Using GIS to Compare Leading Process and Empirically Based Soil Erosion Models within Headwater Watersheds

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A Thesis

Submitted in Partial Fulfillment

of the Requirements for a Degree of

Master of Science

in Applied Geospatial Sciences

Northern Arizona University

May 2017

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ABSTRACT

USING GIS TO COMPARE LEADING PROCESS AND EMPIRICALLY BASED SOIL EROSION MODELS WITHIN HEADWATER WATERSHEDS

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Changes in North American ponderosa pine ecosystems in relation to wildland fire severity are taking place due to human influence and the tools to asses these changes vary greatly. These fires alter the types of vegetation, streambed composition, and cause severe erosion events, as well as make freshwater resources harder to manage in headwater watersheds. The purpose of this study is to analyze and investigate the differences of the two leading GIS based soil erosion models, the Revised Universal Soil Loss Equation (RUSLE) and the Water Erosion Prediction Project (WEPP). In particular, the models will be compared to address which one better predicts the state of two neighboring watersheds that endured the same high severity burn and flooding events. These watersheds reacted differently as noted by the streambed composition. Parameters were created using a land manager's approach. The results of this study found that the process-based WEPP model outperforms the RUSLE model in its ability to assess post-burn flooding events through its ease of implementation and inclusion of climate and erosion processes in complex topography and therefore should be used by land managers interested in studying erosion events in similar circumstances.

Keywords: WEPP, RUSLE, modeling, flooding, soil erosion, fire, forest, watershed, GIS, geographic information systems, remote sensing, ArcMap, ENVI, Arizona, Ponderosa Pine

ACKNOWLEDGEMENTS

I would like to thank my parents for supporting me throughout my endeavors. My parents have provided me with guidance and inspiration that I will continue to carry with me. I would also like to thank my committee. Dr. Jackson Leonard was the first person to introduce me to the study area. This project would not have happened if it wasn't for his interest and passion for ecology, fire sciences, and the surrounding landscape. His continual support for my research is greatly appreciated. Finally, the Northern Arizona University, Master of Applied Geospatial Science program is gratefully acknowledged. Due to the continued guidance of Mark Manone and Dr. Amanda B. Stan I would not have refined the skills or knowledge to the same degree throughout my time here at Northern Arizona University.

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Chapter 1: Introduction

1.1 Background

Assessing the conditions of public land and natural resources is challenging because of the complexity of geographic areas, resources, and social constructs. Within ponderosa pine ecosystems in the southwestern United States, wildland forest fires have increased in occurrence and severity due to decades of fire suppression and climate change (Fitzgerald, 2005; Veblen et al., 2000). These fires have changed from frequent, generally low severity events occurring on average 5-7 years, to less frequent high severity wildfires (Moore et al., 1999). These types of events threaten to permanently alter vegetation across the landscape (Balch et al., 2013).

High severity fire can cause soil water repellency, leading to a reduced rate of water infiltration, severe erosion events, charring of surface fuel, increase exposure to soil, and a large percentage of tree mortality (DeBano, 2000; Fitzgerald, 2005; McHale et al., 2005). Soil erosion can occur over decades following a wildfire event in which it can be unnoticed and vegetation is unaffected, or it can happen at distressingly high rates that disrupt ecosystem function. Excessive soil erosion causes the removal of nutrient rich topsoil and affects the soil structure, stability, and texture. Due to this change in soil characteristics, it has shown to change large-scale landscape vegetation type (Beyers, 2004; Raison, 1979; Zedler et al., 1983).

Headwaters are composed of the tributary sources near the formation of a watershed. Factors making up headwaters include springs and their corresponding intermittent and tributary rills, which are crucial to the health of the stream, the watershed ecosystems in which they form, as well as the ecosystems they feed downstream. Monitoring and protecting these freshwater ecosystems provide us with vital resources, recreation areas, biodiversity and bionetworks for flora and fauna. Often times the forests found in these watersheds provide natural buffers protecting from contaminants or disturbances.

Using a combination of geographic information systems (GIS) and remote sensing allows natural resource managers to utilize several inputs in a systematic way. It also allows for an interface in which data can be edited, visualized, and analyzed at different scales. Modeling is defined as a mathematical representation of real world processes. Models vary in scale, accuracy, and design. The two models used in this research include the older and more universally applied Revised Universal Soil Loss Equation (RUSLE) and the more recently created Water Erosion Prediction Project (WEPP).

The RUSLE and WEPP are different in build and implementation commonly generating varying results. The aim of this research is to compare the RUSLE and the WEPP within two headwater watersheds: Dude and Bonita Creeks. While these two watersheds boarder each other thus sharing similar topography, disturbance and weather events, they responded very differently to the flooding that took place after a high severity burn. Using these models, input parameters can be modified to allow land managers to study how possible changes in weather, land management practices, vegetation and soil composition affect the watersheds. Using a variety of methods to mimic the conditions of the watersheds directly after a high severity burn, the characteristics of two headwater stream systems will be compared to the results of the models to best assess which model best predicted the current conditions of the streams.

1.2 Purpose

This research aims to investigate differences between two leading soil erosion models when implemented within headwater watersheds along the Mogollon Rim, Arizona. A case study approach will be used in which the methodology applied to and results derived from each model will be analyzed and compared. Using field collected, remotely sensed, and spatially interpolated data, model parameters will be created, or collected from online databases to mimic immediate post-fire flooding conditions. Subsequently, model best predicts the post-flooding conditions of these watersheds will be determined. The results will be compared to stream channel entrenchment estimates to deduct if the models successfully mimicked the minor channel entrenchment of Bonita Creek or the severe erosion and deep channel entrenchment events of Dude Creek. In addition to the results, the methodology will be discussed to infer what model works best in these relatively small headwater watersheds for use by land managers in similar environments.

1.3 Research Questions

1. Which soil erosion model best predicts the post-burn flooding event conditions following a high severity wildfire event?
2. How do the methods of implementation of the models compare?
3. What model provides the most useful applications and results for land managers studying similar post-fire conditions?

1.4 Research Objectives

In order to address the questions posed above, several research objectives were met. First, a review of literature was conducted in order to provide a background in local forest management and policy. This identified the interests of land managers in relation to modeling. Additionally literature regarding the role of modeling to study climate change was addressed. A case study approach was used to summarize the best methods of model parameter creation for both models.

The soil erosion models were created and run using data gathered from prevalent online databases or generated using remote sensing software. A model was constructed in ArcGIS to determine the extent of soil erosion using the RUSLE methodology. The WEPP model was run by utilizing an extension of ArcMap named GeoWEPP developed mostly in part by Department of Geography at University of Buffalo, New York. The WEPP and RUSLE model were both run using the parameters most likely to be used by land managers, such as the Burned Area Emergency Response (BAER) GeoWEPP inputs database which is an interactive spatial WEPP models input generator hosted by Michigan Technological University Research Institute.

The models were compared in their implementation, results, and their accuracy. The results themselves were discussed in their application to land management policy stemming from the Four Forest Initiative (4FRI). Methods of assessing the accuracy of the models was done using data acquired from field work in which streambed pebble size was measured, and channel area change was estimated for the creeks of interest. This data provides estimates of the severity of the flooding events.

1.5 Study Area

The area of interest falls within the boundary of the Dude Fire located in central Arizona (Figure 1). The Dude Fire was lightning caused and lasted from June 25th until July 1st 1990. It burned over 10,000 hectares of pine-juniper and oak woodland. It took the lives of 6 wildland firefighters and burned over 60 structures within its 100-square kilometer perimeter (Figure 1).

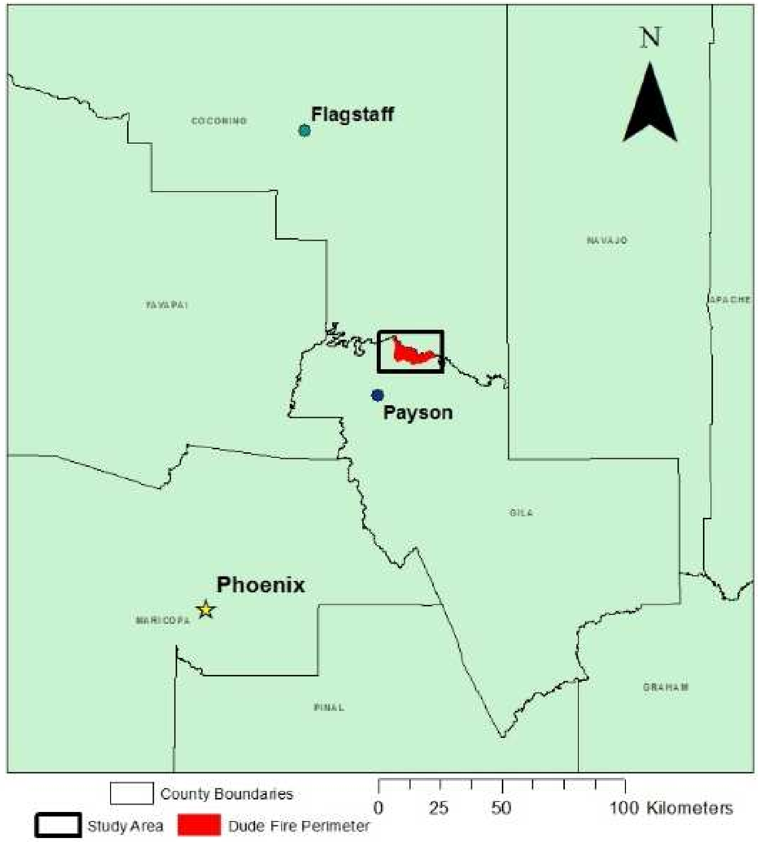


Figure 1 - Dude Fire Boundary

The fire was contained by the Mogollon rim along its northern border. The Mogollon rim is defined as an escarpment that forms the southern edge of the Colorado Plateau consisting of cliffs faces made up of Kaibab Limestone and Coconino Sandstone. Due to its topography, it creates a natural boundary for flora and fauna and marks the headwaters for several vital watersheds in Arizona. These watersheds provide vital freshwater to the town of Payson, habitat for flora and fauna, and key recreation areas. The two watersheds of study feed Dude and Bonita Creeks (Figure 2) which then in turn directly feed the water supply of Payson and the greater Verde River watershed. The Dude watershed has an area of 13.36 SqKm. It stretches from latitudes 34°25’55.52” to 34°22’49.48” and longitudes 111°16’22.61” to 111°12’51.07. The

Bonita watershed is 18.6 square kilometers. It stretches from latitudes 34°24’50.28 to 34°21’1.01” and longitudes 111°15’18.15” to 111°11’4.36”. The elevation ranges from 1610 meters to 2387 meters, with the higher portion making up the top of the Mogollon rim.

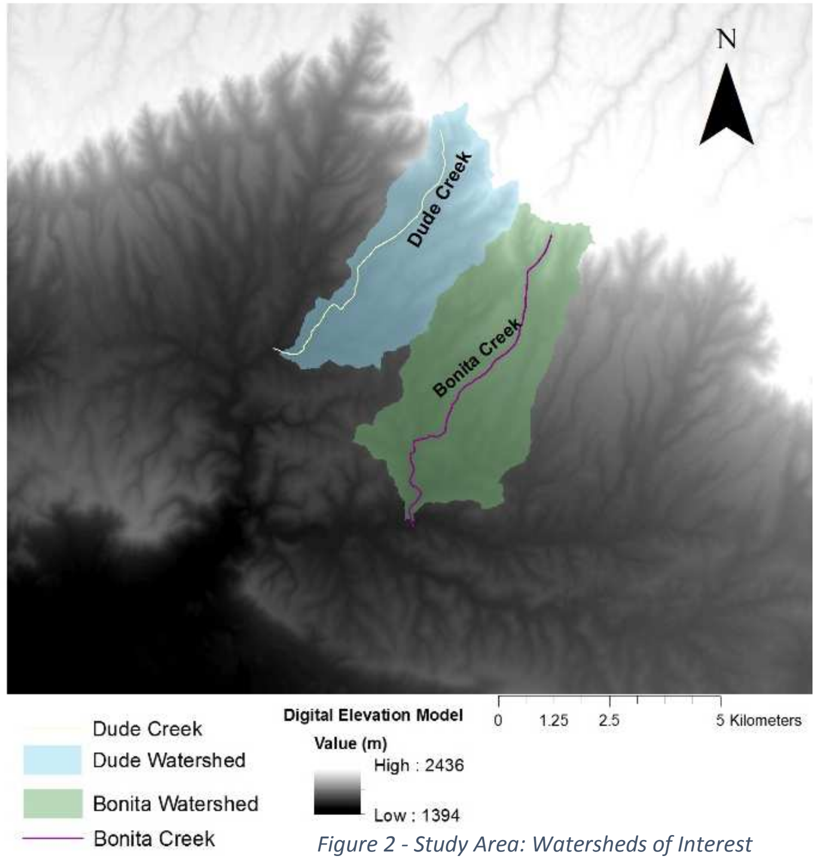


Figure 2 - Study Area: Watersheds of Interest

The town of Payson, AZ is located in Gila County and is roughly 17km southwest from the center of the watersheds. Payson stands at around 1,490m in elevation and has a mean minimum and maximum temperature of 4°C and 22.9°C, respectively, with an average temperature of 13.2°C. The average annual precipitation is 560mm with an average annual snowfall of 59cm. The average amount of precipitation days (greater than or equal to 0.254cm) is 69.5 per year.

Twenty years post-burn the vegetation has transitioned from a ponderosa pine forest to a plant community almost fully made up of a manzanita/oak overstory with an understory dominated by weeping lovegrass (Leonard, et al; 2015). Weeping lovegrass was introduced into sections of the burn zone in an attempt to mitigate the effects of erosion, which was a widely used post-fire treatment at the time. However, the effectiveness of this practice has been found to be minimal in increasing soil stabilization (Beyers, 2004;Peppin, 2010). Attempts to plant ponderosa seedlings in the burn area occurred for three years following the fire yet most of the sites contain no evidence of pine growth twenty years later. This can possibly be attributed to the aggressive and invasive chaparral species, a shift in soil make-up, and elk grazing (Beyers, 2004; Raison, 1979; Leonard, 2015; Zedler et al., 1983).

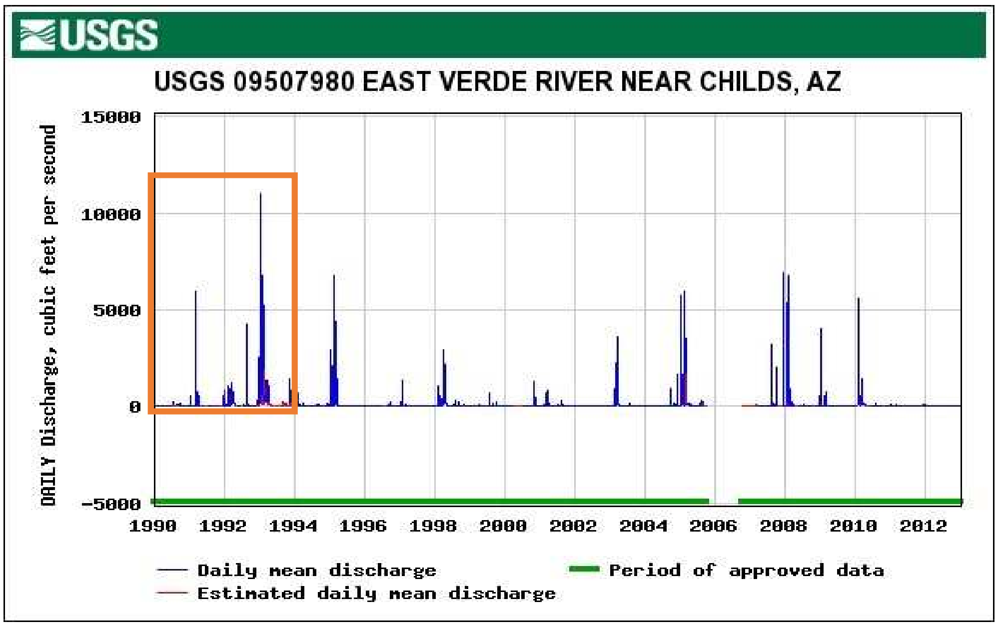


Figure 3 - Verde River Stream Gauge

Time of interest highlighted. Adapted from USGS National Water Information System. Site Number: 09507980.

Following the Dude fire, from July 1st 1990, through the end of 1993, weather stations surrounding the study area recorded higher than average precipitation events for the region. These three weather stations consist of: Station 1, Baker Butte (Identification code: GHCND:USS0011R06S. Latitude: 34.46° Longitude: -111.41°. Station 2, Payson (Identification code: GHCND:USW00093139. Latitude: 34.2326°. Longitude: -111.3446°). Station 3, Promontory (Identification code: GHCND:USS0011R10S. Latitude: 34.37°. Longitude: -111.01°).

Due to the hydrophobic layer left in the top layer of soil caused by the fire, the watersheds underwent large flooding events. Daily discharge meters located along the Verde River recorded major regional flooding during this time period, one of which was over 10,000 cubic feet per second (Figure 3).

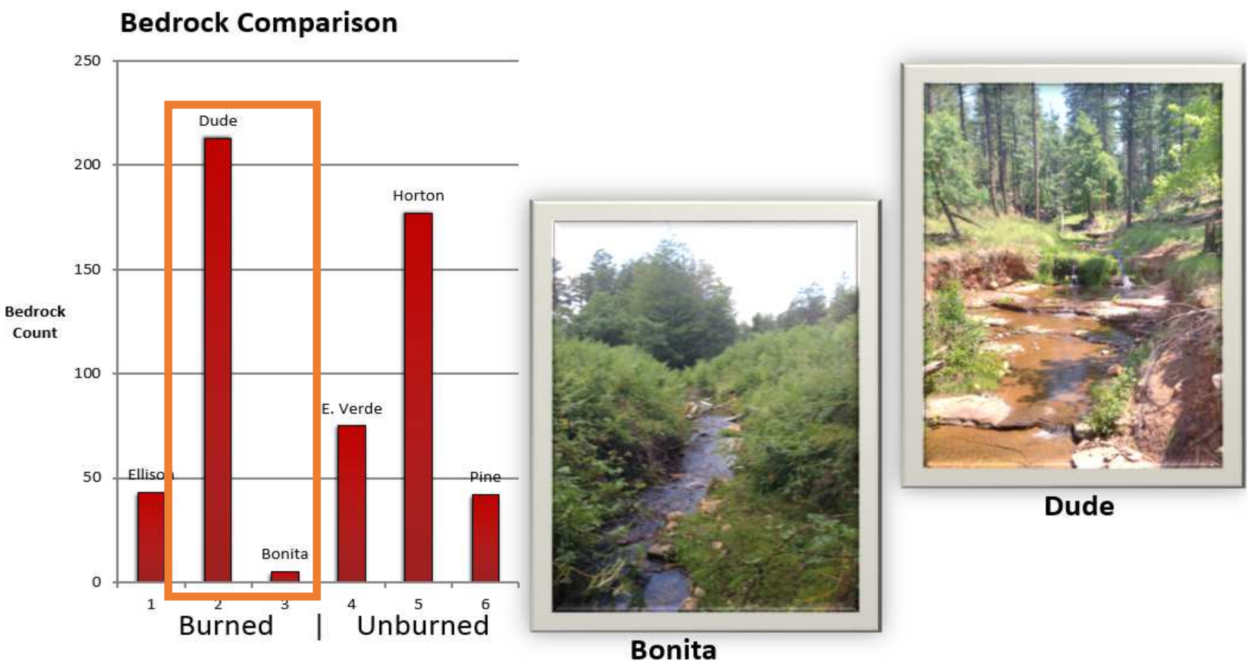


Figure 4 - Watershed Bedrock Comparison and Streambed Pictures

Data collected within watersheds of interest in June 2014. Three transects were chosen to best mimic overall stream conditions. Three hundred pebble size measurements were taken at each of the three transects. The comparison of bedrock within Dude Creek versus Bonita Creek can be seen (left).. Note the blackberry found along Bonita Creek (center) and bedrock exposed as well as Lovegrass found along the banks of Dude Creek (right).

After the fire, the soils of both watersheds were hydrophobic. Hydrophobicity is a result of the formation of a waxy layer in the soil profile caused by the high severity burn (DeBano, 2000; McHale et al., 2005). The summer storms following the burn caused a large amount of soil erosion, especially in Dude Creek. Decades later this stream can still be characterized by its streambed consisting generally of bedrock due to the flooding (Figure 4). Bonita Creek experienced similar precipitation events, being adjacent to Dude Creek yet this stream responded differently as it did not undergo streambed erosion to a similar same scale. It has been speculated that this was due to differences in vegetation, such as the small stands of ponderosa pine found along the banks of the stream, stream morphology and streamflow amount (Leonard, 2014). Decades following the burn a large increase in Himalayan Blackberry has been noted along the stream banks (Figure 4), which may have also contributed to the stability of the soil.

Chapter 2: Literature Review

2.1 Forest Management and Policy

Natural resource policy within the United States has resulted in the exclusion of forest fire thus contributing to an altered fire regimen in ponderosa pine ecosystems. (Stephens and Ruth, 2005). The majority of these ecosystems are now altered to support severe fire behavior (Reiner et al., 2012), and no longer support the functions it did in pre-settlement forests (Moore et al., 1999). Building on science based programs that use modeling will allow agencies to better utilize information in pursuit of reducing severe wildfire (Stephens and Ruth, 2005). National forest managers in Arizona have been working to reduce the threat of high-severity fire using restoration treatments such as prescribed burns and the mechanical thinning of trees, yet these costly efforts have not sufficiently reduced the threat of these severe large-scale fires (Fitzgerald. 2005).

A ten year restoration project called the Four Forest Initiative (4FRI) has already begun to take place within the ponderosa forests in Arizona (Fredette, 2016; Robles et al., 2014). The overall goal of 4FRI is to plan and implement landscape-scale restoration approaches in order to reduce fire fuels and improve forest health (USDA, n.d.). 4FRI is located within the Kaibab, Coconino, Apache-Sitgreaves and Tonto National Forests and will utilize mechanical thinning and prescribed burning treatments across an estimated 586,000 acres over a ten year period with the objective to re-establish forest structure, pattern, and composition (Fredette, 2016; Robles et al., 2014). Within the project boundary lies the Mogollon rim and several headwater watersheds.

These watersheds containing ponderosa pine over-story produce 50% of the runoff in the Salt and Verde watersheds even though it accounts for only 20% land cover of the area (Robles et al., 2014). Model predictions in mechanically thinned forests are forecasted to provide around 20% more runoff than unthinned forests and increase the mean annual runoff from between 0-3%. These models run by the Nature Conservancy and Northern Arizona University, support the idea that accelerated forest thinning at large scales could improve the water balance and resilience of forests and sustain the ecosystem services they provide (Robles et al., 2014). The continued use of hydrological models in which land management practices, vegetation cover, climate, and hydrological processes are all included would further assist land management agencies in evaluating proper management practices.

Land management agencies in the US are required to assess conditions post wildfire and when deemed necessary implement watershed rehabilitation practices (Beyers, 2004; USDA, 1985). The Burned Area Emergency Response (BEAR) program was designed by the USFS to address these needs. The BAER team aims to stabilize wildland fire zones to prevent further damage by protecting life, property, and natural and cultural resources. Staffed by a specialized team, the burn zone is rapidly evaluated and stabilization treatments are implemented. BAER assessment and implementation plans are often a cooperative effort between federal agencies (Forest Service, Natural Resources Conservation Service, National Park Service, Bureau of Land Management, U.S. Fish and Wildlife Service, Bureau of Indian Affairs, U.S. Geological Survey), and state, tribal and local forestry and emergency management departments (Witt, 1999).

To simplify the rapid response for post-fire remediation and facilitate the use of hydrological modeling, online spatial databases offer formatted parameters using BAER assessments (Flanagan et al., 2007; Miller, 2016). These modeling tools help foresee impacts of treatments and increase the understanding of the effects of fire on watersheds. Without the use of these modeling input generators, it is impracticable for BAER teams to apply quick and effective watershed erosion mitigation practices (Miller, 2016).

4FRI considers all ongoing and proposed forest restoration projects under the National Environmental Policy Act (NEPA) within these forests to be considered part of the initiative (Fredette, 2016). Land managers working under the 4FRI objectives aim to mitigate the adverse effects of high-severity fire on soil and water resources through the use of best management practices. Best management practices for watersheds are defined as follows "Minimize impacts on soil and water resources from all ground disturbing activities. Manage vegetation to achieve satisfactory or better watershed conditions. Prepare flood hazard analyses on proposed projects in flood prone areas per Executive Order 11988. Mitigate the adverse effects of planned activities on the soil and water resources through the use of Best Management Practices. Avoid channel changes or disturbance of stream channels and minimize impacts to riparian vegetation." (Unites States Department of Agriculture, 1985, p. 7-8). Using these management guidelines as objectives, modeling implementation methods and results can be compared to assess what model preforms best.

2.2 Climate Change and Modeling

Climate change is projected to increase likeliness of extreme weather associated wildfire intensity (Karl et al., 2008). The joined effects of climate change and high severity fires are predicted to alter forested areas in the Southwest United States by triggering a shift from ponderosa pine to juniper dominated forests (Bell et al., 2013; Schlaepfer et al., 2012).

Modeling in conjunction with GIS has proven to assist in identifying areas at-risk for wildland fire due to changes in climate (Bell et al., 2014; Vadrevu, 2010). As climate suitability for southwest ponderosa forests in the United States will decline, modeling provides land managers with ideas as to what the best management practices may be. Models such as RUSLE and WEPP can assist land managers in assessing what remediation efforts provide the most effective results in reducing the risk of high-severity burns, soil erosion, and a shift in forest species (Gould et al., 2016; Prasannakumar et al., 2012).

2.3 Dude Fire Landscape Vegetation Change

Fire has played a key role in ponderosa forests in the United States Southwest. These forests have evolved to survive low-intensity wildfires that occurred typically during pre-settlement times in which fire returned approximately every 2-47 years (Fitzgerald, 2005). This can be attributed to evolutionary traits such as protected buds, thick bark, high-volume seed production, highly flammable litter, basal sprouting patterns, and deep rooting (Balch et al., 2013;, Moore et al., 1999). These low-intensity fires would consume accumulated fuels and smaller plants, thin the younger tree populations, leaving the large, fire-resistant trees intact (Fitzgerald, 2005)

Ponderosa pine ecosystems have changed drastically in the last 140 years due to the disruption of fire regimes. Due to livestock grazing, logging, and fire suppression current conditions consist of an over-abundance of fuel (Moore et al., 1999). Severe wildfires and drought have caused up to 20% tree mortality in forests and woodlands in Arizona and New Mexico (Robles, et al. 2014). Dense, over-stocked forests increase the risk of insect and disease outbreaks, high-intensity wildfires, and conditions that are unsustainable for these ecosystems

(USDA, n.d.). Average ponderosa stand densities have increased over 1000 trees per hectare (Fitzgerald, 2005; Moore et al., 1999) and total basal areas range from 2 to 4 times greater (Robles et al., 2014). Research has also pointed out possible flaws in the statistical analysis of the United States Forest Service Inventory data indicating that high severity fire frequency was less common pre-industrialization that originally thought (Stevens et al., 2016).

The Dude Fire site provides an opportunity to study the long-term effects of high-severity fire on the Mogollon Rim. Twenty years after the Dude Fire, findings by Leonard et al. (2015), demonstrated that oak tree density had increased over 400% from unburned to burned sites. Non-native weeping lovegrass now makes up 81% of the total herbaceous cover. Furthermore, bare ground cover is 150% higher and litter cover is 50% lower in the burned area. Lead soil erosion models can be used address the effects of large-scale vegetation change and establish vegetation restoration models (Han et al., 2016).

2.4 Soil Response to Fire

Disrupted fire regimens have put ponderosa forests in conditions for high severity burns and therefor at risk for severe soil erosion and flooding. Water repellency produced by low to moderate severity fires is usually of shorter duration and intensity than that produced by high severity fires (Cawson et al., 2016; DeBano, 2000). High severity fire in ponderosa pine forests result in increased soil exposure causing vapor deposition of wax into the soil due to the burning of organic material. This causes intensified water repellency in the upper level of the soil profile (Fitzgerald, 2005; McHale et al., 2005). Soil conditions and characteristics can cause differences in water infiltration and overland flow, thus escalating erosion (DeBano, 2000; McHale et al., 2005). Due to the removal of the vegetation cover and the increased water repellency these areas are prone to an increase in runoff and erosion during post-fire rain events (Beyers, 2004).

In order to mitigate the effects of wildland fire on erosion and reduce the chances of severe flooding a variety of management practices have been implemented and studied. One method consists of using budget friendly chemical treatments to reduce erosion, yet this has not provided noticeable results (DeBano, 2000). Techniques using heavy machinery to break up water repellent layers are impractical when implemented at a large scale or in complex terrain. Recent management practices introduce mulching to reduce post-fire erosion rates. Studies conducted by Robichaud et al., (2012) found variability in its effectiveness and deemed the method of mulching to be considered fire specific.

The Dude Fire area underwent one of the more common practices for post-wildfire erosion remediation. Broadcast seeding consists of distributing perennial grasses to provide quick ground cover and soil retention. Minimal data exists supporting the effectiveness of this erosion control (Beyers, 2004). As sampling designs for the effectiveness of broadcast seeding in the western United States has become more rigorous, the evidence of the effectiveness of seeding has declined and additionally the seeding of invasive non-native species can have negative effects on native vegetation recovery (Beyers, 2004; Peppin et al., 2010). Using frequent prescribed fire treatments in ponderosa ecosystems to manage fire-induced soil hydrophobicity is the most practical solution (DeBano, 2000).

2.5 RUSLE Model

The RUSLE is an empirically based model easily integrated with GIS (Ashiagbor et al., 2016; Ganasri and Ramesh, 2016). Empirical observations consist of using knowledge acquired by the means observation and experimentation which RUSLE does by relating management and environmental factors directly to soil loss and sedimentary yields. RUSLE models how climate, soil, topography, and land use affect soil erosion caused by raindrop impact and surface runoff. Manipulating five raster formatted factors consisting of rainfall erosivity, soil erodibility, slope, cover management, and support practice also allows the user to view the spatial heterogeneity of soil erosion and the possible effects of each individual parameter.

In 1965, the USDA created the Universal Soil Loss Equation (USLE). This equation proved to be optimal and very accurate in uniform slopes, more so than WEPP (Tiwari et al., 2000). As the equation was updated, it was adapted for other regions through the improvement of determining factors and the implementation of new ones thus creating RUSLE. RUSLE is the most commonly used model by scientists worldwide (Alexakis et al., 2013).

One of the characteristics of RUSLE that impedes its ability to predict soil erosion is its limitation in properly developing factors to represent the effects of complex hydrographic basins commonly found in mountainous watersheds (Oliveira et al., 2013). This issue has been alleviated using data acquired through the means of remote sensing within a watershed (Bhandari and Darnsawasdi, 2014;, Ganasri and Ramesh, 2016). Remote sensing provides a tool for identifying land cover, elevation differences, and aspects of management with relatively high resolution for small areas (20-50 square kilometers) that are easily integrated with GIS (Bhandari and Darnsawasdi, 2014; Reed et al. 1994; Yaolong, Ke, Yingchun and Hong. 2012).

Remotely sensed data can identify land cover in a variety of ways. Using multi-band imagery, NDVI indexes that indicate phonological events can be used to evaluate the variability of the phenology of land cover types. Implications for land cover mapping suggest that remotely sensed data using NDVI indexes are appropriate as input to vegetation mapping, but needs to be cross referenced with field data for accuracy (Reed et al., 1994). Alternatively land cover classification methods can classify vegetation types and can be used as an input parameter for model running for fire behavior or soil erosion (Yaolong et al., 2012). When stacked and compared over time, imagery can provide land use and cover change as well as clues to possible causes of erosion. After creating the land cover classes, change detection can be ran on multitemporal data sets in order to derive vegetation cover change, observe urban development, or even make implications as to the effects of climate change (Yaolong et al., 2012).

2.6 WEPP Model

The WEPP is a process based model which is founded upon the theoretical understanding of relevant ecological processes. In this case, WEPP calculates erosion processes of sediment transportation mathematically through the solutions of the equations describing those processes. This model provides an assessment of soil loss severity and can be combined with GIS to estimate average soil loss in watersheds (Flanagan et al., 2007). WEPP uses quantitative data to identify critical areas where soil erosion is most anticipated within both the watershed rills and streams (Han et al., 2016). The WEPP model has evidence to support that with minimal parameter calibration it provides accurate and tested results demonstrating its utility as a management tool in both gauged and ungauged basins (Brooks et al., 2015).

WEPP is based on research in which various interacting natural processes in hydrology, plant sciences, soil physics, and erosion mechanics were studied and applied. WEPP offers advantages to empirical modeling since it can accommodate spatial and temporal variability in climate, topography, soil properties, management, as well as sediment transportation processess. WEPP can be manipulated in order to study the effects of different parameters on net soil loss or gain for the entire hillslope for any period of time (Tiwari et al., 2000) and therefor can be used to measure the effects of climate change on watersheds by allowing for the manipulation of different factors as to model future climate scenarios (Gould et al., 2016).

Since its development it has been further enhanced in order to increase its applicability to small forested watersheds. Through the development of GeoWEPP, GeoWEPP-BAER, and WEPP parameter databases, the model can use complex inputs provided by peer reviewed sources in user-friendly formats (Dun et al., 2009; Flanagan et al., 2007).

When using GeoWEPP, the Parameter-elevation Regressions on Independent Slopes Model (PRISM) and Climate Generator (CLIGEN) tools are used in order to create its precipitation and temperature inputs. PRISM is a climate analysis system in which specified point and digital elevation data supplied through GeoWEPP and ArcMap works with spatial datasets to generate estimates of precipitation and climate in grid format (Daly et al., 2002). PRISM has been designed to accommodate difficult climate mapping situations by including vertical extrapolation of climate, reproducing gradients caused by rain shadows and coastal effects and taking into account the possible complexity of terrain on precipitation by identifying features that rise above the large-scale terrain and adjusting its predicted measurements for these areas (Daly et al., 2002). CLIGEN provides the point data for the PRISM model by using historic climate measurements (Flanagan et al., 2007; Meyer, 2010).

GeoWEPP uses the Topographic Parameterization (TOPAZ) digital landscape analysis tool in order to delineate channels, watersheds and subcatchments. This model provides slope inputs for each of the subcatchment hillslope and channel profiles for GeoWEPP (Flanagan et al., 2013). As WEPP uses complex hillslope data and takes climate variability on hydrological factors into account inferences as to best stormwater management practices can be made (Landi et al., 2011; Brooks et al., 2015).

2.7 Data Resolution Effects on Modeling Results

One of the most important parameters for RUSLE and WEPP models are the Digital Elevation Models that spatially tie the soil, weather and other factors to the study areas. DEMs also provide the data is manipulated to identify hillslope, channels, and catchments. These models can vary as the intervals between elevation points determines the resolution, and the precision of ground trued points determine the accuracy. The resolution and accuracy of the DEMs themselves can greatly affect the results of soil erosion models (Zhang et al., 2008). When comparing publically accessed DEM data, LIDAR satellite images with finer resolution commonly provide the most accurate results for small-scale (1000 square foot) watersheds (Zhang et al., 2008).

Chapter 3: Models and Methods

3.1 RUSLE Introduction

The Revised Universal Soil Loss Equation started as the Universal Soil Loss Equation (USLE) which was created in 1965 by the USDA with the goal of monitoring soil erosion along agricultural type land of the Corn Belt region of the United States. Development of USLE began with scientist Hugh Bennet, who highlighted the issue of soil erosion during the dust bowl leading to the federal funding for related research. Stations were established for experimental studies in which factors affecting erosion were identified and studied. The mathematical portion began to take shape in the early 1940s (Zingg and Smith, 1940). By 1961 the general factors identified and agreed upon by the array of leading researchers were rainfall, soil erodibility, cropping management and slope (Tiwari et al., 2000).

By 1965 two key scientists Wischmeier and Smith published a section in the USDA Agricultural Handbook in which the completed technology for USLE was presented. With the majority of the development coming from USDA and Peurdue University affiliated scientists, a process in which data was analyzed in simulations using computers began to take place in the 1960s. USLE was quickly adopted as the lead soil erosion modeling tool throughout the world (Ouyang et al., 2002; Tiwari et al., 2000; USDA, 2016)

With additional research and data, the USLE equation became RUSLE which uses the same formula but revised several of the factors used. This model provides the same empirical approach that predicts erosion rates and presents the spatial heterogeneity of soil erosion using uniform flow hydraulics. The RUSLE model similarly consists of an equation that ties in raster formatted factors that include rainfall erosivity (R factor), soil erodibility (K factor), slope length and steepness (LS factors are combined), cover management (C factor), but additionally introduced the support practice (P factor). Other key modifications consisted of the computation of the slope length and steepness factors. When these factors are multiplied they compute “A” which is an estimated average soil loss in tons per acre per year (Tiwari et al., 2000).

RUSLE was completed and formatted for computer use and was re-released in 1992. As it became more popular in studying erosion, the need to quantify the amount of erosion had become less important than identifying the spatial distribution of erosion sources (Ashiagbor et al., 2013). By accurately identifying the highest risk areas, land managers could then implement the most cost effective erosion control practices. For easy integration with GIS, several factors can be computed using variety of databases and tools such as the USDA Geospatial Data Gateway, the United States Forest Service (USFS) Geodata Clearinghouse, the Environmental Protection Agency (EPA) Rainfall Erosivity calculator and ArcGIS.

3.2 RUSLE Methodology

RUSLE Equation: A = R*K*LS*C*P

A = Soil loss in tons per acre per year

R = Rainfall-runoff erosivity

K = Soil Erodibility

L = Slope length

S = Slope Steepness

C = Cover-management factor

P = Support Practice

*For in-depth methodology for RUSLE using ArcMap see Appendix (A).

**All factors were attributed 10mX10m cell resolution as that is the lowest resolution the data obtain contained. These factors were also all projected in the “NAD1983_utm_zone 12n” in ArcMap.

Watershed Delineation – ArcMap Hydrology Toolset

As the RUSLE model does not provide an interface for ArcMap, the watersheds were delineated used the *ArcMap Hydrology Toolset*. By using the highest resolution DEM and this hydrological model, the watersheds were able to be accurately delineated (Figure 2), as well as provide layers for future use such as “flow direction”, “flow accumulation”, “stream order”, and “flow length”.

R Factor – Rainfall Runoff

The Rainfall Runoff factor represents the effect of raindrop impact and the amount and rate of runoff associated with the precipitation. While the USDA RUSLE handbook (Rendard et al.,1997) provides several equations for calculating an R-factor using weather station data, the topographic complexity provided extremely high results when compared to other case studies. In order to address this, the factor was created using the EPA Rainfall Erosivity Factor Calculator. This tool is commonly used to determine if small construction projects are eligible to waive the permitting needed through the National Pollutant Discharge Elimination Systems. This tool takes elevation, the date range, latitude, and longitude into account and supplies the user with point specific data (Table 1). This data was spatially interpolated to give the final R-factor (Figure 5).

Location ID	1	2	3	4	5	6	7	8	9	10
RValue	266	290	266	240	266	240	217	217	266	266
Latitude	34.4305	34.4247	34.4165	34.4038	34.415	34.4035	34.3892	34.3852	34.4088	34.4042
Longitude	-111.229	-111.223	-111.216	-111.224	-111.246	-111.24	-111.239	-111.266	-111.198	-111.208
Location ID	10	11	12	13	14	15	16	17	18	
RValue	266	217	217	217	217	217	290	266	217	
Latitude	34.4042	34.3886	34.3758	34.3669	34.35	34.3569	34.437	34.4064	34.3848	
Longitude	111.208	111.21	111.229	111.25	111.241	111.22	111.238	111.193	111.274	

Table 1 - EPA R-Factor Locations

These are the geographic points in which the R factor was calculated for. Latitude and longitude displayed in degrees

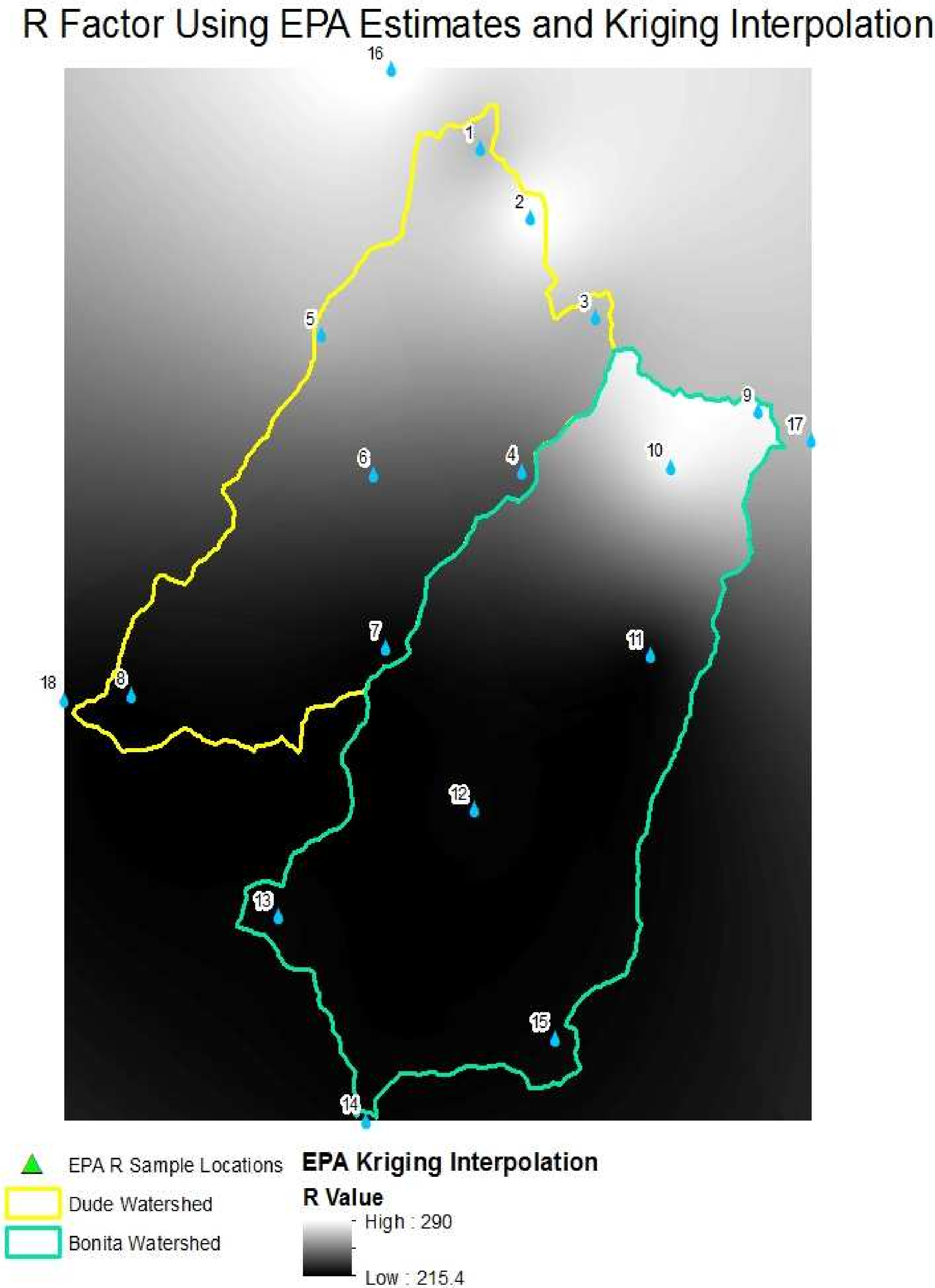


Figure 5 - RUSLE EPA R-Factor Locations

K = Soil Erodibility

This factor represents the ease of which the soil is detached by splash during rainfall and or surface flow (Renard et al., 1997). The USDA RUSLE Guide provides methods to identify the K-value in which soil characteristics such as particle size, organic matter content and structure is analyzed and use an inputs in a series of equation. As this would require physical access to the study area, timely analysis, and specific tools, an alternative method was used. The USFS database provides K-values for RUSLE throughout the contiguous United States. This data was used and compared to a nomograph provided by the USDA RUSLE Guide (Renard et al.,1997) in which the dominant rock type of limestone and sandstone were compared. The K-factor of .2 was used for the entire study area (Figure 6).

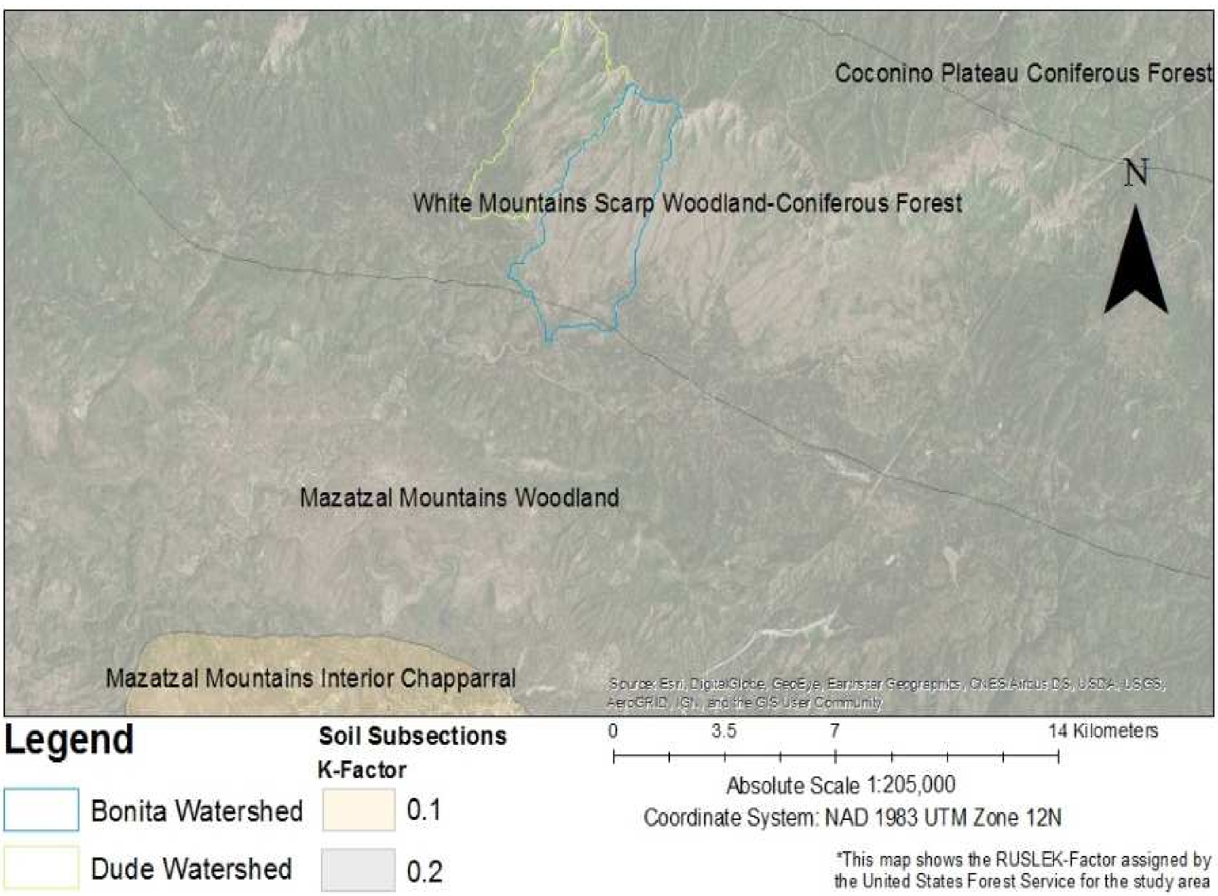


Figure 6 - RUSLE K-Factor

LS = Slope length and steepness.

These factors aims to address the effects of topography on erosion. The slope length factor represents the increase in erosion due to the horizontal distance in which the overland flow either is effected by a decrease in slope causing deposition, or the flow becomes concentrated in a defined channel. The slope steepness factor aims to reflect the influence of slope gradient on erosion (Oliveira et al., 2013; Renard et al., 1997). While slope length and steepness is best calculated in the field (Renard et al., 1997) it is not feasible in such large and topographically complex areas (Oliveira et al., 2013). For this reason the highest resolution and most accurate DEM was used in conjunction with GIS. Equations have been created to address the L and S factors to best reflect the influence of slope gradient on erosion and have been formatted to be used with GIS software (Oliveira et al., 2013). Subfactors for the equations chosen were selected to best compute accurate results in accentuated slopes. These factors are combined and computed using the *Raster Calculator* before being used in RUSLE.

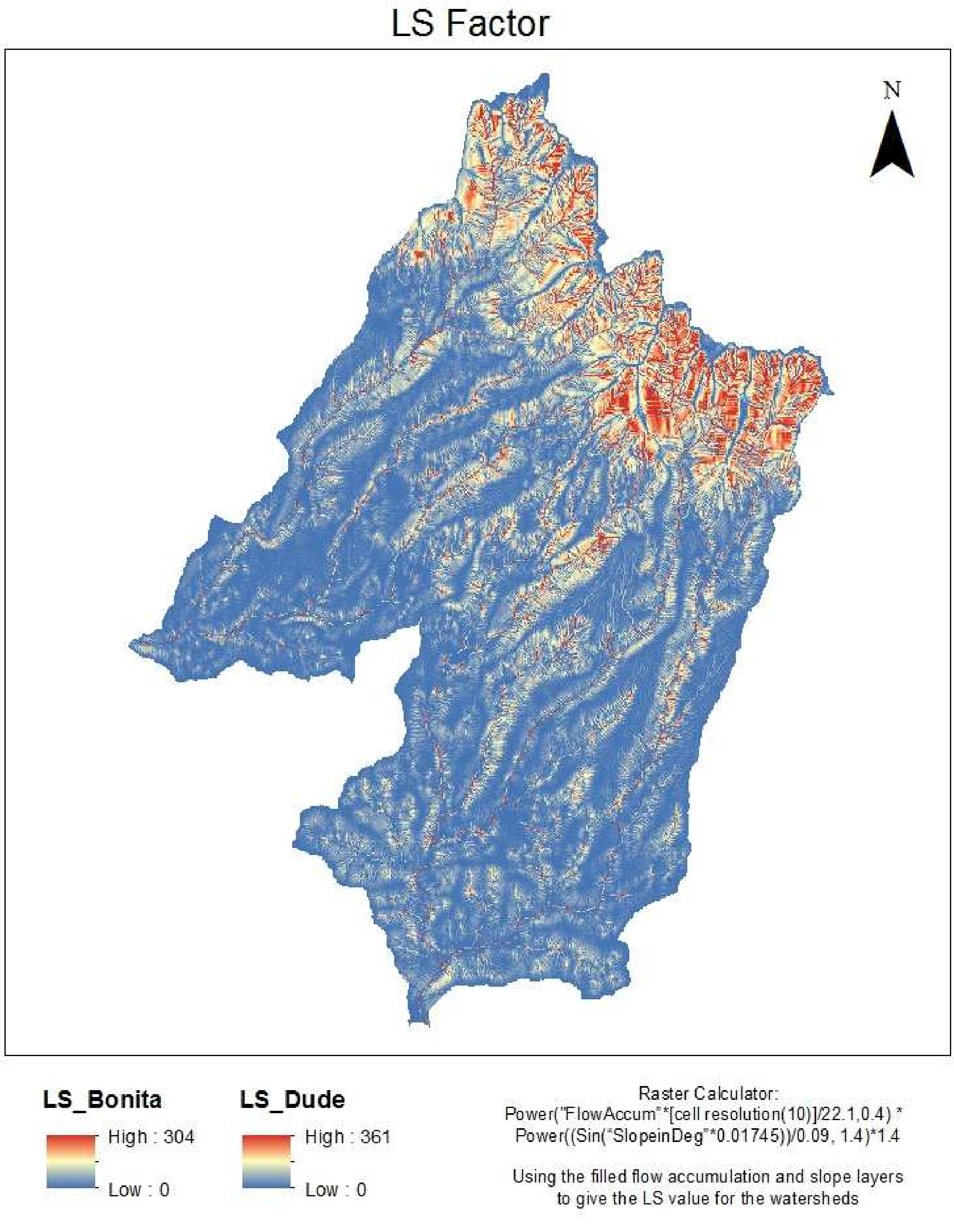


*Figure 7 - RUSLE L*S Factors*

C = Cover-management factor

This factor aims to reflect the effect of vegetation and other influencing factors on erosion rates. This factor was created using ENVI and ArcMap software. Having relatively small watersheds high resolution data was needed in order to create the proper land cover factor. While a land cover classification shapefile for RUSLE has already been created by the United States Geologic Survey, it is of poor resolution as it has been created to cover all of Arizona in order to study largescale watersheds such as the Bill Williams or the Verde.

In order to create the most accurate land cover factor, high resolution 1 meter data was used and edited in Environment for Visualizing Images (ENVI) software. A supervised land cover classification method allowed for the identification of three land cover types (Figure 8). As the imagery at this resolution was available for several years, the accuracy for each year was calculated. The 2015 imagery provided the highest accuracy data and was therefore used.

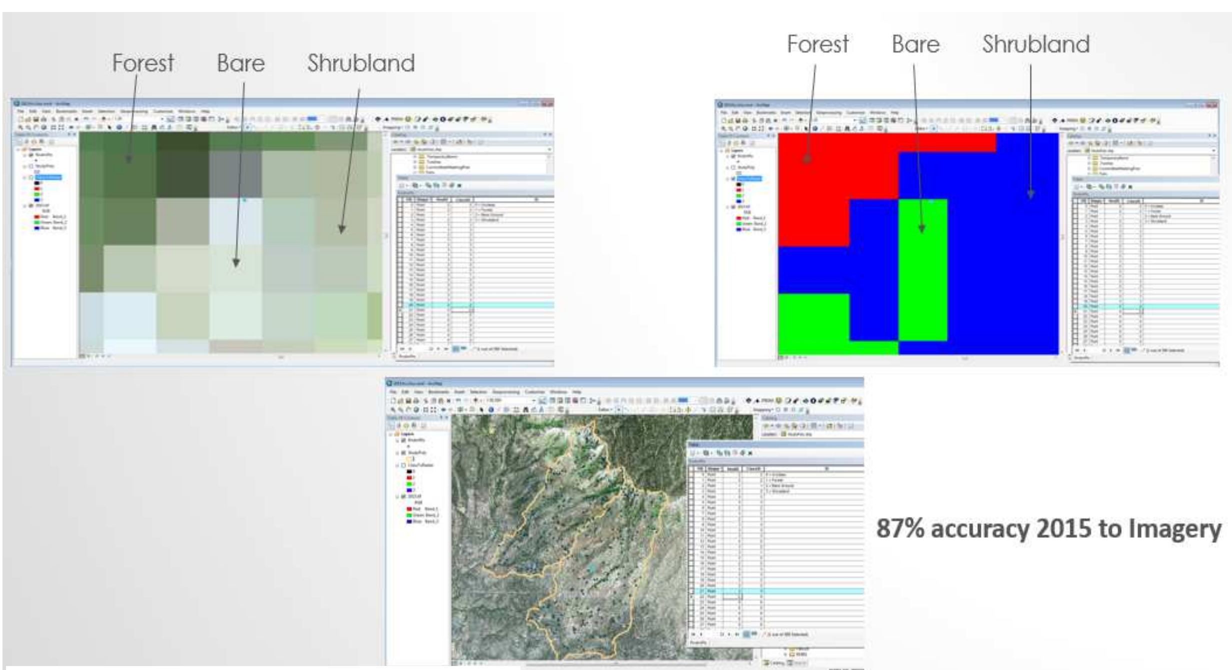


Figure 8 - Land Cover Accuracy Assessment Method

Having used imagery obtained 25 years after the fire, the immediate effects of the severe burn needed to be addressed. A burn severity map was acquired from the USFS (Figure 9). The polygons representing different degrees of burn severity were digitized in ArcMap. These polygons were then overlaid with the land classification results. The high severity polygons were given a high C-value and eradicated any vegetation that intersected them to represent the effects of the high severity burn. The additional land cover values were identified using the USDA RUSLE handbook, yet the values were increased to represent the effects of the moderate and low severity areas. The ponderosa pine forest identified that did not intersect the high severity burn was attributed a very low C-value as this species has evolved to be resistant to low intensity fire and is described to have deep soil retaining roots (Balch et al., 2013; Fitzgerald, 2005; Moore et al., 1999)

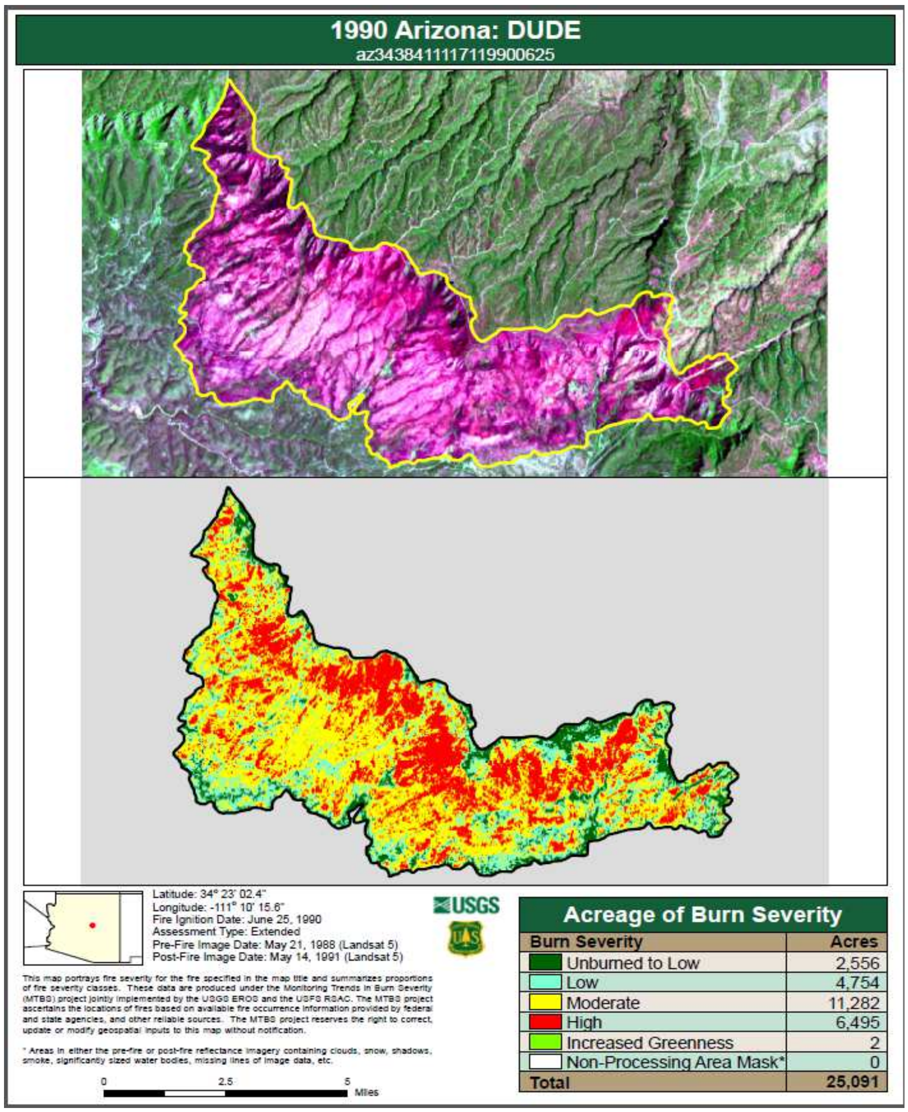


Figure 9 - Dude Fire Severity Map. Adapted from USFS Rocky Mountain Research Station

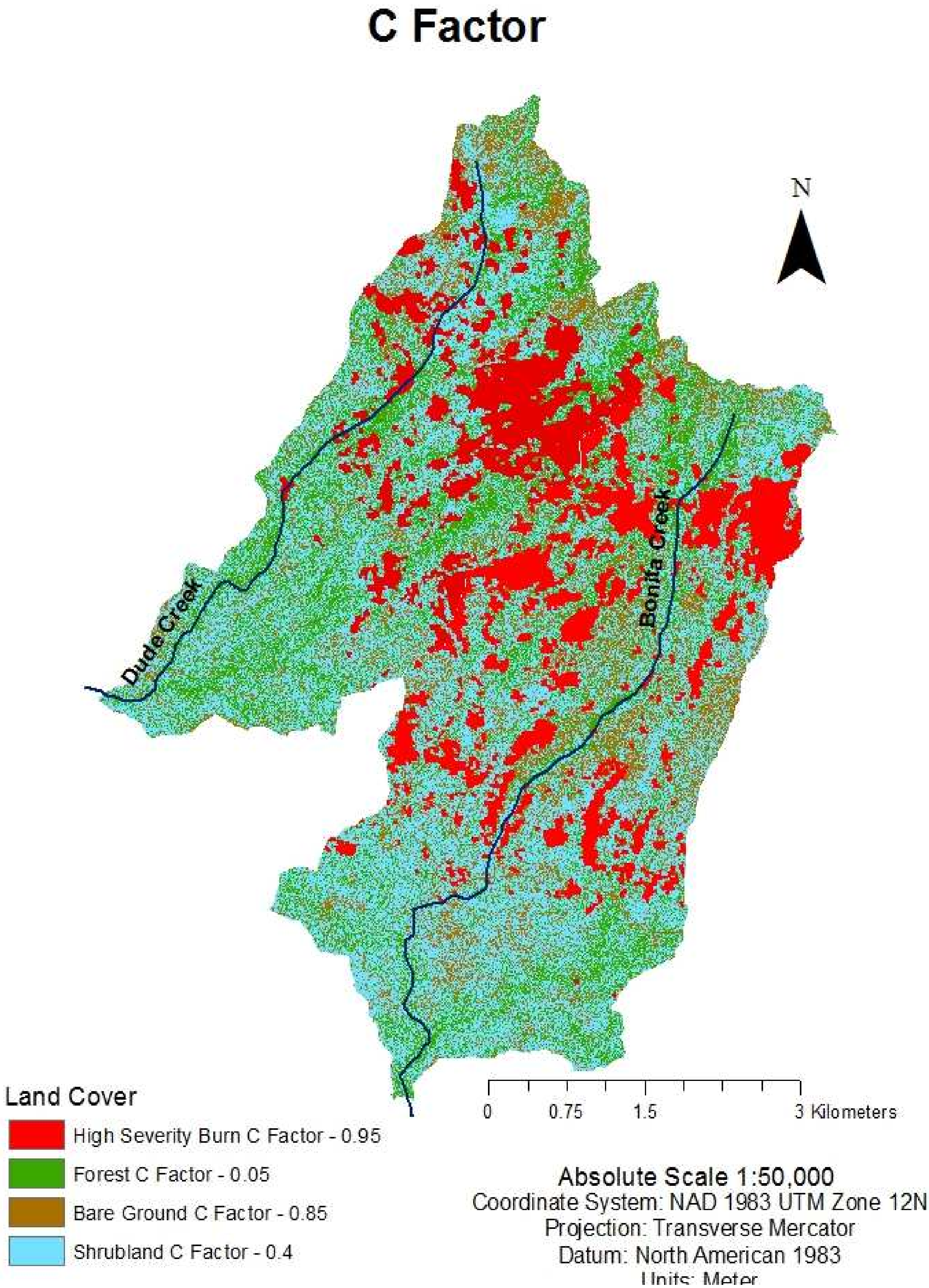


Figure 10 - RUSLE C-Factor

P = Support Practice

This factor represents the ratio of soil loss with a specific support practice in which erosion is effected by modifying the flow pattern or by reducing the amount and rate of runoff. This value ranges from 1-0, with one being no support practice used. Following the burn, the area was aerially seeded with a variety of grasses to reduce erosion. The value 0.98 was attributed to the seeded area as very little data exists that supports the effectiveness of seeding for erosion control (Beyers, 2004; Peppin et al., 2010).

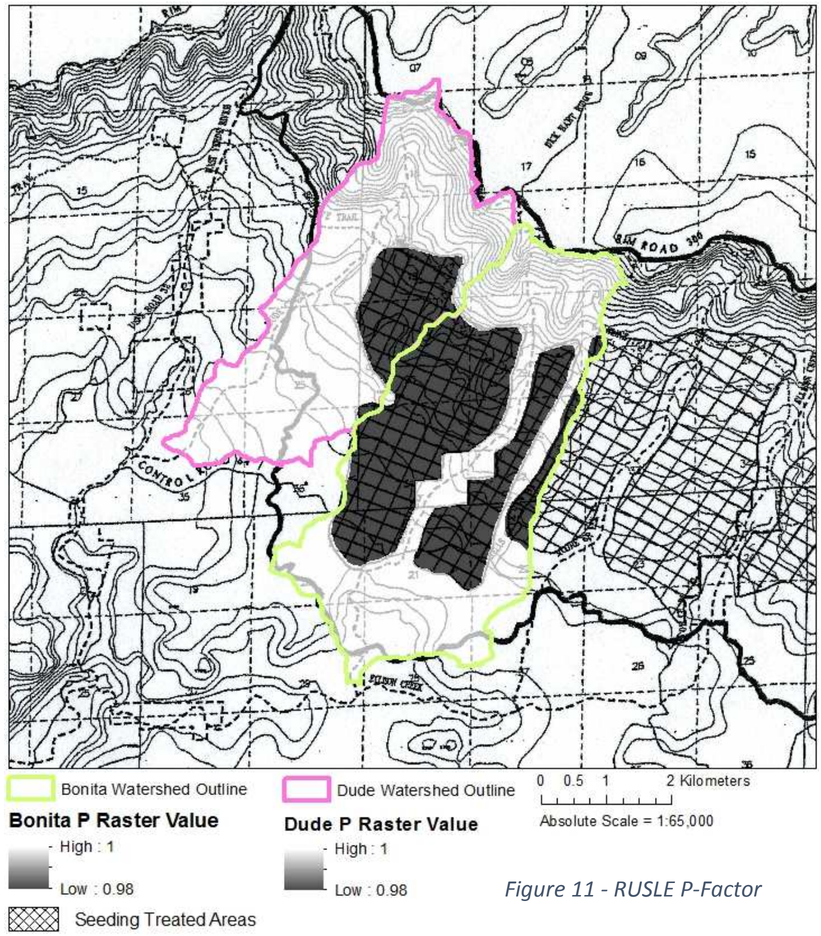


Figure 11 - RUSLE P-Factor

RUSLE Model Output Computation

The factors were multiplied providing the output for the RUSLE model for both watersheds (Figures 17,16). Using the parameters calculated above, the ArcMap *ModelBuilder* tool was used to multiply the factors to calculate the soil loss in tons per hectare per year for each 10 by 10 meter cell. Additionally, the results were categorized into classes to identify the areas at highest risk for erosion (Figures 18, 19).

3.3 WEPP Introduction

The Water Erosion Prediction Project (WEPP) is a computer model that was developed largely in part by the USDA's Agricultural Research Service, the Natural Resources Conservation Service and the U.S. Department of the Interior's Bureau of Land Management. Four senior scientists G. Foster, L. Lane, J. Laflen and D. Flanagan were termed the project leaders over a span of 22 years. WEPP simulates soil erosion processes taking a quantitative process-based approach founded upon observed erosion mechanics and interacting natural processes using non-geographically tied and geographically tied data to then calculate net soil loss or gain for a hillslope for a specified amount of time.

The original software version of WEPP was difficult to manage and therefore a new version integrated with GIS software was created (Elliot et al., 2006). With the help of the USDA National Soil Erosion Research Laboratory, scientists from Peurdue University, and the department of geography at the University of Buffalo led by Chris Renschler, a geospatial interface for WEPP with ArcMap was developed and named GeoWEPP. This software allows for the integration of personalized data allowing the user to create, assess, and study the effects of a variety of parameters on soil erosion processes within watersheds (Elliot et al., 2006).

Through its use, users are able to define the influence of localized climate variability on daily runoff, soil erosion, and sediment yield. The model created estimates of net detachment and deposition using steady state sediment continuity equation. This is done by using a fixed approach describing the movement in soil caused by overland flow in dynamic equilibrium (Landi, 2011) and by predicting rill and interrill erosion separately. Rill erosion is defined as the occurrence of soil removal due to water running over the soil while interrill erosion is caused by raindrop impact and splash. GeoWEPP uses GIS data to first delineate the watershed based upon a channel. Parameters needed to run GeoWEPP include climate, soil type, land cover, and a digital elevation model (DEM). GeoWEPP used in conjunction with ArcGIS allows the user to use a large extent of data in regards to resolution and detail. The creation and application of these parameters will be explained in the following pages.

Before running a WEPP simulation, a DEM and optional land cover and soil data are selected in order to create the study area. If these parameters are not selected, default values will be assigned for them. This data selection is done outside of ArcMap, in a GeoWEPP for ArcGIS 10.3 wizard. The DEM must be provided in ASCII format. This also is the required format for the land cover and soil files. When providing personal land cover and soil data, description and database text files need to be created and properly formatted. The DEM data should ideally be limited to the area of interest, as a larger and higher resolution DEM will more likely produce errors.

Within ArcMap GeoWEPP is used as an extension with a specific toolbar. Basic navigation tools included in the toolbar allow the user to pan around the area of interest, zoom, and view the full extent of the area much like the traditional tools ArcMap offers. The *Modify Channel Network Delineation* Tool creates a channel network based upon the DEM supplied. It creates these channels using two parameters. The first is the Critical Source Area (CSA) in which the user must define (in hectares) the minimum source area needed to generate a channel. The second parameter is the Minimum Source Channel Length (MSCL) in which the user must define the shortest distance a first order channel needs to travel before joining another before it is classified. Both of these must be met in order to be represented as a channel in the model. This tool provides an easy way to modify the channels found in the DEM.

After having created a channel network, the *Watershed/Subcatchment Generation* tool can then be used in order to identify the subcatchment of the watershed by choosing a cell within the previously generated channel network. This cell has been termed the outlet point. Subcatchments are a hydrologic unit that are part of the hierarchical system that make up watersheds. This tool will generate polygons that identify the hillslopes that join together to create the watershed that feeds up to the selected cell or “outlet point” of the watershed. The polygons representing the subcatchments will vary in number, shading, and or color. This tool as well as the *Channel Delineation* Tool is run using *Topographic Parameterization* (TOPAZ) which is defined as a digital landscape analysis tool used for subcatchment parameterization, drainage delineation, and watershed dissection. The analysis is based on the application of the deterministic eight-neighbor method to simulate flow across a land surface represented by a DEM, (Garbrecht and Martz, 2015).

Climate within the GeoWEPP model is modified using the Parameter-Regressions on independent Slopes Model (PRISM). This interlinked model allows the user to easily modify the climate for the study area. The user can either choose the closest climate station to the outlet point, pick a separate weather station, edit existing climate stations, or the user can create personal climate parameter files. PRISM is defined as a climate analysis system in which point data is used along with a digital elevation model (DEM) to then give estimates in climate for geographic areas in which point data is not sufficient (Daly, 2002). Through PRISM, point specific climate data can be extrapolated over large areas which is easily integrated with GIS

(Johnson, 1998). The point data used for the PRISM are weather stations that are generated through CLIGEN. CLIGEN provides storm parameter estimates from a single geographic point (Meyer, 2016). This includes estimates in regards to storm time to peak, peak intensity, and duration, all being vital in regards to soil erosion events.

When modifying climate data, the user may select to use the Climate Modification window. Here mean maximum, mean minimum temperatures as well as mean precipitation and number of wet days can be edited if the attributed parameters derived from PRISM are not to the users liking. When modifying the climate the user may edit the new climate station name, latitude and longitude, elevation, as well as the recently mentioned temperature and precipitation parameters. In addition to modifying the climate data, users can adjust 2.5 minute grid values for both elevation and annual precipitation in inches.

After creating and accepting the parameters, the user can begin the WEPP simulation by clicking the Accept Watershed button located on the WEPP toolbar, this will produce results in map and text form as well as allow the user to access a variety of new tools. When finished running, the model will provide two different model outcomes from two different methods. The first is named the Watershed Method, in which the model assigns one soil and one land use for each hillslope. This hillslope profile is chosen by combining all the flow paths found in the hillslope where they are then aggregated to create a profile that best represents the hillslope. The dominant soil type is then chosen for the hillslope and it is assigned to its profile. This simulation is then ran on each hillslope and is given the label “Offsite assessment” as the value reported for each hillslope represents the sediment flux at the given outlet point. This process better allows the user to assess which hillslopes are at the highest risk.

The other method that the model can use is called the Flowpath Method. This supplies results for each flow path in the subcatchment. It differs to the Watershed Method as it does not use generalized parameter profiles for each hillslope but allows each cell to be labeled a soil and land use factor independently. This allows for the slope, soil and land use layers to work together within a flow path. While no aggregation occurs at the sources of the different flow paths, several of the flow paths share the same destination in which here the aggregation occurs. The map produced using this method supplies the user with estimates of erosion occurring in each raster cell and therefore shows what portion of the hillslope are the main contributors to the erosion. Both these methods provide estimates of erosion in tons per acre per year.

Once the WEPP has been run a variety of tools will be newly accessible. The "*Remap With New T-value*" tool allows the default value of erosion loss and sediment yield threshold to be edited. By default, this value is set to one ton per hectare per year. This change can be toggled on the Change T-value window. The *WEPP Hillslope Information* tool allows the user to identify what soil and land use parameters a certain hillslope was assigned. These parameters can then be changed using the change WEPP hillslope parameters which will be implemented after the model has been reran using the rerun WEPP button. Another way of running the WEPP model is by using the WEPP on a Hillslope function in which, once the parameters are identified, the model will be ran on only that one identified hillslope.

In addition to the editing of the results, GeoWEPP creates three text formatted reports. The "Offsite Events" report provides estimates as to how much discharge occurred from the user specified watershed outlet point. Only results for runoff volume > 0.005m^3 are listed.

This is done on the format of providing the day, month and year of each precipitation event. For each date, precipitation Depth (mm), runoff volume (m^3), peak Runoff (m^3/s), and sediment Yield (kg) are calculated.

The second text report that is created is the “Offsite Summary” which provides an estimation of hillslopes Runoff Volume (m^3/yr), Subrunoff Volume (m^3/yr), Soil Loss (kg), Sediment Deposition (kg), and Sediment Yield (kg) per each hillslope identified by the TOPAZ model. It similarly identifies the Discharge Volume (m^3/yr) Sediment Yield (ton/yr) Soil Loss (ton/yr) Upland Charge (m^3), and Subsurface Flow (m^3) per each channel and impoundment. This report also provides information regarding the number of storms and amount of rainfall (mm) produced on an average annual basis. It also informs the number of events and the amount of produced runoff (mm) passing through the watershed outlet on an average annual basis. It creates estimates regarding the average annual delivery from the channel outlet point, the sediment particle leaving the channel information, as well as the distribution of primary particles and organic matter in the eroded sediment.

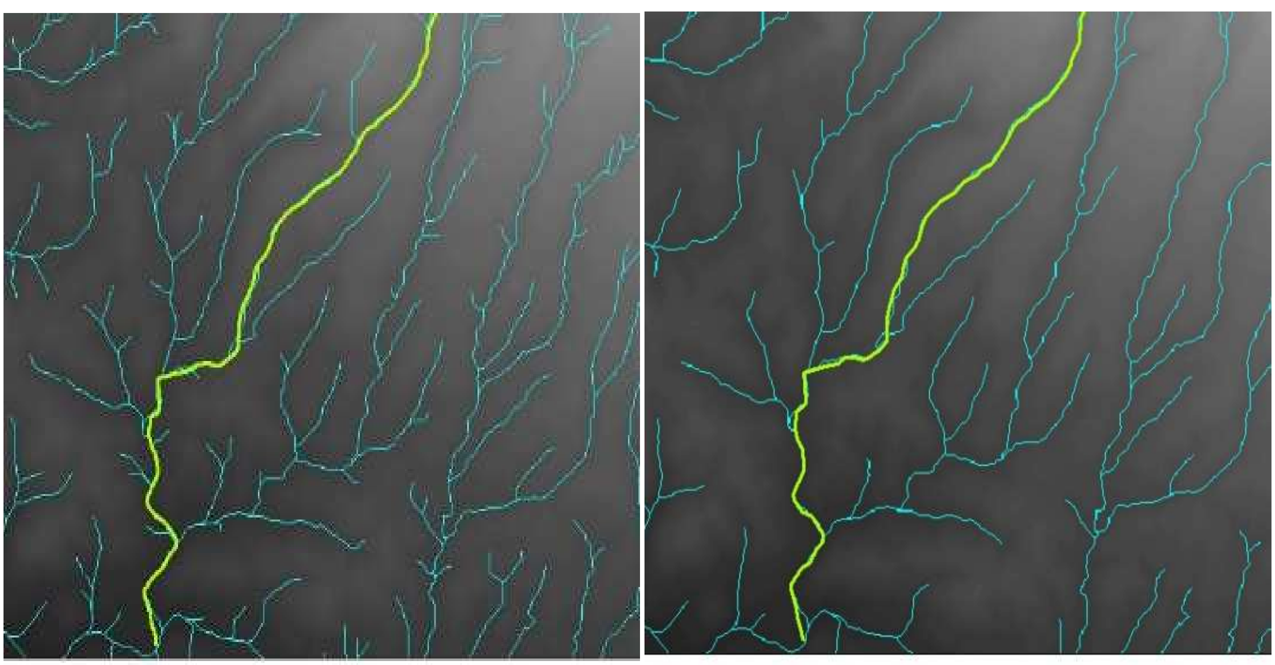
The last report is named the “Onsite Summary” and it provides the four year average annual values for the watershed. The reports identifies the hillslopes both attribute values provided by the TOPAZ model. These values allow the user to observe the estimated runoff volume (m^3/yr), soil loss (ton/yr), sediment yield (ton/yr), area (ha), soil loss (ton/ha/yr), and mapped sediment yield (ton/ha/yr) calculated. The report then calculates a channel summary watershed method off-site assessment by providing the channel WEPP and TOPAZ attribute identification numbers, and their matching discharge volume (m^3/yr), sediment yield (ton/yr), length (m) and Length in raster cells. Lastly, the onsite report supplies a report for the WEPP watershed simulation for all flow paths averaged over subcatchments, using the Flowpath Method as an on-site assessment. This section identifies the hillslopes using the WEPP and TOPAZ identification numbers, and their coinciding runoff Volume (m^3/yr), soil Loss (ton/yr), area (ha) and mapped soil loss (ton/ha/yr).

When studying soil erosion within burn areas a database hosted by Michigan Technological Research Institute provides the DEM, land cover and soils data in proper ASCII format as well as the necessary text formatted documents to integrate them with the GeoWEPP software for several historical burn areas. This database was created to merge soil burn severity maps derived from data collected from Burned Area Emergency Response (BAER) teams with land cover and soils data in order for natural resource managers to make more informed decisions when focusing on post fire remediation (Miller, 2016).

3.4 WEPP Methodology

*For in-depth methodology for usage of the WEPP model through GeoWEPP and ArcMap see Appendix (B).

The majority of parameters needed to run GeoWEPP were downloaded from the BAER Spatial WEPP Model Inputs Generator hosted by Michigan Technological institute. These parameters are based upon data derived from the BAER team. Using the GeoWEPP interface for ArcMap, adjustments were made to the delineation of the watersheds using the TOPAZ model (Garbrecht and Martz, 2015). The channels identified were lowered in detail by adjusting the Critical Source Area (CSA) and the Minimum Source Channel Length (MSCL) to reduce the amount of subcatchments and channel sections identified (Figure 12). By doing this, the risk of crashing is reduced.



Critical Source Area (CSA): 5 Hectares
Minimum Source Channel Length (MSCL): 100 Meters

Critical Source Area (CSA): 10 Hectares
Minimum Source Channel Length (MSCL): 120 Meters

Figure 12 - WEPP Modify Delineation Network Comparison

Subcatchments are delineated for each watershed using the *Select a Watershed Outlet Point* tool. The TOPAZ model then calculates the entire perimeter and subcatchments feeding into the selected point for each watershed (Figure 13).

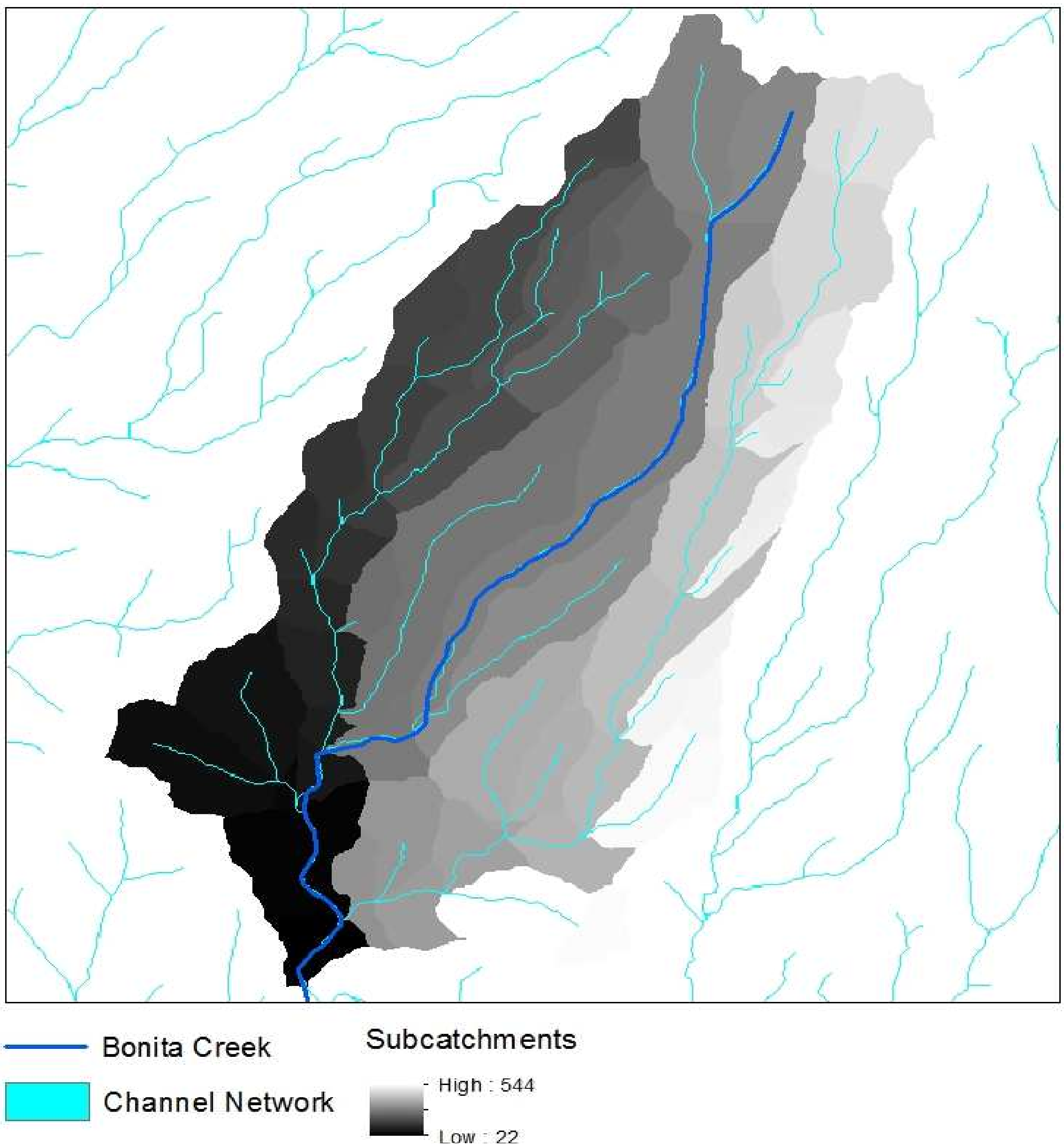


Figure 13 - WEPP's TOPAZ Delineated Watershed for Bonita

To best represent the flooding following the fire, the PRISM model was used. The PRISM model takes climate data from single "CLIGEN" point and spatially interpolates it (Daly et al., 2002; Meyer, 2010). As this data needed weather measurements specifically following the fire, three surrounding weather stations provided inputs to calculate parameters for a single CLIGEN point that acted as the input for the PRISM (Figure 14). This CLIGEN point represented data that was obtained by calculating weather averages for the four years following the fire, as this is when the regional flooding occurred.

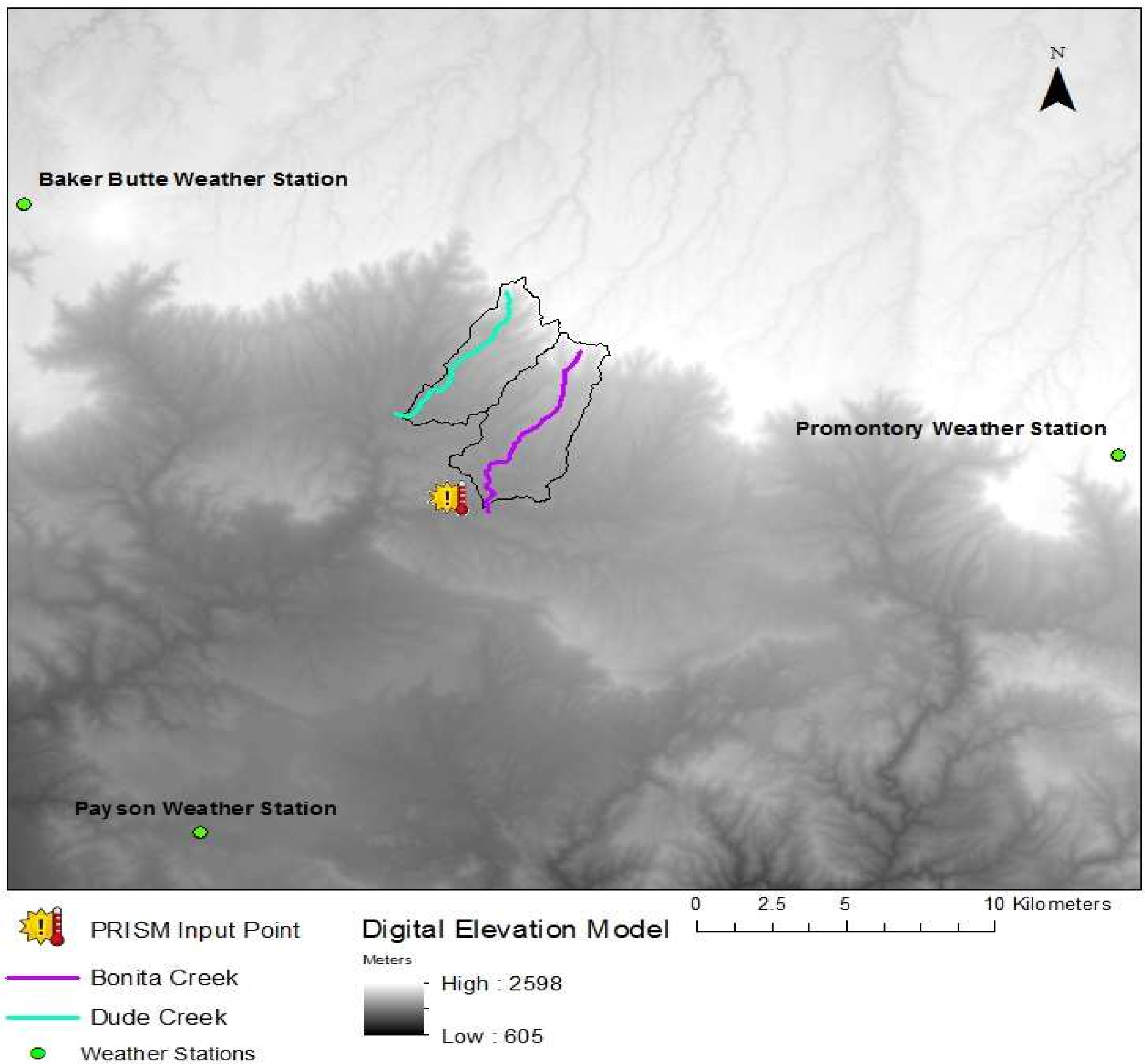


Figure 14 - Weather Stations and PRISM Input Locations

The model provided outputs for both simulation methods. The Flowpaths method calculates an onsite assessment (Figures 20,22) and the Watershed method provides an offsite assessment (Figures 21,23)

3.5 Model Results Comparison

In order to compare the results of the models, stream channel area change data was obtained (Figure 15). This data was collected by the USFS by surveying established transects and calculating the area of change between them over time. These estimates show that the erosion that occurred in Dude Creek was severe as the symbol falls well below 0 when comparing 1992 to 1996, or 1996 to 2001. Being relatively small channels, an estimated area change of negative 7 square meters signifies a catastrophic erosion event. While Bonita did not have transects established until 1996, the visible data shows that the channel erosion was minimal.

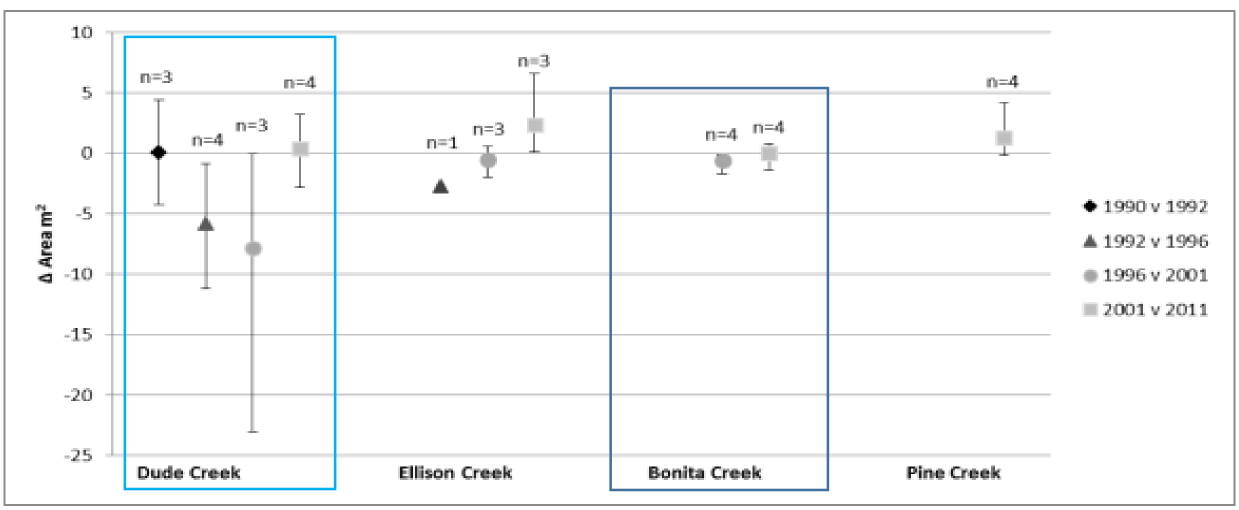


Figure 15 - Estimated Stream Channel Entrenchment (Unpublished data, Jackson Leonard)

Each shape represents a different time period as well as the mean entrenchment. These shapes are surrounded by an error bar. "n" stands for the number of transects surveyed. The predicted change was calculated using WinXS Pro which compares different survey transects over time and calculates the area of change between them.

Using field GPS recorded data, (Table 2) was created showing the location of the relevant transects in which the stream channel erosion estimates (Figure 15) and the streambed pebble counts (Figure 4) were calculated. The locations of the transects were recorded in ArcMap (Figure 18).

	Transect #	Elevation	UTM	X:Meters	Y:Meters
Dude Creek	1	5722 ft	12 N	476686	3806394
Dude Creek	3	5774 ft	12 N	476706	3806691
Dude Creek	5	5785 ft	12 N	476904	3806900
Bonita Creek	1	6005 ft	12 N	479841	3804646
Bonita Creek	3	6036 ft	12 N	480044	3804791
Bonita Creek	5	6134 ft	12 N	480256	3805079

Table 2 - Transect Locations

These transect points were used to identify the raster cells in which the RUSLE output value was recorded (Table 3). Alternatively, a mean value that included all values included in a a 10 meter buffer was calculated to address possible outliers (Table 4).

The GeoWEPP model provides subcatchment and channel erosion estimations in text format. The GPS locations of the transects were used to identify the contributing subcatchments and channels (Figure 27). Once the channel in which the transects reside were pinpointed (Figures 24,25), the text reports provided discharge volume (m^3/yr), yield (ton/yr), length of channel (m) soil loss of the channel (kg), upland charge (m^3), and subsurface flow (m^3) specific for each channel (Tables 5,6) . This allows a comparison of the Dude and Bonita channel area change to the estimations made by the WEPP model. This information was then compared to the WinXS Pro estimates.

Chapter 4: Results and Discussion

4.1 RUSLE

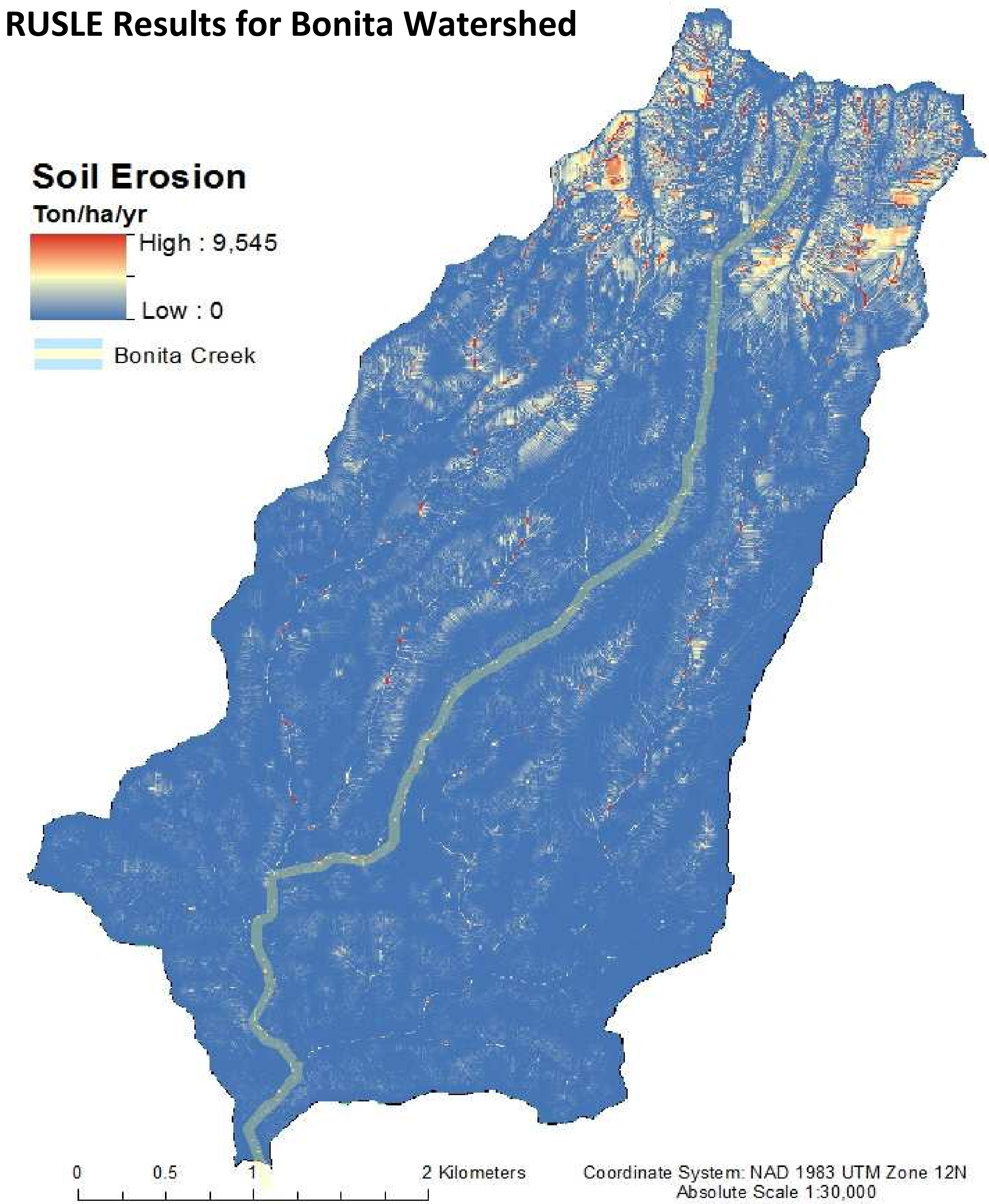


Figure 16 - RUSLE Output for Bonita Watershed

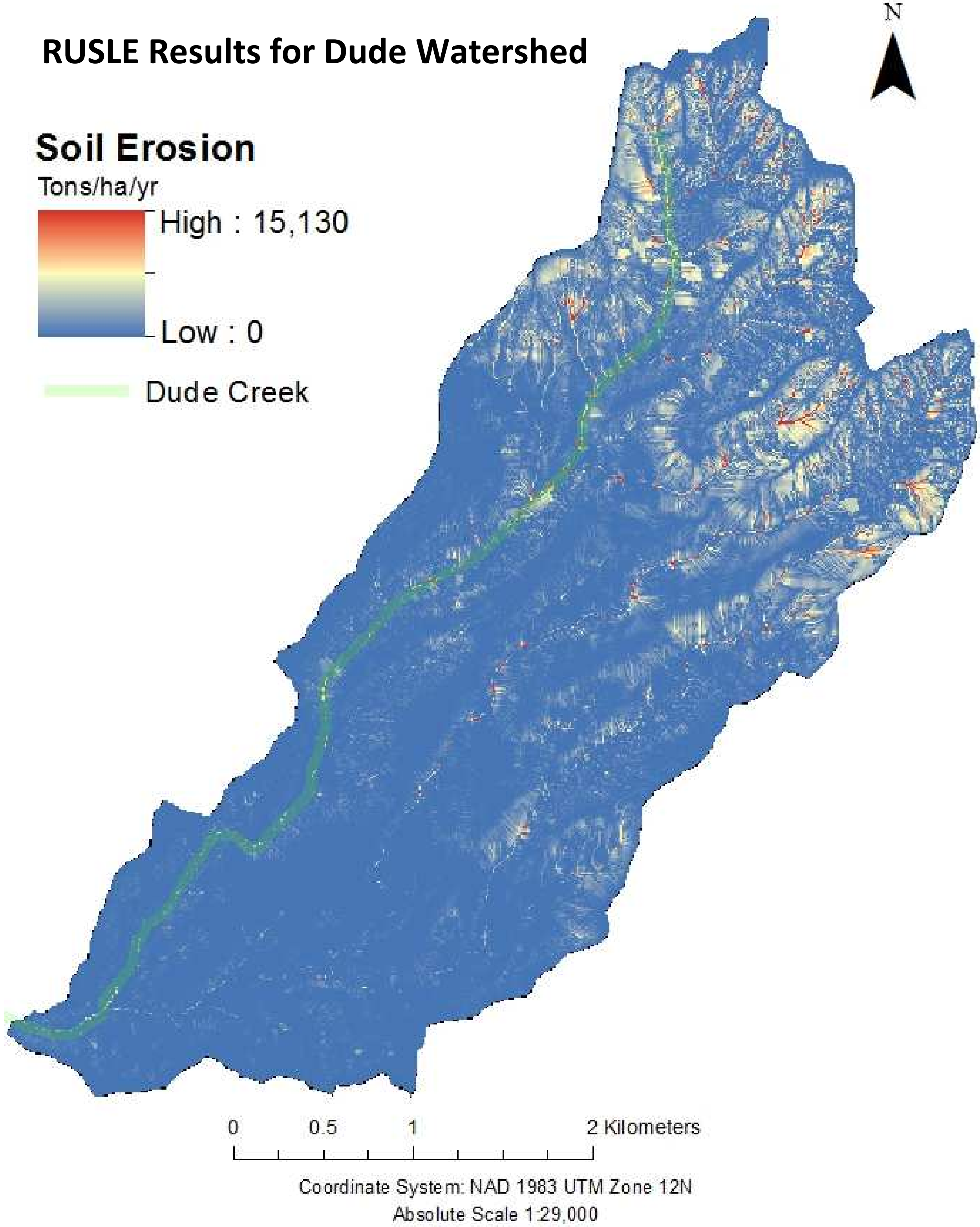


Figure 17 - RUSLE Output for Dude Watershed

The RUSLE model successfully estimated higher rates of erosion in the Dude watershed, yet due to its lack in including vital process-based erosion processes and inability to properly address complex topography, the model provided inaccurate estimates of soil erosion. The range of erosion for the Bonita watershed was between 0-9,545 tons per hectare per year. The maximum erosion estimate for the Dude watershed was at a much higher 15,130. The majority of this difference is attributed to the slope length and steepness factors (LS). These factors had by far the highest influence on the results, and were much higher in the Dude watershed. While these factors were able to address immediate upslope influence on erosion, cumulative upland charge within the channels failed to be included, thus not representing the channel entrenchment accurately.

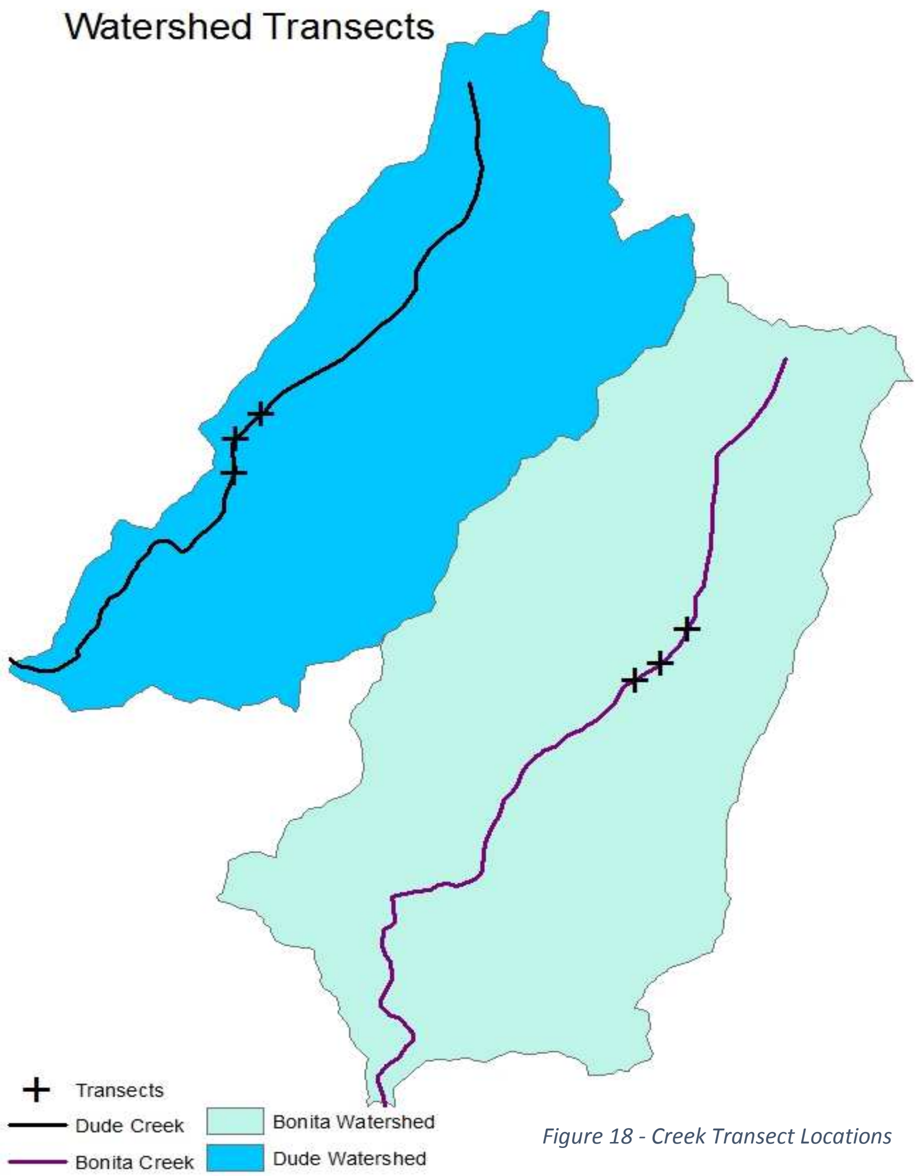


Figure 18 - Creek Transect Locations

4.2 RUSLE Transect Erosion Assessment

Watershed	Transect	Value (t/yr/ha)
Dude	1	454
Dude	3	91
Dude	5	141
Bonita	1	58
Bonita	3	15
Bonita	5	1209

Table 4 - RUSLE Transect Single Cell Erosion Value

*Displays the values of erosion generated by the RUSLE model for the cell in which the transect location fell.

Watershed	Transect	Mean Value (t/yr/ha)
Dude	1	118.3
Dude	3	171.4
Dude	5	74
Bonita	1	126.2
Bonita	3	41.6
Bonita	5	240.3

Table 3 - RUSLE Transect 10 Meter Buffer Mean Cell Value

*Displays the mean value of the cells of the RUSLE model output that were located within a 10 meter buffer of the transect location.

When observing the results of RUSLE per cell, it is evident that precise estimations of erosion could not be calculated for the stream channel transect areas (Figure 18, Tables 3,4). Stream geomorphology such as channel slope, confinement, and flow velocity can cause substantial changes in channel degradation (Juracek, 2015) and were not represented in the RUSLE model. Additionally, key processes of sediment transportation is not represented at all. Due to these key differences and the complexity of the variables, precise estimations or predictions of erosion within these watersheds is difficult.

4.3 Classified RUSLE Results

As channel erosion is not properly modeled, RUSLE primality provides a guide in identifying at-risk areas (Figure 18,19).

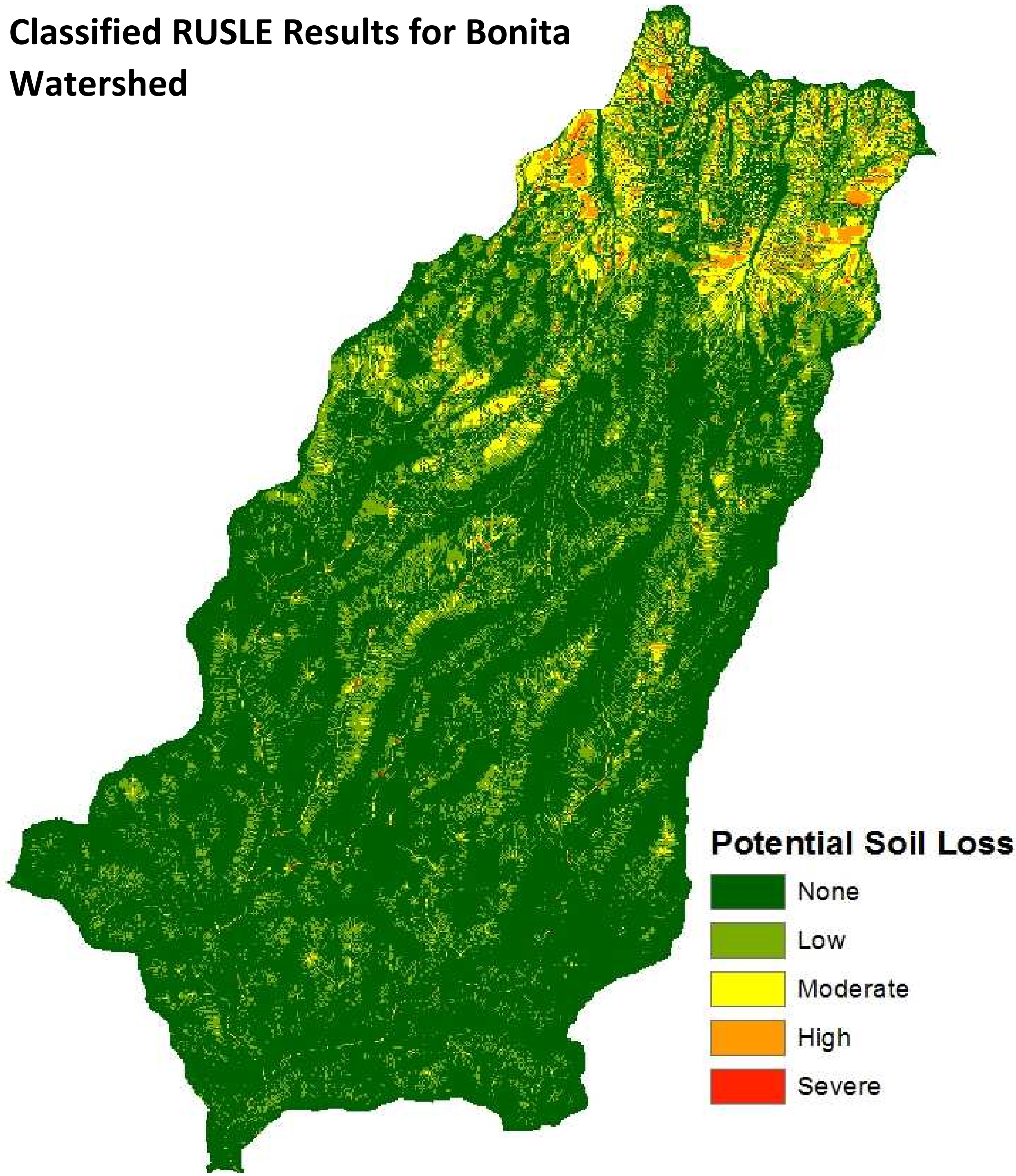


Figure 19 - Classified RUSLE Results for Bonita Watershed

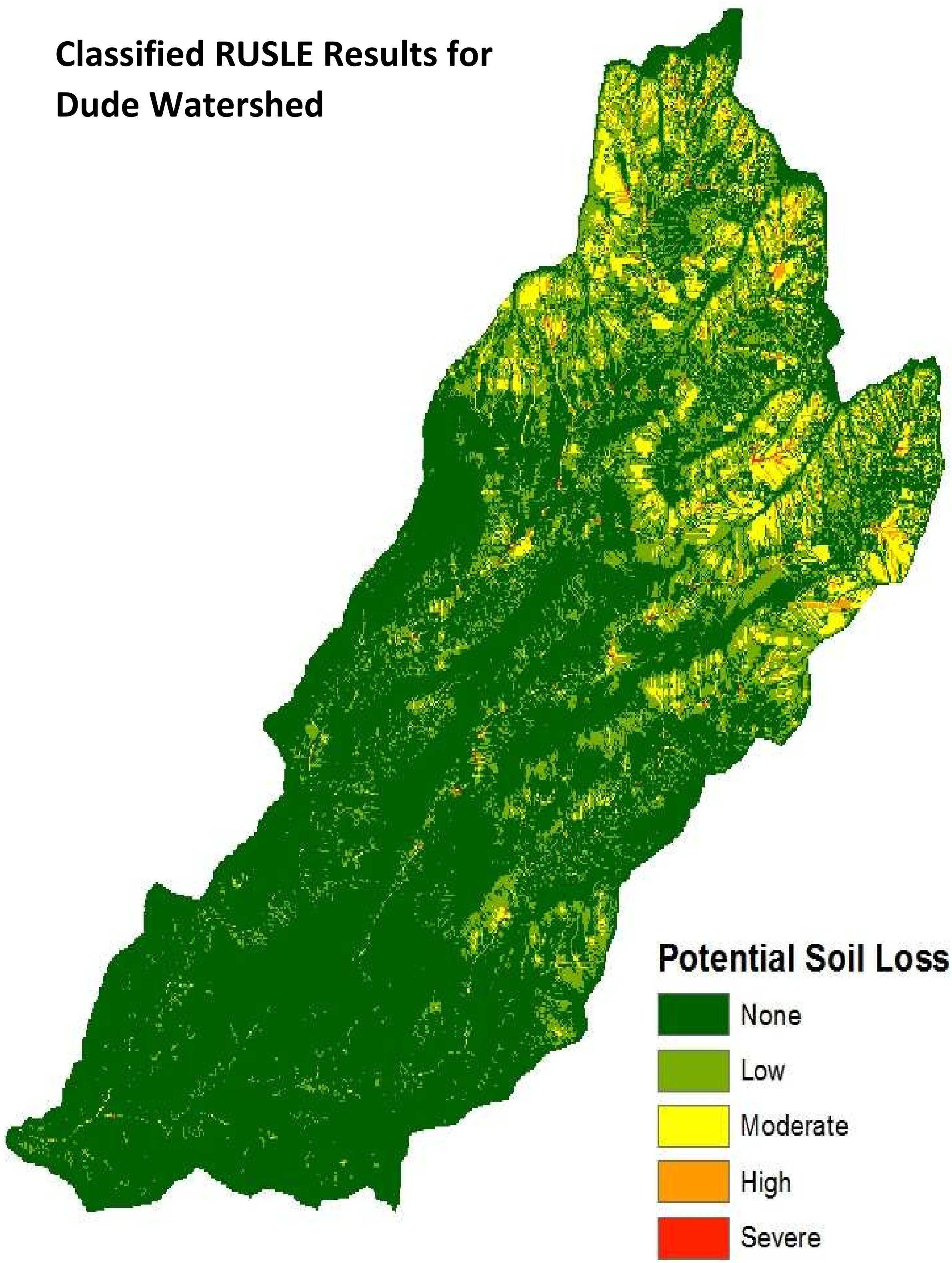


Figure 20 – Classified RUSLE Results for Dude Watershed

4.4 RUSLE Parameters

The methodology for creating parameters for the RUSLE model are complex and do not incorporate vital erosion processes thus providing inaccurate results for this study. As RUSLE was originally created to study erosion in uniform slopes of croplands, new GIS integrated methods to address complex parameters were created yet they still do not provide accurate results in the study area.

The slope length (L) and steepness (S) factors are usually the most difficult parameters to create for RUSLE. As the USLE model began to be revised and reformatted with land manager needs, several different ways of creating these factors were developed and the array of available methods to address complex topography can provide highly variable results (Oliveira et al., 2013). As RUSLE began to be applied to more complex terrain GIS became the primary tool used to compute the empirical model as landscapes could be represented using elevation models (Oliveira et al., 2013).

The L and S factors rely upon DEMs which vary in resolution and accuracy. In order to create the parameter properly a high resolution DEM was used. As this study used orthorectified 10 square meter resolution data for the DEM, the highest resolution data readily available, the analyses of the development of the DEM is not an issue as it best represents the topographic reliefs and other variations presented.

The L and S factors are missing some vital process based aspects. The equation used to create the output of L and S took into account the flow direction and accumulation. This addressed the immediate upslope contributing area, slope gradient, and channel length yet it did not calculate the effects that stream velocity and upland charge have on the groundwater. The hydrological process of runoff buildup in channels downstream is not represented. As this area experienced severe flooding, the effects of groundwater movement on erosion are vital to modeling processes within the study area. Additionally, this method assumes the process of the loss or gain to or from groundwater is not taking place as these are also process based concepts.

In order to properly map sediment movement the L and S factors need to incorporate dynamics of the erosive process in complex reliefs and hydrographic basins (Oliveira et al., 2013). The study area resides along the southern edge of the Colorado Plateau that contains several sudden cliff edges and a dramatic changes in elevation. The L and S factors were originally developed for uniform slopes using dependent field measurements, thus making complex topographic regions difficult to address. With the revisions of USLE to RUSLE, came the development of several subfactors in the equations used for calculating the L and S factors. The "m" subfactor used in slope length equation represents general slope accentuation and ranges from .01-1 with research attributing .4-.6 the best value for accentuated slopes (Oliveira et al., 2013). While the study area contains portions of accentuated slope along the rim, the creek transect locations had a general slope gradient of 13%. The value .4 was chosen for this study as it is not considered an extreme slope such as 30%, yet ranges far from the 1-7% slope that USLE calculations were originally created upon (Renard et al., 1997). While this research used the most commonly used estimates for subfactor calculation, further research as to how to compute subfactors within areas with highly variable amounts of slope in GIS is needed.

Developing values for the R factor was done with the EPA calculator. The benefit of identifying the value for R this way is that it provides the user with an easy and scientifically accepted approach as its methodology has been heavily examined (Renard, et al., 1997). While this method only allowed for the calculation of point specific data (Table 1), the spatial interpolation method of ordinary Kriging was used to develop a raster formatted factor through ArcMap.

Studies have shown that ordinary Kriging provides the most accurate estimations of precipitation data when compared with field data accuracy assessments (Xian et al., 2011). Kriging is the most widely applied method in spatial interpolation for precipitation when using point measurements (Ly et al., 2011). While ordinary CoKriging takes a correlating coefficient such as elevation into account, it was not used as the EPA R-factor calculator already integrates this important factor (Renard et al., 1997). The accuracy of this method is dependent on the amount of point measurements used.

While several RUSLE studies have used a range of equations to calculate the R-factor properly in relatively noncomplex terrains (Alexakis et al., 2013; Bhandari and Darnsawasdi, 2014; Prasannakumar et al., 2012) common interpolation methods that make elevation a secondary variable encounter several problems in mountainous areas. This is due to the complexity of the atmospheric processes such as interception and evapotranspiration (Ly et al., 2011, Xian et al., 2011) thus leading this study to use the EPA calculator and ordinary kriging. The other negative aspect of using the R-factor calculator is that it does not include the erosive forces of runoff from snowmelt or rain on frozen soil (Renard et al., 1997).

The RUSLE model allows for a variety of methods for developing K-factor values. While the U.S. Forest Service provides soils data for the contiguous United States including predicted K-factors, it is relatively low resolution and attributed the value .2 for the entire study area. This layer is derived from cross-referencing the general soil characteristics to tables found in the USDA RUSLE Guide nomograph (Renard et al., 1997). One of the benefits of RUSLE is that it allows for a more in-depth analysis of the soil when physical access, time and the proper tools are available. The USDA RUSLE guide supplies methods in which seasonal variation, orthographic influences and soil texture can be analyzed to provide proper K-factor values. These calculations can be spatially interpolated to provide an input for RUSLE. As physical access, data, time and soil analysis tools were limited, the USFS developed K-factor was used.

The performance of the RUSLE model in burned forests has yielded questionable results as common methodology does not provide peer-reviewed parameter creation methods for the Cover-Management factor (Fernández and Vega, 2016; Larsen and MacDonald, 2007). The C-factor was created using remotely sensed imagery. As the high resolution imagery was not collected until 25 years after the fire, the immediate effects of the fire had to be addressed to better reflect the effects of disturbances on vegetation. The immediate effects were represented using a burn severity map to create the estimated C-values. No nomographs or suggested values exist for burn areas for RUSLE so the C-values were estimated thus allowing for a wide range of interpretations from the user.

The P or Conservation Practice factor used a proposed aerial seeding map in order to create a boundary for the value yet the effects of seeding on soil retention has since been disputed (Beyers, 2004; Kulpa et al., 2012; Peppin et al., 2010; Pyke et al., 2013). The dominant species seeded have little to no evidence supporting their effects on soil retention post-fire (Peppin et al., 2010; Pyke et al., 2013). In order to better calibrate the P-factor for the study area a more comprehensive review of the post-fire monitoring reports needs to be conducted as several erosion control practices work on a per-case basis (Beyers, 2004; Robichaud et al., 2012).

4.5 GeoWEPP Results

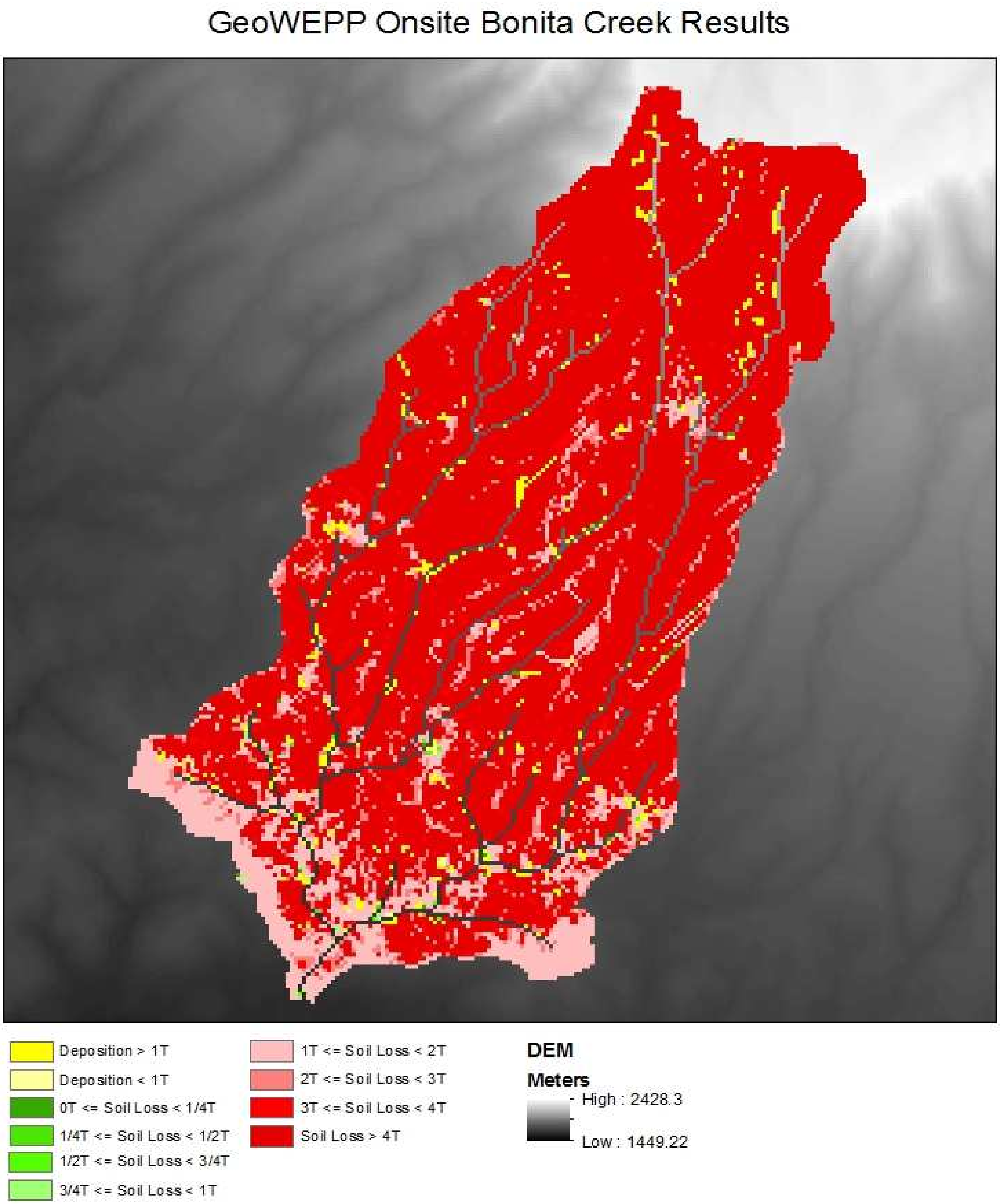


Figure 21 - GeoWEPP Onsite Bonita Results

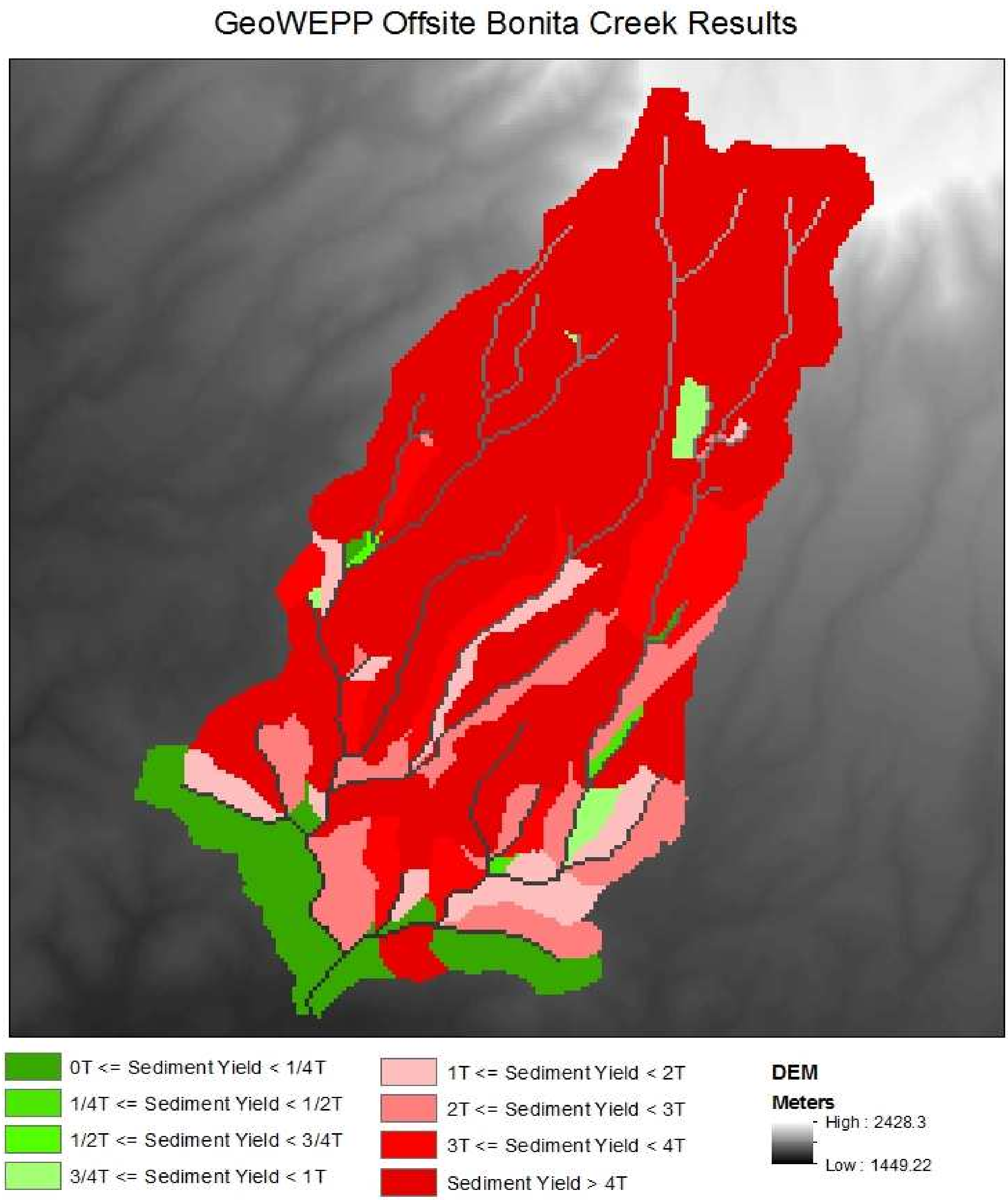


Figure 22 - GeoWEPP Offsite Bonita Results

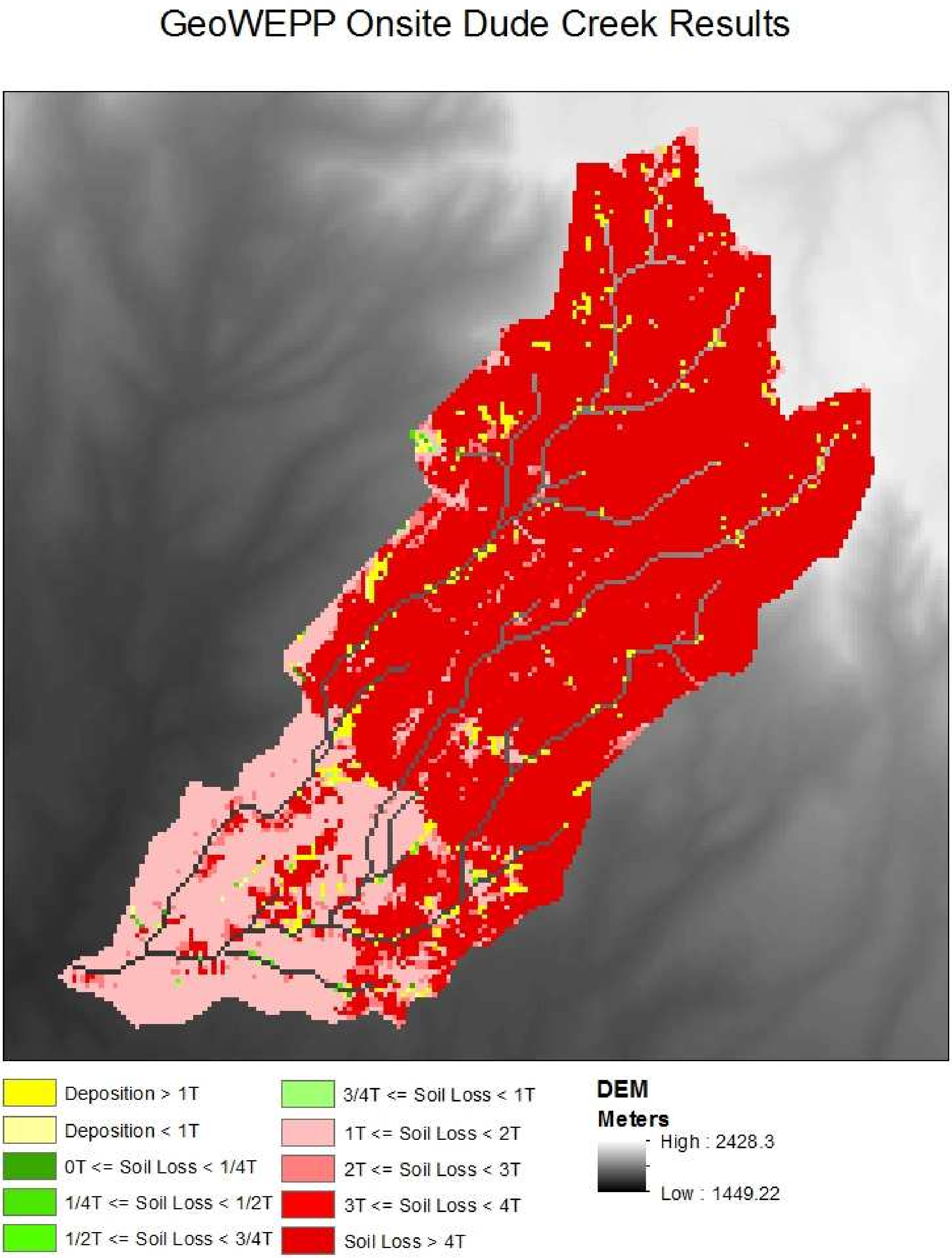


Figure 23 - GeoWEPP Onsite Dude Results

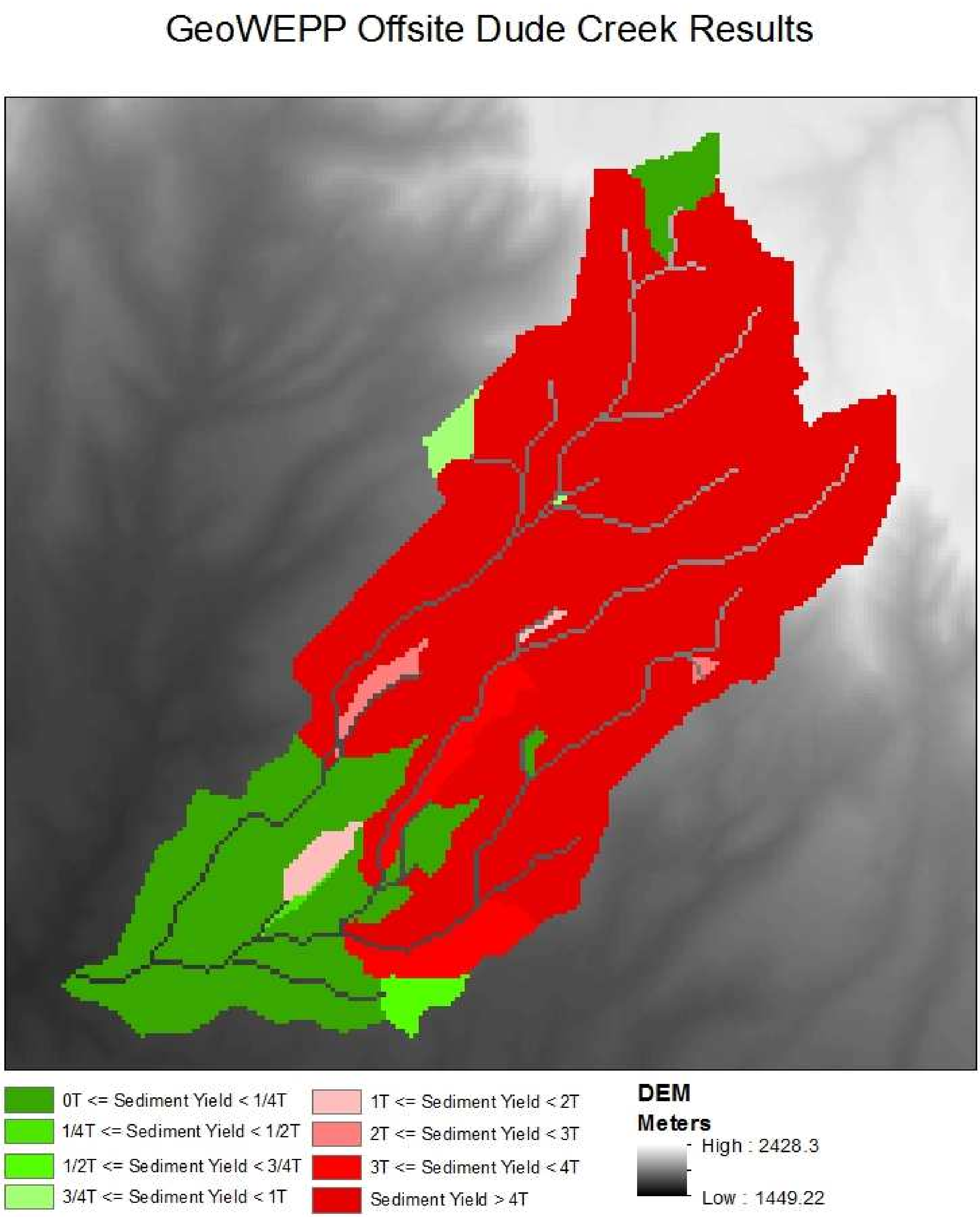


Figure 24 - GeoWEPP Offsite Dude Results

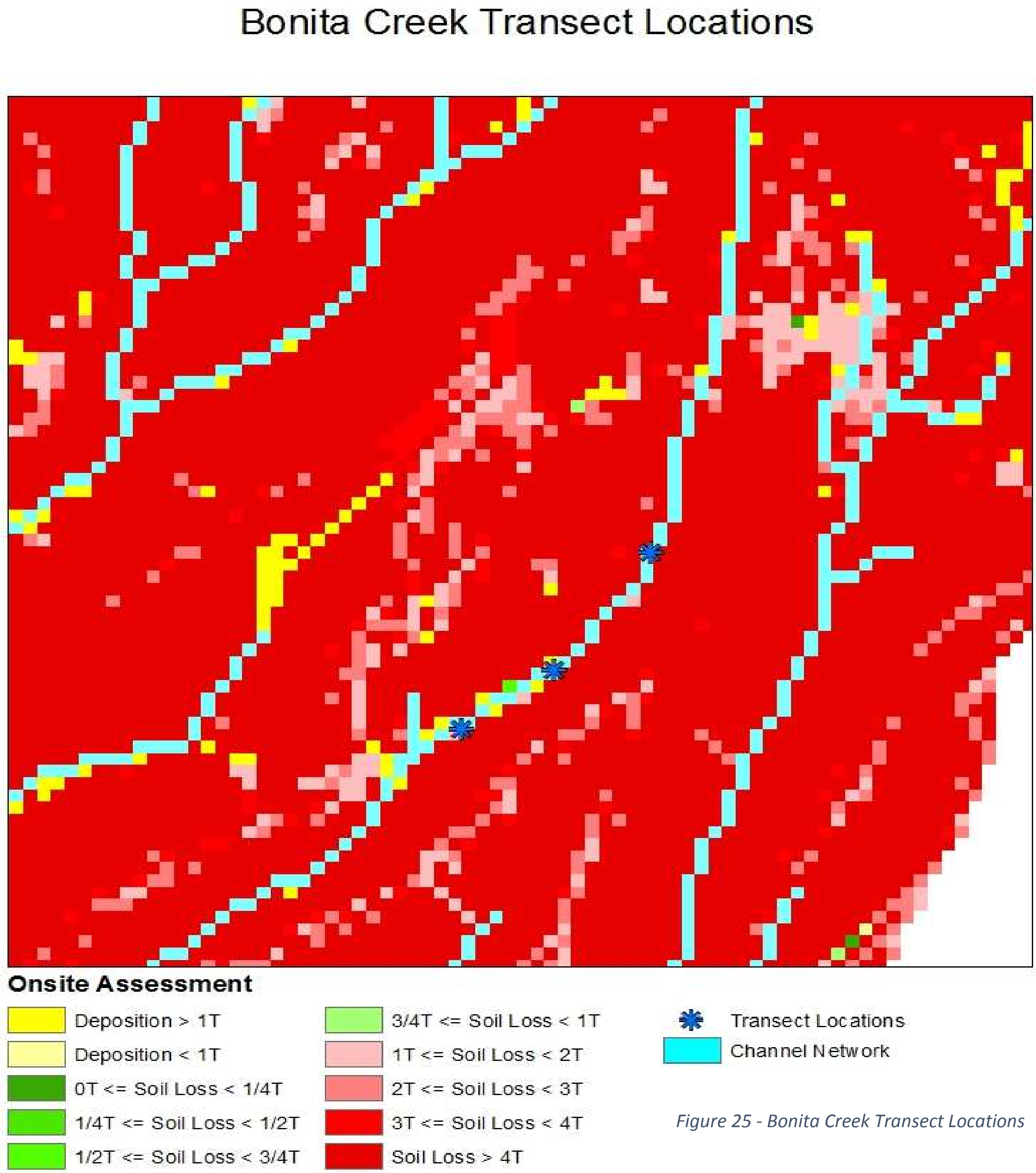


Figure 25 - Bonita Creek Transect Locations

Subcatchment Attribute ID	Discharge Volume (m^3/yr)	Yield (ton/yr)	Channel Length (m)	Channel ID	Soil Loss (kg)	Upland Charge (m^3)	Subsurface Flow (m^3)
304	96,475.1	4,492.4	2,470.7	27	754,586.1	96,998.6	0.1

Table 5 - GeoWEPP Text Report for Subcatchment and Channel Erosion of Bonita Creek

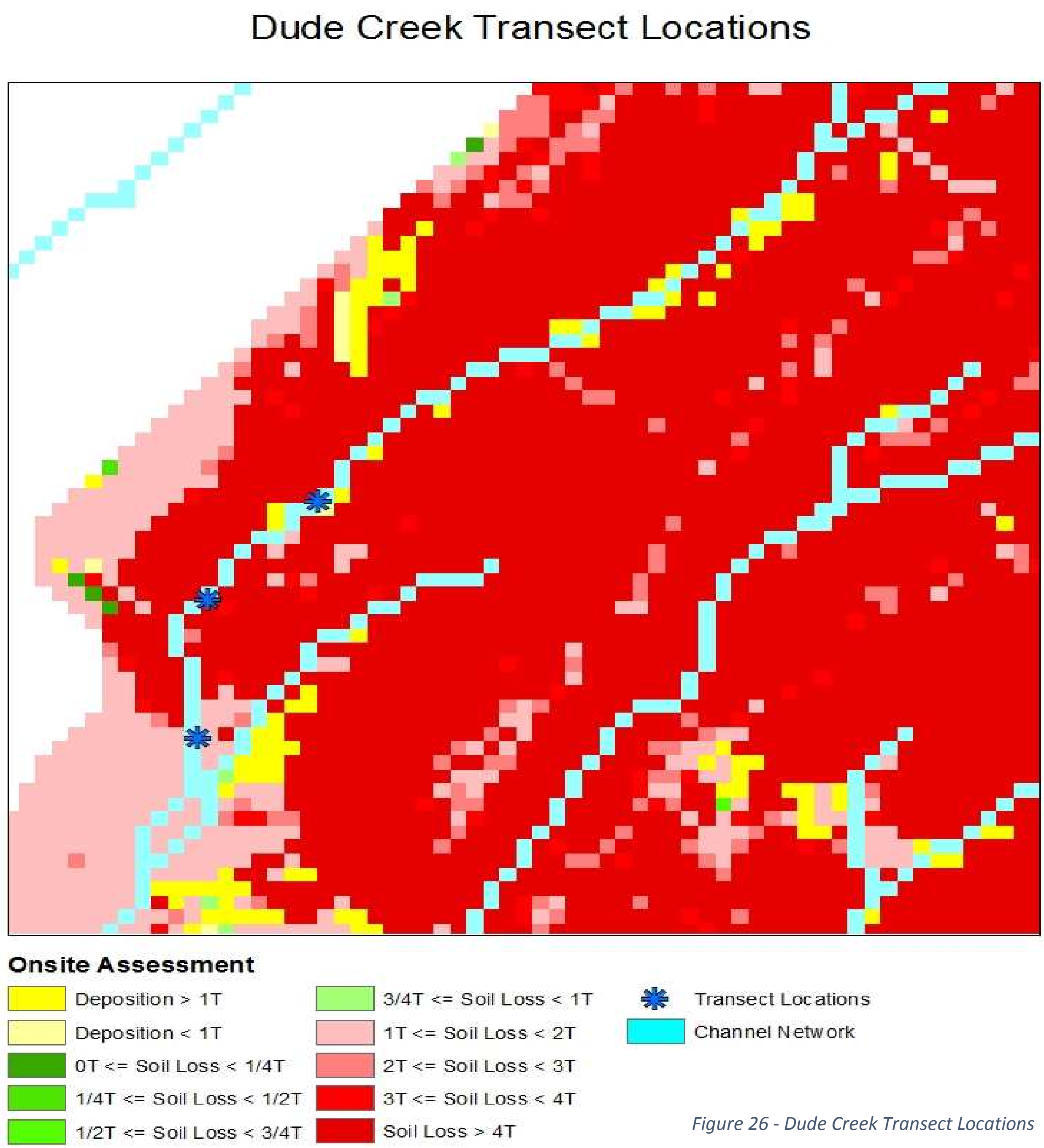


Figure 26 - Dude Creek Transect Locations

Channel and Subcatchment Results

Subcatchment Attribute ID	Discharge Volume (m^3/yr)	Yield (ton/yr)	Channel Length (m)	Channel ID	Soil Loss (kg)	Upland Charge (m^3)	Subsurface Flow (m^3)
44	221,933	11,169.5	2,270.1	35	3,924,967.3	223,352.8	0.1

Table 6 - GeoWEPP Text Report for Subcatchment and Channel Erosion of Dude Creek

Dude Creek was significantly impacted by the flooding events from 1992-2001, where the measured transects indicate it lost a lot of sediment (Figure 15). Data for Bonita Creek is not available for 1992-1996 because transects were not established until 1996, yet judging from data collected after 1996 and its condition following the fire in which minimal bedrock was exposed it is hypothesized it did not undergo such extreme flooding. Using stream channel entrenchment estimations for comparison, the WEPP model provided more useful results as it contains channel specific data (Tables 5 and 6). These text style reports give land managers inferences as to the discharge volume from the outlet point of the channel, the yield, estimated soil loss, subsurface flow and upland charge. When comparing the WEPP Dude and Bonita channel model outputs several things become apparent. The channel in which the Dude Creek transects reside, more than doubles in its estimated discharge volume, yield and upland charge and quadruple in its estimated soil loss when compared to that of Bonita Creek. These findings support the stream channel area change calculations (Figure 15).

These results can be attributed to a number of reasons. While the channel lengths in which the transects reside for both creeks are around 2300 meters, the contributing upstream area and channel network for Dude is more than double that of Bonita (Figure 27). The Topaz model was used to delineate the contributing area upstream of the lowest transect points for the watersheds. The contributing catchment area for the Dude Creek transect was 5.12 square kilometers while Bonita only had a contributing area of 2.15 square kilometers. Additionally, Dude Creek had a contributing 53 subcatchments and 8 upstream channels, while Bonita Creek had 11 subcatchments and 2 contributing upstream channels. When stream geomorphology and its process based aspects such as its hydraulic velocity profile, flow direction, channel roughness, substrate, and contributing landforms all play a role in determining sediment transportation and erosion, the WEPP model proves that it is highly superior. The RUSLE model provided little evidence based results as to the entrenchment occurring at the transects. The single cell and mean cell values for the creek beds (Tables 3,4) do not supply accurate information for land managers.

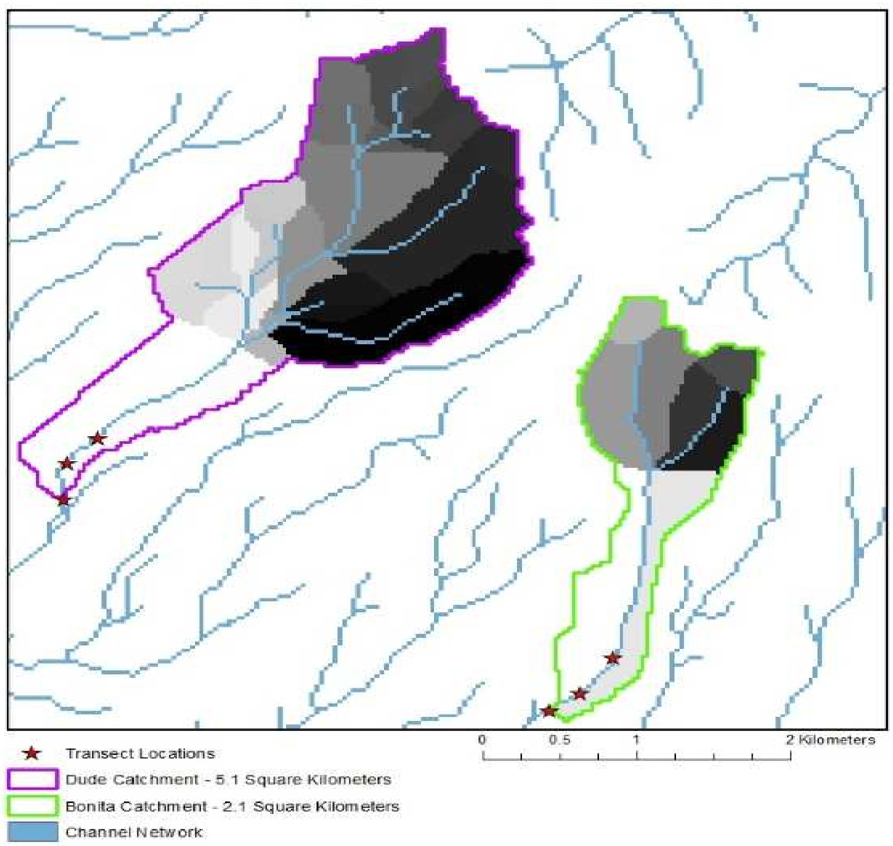


Figure 27 - Subcatchment Comparison

4.6 WEPP Parameters

The TOPAZ model uses the DEM and user specified calibrations to identify characteristics of the watershed, which had to be lowered in resolution to prevent the model from crashing. When delineating the watershed for complex topography in GeoWEPP, the CSA and MSCL were both lowered as to identify only the significant subcatchments and channels. When using higher resolution data, the model could not finish computing. Upgraded hardware allows for the usage of higher resolution data, yet in this study that used lower resolution data the WEPP model still provided adequate results.

The climate parameter for WEPP was customized to best represent the weather four years after the fire. By including precipitation, temperature, and storm specific weather events using data collected from the NOAA, the model calculated storm events that led to the severe flooding successfully.

Using the online WEPP database provided inputs that represented findings from the BAER team yet it did not successfully label all of the data types. The land use and soil parameters were obtained from the Michigan Technological Institute BAER Spatial WEPP Model Inputs Generator. This data provided text labels as to what the land cover types were throughout the study area, yet did not supply the user with soils data interpretations. Soil inputs were created by Michigan Technological Institute and therefor had to be downloaded and mapped into the GeoWEPP soils files. The soil types that the database supplied were missing descriptions, not allowing for the interpretation of the varying effects of the soil identified by the BAER team.

Chapter 5: Comparison and Conclusion

5.1 Parameter Comparison

The GeoWEPP and RUSLE models identified similar boundaries for the watersheds, while GeoWEPP called for much fewer steps and additionally identified contributing hillslopes, channels, and subcatchments. For assessing erosion and channel entrenchment in mountainous regions the delineation of these subcatchments, hillslopes, and channels are vital. RUSLE inadequately addresses the influences of hillslope and channels using the L and S factors. Having an empirically based mathematical foundation, RUSLE is better applied in more uniform slopes (Renard et al., 1997). This in turn, deems the WEPP model superior in delineating watersheds and calculating channel entrenchment.

RUSLE took into account the seeding that took place through the P-factor, in which the WEPP model did not take the seeding event into account at all. In order to ensure that the effects of the post-fire seeding was represented, a thorough understanding of the WEPP management file development is needed. Unfortunately, this is not covered in the GeoWEPP for ArcGIS 9.x Full Version Manual.

The WEPP model allows users to modify climate parameters in an environment that includes peer reviewed methodology. The GeoWEPP PRISM tool allows for the input of time specific NOAA weather data that addresses the effects of complex topography and flooding (Daly et al., 2002; Flanagan et al., 2007; Meyer, 2010). Using PRISM the vertical extrapolation of climate and its associated effects on weather processes within complex topographic regions provides superior results to RUSLE. Individual flooding events are modeled which provides the user with more accurate results as they include erosional processes such as upland charge of surface water in channels. This can additionally be used for managing flood events and stormwater since the effects of land management practices on discharge can be studied.

The climate parameter in WEPP allows land managers to study the effects of climate change better than RUSLE. GeoWEPP provides event specific weather data that better represents the effects of an altered climate. WEPP includes the effects of winter hydrological processes (Flanagan et al., 2007) which RUSLE does not. As climate change is predicted to lead to severe weather events (Karl et al., 2008) the role of seasonal variability on hydrological erosion processes should be incorporated. By including the effects of physical weathering due to climate variation, water movement in channels, and using specific storm parameters to model erosion events, the WEPP model used through GeoWEPP provides land manager with a superior way to study the effects of climate change.

5.2 Empirical and Process-Based Results Comparison

RUSLE easily identifies the general areas at-risk for erosion within relatively non-complex watersheds, while WEPP provides more applications and detailed results for a variety of watersheds. Within this study area, consisting of a historical high severity fire taken place within intricate terrain and land cover, the GeoWEPP interface combined with the BAER spatial WEPP model inputs generator hosted by Michigan Technological University provided much easier creation and adjustment of parameters as well as more feasible results within an user friendly interface.

While RUSLE is generally considered less data demanding and is implemented easily in comparison to other widely known soil erosion models, when applied to complex study areas it requires timely processing and provides inaccurate results (Fernández and Vega, 2016; Tiwari et al., 2000). Inputs for RUSLE supplied by USFS and USGS databases did not have the high resolution needed for these relatively small-scale watersheds thus requiring time intensive work to create suitable factors. These factors do not account for important characteristics such as water infiltration and evapotranspiration, or sediment deposition and therefore influenced the trend to develop process-based models (Tiwari et al., 2000).

A few benefits exist when using an empirically based model for similar studies. RUSLE allows for the processing of high resolution data with a low risk of crashing. The factors are represented as layers in raster format, therefor attributing a value to each cell. These values are then multiplied to compute “A” soil loss in tons per hectare per year. Due to the simplicity of the model these computations do not require specialized software and can be used with open source GIS software.

5.3 Limitations, Recommendations, and Suggestions for Future Work

Although WEPP best predicted the post-burn erosion event for these watersheds the methodology of this model is not without limitations. The WEPP model is missing some influential process based factors. The study area provides an outlet for several springs evident from the perennial existence of Dude and Bonita Creeks. While subsurface water flow due to precipitation is already accounted for, the interface does not allow the user to edit a channel network to include the processes of spring fed surface water flow. The representation of spring fed surface water would increase modeling accuracy as it could address the effects on upland charge and streambed composition.

GeoWEPP restricts soil and land cover options as directions to create personalized land cover files is not available. Once users have created land and soil type polygons they are required to pick from the management database list of soils and land use types. GeoWEPP does not provide directions as to how to create their own. While additional management and soil files can be downloaded, a guide describing the file creation process would assist in creating unique parameters.

Currently the storm events generated by the GeoWEPP model cannot incorporate precise historical storm events. While the current methods provide a way to predict future conditions, it doesn't allow precise modeling of past weather events. If available, using historical weather station data to mimic exact storm parameters would provide more accurate results as storm intensity, duration, and seasonal variability could be better represented.

If this study were to be extended, different parameters would be compared in order to study the effects of land management and fire on erosion. Pre-fire parameters would provide references as to the condition of the watershed beforehand. This helps assess the effects of the fire. GeoWEPP inputs for pre-fire are available through the BAER Spatial WEPP Model Inputs Generator. Closely comparing the results of model outputs would provide further insight as to how fire effects erosion in ponderosa forests, as well as help study the effects of different land management practices.

The RUSLE provides methodology for using field collected data to study the effects of erosion within small uniform plots in the study area. RUSLE supplies an in-depth guide in which soil characteristics, rainfall, vegetation type, and support practice are calculated to provide erosion estimates for field plots with uniform slope (Renard et al., 1997). While this would not supply data for comparing stream entrenchment, it could assess the effects of vegetation, soil, or erosion management practices such as the aerial seeding of weeping lovegrass and its effects on erosion. Comparing data in from a burn zone to that of a similar non-burn zone using the field parameter calculations offered by RUSLE, scientists could better address the effects of high severity fire.

5.4 Conclusion

RUSLE does not take important aspects such as sediment deposition or water infiltration into account because it is an empirically based model. Thus, it creates the possibility of supplying the user with seemingly very high estimates of erosion and inaccurate representations of the effects of stream geomorphology and general geographic land composition and land cover. Due to the fact that RUSLE was originally created to study erosion on uniform slopes of croplands and not of complex terrain with varying types of land cover and soil, the modeling of sediment deposition, water infiltration and channelization and the effects these processes have on erosion are better analyzed through WEPP.

The WEPP model is becoming the norm for land managers assessing the effects of soil erosion within forested mountainous regions. Its user friendly interface, peer reviewed methodology of parameter creation and calibration, integration of parameter databases, ability to identify and assess channel sediment transportation, as well as its ability to conduct preprocessing and create text reports with ease highly outweighs the minimal benefits of RUSLE. When applied to single land cover at basic uniform slope, RUSLE provides accurate erosion assessments with simple processing steps, but when applied to complex geographic locations it lacks what the WEPP model makes up. The GeoWEPP model would benefit in the ability to change the amount of upland flow, in order to assess the effects of streams on a watershed and channels. It additionally could benefit from supplying its users in a manual of customized soil and land cover file creation, yet currently the database to choose from is expansive and should meet most land manager's needs. When comparing these models, the WEPP model outperformed the RUSLE model in its ability to assess the post-burn flooding events, ease of implementation, include erosion processes and should be used by land managers interested in studying erosion events in similar circumstances.

BIBLIOGRAPHY

Alexakis, D. D., Hadjimitsis, D. G., & Agapiou, A. (2013). Integrated use of remote sensing, GIS and precipitation data for the assessment of soil erosion rate in the catchment area of "Yialias" in Cyprus. *Atmospheric Research, 131*, 108-124. doi://dx.doi.org/10.1016/j.atmosres.2013.02.013

Ashiagbor, G., Forkuo, E., Laan, P., & Aabeyir, R. (2016). Modeling soil erosion using RUSLE and GIS tools. *International Journal of Remote Sensing & Geoscience, 2*(4), 2-12.

Balch, J. K., Bradley, B. A., D'Antonio, C. M., & Gómez-Dans, J. (2013). Introduced annual grass increases regional fire activity across the arid western USA (1980–2009). *Global Change Biology, 19*(1), 173-183. doi:10.1111/gcb.12046

Bell, D. M., Bradford, J. B., & Lauenroth, W. K. (2014). Mountain landscapes offer few opportunities for high-elevation tree species migration. *Global Change Biology, 20*(5), 1441-1451. doi:10.1111/gcb.12504

Beyers, J. L. (2004). Postfire seeding for erosion control: Effectiveness and impacts on native plant communities. *Conservation Biology, 18*(4), 947-956. doi:10.1111/j.1523-1739.2004.00523.x

Bhandari, K. P., & Darnsawasdi, R. (2015). Application of remote sensing and participatory soil erosion assessment approach for soil erosion mapping in a watershed. *Walailak Journal of Science & Technology, 12*(8), 689-702.

Brooks, E., Dobre, M., Elliot, W., Wu, J., & Boll, J. (2015). Watershed-scale evaluation of the water erosion prediction project (WEPP) model in the lake tahoe basin. *Journal of Hydrology, 533*, 389-402. Retrieved from http://dx.doi.org/10.1016/j.jhydrol.2015.12.004

Cawson, J., Nyman, P., Smith, H., Lane, P., & Sheridan, G. (2016). How soil temperatures during prescribed burning affect soil water repellency, infiltration and erosion. *Geoderma, 278*, 12-22. Retrieved from www.elsevier.com/ locate/geoderma

Cooper, K. *Evaluation of the relationship between the RUSLE R-factor and mean annual precipitation*

Daly, C., Taylor, G., & Gibson, W. (2002). A PRISM approach to mapping precipitation and temperature. *Climate Research,* doi:10.3354/cr022099

DeBano, L. F. (2000). The role of fire and soil heating on water repellency in wildland environments: A review. *Journal of Hydrology, 231*, 195-206. doi:10.1016/S0022-1694(00)00194-3

Donovan, G. H., Butry, D. T., & Mao, M. Y. (2016). Statistical analysis of vegetation and stormwater runoff in an urban watershed during summer and winter storms in portland, oregon, U.S. *Arboriculture & Urban Forestry, 42*(5), 318-328.

Dun, S., Wu, J. Q., Elliot, W. J., Robichaud, P. R., Flanagan, D. C., Frankenberger, J. R., . . . Xu, A. C. (2009). Adapting the water erosion prediction project (WEPP) model for forest applications. Journal of Hydrology, 366(1–4), 46-54. doi://doi.org/10.1016/j.jhydrol.2008.12.019

Elliot, W., Miller, I., & Glazer, B. (2006). *Using WEPP technology to predict erosion and runoff following wildfire.* (). Portland, Oregon: American Society of Agricultural and Biological Engineers.

EPA RUSLE rainfall erosivity factor. Retrieved from https://www.epa.gov/waterdata/rainfall-erosivity-factor-calculator

Fernández, C., & Vega, J. A. (2016). Modelling the effect of soil burn severity on soil erosion at hillslope scale in the first year following wildfire in NW spain. *Earth Surface Processes and Landforms, 41*(7), 928-935. doi:10.1002/esp.3876

Fitzgerald, S. A. (2005). Fire ecology of ponderosa pine and the rebuilding of fire-resilient ponderosa pine ecosystems. *USDA Forest Service General Technical Reports,* , 197-255.

Flanagan, D., Gilley, J. E., & Franti, T. G. (2007). Water erosion prediction project (WEPP): Development history, model capabilities, and future enhancements. *Transactions of the ASABE, 50*(5), 1603-1612. doi:10.13031/2013.23968

Flanagan, D., Frankenberger, J., Cochrane, T., Renschler, C., & Elliot, W. (2013). Geospatial application of the water erosion prediction project (WEPP) model. *Transactions of the ASABE, 56*(2), 591-601. doi:10.13031/2013.42681

Forkuo, E. K., and Adubofour. Y., 2012. Analysis of Forest Cover Change Detection. International Journal of Remote Sensing Applications, Volume 2, Issue 4,

Fredette, A. (2016). 4fri and the nepa process. *Arizona State Law Journal, 48*(1), 139-143.

Ganasri, B. P., & Ramesh, H. (2016). Assessment of soil erosion by RUSLE model using remote sensing and GIS - A case study of nethravathi basin. *Geoscience Frontiers, 7*(6), 953-961. doi://dx.doi.org/10.1016/j.gsf.2015.10.007

Garbrecht, J., & Martz, L. (2015). TOPAZ: Digital topographic and watershed analysis. Retrieved from http://homepage.usask.ca/~lwm885/topaz/

Gould, G. K., Liu, M., Barber, M. E., Cherkauer, K. A., Robichaud, P. R., & Adam, J. C. (2016). The effects of climate change and extreme wildfire events on runoff erosion over a mountain watershed. *Journal of Hydrology, 536*, 74-91. doi://dx.doi.org/10.1016/j.jhydrol.2016.02.025

Grigar, J. J., Frederick, B., Asher, J. & Ouyang, D. (2002). RUSLE - an online soil erosion assessment tool. Retrieved from http://www.iwr.msu.edu/rusle/

Han, F., Ren, L., Zhang, X., & Li, Z. (2016). The WEPP model application in a small watershed in the loess plateau. *PloS One, 11*(3), e0148445. doi:10.1371/journal.pone.0148445

Huffman, D. W., Zegler, T. J., & Fule, P. Z. (2015). Fire history of a mixed conifer forest on the mogollon rim, northern arizona, USA. *International Journal of Wildland Fire, 24*(5), 680-689. doi:10.1071/WF14005

Juracek, K. (2015). Fluvial geomorphology studies in kansas. Retrieved from https://ks.water.usgs.gov/fluvial-geomorphology

Karaburun, A., Estimation of C Factor for Soil Erosion Modeling Using NDVI in Buyukcekmece Watershed. Ozean Journal of Applied Sciences 3(1) ,pp 77-85 (2010).

Karl, T., Meehl, G. A., Miller, C., Hassol, S., Waple, A., & Murray, W. (2008). *Weather and climate extremes in a changing climate.* (). Washington, DC: U.S. Climate Change Science Program.

Kulpa, S. M., Leger, E. A., Espeland, E. K., & Goergen, E. M. (2012). Postfire seeding and plant community recovery in the great basin. *Rangeland Ecology & Management, 65*(2), 171-181.

Landi, A., Barzegar, A. R., Sayadi, J., & Khademalrasoul, A. (2011). Assessment of soil loss using WEPP model and geographical information system. *Journal of Spatial Hydrology, 11*(1), 41-51.

Larsen, I. J., & MacDonald, L. H. (2007). Predicting postfire sediment yields at the hillslope scale: Testing RUSLE and disturbed WEPP. *Water Resources Research, 43*(11), n/a. doi:10.1029/2006WR005560

Lee, G. S., & Lee, K. H. (2006). Scaling effect for estimating soil loss in the RUSLE model using remotely sensed geospatial data in korea. *Hydrology and Earth System Sciences Discussions, 3*(1), 135-157. doi:10.5194/hessd-3-135-2006

Leonard, J., Medina, A. L., Neary, D. G., & Tecle, A. (2015). The influence of parent material on vegetation response 15 years after the dude fire, arizona. *Forests, 6*, 613-635. Retrieved from http://www.mdpi.com/journal/forests

Ly, S., Charles, C., & Degre, A. (2011). Geostatistical interpolation of daily rainfall at catchment scale: The use of several variogram models in the ourthe and ambleve catchments, belgium. *Hydrol. Earth Syst. Sci, 15*, 2259-2274. doi:10.5194/hess-15-2259-2011

Martnez-Lopez, J., Carreo, M. F., Palazn-Ferrando, J. A., Martnez-Fernndez, J., & Esteve, M. A. (2014). Free advanced modeling and remote-sensing techniques for wetland watershed delineation and monitoring. *International Journal of Geographical Information Science, 28*(8), 1610-1625. doi:10.1080/13658816.2013.852677

McHale, G., Newton, M. I., & Shirtcliffe, N. J. (2005). Water-repellent soil and its relationship to granularity, surface roughness and hydrophobicity: A materials science view. *European Journal of Soil Science, 56*(4), 445-452. doi:10.1111/j.1365-2389.2004.00683.x

Meyer, C. (2010). *General description of the CLIGEN model and its history.* (n.d.). West Lafayette, IN:

Miller, M., Elliot, W., Billmire, M., Robichaud, P., & Endsley, K. (2016). Rapid-response tools and datasets for post-fire remediation: Linking remote sensing and process-based hydrological models. *International Journal of Wildland Fire, 25*(10), 1061. doi:10.1071/WF15162

Miller, M., & Elliot, W. (2016, A rapid response database in support of post-fire hydrological modeling *The Technical Newsletter of the National Stream and Aquatic Ecology Center,* , 1-10.

Minkowski, M., & Renschler, C. (2008). *GeoWEPP for ArcGIS 9.x full version manual.* (). Buffalo, New York:

Moore, M. M., Covington, W., & Fulé, P. Z. (1999). Reference conditions and ecological restoration: A southwestern ponderosa pine perspective. *Ecological Applications, 9*(4), 1266-1277. doi:RCAERA]2.0.CO;2

Nangia, V., Wymar, P., & Klang, J. (2010). Evaluation of a GIS-based watershed modeling approach for sediment transport. *International Journal of Agricultural & Biological Engineering, 3*(3), 43-53. doi:10.3965/j.issn.1934-6344.2010.03.043-053

Nioti, F., Xystrakis, F., Koutsias, N., & Dimopoulos, P. (2015). A remote sensing and GIS approach to study the long-term vegetation recovery of a fire-affected pine forest in southern greece. *Remote Sensing, 7*(6), 7712-7731. doi:10.3390/rs70607712

Odion, D. C., Hanson, C. T., Arsenault, A., Baker, W. L., DellaSala, D. A., Hutto, R. L., . . . Williams, M. A. (2014). Examining historical and current mixed-severity fire regimes in ponderosa pine and mixed-conifer forests of western north america. *PLoS ONE, 9*(2), 1-14. doi:10.1371/journal.pone.0087852

Oliveira, A. H., Aparecida da Silva, M., Silva, M. L. N., Curi, N., Neto, G. K., & França de Freitas, Diego Antonio. (2013). Development of topographic factor modeling for application in soil erosion models. *Soil Processes and Current Trends in Quality Assessment,* , 111-138. doi:10.5772/54439

Pandey, A., Chowdary, V. M., & Mal, B. C. (2007). Identification of critical erosion prone areas in the small agricultural watershed using USLE, GIS and remote sensing. *Water Resources Management, 21*(4), 729-746. doi:10.1007/s11269-006-9061-z

Paparrizos, S., Maris, F., Kitikidou, K., Anastasiou, T., & Potouridis, S. (2015). Comparative analysis of soil erosion sensitivity using various quantizations within GIS environment: An application on sperchios river basin in central greece. *International Journal of River Basin Management, 13*(4), 475-486. doi:10.1080/15715124.2015.1025274

Peppin, D., Fulé, P. Z., Sieg, C. H., Beyers, J. L., & Hunter, M. E. (2010). Post-wildfire seeding in forests of the western united states: An evidence-based review. *Forest Ecology and Management, 260*(5), 573-586. doi:10.1016/j.foreco.2010.06.004

Prasannakumar, V., Vijith, H., Abinod, S., & Geetha, N. (2012). Estimation of soil erosion risk within a small mountainous sub-watershed in kerala, india, using revised universal soil loss equation (RUSLE) and geo-information technology. *Geoscience Frontiers, 3*(2), 209-215. doi://dx.doi.org/10.1016/j.gsf.2011.11.003

Pyke, D. A., Wirth, T. A., & Beyers, J. L. (2013). Does seeding after wildfires in rangelands reduce erosion or invasive species? *Restoration Ecology, 21*(4), 415-421. doi:10.1111/rec.12021

Reed, B., Brown, J., VanderZee, D., Loveland, T., Merchant, J., & Ohlen, D. (1994). Measuring phenological variability from satellite imagery. *Vegetation Science, 5*(5), 703-714.

RAISON, R. J. (1979). Modification of the soil environment by vegetation fires, with particular reference to nitrogen transformations: A review. *Plant and Soil, 51*(1), 73-108.

Reiner, A. L., Vaillant, N. M., & Dailey, S. N. (2012). Mastication and prescribed fire influences on tree mortality and predicted fire behavior in ponderosa pine. *Western Journal of Applied Forestry, 27*(1), 36-41.

Renard, K., Foster, G., Weesies, G., McCool, D., & Yoder, D. (1997). *Predicting soil erosion by water: A guide to conservation planning with the revised universal soil loss equation (RUSLE)* (703rd ed.). Washington, DC: Agricultural Research Service.

Richards, J. (2017). ENVI maximum likelihood. Retrieved from https://www.harrisgeospatial.com/docs/MaximumLikelihood.html

Robichaud, P. R., Lewis, S. A., Wagenbrenner, J. W., Ashmun, L. E., & Brown, R. E. (2013). Post-fire mulching for runoff and erosion mitigation: Part I: Effectiveness at reducing hillslope erosion rates. *Catena, 105*, 75-92. doi://doi.org/10.1016/j.catena.2012.11.015

Robles, M. D., Marshall, R. M., O'Donnell, F., Smith, E. B., Haney, J. A., & Gori, D. F. (2014). Effects of climate variability and accelerated forest thinning on watershed-scale runoff in southwestern USA ponderosa pine forests. *PLoS ONE, 9*(10), 1-15. doi:10.1371/journal.pone.0111092

Schlaepfer, D., Lauenroth, W., & Bradford, J. (2012). Effects of ecohydrological variables on current and future ranges, local suitability patterns, and model accuracy in big sagebrush. *Ecography, 35*(4), 374-384. doi:10.1111/j.1600-0587.2011.06928.x

Stephens, S. L., & Ruth, L. W. (2005). Federal forest-fire policy in the United States. *Ecological Applications, 15*(2), 532-542. doi:10.1890/04-0545

Stevens, J. T., Safford, H. D., North, M. P., Fried, J. S., Gray, A. N., Brown, P. M., . . . Taylor, A. H. (2016). Average stand age from forest inventory plots does not describe historical fire regimes in ponderosa pine and mixed-conifer forests of western north america. *PLoS ONE, 11*(5), 1-20. doi:10.1371/journal.pone.0147688

Terranova, O., Antronico, L., Coscarelli, R., & Iaquinta, P. (2009). Soil erosion risk scenarios in the mediterranean environment using RUSLE and GIS: An application model for calabria (southern italy). *Geomorphology, 112*(3–4), 228-245. doi://dx.doi.org/10.1016/j.geomorph.2009.06.009

Tiwari, A., Risse, L., & Nearing, M. (2000). Evaluation of WEPP and its comparison with USLE and RUSLE. *Transactions of the ASAE, 43*(5), 1129-1135. doi:10.13031/2013.3005

USDA (n.d.). History of 4FRI. Retrieved May 3, 2017, from https://www.fs.usda.gov/main/4fri/about-history

United States Department of Agriculture Forest Sevice. (1985). *4FRI planning: Tonto national content for soils, water, riparian and roads.* .USDA.

United States Geologic Survey, & Department of Agriculture Forest Service.*1990 dude fire severity.* Unpublished Data

USLE history. (2016). Retrieved from https://www.ars.usda.gov/midwest-area/west-lafayette-in/national-soil-erosion-research/docs/usle-database/usle-history/

Vadrevu, K., Eaturu, A., & Badarinath, K. (2010). Fire risk evaluation using multicriteria analysis—a case study. *Environmental Monitoring and Assessment, 166*(1), 223-239. doi:10.1007/s10661-009-0997-3

Veblen, T. T., Kitzberger, T., & Donnegan, J. (2000). Climatic and human influences on fire regimes in ponderosa pine forests in the colorado front range. *Ecological Applications, 10*(4), 1178-1195. doi:CAHIOF]2.0.CO;2

Witt, S. (1999). Watershed burned area emergency response, BAER. Retrieved from https://www.fs.fed.us/biology/watershed/burnareas/index.html

Xinxin Zhang, J., Kang-Tsung, C., & Qiong Wu, J. (2008). Effects of DEM resolution and source on soil erosion modelling: A case study using the WEPP model. *International Journal of Geographical Information Science, 22*(8), 925-942. doi:10.1080/13658810701776817

Xian, L., Youpeng, X., & Yi, S. (2011). Comparison of interpolation methods for spatial precipitation under diverse orographic effects. *National Natural Science of China, 8*(11), 1-5. doi:978-1-61284-848-8

Yaolong, Z., Ke, Z., Yingchun, F., & Hong, Z. (2012). Examining land-use/land-cover change in the lake dianchi watershed of the yunnan-guizhou plateau of southwest china with remote sensing and GIS techniques: 1974–2008.*9*, 3843-3865. doi:10.3390/ijerph9113843

Zedler, P. H., Gautier, C. R. and McMaster, G. S. (1983), Vegetation Change in Response to Extreme Events: The Effect of a Short Interval between Fires in California Chaparral and Coastal Scrub. Ecology, 64: 809–818. doi:10.2307/1937204

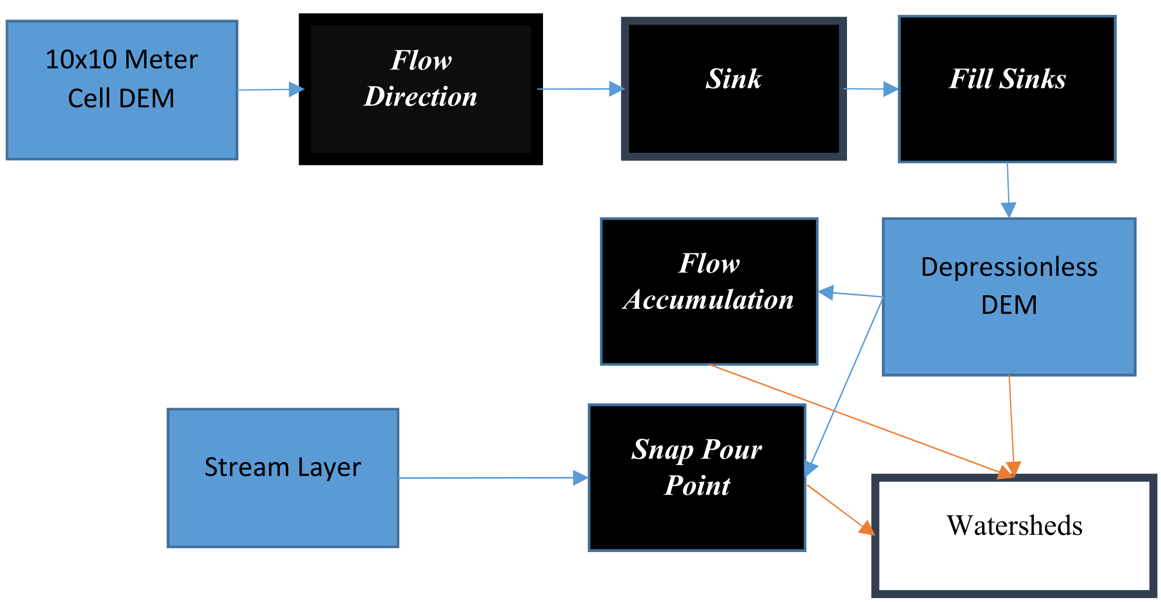
APPENDIX A

DISCUSSION OF METHODS FOR RUSLE

In chapter 3 section 2, inputs were created for the RUSLE model. This methodology aimed to mimic the most common practices that a land manager working under the objectives of the 4FRI would use.

RUSLE Preprocessing: Watershed Delineation

Before the factors for RUSLE were obtained, the watersheds of interest were identified using the ArcMap Hydrology toolset. The 10mx10m resolution DEM raster and a line shapefile representing creeks, streams and rivers was obtained from the USGS Geospatial Data Gateway and loaded into ArcMap.



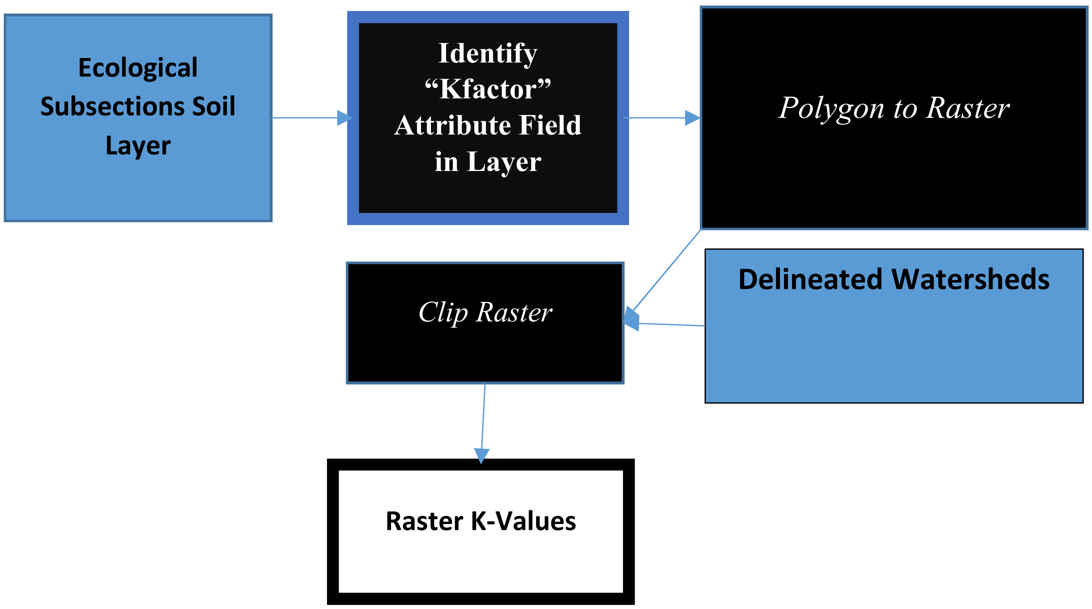
The *select by attribute* tool was used with the stream layer to identify the two creeks “Dude” and “Bonita” through the name field provided in the attribute table. The *flow direction* ArcMap hydrology tool uses a DEM as an input to create a raster showing the direction of flow out of each cell to its steepest downslope neighbor. The *sink* tool identified "sinks" in the digital elevation model that would have otherwise resulted in an error if they were not filled; so the *fill* tool was then used to fill the sinks to create a depressionless DEM. The *flow accumulation* tool was then used on the new DEM. A cell that was identified as part of the flow accumulation, was chosen using the *snap pour point* tool at the base of the creek of interest that was identified using the stream line layer. The *flow direction* tool output raster layer was then used in conjunction with the *snap pour point* output and the depressionless DEM to identify the two watersheds of interest (Figure 2).

R-Factor: Rainfall Erosivity

As defined in the EPA R-factor Calculator manual, this parameter builder takes elevation, dates of interest, and the latitude and longitude into account. As the study area is larger than the average construction site, the R-factor was calculated for several point locations throughout the watersheds (Table 1). The dates inserted into the calculator were June 1st, 1990 through December 31st, 1993 as these are the dates in which relatively heavy rainfall followed the fire event and caused largescale regional flooding (Figure 3). A spatial interpolation method was used in order to create estimates in raster format for the study area. Kriging works by taking the values of the surrounding points to then derive a prediction of the unmeasured location. ArcMap's spatial analyst *Kriging* tool then allowed for these point values to interact to create the raster formatted factor of R. Ordinary Kriging was used as opposed to CoKriging as elevation was already accounted for in the EPA R-factor Calculator.

K-Factor: Soil Erodibility

The USDA USFS provides a soils layer that includes the K-factor for the watersheds of interest. This data was used in the steps below to create a raster formatted parameter for the RUSLE model for both watersheds.



L and S Factors: Slope Length and Steepness

The slope length (L) factor is defined as the soil-loss ratio from a 22.13 meter long plot at a set 9% slope in continuous clean-tilled fallow (Renard et al.,1997).

The equation for L is as follows: $L = (m+1)(\frac{\lambda}{22.13})^m$

Where λ stands for the horizontal plot length. The variable m stands for the exponent calculated from the ratio of rill-to-interrill erosion. As the exponent "m" varies greatly in its value depending on the topography, the numerical value assigned was 0.4 as this provides a better subfactor for accentuated slopes (Bhandari and Darnsawasdi, 2014; Martnez-Lopez, 2014; Oliveira et al., 2013).

S = Slope Steepness $$S = (\frac{\sin(0.01745 \times \theta_{deg})}{0.09})^{n}$$

The *slope* tool found in ArcMap was used on the DEM, in which the output was designated to be in degrees, thus giving us the value for θ. The "n" value is related to the soil's susceptibility to erosion and was attributed 1.4 as this value has been proved to produce more accurate results when in a mountainous and topographically complex region. (Bhandari and Darnsawasdi, 2014; Martnez-Lopez, 2014; Oliveira et al., 2013).

The L and S factors were calculated at the same time using a variety of raster data inputs, in which the following expression was used in the ArcMap raster calculator.

Raster calculator input: $Power(\text{“}flowacc\text{”} * [cell\ resolution]/22.1, 0.4) * Power(Sin(\text{“}sloperasterdeg\text{”} * 0.01745))/0.09, 1.4) * 1.4$

The "flowacc" represents the values from the output from the *flow accumulation* tool used previously in the ArcMap Hydrology Toolset. Cell resolution was attributed 10, as the DEM has a 10mX10m cell resolution. "Sloperasterdeg" raster input was created using the output of the *slope* tool using the clipped DEM of the watershed of interest and ensuring that the output of the *slope* tool was set to degrees (Figure 7).

C-Factor: Land Cover

The imagery used for this project was provided by the National Agriculture Imagery Program (NAIP) through the USGS Earth Explorer Database. This imagery is funded by the USDA and provides high resolution 1- meter aerial imagery obtained during the peak of the growing season. For the study area, it provided images throughout the years 2007, 2010, 2013 and 2015 with 4 bands that consist of a red, green, blue and infrared. Being orthoimagery, the raster formatted images have been geometrically corrected or orthorectified to remove distortion caused by camera optics, camera tilt and differences in elevation. This imagery was referenced using absolute accuracy specification in which the imagery was tied to true ground. The contract used by the USDA issued to the private contractors states that when tested for accuracy it must fall within 6 meters of the true ground at a 95% confidence level.

After downloading the imagery, it was opened in the ENVI software and was merged using the mosaic tool to create a seamless image of the study area for the 4 different years. The watersheds were outlined on the imagery using the polygons made in ArcMap with the hydrology toolset by displaying the shapefile on the mosaicked images in ENVI. This was done using by importing the vector file and exporting the active layers to the region of interest (ROI).

Several literature reviewed examples used land cover classification in which training pixels were identified to allow the software to then create a map in which similar pixels were arranged into classes of land cover type (Ashiagbor et al., 2016;Forkuo and Adubofour, 2012). Other published studies used band math with the Normalized Difference Vegetation Index (NDVI) was calculated and used to identify vegetation density. The NDVI values were then categorized and attributed a C-Value from 0-1 (Ashiagbor et al., 2016; Bhandari and Darnsawasdi, 2014; Ganasri and Ramesh, 2016; Karaburun, 2010; Prasannakumar et al., 2012), with the higher end attributed to fallow conditions and maximum erosion. Both land cover classification methods were used and compared, in which the land cover Maximum Likelihood Classification Method through ENVI was used to create the final C-Values.

In order to test the NDVI and band math approach, the NDVI values needed to be calculated for the study area. The band math equation (b4-b3)/(b4+b3) was applied thus calculating the NDVI, where b3 represented the red band and b4 represented the near infrared band. Having the NDVI values, the following band math equation was inserted in the ENVI *band math* tool: exp((float(b1))/(2-(float(b1)))*(-1.0)), where β was the NDVI band that had originally been calculated. This equation transformed the NDVI values that ranged from .2-.8 to the proper C-value range.

The land cover supervised classification method was then executed using the ENVI software as well. Having four bands, three land cover classes were the limit and forest, shrub land, and bare ground were chosen. The land cover classification was done using the maximum likelihood classification method. This method is defined as a supervised method in which the statistics for each class in each band are normally distributed. It calculates the probability of each pixel belonging to the specific land cover classes using an array of discriminant functions, (Richards, 2017). The *region of interest* (ROI) tool was used to create the training pixels of the three different cover types. Each year's imagery was scanned and land cover types were individually identified by eye. Using these training pixels stored in the *ROI* tool in conjunction with the *maximum likelihood* tool the land cover classes were created with a selected error margin of .95, which allowed for the user to identify the unidentified pixels by hand. The 2013 NAIP imagery was excluded as a large portion of the cliff area was identified as forest. This was due to the large amount of shadow as the imagery was obtained at a time of day in which the sun was too low.

The resulting land cover classification for 2007, 2010 and 2015 were brought into ArcMap in order to run an accuracy assessment to determine what image produced the most accurate result (Figure 8). The *Create Random Points* tool was used within ArcMap to create 300 points within the area of interest, being the two watersheds. The watershed polygons were combined and the resulting polygon was used as the constraining feature class. The NAIP 2007, 2010 and 2015 imagery was displayed in ArcMap using the red green and blue bands as to show the imagery in true color. The 300 random points created were then classified by the user using the true color maps in order to create a reference assessment matrix for the accuracy assessment. The three different classified maps were then compared individually to the true color imagery assessment matrix by exporting the attribute table to excel in CSV format. The 2015 classification raster was chosen as it had the highest percentage accuracy to the true color user generated matrix at 87%.

The supervised maximum land cover classification of 2015 was chosen over the band math classification as this method provided the ability to identify general vegetation types in which a direct C-factor value could be attributed when supplemented with the literature review (Ashiagbor et al., 2016; Bhandari and Darnsawasdi, 2014; Ganasri and Ramesh, 2016; Karaburun, 2010; Prasannakumar et al., 2012). While the band math provided the knowledge of where the vegetation was located and how dense the vegetation within each pixel was, it did little to inform how the vegetation may differ in root structure that then may hold soil differently. The land cover types were attributed C factor ranging 0-1, with 0 being total soil retention. The pixels identified as ponderosa forest were attributed 0.05, shrub land was attributed 0.4 and the bare ground was marked at 0.85. These values related with similar factor values found among case studies and the USDA RUSLE guide. The ponderosa pine, which is not included in the USDA RUSLE table, was credited a higher C-factor as ponderosa pine are deep rooting conifers compared to other western species. Although a surface fire may heat the soil and kill some surface roots, deeper roots remain intact and allow for continued uptake of water and prevent soil erosion (Fitergerald, 2005).

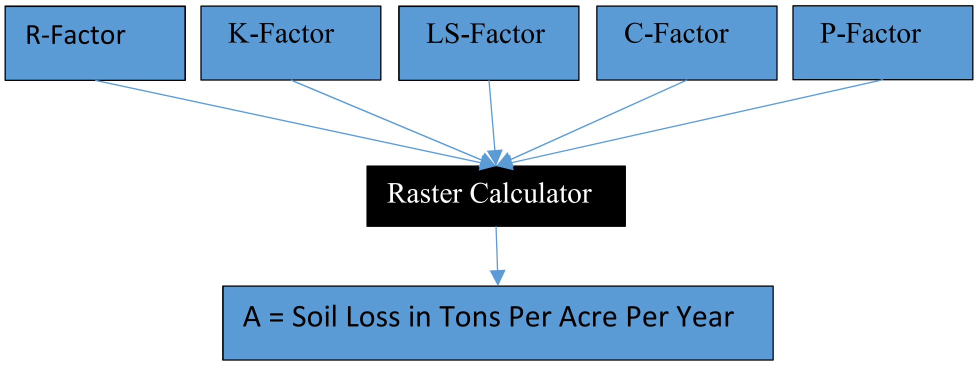
As the land cover map created from the supervised classification was obtained from 2015 imagery, the fire's immediate effects needed to be represented in order to make the C-factor data better represent the land cover immediately post burn. A burn severity map (Figure 9) was acquired from the USFS. This map was brought in to ArcMap as a .tiff image. The image was georeferenced using the Dude Fire perimeter polygon (unpublished data, Christopher Barrett, USFS). The watershed polygons were then used to clip the image. Moderate and high severity burn areas were digitized as polygons within the watersheds using the ArcMap editor and the *create feature* tool. These polygons were then overlaid with the land cover classification data created earlier using the merge function. As the moderate severity burn covered a majority of these watersheds, it was not included as it would have replaced all of the vegetation data. Alternatively, the moderate severity burn was represented by increasing the C-factor values for the regions in which the land cover and the burn area intersected. The high severity burn polygons were overlaid with the land cover data, and it was attributed a very C-factor value of 0.95, due to the immediate hydrophobicity of the soil caused by the high severity fire, (Figure 10).

P-Factor: Support Practice

The P-factor was created by digitizing a seeding treatment map created by the United States Forest Service. This image was brought in to ArcMap as a .tiff file. The *georeferencing* tool was then used along with the shapefiles of the streams and the watersheds created earlier to register the image to the proper area and scale. ArcCatalog was then used to create a new polygon in the proper coordinate system. This new polygon feature was then edited in ArcMap to outline cross-hatched areas. These areas represented were seeding had anticipated to have taken place. These polygons representing the seeded area was used as the update feature with the watershed polygon being the input in the overlay toolset. A float type attribute field was created named “Pfact” in which the seeded area was attributed a value of 0.98, and the rest was given the value 1 as a value of 1 indicates no support practice was carried out. These polygons with the edited attribute tables were then used as inputs with the *polygon to raster* tool, with the value field input being “pfact” to create the proper input for the model.

RUSLE Model Output Computation

The factors created above were then organized into a file geodatabase through ArcCatalog. This not only reassured that the raster formatted parameters were in the same coordinate system, but also allowed for easy confirmation that they all had a cell size of 10mX10m. The factors were loaded into ArcMap and the *ModelBuilder* tool was used to allow for a visual interpretation and geoprocessing of workflows. This tool documents the spatial analysis and data management steps in a diagram format. It also allowed for the easy creation of a Python script that can be edited in the programming language. The model created simply used the factors provided and the raster calculator to then multiply them and to derive the RUSLE output.



Two models were created, one for the Bonita watershed specific parameters and one for the Dude watershed parameters. The model was run and the outputs (Figures 16,17) were assessed for accuracy. Points were then chosen at random within the output "A" maps and calculated by hand to ensure of proper function of the *raster calculator* tool. In order to do this the ArcMap identify function was used for the areas of choice, in which the factor values where displayed for a specific cell.

APPENDIX B

DISCUSSION OF METHODS FOR WEPP

The parameters needed to run GeoWEPP were downloaded from the BAER Spatial WEPP Model Inputs Generator hosted by Michigan Technological University. The state, year, and fire was selected as follows AZ, 1990 and Dude_E. In this instance, the user has the option of selecting the lower resolution 30 meter DEM or the 10 meter DEM, in which the 30 meter DEM was used for the model as the 10 meter resulted in the crashing of the software as discussed in chapter five. The files were mapped properly within the GeoWEPP software folder directory for functionality as the file mapping is familiar to the software for accessing customized soil data. The GeoWEPP for ArcGIS 10.3 wizard was opened and used to apply the recently downloaded parameters. This was done by selecting the *Use Your Own GIS ASCII Data* and creating a project name in which the current watershed of interest was applied.

The *Modify Delineation Network* tool was used and the value for the Critical Source Area (CSA) was changed from its default setting at 5ha to 10ha and the Minimal Source Channel Length (MSCL) was changed from the default 100m to 120m, in which the results can be compared in (Figure 12). The default settings were changed as to best approximate and define the channel network by reducing the number of small tributaries that additionally risked crashing the TOPAZ model.

The watershed was then defined using the *Select a Watershed Outlet Point* tool. Having the creek line feature shapefile created earlier, it was brought in to ArcMap in which a cell located at the end of the identified stream of interest along the channel was selected. This then used TOPAZ to delineate the watersheds and resulted in presenting the subcatchments (Figure 13).

The climate parameter created best represented the events that lead to the flooding by using the surrounding weather station data. Weather data for Baker Butte, Promontory and Payson weather stations was acquired from the National Oceanic and Atmospheric Administration (NOAA) website in comma-separated values (CSV) format. An average precipitation value was created for each month for using the date range of interest. A mean per-month value for all three stations was calculated. This value represents an average of all three stations for the dates of interest, for each month, in a format of one geographic location as to be easily integrated with the PRISM GeoWEPP interface.

Identifying the location of the CLIGEN point was then computed. The latitudes and longitudes for each weather station were recorded and used to create point shapefiles in ArcMap using the "*Go To XY*" and "*Create Feature*" tool. Fields labeled "Latitude" and "Longitude" were created in the attribute tables for the shapefile and the decimal degrees were double checked for accuracy using the calculate geometry feature. The *Mean Center* tool was used to identify the geographic center for the set points representing weather stations. This point generated provided a point to then geographically tie the precipitation data and be used with PRISM to rasterize the data (Figure 14). The CLIGEN input point is located at latitude 34.35 and longitude -111.25 with an elevation of 1625.39m and is located directly south of the areas of interest.

This data was used with PRISM by inserting it within the Climate Modification window, making sure to include the longitude, latitude, elevation, mean minimum temperature monthly, mean maximum temperature monthly, mean precipitation monthly, and number of wet days per month for the input CLIGEN point data. This edited data, that best represented the weather parameters of the four years following the fire, was saved as a new PRISM climate input station named "mod_Payson".

The *Run WEPP* command was then executed where the program was set to use the modified climate named "mod_Payson". The WEPP Management and Soil Lookup window appeared in which the Land use and Soil parameters were checked and could have alternatively been edited. The WEPP/TOPAZ Translator window then prompted for an input of the number of years simulated in which four was selected as only integers were allowed. The GeoWEPP simulation method selected was both: "Watershed and Flowpaths". The results of both the onsite and offsite methods correspond to the T-Value, which is the tolerated rate of erosion (in tons per hectare per year) which was left at its default of 1 as previous modeling runs indicated this value as a good median.