The Impact of Definition Criteria on Mapped Wildland-Urban Interface:

A Case Study for Ten Counties along the Oregon-California Border

by

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Table of Contents

List of Tables

List of Figures

Abbreviations

ACS	American Community Survey
BLM	Bureau of Land Management
FEMA	Federal Emergency Management Agency
GIS	Geographic information system
MAUP	Modifiable areal unit problem
MRLC	Multi-Resolution Land Characteristics
NIFC	National Interagency Fire Center
NLCD	National Land Cover Database
WUI	Wildland-Urban Interface
USDA	US Department of Agriculture
USDI	US Department of Interior
USFS	US Forest Service
USGS	US Geological Survey

Abstract

Large and severe wildfires have become the norm in many parts of the western US, including the region along the Oregon-California border. As populations in this area continue to grow, they encroach on undeveloped land with abundant wildland fuels and high fire risk. Communities that inhabit this wildland-urban interface (WUI) are increasingly imperiled as climate change exacerbates catastrophic fire activity. While previous, national-level studies have established a methodological baseline for WUI identification using vegetation and population density data, the impacts of variable criteria on small-scale study areas remains under investigated. This is a key area of concern because the adequate identification of WUI communities is a vital first step for effective public policy decision making, emergency planning, and resource allocation. This project attempts to bridge the current research gap by analyzing the impact of vegetation and population variable parameters on the size and character of identified WUI areas for ten counties along the Oregon-California border. This analysis is used to generate an optimal WUI definition for the project area, which defines the WUI as census block groups with ≥1 household/400 acres and ≥25 % wildland vegetation cover. This project finds that, compared with previous national-level studies, a much lower population density threshold is necessary to adequately identify plausible WUI communities. This study also supports previous findings, which indicate that vegetation density thresholds are of secondary importance when compared to population density. These findings are of interest to land managers who are tasked with resource allocation and wildland firefighting in the WUI, along with residents who inhabit these communities.

Chapter 1 Introduction

In recent years residents of western states have come to begrudgingly expect a fifth season in late summer. Driven by catastrophic, landscape-level wildfires, the “smoky” season typically includes weeks of poor air quality and the evacuation of rural communities, followed by multi-year rebuilding efforts. Though different regions are spared in a given year, this new paradigm, endemic to the Anthropocene in the era of climate change, is annually consistent. One only needs to skim the headlines in late summer to read an updated report of acres burned and homes lost in a given year’s mega-fire. Fire is, of course, ecologically indigenous to the western landscape. Natural and anthropogenic fire has long been a fact in many environments across the globe, leading to a proliferation of fire-adapted species and ecological communities reliant on routine, low intensity fires (Pyne 1997). What is unique about the current fire paradigm is the abundance of people and infrastructure vulnerable to fire and the increased frequency of severe, large-scale fire events resulting from a hotter, drier climate and alteration to historic fire regimes.

Wildland-urban interface (WUI) communities are located where “humans and their development meet or intermix with wildland fuels” (USDA and USDI 2001, 752-753). WUI communities across the US have seen sustained growth in recent decades (Hammer, Stewart, and Radeloff 2009) and have emerged as the fastest growing land use type in the country (Radeloff et al. 2018). With their close proximity to abundant, fire-prone fuels, WUI communities and homes frequently receive the brunt of wildfire impacts. While drier and hotter conditions continue to increase the frequency and severity of wildfires across the west, wildfire impacts to homes and communities have become a standard feature of the annual fire season. As communities grapple with frequent and severe fire events, the onus for prevention and risk reduction on private property is placed on individual home and landowners (Downing et al. 2022). The presence of homes and related infrastructure also complicates firefighting efforts (Radeloff et al. 2018) and increases the probability of catastrophic outcomes for individuals and communities. Between 1990 and 2014, the number of homes lost in wildfires in the US increased by 300% (Downing et al. 2022). This issue has also led to a marked increase in fire suppression costs by government entities that are tasked with protecting private property adjacent to public lands (Mell et al. 2010). Likewise, wildfire risk reduction and fire prevention has seen increased political prominence in recent years, as worsening fire conditions near populous western communities have garnered national attention.

Understanding the location and geographic extent of the WUI is a fundamental issue for wildfire planning, hazard mitigation, and related resource allocation. For instance, fuels reduction programs are a common method of wildfire hazard mitigation by land management agencies. Logistically, it is often not feasible to uniformly conduct these treatments across an entire landscape, so identifying high priority areas, such as the WUI or especially vulnerable portions of the WUI, is imperative (Wimberly, Zhang, and Stanturf 2006). Though the general definition of the WUI is easily understood, the question of how to actually demarcate WUI from non-WUI locations is much more complicated. Methodological approaches to WUI identification vary, but they typically combine population and landcover data or, for smaller scale studies, remote sensing and object detection. WUI identification is often the preliminary step for a wider analysis of emergency preparedness or risk assessment.

Extant research has provided a solid methodological framework that combines vegetation and population data, but the impact of variable thresholds on mapped WUI locations remains under-investigated. For instance, a given proportion of wildland vegetation cover is a common WUI identifier, but the selected proportion (e.g. 20% versus 40% of the landcover in a given area) might significantly impact the geographic extent of the area defined as WUI. This is especially true for smaller, regional study areas where variable characteristics may differ from the national norm established in large scale studies. This project attempts to bridge this research gap by investigating the impact of land cover and population density variable thresholds on WUI identification for ten counties along the Oregon-California border. By testing variable threshold combinations, this study attempts to identify the relative impacts of vegetation and population density and determine the optimal combination of variables for the project area.

1.1. Defining the WUI

Across the western US, much of the land that abuts private property in the WUI is administered by various federal, state, and local government agencies. Federal land management agencies administer the largest swathes of public wildland. The five largest federal land managers (Department of Defense, Bureau of Land Management (BLM), US Forest Service (USFS), National Park Service, and Fish and Wildlife Service) collectively administer over 600-milion acres of the country. These agencies administer 52.3% of the state of Oregon and 45.4% of California (Congressional Research Service 2020). Often, federal agencies and their state counterparts are tasked with wildfire risk mitigation, prevention, and emergency response. In the 1980s, the USFS, along with the National Fire Protection Association and the Federal Emergency Management Agency (FEMA), formed a partnership to address fire and the WUI. This partnership, which later drew collaboration with the BLM and the National Association of State Foresters, held the first conference dealing with fire and the WUI in 1986 (Cortner and Gale 1990). National, state, and local governments continue to prioritize WUI community planning and resilience. As recently as 2021, the Bipartisan Infrastructure Bill allocated funding to improve the fire regime condition and restore 10,000,000 acres of land in the WUI by 2027 (Public Law 117–58, Sec. 40803. Wildfire Risk Reduction).

Defining and identifying WUI communities is a fundamental task for emergency planning and resource allocation. Definitions vary slightly, but ultimately describe the same core phenomenon (Stewart et al. 2007). An official definition was established in a 2001 Federal Register article: “the urban wildland interface community exists where humans and their development meet or intermix with wildland fuel” (USDA and US Department of Interior (USDI) 2001, 752-753). The Federal Register publication identifies three categories of WUI: interface, intermix, and occluded (Table 1). Interface communities are those that abut wildland fuels, with a “clear line of demarcation” between the two (2001, 753). These areas are defined as having a density of three or more structures per acre or a population density of 250 or more per square mile. Intermix WUI lacks a “clear line of demarcation” and has more intermixing of wildland fuels and development (2001, 753). Structure density can be as low as one structure per 40 acres or 28-250 people per square mile. Occluded WUI occurs where structures abut an island of wildland fuel in otherwise developed areas, such as an urban park. The Federal Register definition has become the baseline for WUI research because it provides a standardized, quantifiable measure.

Table 1. Federal Register WUI types

WUI Type	Definition	Criteria
Interface	Settlement borders wildland fuels	≥3 structures/acre or ≥250 people/sq mi
Intermix	Settlement mixed with wildland fuels, no separation	≥1 structure/40 acres or 28-250 people/sq mi
Occluded	Island of fuels surrounded by settlement	No specific criteria

In the western US, the geographic extent of the WUI has increased dramatically over time. Between 1990 and 2000, the WUI in western states grew 25%; collectively, this comprised 45% of housing units in the region (Hammer, Stewart, and Radeloff, 2009). This trend has continued into the 21st century. The WUI collectively increased by 25-million residents between 1990 and 2010. In that same span of time, the number of houses within fire perimeters grew 62%, to 286,000 (Radeloff et al. 2018). Though the long-term impacts of the 2020 COVID-19 pandemic are still playing out, WUI growth has almost certainly escalated in the first years of the decade. Outmigration, prompted by remote work opportunities and rising housing costs in urban areas, has led to an influx of new residents into smaller communities (Frey 2022).

1.2. Motivation

Previous GIS-based WUI identification projects often focus on determining and operationalizing the criteria for identifying the WUI at a national or regional scale. Though a useful exercise for broad decision-making and emergency planning, national level WUI mapping does not account for nuanced local differences. Factors like local economic history, geography, and land management practices have varying degrees of impact on local settlement patterns and community makeup, and therefore, the contemporary WUI. The social and demographic makeup of WUI communities can also vary greatly, which has real-world ramifications for fire resiliency and economic capacity. Because of the nuanced nature of WUI communities and fire behavior across the country, localized, smaller-scale mapping projects have the potential to yield greater insight into a specific area, making them a valuable tool to improve wildfire planning. Small, geographic regions provide an optimal area to test and improve up the federal definition and criteria established in national-level studies.

Though federal and state agencies are directly involved in fire suppression and fuels reduction, the responsibility for risk mitigation in the WUI is shared with homeowners and local communities. Recent research demonstrates that the majority of wildfires in the US that burn structures begin on private property before spreading across ownership lines onto USFS land (Downing et al. 2022). The authors suggest that, while fire is inevitable, private landowners and homeowners are “the actors best positioned to reduce fire risk to homes and other high-value assets” (2625). It is also the case that most wildfires are caused by humans. Between 1992 and 2012, the majority (84%) of wildfires in the US were anthropogenic (Balch et al. 2017). Common sources of anthropogenic fire include arson, debris burning, campfires, and equipment or vehicle use (NIFC n.d.). Though human-caused wildfires do start in more remote areas, it is inevitable that the majority occur along the WUI where people and their activities are more concentrated. Fire in the WUI has been a topic of increased importance in recent years, especially as fire seasons have become more severe and long-lasting across much of the western US. This issue is not unique to the American West. Recent summers have seen above-average fire severity in Siberia (Patel 2021), the Mediterranean (Abnett 2021), and Australia (Gramling 2021), among other parts of the world. Continued population growth and sprawl into WUI areas, along with the deleterious impacts of climate change, indicate that proactive WUI identification and resource allocation will be essential for public planning and protecting communities and their residents.

1.3. Study Area

The ten counties selected for this project encompass the entirety of the Klamath-Siskiyou region and incorporate portions of the southern Willamette Valley and the very northern portion of California’s Central Valley. The project area is bounded by the Cascade Mountains in the east and the Coast Range in the west. These north/south trending ranges are connected by the Umpqua and Klamath Mountains, which include many subranges such as the Calapooya, Siskiyou, Marble, Scotts, Salmon, Russian, Trinity Alps, and Yolla-Bolly mountains. Much of the project area is characterized by rugged topography with most larger settlements occupying the Umpqua, Rogue, Klamath, and Upper Sacramento River valleys. Climatically, the area occurs at the junction of numerous ecological zones, including the Great Basin, Sierra Nevada, Cascade Mountains, Central Valley, and Coastal temperate zone. The region experiences a generalized west-east rain gradient, with higher precipitation along the Pacific coast, generally tapering off as weather systems move inland and over mountainous terrain. The rugged topography and high relief create complex, localized climatic zones, as well as numerous vegetation communities and microclimates, all of which impact localized fire regimes (Morton 2017). Portions of the project that lie east of the Cascade mountains, such as eastern Siskiyou, are given a Köppen Climate Classification of “Humid Continental Climate - Dry Cool Summer.” Most of the project area that lies between the Cascades and Coast Ranges is categorized as “Warm-Summer Mediterranean Climate” or “Hot-Summer Mediterranean Climate” (Kottek et al. 2006). These areas experience comparatively hot, dry summers, and tend to have the highest burn risk and most frequent fire intervals.

This study area straddles the Oregon-California border (Figure 1). Together, the ten counties studied encompass 30,746 square miles and approximately 800,000 residents. In addition to many smaller communities, the main urban spheres are Eureka-Arcata and Redding on the California side and Medford-Ashland-Grants Pass and Roseburg on the Oregon side. This area has mostly seen sustained population growth through the first decades of the twenty-first century (Table 2). Population growth is most pronounced in counties with larger urban centers, while more rural counties such as Siskiyou and Coos counties have seen a slower increase. Only one county, Del Norte, has experienced a slight decrease in residents over the last twenty years. Curry county has the lowest population, at just over 23,000. Jackson county is the most populous, with over 223,000 residents.

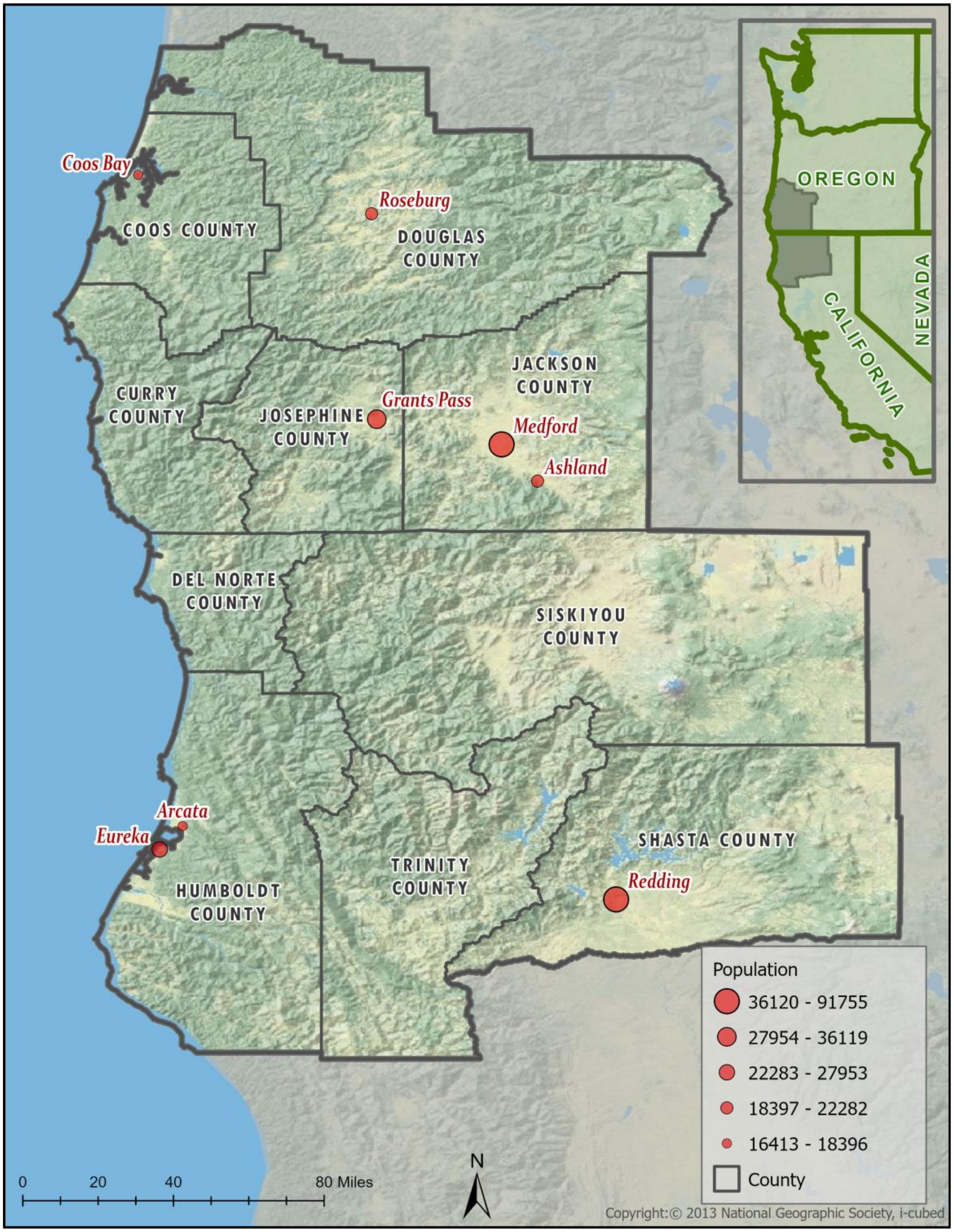

Figure 1. Study area and major population centers

Table 2. Population totals for study area by county and 20-year population change

County	State	2000 Population	2010 Population	2020 Population	Population Change
Del Norte	CA	27509	28565	27221*	-1.04 %
Humboldt	CA	126476	134353	136002*	7.50 %
Shasta	CA	162889	177248	178271*	9.40 %
Siskiyou	CA	44281	44962	44612*	0.74 %
Trinity	CA	13031	13811	13635*	4.63 %
Coos	OR	62779	63043	63315	0.85 %
Curry	OR	21137	22364	23005	8.83 %
Douglas	OR	100399	107607	112530	12.08 %
Jackson	OR	181269	203206	223240	23.15 %
Josephine	OR	75726	82713	86560	12.51 %

* 2018 population

Source: State of Oregon (2021) and California State Association of Counties (2019)

For context, a 2001 Federal Register listing identified 23 WUI communities in the project area. Though the identification methods are not clarified, and the list is clearly incomplete for anyone familiar with the area, it nonetheless serves as a convenient starting point for contextualizing the region (Figure 2). In Oregon, the listed WUI communities include Applegate, Ashland, Merlin, Murphy, Ruch, Sam’s Valley, Shady Cove, and Williams. On the California side, Burney, Dorris, Dunsmuir, Etna, Fort Jones, Happy Camp, Hayfork, Hoopa, Klamath, McCloud, Mount Shasta, Redding, Weed, Willow Creek, and Yreka were identified (USDA and USDI 2001).

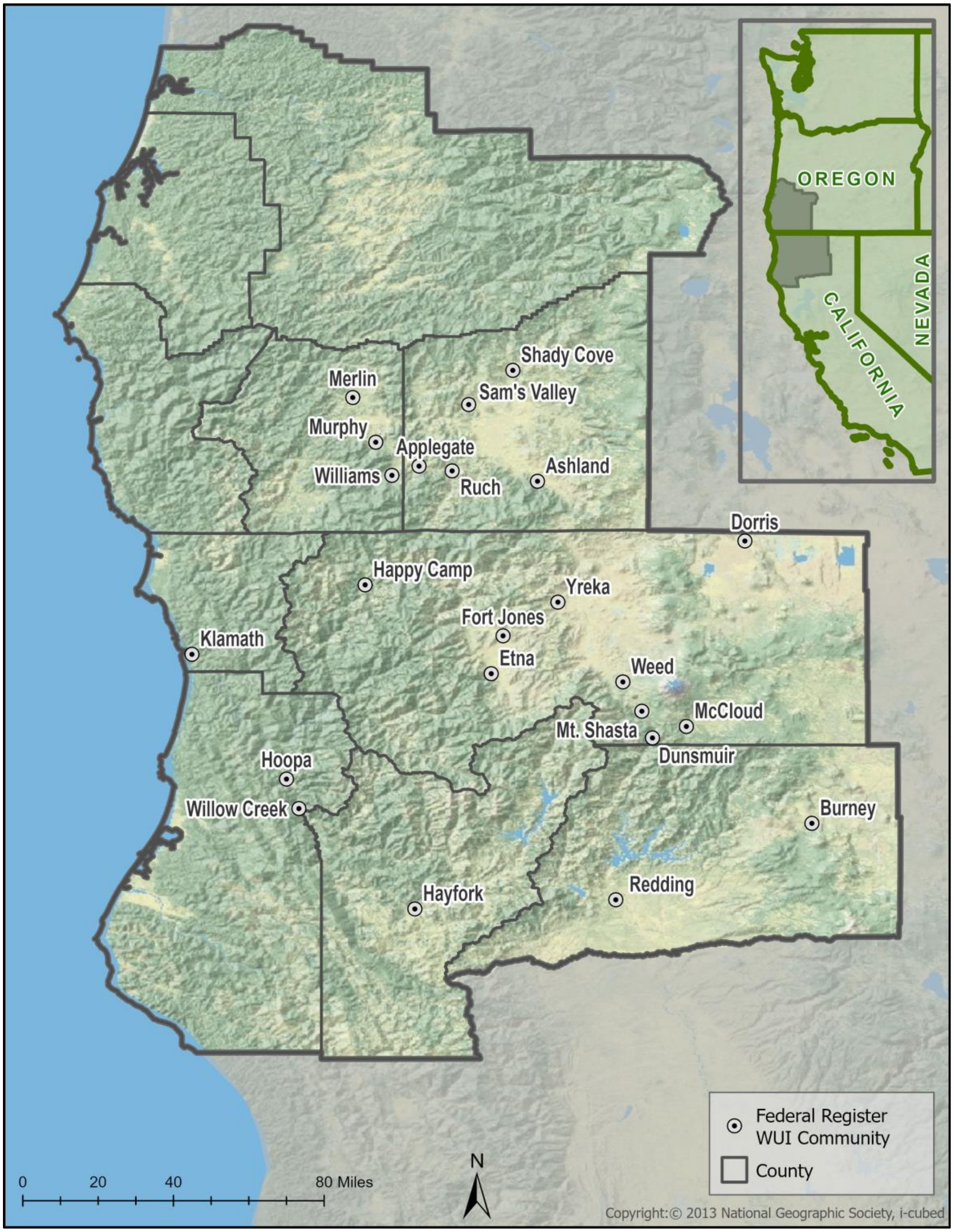

Figure 2. Federal Register listed WUI communities

According to the US Census Bureau's 2021 population estimates, the mean poverty rate for the project area is 15.1%. Del Norte County has the highest poverty rate of 18.5%, while the lowest is 11.9% in Jackson County. Median annual household income ranges from $57,139 in Shasta County to $41,780 in neighboring Trinity County. The largest proportion of the population, 78.6%, is White alone, not Latino or Hispanic. Hispanic or Latino residents are the next largest demographic group within the project area, accounting for 11.2% of the population. In descending order, the next largest demographic groups are people of two or more races, Native Americans, Asian Americans, and Black or African Americans.

Historically, the region was typified by frequent, naturally occurring, low-intensity fires. Beginning in the late 19th century, this regime has been interrupted by fire suppression policies (Frost and Sweeney 2000). Routine landscape-level burning by Native American groups prior to colonization was also ubiquitous across Oregon (Boyd 2019) and California (Marks-Block et al. 2021). Seasonal low-severity burning of the landscape helped to improve habitat for game animals and plant foods while maintaining a more fire-resilient landscape with less fuel buildup. Following the establishment of land management agencies like the USFS and BLM in the early twentieth century, wildfire suppression became the common approach to land management. Suppression of low-severity burns, in addition to myriad other factors, laid the groundwork for comparatively infrequent, but much more severe fire seasons.

The project area has seen a number of large fires in recent decades including many high profile, destructive fires that have ravaged homes and communities. According to the National Interagency Fire Center's (NIFC) "Wildland Fire Perimeters" dataset, over 5.2 million acres burned in the project area between 2000 and 2018 (Figure 3). Recent fires of note include the 2018 Carr Fire, which burned into the outskirts of Redding, California. According to CalFire, the

Carr Fire ultimately killed three people, torched 229,651 acres, and destroyed over 1,600 structures. On the Oregon side of the project area, similarly large and catastrophic fires have occurred in recent years. Early in the century, the 2002 Biscuit Fire burned over 500,000 acres, setting records as the largest fire in Oregon history (LaLande 2022). In early September 2020, a number of fires occurred. These included the Obenchain, Almeda, Slater, Archie Creek, and Thielson. Together, the Labor Day fires burned over 300,000 acres and destroyed more than 3,000 structures.

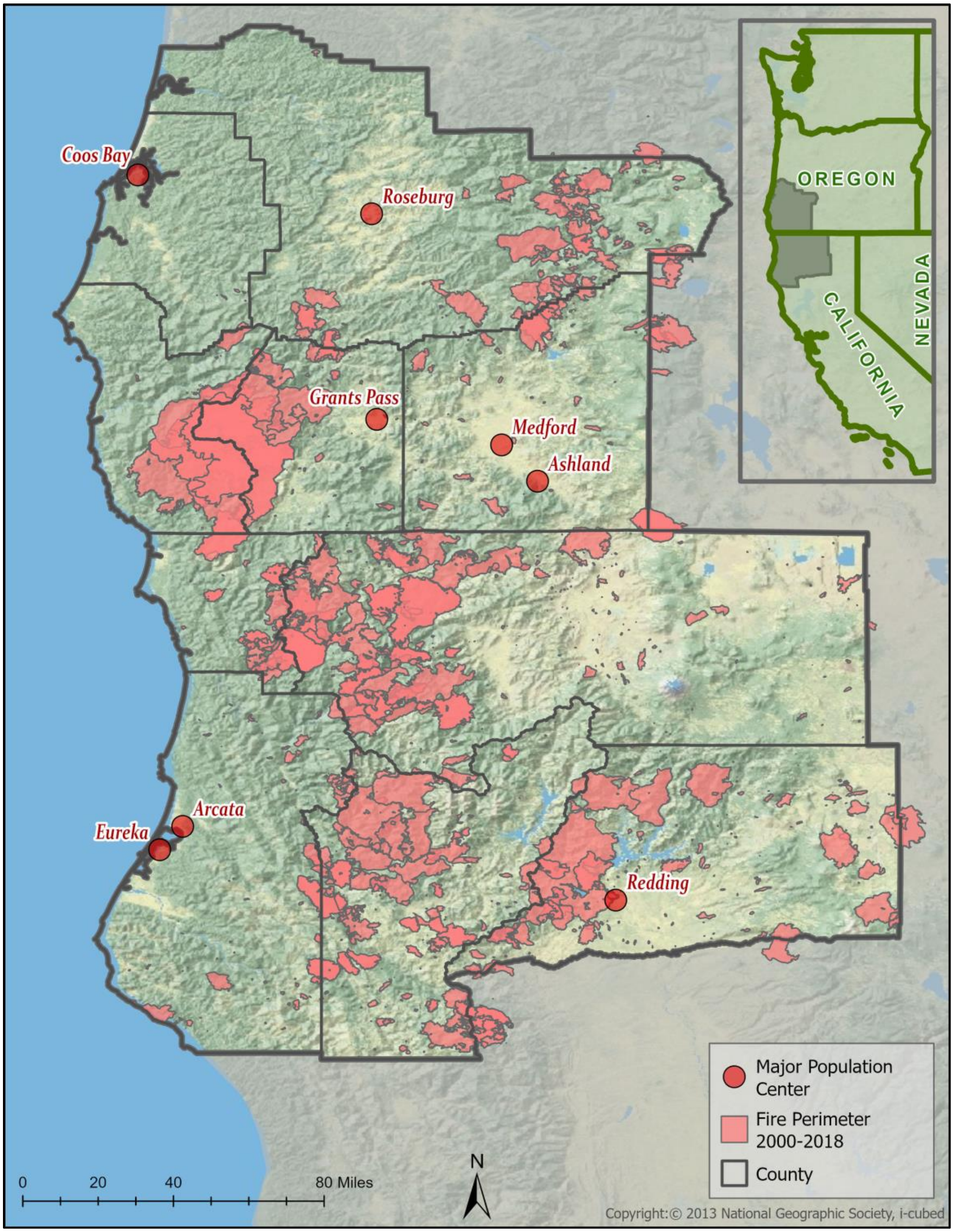

Figure 3. National Interagency Fire Center (NIFC) Fire Perimeters 2000-2018

1.4. Project Overview

The overarching hypothesis of this project is that the choice of thresholds set for the levels of vegetation coverage and population density, which serve to demarcate areas as "WUI", has an impact on the extent and location of areas identified as WUI, and further that, because both vegetative and population landscapes vary from place to place, different thresholds might be appropriate in different regions for designating the WUI. Though the 2001 Federal Register listing provided a consistent definition, the effect of vegetation and population criteria remains under-investigated for small study areas. The effects of variable thresholds are potentially significant and may be the source of under- or over-representation of the WUI in a given area. This could have substantial consequences if a given WUI definition is the basis for public planning and resource allocation. This impact inevitably differs based on local variables, and is therefore best assessed in relatively small, homogenous study areas. Because of the importance and sensitivity of WUI areas, a more nuanced understanding of how selection criteria can impact WUI designation is necessary for better GIS-based identification. This is especially true given the nuanced, mosaic quality of WUI, demonstrated by the suite of sociological research described in the next chapter. To better understand the relationship between thresholds for WUI criteria and the specific portions of a landscape which are designated as WUI according to a chosen set of thresholds, this project tests different WUI variable thresholds, adjusting and combining wildland vegetation cover and population density proportions. The goal of this research is to identify the optimal criteria and thresholds for WUI identification in the project area.

More specifically, this study attempts to answer the following questions: How does the areal extent of WUI differ when the proportion of wildland vegetation landcover is adjusted?

What impact does the population density threshold have on the WUI extent? Which combination of landcover and population density parameters is most suitable for the project area? A number of smaller hypotheses can also be tested. For example, it is reasonable to suspect that a lower population density threshold may better represent (or over-represent) higher income WUI areas by including households on larger plots of land. Conversely, a higher population density threshold may better account for lower income WUI areas such as rural trailer parks or residences associated with smaller plots of land. This could be especially significant as a way to better incorporate interface homes on the outskirts of larger communities, which may not be associated with large land holdings despite occupying a wildland interface. Similarly, adjustments to the wildland vegetation cover part of the equation could reasonably be expected to have a diminishing level of return. Wildland vegetation covers as low as 10% have proven efficacy in other studies (Hanberry 2020), but those effects inevitably vary based on local environmental factors. Portions of the project area, especially nearer the Pacific Ocean, have comparatively dense vegetation due to abundant moisture and a relatively moderate climate. For these areas, then, a higher vegetation threshold may be ideal to definitively rule out non-wildland areas. Conversely, interior valleys dominated by sparse chaparral or juniper scrub may require a lower vegetation threshold to adequately identify wildland areas. The findings of this project, regardless of which pattern they support, would be valuable to land managers and other researchers who are interested in the relationship described above. The findings could help inform public policy and resource allocation, along with community planning efforts and emergency preparedness.

Chapter 2 Related Work

This project integrates methodology from a selection of previous WUI identification projects. Previous scholarship can be broken down into a few broad, overlapping categories. First are the studies that have set the groundwork for the standard approach to WUI designation, which integrate vegetation and population density data to identify areas that meet the Federal Register definition. The second body of research incorporates various technical and methodological improvements for identifying aspects of a landscape that support a WUI designation, such as dasymetric mapping and object detection to more accurately locate settlements and apportion populations across a landscape. A final section provides greater context for the project by describing the sociological nature of WUI communities.

2.1. Vegetation and Population-Based WUI Delineation

The most common approach to WUI identification combines population and vegetation data to identify communities that fit the minimum Federal Register thresholds for settlements and wildland vegetation. Radeloff et al. (2000) provide an early example of GIS-based integration of vegetation and population data, setting the groundwork for ensuing WUI-oriented research. Recognizing the potential of GIS for data integration and interdisciplinary research, the authors combine census block data with Landsat imagery to assess the relationship between housing density and vegetation for a region in northern Wisconsin. Methodologically, the study uses total housing and land area at the census block level to calculate housing density. The housing data is overlaid with a classified Landsat raster. Spatial patterning of population density is first visually assessed before the population density data is converted to a raster at the same resolution as the Landsat data. The two raster layers are then overlaid and the housing density and land cover classification for each cell is determined. Though not specifically WUI-related, this project provides a methodological groundwork that the authors expand upon in later WUI identification efforts.

Developing on this previous study, Radeloff et al. (2005) undertake a national-level assessment of the WUI using a similar methodology. The study also incorporate a sensitivity analysis of WUI mapping criteria using California, New Hampshire, and North Carolina as test samples. The authors overlay census block-level housing data with land cover data from the National Land Cover Database (NLCD), calculating the housing density and percentage of wildland vegetation cover for each block. The result is then considered against the 2001 Federal Register definitions for interface and intermix WUI. Next, a sensitivity analysis of housing density and vegetation cover is performed for the three states. The test varies the vegetation and housing density criteria to assess changes in the WUI output. The results indicate that the choice of housing density threshold tends to have a more significant impact on amount of land designated as WUI than the threshold of vegetation cover. Of the three sample states, this finding is especially true for California. The authors have two additional findings that are significant for the methodology developed in the project herein. First, they find that, nationally, intermix WUI accounts for over 80% of the WUI. The second finding is that the WUI proportion by state follows an east-west gradient, where WUI accounts for a higher proportion of the eastern area of each state.

The approach developed in Radeloff et al. (2005) has been improved upon and validated in follow up studies. For example, Stewart et al. (2007) runs through essentially the same methodology as the Radeloff et al. (2005) study, using updated datasets. A similar sensitivity analysis is conducted, this time for seven sample states: California, Colorado, Florida, Michigan, North Carolina, New Hampshire, and Washington. As with the previous study, vegetation and housing density parameters are adjusted above and below the Federal Register thresholds. The findings indicate that adjusting housing density thresholds has the most statistically significant impact on the WUI output, with Florida and California especially sensitive to these adjustments. Overall, the authors find that operationalizing the Federal Register WUI definition leads to plausible outcomes and that altering individual parameters did not significantly alter the "prevalence or pattern" of WUI at a national level (Stewart et al. 2007, 206).

The Modifiable Areal Unit Problem (MAUP) refers to an issue inherent in overlaying spatial data. Depending on the size and location of a polygon, the individual data that it encompasses will differ. If census blocks are used to determine population density, as is the case with WUI identification, the size and extent of the census polygon is somewhat arbitrary. If shifted or expanded, the population density could differ significantly (Bolstad 2017, 392). A few generalized approaches to addressing the MAUP have been suggested. First, if possible, data should be addressed individually instead of at the aggregate level. A second approach is to optimize zoning by minimizing differences within individual aggregations. Finally, a third recommendation is to conduct a sensitivity analysis by comparing aggregations at different levels (Bolstad 2017, 393).

Zhang and Wimberly (2007), address the MAUP issue inherent in using census data for identifying WUI areas, basically selecting the latter two options. As the authors describe, "the hierarchal way census data are organized provides researchers with various potential scales of analysis. However, it is not immediately clear which scale is the best for specific research questions" (Zhang and Wimberly 2007,139). Regarding methodology, the authors aggregate census data at the county, tract, census block group, and census block. These census aggregations are then used to compare WUI growth in southern states between 1990 and 2000. Significantly, the study uses housing density instead of population density to account for secondary homes, which may be underrepresented when using population. The study demonstrates a key point: county-level census data provides a comparatively coarse WUI output and is most suitable for looking at broader regional trends. The census block level was found to be most suited to more nuanced for landscape-level analysis that requires the inclusion of demographic data (145-146). The smallest possible level of aggregation, then, provides the most detailed and accurate WUI.

Dasymetric mapping is "a geospatial technique that uses information such as land cover types to more accurately distribute data that have been assigned to selected boundaries like census blocks" (US Environmental Protection Agency 2022). Phrased differently, dasymetric mapping is an additional set of steps that categorically excludes geographic portions of an area based on a specified criterion. Many of the above studies implicitly integrate dasymetric mapping by counting only wildland fuel portions of a given study area, but more overt and intentional dasymetric mapping steps can be added to the WUI identification workflow.

Wilmer and Aplet (2005, as cited in Greetan 2016) integrate a dasymetric mapping step that is especially apt for the study area in this project. The authors, as part of their workflow for identifying the WUI for three case study areas, omit public land from the census blocks before calculating population density. This is a key step because, if much of the land area within a census block is public land, the population density will skew lower than it actually is. If a minimum housing density of ≥1 household/40 acres is used, census blocks with already low population densities may not be included at all if they have enough public land within their boundaries. By only calculating population density for residential portions of the census block, the authors are able to get a much more accurate measure.

2.2. Identifying the WUI with Indirect Evidence of Human Presence

The process of WUI mapping is iterative, with successive studies providing small improvements and alterations, adding to the established methodology. This section describes recent studies that rely upon data that suggests the presence of humanity rather than or in addition to direct population data via the census.

Greetan (2016), in developing a WUI identification methodology for Lassen County, California, incorporates more extensive dasymetric mapping steps than previous studies. In lieu of census data, the author uses county cadastral data to identify residential plots. The use of residential parcels allows for the inclusion of only demonstrably occupied areas. This is an improvement on previous studies which ascribe a uniform population density across an entire census block. The integration of cadastral data is not possible for all studies, due to data accessibility and privacy issues, but the higher resolution is well-suited to very fine scale studies. Compared with census block data, residential parcel-level data allows for a more accurate WUI output, especially when paired with quality land cover data. Greetan's (2016) workflow also integrates vegetation data by including a .5-mile buffer around residential areas in the final WUI output (to account for the community's footprint) and omitting non-wildland NLCD data.

Though census-based population data combined with landcover is the most common approach to WUI identification, a number of other methods have been successfully employed. For example, Johnston and Flannigan (2018) take a novel approach to mapping the Canadian WUI based on the presence of infrastructure rather than population data. The authors add greater nuance to the standard WUI by distinguishing between three types of interfaces. The "wildland-industrial interface (or WUI-Int)" occurs where industrial "values", like oil and gas facilities, electricity stations, and industrial areas, intermingle with wildland fuels. The "wildland-infrastructure interface (or WUI-Inf)" similarly incorporates infrastructural values like powerlines, roads, and transmission lines. Finally, "wildland-human interface" is selected based on the presence of public or private structures like homes, hospitals, and railway stations. Identification of these areas was accomplished via CanVec+, a government produced public data source that includes structure information. Methodologically, these areas are rasterized, buffered, and overlain with landcover data to identify each WUI type. This project is unique because it distinguishes different WUI types based on remote sensing data. By integrating building presence data, rather than assuming a census block is uniformly populated, the study may be better able to account for actual residential habitation for human interface areas. For example, small rural communities may cluster within a fraction of the area of a census block, but if population data alone is used without further dasymetric steps, the entire block is assumed to be inhabited. The effects would be less pronounced in core urban or suburban locales, but may be significant in rural settings. Further, distinguishing industrial and infrastructural interfaces can generate a more useful end product, which is ultimately the goal of WUI mapping. The identification of key economic resources allows for better proactive planning and risk reduction and, as the authors demonstrate, is well-suited for national-level mapping.

Caggiano et al. (2016) offer an alternate approach to WUI mapping. Using National Agriculture Imagery Program (NAIP) imagery, the authors utilized semi-autonomous object-based image extraction to identify structures within ten small (5.28 km x 6.94 km) sample blocks in northern Colorado. In comparing their results with county structure data, the study concludes that this approach is potentially more accurate than census data based approaches at similarly small scales. The authors argue in favor of this approach by detailing some of the shortcomings of census based WUI mapping. The central concern is inaccuracy due to census data being based on the aggregation of individual population data (e.g. households or persons) into a census block. Though dasymetric mapping steps can help remedy this issue, the authors argue that, at small scales, object-based image extraction is more accurate.

In a recent study, Hanberry (2020) advocates a more deductive approach by using previous fire locational data to identify and classify WUI areas. Methodologically, the project utilizes a fire occurrence database, in conjunction with vegetation and decadal census data, for classifier-based statistical modeling. The author demonstrates that fire is statistically likely to occur in areas with as little as 10% vegetation cover. Given the Federal Register WUI threshold of at least 50% vegetation cover, this is a key finding, because depending on nearby vegetation type, land cover data may not adequately capture fire risk. For example, lower elevation chapparal may appear sparsely vegetated when using NLCD data but is comparatively high fire risk relative to higher elevation conifer forests which appear more densely vegetated. The study also reaffirms previous findings that indicate housing density is a more sensitive determinant of a WUI designation than vegetation density in ecologically homogenous areas.

2.3. Sociology of WUI Communities

To better understand what a map of the WUI represents, it is important to have a nuanced understanding of the sociological characteristics of those communities. The WUI is not a uniform entity, but instead a complex patchwork with varying demographic, economic, and cultural contexts, which act together to influence response and adaptive capacity to wildfire risk. Paveglio et al. (2009) provide a useful starting point for contextualizing these differences. The authors demonstrate that WUI communities are better understood as a “mosaic,” which are distinguished by their demographic and social context. They determine that a community’s adaptive capacity is the result of its demography, access to information, place-based knowledge, and informal relationships. Differences in these criteria between communities results in varying capacities and approaches to firewise planning, even in geographically similar contexts.

Winkler et al. (2007) add greater nuance to this discussion, addressing the shifting "social landscapes" of the intermountain west. The authors distinguish between "old west" and "new west" communities. Old west communities are characterized by a continued reliance on extractive industries like logging, mining, and ranching. New west communities, in contrast, are typically associated with in-migration of more affluent and educated populations and a shift towards natural resource tourism, conservation, and development. Discussing trends more broadly in the west, Paveglio et al. (2015) add an important caveat to the new west demographic shift. These changes are not uniform across the landscape. The influx of the new west and associated demographic and economic trends is concentrated in areas that are "particularly scenic or resource rich…with cultural and recreational resources" (300). The expansion and sprawl of WUI areas away from city centers was also found to exacerbate urban poverty and reify greater sprawl in the southeast US. Cho et al. (2012) examined this relationship, showing the impacts of white outmigration. Outmigration to WUI communities and homes has the dual effect of drawing money out of cities and shifting businesses into exurban areas, both of which have the potential to exacerbate urban poverty.

Collectively, these sources suggest broad demographic shifts in WUI areas, in which higher income residents move away from city centers, increasing urban poverty, and supplant or change existing rural communities. Per Paveglio (2015), this relationship is not equal across space but is concentrated in high amenity areas. The relationship between this demographic force and fire preparedness is not overtly clarified but is alluded to in various studies. For example, Bright and Burtz (2006b) look at differences in perceptions and behaviors about fire-wise activities for year-round versus seasonal residents in northern Minnesota. The authors find that seasonal residents are less likely to engage in and have favorable opinions of firewise activities. This would suggest that permanent residents, with deeper local knowledge, may have greater personal investment in wildfire preparedness. Though an overt connection between year-round residency and economics was not made in this study, seasonal residents were largely comprised of people who own summer vacation homes in the community, suggesting a degree of economic privilege.

This body of research suggests that higher income, new west communities may be less invested in and knowledgeable of local fire issues. Interestingly, though, the opposite relationship is suggested in other research. For example, Paveglio et al. (2015) describe community archetypes and their WUI adaptive capacity. This study finds that "working landscape/ resource dependent WUI communities," which closely align with the old west communities described by Winkler et al., have the highest "local ecological knowledge", but tend to be "highly independent and distrustful of the government" (306). Individual and community political ideology undoubtedly plays a role in firewise planning. This is shown in Bright and Burtz (2006a), which notes the influence of individualistic values, personal property rights, and personal freedom on defensible space. This would, presumably, suggest greater reluctance to follow government advice about fuels reduction and firewise planning. Typical advice, such as removing vegetation, replacing roof material, and landscaping with native plants (Radeloff et al. 2018) would likely be met with relatively greater resistance, and perhaps, less economic capacity.

By focusing on an explicitly spatial workflow, this project is unable to integrate a full sociological synthesis of WUI communities in the project area. The above body of research, though, suggests some of the broader demographic trends that occur within various WUI communities. These trends undoubtably occur, to some degree, within the current project area and could be investigated further in future research.

Chapter 3 Methods

As demonstrated in the previous chapter, previous WUI assessments have generated a series of overlapping methodological approaches and refinements. The scope and methods employed in this project attempt to combine relevant methods developed in previous studies, while avoiding potential downfalls. WUI identification typically combines two key data types: vegetation and population. As Zhang and Wimberly (2007) demonstrate, this can be done at different hierarchical scales, depending on the requirements and logistics of the study. The geographic scope of this project is local, focusing on a discrete area with common ecological and demographic characteristics. This scale allows for a more nuanced level of data relative to national or state-level WUI mapping, which is in direct response to the MAUP issue inherent in large scale WUI mapping. The overall goal of the project is to evaluate different land cover and population density thresholds for identification of the WUI in the study area.

It is impossible to fully integrate every refinement and method described in the previous chapter. Many key findings, though useful, may apply only to a specific study area and remain untested for other geographic locations. For example, Radeloff et al. (2005) find that California is most sensitive to changes in housing density thresholds, compared with New Hampshire and North Carolina. This finding is echoed in Stewart et al. (2007), which finds Florida and California more sensitive to housing density adjustments compared to other sample states. This is an interesting finding, but its significance is unclear. Would this result hold true across other larger states when compared with smaller states in the northeast? Because California and Florida are large, diverse, densely populated states, is this finding the result of an inherent MAUP issue when using state-level aggregations? If, for example, the same relationship was examined at a county level across California, would this finding be true across the board or is it skewed by more populous urban nodes? Radeloff et al. (2005) also find that the proportion of WUI land relative to the state was higher on the east coast compared to the west coast. Is this due to the fact that states on the east coast are smaller and have less public land? Would the relationship hold consistent if dasymetric mapping was added to the workflow, omitting public land in western states?

3.1. Methods Overview

This project seeks to better understand how WUI mapping parameters impact the extent and character of a mapped WUI output. As described earlier, the way a study or project defines and identifies the WUI can have significant downstream impacts, with real-world consequences if that data is used to support public planning and resource allocation. Ten counties on either side of the Oregon-California border were selected as a case study for this project. These counties encompass the entirety of the Klamath-Siskiyou region and surrounding areas, which, due to their geographic proximity, share many characteristics such as climate, fuel type, and settlement patterns. This relative homogeneity across the project area allows for a sort of control variable, where regional differences are less likely to skew results compared with national or statewide WUI mapping.

Methodologically, this project overlays data layers showing vegetation cover and total household density to test a series of WUI variable thresholds. Household density was used as the population input and was derived from the total number of households per block group and the total geographic area of residential land per block group. As argued in Stewart et al. (2007), housing is a better suited metric for human habitation when compared with other potential measures like population density. This is due, in part, to the importance of structure protection in WUI fire suppression and the growth of housing density compared to population. Depending on the family makeup of an area, total households may represent different population totals. Households, though, measure the number of housing units, which is a better metric when looking at the WUI. Because most construction in rural areas is single family housing, a household can be reasonably expected to be a single structure, with associated outbuildings like sheds or garages.

Based on previous research, several additional steps were added to this basic workflow. This project incorporates robust dasymetric mapping steps to refine the extent of areas that meet the vegetation and population density criteria. This additional step is not included in Stewart et al. (2007) or Radeloff et al. (2005) but is particularly well-suited to the project area. As described in Section *3.4.2*, this step allowed for the exclusion of large swathes of federal and state land, in addition to unoccupied census blocks. This step is especially appropriate for western states where a large proportion of the total and area is administered by federal and state agencies and is, by definition, non-residential. Omitting these plots of land from the workflow before calculating housing density generated a more accurate household density measure, in turn enabling a more accurate assessment of WUI criteria.

The entirety of this workflow was completed via ArcGIS Pro using various cartographic and geoprocessing tools (Figure 4). Data for this project, described more extensively later in this chapter, was projected using the North American Albers Equal Area Conic coordinate system. This is the default projection for the land cover and census data used in the analysis. State ownership data was reprojected into this coordinate prior to analysis. Generally, the methods employed in this project condense and aggregate WUI identification data to the census block group level. Land cover data was clipped and reclassified into wildland and non-wildland vegetation types, before being summarized based on census block groups. With the requisite land cover and population data appended, census block groups were next whittled down to only populated areas in a dasymetric mapping step. Finally, WUI selection criteria were used to select and export block groups that met the appropriate criteria. WUI selection criteria tested for wildland vegetation cover ranged from 0-75%, while household density thresholds of ≥1 household/20 acres, /40 acres, and /60 acres were tested. The output WUI from each criteria combination was then assessed based on its total population, area, relative poverty status, and identification of Federal Register WUI communities.

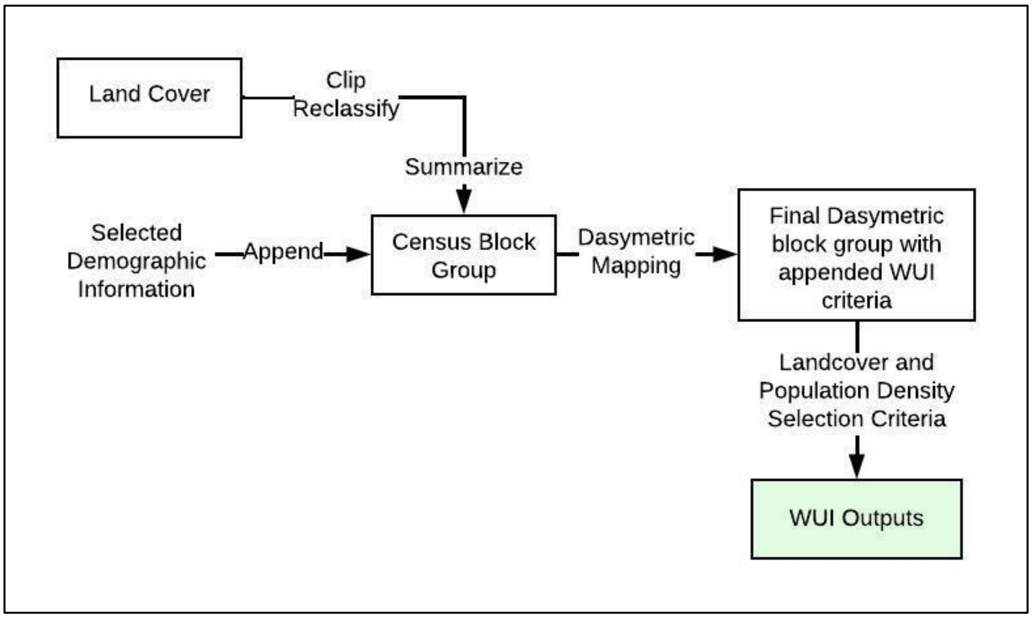

Figure 4. Generalized WUI identification workflow

3.2. Selection of Variable Thresholds

Variable thresholds for the workflow described above were determined based on previous sensitivity analyses detailed in Stewart et al. (2007) and Radeloff et al. (2005) (Table 3). The standard wildland vegetation cover of ≥50% was used as the control. The value is increased and decreased by half for comparison. A low range of ≥10% was also used, based on the findings by Hanberry (2020). Previous studies found that household density was the most significant variable for WUI identification, so a wildland vegetation threshold of ≥0% was also tested to address the impact of household density alone. For household density, the same thresholds used in previous studies were selected, with ≥40 acres/household as the control and ≥60 acres and ≥20 acres, a 50% increase and decrease, as test parameters. As with vegetation criteria, a test null household density was also included to show the effects of wildland vegetation cover alone.

Table 3. WUI identification criteria and thresholds from previous studies

Author	Land Cover Criteria	Population/Housing Density	Buffer Distance	Additional Steps
Radeloff et al. (2005)	NLCD >50% wildland veg cover	Census block. Minimum density of 1 house/40 acres	<2.4 (≈1.5 mi) from heavily vegetated area = interface	Sensitivity analysis of vegetation and population density.
Stewart et al. (2007)	NLCD >50% wildland veg cover	Census block. Minimum density of 1 house/40 acres	<2.4 (≈1.5 mi) from heavily vegetated area = interface	Sensitivity analysis of vegetation and population density.
Zhang and Wimberly (2007)	Does not include vegetation criteria	Housing density between 1/40 acres to 1/1.67 acres	No buffer distance used, only housing density	Test WUI output using county, tract, census block group, and census block
Greetan (2016)	Reclassified NLCD	Buffered parcel ownership	.5 mi around houses	Dasymetric mapping to omit uninhabited areas
Hanberry (2020)	As low as 10% valid	Census block. Determines high-med-low density classes for WUI type. Low end is <6.17 houses/km^2	None	Uses fire locations to determine WUI location

3.3. Data

This project made use of six datasets for the identification of WUI areas (Table 4). Each is described in more detail below.

Table 4. Project data

Dataset	Description	Format	Source and Date
National Land Cover Database	Land cover classified into 16 categories	30-meter raster	MRLC Consortium 2019
TIGER/line Shapfile	County, census block group, and census block	Polygon	US Census Bureau 2019
American Community Survey	Demographic characteristics at census block group level	Tabular	US Census Bureau 2015-2019
Federal Lands	Land administered by federal agencies	Polygon	Esri Living Atlas of the World 2022
California State Lands	Land administered by the state	Polygon	California State Geoportal 2022
Oregon State Lands	Land administered by the state	Polygon	Oregon Dept of Forestry 2022

Landcover data, used to identify wildland fuels, was derived from the 2019 National Landcover Database (NLCD). This raster dataset is freely available via the Multi-Resolution Land Characteristics (MRLC) Consortium, "a group of federal agencies who coordinate and generate consistent and relevant land cover information at the national scale for a wide variety of environmental, land management, and modeling applications" (MRLC, n.d.). NLCD data is generated from Landsat imagery at a 30-meter resolution. After testing with finer resolution data, it was determined that the 30-meter resolution of the NLCD raster was most suitable for the current mapping scale. For example, Esri hosts a 10-meter resolution land cover dataset derived from the European Space Agency Sentinel-2 Imagery. Though providing greater detail, the dataset has less land cover classifications (ten instead of sixteen) and proved to be unwieldy during geoprocessing tasks due to its comparatively large size. NLCD data is also advantageous because of its geographic and temporal extent. The same high-resolution dataset covers the entire continental US with the same vegetation classifications. At present, NLCD data is available in two to three-year increments going back to 2001. The ubiquity and availability of this dataset allows for scalability and consistency for WUI mapping across geographic and temporal extents.

The second key data source is the US Census Bureau, a federal agency under the Department of Commerce. The mission of the US Census Bureau is to collect and provide demographic and economic data about the US. This project used two Census Bureau datasets, both made available to the public through the US Census Bureau data interface. First are TIGER/Line shapefiles. TIGER (short for Topologically Integrated Geographic Encoding and Referencing)/line shapefiles are “extracts of selected geographic and cartographic information from the Census Bureau's Master Address File” (US Census Bureau 2019, 1-1). In short, they are polygon shapefiles representing, among other things, various levels of census statistical units. The US Census Bureau collects several types of data at different hierarchal levels (Figure 5). Below the state and county level are census tracts. According to the US Census Bureau, these are “relatively permanent statistical subdivisions of a county or equivalent entity,” comprised of “1,200 to 8,000 people with an optimum size of 4,000” (2021, 4-22). The census tract is subdivided into one or more census block groups, which contain 600 to 3,000 people. The smallest unit of aggregation is the census block, which are subdivisions of the block group. Census blocks are bounded on all sides by roads, city boundaries, or other geographic features. In urban areas, they often consist of a single city block, though they can be geographically larger in more rural locales to encompass a similar amount of people (US Census Bureau 2019). This project used census block groups as the primary unit of aggregation, but also incorporated census blocks as part of the workflow. The county boundaries used for the project area were also sourced from the same dataset. For consistency with the NLCD data, this project used 2019 TIGER/Line shapefiles.

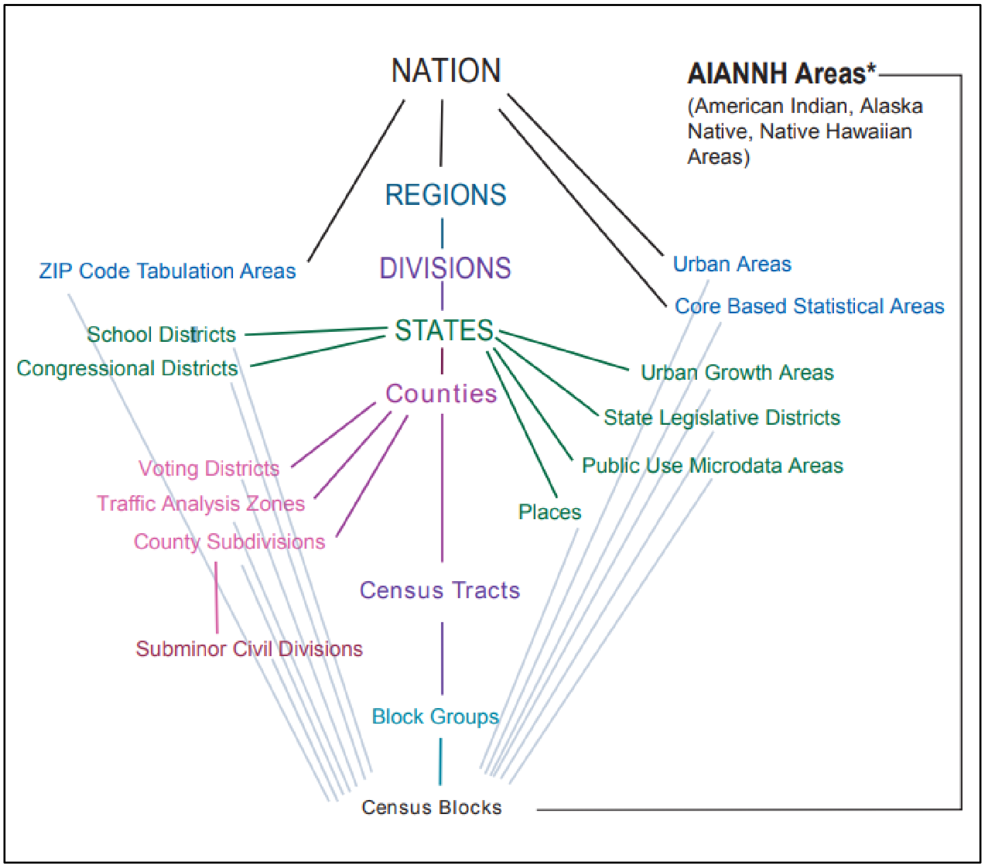

Figure 5. Hierarchy of census geographic entities (via census.gov)

The US Census Bureau was also the source for the demographic data, which is appended to the block group polygons based on a shared identification code. This project specifically incorporated American Community Survey (ACS) population and poverty data published in 2019 based on 5-year estimates from 2015-2019. The ACS is an annual survey used to supplement the decadal census. The survey consists of various "social, economic, housing, and demographic" questions, which are more detailed than the shorter questions asked on the decennial census (US Census Bureau 2017, 1). The annual ACS is sent to a sample of the population and is aggregated at various scales. For privacy reasons, the smallest level at which ACS data is available is the census block group level. ACS data is available at 1-year and 5-year estimates. Because ACS data is based on sampling of the general population, 5-year estimates contain a larger breadth of data and are more statistically reliable, especially for less populated areas (US Census Bureau 2022).

One key question when mapping WUI areas is the appropriate scale of the data. This determination is inevitably made based on both logistical constraints (e.g. data size and geoprocessing capability) and on the required level of detail for the output. For the given project area, comprised of ten counties, there are a total of 651 census block groups, a manageable number for use with geoprocessing tools. In comparison, there are over 44,000 census blocks for the same area. Though a robust and detailed data source, the 44,000 plus census blocks proved to be inefficient during geoprocessing tasks. This project, then, used census block groups as the main areal population unit. Though geographically larger, this dataset was much more suitable for efficient geoprocessing and provided a sufficient level of detail for WUI identification, especially after the dasymetric mapping steps described later in the chapter. Because the census block group is also the smallest scale for which ACS data is available, using block groups allowed for the integration of detailed demographic data. This became important later in the workflow to determine household density and poverty status.

The final category of data includes the miscellaneous sources for land ownership, which were combined in the WUI mapping workflow for dasymetric mapping. Three different sources of information were incorporated. Federal lands in the project area, administered by the BLM, USFS, National Park Service, Bureau of Reclamation, Department of Defense, and Fish and Wildlife Service, were sourced from Esri's Living Atlas of the World. The Living Atlas is a curated collection of ready-to-use spatial data provided by Esri for visualization and analysis (ESRI n.d.). According to the source's metadata, it was compiled using data from each of the federal agencies it represents and was last updated earlier in 2022. Though federal land data can be acquired from other sources, the Esri provided data was preferable because the various datasets were already aggregated into one comprehensive feature class. State land ownership was sourced separately for Oregon and California. The Oregon ownership data was provided by the Oregon Department of Forestry. This shapefile was last updated earlier in 2022 and depicts state owned forest lands. For California, state ownership data was sourced from the California State Geoportal, which provides centralized, authoritative spatial data for the public. This dataset was also last updated in 2022. Notably, it also includes county and city ownership categories. Only state ownership was included in this project because a similarly authoritative data source for Oregon was not available.

3.3.1. NLCD Pre-processing

A number of pre-processing steps were taken to prepare each dataset for further analysis. The workflow to process the land cover data had two main steps (Figure 6). The first step was to limit the data to the study area boundary. First, the study area counties were selected from the county TIGER/line shapefile and exported as a separate layer. The raster data was then clipped to the project area using the *Clip Raster* tool. NLCD data is only available at a much larger extent than is needed for this study, so this initial step was necessary to whittle down the raster to a more manageable size. The *Clip Raster* tool maintains individual raster cells, but consequently does not match the raster to the exact clipping input, so additional steps are necessary. The clipped raster was run through the *Extract by Mask* tool. This tool is similar to the *Clip Raster* tool, but the output raster is defined exactly by the mask, in this case the project area counties. The *Extract by Mask* tool also differs from the *Clip Raster* tool because it resamples cells along the edge of the mask. According to the Esri technical guidance for the tool: “when the input mask is feature data, cells in the input raster whose center falls within the perimeter of the feature will be included in the output, while cells whose center falls outside it will receive No Data" (ESRI n.d.b). For certain types of raster analysis, this may represent a potential issue. For this project, a sufficient number of cells with vegetation values remained in each catchment (census block group) that the effect of resampled null values was negligible when the mean vegetation value was calculated in later steps.

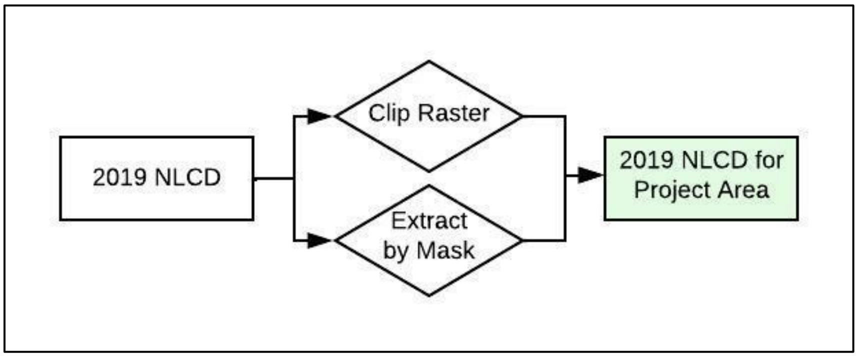

Figure 6. NLCD pre-processing workflow

3.3.2. Census Data Pre-Processing

As with the NLCD raster, the census block group data required a number of pre-processing steps to generate a dataset with the appropriate information and geographic extent (Figure 7). To start, TIGER/Line shapefiles for California and Oregon Census block groups were added. The appropriate ACS tables were selected and joined with each state's block groups based on their matching GEOIDs. For this project, the "Poverty" and "Household, Family, and Subfamily" ACS tables were used. Specifically, this project utilized the total household and ratio of income to poverty level data. The latter is a measure of the total number of people per census block whose income was below the poverty income level. Other similar poverty measures could be used in lieu of poverty income level. This variable was selected because it provided a general baseline to measure poverty relative to the total population. Similar ACS poverty measures breakdown populations based on race/ethnicity, education, et cetera. While these variables could be integrated into a deeper analysis of WUI demography, they were too nuanced to provide the generalized information needed in this project. With poverty and population data appended, the next step was to export the California and Oregon block groups, which makes the joins permanent and allows the features to be more easily edited later. Similarly, the two block group datasets (for Oregon and California) were clipped to the project area and merged together into a single feature class.

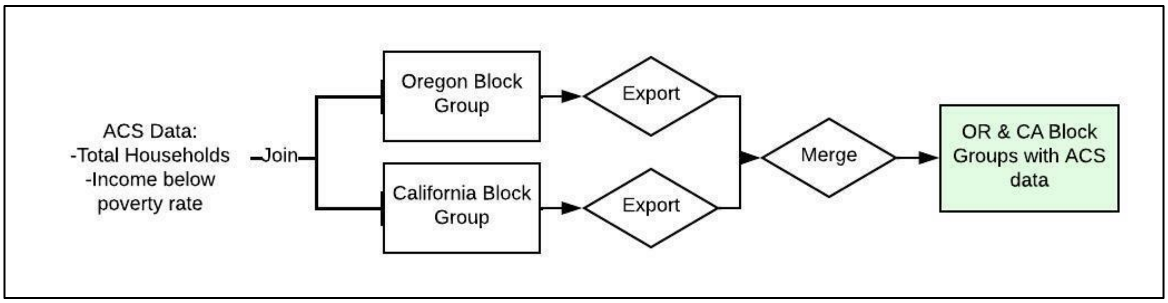

Figure 7. Census block pre-processing workflow

3.4. Identifying the WUI

With data pre-processing complete, this section describes the overarching workflow developed to identify WUI areas. Methodology pulled from Radeloff et al. (2005), Stewart et al. (2007), Zhang and Wimberly (2007), Greetan (2016), and Hanberry (2020).

3.4.1. Calculation of Wildland Vegetation Cover

With the block group data and the NLCD raster prepared, the next step in the process was to use both datasets as inputs for the *Zonal Statistics as Table* tool to calculate wildland vegetation cover proportions by block group. First, the NLCD raster needed to be reclassified based on cover type. As produced by the MLRC, NLCD raster cells are assigned one of sixteen landcover classifications. For this workflow, the raster was simplified into Boolean categories of non-wildland and wildland fuel. The categorization of land cover type borrows from Radeloff et al. (2005) and Stewart et al. (2007). Both studies are fairly intuitive in their classifications, defining any developed land, including agricultural land, as non-wildland. Open water, ice, and bare rock/sand/clay are also considered non-wildland vegetation land cover. The remaining land cover classes are defined as wildland. Using the 2019 NLCD data, the following categories were defined as non-wildland fuels: open water, perennial ice/snow, developed open space, developed low intensity, developed medium intensity, developed high intensity, pasture/hay, cultivated crops, barren land (rock/sand/clay), and no data. All of these categories are present in the study area. Wildland vegetation includes all remaining categories, which are deciduous forest, evergreen forest, mixed forest, dwarf scrub, shrub/scrub, grassland/herbaceous, sedge/herbaceous, lichens, moss, woody wetlands, and emergent herbaceous wetlands. Of these landcover types, dwarf scrub, sedge/herbaceous, lichens, and moss do not occur in the study area. Logistically, this recategorization was accomplished using the *Reclassify Raster* tool. The numerical code for each landcover type is changed to either 0, for non-wildland vegetation, or 1, for wildland vegetation (Table 5).

Table 5. Land cover type and reclassification values

Original Classification	Land Cover Type	Reclassification Value
11	Open Water	0
12	Perennial Ice/Snow	0
21	Developed, Open Space	0
22	Developed, Low Intensity	0
23	Developed, Medium Intensity	0
24	Developed, High Intensity	0
31	Barren Land	0
41	Deciduous Forest	1
42	Evergreen Forest	1
43	Mixed Forest	1
51	Dwarf Scrub	Not Present
52	Shrub/Scrub	1
71	Grassland/Herbaceous	1
72	Sedge/Herbaceous	Not Present
73	Lichens	Not Present
74	Moss	Not Present
81	Pasture/Hay	0
82	Cultivated Crops	0
90	Woody Wetlands	1
95	Emergent Herbaceous Wetlands	1

The next step used the reclassified raster and block groups to calculate zonal statistics. As the name suggests, this tool calculates various statistical outputs for a dataset based on specified zones, with the end result being a separate table that contains the specified values. In this case, the zones were the census block groups, with the GEOID specified as the zone field for each block group. The GEOID was used so the table output could be joined to the block group later. The target zonal statistic was the mean of the reclassified landcover value representing wildland vegetation in each zone. The output table, then, indicated the mean wildland vegetation percentage for each census block group. Because non-wildland vegetation was given a reclassified value of 0 and wildland vegetation is given a value of 1, a zonal mean of .4 would indicate that, in the given block group, 40% of the landcover is wildland vegetation. As a final step, this value was multiplied by 100 to give a whole number percentage. Finally, the new zonal statistics table was joined to the block group dataset based on matching GEOIDs, completing this portion of the workflow. The end result of this section of the workflow (Figure 8) was a block group feature class with the percentage of wildland vegetation (Figure 9) and selected ACS demographic data appended as attributes of each polygon.

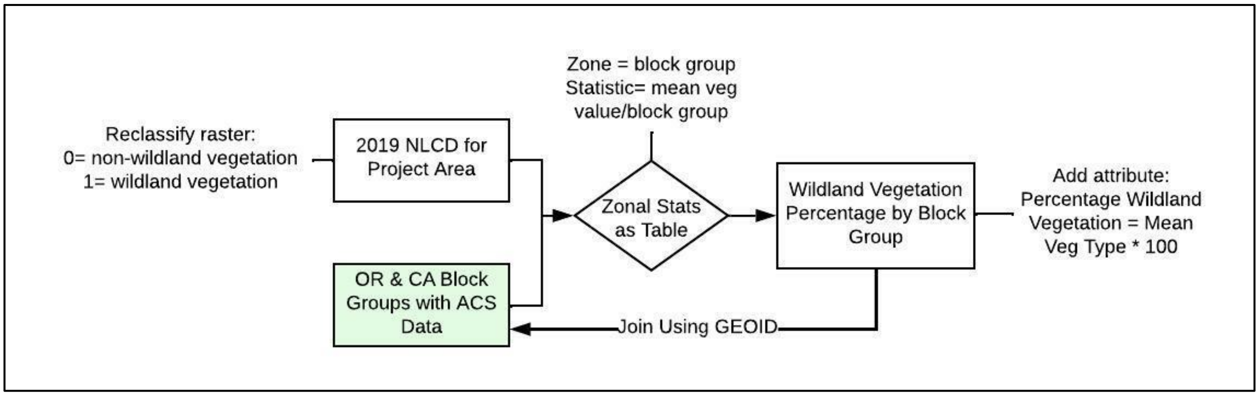

Figure 8. Calculation of wildland vegetation cover workflow

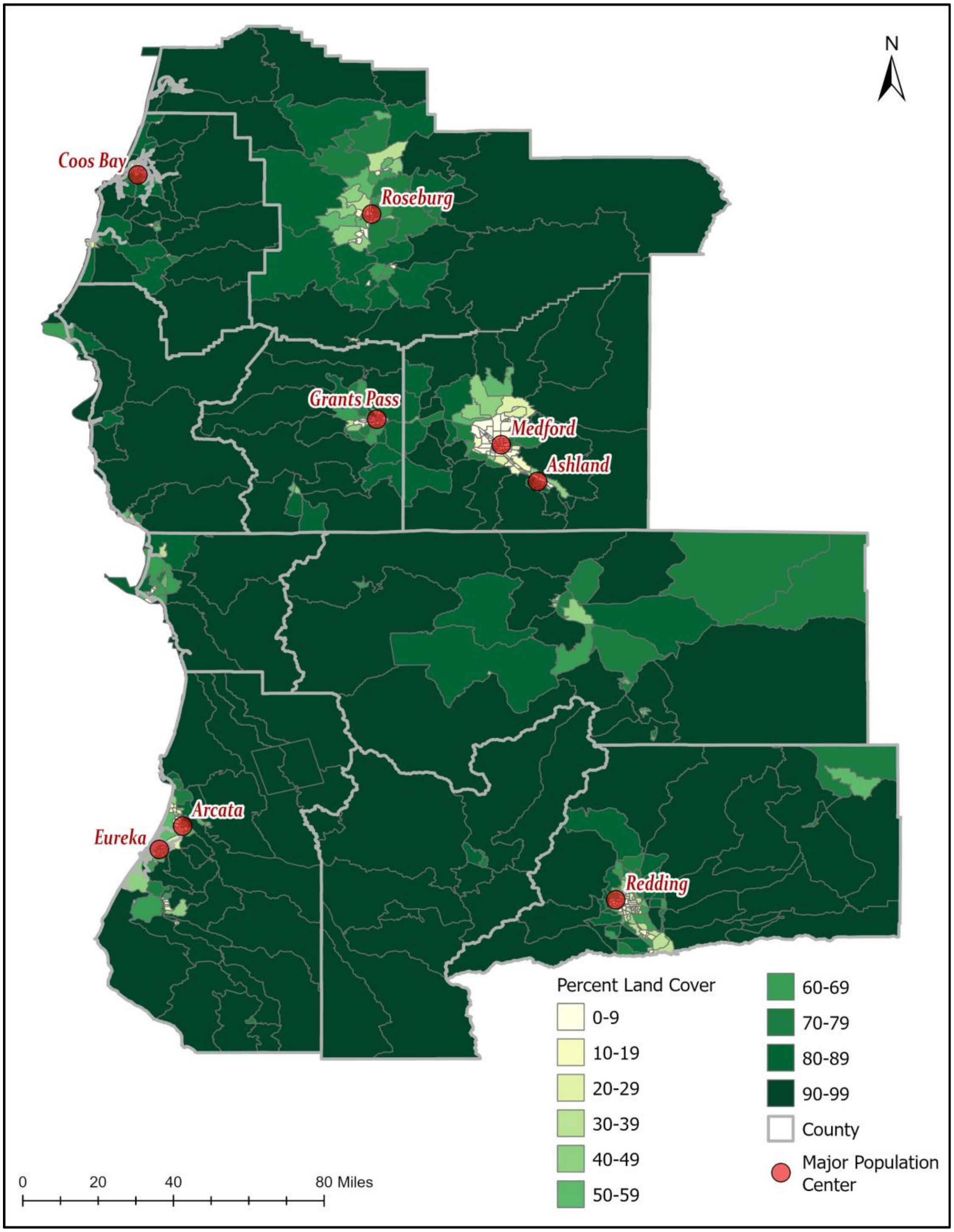

Figure 9. Wildland vegetation landcover percentage by block group

3.4.2. Dasymetric Mapping

The next step of the process involved refining the block groups, with appended data, to a more accurate geographic extent. Put simply, this was accomplished by omitting portions of the block group that were unoccupied. Compared with other population aggregations, such as counties and census blocks, census block groups vary greatly in size. In rural portions of the project area (i.e., where WUI areas are most likely to occur) individual block groups are much larger than in more urban areas. Amongst the larger, rural census block groups, much of the land is not actually inhabited or zoned for residential use. There is the potential for overestimating the extent of the WUI in these areas if it is assumed that the entire landscape is uniformly sparsely populated, instead of populated with small clusters of settlement amidst large swathes of uninhabited land. This issue underscores the importance of additional dasymetric mapping steps that provide more nuance when added to population density and vegetation cover.

To counteract the large scale of census block group data, this project omitted portions of the census block group based on two criteria. The first was census blocks with a total population of zero. The second criterion was land that is, by definition, not occupied. This includes federal and state lands administered by agencies such as the US Forest Service, the BLM, and the Oregon Department of Forestry.

Methodologically, the dasymetric mapping was straightforward. Government-administered state and federal land polygons were merged and given a negative 1-mile buffer. The negative buffer excludes a 1-mile internal band within the boundary of a given polygon. The negative buffer is used to account for wildland adjacent to private property. Due to the proximity to residential land, adjacent public land acts as a WUI extension. Statistically, fire incidents that occur on public land often occur near private property (and are therefore likely the result of actions by nearby residents) (Downing et al. 2022). Previous projects typically employ a buffer distance of 1 to 1.5-miles to account for the distance a firebrand can travel and ignite (e.g., Greetan 2016 and Stewart et al. 2007). The distance is typically based on local slope and fuel conditions. Because this project area encompasses a large region with mixed fuel types and topography, a 1-mile distance for the buffer was selected as a conservative estimate. Instead of buffering the entire WUI output, as is typically done, this project applied only a negative buffer to public land. This accomplished basically the same thing, but only incorporated areas that are actually adjacent to wildland by targeting only public land. In comparison, buffering the census block group would have also included more densely populated urban areas that border WUI block groups in exurban areas. Public land data, after being merged, was laid over the census block group dataset prepared in the previous steps. Areas of the block group that were overlapped by the public land layer were omitted using the *Erase* tool.

Next, unpopulated census blocks were reincorporated using a similar workflow (Figure 10). As described earlier, census blocks are a smaller level of aggregation than the block groups. Within each block group are numerous census blocks with different population totals. Of the over 44,000 census blocks within the study area, approximately half are unoccupied. These census blocks were selected and exported as their own feature class, which was then overlaid on the block group data. As with federal and state land, the areas of the block group layer that overlapped unoccupied blocks were erased. The rationale for this step was straightforward. Block groups in rural areas tend to be very large, so omitting demonstrably unoccupied census blocks allowed the block group to be whittled down to only its occupied portions.

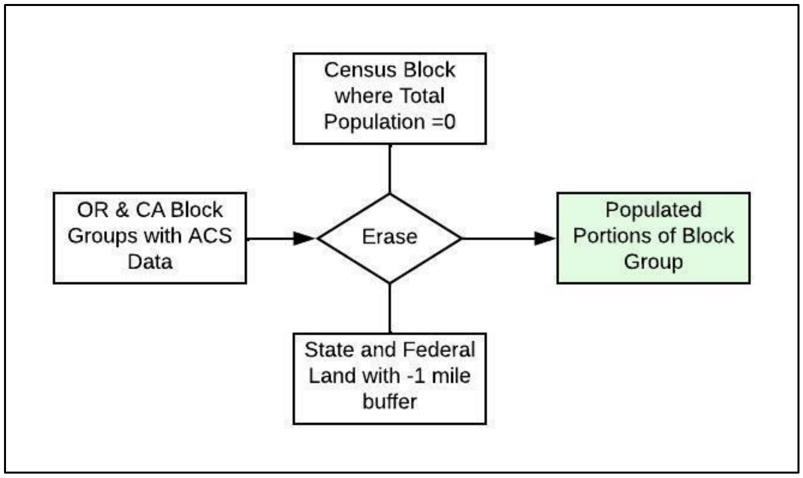

Figure 10. Dasymetric mapping workflow

3.4.3. WUI Outputs

The final product of the above workflow was the dasymetric block group with appended data. In summary, this feature class shows the geographic extent of the inhabited portions of each census block group. With a more accurate geographic extent of the occupied portions of the block group complete, household density was then calculated and added as an attribute to the dasymetric block groups. Based on Stewart et al. (2007) and Zhang and Wimberly (2007), household density was used in lieu of other population figures. Four household density attributes were added to the census block groups (Figure 11). First, the acreage of each block group, minus the portions erased during previous dasymetric mapping, was calculated. Next, the total number of households per 20, 40, and 60 acres was calculated. Total household density attributes were important when selecting blocks that meet WUI criteria, which was the next step in the workflow.

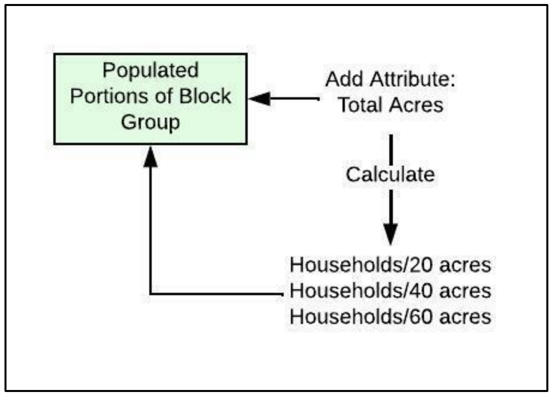

Figure 11. Appending population density attributes

At this point in the workflow, each block group had all of the key attributes to identify WUI status. This included the percentage of wildland vegetation landcover and the household density per 20, 40, and 60 acres. The total population and total population below poverty income were also appended to the census blocks. With this main dataset ready, WUI outputs were generated by selecting the features with attributes that fit the WUI criteria for landcover and population density. Because all essential data is joined to the same feature class, generating WUI outputs only required the input of relevant selection criteria using the *Select by Attributes* query builder. For example, the following input was used to select block groups with ≥10% wildland vegetation and ≥1 household per 20 acres:

"SELECT WHERE Percent Land Cover >= 10 And Household per 20 acres >= 1"

The selected blocks that met those criteria could then be exported as a unique feature class.

To track the effect of WUI definition criteria, different combinations of landcover percentage and population density were tested. A table was generated so that combinations of each variable could be tracked. For each combination of vegetation cover and household density, four attributes were recorded: the total land area, the population percentage relative to the entire population, the proportion of the WUI population below poverty income, and the number of federal register communities identified. To measure the total land area of the given WUI output, a new attribute called “Sq Mi” was added to each WUI attribute table. The square mileage was then calculated using the *Calculate Geometry* function. The population percentage relative to the entire population was calculated by adding up the total population of each selected block group in each WUI output. The total population of the given WUI was then compared with the total population of the entire project area and the percentage of the population present in the selected WUI was calculated. The same basic process was followed to determine the proportion of residents with a monthly income below the poverty rate. The total number of residents with below poverty income was calculated using the *Statistics* attribute tool and the sum calculated against the total population of the WUI to determine the relative proportion. To identify Federal Register WUI communities identified by each WUI output, the *Select by Location* tool was used. The selection criteria identified Federal Register WUI communities that intersected the WUI output. Because points were used for each WUI community, this tool was supplemented by visual inspection. In some cases, only some of the block groups around a community were identified as WUI without clearly overlapping the community point. When this occurred, visual inspection was used to determine if the community was included in the output. Pending data availability, future studies may opt to use community polygons for larger datasets where visual inspection would be impractical.

Chapter 4 Results

This chapter describes the results of the WUI identification process. It first discusses the dasymetric mapping results, demonstrating the effectiveness of omitting the specified areas. The next section compares the results from combining different variable parameters, drawing conclusions based on the performance of each variable. The third section evaluates the WUI outputs based on their ability to adequately identify known WUI communities. Finally, the information gained from the analysis is used to determine optimal WUI parameters for the project area.

4.1. Dasymetric Mapping Results

Following the extensive data processing steps described in the previous chapter, dasymetric mapping proved effective for excluding unoccupied areas. As previously described, this is an important step prior to identifying WUI areas because it provides a better indicator of actual residential areas and, therefore, likely household density. The first step in the dasymetric mapping workflow allows for the exclusion of unoccupied census blocks. Of the 44,000+ census blocks in the project area, approximately half are uninhabited (Figure 12). The next step omits public (state and federal administered) lands, with a negative 1-mile buffer (Figure 13). In total, these unoccupied lands accounted for approximately 18,000 square miles, out of a total project area of approximately 31,000 square miles (Figure 14).

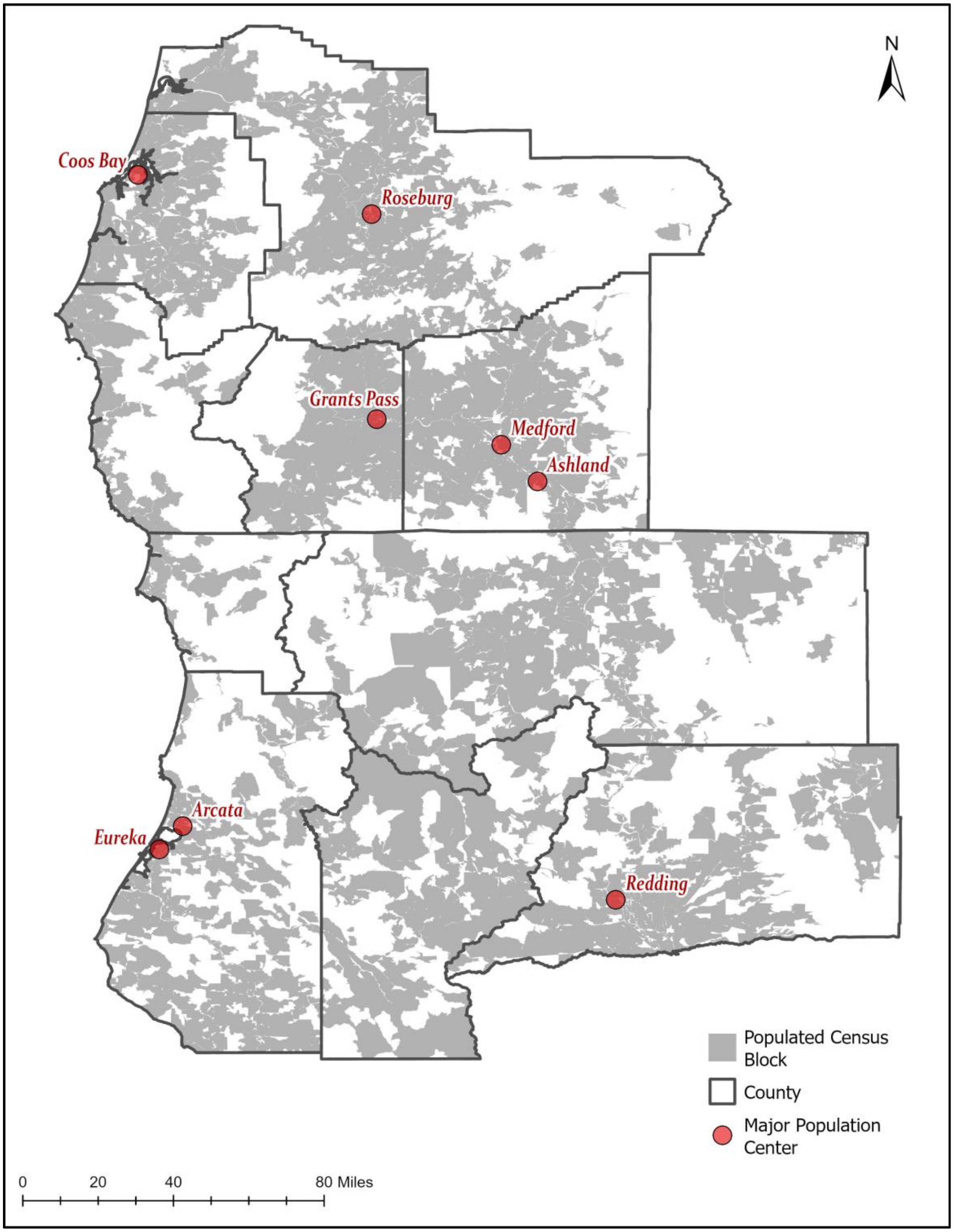

Figure 12. Populated census blocks used as input for dasymetric mapping

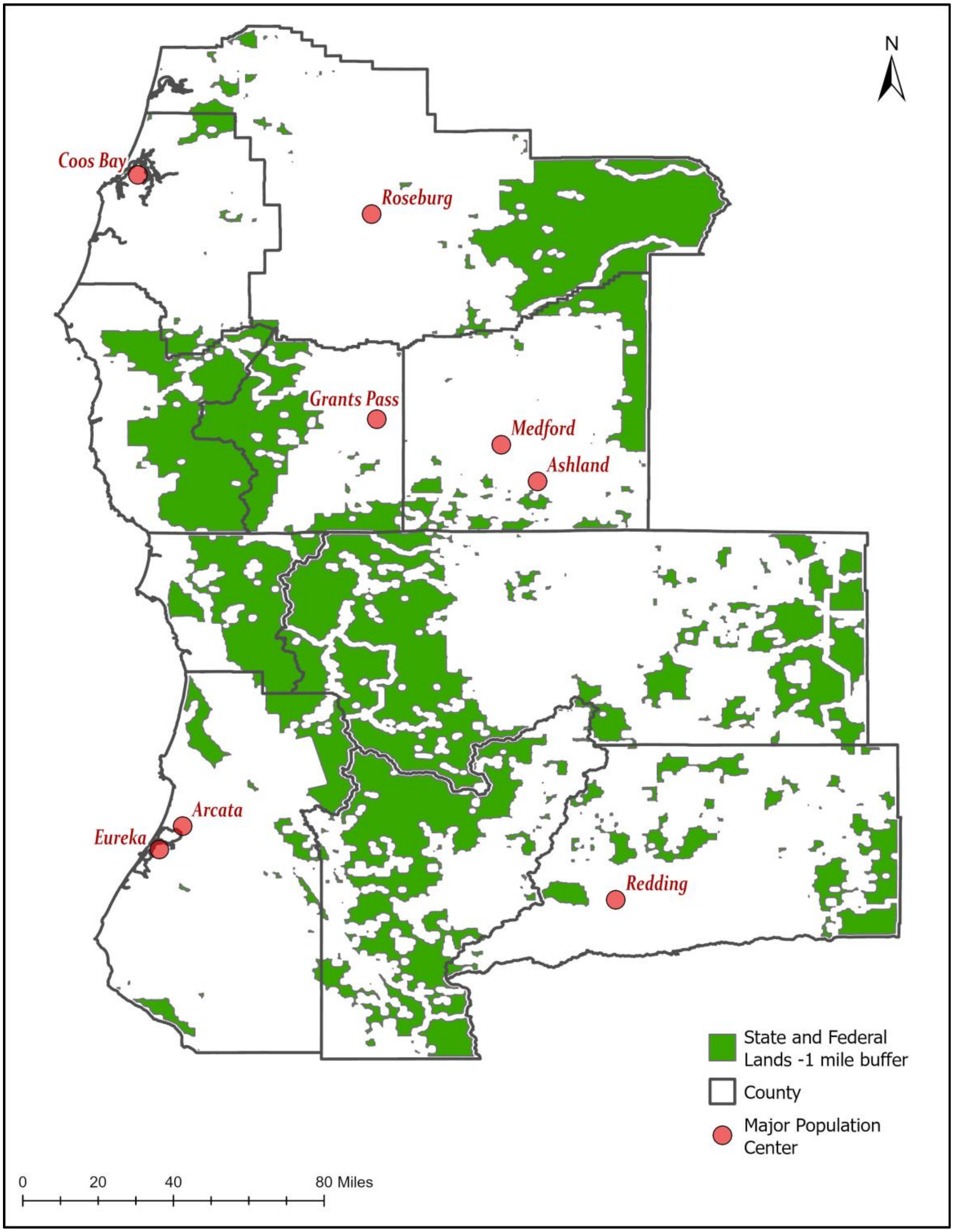

Figure 13. Federal and state lands used as input for dasymetric mapping

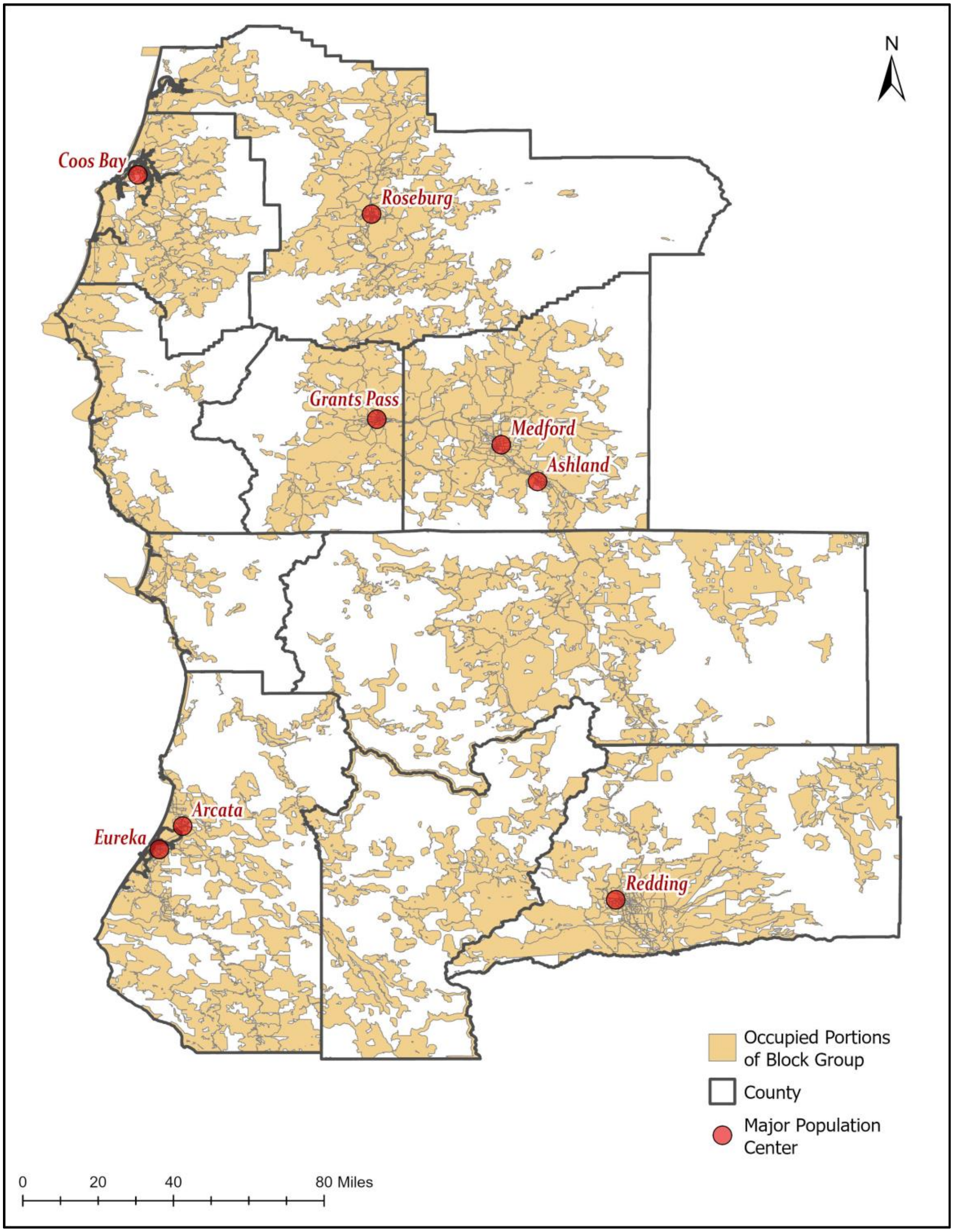

Figure 14. Final occupied census block groups

4.2. Comparing Input Parameters

The above methods were employed to successfully generate nineteen unique WUI extents and populate a WUI parameter matrix (Table 6).

Table 6. Complete WUI parameter matrix

Household (hh) Density		Wildland Vegetation Cover				
		Least Restrictive				Most Restrictive
		≥0% (test)	≥10%	≥25%	≥50%	≥75%
Least Restrictive	All hh (test)	Area: 12,700mi^2 Pop: 897,090 Below Pov Income: 16.5%	a)12,576 mi^2 b) 65.3 % c) 15.1 %	a) 12, 482 mi^2 b) 55.4 % c) 15.2 %	a) 12,125 mi^2 b) 43.4 % c) 14.8 %	a) 11,040 mi^2 b) 26.9% c) 14.4 %
	1hh/60 acres	a) 3,069 mi^2 b) 87.9 % c) 16.6 %	a) 2,945 mi^2 b) 53.3 % c) 14.9 %	a) 2,851 mi^2 b) 43.4 % c) 15.0 %	a) 2,494.1mi^2 b) 31.4 % c) 14.4 %	a) 1,956 mi^2 b) 15.6 % c) 13.2 %
	1hh/40 acres	a) 2,265 mi^2 b) 84.9 % c) 16.7 %	a) 2,141 mi^2 b) 50.3 % c) 15.0 %	a) 2,047 mi^2 b) 40.4 % c) 15.1 %	a) 1,713 mi^2 b) 28.5 % c) 14.5%	a) 1,268 mi^2 b) 13.1 % c) 13.0 %
Most Restrictive	1hh/20 acres	a) 1,205 mi^2 b) 78.7 % c) 17.1 %	a) 1,083 mi^2 b) 44.0 % c) 15.4 %	a) 989 mi^2 b) 34.2 % c) 15.6 %	a) 808 mi^2 b) 23.0 % c) 14.8 %	a) 499 mi^2 b) 8.7 % c) 12.6 %

a) Land Area
b) Percentage of Total Population
c) Percentage of Population Below Poverty Income

Five wildland vegetation cover thresholds were tested between ≥0% and ≥75%. The correlation is straightforward, but ≥0% was the most permissive vegetation criterion because does not exclude any area based on vegetation cover. Though the WUI extents generated are insufficient because they only incorporate the household density variable, the inclusion of this null criterion yielded interesting results. Adjusting the wildland vegetation cover from ≥0% to ≥10% led to the exclusion of approximately 30% of the total population. For instance, at the ≥1 household/60 acres, adjusting the wildland vegetation criteria from 100% (≥0%) of block groups to 90% (≥10%) led to a 34% decrease in total population. This relationship holds true across other household density levels. At the ≥0% wildland vegetation level, the effects of household density alone are most pronounced. Predictably, the land area decreases substantially as the household density input is made more restrictive (from ≥60 acres to ≥40 to ≥20). Interestingly though, the proportion of the total population remains relatively homogenous (87% to 78%). This indicates that most of the block groups that have a household density of ≥1 household/60 acres also have three times that quantity i.e. ≥1 household/20 acres. The proportion of the block group population who makes less that the poverty rate also stayed fairly static. This is likely the result of the dasymetric mapping step, which, by omitting large geographic areas, more accurately represents a higher household density in rural areas.

As with vegetation parameters, a null population density input was used, allowing for the inclusion of all block groups based on the number of households per acre. Similar to the null vegetation input, the WUI generated without a household density limit is insufficient as an accurate rendition of the WUI but is useful for looking at the role vegetation plays in the equation. As wildland vegetation parameters increase from ≥10% up to ≥75% a unique trend plays out. The land area remained fairly static, decreasing by only 1,536 square miles or 8% as the vegetation criterion became more restrictive. Across that same span, the percentage of the WUI population decreased dramatically from 53% to approximately 16% of the total population. This indicates that, as the vegetation criterion is increased, it effectively omits smaller, sparsely vegetated, populous areas (Figure 15). This suggests that the ≥10% wildland vegetation parameter might be overly permissive. Conversely, it suggests that the ≥75% wildland vegetation parameter might be overly restrictive, potentially excluding interface WUI.

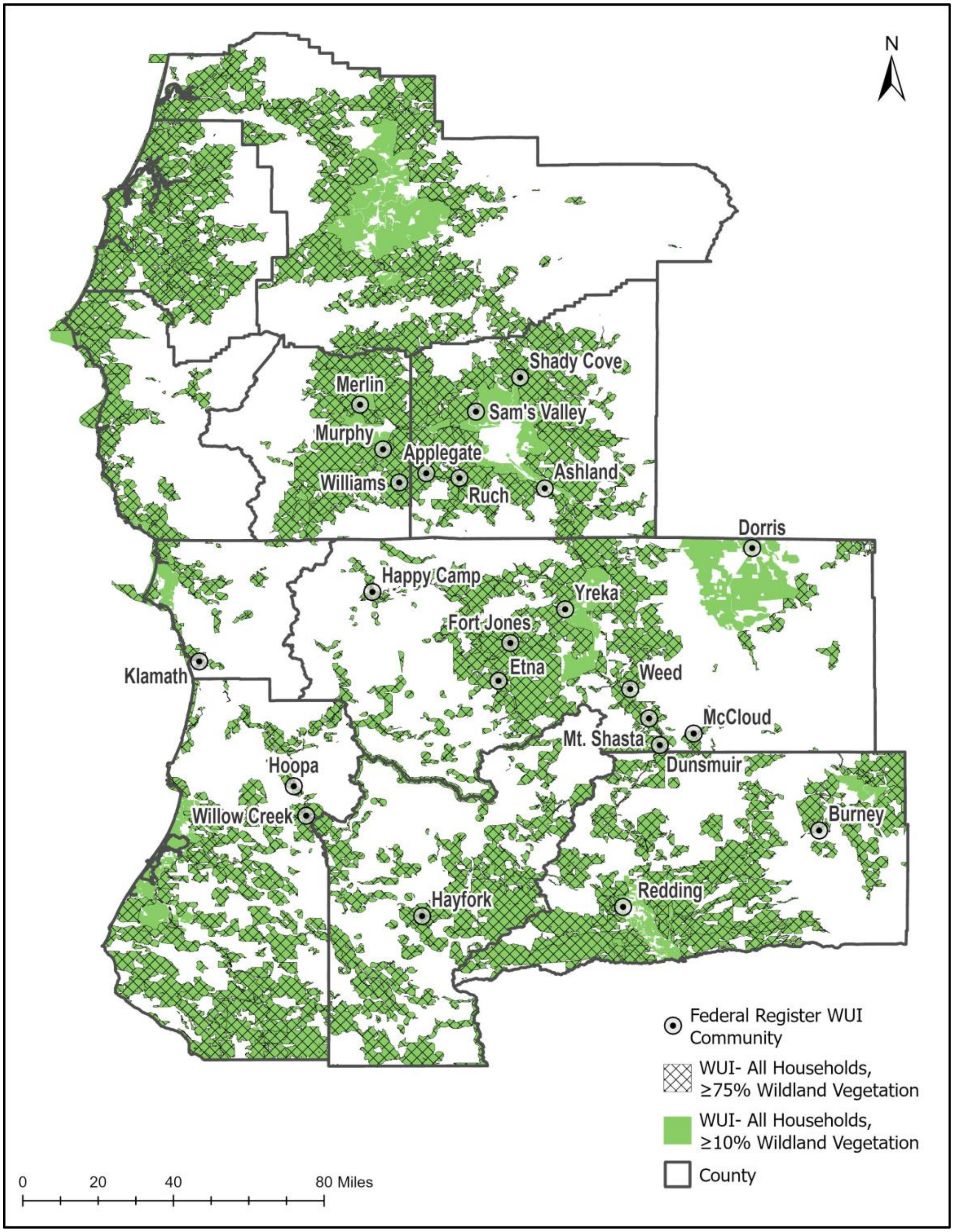

Figure 15. Comparison of WUI outputs at ≥10 % wildland vegetation compared with ≥75 % wildland vegetation

Outside of the test null parameters, the analysis produced a total of twelve potential WUI outputs. These test vegetation criteria from 10-75% and household density criteria between 20 acres per household and 60 acres per household. The overall, obvious trend is, as each variable gets more restrictive, the output decreases in land area, percentage of the population, and percentage of population below poverty income. Land area decreased most notably as household density parameters increased. This is reasonable as, all block groups with ≥1 household/60 acres necessarily also have at least 1 household/20 acres. The same relationship was not true when looking at increases in wildland vegetation cover. Land area decreases were small or negligible as vegetation cover requirements increased. As suggested above, the decrease in area was largely in urban or suburban area, indicated by a comparatively high decrease in population as vegetation requirements increase. This finding is supported by the previous vegetation density map (Figure 10), which shows relative uniformity in wildland vegetation cover outside of urban areas around cities like Medford and Redding.

4.3. Evaluating WUI Outputs

The above findings are interesting but do not readily offer a way to compare mapped WUI results. One reasonable way to evaluate the various outputs is to compare mapped WUI coverage to known WUI communities. As discussed in the introductory chapter, 23 WUI communities were identified in the project area for a 2001 Federal Register listing (see Figure 2). The original rationale for selecting these communities was not clarified and the list is incomplete. Nonetheless, an adequate GIS-based WUI assessment ought to be able to reidentify these known communities.

As with the above table detailing geographic extent and demographic character, a table was generated to track the total number of Federal Register WUI communities identified at each pair of variable parameters (Table 7). Generally speaking, the number of Federal Register WUI communities identified decreases when vegetation density thresholds are increased. This effect is more pronounced with household density, but a slight decrease from 23 to 22 occurs when wildland vegetation cover is increased from 10% to 75% when household density is not accounted for. Similarly weak decreases occur at all household density levels between 25 and 50% wildland vegetation cover. Household density had a strong impact on the number of Federal Register WUI communities identified. From ≥1 household/60 acres to ≥1 household/20 acres, the total number of WUI communities decreased by almost half across all vegetation densities, with the strongest drop at 75% wildland vegetation cover.

Table 7. Federal Register WUI communities identified at each variable threshold

Household (hh) Density	Wildland Vegetation Cover					
		≥0% (test)	≥10%	≥25%	≥50%	≥75%
	All hh (test)		23/23	23/23	23/23	22/23
	1hh/60 acres	20/23	20/23	20/23	19/23	15/23
	1hh/40 acres	17/23	17/23	17/23	16/23	13/23
	1hh/20 acres	13/23	13/23	13/23	12/23	9/23

Population totals for the Federal Register WUI communities are not uniformly available because many are technically unincorporated and often lumped into larger neighboring communities. Available population data, sourced from the US Census Bureau, shows that some degree of population change has occurred since 2001 (Table 8). For example, Shady Cove and Redding both grew considerably (33% and 15%) over the twenty-year period. Conversely, Dunsmuir and Etna both decreased by over 10% in the same period. These shifts in population do not necessarily prohibit comparison with WUI identified using more recent data. Instead, these changes indicate that the population density criteria used to identify the same WUI communities today will be slightly different than they would have been when they were first listed in 2001. For instance, communities that grew over time would qualify as WUI using more densely populated household criteria (e.g. 1 household/20 acres versus 1 household/40 acres). The opposite would be true for communities with shrinking populations.

Table 8. Federal Register WUI community population change 2000-2020, based on available US Census Bureau Data

WUI Community	2000 Population	2020 Population	Population Change
Ashland	19,522	21,413	+ 9.6 %
Shady Cove	2,307	3,085	+ 33.7 %
Dorris	886	863	- 2.6 %
Dunsmuir	1,923	1,705	- 12.6 %
Etna	781	677	- 11.3 %
Fort Jones	660	696	+ 5.5%
Redding	80,865	93,559	+ 15.7 %
Weed	2,978	2,864	+ 3.8 %
Yreka	7,290	7,809	+ 7.1 %

To simplify the visualization of results, this study will look at four of the twelve WUI outputs. First, the WUI output using ≥10% wildland vegetation cover and ≥1 household/60 acres will be assessed. This output is the most permissive in the sense that it incorporates the largest area and population. On the opposite end of the spectrum is the WUI output generated with ≥75% wildland vegetation cover and ≥1 household/20 acres. This pair of criteria is the most restrictive and generated the smallest WUI output, both in geographic extent and population. Two additional WUI outputs will be tested alongside this pair. The WUI output from ≥50% vegetation and ≥1 household/40 acres, which is the basic WUI mapping criteria, will be tested.

Finally, the WUI output using ≥10% wildland vegetation and ≥1 household/40 acres will be used, as these values are around the median for area and population percentage.

The WUI output at ≥1 household/60 acres and ≥10% wildland vegetation cover performed best when compared with the Federal Register WUI communities (Figure 16). Of the 23 listed, all but three were within the mapped WUI. The communities of Dorris, Fort Jones, and McCloud were missed using this output. Interestingly, further experimentation indicates that this is due to a lower population density than ≥1 household/60 acres. Of the four test outputs, the WUI at ≥1 household/20 acres and ≥75 % wildland vegetation cover performed the worst (Figure 17). This output only overlapped nine of the 23 listed WUI communities. Experimentation and comparison with other WUI outputs indicates that the higher vegetation threshold has little impact on the overlap with WUI communities, instead it is due, almost entirely, to population density. This finding is reaffirmed when comparing the results of ≥50% (Figure 18) and ≥10% (Figure 19) vegetation, both at ≥1 household/40 acres. Both outputs are visually similar, with the lower vegetation threshold incorporating more small block groups near cities. At ≥50% vegetation cover, seven Federal Register WUI communities are missed (Ruch, Applegate, Fort Jones, Dorris, McCloud, Klamath, and Etna. Adjusting the from ≥50% to ≥10% only allows for the identification of Etna, still missing the other six communities.

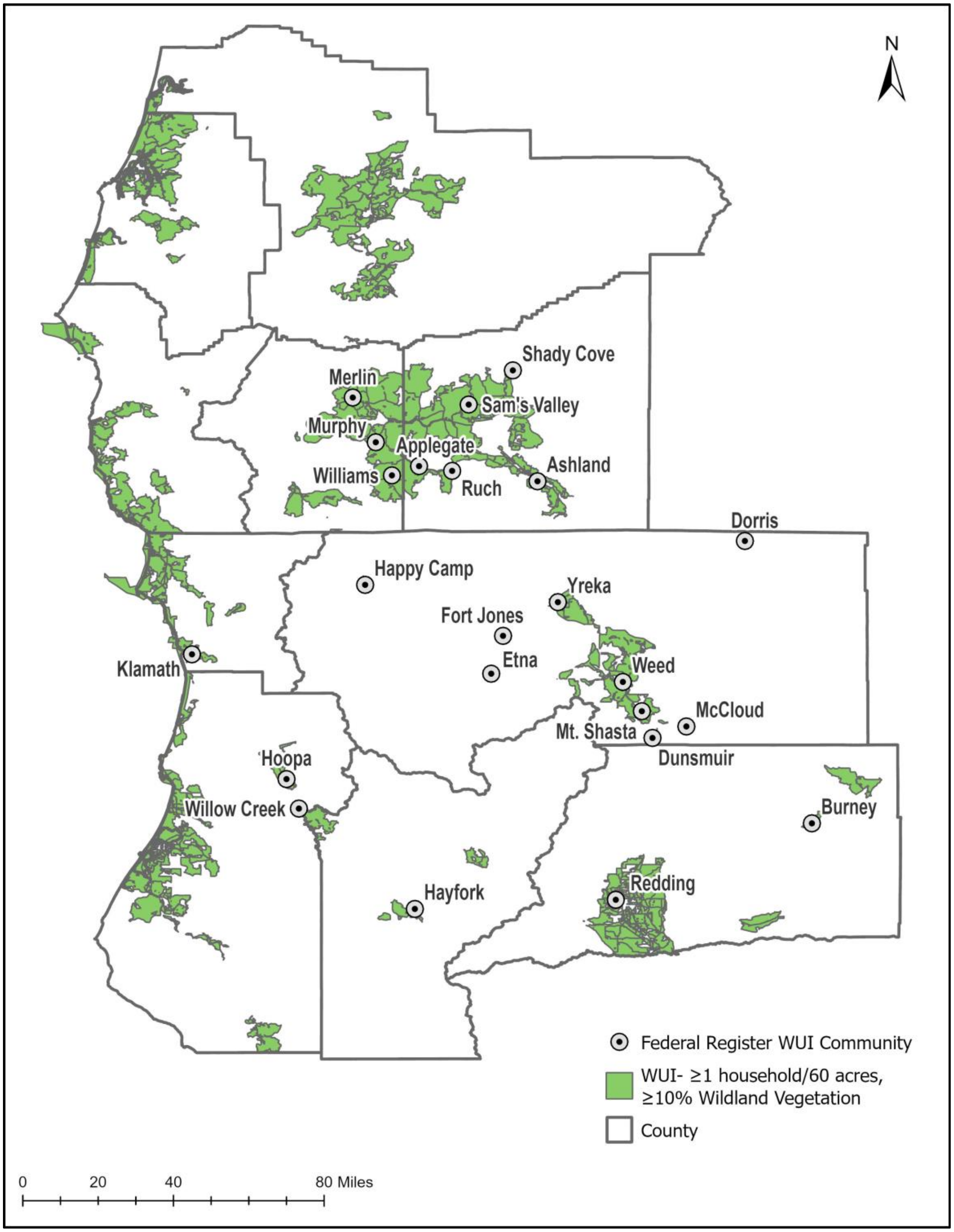

Figure 16. WUI at ≥1 household/60 acres and ≥10% wildland vegetation cover, with Federal Register WUI communities

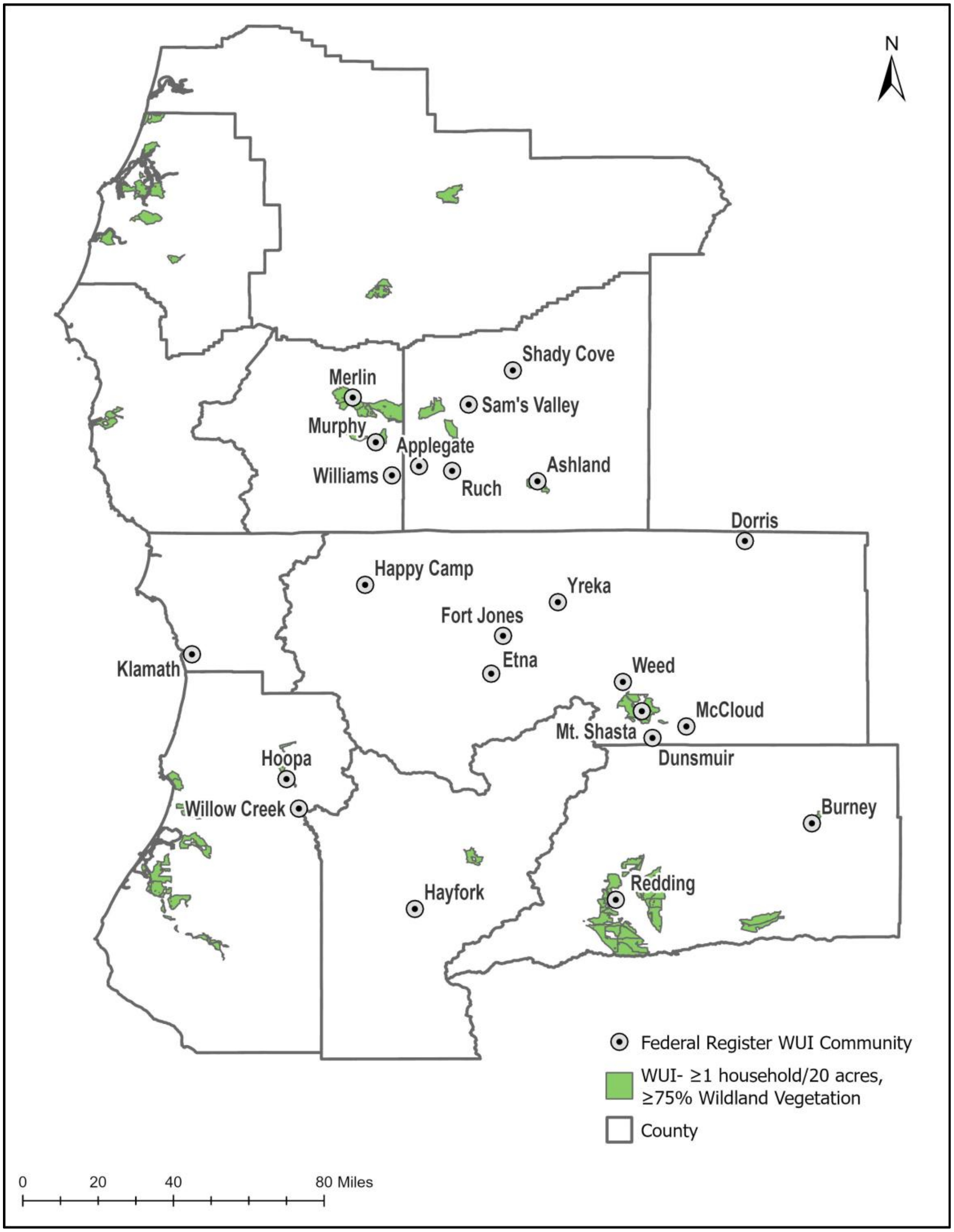

Figure 17. WUI at ≥1 household/20 acres and ≥75 % wildland vegetation cover, with Federal Register WUI communities

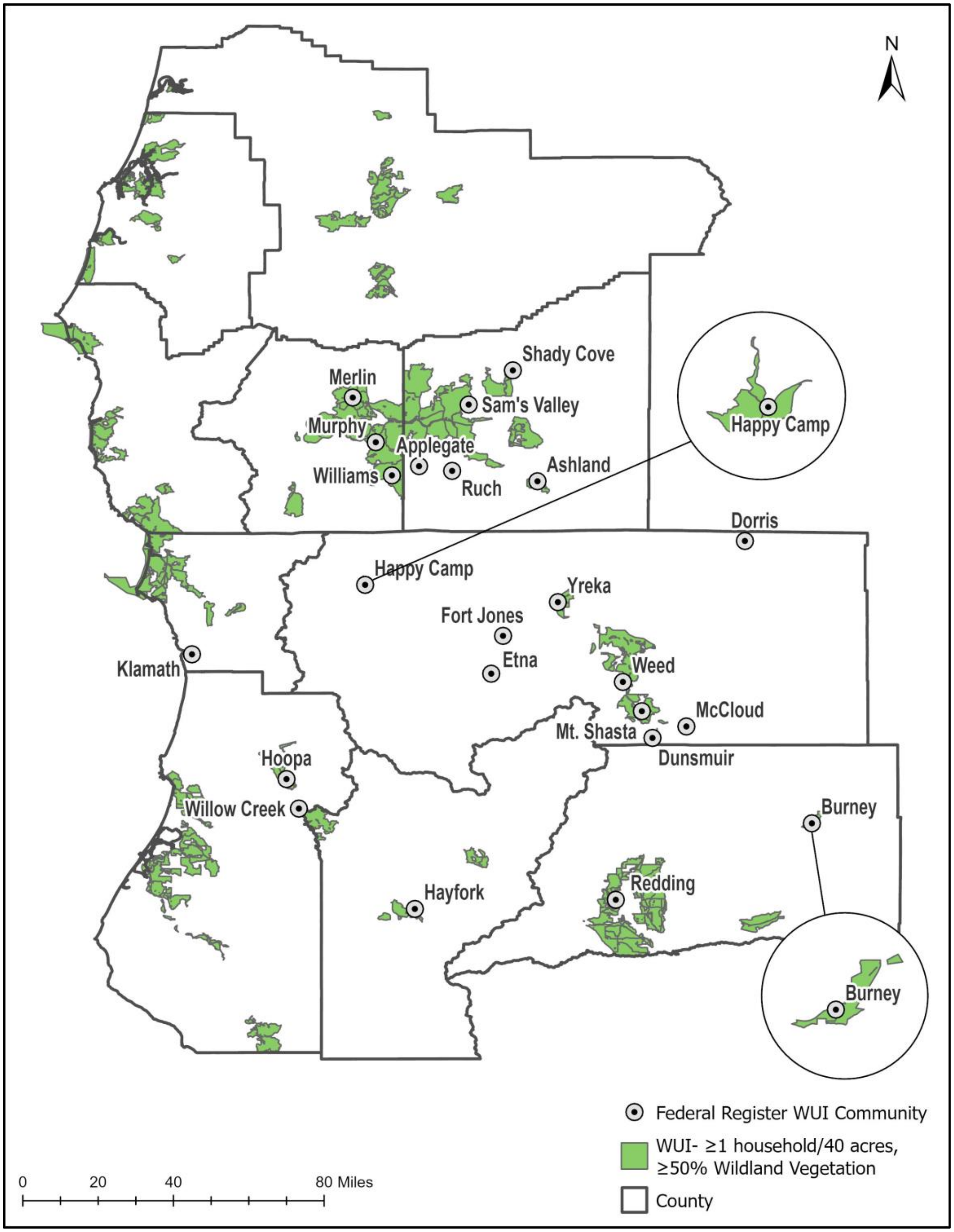

Figure 18. WUI at ≥1 household/40 acres and ≥50 % wildland vegetation cover, with Federal Register WUI communities

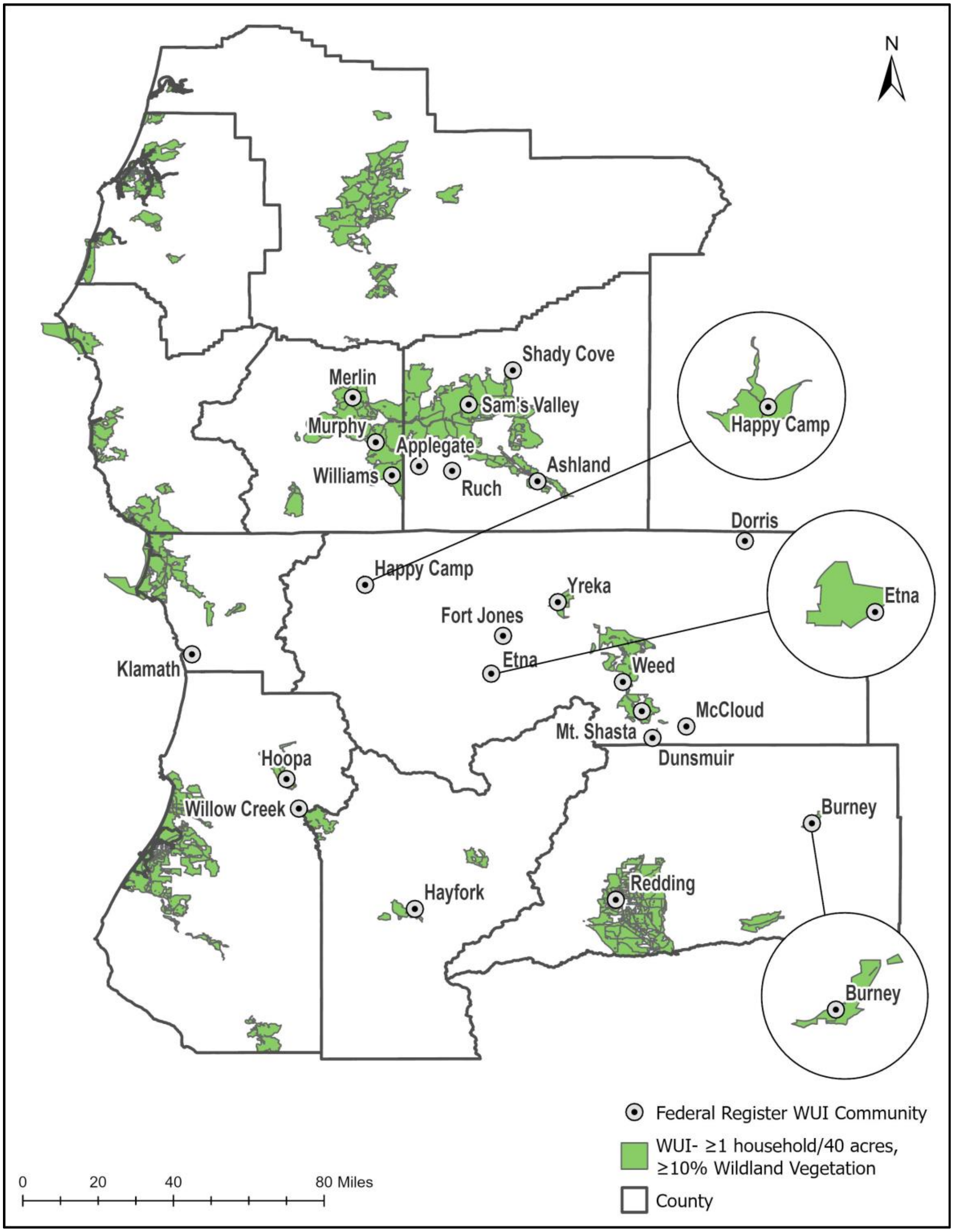

Figure 19. WUI at ≥1 household/40 acres and ≥10 % wildland vegetation cover, with Federal Register WUI communities

Based on these findings, the optimal WUI criteria for the project area needs a lower population density than ≥1 household/60 acres to account for the most sparsely populated areas, such as Dorris. The effects of the vegetation criteria have been shown to be most pronounced in including or omitting areas near urban cores. At ≥10%, this variable may overcount non-WUI urban areas. Conversely, a high threshold of ≥75% visibly decreases the amount of land on the outskirts of cities, where interface WUI is also likely to occur. An optimized ≥25% wildland vegetation would incorporate some areas near urban cores, without overestimating the extend of WUI in those areas. For population density, a much lower criterion is necessary to incorporate very sparsely populated areas. The community of Dorris, for example, has a population density of ≥1 household/400 acres. This low density threshold was determined by slowly decreasing the household density from 80, testing progressively smaller densities until the block groups around Dorris qualified for the selection criteria. This optimized WUI (Figure 20) covers 11,860 mi^2, much more than any of the other outputs. This total accounts for 93% of the total land area. Even though this proportion of the land area skews much higher than any other WUI test, it makes intuitive sense. The study area only has a handful of population centers, with most of the area being sparsely populated. In contrast, the total population for the optimized WUI is only 495,794, 55% of the total population. The proportion of people below poverty income in 15.1%, similar to most of the other outputs and 1% below the proportion of the entire project area population.

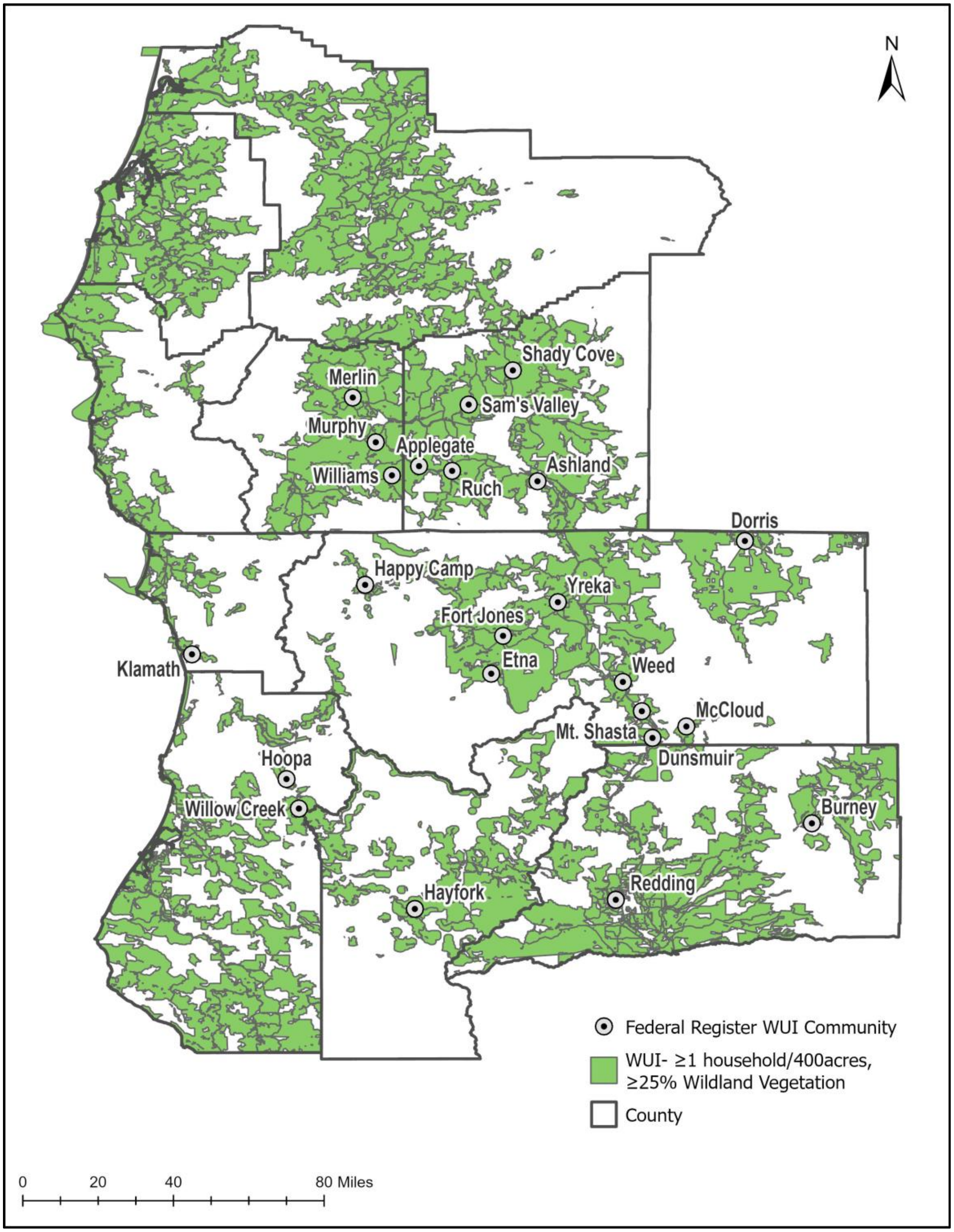

Figure 20. Optimal WUI at ≥1 household/400 acres and ≥25 % wildland vegetation cover, with Federal Register WUI communities

Interpretation of the results can be based both on technical measures of the output, but also on an understanding of how the WUI should reasonably be distributed in the study area. This is one of the advantages to limiting the geographic scope to a specific area. The WUI ultimately describes locations where human development meets wildland fuels. This area is at a comparatively high risk of being impacted by catastrophic wildfire due to proximity to wildland vegetation. In this specific project area, dense urban settlement occurs only in the small handful of urban cores (see Figure 1). Outside of these communities, most residential areas sprawl outwards from cities, along highways, and around small towns. Generally speaking, much of the non-public land is sparsely occupied outside of cities and towns. The WUI output with the most verisimilitude, then, would error on the side of expansive rather than restricted.

Chapter 5 Conclusion

This project demonstrates how a streamlined and location specific WUI mapping methodology can be established based on existing research. The impacts of different combinations of vegetation cover and population density were tested and an optimal WUI definition was established for the project area. This definition employs ≥1 household/400 acres and ≥25% wildland vegetation cover as WUI identification criteria for the given study area. Despite the expedience of national WUI mapping efforts, this study demonstrates that standardized variable definitions may not be uniformly optimal across the country. Before moving forward with WUI locational data, then, it is necessary to assess whether the selected criteria are well-suited for the project area or selected arbitrarily based on previous projects.

The heighted vulnerability of WUI communities in the age of climate change necessitates an honest and good faith effort to adequately identify vulnerable communities, especially if their identification is tied to resource allocation and public policy decision making. This chapter demonstrates how the main methodology for identifying WUI can be augmented by teasing out the differing vulnerabilities of communities within the WUI. The chapter then discusses the long-term utility of the project's results before considering the project's limitations and proposing future work that could continue this research.

5.1. Identification of Vulnerable Communities

With an optimized WUI established, the identification of especially vulnerable interface communities is an important next step. To demonstrate this workflow, the process was completed using the optimized WUI established in Chapter 4. First, the proportion of people with below poverty income relative to the total population is calculated for each WUI block group. The feature class is then symbolized using graduated colors and natural breaks, which divides the feature into five categories (Figure 21). Based on the sociological context described in Chapter 1, there is reason to believe that both higher and lower income communities may be vulnerable to wildfire based on demographic characteristics. For demonstration purposes, vulnerable communities will be defined as those with the highest proportion of poverty income relative to the total population (33%+).

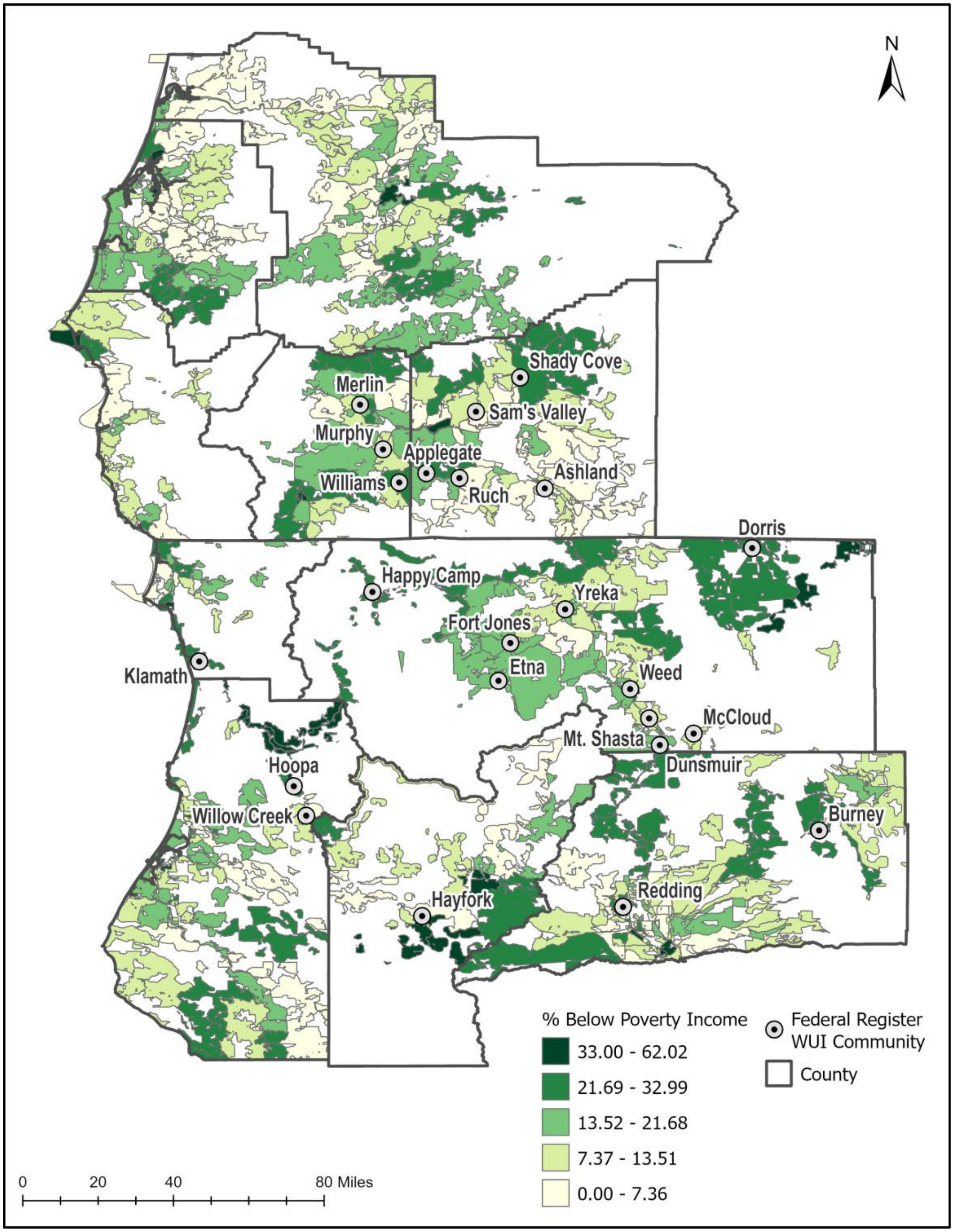

Figure 21. Optimized WUI with proportion of population below poverty income

Identification of the poorest communities may be sufficient to identify vulnerability, but an additional step is to overlay fire risk data. This allows for the identification of the poorest communities with the highest burn risk. Wildfire hazard potential data is sourced from the Esri Living Atlas. The dataset depicts relative burn risk on a ranking of one to five, with five being the highest (Figure 22). Data is aggregated at various levels from state and county to block group and hex bin. For consistency across datasets, the median burn risk by block group was used. The median burn probability data is ultimately derived from the USDA's Fire Modeling Institute, which represents fire risk in a 270-meter resolution raster (Holtzclaw 2020). Sourcing the data from Esri provides a convenient shortcut, skipping extensive pre-processing steps necessary to prepare the dataset as it comes from the USDA.

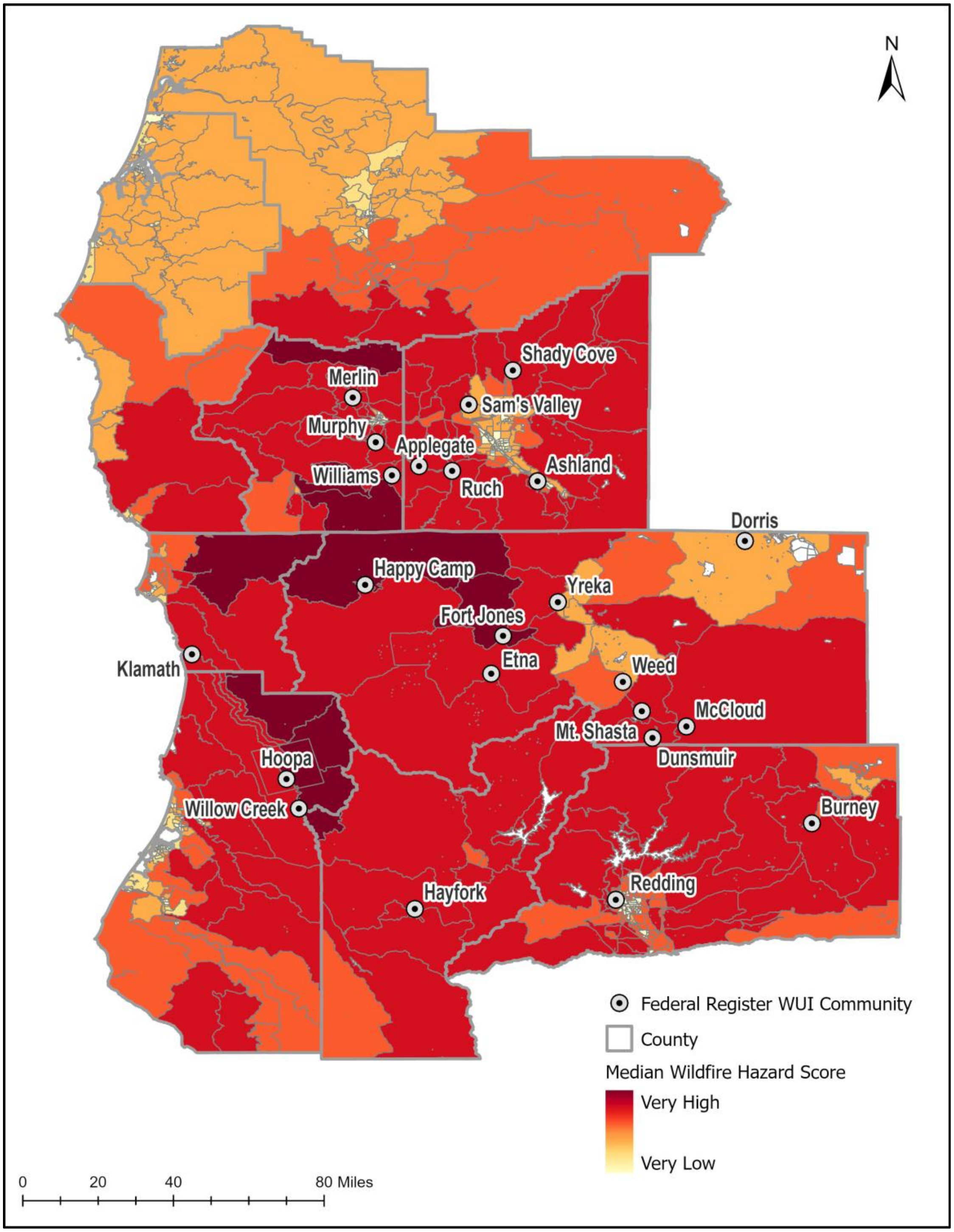

Figure 22. Wildfire hazard potential by block group

This dataset was clipped to the optimized WUI, and the union tool was used to combine the two datasets. From here, the select by attributes tool was used to identify most vulnerable, second most vulnerable, and third most vulnerable communities (Figure 23). The selection criteria are as follows:

- Most vulnerable = % of population below poverty income>= 33 AND Median Wildfire Potential Score = 5
- Second most vulnerable= % of population below poverty income >= 21 AND Median Wildfire Potential Score = 4
- Third most vulnerable= % of population below poverty income >=13 AND Median Wildfire Potential Score = 3

The results of this analysis indicate that the most extensive area of high burn risk and high poverty status occurs near the community of Hoopa, California. This area includes the reservation of the Hoopa Valley Tribe and other communities adjacent to the Six Rivers National Forest. Additional small pockets are located around Happy Camp, California and west of Williams, Oregon near the communities of Cave Junction and Kerby.

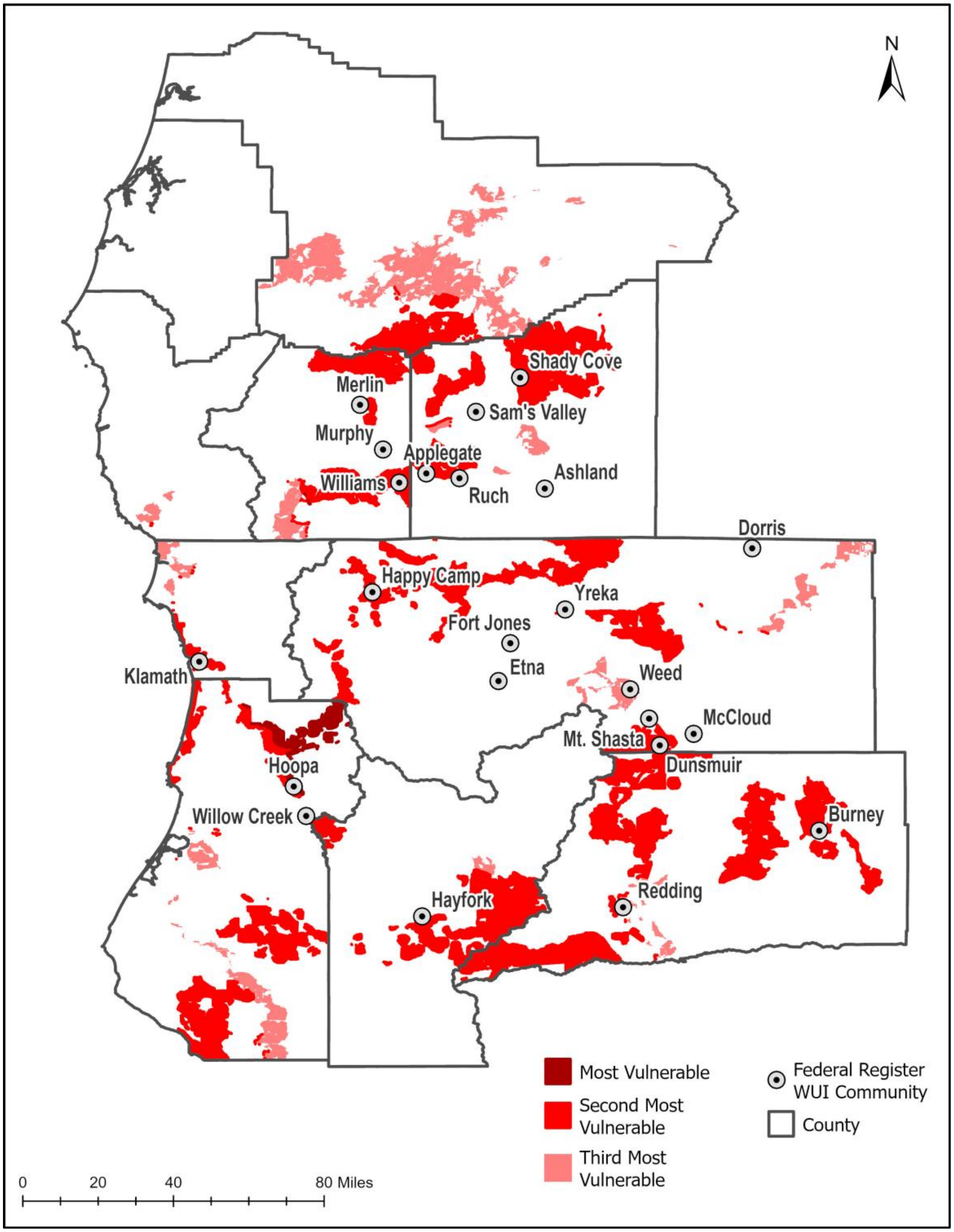

Figure 23. Most vulnerable WUI areas based on fire risk and poverty status

5.2. Long-Term Functionality

For long-term WUI data functionality, variable parameters should be retested using new census and landcover data as it is released and updated WUI extents should be generated. In any region with sustained and consistent population growth (or decline), the WUI is constantly expanding and shifting over time. This means that any estimation of WUI extent is necessarily approximate and, depending on the rate and nature of local growth, may be quickly outdated. The nature of this shift may differ across an area too. For example, WUI areas that abut federal and state land, which are common across the west, may be limited in their geographic spread. By definition, public land is not open for residential development and represents a growth barrier. As populations in these types of communities grow, population density rather than physical extent is more likely to increase. The opposite may be true along the periphery of urban centers, where new construction tends to sprawl outwards across previously undeveloped, private lands. ACS data is available annually and updated population and demographic data can be reintegrated into the workflow. As decadal census data is released, it can also be integrated.

In the longer term, land cover can also be expected to shift and change. Urban sprawl is inevitably the likeliest source of land cover change, from wildland vegetation to developed, non-wildland categories. But landcover change may also occur over time due to climate change and wildfire events. In some areas, warmer and drier conditions may shift vegetation communities e.g. from mixed forest to scrub. While these would both register as wildland vegetation, they may represent different levels of fire risk. It is also feasible that severe enough burn scars may be reclassified from forest to bare land cover types in some areas. Finally, areas previously classified as open water or perennial snow/ice may transition to bare ground or vegetation as a result of drier, hotter conditions. NLCD data is typically available in 2 to 3-year increments. At this time, the 2019 NLCD data used in this study is the most updated version. As with population data, newer versions should be integrated as they are released. More detailed landcover data can also be substituted in future iterations of this workflow.

5.3. Limitations

Any GIS-based analysis is limited by data quality. This project relies extensively on NLCD and US Census Bureau data. Both of these datasets are considered authoritative resources and are sufficiently accurate for the project at hand. Both have some amount of inherent inaccuracy that is worth mentioning though. The metadata associated with the 2019 NLCD dataset clarifies that a formal accuracy assessment has not been made for that year. The previous edition, which dates to 2016, includes an overall accuracy assessment of 91% for landcover data for the conterminous US. Similarly, because ACS data is based on a sample of the population, there is an intrinsic amount of statistical error when extrapolating population level conclusions. ACS datasets also have “non-sampling error,” which are non-statistical errors that effect data accuracy (US Census Bureau 2019b, 20). The US Census Bureau gives data entry errors and systematic undercounting of “groups who are difficult to enumerate” (US Census Bureau 2019b, 20). The latter category is especially important when considering the role of socioeconomic status in WUI communities. For example, undocumented farm workers and rural homeless residents may be underrepresented in rural census data.

An additional source of potential inaccuracy can arise from mismatched census and landcover data. This project matches 2019 census data with 2019 NLCD data. Both datasets include data from previous years, due to the lapse of time between observation and data publication. Direct temporal correlation between datasets is not possible but using roughly contemporaneous data is preferable. For example, pairing 2010 census data with 2016 NLCD data would likely yield decent WUI results, but more inaccuracy would be introduced because of the temporal difference between the datasets.

Beyond data accuracy and compatibility, the nature of this project represents a potential limitation. GIS-based research can be an invaluable tool. The project described here enables the remote and fairly accurate identification of large expanses of WUI areas. This identification is an important first step for a number of potential actions, but GIS-based research needs to be integrated with other research methods to fully understand, not just where the WUI is, but what that finding implies. For example, after identifying potential WUI locations, a reasonable next step would be applied sociological or ethnographic research to better understand the issues and challenges residents face and how they might interact with wildfire risk. If, for example, cost is a major limiting factor in firesafe planning for local residents, a grant system could be established by policy makers to better meet community needs. Alternatively, if negative perception of government and authority is a factor (as suggested in Bright and Burtz 2006a), then rapport building with the local community may be imperative to build trust and collaboration.

5.4. Next Steps and Future Research

With an optimized WUI definition established for the study area, a number of next steps are possible for policy makers and future researchers. In their analysis of WUI areas across the US, Radeloff et al. (2005) suggest that WUI locational data needs to be integrated with other detailed spatial data, such as a building materials database, detailed topography, and accessibility, to fully ascertain fire risk across the interface. This sentiment is echoed in Mell et al. (2010) who argue that, to assess the effectiveness of WUI wildfire risk mitigation programs, community characteristics and structure exposure conditions need to be integrated into a wider WUI model. Because the WUI extent is necessarily generated at a specific time series based on the census and vegetation data used in the workflow, the mapping process is well-suited to longitudinal assessments of WUI change through time. Currently, the temporal scope is limited by the range of NLCD data, which is available as far back as 2001. As new NLCD datasets are released in the future, the temporal scope of WUI data will grow and be a potentially fruitful avenue for analysis.

As is, the dataset generated here could be a valuable decision-making tool. For instance, if any of the neighboring land management agencies were tasked with WUI adjacent wildland fuels reduction, they could prioritize land near lower income, higher fire risk communities. Similarly, if state or county governments received funding to construct new rural fire infrastructure, they might identify high priority areas based on the same criteria. Individuals within communities might also use the dataset to understand their relative risk and, potentially, use it as an impetus for community-level planning and organization.

The full realization of WUI mapping, then, is not in the minutiae of variable selection, but in the big picture functionality and integration of a well-designed dataset for long-term planning and analysis. Effective research approaches can integrate quality WUI locational information, using it as a building block to address key public planning and emergency preparedness decisions. Because of the foundational importance of WUI locational information, it is imperative to have a fully realized mapping methodology, such as the one developed in this project.

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Appendix

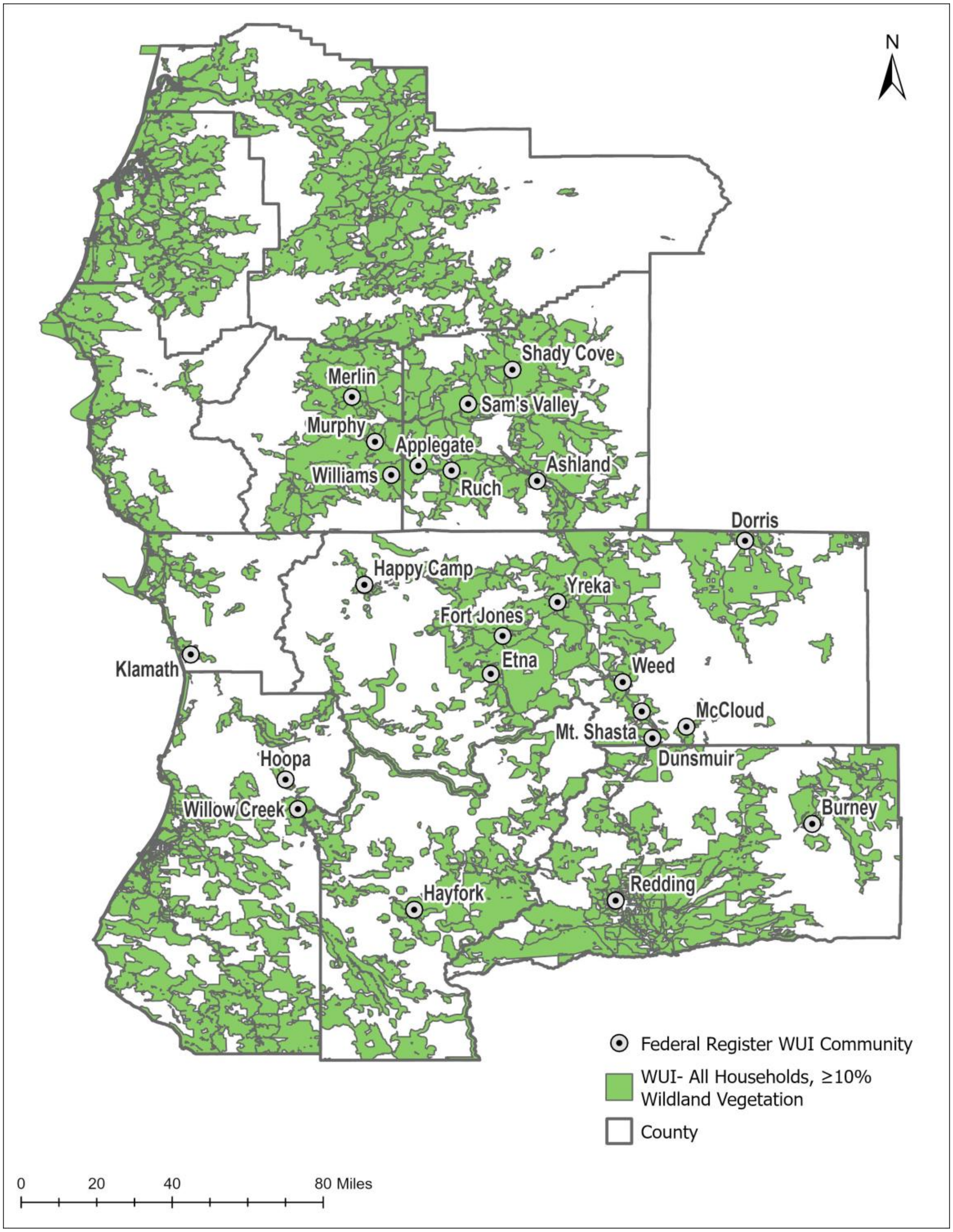


Figure 24. WUI output with all households and ≥10 % wildland vegetation cover

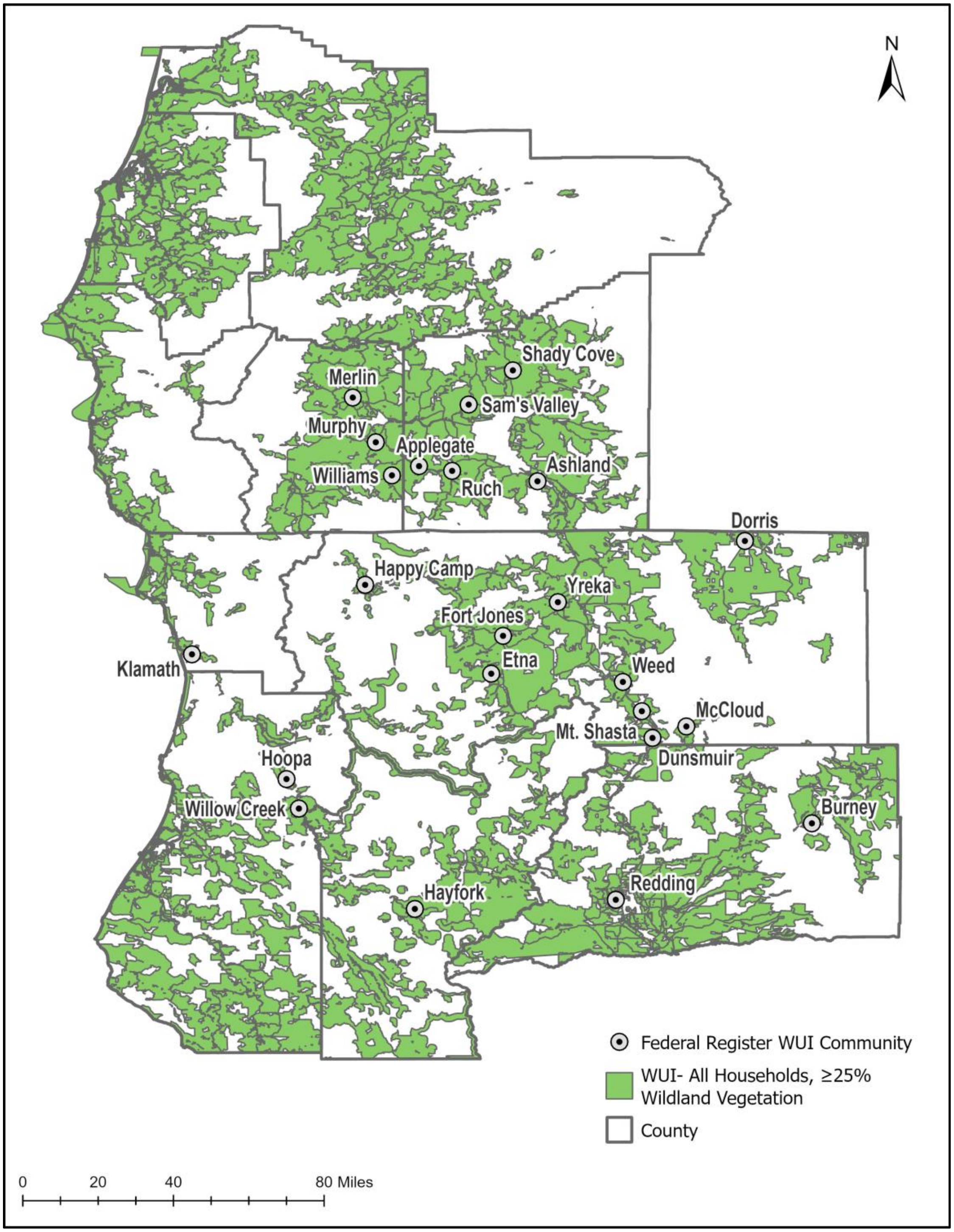


Figure 25. WUI output with all households and ≥25 % wildland vegetation cover

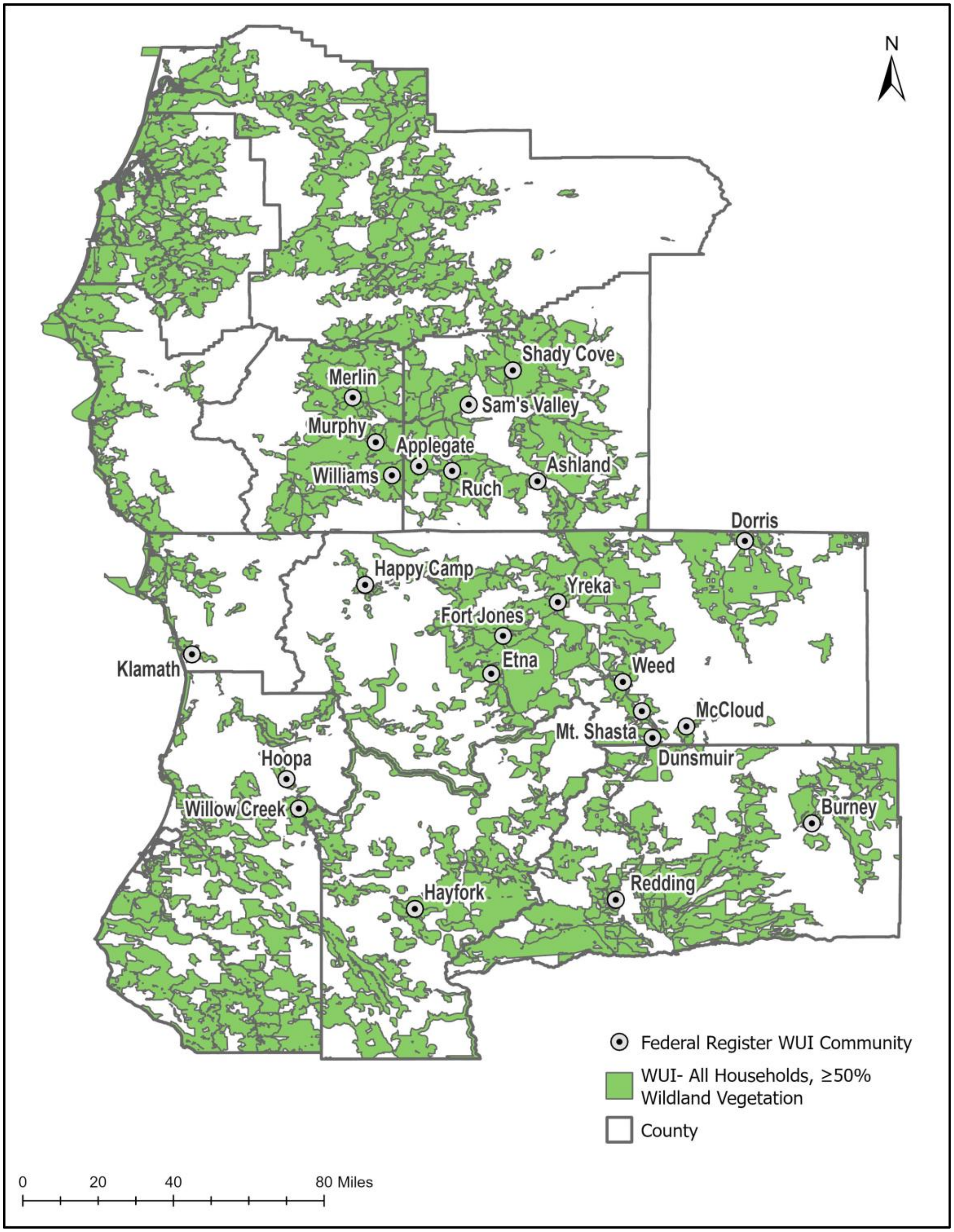


Figure 26. WUI output with all households and ≥50 % wildland vegetation cover

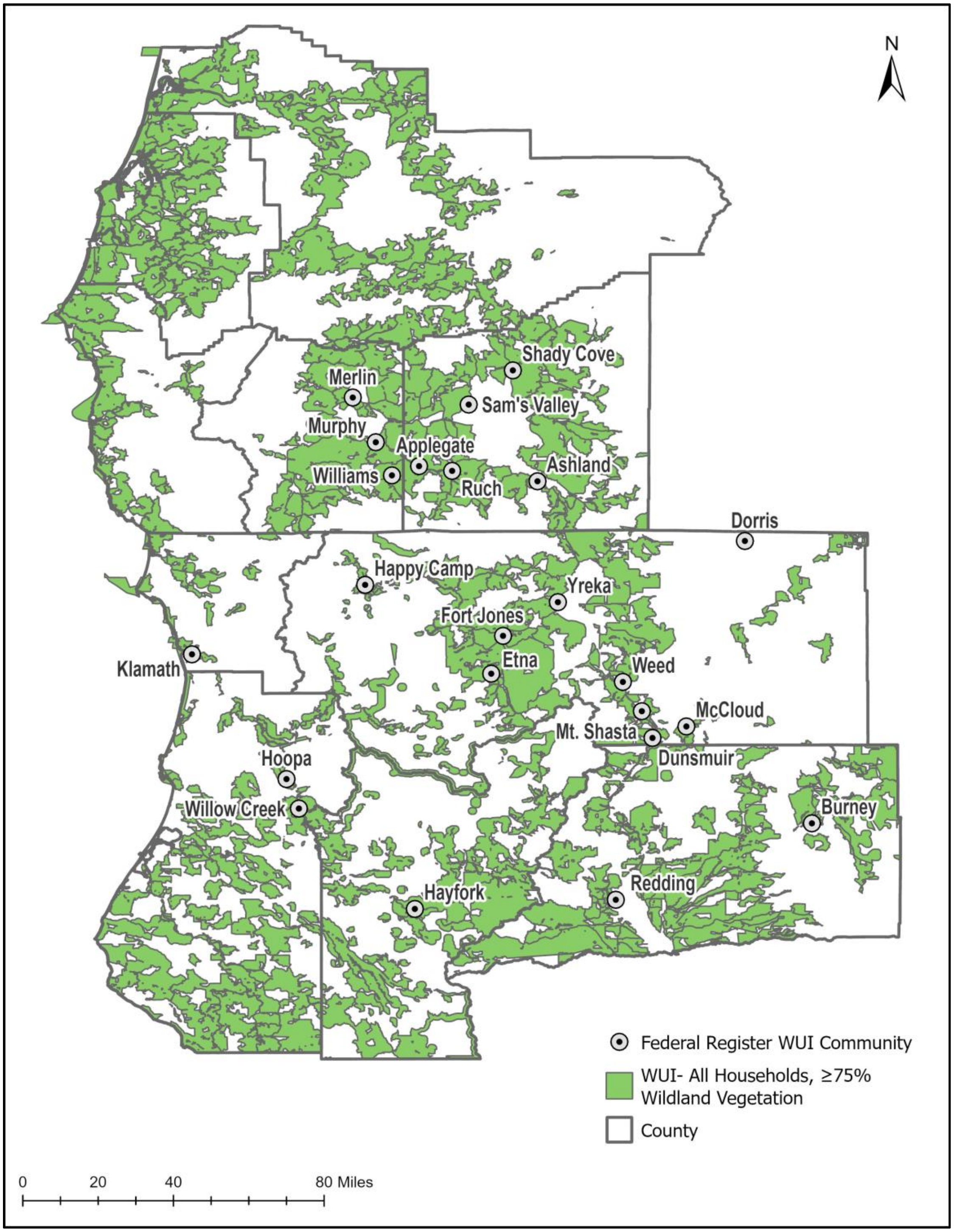


Figure 27. WUI output with all households and ≥75% wildland vegetation cover

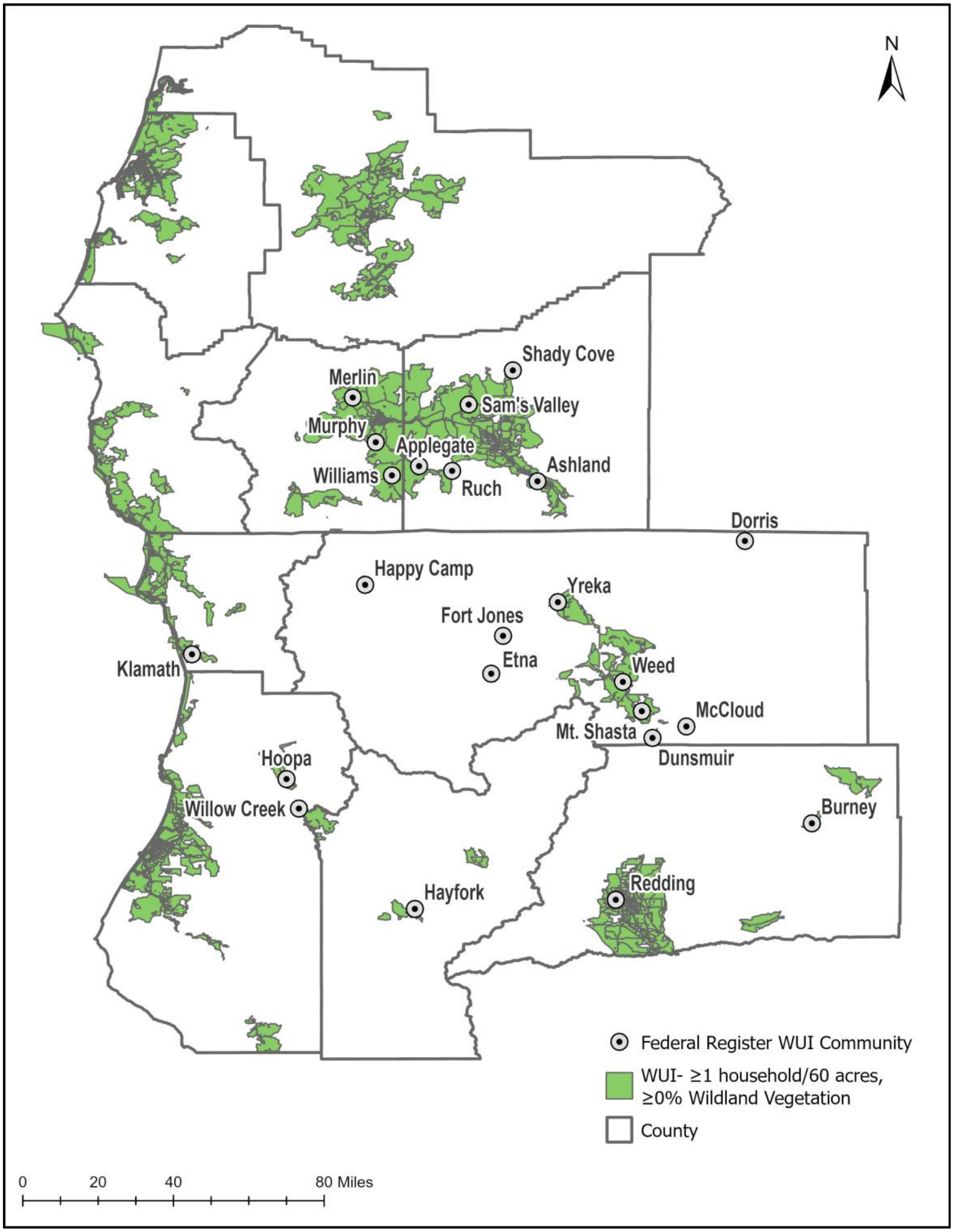
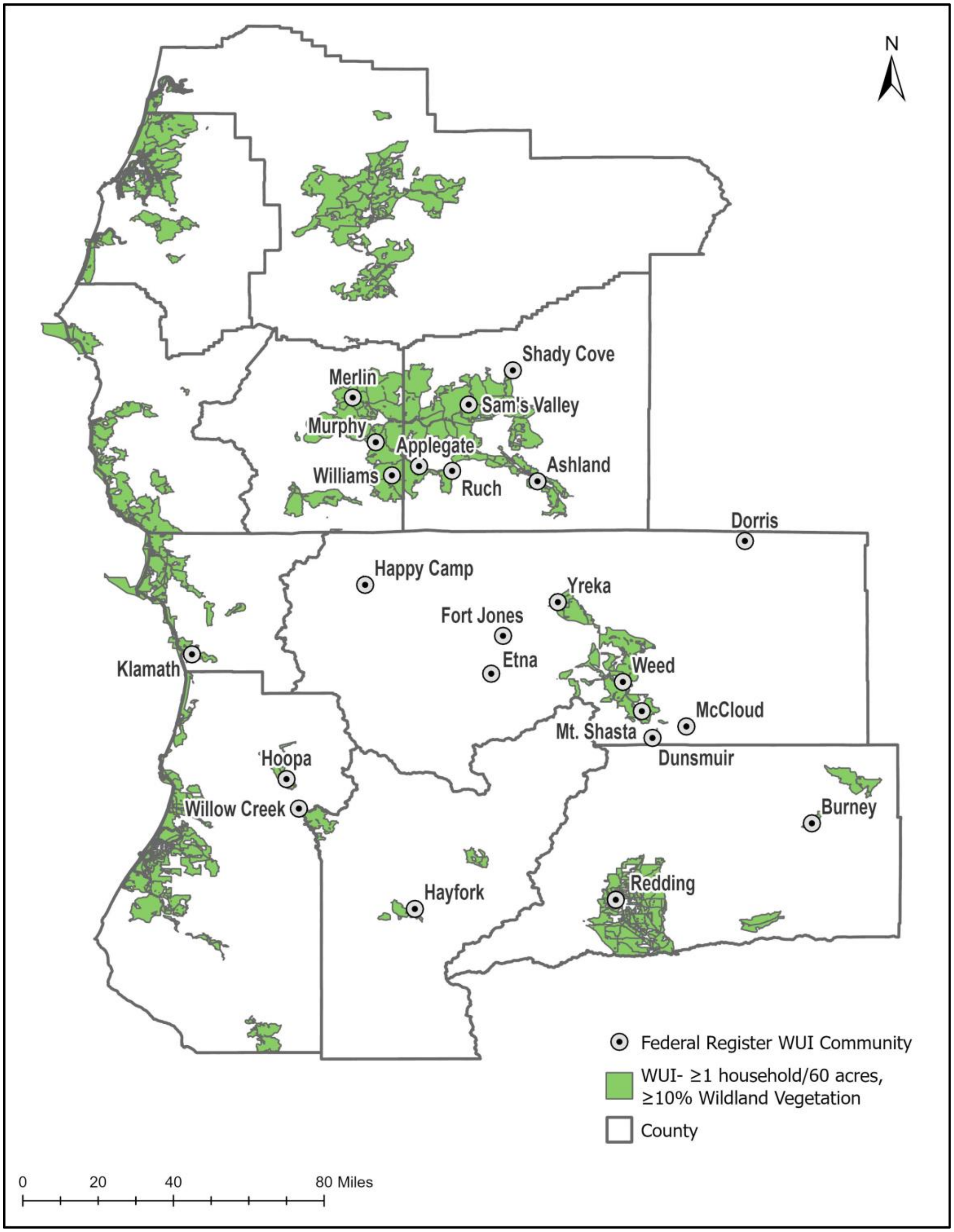


Figure 28. WUI at ≥1 household/60 acres and no wildland vegetation criteria



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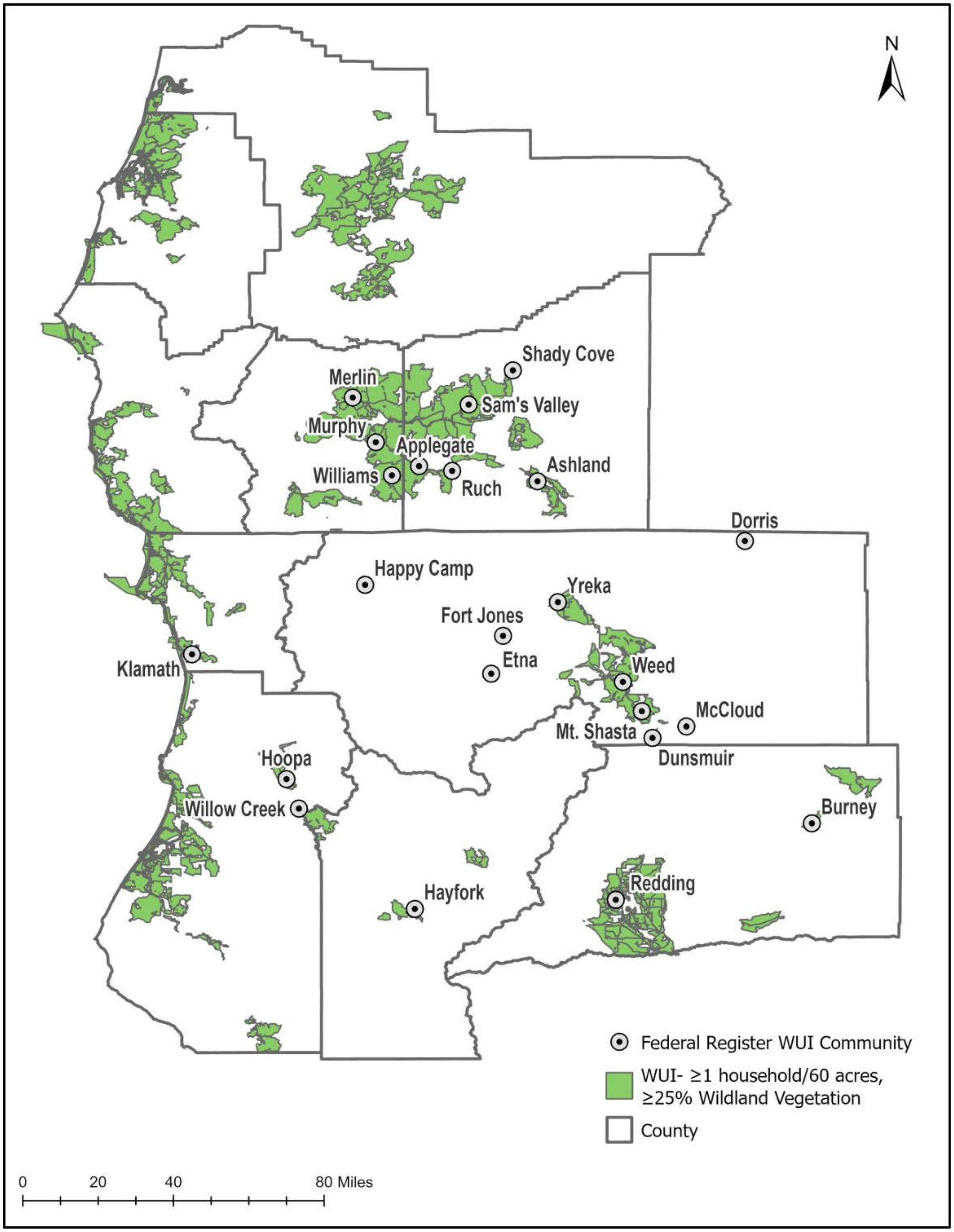

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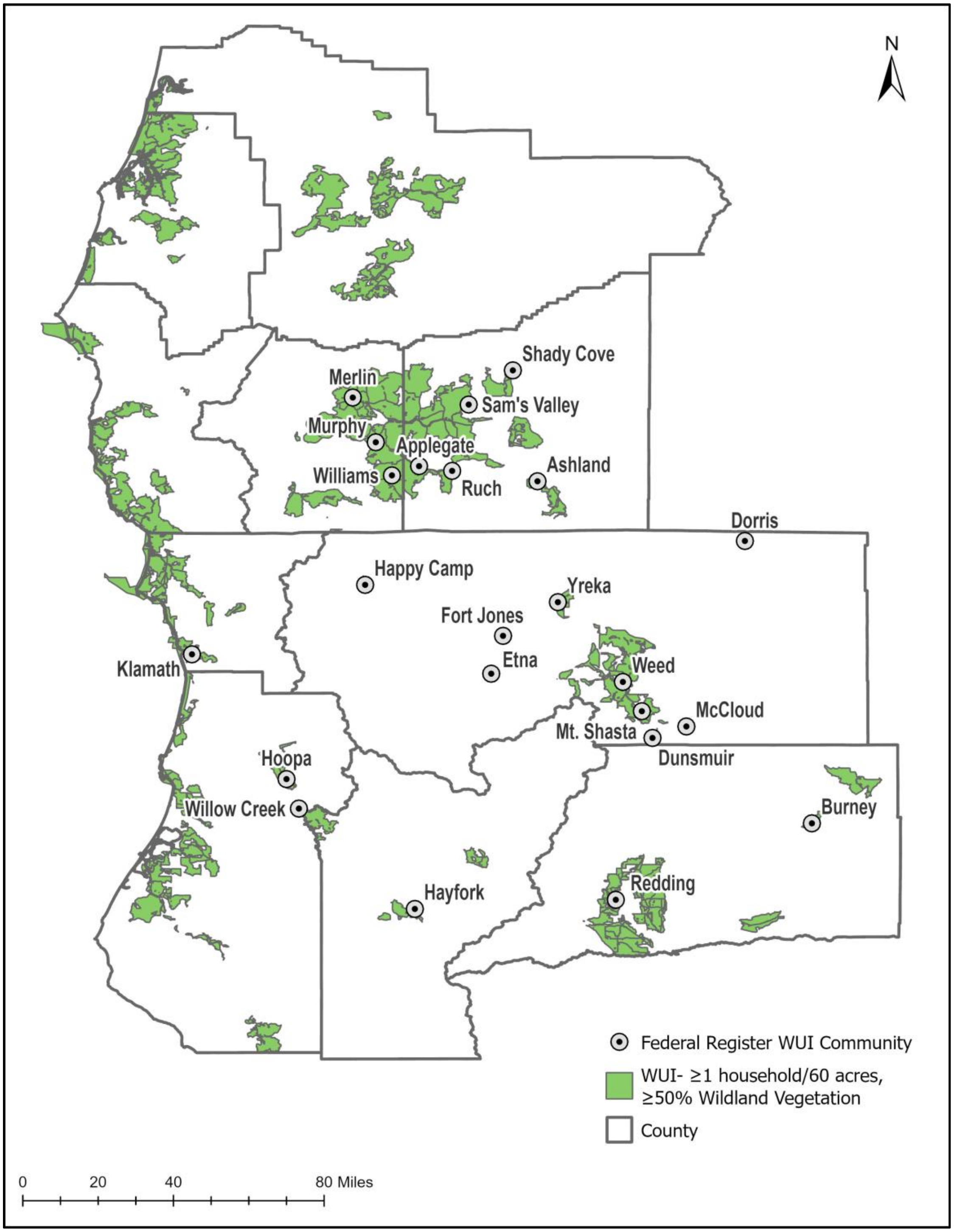

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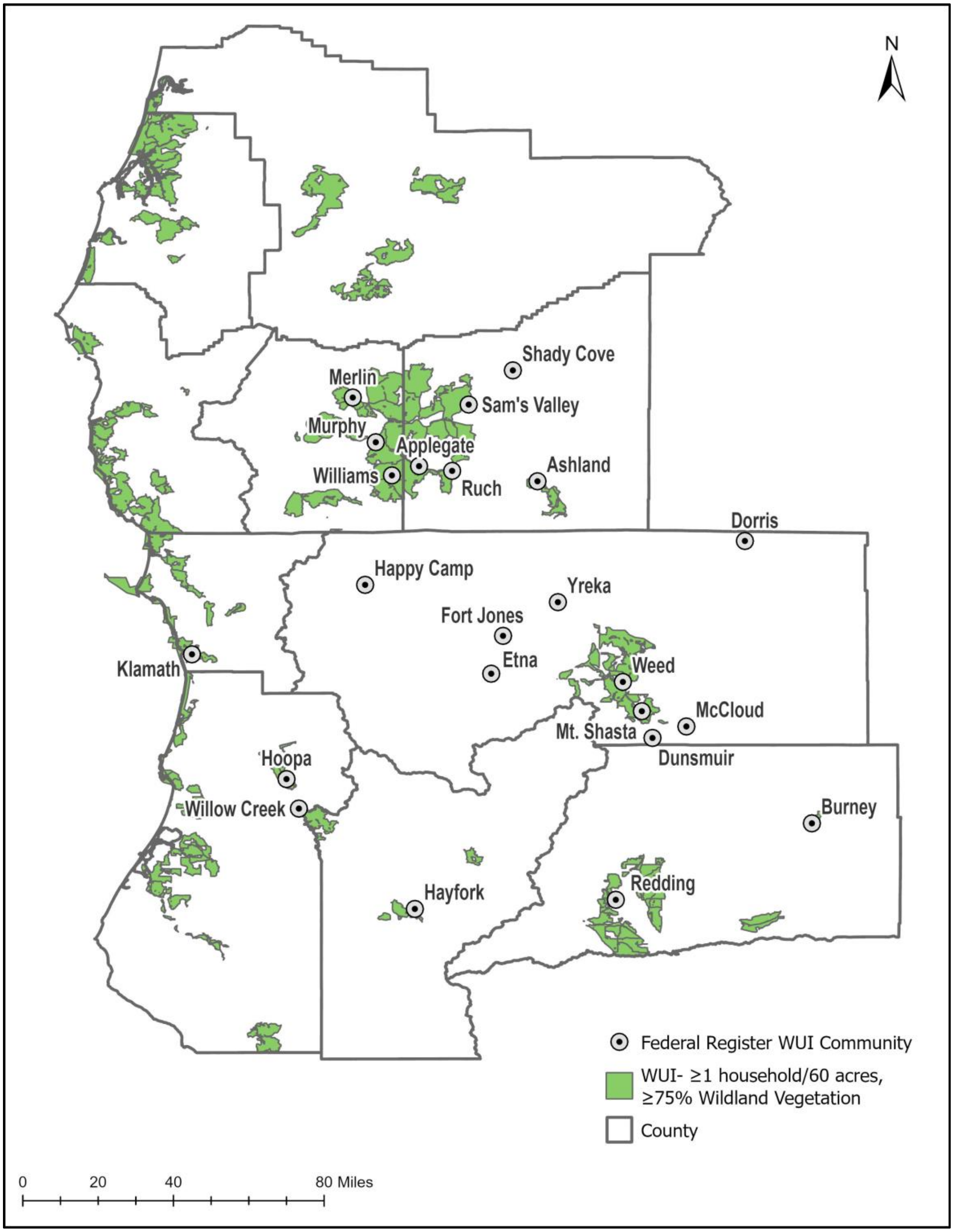


Figure 32. WUI at ≥1 household/60 acres and ≥75% wildland vegetation cover

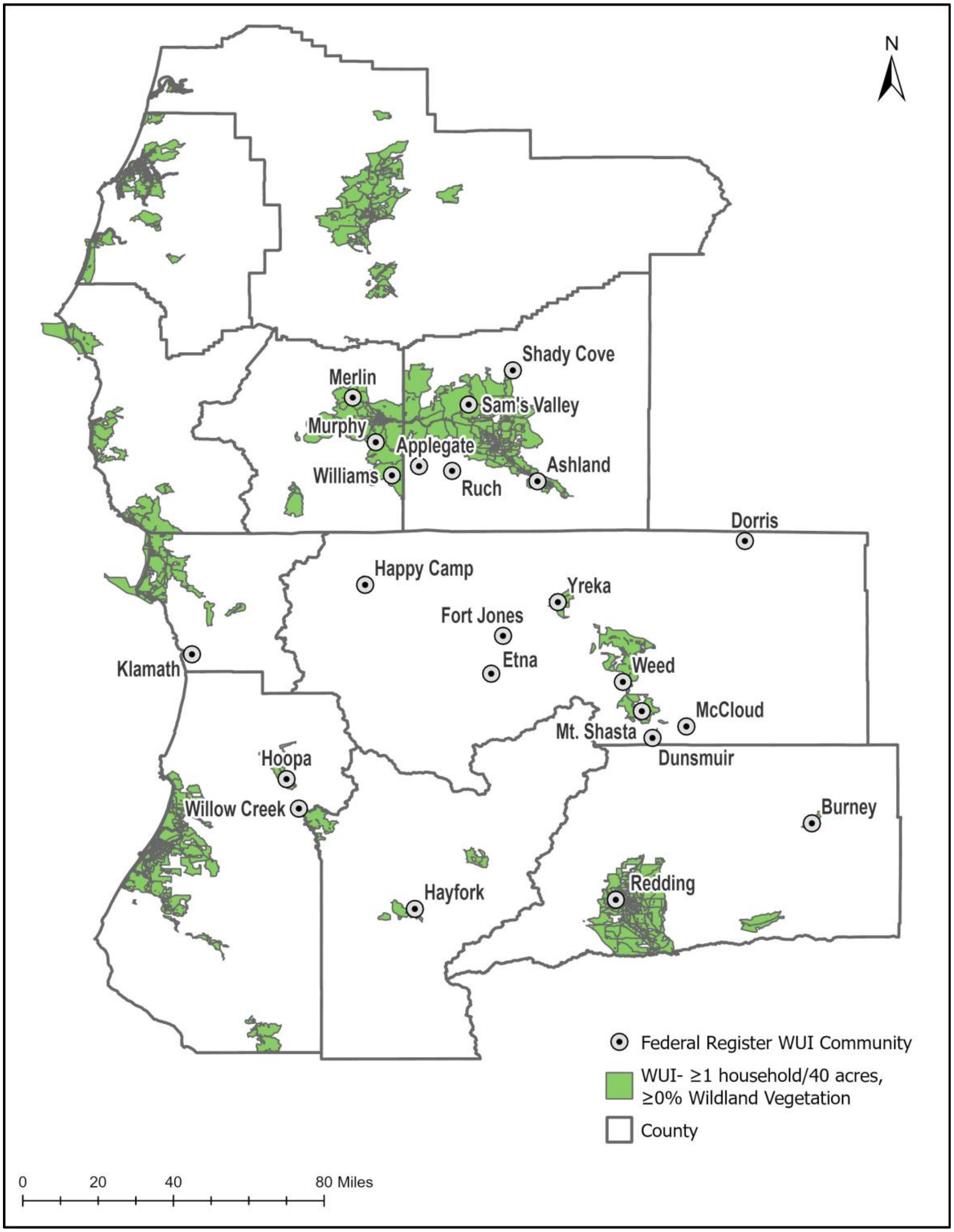
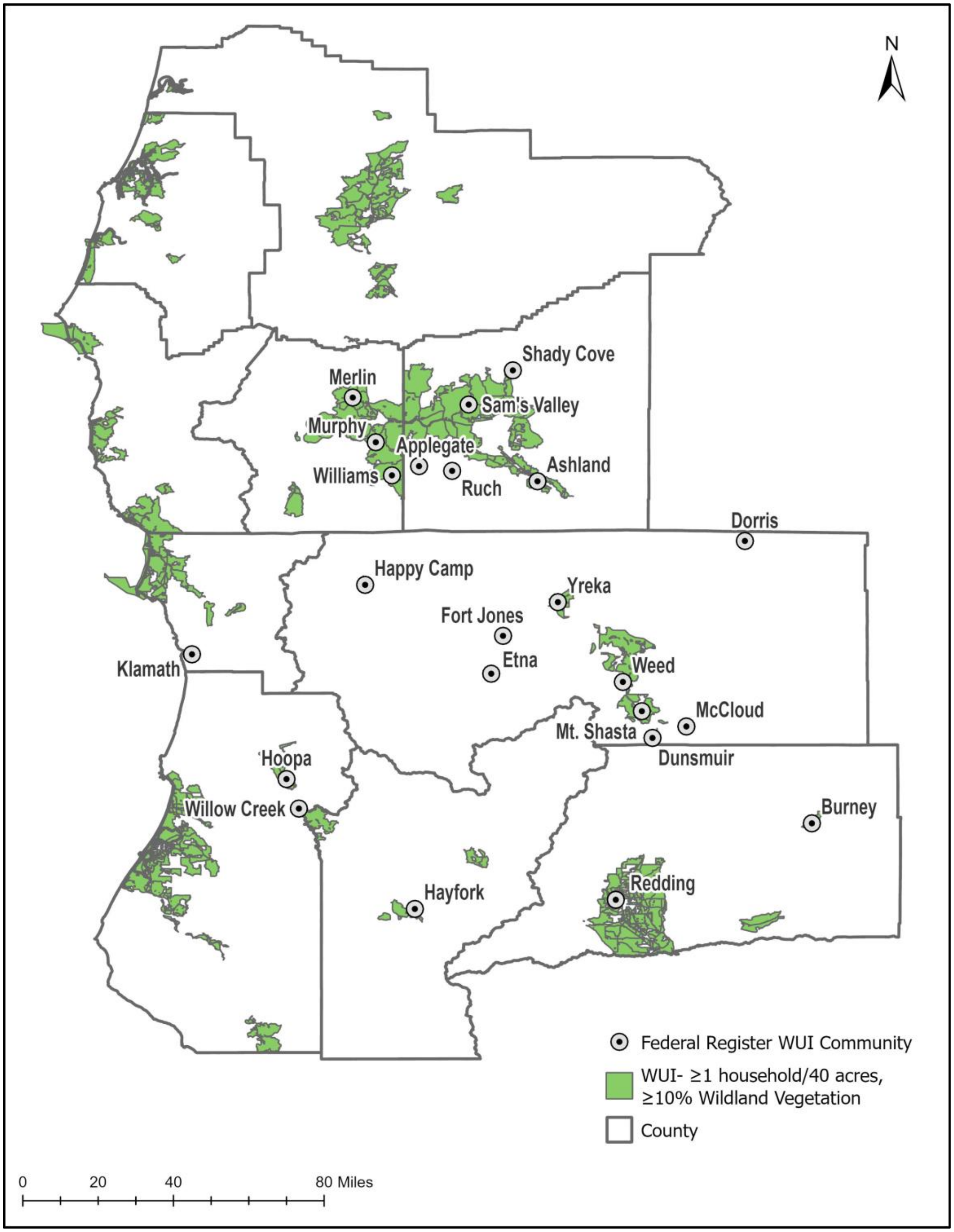


Figure 33. WUI at ≥1 household/40 acres and no minimum wildland vegetation criteria



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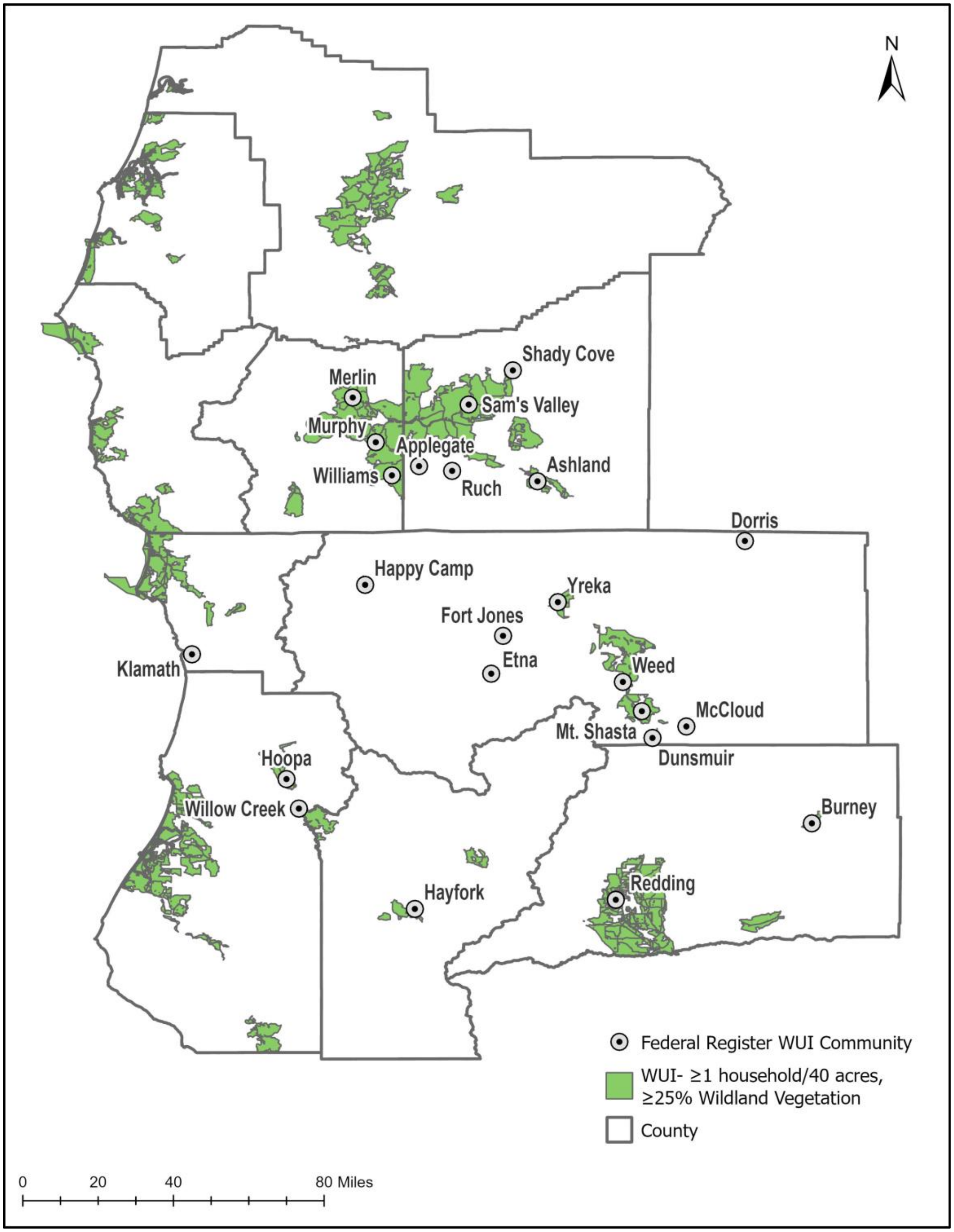

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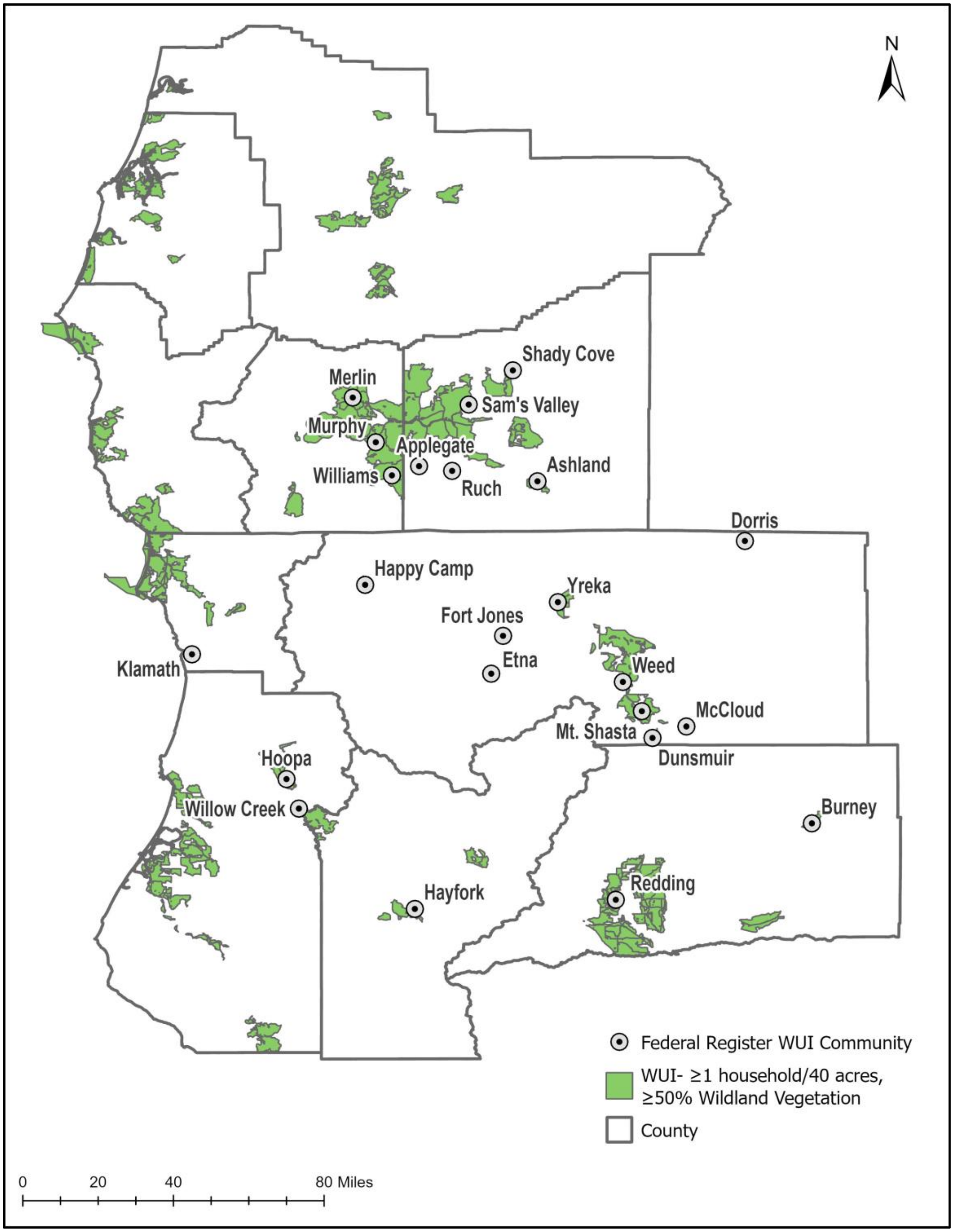

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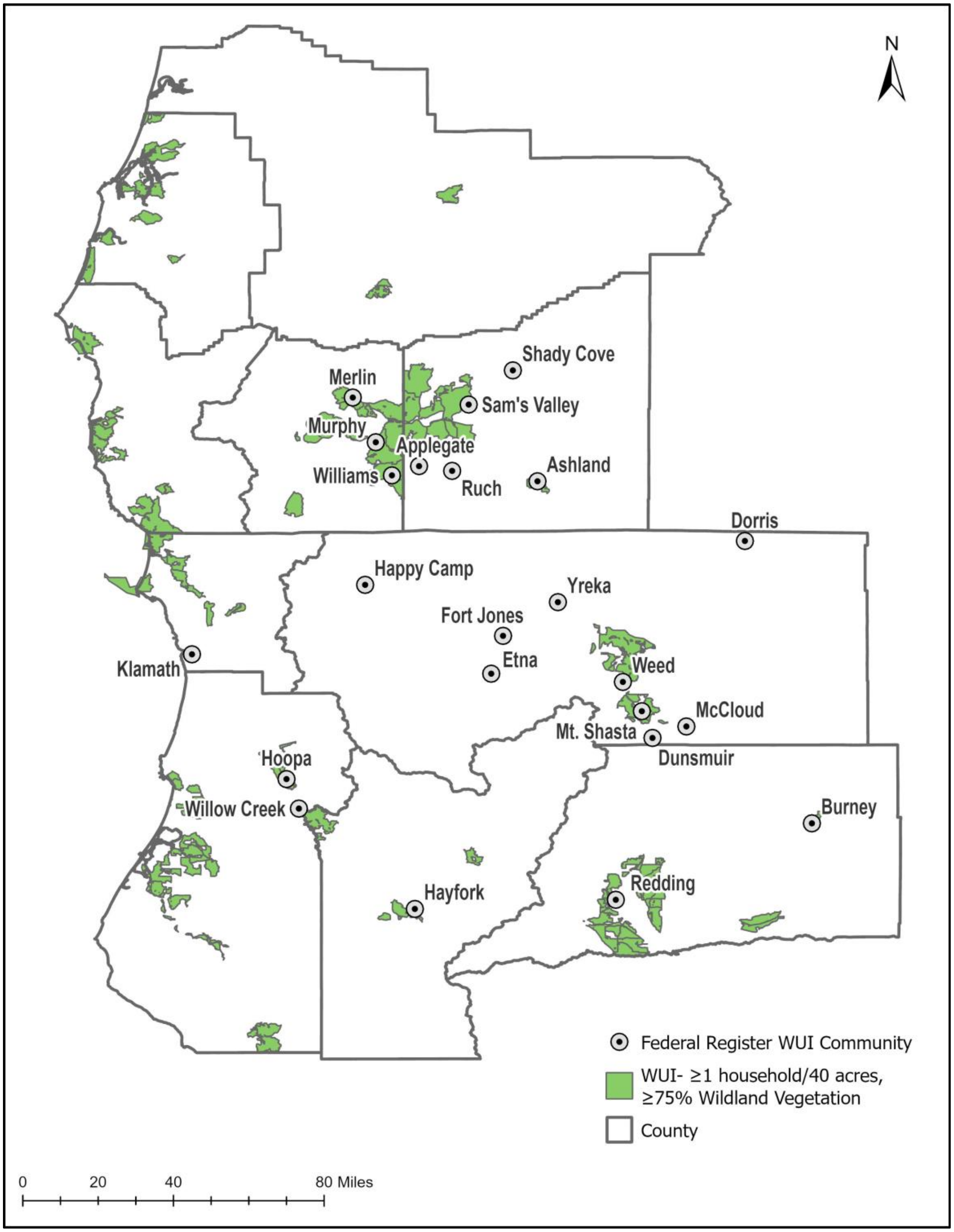

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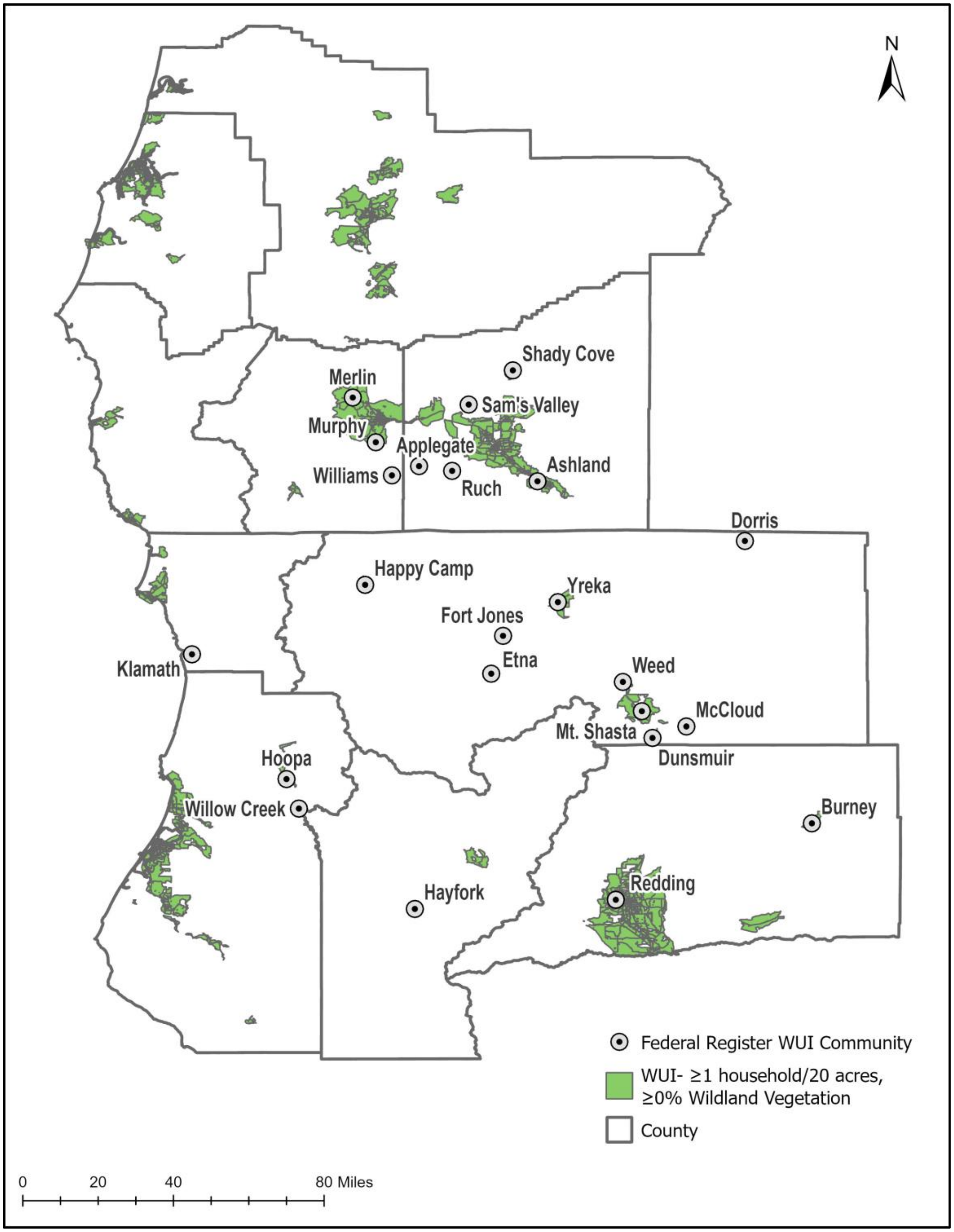

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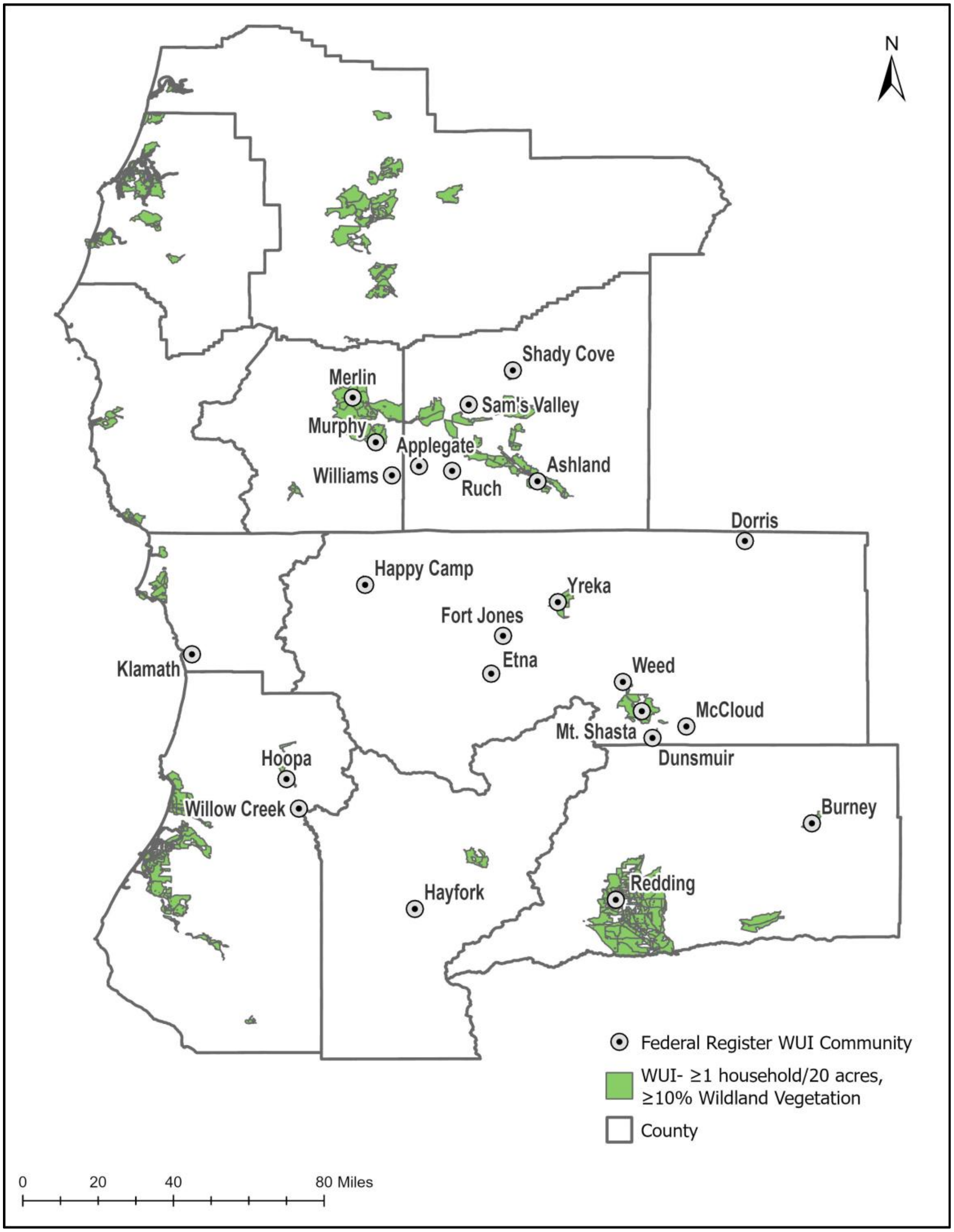

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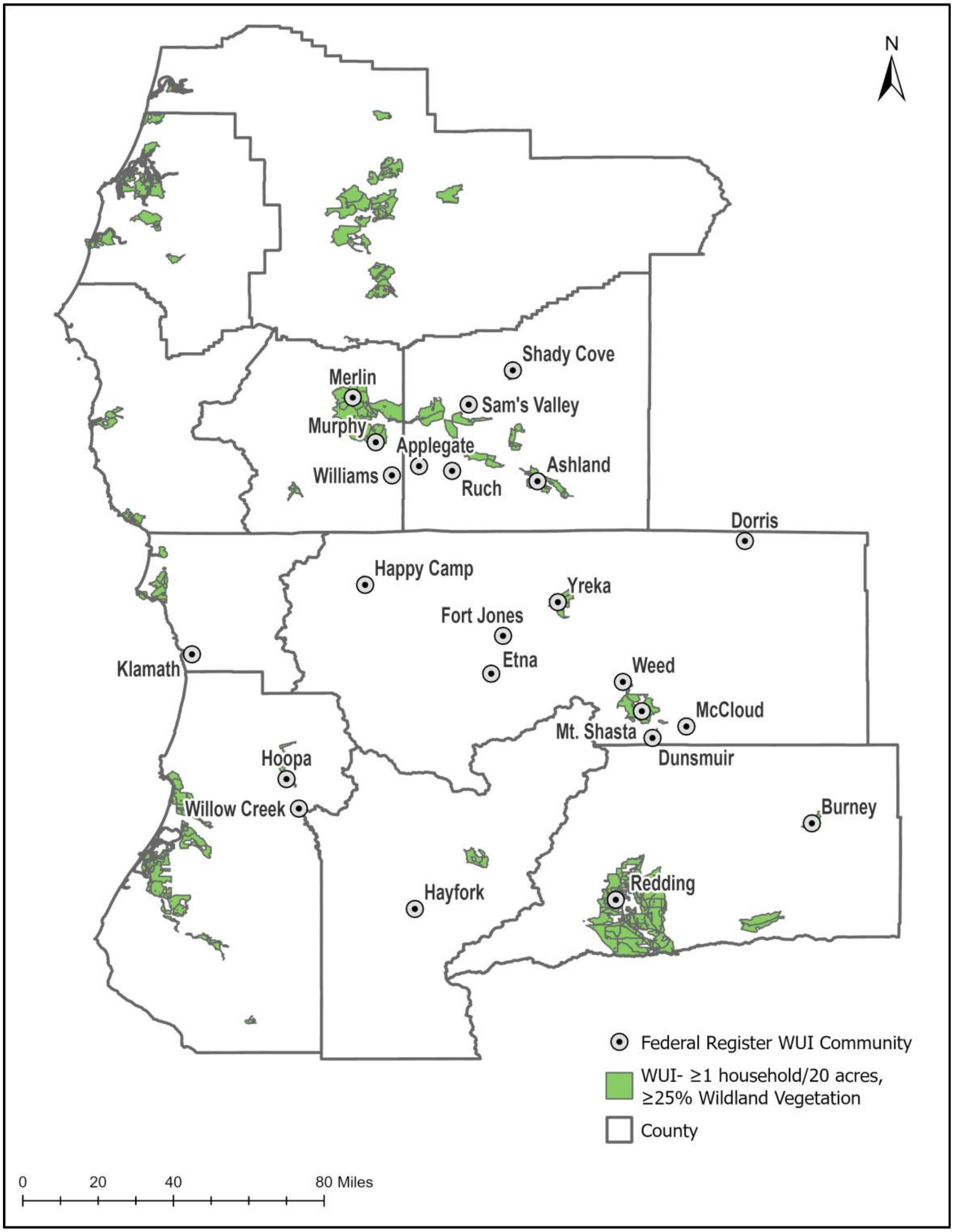

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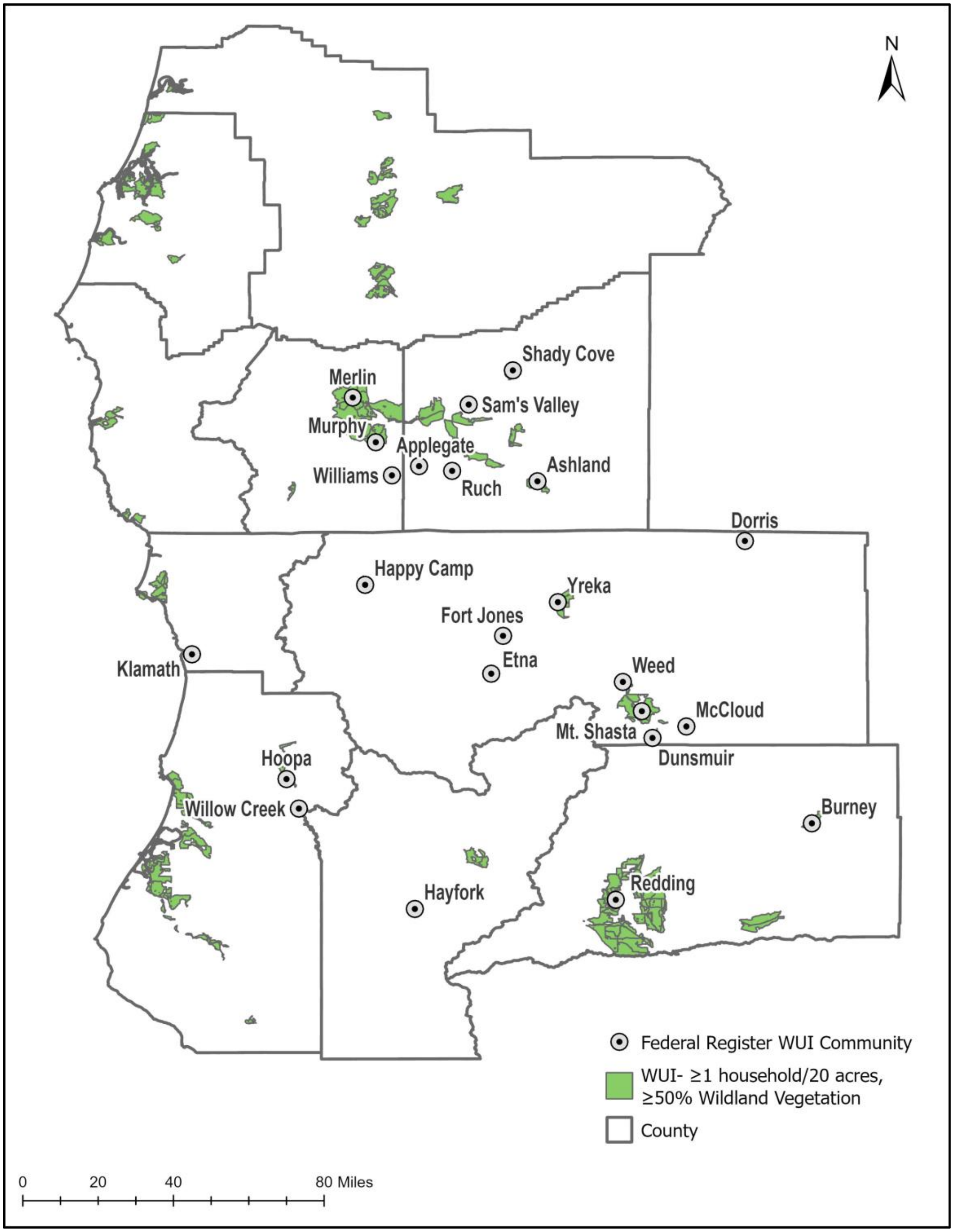

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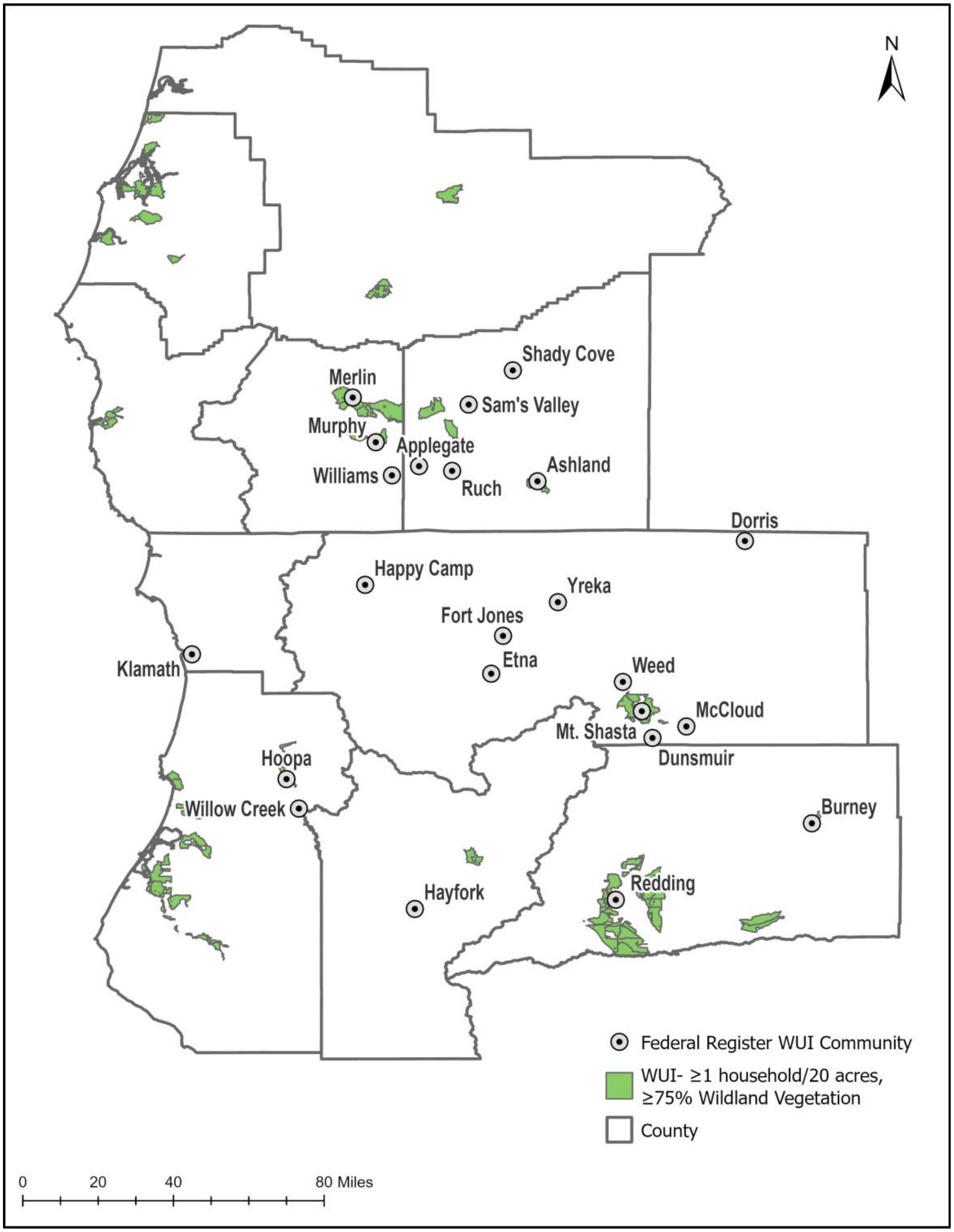

Figure 42. WUI at ≥1 household/20 acres and ≥75% wildland vegetation cover