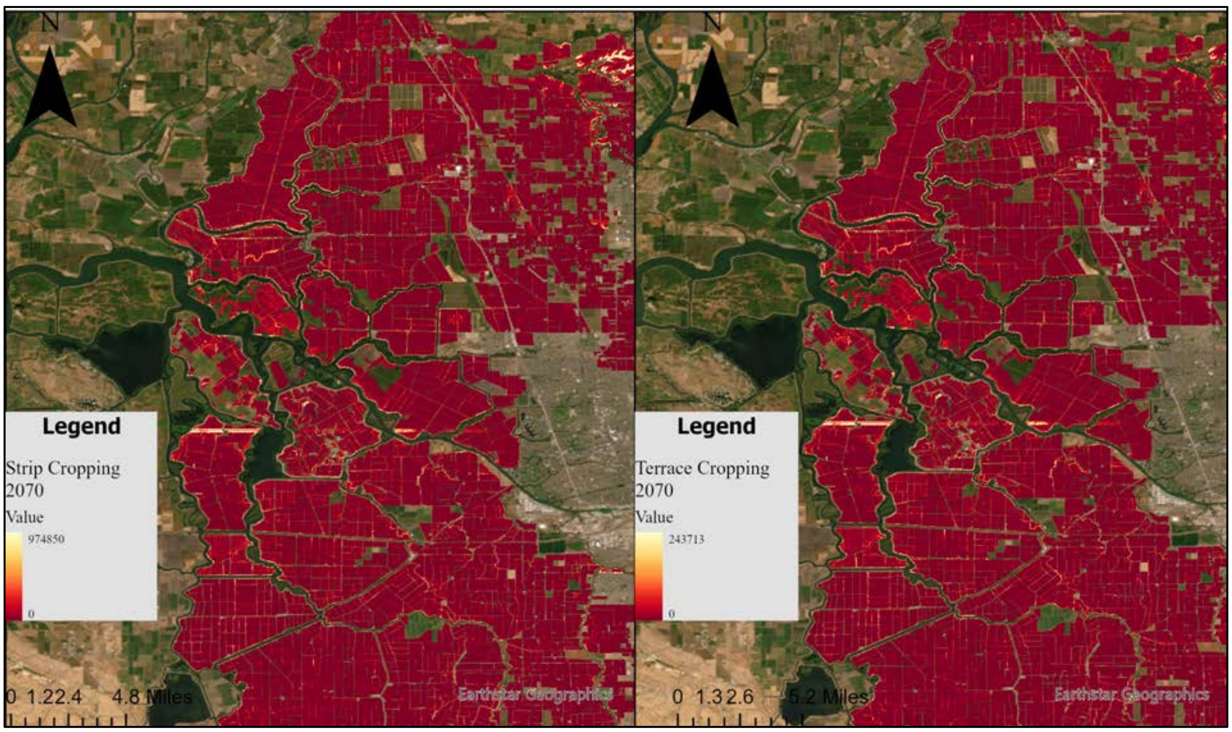

Figure 19. The amounts of soil erosion that occur for the year 2070.

Chapter 5 Discussion

This chapter discusses the results from Chapter 4, analyzing the implications between the three land management practices, strip cropping, contour cropping and terrace cropping. Overall, it is evident that strip cropping is the most destructive land management practice and terrace cropping was the least for every study year evaluated. This chapter also reviews the limitations of using the RUSLE equation for soil erosion, mainly that it does not account for soil deposition, a critical component to soil erosion processes. Lastly, recommendations for future land management practices are discussed to provide better conservation planning and policy implementation to secure agriculture production for the future.

5.1. Conclusion: Soil Erosion is Dependent on Land Management Practices

The general argument for ignoring soil erosion from agriculture land is that they are naturally flatter areas with little to no elevation changes and if any exists, are intentionally levelled by farmers. This practice, along with the natural landscape, creates a rate of erosion that is so minimal, it is considered negligible. In Figure 15 the basic RUSLE calculations for the year 2021 for the three different land management practices, reveal that soil loss is not just dependent upon a mountainous or steep terrain but as was explained in Chapter 2, is highly interdependent on land management practices. In Figure 15, it is clear that terrace cultivation practices result is less soil erosion than strip cropping and slightly less amounts than contour cropping. This is again reflected in Figure 16, which displays the effects of traditional strip cropping on each year: 2021, 2030, 2050, 2070 and 2100. From this figure, it is apparent that irrigation channels and the depressed lands between rows of crops are just as susceptible to the processes of erosion as are displayed in the hillsides in the east and west of San Joaquin County.

This means that soil loss is occurring across all aspects of the land, including cultivated, arable lands and more importantly, are occurring consistently for every year tested. It is therefore arguable to assume that soil erosion continues to take place in-between the selected tested years, resulting in soil loss totals that can effectively endanger agriculture lands, damaging the agricultural industry and threatening the food supply chain. When adding up each study year, a projected total of 2,180,090 tons (around 4,360,180,000 lbs. or 120,690,000,000,000 cubic inches) of soil are loss in just the five years selected for analysis under the land management practice strip cropping. Again, it should be stated that planting depth has direct impact on seed-to-soil contact as well as seeds' access to adequate moisture and temperature. Planting too shallow may result in poor germination due to low soil moisture retention near the soil surface or seed injury due to insects or disease. Therefore, agriculturists need at minimum 6 inches of depth for even just small plant cultivation. At this amount totaling 120 trillion cubic inches, farmers are likely to lose the necessary topsoil for plant cultivation in just one or two generations. As agricultural lands become depleted in natural topsoil, farmers will have to implement more additives into the soil to preserve what soil remains as well as make it viable for agriculture production at the scale required to feed the growing global population. In addition to the threat of losing necessary topsoil, these additives will also cost farmers more time, more money, and will damage the environment further through excess pollution.

In addition to these threats, as soil erosion occurs even in minute scales across flat areas, it inevitably becomes more susceptible to other natural processes such as wind erosion. Although wind erosion calculations are not included in this work, its effects on soil erosion are noted by the Stockton NRCS office, who state that wind erosion is of the highest concern due to the flat terrain of San Joaquin County and global climate change. The combination of both water and wind erosion, as well as considering climate change conditions, are forcing the NRCS to work closely with farmers in adopting new cultivation methods in order to mitigate erosion.

5.2. Limitations of RUSLE Equation

Although RUSLE is heavily used around the world, it must be noted that there are limitations to its applicability. The main limitation of the RUSLE methodology is that it only accounts for soil loss through the impact of raindrops and the subsequent detachment of soil particles downslope by water flowing overland as a sheet. It does not account for runoff water that develops along channels as it travels down a slope. It also completely ignores structurally unstable soil that does not or cannot aggregate, becoming more sensitive to dispersion when it gets wet because the individual clay particles disperse into solution. There is also no accounting for the deposit of sediment before reaching the waterway, which is likely to occur as soil and water move through irrigation channels in agriculture lands. In addition to this, the model neglects certain interactions between factors in order to distinguish more easily the individual effect of each. For example, it does not take into account the effect on erosion of slope combined with plant cover, nor the effect of soil type on the effect of slope. It also fails to calculate more accurately for other factors that are indicative of healthy soils, such as carbon levels, mineral and organic material, water content and low salinization levels.

5.3. Recommendation for Future Land Management Implementation

The suggestion of this paper is to begin the implementation of terrace cropping. Terrace structuring on land reduces both the amount and velocity of water moving across the soil surface, which greatly reduces soil erosion. Although terrace cropping is traditionally done in hillsides, it arguable that A) as global population increase, cultivated lands will also increase into more hillsides and mountainous terrains, making the implementation of terrace cropping an instinctive choice for cultivation. B) Agricultural land is already steadily working into the hillsides and mountainous terrain of San Joaquin County. As can be seen in Figure 20 (below), CropScape data shows that agriculture is being conducted in the foothills on both the east and west sides of the county and is encroaching more into the hillsides, especially in the eastern side of the county where soil erosion was calculated to be the worst. C) Terrace cropping can be engineered over time into a flatter terrain to protect soil from both wind and water erosion. Although more time intensive than applying additives, terrace cropping is a better solution than the alternatives at this time. It is a natural way of mitigating the problem that does not involve the implementation of additional chemicals into the soil, the construction of energy-intensive indoor cultivation buildings (that are nonetheless limited in the types of food that can be grown) while providing a built-in structure into the farmland that creates enough protection for farmers to allow their land to stay follow without further damage. This gives the land time to recoup after harvesting and rebuild nutrients that was lost from the cultivation season. It has been suggested that cover crops are a reliable alternative to protecting soil and preventing soil erosion, however, cover crops are water intensive, which is not practical for a drought-ridden state such as CA.

In addition to this, the major benefits of terrace cultivation besides conserving soil is also conserving water (Wheaton and Monk 2001). Terrace cropping allows the total area of an agriculture plot to be farmed because grassed waterways are no longer needed (Wheaton and Monk 2001). By eliminating grassed waterways, farmers no longer have the inconvenience they cause when tilling or applying herbicides (Wheaton and Monk 2001). Peak discharges of soil, water, fertilizers and pesticides are reduced because runoff that would normally occur is temporarily stored instead in the land (Wheaton and Monk 2001). Lastly, soil and other contaminants settle behind the terrace ridges before continuing down, polluting water in a receiving stream or reservoir (Wheaton and Monk 2001).

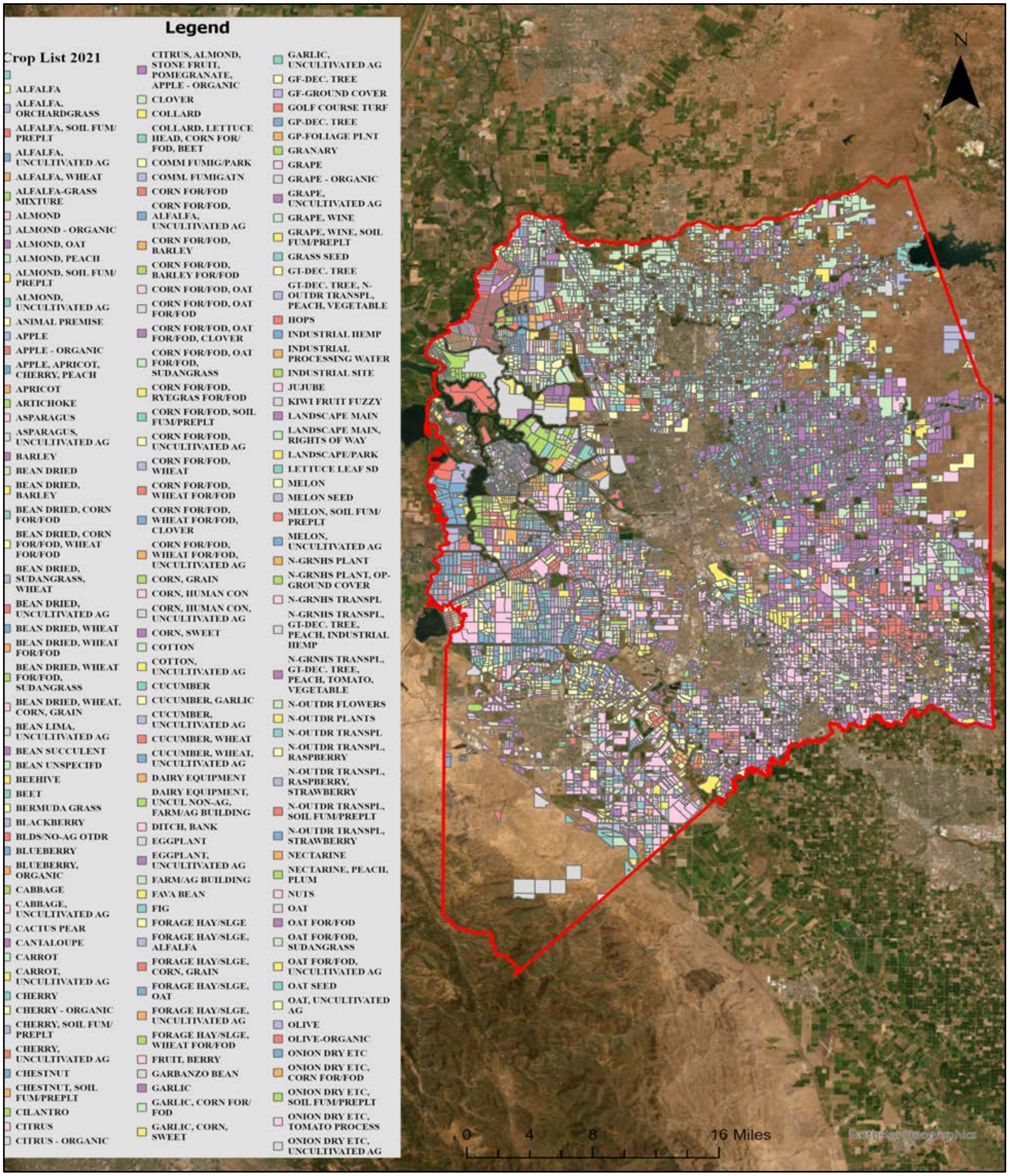

Figure 20. Crop cover in San Joaquin County for the year 2021.

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