

From Measurement to Mitigation:
Wildfire Hazard, Social Vulnerability, and Federal Funding
in the Wildland-Urban Interface

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Abstract

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This dissertation focuses on the methods used to quantify wildfire risk to communities and on the effects of the operationalization of risk on the distribution of federal funding for community-level mitigation efforts. The first chapter evaluates methods used to map the extent of the wildland-urban interface (WUI), a designation that is widely used to identify communities exposed to wildfire potential. The second and third chapters center on the federal Community Wildfire Defense Grant (CWDG) program, the criteria used by the program to determine eligibility and evaluate applications, and the program's distributional outcomes. Together, these chapters address the three determinants of wildfire risk — hazard, exposure, and vulnerability — and their use in the targeting of federal funding for risk mitigation.

The first chapter compares three existing methods for mapping the WUI — zonal, point-based, and raster — and develops an additional cadastral method that identifies human habitation based on a longitudinal dataset combining remotely-sensed building footprints with property records. I

tabulate the number of people and structures within the areas classified as WUI by these mapping methods, stratified by a measure of wildfire hazard, to estimate regional and temporal patterns in exposure to high wildfire hazard. While the methods produce a wide range of estimates, the broader trends identified are similar. The largest number of people and structures within the WUI are located in the Southern and Eastern regions, but exposure to high wildfire hazard is greatest in Southern California and Northern California. Additionally, I find that WUI growth over the period from 2000–2020 was most extensive in the Great Basin and Southwest regions. The differences between the mapping methods are significant — the raster method classifies an area 2.4 times larger than the cadastral method as WUI — and vary spatially, suggesting that local factors such as data quality should be considered when choosing a mapping approach for a given application.

The second chapter evaluates two aspects of the CWDG evaluation criteria: the spatial units commonly used to aggregate hazard and the low-income threshold used to prioritize communities. I construct an alternate set of aggregation units — place catchments — that may better characterize wildfire hazard within communities that are not designated as Census places. The program’s low-income criterion is contrasted against the CDC’s Social Vulnerability Index (SVI) to assess the degree to which the income-based threshold proxies for different aspects of community vulnerability. I find that the place catchment approach produces a different spatial distribution of hazard classes in many regions and shows better agreement with fine-scale hazard classes (produced across a 30-meter grid) than the commonly-used method of backfilling gaps between Census places with county-level hazard metrics. The low-income criterion prioritizes many at-risk communities that are not considered socially vulnerable: over 60% of the least vulnerable communities (lowest SVI decile) are considered low-income. Additionally, a significant

number of vulnerable communities exposed to wildfire hazard — particularly those whose vulnerability derives from housing characteristics, access to transportation, race, and language — are not prioritized by the low-income criterion.

The third chapter delves into the quantitative scoring rubric used to evaluate CWDG applications and the distribution of program funds based on hazard and vulnerability. To enable this analysis, I construct a dataset that matches grant applications and awards to community characteristics. I find that grant awards are largely determined by application scores, with a small amount of undocumented selection occurring among applications with marginal scores. While several of the scoring components are highly influential on grant awards, the scores assigned to the qualitative sections of grant applications are highly correlated and do not appear to capture distinct application characteristics. Communities facing the highest levels of wildfire hazard make up the majority of grant applications and awards, and higher-hazard communities that apply are more likely to be funded. However, higher levels of social vulnerability are not associated with increased odds of grant approval, and the distribution of vulnerability within the applicant and award pools is similar to the overall vulnerability distribution among at-risk communities. These findings indicate that, while the program succeeds in prioritizing grant funding in accordance with its statutory mandate, the program's evaluation criteria do not produce distributional outcomes that favor socially-vulnerable communities.

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Introduction

The wildland-urban interface (WUI), the space where human habitation meets and intermingles with wildland vegetation, has become an area of growing concern due to increasing wildfire risk. Mitigating this risk requires not only effective policy responses, but also clear understanding and measurement of the determinants of risk, which is jointly determined by *hazard*, *exposure*, and *vulnerability* (Ward et al., 2020). In this dissertation, I examine the methods used to quantify these elements of wildfire risk, as well as the implications of the operationalization of risk for the allocation of federal funding to communities.

Hazard captures the properties of a potential threat and is independent of the characteristics of people or assets that may be impacted. Wildfire hazard in the United States has increased significantly since the start of the 21st century, particularly in the West, as evidenced through both record levels of burned area (Higuera & Abatzoglou, 2020) and increasing occurrence of simultaneous significant wildfires (Podschwit & Cullen, 2020). Annual burned area in the West is projected to increase through at least 2050 (Abatzoglou et al., 2021), alongside more simultaneous wildfire activity and longer fire seasons (McGinnis et al., 2023). Much of the increase in wildfire hazard is linked to increasingly frequent and severe fire weather (Jones et al., 2022; Kalashnikov et al., 2026), although aggressive wildfire suppression policy has also exacerbated wildfire hazard

by contributing to the accumulation of fuels ([Calkin et al., 2015](#)).

Exposure quantifies the people and assets that may be affected by a hazard. Between 2000 and 2019, there was a 35% increase in the number of people exposed to wildfire (within 5 km of a large fire) in the continental United States — over 16,000 additional people each year ([Modaresi Rad, Abatzoglou, Kreitler, et al., 2023](#)). This increase in exposure is largely due to growing populations living in proximity to wildlands ([Radeloff et al., 2018](#)). The concept of the WUI reflects exposure by identifying areas where people and structures are proximate to wildland fuels, and the methods used to map the WUI can produce significantly different results ([Platt, 2010](#)).

Vulnerability captures variation in the extent to which people and assets will be affected if exposed to a hazard. Many of the WUI residents exposed to wildfire are considered to be socially vulnerable, creating additional challenges for risk mitigation. In Washington state, for example, 43.8% of residents in areas exposed to wildfire between 2000 and 2021 were considered highly vulnerable, compared to only 17.7% of the overall state population ([Modaresi Rad, Abatzoglou, Fleishman, et al., 2023](#)). In addition to concerns around the capacity of socially vulnerable populations to respond to active wildfire, socially vulnerable communities are less likely to engage in proactive wildfire mitigation activities ([Ojerio et al., 2011](#)).

This dissertation examines the measurement of wildfire hazard, exposure, and vulnerability, with an emphasis on the distributional effects of the operationalizations of risk used by the federal Community Wildfire Defense Grant (CWDG) program. This program, administered by the USDA Forest Service, is the largest federal investment in community-level wildfire risk mitigation and aims to distribute \$1 billion dollars across fiscal years 2022–2026 ([Infrastructure Investment and Jobs Act, 2021](#)). In the first chapter, I investigate methods used to map the WUI and identify communities exposed to wildfire hazard. The second chapter focuses on the eligibility and scoring

criteria used by the CWDG program, and considers alternate approaches that may better prioritize vulnerable communities for grant funding. The third chapter delves into the operation of the CWDG evaluation process, and explores the distribution of social vulnerability and wildfire hazard among applicants and grant recipients.

Summary of Chapter 1: Wildfire exposure and hazard in the wildland-urban interface

Chapter 1 examines wildfire exposure and hazard by comparing several approaches used to map the WUI, and quantifies the number of people and structures facing varying levels of wildfire hazard within the areas that each method classifies as WUI. The analysis includes a novel approach to WUI mapping that identifies the location of human settlements using the HISDAC-US dataset, which is based on remotely-sensed building footprints and property records ([Ahn et al., 2024](#)). This cadastral mapping method is contrasted against zonal ([Radeloff et al., 2023](#)), point-based ([Carlson et al., 2022](#)), and raster-based ([B. Chen et al., 2024](#)) approaches. The WUI designations produced by these methods are then stratified by hazard, represented by the Risk to Potential Structures (RPS) metric, which integrates simulations of wildfire likelihood with expected consequences to buildings ([Scott, Dillon, et al., 2024](#)). Finally, I tabulate the land area, number of people, and number of structures within each WUI-RPS intersection to track changes in values at risk over time as well as differences between mapping methods.

This analysis reveals significant variation between mapping strategies in the absolute number of people and structures each identifies as exposed to wildfire hazard, but the methods largely

agree on the relative distribution of wildfire hazard and exposure across regions. While all four methods indicate that the largest WUI area, population, and number of structures are found within the Southern and Eastern regions, stratifying by wildfire hazard shows that Southern California and Northern California have the greatest number of people and structures within the WUI facing 90th percentile RPS. The longitudinal methods — cadastral, zonal, and raster — each uncover similar growth trends, identifying the Great Basin and Southwest regions as experiencing the most extensive growth in WUI population and structures from 2000–2020. The raster-based method consistently produces the largest estimates of WUI area, followed by the point-based and zonal methods, with the cadastral method classifying the smallest area as WUI. This variation is significant — the raster-based method designates over 2.64 times more area as WUI than the cadastral method — and is driven not only by differences in the methods themselves, but also by the quality of source datasets, which varies spatially. The choice of mapping method for a particular application, therefore, should carefully consider data quality within the focal area.

Summary of Chapter 2: Assessing hazard and vulnerability metrics in community wildfire risk mitigation funding

Chapter 2 investigates the eligibility and scoring criteria used to evaluate applications to the CWDG program. Many grant applicants rely on the [CWDG Dashboard tool](#) to establish eligibility and scoring priority in their applications. The importance of this tool motivates an evaluation of its methodology for quantifying wildfire hazard within communities. While the tool aggregates wildfire hazard metrics within Census places, counties, and tribal areas, this approach

potentially distorts the measurement of hazard in certain areas, specifically within communities that are not recognized as Census places. I therefore evaluate the effect of aggregating hazard within alternative spatial units — place catchments — which fill gaps between Census places by matching all areas within the conterminous United States to their nearest Census place. Additionally, I investigate the relationship between the CWDG program’s low-income criterion and the CDC’s Social Vulnerability Index ([Flanagan et al., 2018](#)) to identify disconnects between these two representations of community need.

I find that these two design choices — the spatial units used to aggregate hazard and the use of the low-income criterion in grant evaluation — have significant consequences for determining the eligibility and prioritization of grant applications. The use of place catchments as a unit of aggregation changes eligibility and prioritization in many areas of the United States. Overall, this approach results in more accurate classification of hazard, as evaluated by comparing against hazard classes assigned at the level of 30-meter pixels. The analysis of the low-income criterion finds that 74% of at-risk Census places meet this threshold, including many communities that are not considered socially vulnerable based on the broader SVI metric. Additionally, the low-income criterion fails to identify a large number of at-risk communities with high social vulnerability — 915 of the 7,132 at-risk Census places that do *not* meet the low-income criterion are highly vulnerable (at or above 80th percentile SVI) with respect to housing & transportation characteristics and 1,746 are highly vulnerable due to the prevalence of racial minorities and individuals with limited English proficiency. The analysis shows that these two aspects of the CWDG program may not prioritize vulnerable communities facing the highest levels of wildfire hazard.

Summary of Chapter 3: Application evaluation and distributional outcomes in the Community Wildfire Defense Grant program

Chapter 3 examines the operation of the CWDG scoring rubric and the distributional outcomes that the grant evaluation process produces. Through an analysis of grant applications and awards data from the first three rounds of the program, I investigate the relationship between the scores assigned based on the application evaluation rubric and grant awards, as well as the influence and independence of rubric scoring components. I match each CWDG application to the Census places that it serves based on spatial reference points and treatment polygons included in the application data. This matched application-place dataset is then used to assess both wildfire hazard and social vulnerability within communities that appear in the applicant and award pools. Finally, I fit a logistic regression model that estimates the association between community-level hazard and vulnerability and expected award rates.

The analysis of the grant evaluation process and scoring rubric reveals that, while applications that are awarded funding generally have higher scores than those that are denied, there is a small degree of unexplained selection among applications at the scoring margin. I find that the rubric's three binary scoring criteria, which provide a scoring advantage to low-income, high-hazard, and disaster-impacted communities, function as virtual gatekeepers to grant award, especially in the program's more competitive later rounds. Additionally, the scoring criteria used to evaluate the qualitative sections of a grant application are highly correlated with one another, suggesting that they may not capture distinct application characteristics.

The distributional analysis shows that roughly half of the grant funds requested were applied for by communities facing wildfire hazard in the top decile nationwide. However, the distribution of social vulnerability among applicants is nearly uniform, indicating that more-vulnerable communities are not disproportionately self-selecting into the applicant pool. The distribution of hazard and vulnerability among grant recipients is similar to that of the overall applicant pool. Among applicants, wildfire hazard has a significant positive association with award rates, while vulnerability does not have a significant association. These results from the logistic regression model suggest that the CWDG program's evaluation process does not produce distributional outcomes that favor socially-vulnerable communities that submit grant applications.

Chapter 1

Wildfire exposure and hazard in the wildland-urban interface

1.1 Introduction

The wildland-urban interface, or WUI, is a central concept in the design and implementation of wildfire management policy. Fundamentally, the WUI represents the geographic space proximate to both human settlements and wildland fuels. People, homes, and infrastructure located within the WUI are uniquely exposed to the risks posed by wildland fires, so the identification of these areas is critical for the targeting and prioritization of wildfire risk mitigation policies. A number of methods have been developed for mapping the spatial extent of the WUI, and variation in the results of these methods can have significant implications for both the communities facing wildfire risk and the policymakers tasked with managing these risks.

While the WUI often serves as a proxy for wildfire risk in the targeting and prioritization of risk mitigation, it does not fully encompass all dimensions of wildfire risk. Formally, *risk* is

jointly determined by hazard, exposure, and vulnerability ([Ward et al., 2020](#)). The WUI identifies human habitations that are proximate to wildland fuels, and therefore functions as an indicator of *exposure* to wildfire potential. The *hazard* of wildfire is defined by its likelihood and expected intensity, neither of which are captured by WUI classifications. Wildfire *vulnerability*, which relates to the consequences of exposure, is determined primarily by the physical characteristics of exposed structures ([Affif et al., 2025](#)) and the socioeconomic characteristics of exposed residents ([Lambrou et al., 2023](#)). When assessing wildfire risk to communities, the consideration of each of these three elements facilitates better prioritization of mitigation actions, allowing resources to be allocated to areas where they will be most impactful in reducing risk.

Despite their incomplete characterization of wildfire risk, maps of the WUI are widely used to set management priorities, allocate funding for risk mitigation, and target building codes. For example, the National Cohesive Wildland Fire Management Strategy uses the number of homes within the WUI as key criterion in the prioritization of counties for community action ([Jewell & Vilsack, 2014](#)). The Healthy Forests Restoration Act of 2003 also specifically relies on the definition of the WUI to identify “at-risk communities” to be targeted for hazardous fuel reduction projects ([Healthy Forests Restoration Act of 2003, 2003](#)). Additionally, Executive Order 13728 mandates that federal buildings within the WUI at “moderate or greater wildfire risk” must conform to the International Wildland-Urban Interface Code ([Executive Office of the President, 2016](#)).

The Wildfire Risk to Communities (WRC) project, which was initiated in response to 2018 legislation directing the Forest Service to produce a set of nationwide maps of wildfire risk, attempts to capture a broader range of the determinants of wildfire risk ([Scott, Dillon, et al., 2024](#)). The WRC project has produced data products that represent wildfire hazard, through simulations of burn probabilities and fire intensity ([Dillon et al., 2023](#)), as well as exposure, through estimates

of building density, population density, and housing unit density (Jaffe et al., 2024). The intersection of hazard and exposure is reflected in the WRC project’s Community Wildfire Risk Reduction Zones, which identify areas where mitigation efforts will be most impactful (Dillon et al., 2024).

While the WRC data products represent a significant improvement over exposure-based WUI mapping methods in identifying areas facing high wildfire risk, the approach used by the WRC project has much greater data requirements than WUI mapping methods. In particular, the simulation of the likelihood and expected intensity of wildfire requires data on fuels, topography, climate, and historical wildfire occurrence (Scott, Dillon, et al., 2024). While all of these data inputs vary over time, the fuelscape is especially dynamic as it changes in response to human development, ecological succession, and past wildfires. A result of these stringent and temporally-dependent data requirements is that the WRC products represent a snapshot of wildfire risk rather than a historical timeseries.

Due to their more modest data requirements, many WUI mapping methods can be implemented across multiple points in time to produce a timeseries of exposure to wildfire risk. These changes in risk over time have important implications for managing wildfire risk to communities. Growing communities are likely to have greater *future* exposure, so these areas may be more important for risk mitigation than communities of a similar present size that are not actively expanding. Additionally, growing communities may present opportunities to employ risk mitigation strategies that are less effective in static communities. For example, policies that mandate the use of fire resistant building materials in new construction, as well as zoning policies that direct future development, are more likely to be effective in communities that are actively growing (Jewell & Vilsack, 2014).

The importance of the dimension of time motivates the development of the novel WUI map-

ping method described in this paper, as well as the evaluation of other WUI mapping methods that may be used to produce timeseries of exposure to wildfire risk. Prior studies have focused on identifying the overlap between designated WUI and burned area (Kumar et al., 2022) or destroyed structures (Kramer et al., 2019) as a way of evaluating WUI mapping methods, but a lack of prior wildfire in a given area does not preclude the possibility of future occurrence. The comparison of WUI mapping methods conducted herein, therefore, examines the intersection between the WUI and simulated wildfire hazard to evaluate the utility of these methods in identifying wildfire risk.

The present study aims to improve the assessment of wildfire risk to communities by (1) producing a set of longitudinal WUI maps using a dataset of human habitation not previously applied to WUI classification, (2) identifying areas within the WUI facing high levels of wildfire hazard, (3) tabulating values at risk over time within these areas, and (4) comparing values at risk identified by different WUI mapping methods. Through this analysis, I address the following research questions:

How do different WUI mapping methods vary in the area, population, and number of structures they classify as WUI?

How do WUI classifications produced by different WUI mapping methods intersect with simulations of wildfire hazard?

What regional WUI growth trends are identified by different WUI mapping methods?

1.1.1 Approaches to mapping the WUI

Methods for mapping the WUI have been heavily influenced by definitions originally published in 2001 by the United States departments of the Interior and Agriculture ([Department of Agriculture, 2001](#)). These definitions, which were designed to identify communities facing high levels of wildfire risk, distinguished between three types of WUI: interface, intermix, and occluded. Interface WUI is the area where human habitation directly abuts wildland vegetation; intermix WUI includes houses that are interspersed with wildland vegetation; and occluded WUI refers to wildland vegetation surrounded by developed land. The distinction between interface and intermix WUI has been preserved in subsequent WUI mapping efforts due to its management implications — significantly more structures are destroyed by wildfire in intermix than interface WUI ([Caggiano et al., 2020](#)). The occluded category, however, has not been included in subsequent WUI mapping efforts ([Carlson et al., 2022](#); [B. Chen et al., 2024](#); [Radeloff et al., 2023](#)). These categories, and the criteria that define them, have been operationalized using a number of approaches to mapping the WUI.

Fundamentally, WUI mapping methods fuse two different data sources: the location of wildland vegetation and the location of human habitations. While wildland vegetation is generally identified using raster datasets that assign each pixel on the landscape to one of a number of discrete land cover classes, WUI mapping techniques identify human habitation using a much wider variety of methods. The methods for representing human habitation can be divided into three main groups: zonal, point-based, and raster. These methods vary in their accuracy of identification, their spatial resolution, and their availability at different points in time. The characteristics of these WUI mapping techniques have important implications. Communities with

under-identified WUI may be assigned a lower priority for risk mitigation, and communities with over-identified WUI may divert resources from areas at greater risk.

Zonal methods represent human habitation as the density of development within polygonal areas. The zonal WUI maps assessed in this paper use housing densities from the U.S. Decennial Census at the level of census blocks, which are combined with landcover data from the National Land Cover Dataset, to identify interface and intermix WUI classes for 1990, 2000, 2010, and 2020 ([Radeloff et al., 2023](#)). While this set of WUI maps is widely used, a disadvantage of the zonal approach is that it assumes a fixed housing density within the entire census block, which may limit the ability of this method to accurately identify WUI in large heterogeneous census blocks, such as those commonly found in rural areas. Additionally, the housing densities used in this type of WUI classification do not include non-residential structures.

The point-based approach to WUI mapping uses discrete spatial points to represent the location of structures. In my comparative analysis, I assess the WUI map developed in Carlson et al. ([2022](#)), which identifies WUI based on Microsoft's [US Building Footprints](#) data, which are classified from satellite imagery. While point-based methods improve upon zonal methods by avoiding the assumption of constant structure density within spatial units, they are limited by the availability of structure location data, which is generally not available at different timesteps. Although up-to-date building locations are desirable for identifying current WUI, they are not able to discern WUI growth, which is also important for targeting mitigation policy.

Raster methods identify human habitation using fixed-size pixels (e.g., 30x30 meters) that represent the intensity of development. The availability of global datasets of built-up area derived through the classification of satellite imagery, including the Global Human Settlement Layer ([Pesaresi & Politis, 2023](#)) and GlobeLand30 ([J. Chen et al., 2015](#)), has enabled the production of mul-

multiple global WUI products ([B. Chen et al., 2024](#); [Guo et al., 2024](#); [Schug et al., 2023](#)). However, a disadvantage of these built-up area datasets is that they do not count discrete building locations, but rather the proportion of each cell that is identified as within the perimeter of a building. In my comparative analysis, I assess the global longitudinal WUI maps developed in [B. Chen et al. \(2024\)](#), which use the Global Human Settlement Layer to identify human habitation.

While the zonal, point-based, and raster methods described above fully rely on data from either the Decennial Census or satellite imagery, the cadastral method I develop in this paper also incorporates data from property records and real estate transactions. To construct these cadastral WUI maps, I use structure density rasters from the Historical Settlement Data Compilation for the United States (HISDAC-US), which combines building footprint data, parcel data, and property records ([Ahn et al., 2024](#)). Using this dataset to represent human habitation allows for the creation of WUI maps that capture variation over time — enabling the measurement of WUI growth — while avoiding the constant structure density assumption imposed by zonal methods as well as the disconnect between built-up area and discrete structure counts that is inherent to raster approaches.

1.2 Methods

In this study, I produce a set of longitudinal WUI maps for the conterminous United States (CONUS) at a 30-meter scale by pairing data on structure density from HISDAC-US with data on wildland vegetation from the National Land Cover Dataset (NLCD). These datasets are used to identify areas of intermix and interface WUI by applying methods adapted from [Bar-Massada et al. \(2013\)](#) to use structure density rasters rather than discrete building locations. I spatially

intersect these WUI classifications with data on wildfire likelihood and expected intensity from the WRC project ([Scott, Dillon, et al., 2024](#)) to identify areas within the WUI that also face high wildfire hazard.

I then tabulate, across a 10-km grid that covers the CONUS, the area, population, and number of structures within each of these WUI-hazard classes. This scale allows for the identification of broad patterns in the distribution and growth of the WUI. These tabulations of values at risk are produced for cadastral, zonal, point-based, and raster WUI maps, enabling comparisons both over time and between mapping methods. Additionally, I conduct regional assessments by aggregating these estimates of values at risk within the boundaries of Geographic Area Coordination Centers (GACCs). The GACC is an important spatial unit for wildfire management because wildfire suppression resources are pooled within and shared across GACCs ([Jarvis, 2010](#)).

1.2.1 Data

The wildfire risk maps produced in this study are constructed from datasets representing land cover, structure density, population density, and estimates of wildfire likelihood and expected intensity. These datasets are combined to identify values at risk within the CONUS, taking into account both the exposure and hazard dimensions of wildfire risk. A timeseries of wildfire risk maps is created for 2000, 2005, 2010, 2015, and 2020. Fig. [1.1](#) illustrates each of the input datasets for the area around Bend, Oregon.

I use the NLCD Annual dataset ([United States Geological Survey, 2025](#)) to identify the wildland vegetation used to classify WUI areas. This dataset is produced for each year from 1985 to 2024 at a 30-meter resolution and uses an ensemble of algorithms to classify Landsat imagery into 16

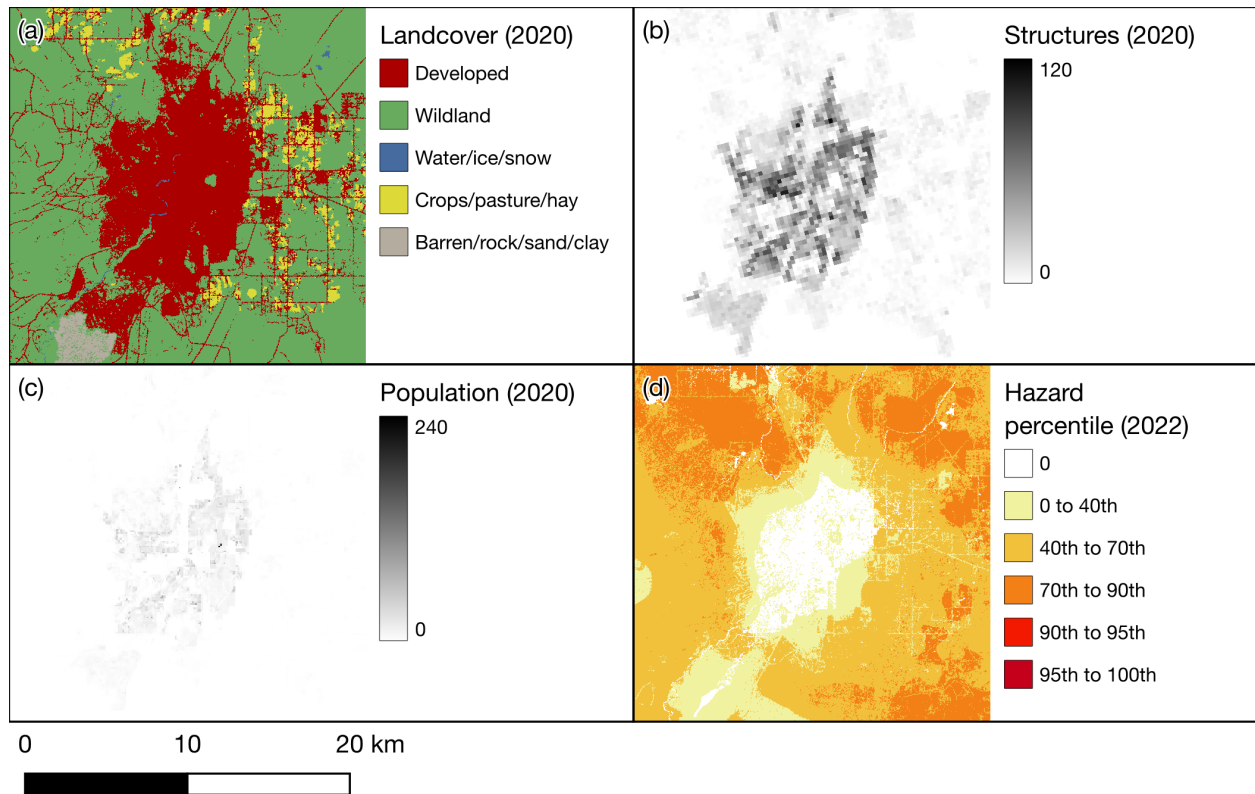


Figure 1.1: Data layers used to identify values at risk within the WUI for the area around Bend, Oregon. Panel (a) shows landcover classes derived from National Land Cover Dataset (NLCD) classifications. Panel (b) shows the number of structures within each 250-meter pixel identified in the HISDAC-US built-up property locations (BUPL) dataset. Panel (c) shows the number of people within each 100-meter pixel, as estimated by the WorldPop dataset. Panel (d) shows the percentile of risk to potential structures (RPS) within the CONUS, as estimated by the Wildfire Risk to Communities (WRC) project.

different land cover classes ([U.S. Geological Survey, 2024](#)). The annual availability of this dataset represents a significant improvement over prior NLCD data products, which were released at 2–3 year intervals ([U.S. Geological Survey, 2025](#)), and ensures that the landcover data are temporally aligned with other source datasets.

This study uses the HISDAC-US dataset ([Ahn et al., 2024](#)) to identify the location of built structures. HISDAC-US integrates data from multiple sources — parcel data from ParcelAtlas, property records from ZTRAX, and building footprints from OpenCityModel — to construct a longitudinal dataset of historical settlement from 1810 to 2020 at five-year timesteps. Three of the HISDAC-US data products are used in the analysis: Built Up Property Locations (BUPL), Built Up Property Records (BUPR), and the No Built Year (NBY) raster. The BUPL dataset represents the number of *structures* within each 250-meter grid cell and is used to calculate the building densities that distinguish the WUI from wildlands. The Built Up Property Records (BUPR) dataset, in contrast, represents the number of property *records* in each grid cell. In multi-family buildings and apartments, multiple records may be associated with the same physical structure; the BUPL dataset collapses these multiple BUPRs into a single entry per structure.

The WUI classification method implemented in this study is sensitive to omissions in the BUPL timeseries. There are two reasons why a structure may be omitted from the BUPL timeseries. First, structures that are not represented in any of the three source datasets used to build HISDAC-US will not appear in the BUPL timeseries. Second, structures whose built-year is missing in their associated property records are not included in any of the BUPL timesteps. The magnitude of the full-omission problem cannot be identified from the HISDAC-US datasets without an external reference. For this purpose, I employ housing unit counts from the Decennial Census. To estimate omissions due to missing built-year data, I use the NBY raster, which repre-

sents the number of records without built-year data. Built-year missingness rates for BUPRs can be calculated as $NBY/(NBY + BUPR)$. Because each BUPR is associated with at most one BUPL, this BUPR-level rate represents an upper bound on the BUPL built-year missingness rate.

To assess wildfire hazard, I use a metric called *risk to potential structures* (RPS) produced as part of the WRC project (Scott, Dillon, et al., 2024). RPS represents expected losses for each 30-meter pixel and is based on annual burn probabilities and the potential consequences to structures, assuming that structures are present within the pixel. The annual burn probabilities used to calculate RPS are derived from Dillon et al. (2023), which simulates wildfire likelihood across a 270-meter grid based on 2022 fuels from LANDFIRE (La Puma, 2023) and observed weather from 2004–2018 using the FSim software (Finney et al., 2011). Scott, Dillon, et al. (2024) upsamples these simulated burn probabilities to a 30-meter grid and performs a post-processing step that “oozes” wildland burn probabilities into adjacent developed areas. The oozing procedure addresses a limitation of FSim that assigns developed areas a burn probability of zero, as these pixels are marked in LANDFIRE as “non-burnable” since fuel models for housing areas have not yet been developed. After applying these burn probability adjustments, the risk to potential structures metric is constructed by multiplying the likelihood of wildfire by its expected consequences, which are simulated using the WildEST software (Scott, Moran, et al., 2024).

To quantify the WUI population at risk, I use gridded population data from the unconstrained WorldPop dataset (Stevens et al., 2015). This dataset uses dasymetric methods to downscale population estimates from the U.S. Census Bureau to a 100-meter grid and is available for every year from 2000 to 2020. Dasymetric methods use ancillary datasets on the location of roads, infrastructure, nighttime lights, and other factors to distribute population estimates across a spatial grid that is more fine-grained than the original sampling units (Leyk et al., 2019).

1.2.2 Cadastral WUI mapping

Wildland vegetation cover and structure density — the two determinants of WUI classifications — are calculated for each pixel within a circular neighborhood centered around that pixel. A key consideration in this WUI mapping method, therefore, is selecting an appropriate neighborhood size. While a number of neighborhood sizes have been evaluated for WUI mapping ([Caggiano et al., 2020](#)), the most commonly used radius is 500 meters ([Bar-Massada et al., 2013](#); [Carlson et al., 2022](#)). For consistency with these prior studies, I also employ a circular kernel with a radius of 500 meters.

The first step in creating the WUI maps is to assign a proportion of wildland vegetation cover to each pixel. To calculate wildland vegetation cover, the NLCD classifications for each 30-meter pixel are recoded to a binary wildland vegetation indicator, according to classification rules consistent with prior WUI mapping methods ([Stewart et al., 2003](#)). The proportion of wildland vegetation cover for each 30-meter pixel is then calculated within a 500-meter neighborhood centered around the focal pixel.

The second step in creating the WUI maps is to identify contiguous areas of heavily-vegetated wildlands. Using the threshold for heavily-vegetated areas applied in [Radeloff et al. \(2005\)](#), I exclude pixels with less than 75% vegetation cover within their 500-meter neighborhood. The remaining pixels are then grouped into spatially-contiguous areas, and only areas that are at least 5 square kilometers are retained.

The third step in determining WUI classifications is to calculate the structure density for each pixel. Structure density is calculated as the sum of structures within the 500-meter neighborhood centered around each 250-meter pixel in the BUPL dataset, which is the native resolution of

the HISDAC-US data. This structure density is then resampled to a 30-meter grid to match the other data layers. I refer to the definitions from the Federal Register to set the structure density thresholds. Since the neighborhood area is equal to roughly 194 acres, I apply a density threshold of 4.85 structures per neighborhood for the classification of both interface and intermix WUI. This lower bound corresponds to the Federal Register definition that specifies a minimum of one structure per 40 acres.

With wildland vegetation density, structure density, and areas of heavily-vegetated wildlands identified, I assign the WUI classifications for the neighborhoods centered around each 30-meter pixel. Neighborhoods that contain at least 50% wildland vegetation and meet the minimum structure density threshold are designated as intermix WUI. Neighborhoods with less than 50% wildland vegetation that meet the minimum structure density and are within 2.4 kilometers of contiguous patches of heavily-vegetated wildlands are designated as interface WUI.

In addition to producing cadastral WUI maps at each timestep using the BUPL structure data, I conduct a sensitivity analysis using a WUI map constructed using structure densities calculated based on the sum of the 2020 BUPL and NBY rasters. Including property records without built-year data — represented by the NBY raster — provides perspective on the magnitude of data missingness issues in the HISDAC-US dataset. In several ways, summing 2020 BUPL and NBY *overestimates* structure density. Because NBY counts property records rather than structures, multi-unit buildings inflate the calculated structure densities. Additionally, the NBY raster may include structures built after 2020 but before HISDAC-US was updated in 2021. However, the approach of including NBY records can only address built-year missingness; it cannot account for buildings that are omitted entirely from the source datasets that HISDAC-US is compiled from. To address this full-omission problem, I construct a data quality mask that flags areas where no

property records are available in the HISDAC-US datasets, but housing unit counts from the Decennial Census are nonzero.

1.2.3 Identifying values at risk

After producing cadastral WUI maps for each timestep, I tabulate the area, as well as the number of people and structures, exposed to various degrees of wildfire hazard within each WUI class (see Fig. 1.2). Wildfire hazard is stratified by RPS percentile within the CONUS, so each hazard class captures both the likelihood and expected intensity of wildfire. These tabulations are calculated for each 10x10 km grid cell within the CONUS. To enable comparison between WUI mapping methods, I construct analogous tabulations for the zonal, point-based, and raster WUI maps.

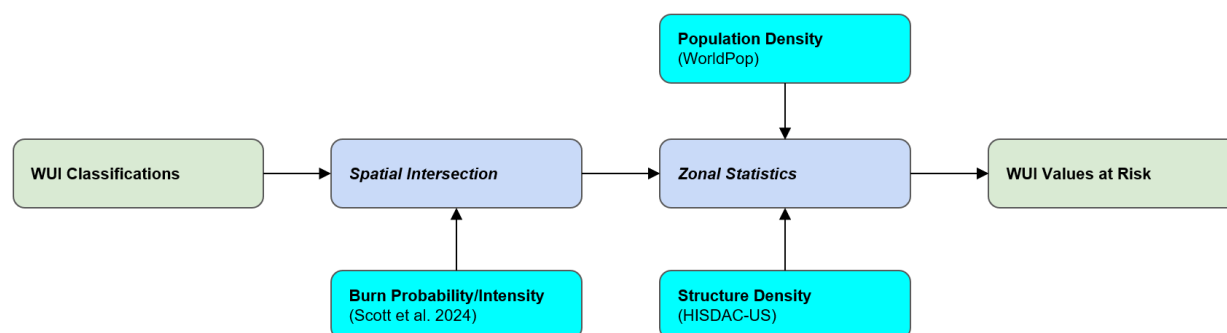


Figure 1.2: Flowchart of methods used for identifying values at risk. WUI classifications from each of the mapping methods are spatially intersected with estimates of wildfire hazard (quantified by the risk to potential structures metric) to produce WUI-hazard classes. The spatial extent, as well as the number of people and structures within these classes, is then tabulated across a 10-km grid to produce a dataset of WUI values at risk.

These tabulations form the basis for subsequent analyses. In addition to comparing the levels and trends in values classified as WUI by each mapping method, both across the entire CONUS and within regions, I examine the relationship between WUI classifications and wildfire hazard using conditional probabilities. These conditional probabilities represent (1) the proportion of

values classified as WUI that are exposed to high wildfire hazard, and (2) the proportion of values exposed to high wildfire hazard that are classified as WUI, and are calculated using the following formulas:

$$P(RPS|WUI) = P(RPS \cap WUI)/P(WUI)$$

$$P(WUI|RPS) = P(WUI \cap RPS)/P(RPS)$$

1.3 Results

1.3.1 Cadastral WUI maps

The cadastral method classifies a total of 470,406 km² as intermix WUI and 180,061 km² as interface WUI in 2020, representing 6.14% and 2.35% of total CONUS land area, respectively (Fig. 1.3). Intermix WUI is visible across wide swaths of the eastern United States, from the Northeast into the South, as well as in more dispersed pockets throughout the West. Interface WUI is difficult to identify at this scale since it exists only in narrow bands around developed areas. Areas designated as wildland dominate the West; these areas have at least 75% wildland vegetation cover and may contain structures, but not at a high enough density to be classified as WUI. Areas designated as non-WUI have insufficient wildland vegetation cover to be classified as intermix WUI or are not close enough to contiguous patches of wildland vegetation to be classified as interface WUI. In addition to urban areas, areas that are predominantly agricultural, such as much of the Midwest, are classified as non-WUI.

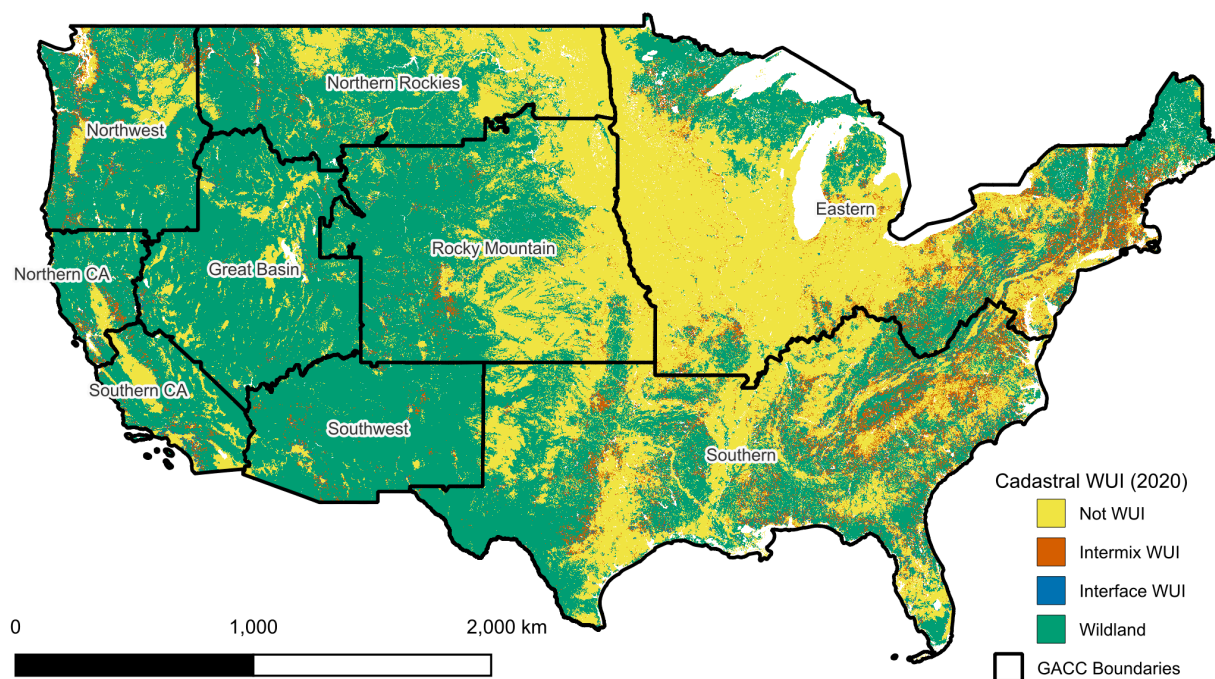


Figure 1.3: WUI classifications for the conterminous United States for 2020 produced using the cadastral mapping method. Intermix WUI is concentrated in a band along the East Coast as well as in pockets throughout the West. Sparsely settled areas in the West are classified as wildlands, while less-developed areas in the Midwest are instead dominated by croplands. Geographic Area Coordination Center (GACC) boundaries, which serve as the units for regional analyses, are outlined in black.

The cadastral WUI map constructed using structure densities based on the sum of the 2020 BUPL and NBY rasters (Fig. 1.4) shows that the impact of built-year missingness in the BUPL dataset on WUI classifications is significant. The substantially larger WUI area classified using the combined BUPL and NBY datasets is likely an overestimate in many areas, but approximates an upper bound within areas where property records are included in HISDAC-US. The area classified as intermix WUI using this approach is nearly 2.6 times larger than in the classifications produced using 2020 BUPL alone, totalling 1,221,822 km². Interface WUI increases by a factor of 1.85, totalling 333,927 km². The relative increase in area classified as WUI is most dramatic in the Northern Rockies, where total WUI area quadruples. Even in the Northwest, where the relative increase was most modest, the area classified as WUI nearly doubles.

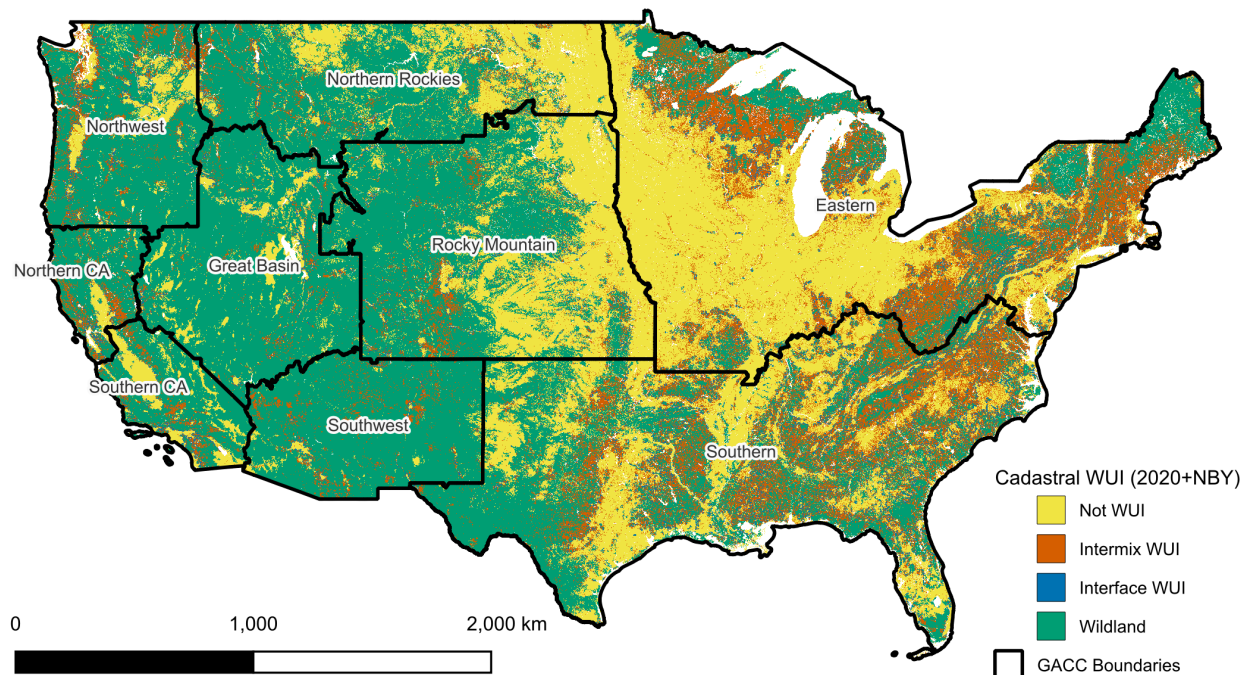


Figure 1.4: Cadastral WUI classifications with structures calculated based on the sum of the 2020 BUPL and NBY layers. This approach approximates an upper-bound on the extent of the WUI by including property records with missing built-year, but likely overclassifies WUI in many areas.

The BUPR data quality map shows that large parts of the CONUS have built-year missingness rates of 100% in the HISDAC-US dataset (Fig. 1.5). Within these areas, shaded in magenta, property records are present but contain no built-year data. WUI within these areas is therefore absent from the timeseries but is included in the 2020 map based on the BUPL and NBY rasters. Green areas contain no property records (with or without built-year data) but also have no housing units recorded in the 2020 Decennial Census data. The absence of structures from the HISDAC-US data in these areas is therefore unlikely to be due to missing data. Red shading indicates areas that have housing units in the Census data but no property records — representing complete missingness in the HISDAC-US data. Areas along the blue–yellow gradient have property records with built-year missingness varying from 0% (blue) to 100% (yellow). The extent of the WUI in areas with high built-year missingness is likely underestimated in the cadastral timeseries.

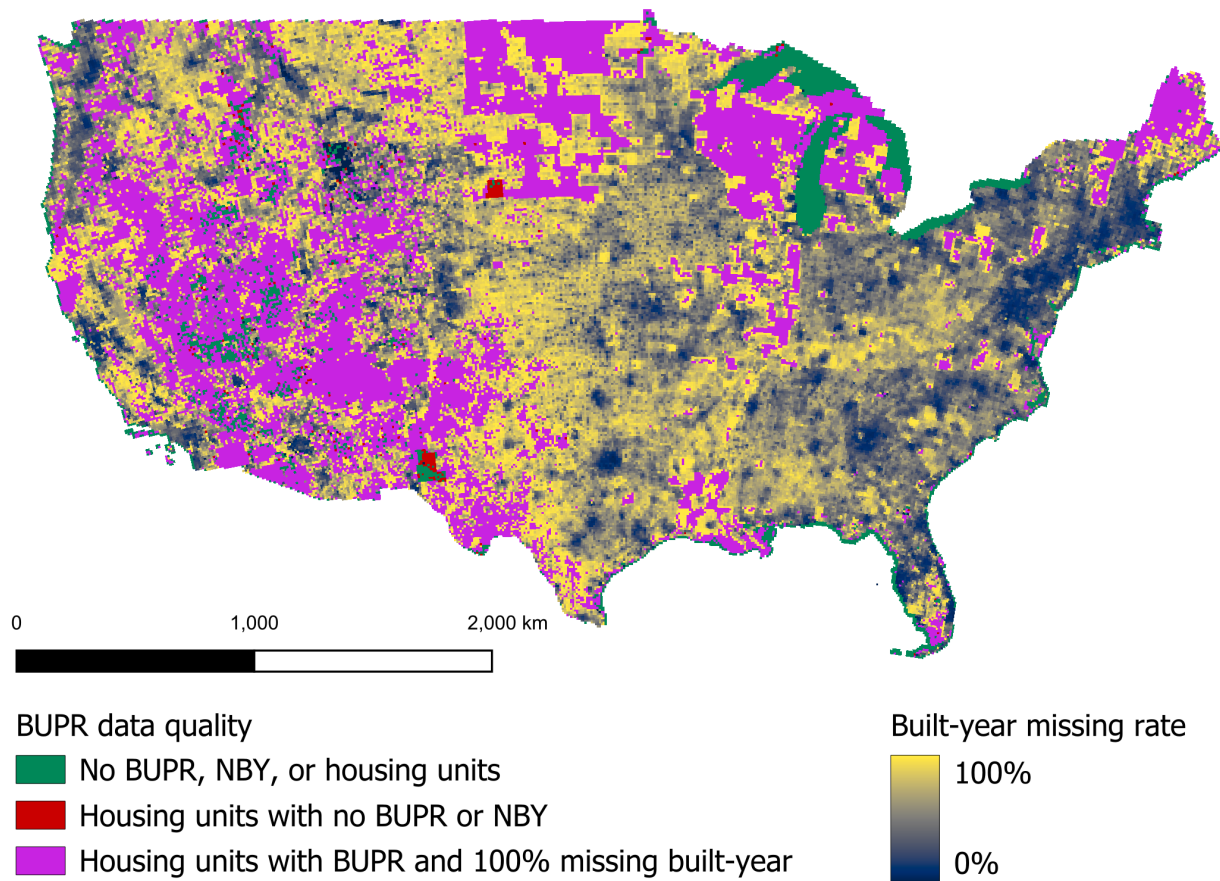


Figure 1.5: Data quality for the BUPR raster. Green areas contain no property records, but also have no housing units in the 2020 Decennial Census. Red areas contain no property records, but have housing units. Magenta areas contain property records, but no data for built-year. Areas along the blue–yellow gradient have property records with built-year missingness indicated by the position along the gradient (blue = 0% missing, yellow = 100% missing).

1.3.2 Comparison of WUI maps

At finer spatial scales, several key differences between the methods are visible. Fig. 1.6 compares WUI classifications for the area around Bend, OR generated using the cadastral, zonal, raster, and point-based methods. First, variation in the choice of spatial unit used for classification is apparent. WUI classification using the zonal method is performed at the level of census blocks, so fine-scale variation that is resolved by the other methods is not present in the zonal map. This effect can be seen in the mountainous area in the northeast quadrant of the map, where the zonal method classifies the eastern slope as intermix WUI while the other methods do not.

Another significant difference is in the classification of the agricultural areas in the eastern half of the map. Unlike the other mapping methods, the zonal method does not classify this area as interface WUI because the structures here are not counted as housing units in the Decennial Census, while non-residential structures are included in the source datasets for the other mapping methods. There is also notable variation in the designation of interface WUI surrounding the urban core of Bend, in the southwest quadrant of the map. The zonal and raster methods identify similarly-sized bands of interface WUI, while the point-based method produces an interface zone that extends farther into the developed area. This discrepancy may be due to the use of 2016 landcover data in the point-based map, which could indicate a higher density of wildland vegetation than was present in later years.

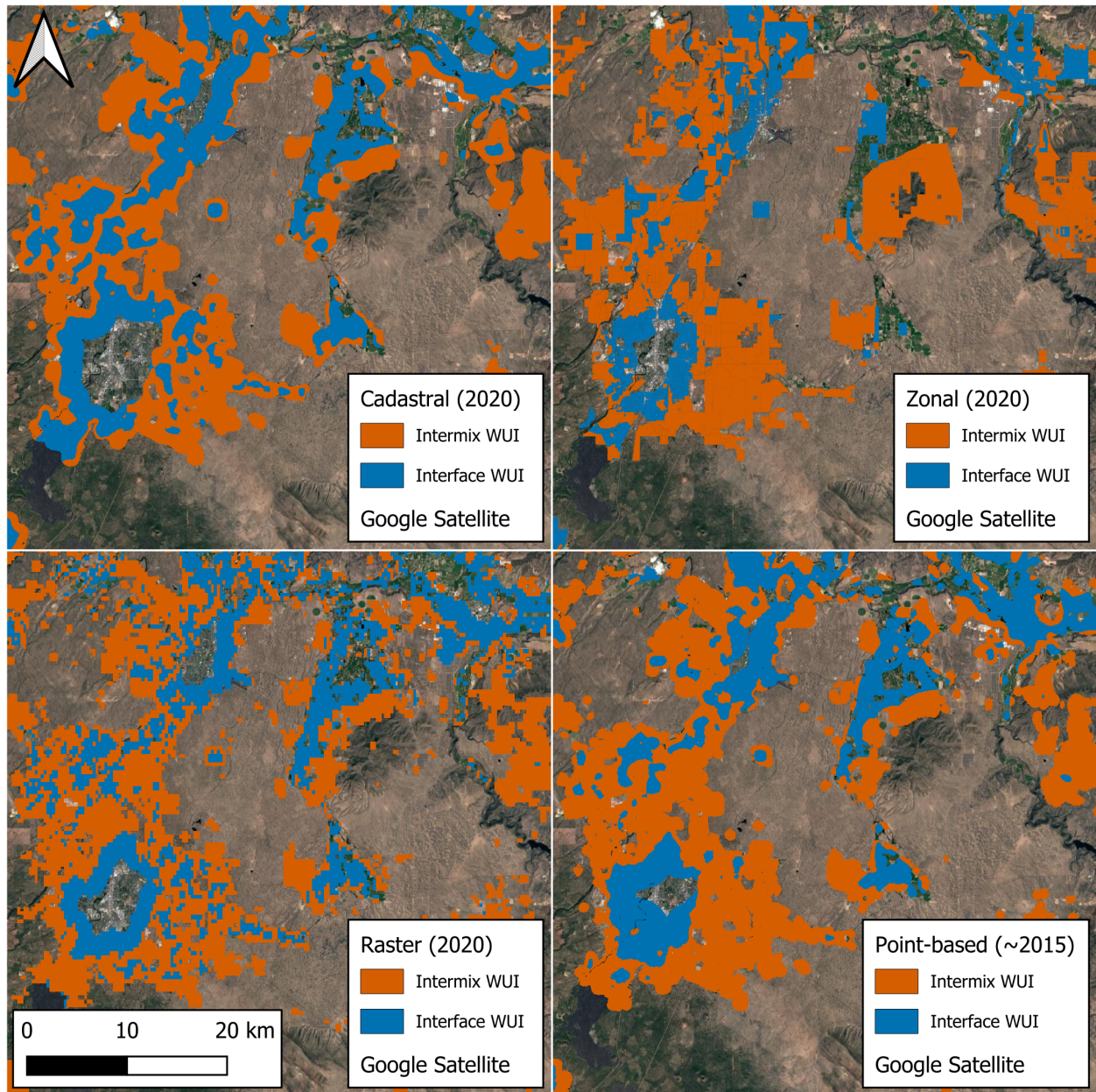


Figure 1.6: Fine-scale comparison between WUI mapping methods for Bend, OR and the surrounding area. Variation in the spatial units used by each classification method is especially visible in the mountainous area to the northeast. The methods also vary in their classification of the urban core to the southwest and the agricultural areas to the east.

1.3.3 Comparison of values at risk

At CONUS-scale, the four WUI mapping methods vary considerably in the area, population, and number of structures that each method classifies as intermix or interface WUI in 2020 (Fig. 1.7). The total area classified as WUI in 2020 — both intermix and interface, at all levels of wildfire hazard — by the cadastral method is 650,466 km² (8.49% of total CONUS land area), which is slightly less than the zonal method (755,800 km² or 9.86% of total CONUS land area). The raster and point-based methods classify significantly more area as WUI: 1,718,362 km² (22.42% of total CONUS land area) and 1,240,432 km² (16.18% of total CONUS area), respectively.

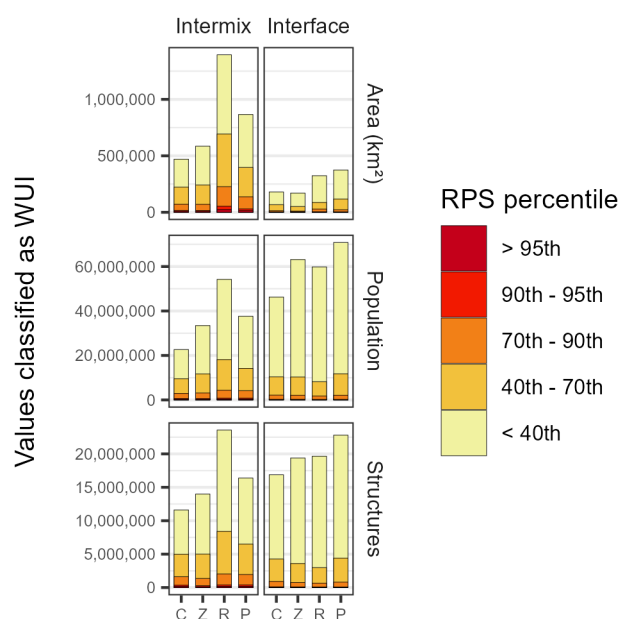


Figure 1.7: Comparison of 2020 values at risk between WUI mapping methods. Subplots show the area, population, and number of structures within intermix and interface WUI, as classified by the cadastral, zonal, raster, and point-based methods (labeled as C, Z, R, and P). The shading of the stacked bars indicates the degree of wildfire hazard faced by the values in each column. The lightest shading (beige–yellow) represents values facing the lowest wildfire hazard (below the 40th percentile of nationwide risk to potential structures), while orange and red indicate values facing high wildfire hazard.

The differences between the methods in their estimation of WUI population and structures are smaller than the differences in the area that each classifies as WUI. While the raster and point-based methods classify 2.64 times and 1.91 times as much total WUI area than the cadastral method, respectively, the number of people these methods classify as living with the WUI are only 1.65 times and 1.57 times higher. The number of structures classified as WUI vary even less between the methods: the raster and point-based method classify 1.52 times and 1.38 times more structures as WUI than the cadastral method.

The stratification of values at risk by wildfire hazard shows that the majority of values at risk within the WUI face low levels of wildfire hazard relative to the CONUS overall. For example, only 2,921,107 of the 22,653,529 people (12.89%) living in areas classified as intermix WUI by the cadastral method in 2020 face wildfire hazard at or above the 70th percentile.

Disaggregating the CONUS-scale tabulations of values at risk reveals significant variation between regions. As illustrated by the top panel of Fig. 1.8, all four of the mapping methods identify the Southern and Eastern geographic areas as having the largest WUI population, number of structures, and area. These two regions also have a much larger proportion of their WUI populations living within the intermix, as compared to the other regions. The bottom panel of Fig. 1.8 shows that while the Southern region has vastly more people and structures exposed to 70th percentile RPS, Southern California and Northern California have the greatest number of people and structures facing 90th percentile RPS.

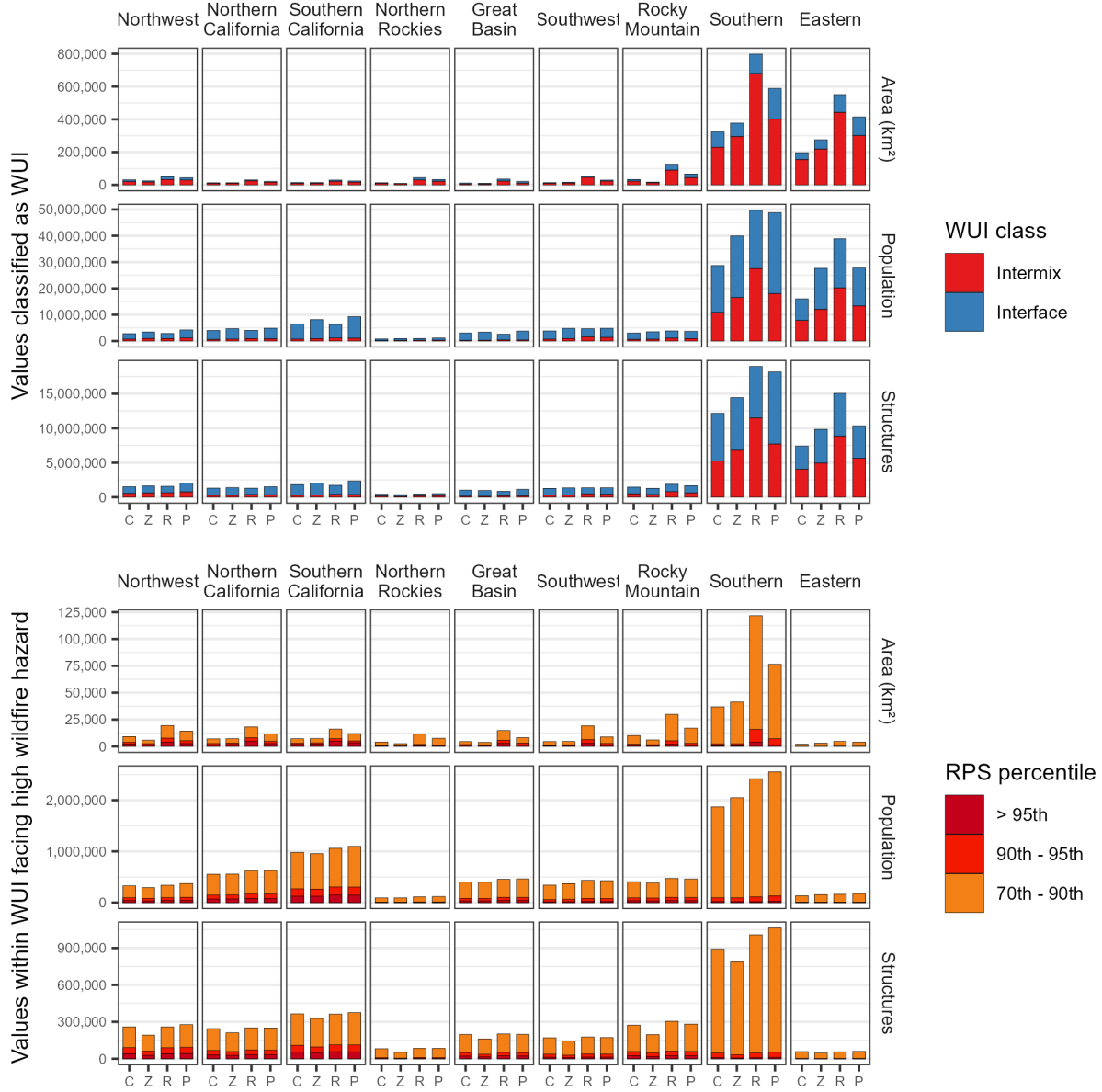


Figure 1.8: Comparison of 2020 values at risk within the WUI by region, as classified by the cadastral, zonal, raster, and point-based mapping methods (labeled as C, Z, R, and P). The top panel shows the total area, population, and number of structures classified as intermix and interface WUI within each geographic area, indicating that the Southern and Eastern regions have the largest area, population, and number of structures classified as WUI by all of the methods. The bottom panel shows only values that face high wildfire hazard — at or above 70th percentile of risk to potential structures (RPS) — within the WUI for each region. The Southern region has the largest number of people and structures facing 70th percentile RPS. However, the largest populations facing wildfire hazard at or above the 90th percentile are located in Southern California and Northern California.

1.3.4 Relationship between WUI classifications and wildfire hazard

The proportion of high-hazard area classified as WUI is considerably smaller than the proportion of high-hazard populations and structures classified as WUI, as shown in the top panel of Fig. 1.9. Only a relatively small proportion of the area facing high wildfire hazard is classified as WUI, which is unsurprising given that the areas facing the highest wildfire hazard are wildlands that are too sparsely inhabited to be considered WUI. In contrast, the majority of people exposed to high wildfire hazard — between 58.2% to 90.1% depending on the region and mapping method — are located in areas classified as WUI. The Northern Rockies, Southern, and Eastern regions have the largest proportions of their high-hazard populations living outside areas classified as WUI.

There is slight variation between mapping methods in the proportion of high-hazard values each classifies as WUI. The zonal method has relatively low WUI classification rates for high-hazard populations in the Northwest and Rocky Mountain regions, with 63.7% and 67.8% of these populations classified as WUI. The zonal method also classifies a notably smaller proportion of high-hazard structures as WUI than the other methods, likely because it considers only housing units in its WUI classification rather than all structures.

The level of wildfire hazard within the WUI varies dramatically across regions. The bottom panel of Fig. 1.9 shows the proportion of values classified as WUI that are exposed to high wildfire hazard for each region and WUI mapping method. Only a very small proportion of people and structures within the Eastern region's WUI — less than 1% — face wildfire hazard at or above the 70th percentile nationwide. In contrast, at least 10% of the population living in areas classified as WUI within the Northern California, Southern California, Northern Rockies, Great Basin, and Rocky Mountain regions face 70th percentile RPS.

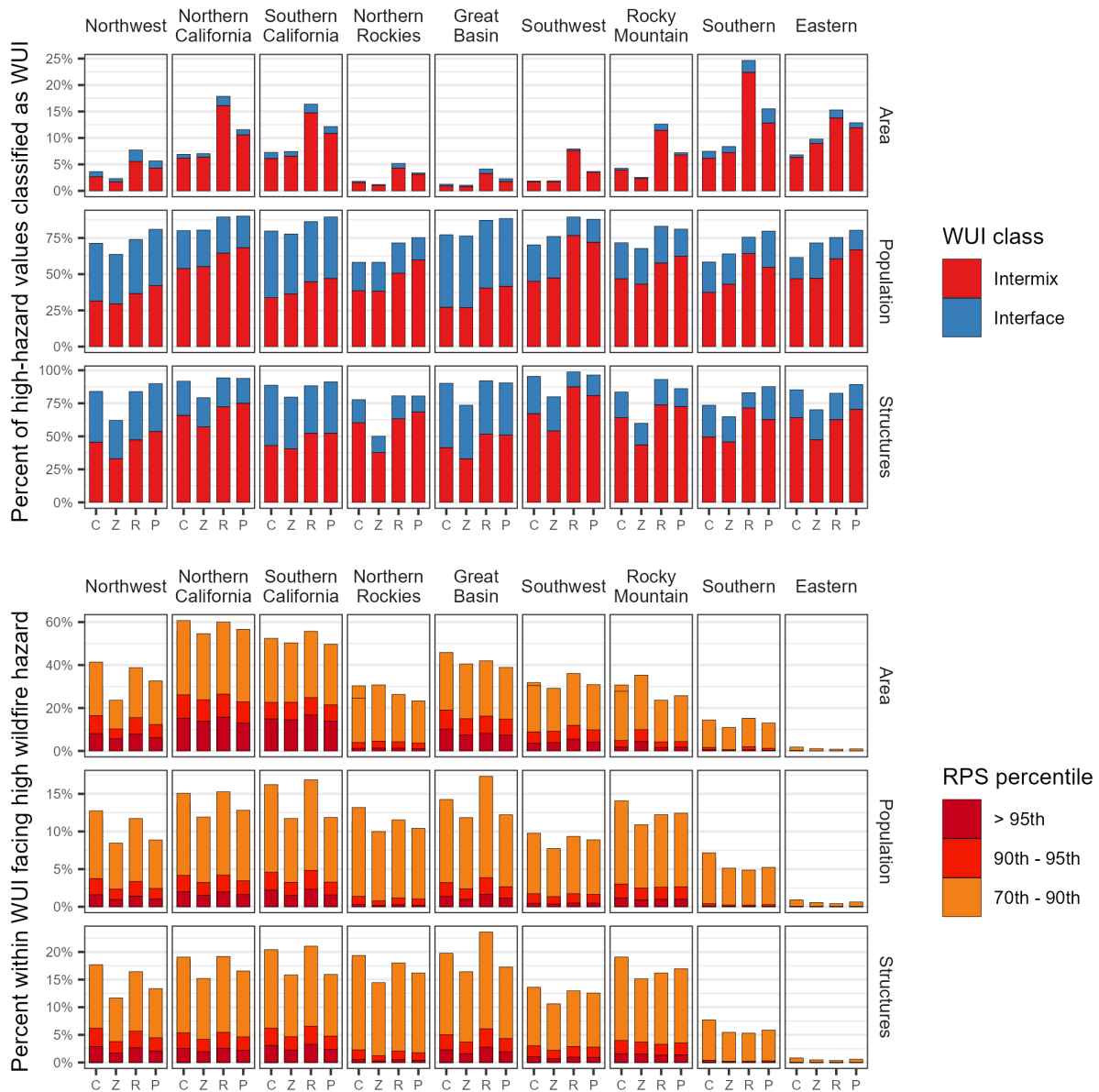


Figure 1.9: Conditional probabilities relating WUI classifications to wildfire hazard. The top panel shows the proportion of high-hazard values (at or above 70th percentile RPS) that are classified as either intermix or interface WUI by each mapping method for 2020. The majority of people and structures facing 70th percentile RPS are classified as WUI by all four methods. The bottom panel shows the proportion of areas classified as WUI in 2020 that face high wildfire hazard. People and structures in WUI areas within the Northwest, Northern California, Southern California, and Great Basin regions are exposed to 90th percentile RPS at the highest rates.

1.3.5 WUI growth and exposure over time

The longitudinal mapping methods identify different regional WUI growth trends from 2000–2020 in area, population, and number of structures (Fig. 1.10). In this figure, intermix and interface categories are combined, since intermix WUI generally transitions to interface WUI as development in an area intensifies. All three of the longitudinal methods identify the Great Basin and Southwest regions as experiencing the highest levels of growth in WUI population and structures from 2000–2020. The raster method shows trends in total WUI population and structures that are similar to the cadastral and zonal methods, but of a considerably smaller magnitude, with negative growth in the Northern California and Eastern regions. This discrepancy is mirrored in the change in total WUI area: the raster method indicates negative growth in the spatial extent of the WUI from 2000–2020 within six of the nine regions.

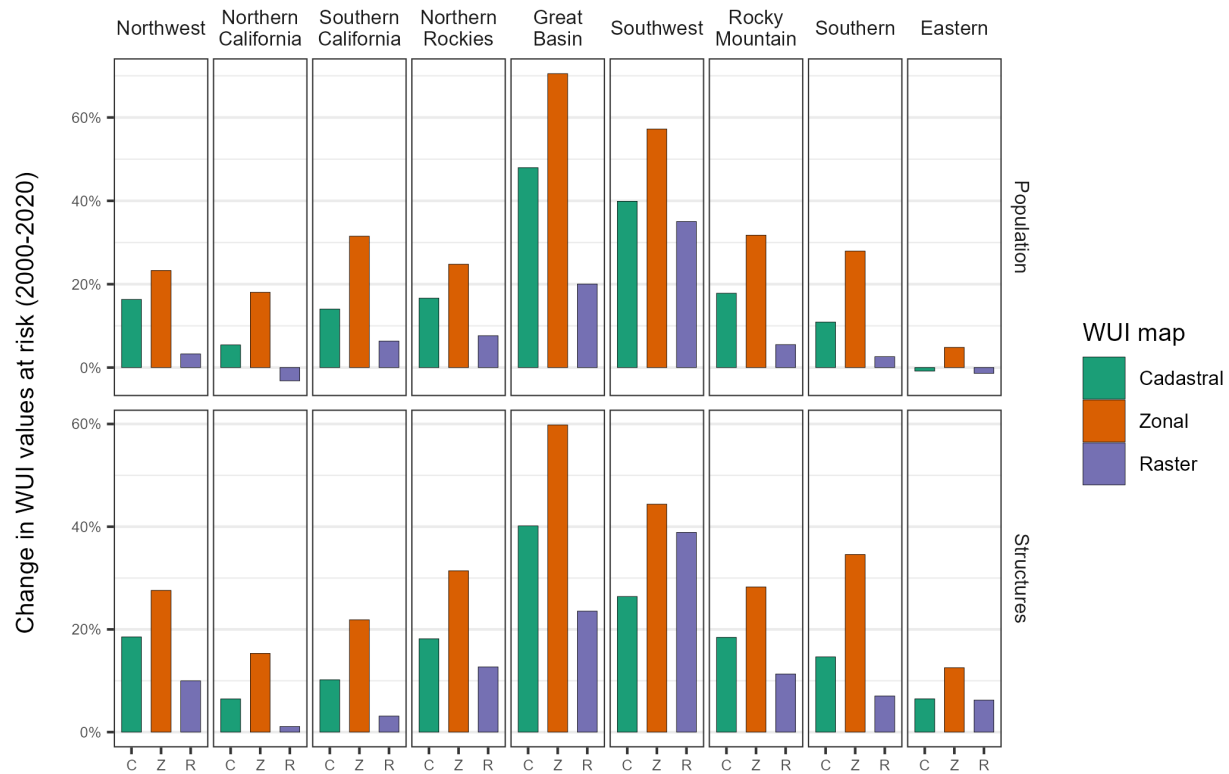


Figure 1.10: Change in WUI values at risk by region from 2000–2020. The regional growth rates calculated using each of the three longitudinal methods — cadastral, zonal, and raster — are labeled with their initials (C, Z, and R). All three methods identify the most significant growth in WUI population and structures in the Great Basin and Southwest regions. The raster method indicates negative growth in WUI area within six of the nine regions, while the cadastral and zonal methods identify only positive growth in WUI area.

1.4 Discussion

While the four WUI mapping methods vary considerably in the area, population, and number of structures that they classify as WUI in 2020, all indicate that the Southern and Eastern regions have the largest WUI area, population, and number of structures. However, the raster method classifies significantly more area as WUI than the other methods. Considering wildfire *hazard* in addition to WUI status highlights different regions. The Southern region has the largest area, population, and number of structures facing wildfire hazard — quantified as risk to potential structures — at or above the 70th percentile. Restricting further to only consider values in the 90th percentile of wildfire hazard, the Southern California, Northern California, and Northwest regions emerge as the regions with the greatest number of people and structures at risk within the WUI.

Variation in the area classified as WUI by the four methods is largely due to differences in the data used to identify habitation. The cadastral method classifies WUI based on the HISDAC-US built-up property locations data, which identified 101,703,300 structures as of 2020. The zonal method performs its classification using the 139,611,470 housing units counted by the 2020 Decennial Census. The point-based method uses the nearly 125 million individual buildings identified in the Microsoft building footprints dataset. The raster method uses the GHS Built-Up Surface Grid to identify habitation, which represents the proportion of each 100-meter pixel that is bounded by the walls of a building (Pesaresi et al., 2024) rather than a count of discrete structures. A key distinction between these measures is whether they consider all structures or only residences. The Federal Register definition is based on the density of *structures*, which is most aligned with the cadastral and point-based methods.

Potential omissions in HISDAC-US dataset have two effects on the analysis: (1) they may result in misclassification of WUI using the cadastral method, and (2) they may understate the structure-count differences in areas where the classification methods disagree. Structures are not included in the BUPL dataset if a built-year cannot be assigned from either ParcelAtlas or ZTRAX, or if the structure is simply omitted from all three of the datasets that HISDAC-US is compiled from. These omissions from the BUPL timeseries can lead to under-classification of WUI. However, in areas where BUPL neighborhood sums exceed the 4.85-structure minimum density threshold, there is no risk of misclassification due to either omitted structures or missing built-year. Misclassification is a concern only in cells where the calculated structure density falls below the threshold but omitted structures could plausibly push it above. The sensitivity analysis conducted using the WUI map derived from structure densities that include property records with no built year indicates that missingness in this variable is a significant concern. The quality mask also suggests that the cadastral method omits significant WUI area. This mapping approach, therefore, should be applied cautiously, taking into account the data quality issues identified in these analyses.

The extent to which the different mapping methods classify high-hazard values as WUI varies between regions. In the Northern California, Southern California, and Great Basin regions, all four methods classify at least 75% of the population facing wildfire hazard in the 70th percentile as living within the WUI. The Northern Rockies and Southern regions have the lowest rates at which populations facing high wildfire hazard are classified as WUI, and more variation between methods, making the choice of mapping method more impactful in these regions.

Longitudinal WUI maps, including those produced by the cadastral method developed here, allow for the assessment of WUI growth over time. Each of the three longitudinal methods as-

sessed identify the highest growth rates in the Great Basin and Southwest regions. However, the growth rates produced using the raster method diverge significantly from the cadastral and zonal approaches. The raster method identifies very little growth in WUI area from 2000–2020, with changes in WUI population and structures driven by increasing population and structure density rather than an increase in the areal extent of the WUI. These low growth rates likely occur because a larger area meets the raster method’s structure density threshold at all timesteps — the densification that produces WUI growth under other methods does not result in threshold crossing.

Quantifying the WUI by area, population, or structures produces different results, with different implications and limitations. Assessing only the spatial extent of the WUI does not introduce additional error into the WUI classifications, but also is less informative than estimating the number of people or structures contained within these areas. Comparisons of the number of people living within the WUI rely on the quality of population data. The WorldPop dataset used here may undercount the number of people living in low-density areas, since its dasymetric mapping procedure distributes populations based on factors including structure locations, which may be more likely to be omitted from very rural areas. The assessment of structures within the WUI is almost certainly an undercount, since buildings with unknown construction dates are omitted from the HISDAC-US dataset.

1.5 Conclusion

The identification of growing WUI areas allows risk mitigation policies to target areas that are actively expanding, where policy interventions such as building codes and zoning will be most

impactful. The cadastral method developed here allows for the construction of the longitudinal WUI classifications needed to identify growing WUI communities by using structure data that integrates building footprints with property records. While this approach addresses some of the disadvantages of other mapping methods, significant missingness in built-year data within property records limits the applicability of the approach in many areas. Every approach to mapping the WUI has limitations, and choosing the most appropriate mapping strategy for a given purpose should take into account both global and local differences between the methods.

The tabulation of values at risk by wildfire hazard, in addition to WUI designation, provides a different perspective on the distribution of the area, population, and number of structures exposed to wildfire risk. The prioritization of areas at risk based on both hazard and exposure can facilitate more efficient use of risk mitigation resources. Further, the analytic approaches applied here at the regional scale may be applied to individual communities, enhancing the ability of policymakers to target interventions to benefit communities facing the greatest risks.

Chapter 2

Assessing hazard and vulnerability metrics in community wildfire risk mitigation funding

2.1 Introduction

2.1.1 Wildfire risk and mitigation

The number of people exposed to wildfire has increased significantly over the last 20 years, both within the United States ([Modaresi Rad, Abatzoglou, Kreitler, et al., 2023](#)) and across most of the world ([Seydi et al., 2025](#)). In the western United States, structure loss more than tripled over the course of a decade ([Higuera et al., 2023](#)). This increasing rate of destruction impacts individuals and communities not only through direct losses, but also by making insurance more expensive and less accessible ([Dixon et al., 2018](#)) and by increasing the cost of construction with fire-resistant

materials ([Quarles & Pohl, 2018](#)).

Efforts to reduce the wildfire risk to homes often focus on the home ignition zone and the community protection zone ([Taccaliti et al., 2023](#)). Risk mitigation within the home ignition zone is generally the responsibility of homeowners, but these individual actions have community-level impacts because a burning home can spread fire through developed areas ([Young et al., 2025](#)). Households tend to under-invest in mitigation both due to the expense and because they do not account for the positive externality of community protection ([Taylor et al., 2019](#)). The presence of these spillover effects suggests that wildfire risk mitigation is most efficiently coordinated and conducted at the scale of communities.

Community-level wildfire risk mitigation projects are supported by a number of federal and state programs. The criteria used to prioritize communities for project funding typically include (1) the degree of exposure to wildfire potential, (2) the likelihood and expected severity of wildfire, and (3) the vulnerability of residents. Programs vary in the specific metrics and criteria that they use to assess exposure, hazard, and vulnerability, and they may also vary in the spatial scales used for assessment. For example, the National Cohesive Wildland Fire Management Strategy prioritizes among counties based on “the amount of area in WUI and density of homes within it, demographic measures of household stress and economic advantage, and measures of area burned by wildfires and ignition density” ([Jewell & Vilsack, 2014](#)). These program design choices impact the allocation of funding and have significant implications for which communities receive support for wildfire risk mitigation.

2.1.2 Social vulnerability and wildfire risk

Wildfire risk is not determined by biophysical hazard alone; the impact of wildfire on a community depends also on social and demographic factors that influence residents' susceptibility to wildfire, their capacity to proactively mitigate risk, and their ability to recover after wildfire incidents. The concept of social vulnerability aims to capture this variation by measuring characteristics of the individuals within communities — including age, gender, race, and socioeconomic status — as well as aspects of the built environment ([Cutter et al., 2003](#)). Many of these same social factors are linked to adaptive capacity, which refers to the ability of people to take proactive actions to reduce the impact of future hazards ([Engle, 2011](#)). Although theoretically distinct, social vulnerability and adaptive capacity tend to be negatively correlated, with more socially vulnerable populations exhibiting lower adaptive capacity ([Jamshed et al., 2019](#)) and community resilience ([Bergstrand et al., 2015](#)). In this paper, I assess the vulnerability of communities using the CDC's Social Vulnerability Index (SVI), which is derived by ranking socioeconomic and demographic variables measured by the U.S. Census Bureau across four domains: (1) socioeconomic status, (2) household composition/disability, (3) minority status & language, and (4) housing type & transportation ([Flanagan et al., 2011](#)).

Wildfire hazard is typically identified using either historical wildfire perimeters or simulations of wildfire behavior. Historical wildfire perimeters, however, may not accurately identify future wildfire potential due to the dynamic nature of both climate and fuelscapes. Areas that have experienced wildfire in the recent past, for example, tend to have a lower incidence of fires that require significant suppression resources ([Cullen et al., 2024](#)). Simulations of wildfire hazard, such as those produced using the FSim software ([Finney et al., 2011](#)) address the issue of

temporally-dynamic fuelscapes, but often have their own shortcomings. One such issue with wildfire simulations is the lack of fire behavior models within developed areas, which results in these areas being marked as nonburnable in the LANDFIRE fuels data that many simulations rely on ([La Puma, 2023](#)). In this paper, I quantify wildfire hazard using data from the Wildfire Risk to Communities project, which aims to address this issue by “oozing” burn probabilities into developed areas ([Scott, Dillon, et al., 2024](#)).

The intersection between social vulnerability and wildfire hazard has been an area of active research over recent years, with studies generally focusing on the co-occurrence of sociodemographic characteristics and wildfire perimeters ([Lambrou et al., 2023](#)). Although communities facing high wildfire hazard do not necessarily have higher social vulnerability, there are a significant number of areas with both high hazard and high vulnerability ([Chas-Amil et al., 2022](#); [Davies et al., 2018](#); [McEvoy et al., 2026](#); [Wigtil et al., 2016](#)). These prior studies characterize the co-occurrence of vulnerability and hazard but do not evaluate whether the specific metrics used to operationalize these constructs in wildfire mitigation funding programs accurately identify the communities most exposed and least resilient.

2.1.3 The Community Wildfire Defense Grant program

The Community Wildfire Defense Grant (CWDG) program provides funding for at-risk communities to plan and implement projects to mitigate wildfire risk. The program is administered by the USDA Forest Service and aims to distribute \$1 billion in funding over five years, from fiscal years 2022 through 2026 ([USDA Forest Service, 2025b](#)). The Infrastructure Investment and Jobs Act of 2021 appropriates funding for the program and directs the Secretary of Agriculture to prioritize

grants to “at-risk communities” that (a) have “high or very high wildfire hazard potential”, (b) are “low-income” communities, and (c) have been “impacted by a severe disaster” ([Infrastructure Investment and Jobs Act, 2021](#)).

The Forest Service operationalized these directives through the quantitative scoring system described in the program’s Notice of Funding Opportunity ([USDA Forest Service, 2025a](#)). CWDG applications are scored on a 100-point scale based on nine criteria. Three of these criteria are binary: 20 points are granted to communities that have “high / very high wildfire hazard potential”, 10 points are awarded to “low income communities”, and 10 points accrue to areas that are “impacted by severe disaster”. The remaining 60 points are based on the content of the grant application, scored across six categories worth up to 10 points each: project description, budget, accomplishments, collaboration, landscape impacts, and project sustainability. While these six qualitative elements of the scoring rubric are consequential to grant awards, the three binary criteria are critical: 100% of the grants awarded in the most recent funding round met all three of these criteria ([USDA Forest Service, 2025b](#)). Whether these indicators select for socially vulnerable communities that are exposed to high wildfire potential is therefore a question of considerable importance.

Many grant applicants rely on the [CWDG Dashboard](#) to determine whether their project areas meet the program’s eligibility and scoring criteria. This tool, which was developed by the Wildfire Risk to Communities project team, provides wildfire risk data for a total of 31,443 communities, 3,142 counties, and 637 tribal areas within the United States ([Pohl & Dillon, 2025](#)). The dashboard classifies each area into one of three hazard classes (see Tbl. 2.1), based on two hazard metrics: Wildfire Hazard Potential (WHP) and Risk to Potential Structures (RPS; reported as “Wildfire Risk to Homes” in the CWDG Dashboard). WHP captures the “potential for wildfire that may be

difficult to control” and RPS represents the risk to “potential” structures, regardless of whether structures actually exist in a given area (Scott, Dillon, et al., 2024). Importantly, an area’s hazard class may be determined using either metric, based on percentiles relative to either the state or the entire nation. Additionally, the dashboard indicates whether the project area is considered “low income” based on whether its median household income is less than 80% of either the state or national median.

Table 2.1: The three hazard classes reported for communities, counties, and tribal areas on the CWDG Dashboard, along with their associated WHP and RPS thresholds. A project area qualifies for the highest hazard class that it meets using either the WHP or RPS threshold, relative to either its state or the nation overall.

Hazard class	WHP threshold	RPS threshold
“ineligible”	< 67th percentile	< 40th percentile
“at risk”	≥ 67th percentile	≥ 40th percentile
“high hazard”	≥ 84th percentile	≥ 70th percentile

One potential concern with the CWDG Dashboard tool relates to the spatial units within which wildfire hazard is aggregated. The choice of spatial aggregation unit can substantially affect conclusions drawn from spatial data — a phenomenon known as the modifiable areal unit problem (Fotheringham & Wong, 1991). The most local (i.e., smallest) spatial unit for which hazard data are provided by the tool is the “community” — which here refers to Census places. The U.S. Census Bureau defines “places” as areas of concentrated population, and includes both incorporated places and unincorporated areas that lack separate governments but have a clear residential core and local identity (Brown, 1994). The CWDG Dashboard uses the set of 31,895 places in the United States that were recognized by the Census Bureau in 2022. While the majority of the population lives within Census places (75.5%), there were just over 81 million people who lived outside these areas in 2022. Grant applications that do not serve a Census place must

either rely on a different data source for determining eligibility or use the county-level measures provided by the CWDG Dashboard tool.

In many cases, county-level hazard data do not accurately reflect local conditions. For example, there are 2,554 Census places that meet the high-hazard criteria but are located within counties that are *not* considered high-hazard. Since place-level data are available for these communities through the CWDG Dashboard, applicants from these communities qualify for the 20 points associated with the high-hazard designation. However, nearby communities within these same counties that are *not* recognized as Census places would not qualify as high-hazard using data from the CWDG Dashboard. Fig. 2.1 illustrates this point by showing several communities in Oregon that are not Census places (e.g., Marion Forks, Santiam Junction, and McKenzie Bridge) located within a county designated as at-risk but not high-hazard based on the county's hazard percentile. These communities are in close proximity to high-hazard Census places and would likely be considered high-hazard themselves if hazard was aggregated at a finer scale. However, since they must instead rely on county-level data from the CWDG Dashboard, mitigation projects within these communities would not qualify for the 20 points allocated to high-hazard communities. The use of county-level hazard data for areas outside of Census places, therefore, may result in improper prioritization of grant funding.

A separate concern with the CWDG Dashboard tool and the CWDG scoring rubric itself is the use of a low-income criterion rather than a more comprehensive measure of social vulnerability. Focusing solely on income disregards other factors that may contribute to the vulnerability of a community, such as household composition & disability, minority status & language, and housing characteristics & transportation. Additionally, the CWDG scoring system uses a binary threshold to identify low-income communities and does not include a mechanism to prioritize

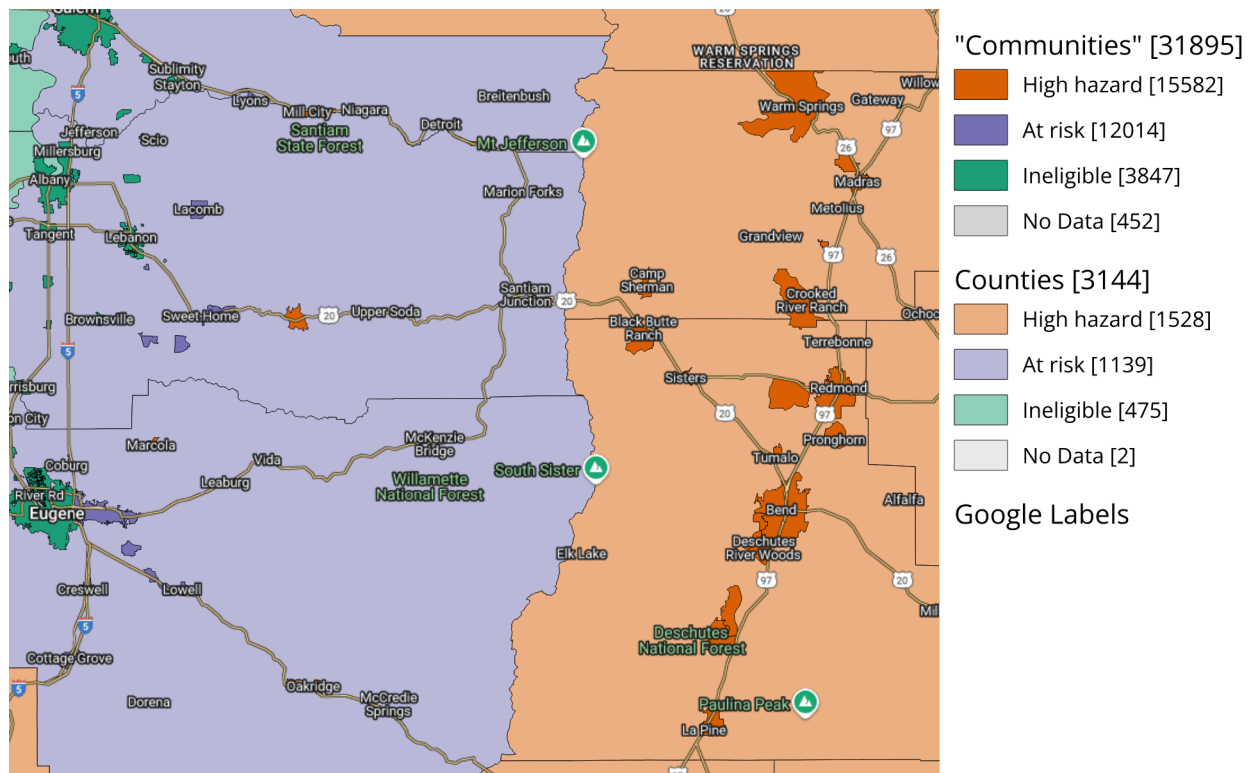


Figure 2.1: Wildfire hazard designations from the CWDG Dashboard tool for central Oregon. The Dashboard reports hazard data for 31,443 of 31,895 “communities” (Census places) and 3,142 of 3,144 counties within the United States.

among communities that meet the threshold. Due to these design choices, the program may not be prioritizing the most vulnerable communities.

To assess the influence of these two design choices on CWDG eligibility and prioritization, I (1) quantify hazard using an alternate spatial unit to represent communities, and (2) evaluate a comprehensive measure of social vulnerability rather than the low-income criterion. The alternate spatial unit — place catchments — eliminates reliance on county-level data on wildfire hazard to fill gaps by matching unassigned areas to their nearest Census place, allowing me to assess whether this aggregation unit captures a larger or smaller proportion of high-hazard areas than the approach used by the CWDG Dashboard tool. To quantify aspects of community vulnerability beyond income, I construct a place-level measure of social vulnerability using the CDC’s preferred method ([Flanagan et al., 2011](#)) and examine the dimensions of vulnerability that are not identified by the low-income criterion.

2.2 Methods

2.2.1 Construction of place catchments

In this study, I assess wildfire hazard and social vulnerability within the 31,895 Census places of the United States and their surrounding areas. Although Census places represent communities more accurately than other spatial units used by the Census Bureau, they do not cover the entire land area of the United States, which leads to gaps that the CWDG Dashboard tool fills using county-level data. The place catchment approach developed here is motivated by concerns about the eligibility of remnants (areas outside of Census places) being determined by county-level

metrics. To address this concern, I construct place catchments by matching areas outside Census place boundaries to the nearest place. Specifically, I match each 30-meter pixel within the United States to the nearest Census place boundary using the Euclidean allocation method implemented in the WhiteboxTools geoprocessing package (Wu & Brown, 2025) for R. Place catchments are constrained such that they do not cross state lines, which allows me to calculate within-state hazard rankings using the same approach employed by the CWDG Dashboard tool. Fig. 2.2 illustrates the spatial relationship between place catchments, communities, counties, and states.

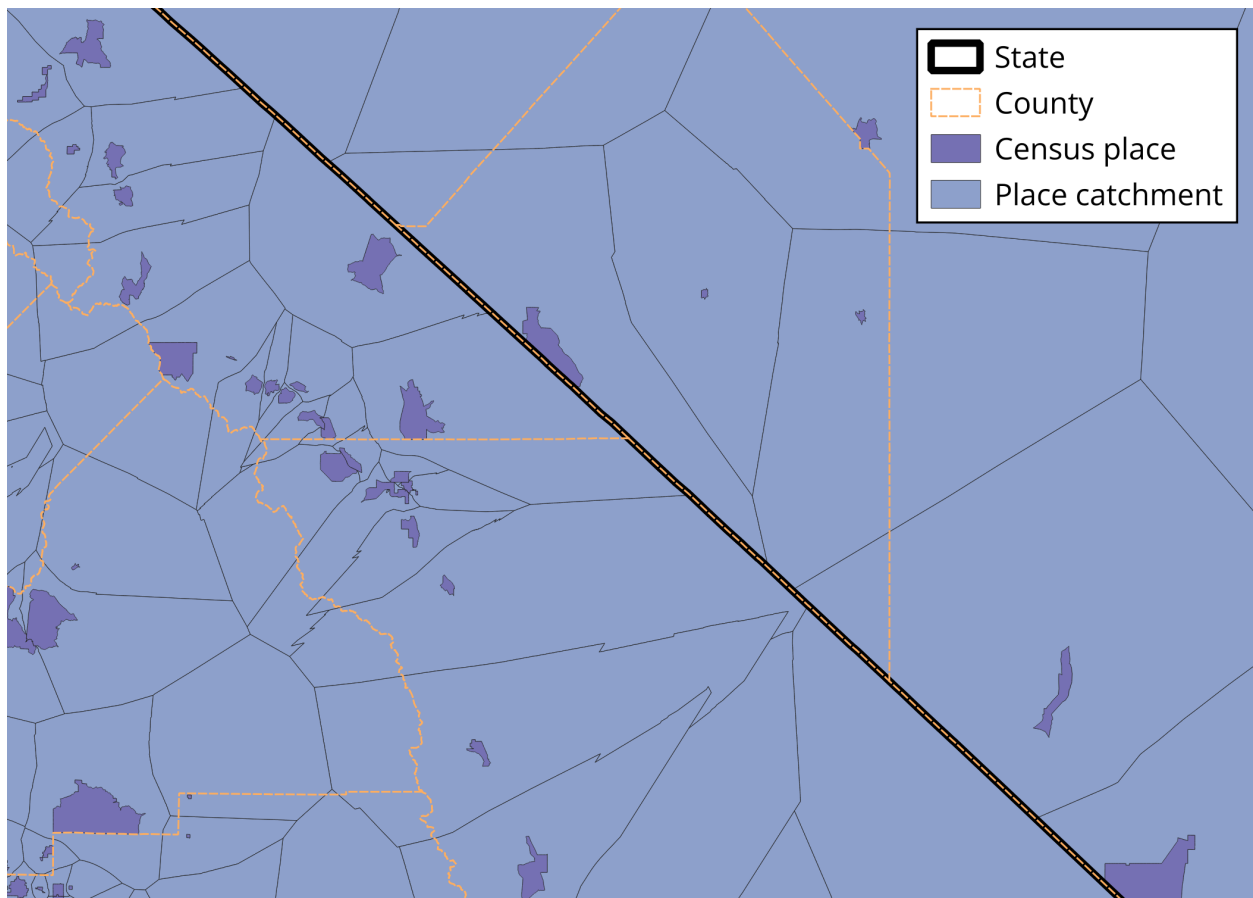


Figure 2.2: Spatial relationship between Census places, place catchments, counties, and states along the California-Nevada border. Each Census place (purple) is surrounded by its catchment (blue). Catchments may extend across county boundaries (dashed orange) but terminate at state lines (solid black).

2.2.2 Evaluation of wildfire hazard aggregation methods

I quantify wildfire hazard for each place catchment using the WHP and RPS metrics from the Wildfire Risk to Communities project ([Scott, Dillon, et al., 2024](#)). Following the approach used by the CWDG Dashboard tool, I aggregate WHP and RPS only within inhabited areas that are exposed to wildfire potential, as identified by the Community Wildfire Risk Reduction Zones (CWiRRZ) data product. The CWiRRZ product classifies each 30-meter pixel within the United States into four zones — Minimal Exposure, Indirect Exposure, Direct Exposure, and Wildfire Transmission Zones — based on input datasets representing building footprints, protected areas, land cover, exposure, and housing unit counts ([Dillon et al., 2024](#)). Aggregating the two hazard metrics only within Indirect Exposure, Direct Exposure, and Wildfire Transmission Zones ensures that hazard estimates are not influenced by hazard within uninhabited areas or areas within urban cores.

After calculating aggregate WHP and RPS for each place catchment, I apply the CWDG Dashboard tool’s hazard thresholds to designate place catchments as either high-hazard, at-risk, or ineligible (see Tbl. 2.1) based on the catchment’s percentile ranking, both nationally and within its state, with respect to both WHP and RPS. A place catchment is designated as high-hazard if: (1) its national WHP ranking is at/above the 84th percentile, (2) its within-state WHP ranking is at/above the 84th percentile, (3) its national RPS ranking is at/above the 70th percentile, or (4) its within-state RPS ranking is at/above the 70th percentile. Similarly, place catchments are considered at-risk if their national/state WHP is at/above the 67th percentile or their national/state RPS is at/above the 40th percentile. Place catchments that do not meet these hazard thresholds are classified as ineligible.

Because WHP and RPS are provided as 30-meter rasters in the source hazard data ([Scott, Dillon, et al., 2024](#)), I assign hazard classes at this scale to evaluate the two aggregation methods. To calculate at-risk and high-hazard indicators for each 30-meter pixel in the US, I first use the CWiRRZ data product to exclude all pixels outside the Indirect Exposure, Direct Exposure, and Wildfire Transmission Zones. Next, I construct thresholds for each state by calculating 67th and 84th percentiles of WHP, along with 40th and 70th percentiles of RPS. Because national percentiles can also be used to establish CWDG eligibility and priority, I calculate these thresholds at the pixel level as well. Due to computational limitations, I calculate percentile breaks within 1% samples of the exposure-zone-restricted pixels in each state. This sampling approach is supported by the strong consistency and asymptotic normality of sample quantiles as estimators of population quantiles under mild smoothness conditions ([Serfling, 2002](#)). WHP and RPS for each pixel are then compared against the state and national thresholds to determine CWDG eligibility and priority.

To compare the place catchment method against the CWDG Dashboard tool's approach of aggregating hazard within Census places and counties, I examine the prevalence of at-risk and high-hazard pixels within aggregation units. I consider four evaluation criteria:

1. Eligibility false negatives: the percentage of at-risk pixels that are designated as ineligible by each aggregation method
2. Eligibility false positives: the percentage of pixels designated as at-risk by each aggregation method that are ineligible at the pixel-level
3. Priority false negatives: the percentage of high-hazard pixels that are not designated as high-hazard by each aggregation method

4. Priority false positives: the percentage of pixels designated as high-hazard by each aggregation method that are not high-hazard at the pixel-level

2.2.3 Comparison of social vulnerability and the low-income criterion

I construct a place-level measure of social vulnerability from the same 15 indicators used to create the CDC’s Social Vulnerability Index ([Flanagan et al., 2011](#); [Flanagan et al., 2018](#)). While the index is available for counties, census tracts, and ZIP-code tabulation areas from the CDC’s Geospatial Research, Analysis, and Services Program (GRASP) website ([CDC, 2026](#)), I calculate the index at the level of Census places so that it can be compared directly to the CWDG Dashboard tool’s low-income criterion. The variables used to construct this index, shown in Tbl. 2.2, are available in the American Community Survey (ACS) 5-year data for 30,653 of the 31,895 places (96.1%) within the United States for 2022.

In addition to calculating overall rankings of vulnerability, the CDC’s Social Vulnerability Index ranks areas across four sub-component themes (see Tbl. 2.2). The first theme — Socioeconomic Status — focuses on employment, income, and education, which makes it most closely aligned with the low-income criterion used in scoring CWDGs. Household Composition & Disability captures factors that can lead to challenges during a wildfire evacuation, such as the presence of children, elderly residents, persons with disabilities, and single-parent households. The Minority Status & Language theme can reflect communication difficulties that affect the ability of households to receive emergency communications, and the Housing & Transportation theme reflects a number of factors that can hinder evacuation and lead to increased susceptibility of structures to wildfire. This set of themes expands considerably on the low-income criterion to

characterize additional dimensions of vulnerability.

Table 2.2: Indicators used in the construction of the CDC’s Social Vulnerability Index, with their associated ACS variables, grouped by vulnerability theme.

Indicator	ACS Variable
<i>Theme 1. Socioeconomic Status</i>	
• Percent individuals below poverty	B17021
• Percent civilian unemployed	B23025
• Per capita income in the past 12 months	B19301
• Percent persons with no high school diploma	B15003
<i>Theme 2. Household Composition & Disability</i>	
• Percent persons 65 years of age or older	B01001
• Percent persons 17 years of age or younger	B01001
• Percent persons more than 5 years old with a disability	B22010
• Percent male or female householder, no spouse present, with children under 18	B11003
<i>Theme 3. Minority Status & Language</i>	
• Percent minority	B02001
• Percent persons 5 years of age or older who speak English less than “well”	B16004
<i>Theme 4. Housing & Transportation</i>	
• Percent multi-unit structure	B25024
• Percent mobile homes	B25024
• Crowding	B25014
• No vehicle available	B25044
• Percent of persons in group quarters	B09019

2.3 Results

2.3.1 Effects of alternate hazard aggregation units

The geographic distribution of at-risk and high-hazard areas identified by the place catchment method is broadly similar to the output of the CWDG Dashboard tool, but differs in several important ways (Fig. 2.3). Across the majority of the United States, there is no change in eligibility

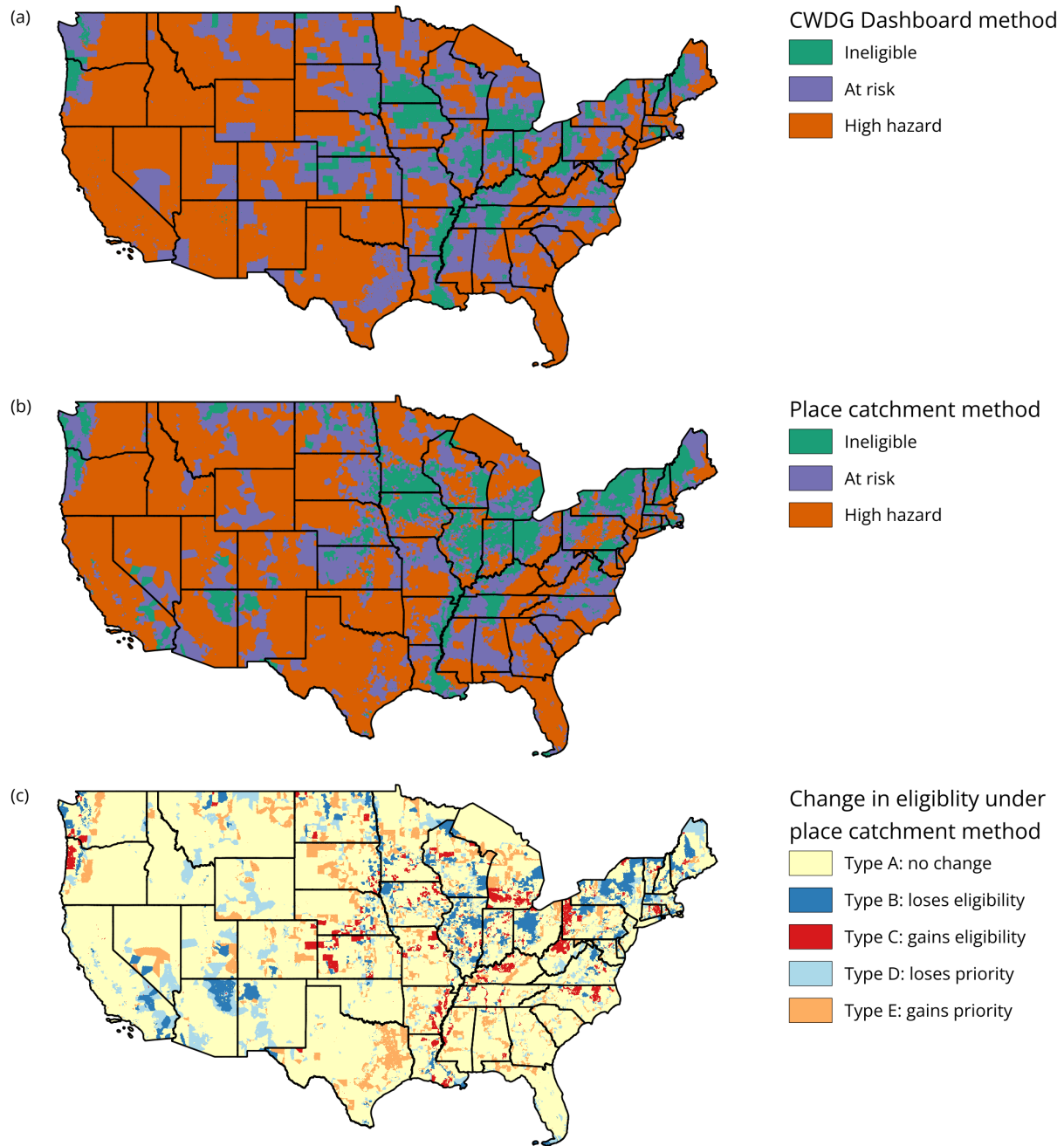


Figure 2.3: Comparison of CWDG eligibility and priority designations across the conterminous United States under the two aggregation methods. Panel (a) shows designations under the CWDG Dashboard method, in which hazard is aggregated within Census places and counties. Panel (b) shows designations under the place catchment method. Panel (c) shows pixels whose designations change between the two methods.

or priority between the two aggregation methods. Changes in eligibility, shown in dark blue and dark red, are more prevalent in the Midwest and Northeast, where wildfire hazard tends to be lower overall. There is also a significantly larger area designated as ineligible for CWDGs in northeastern Arizona and northwestern New Mexico under the place catchment approach. Closer examination reveals that much of this ineligible area was likely “seeded” by ineligible Census places whose catchments override county-level eligibility in their immediate surroundings.

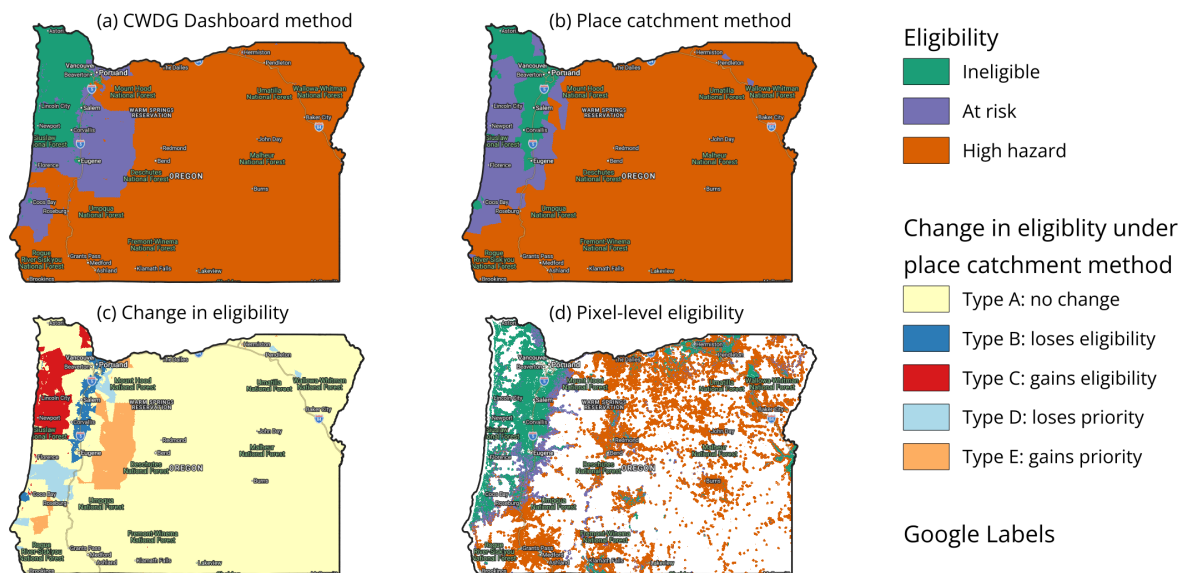


Figure 2.4: Comparison of CWDG eligibility and priority designations in Oregon under the two aggregation methods. Panels (a) and (b) show eligibility designations under the CWDG Dashboard method and the place catchment method, respectively. Panel (c) shows pixels whose designations change between the two methods. Panel (d) shows pixel-level designations as a benchmark; white areas are outside the CWiRRZ Indirect, Direct, and Wildfire Transmission Zones and were excluded from analysis.

Differences between the two hazard aggregation methods are more interpretable at finer spatial scales. Fig. 2.4 examines changes in eligibility and priority in Oregon, alongside hazard designations calculated at the level of 30-meter pixels. Under both hazard aggregation methods, all of eastern Oregon is designated as high hazard, but differences between the methods emerge in several key areas. Importantly, densely-populated areas along the northern extent of the I-5 corridor,

including areas near Portland, Salem, and Corvallis become ineligible under the place catchment approach. These areas are also considered ineligible in the pixel-level analysis. In contrast, the areas surrounding Lincoln City and Newport gain eligibility under the place catchment method, where the pixel-level analysis indicates mostly ineligible pixels. Additionally, the small communities located between Eugene and Bend that were highlighted in Fig. 2.1 are classified as high hazard by the place catchment method, whereas the CWDG Dashboard method only identifies recognized Census places within this region as high hazard.

While there is considerable variation between states in the degree to which the aggregate hazard designations agree with the pixel-level designations (Fig. 2.5), the place catchment method shows less overall disagreement (with respect to all four disagreement metrics) across the entire United States. States with lower pixel-level eligibility (towards the left of the plot) generally have lower false negative rates, while states with higher pixel-level eligibility (towards the right of the plot) have modestly lower false positive rates. Nationally, 2.3% of the total area considered to be at-risk at the level of pixels is ineligible under the place catchment method, compared to 2.8% when aggregated using the CWDG Dashboard method. The false positive rate for eligibility is also lower when aggregating within place catchments — 26.2% versus 28.3% for the CWDG Dashboard method. The same is true for the prioritization of high-hazard communities. The proportion of high-hazard pixels misclassified by the place catchment method is 8.1% compared to 12.2% using the CWDG Dashboard method. 37.0% of the area within high-hazard place catchments is not considered high-hazard at the pixel level, compared to 37.9% of the area designated as high-hazard by the method employed by the CWDG Dashboard tool.

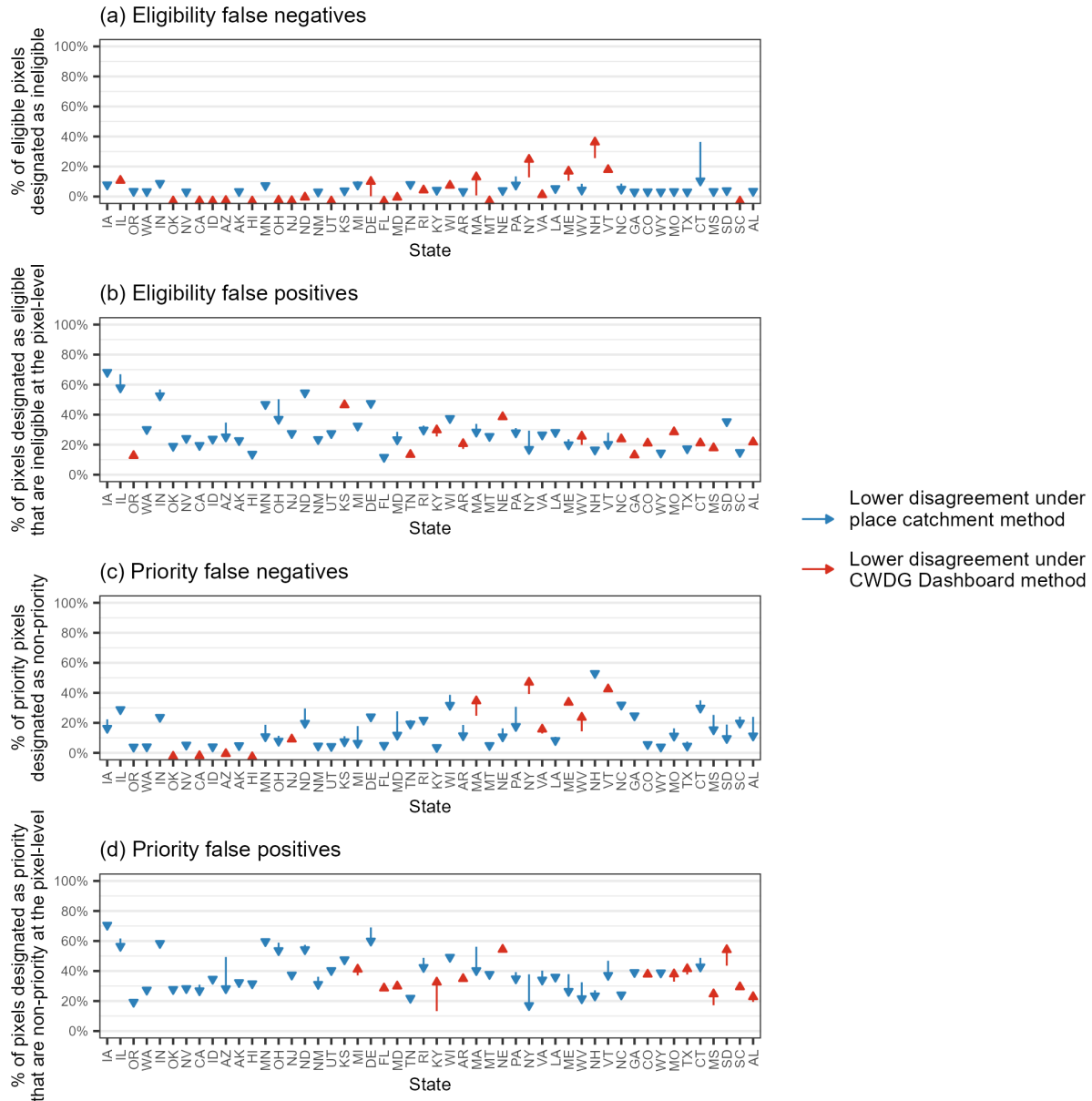


Figure 2.5: State-level disagreement rates under the two aggregation methods. Each arrow points from the CWDG Dashboard rate (tail) to the place catchment rate (head); blue arrows indicate states where the place catchment method has the lower rate, red arrows indicate states where the CWDG Dashboard method has the lower rate. Panels show false negative (a, c) and false positive (b, d) rates for eligibility (a, b) and priority (c, d). States are ordered by the percentage of pixels meeting the CWDG at-risk criterion under either state or national percentile thresholds for WHP or RPS, with the lowest-eligibility states on the left.

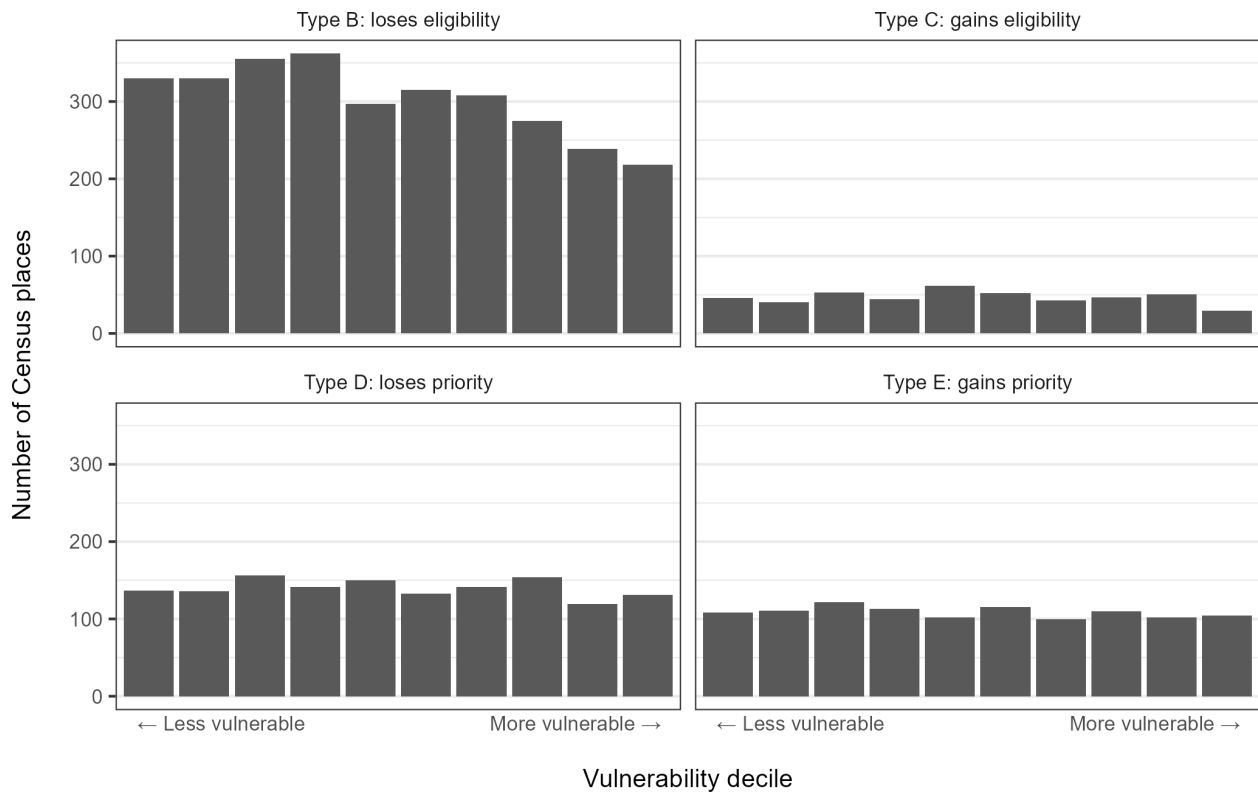


Figure 2.6: Social vulnerability distribution of Census places that switch hazard designations under the place catchment method, by switch type. Each panel shows the number of places in each SVI decile (ordered from least vulnerable to most vulnerable). Type B places lose eligibility under the place catchment method; Type C places gain eligibility; Type D places lose priority designation; Type E places gain priority designation.

The distribution of social vulnerability among Census places that switch hazard designations under the place catchment method is fairly uniform, with the exception of Type B switchers (Fig. 2.6). For places that gain eligibility, lose priority, or gain priority (Types C, D, and E), the SVI distributions are nearly flat, indicating that these changes are not substantively correlated with vulnerability. Among the 3,064 places that lose eligibility under the place catchment method (Type B), however, less vulnerable places are somewhat over-represented, with counts decreasing modestly across vulnerability deciles. This pattern suggests that places losing eligibility under the place catchment method are disproportionately drawn from less vulnerable deciles.

2.3.2 Social vulnerability and the low-income criterion

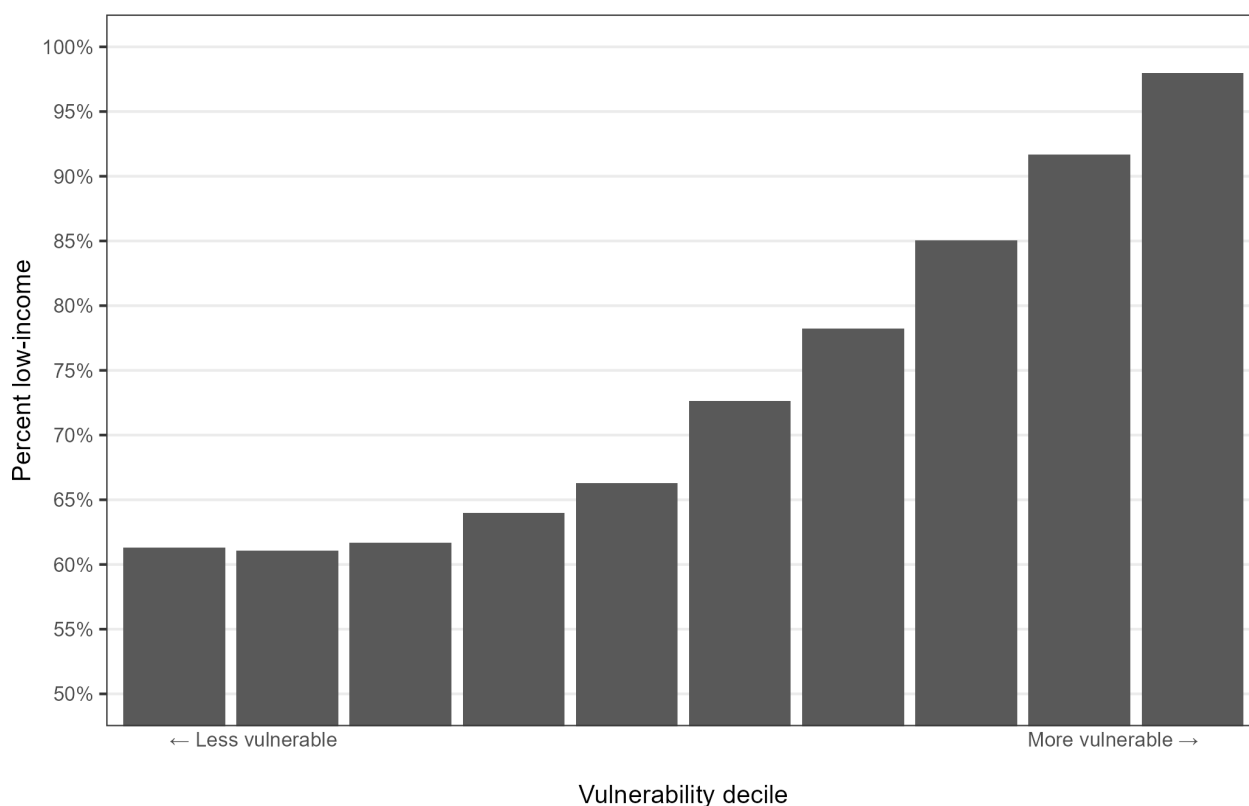


Figure 2.7: Percent of at-risk Census places (places meeting the CWDG eligibility criterion) that also meet the CWDG low-income criterion (median household income < 80% of state or national median), by SVI decile. Bars represent the share within each decile, with the lowest-vulnerability places on the left.

The low-income criterion casts a wide net, including many Census places across the vulnerability distribution. Fig. 2.7 shows the proportion of at-risk places that meet the low-income criterion within each SVI decile. Overall, 74% of at-risk Census places meet the low-income criterion, including a large proportion of the least vulnerable places — for example, over 60% of Census places in the first decile of SVI qualify as low-income per the CWDG criteria. The proportion of low-income Census places within each SVI decile does increase, meaning that more vulnerable places are more likely to fall below the income threshold. This gradient indicates that the low-income criterion is positively correlated with social vulnerability, but the relationship is

loose: a majority of the least vulnerable places still qualify as low-income, while a small fraction of the most vulnerable places do not. Specifically, just over 5% of places at or above the 80th SVI percentile fail to meet the low-income criterion.

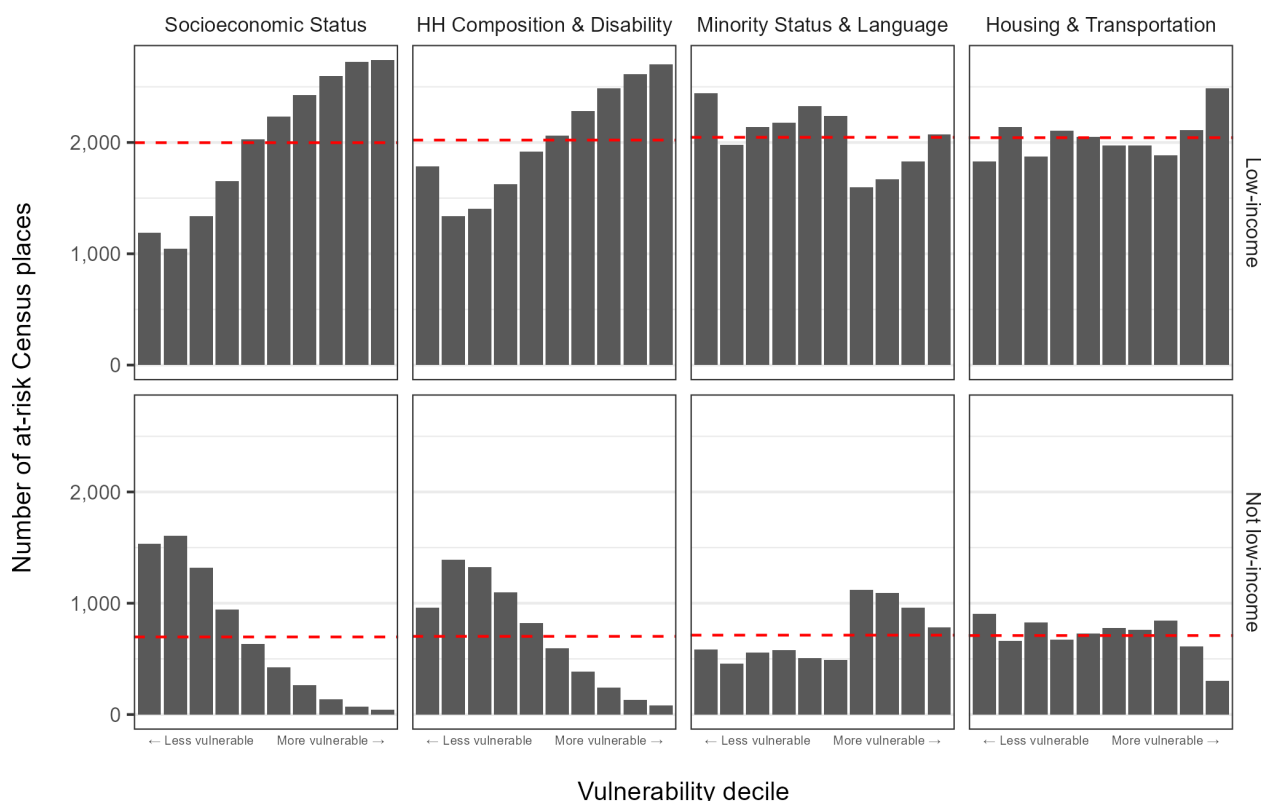


Figure 2.8: Distribution of social vulnerability among at-risk Census places (places meeting the CWDG eligibility criterion), decomposed by SVI theme (columns) and CWDG low-income status (rows). Within each panel, bars show the number of places in each decile of the corresponding vulnerability theme. The red dashed line indicates the count expected if places were distributed uniformly across deciles.

The degree to which the low-income criterion captures variation in social vulnerability among at-risk communities differs considerably between the four vulnerability themes (Fig. 2.8). At-risk communities that qualify as low-income tend to be more vulnerable with respect to the Socioeconomic Status and Household Composition & Disability themes than communities that are not considered low-income. However, the distributions of vulnerability across the Minority Status & Language and Housing & Transportation themes are similar for places that are low-

income and places that are not. That is, the low-income criterion does not select for places that are vulnerable across these two dimensions. Among at-risk places that do not qualify as low-income, a substantial number have high vulnerability across these dimensions but are not prioritized for grant funding through the low-income criterion. For example, 915 of the 7,132 at-risk Census places that do *not* meet the low-income criterion are highly vulnerable (at or above 80th percentile SVI) with respect to the Housing & Transportation theme and 1,746 are highly vulnerable with respect to Minority Status & Language.

2.4 Discussion

The two design choices in the CWDG program investigated in this paper — the spatial units used to aggregate hazard and the binary low-income criterion — materially affect which communities are prioritized for grant funding. Aggregating wildfire hazard within place catchments results in different areas being classified as at-risk and high-hazard, as compared to the CWDG Dashboard tool’s method of aggregating hazard within Census places and counties. Importantly, these classifications are not only *different* under the place catchment approach, but the use of this alternate spatial unit also results in less disagreement with the pixel-level hazard classes. The comparison between the low-income criterion and broader measures of social vulnerability reveals two related shortcomings. First, the low-income criterion includes a large proportion of low-vulnerability places. Second, significant variation in vulnerability among low-income places is not incorporated into the CWDG evaluation process. These findings indicate that the CWDG program may not consistently prioritize communities that face the highest hazard and are the most vulnerable.

The comparison of hazard aggregation methods shows that the place catchment approach has greater agreement with pixel-level hazard classes than the CWDG Dashboard tool’s approach of aggregating within Census places and counties. The place catchment method may also more accurately characterize hazard within project areas because it matches the scale of community-level mitigation projects and eliminates reliance on county-level hazard metrics to fill gaps between Census places. This ameliorates the modifiable areal unit problem inherent in the Dashboard’s mixed-aggregation approach: when areas outside Census places are assigned county-level hazard values, fine-scale variation in hazard is averaged over administrative units that do not necessarily represent local conditions. This methodological change more closely aligns the program with its legislative mandate to target at-risk communities with “high or very high wildfire hazard potential” ([Infrastructure Investment and Jobs Act, 2021](#)).

While the method of aggregating hazard within place catchments addresses the shortcomings of the mixed-unit approach, the method has its own limitations. The place catchment approach assigns areas to Census places based on Euclidean distance, which may not fully capture how neighboring residents identify with and coordinate around community-level concerns. Approaches that instead use driving distance to construct spatial units (e.g., McEvoy et al. ([2026](#))) may better represent cohesive communities, but are also more computationally intensive to produce and may less accurately represent fuel connectivity than simple Euclidean distance. The place catchment method also produces designations that differ substantially from the Dashboard’s approach in some regions. In northeastern Arizona and northwestern New Mexico, for example, Census places designated as eligible under the Dashboard method become ineligible as their catchments absorb lower-hazard surroundings. Whether these changes better or more poorly reflect pixel-level hazard than the Dashboard’s county-level fallback likely varies between regions, even as

nationwide agreement rates improve.

The comparison between SVI and the low-income criterion reveals two related issues with the income-based approach. First, the criterion is overly inclusive: a majority of at-risk places, including most low-vulnerability ones, qualify as low-income. Second, the criterion misses key dimensions of vulnerability — particularly the Minority Status & Language and Housing & Transportation themes — that have little correlation with income. The binary structure of the criterion compounds these issues, since the program has no mechanism to prioritize the most vulnerable places among the 74% of at-risk places that qualify as low-income. Because these disconnects appear specifically within at-risk Census places, the issue directly affects which communities CWDG funding is likely to prioritize.

While the present study focuses on the eligibility criteria of the CWDG program and the data provided by the CWDG Dashboard tool, the issues raised about measurement of hazard and vulnerability are relevant to a variety of policy programs that allocate funding based on these metrics. The issues stemming from the use of mixed-scale aggregation units to quantify hazard are likely present wherever such aggregations are performed. Future research might investigate methods of constructing aggregation units that account for connectivity with respect to both social factors and fuels, which may more meaningfully represent contiguous treatment areas. Similarly, binary thresholds, exemplified here by the low-income criterion, erase significant variation among communities that fall on either side of the cutoff. Additional work could explore the impact of graduated, rather than threshold-based, metrics on community prioritization.

2.5 Conclusion

This study investigates two facets of the CWDG evaluation process: the spatial aggregation of wildfire hazard data and the use of a low-income criterion rather than a broader measure of vulnerability. The current practice of aggregating wildfire hazard within Census places and counties reflects the design choices of the CWDG Dashboard tool, which were driven by data availability and computational practicality rather than by statutory mandate. Although CWDG applicants may provide data from other sources to support their applications, the dominant tool for obtaining hazard data is the CWDG Dashboard, making its design choices a de facto component of the evaluation process. The design choices implemented in the Dashboard are defensible, but the present analysis demonstrates that outcomes are sensitive to alternate choices that may better align with the program's goals. By contrast, the use of the low-income criterion was mandated by the program's authorizing legislation. Relying on income rather than broader measures of social vulnerability, however, does not consistently prioritize the most vulnerable communities. The findings of this study indicate that both statutory and de facto design features meaningfully affect the targeting of community-level wildfire risk mitigation programs.

Chapter 3

Application evaluation and distributional outcomes in the Community Wildfire Defense Grant program

3.1 Introduction

The Community Wildfire Defense Grant program is the largest federal investment in community-scale wildfire mitigation to date and plans to disburse \$1 billion across fiscal years 2022-2026 ([Infrastructure Investment and Jobs Act, 2021](#)). Unlike federal wildfire programs that fund agency-led fuels treatments on public lands, the CWDG program directs resources to community-level planning and projects on non-federal lands. The program's authorizing legislation directs the Secretary of Agriculture to prioritize three specific community types — low-income, disaster-impacted, and high wildfire hazard — which the Forest Service operationalized through a competitive scoring rubric that combines binary criteria reflecting the statutory categories with grad-

uated scoring of qualitative application characteristics.

The discretion exercised in both the construction and application of the program's scoring rubric creates the potential for a gap between program outcomes and intended priorities. Additionally, the priorities encoded in the program's authorizing legislation may not necessarily select for communities facing the highest levels of wildfire hazard and vulnerability. Whether CWDG funds actually reach vulnerable communities facing high wildfire hazard is consequential both because of the program's scale and because federal disaster-mitigation programs with similar design features have been shown to underserve socially vulnerable communities ([Miao et al., 2025](#)). Empirical assessment of the program's first three rounds can inform both the implementation of the remaining funding cycles and the design of future federal programs aimed at community-scale wildfire risk mitigation.

3.1.1 Equity in disaster mitigation funding

Need is a key distributional principle by which to assess the equity of allocation of resources ([Stone, 2012](#)). In the context of disaster mitigation, exposure to hazards is a primary determinant of need. However, social vulnerability also contributes to need through its amplification of disaster impacts ([Cutter et al., 2003](#)). While exposure is typically operationalized directly in program design, vulnerability is more often assessed only indirectly through proxies such as income. The operationalization of need, in addition to other program design choices, can produce distributional outcomes that do not necessarily prioritize communities with the highest need. Concerns around whether disaster mitigation programs actually reach vulnerable communities have motivated research on the role of social vulnerability as a factor in program funding out-

comes ([Domingue & Emrich, 2019](#); [Finucane et al., 2023](#); [Miao et al., 2025](#)).

Federal disaster management programs often produce distributional outcomes that favor communities with greater access to resources. Across a range of these programs, communities with better socioeconomic conditions have received more funding ([Domingue & Emrich, 2019](#); [Miao et al., 2025](#)). This pattern has also been observed in agency-led wildfire mitigation, where the distribution of funding for fuel treatment projects favored communities with higher socioeconomic status ([Anderson et al., 2023](#)).

Competitive grant programs offer two stages at which resources could be directed toward higher-need communities: who applies for funding and who is awarded among applicants. However, this selection toward higher-need communities does not always occur in practice. At the first stage, communities that are vulnerable across certain dimensions — specifically those that are low-income and have greater shares of young or old residents — may be less likely to apply for funding ([Finucane et al., 2023](#)). At the second stage, award rates among applicants are not necessarily well-predicted by either vulnerability or hazard ([Finucane et al., 2023](#)).

3.1.2 Scoring rubrics in competitive grants

Studies of grant programs with quantitative scoring systems find that there can be substantial variation in the relative influence of different scoring rubric elements on grant receipts ([Eblen et al., 2016](#)). However, even when scoring rubrics are designed to evaluate distinct criteria, the resulting scores may not behave as independent measures of those criteria. Halo effects — first described by Thorndike ([1920](#)) — refer to the tendency for raters to score multiple dimensions of a target similarly based on overall impression rather than evaluating each dimension independently

([Murphy et al., 1993](#)). In grant peer review specifically, Lindner et al. ([2016](#)) found that the criteria scores assigned by NIH reviewers were strongly intercorrelated, limiting what can be inferred about the relative influence of individual criteria on overall scores.

3.1.3 The Community Wildfire Defense Grant program

The Infrastructure Investment and Jobs Act of 2021 allocated \$1 billion for Community Wildfire Defense Grants to be spent over fiscal years 2022–2026 ([Infrastructure Investment and Jobs Act, 2021](#)). These grants can be used by communities to fund up to \$250,000 towards the development of a Community Wildfire Protection Plan (CWPP) or up to \$10,000,000 towards the implementation of a project described in a CWPP. In awarding these grants, the Secretary of Agriculture is directed to prioritize “at-risk” communities that (1) have high or very high wildfire hazard potential, (2) are low-income communities, or (3) have been impacted by a severe disaster.

The Forest Service operationalizes the statutory priorities through its grant scoring rubric, which includes six graduated and three binary criteria (shown in Tbl. [3.1](#)). The rubric’s three binary criteria correspond to the legislation’s three directives to the Secretary — Low Income Community, Affected by a Severe Disaster, and Area of Wildfire Hazard Potential — which together add up to 40 points. The six graduated criteria assess specific sections of the CWDG application that speak to proposal quality and account for the remaining 60 points in the scoring rubric. Each application is scored by three reviewers.

Table 3.1: The nine scoring criteria used in the evaluation of CWDG applications, for a maximum total of 100 points. The program’s Notice of Funding Opportunity directs reviewers to assign the graduated scoring criteria scores from zero to ten, while binary criteria are to be awarded either zero or the maximum number of points.

Criterion	Maximum points	Scoring
Project Description	10	Graduated
Budget	10	Graduated
Accomplishments	10	Graduated
Collaboration	10	Graduated
Landscape Impacts	10	Graduated
Project Sustainability	10	Graduated
Low Income Community	10	Binary
Affected by a Severe Disaster	10	Binary
Area of Wildfire Hazard Potential	20	Binary

Three rounds of CWDGs have been awarded to date, for fiscal years 2022–2024, as shown in Tbl. 3.2. Each round disbursed roughly \$200–250 million toward the program’s \$1 billion total. The application window for the third round was extended due to a mid-program rule change ([Fire Adapted Communities Learning Network, 2024](#)).

Table 3.2: Timeline of the first three rounds of CWDG funding. Awarded amounts were sourced from press releases ([US Forest Service, 2023, 2024, 2025](#)) and do not correspond exactly to the sample used in the analysis; see Methods for the exclusion criteria.

Round	Notice posted	Applications Due	Total Awarded
One (FY 2022)	July 27, 2022	October 7, 2022	\$197 million
Two (FY 2023)	July 31, 2023	October 31, 2023	\$250 million
Three (FY 2024)	November 21, 2024	March 14, 2025	\$200 million

3.1.4 Distribution of CWDG funding

Studies on the distribution of CWDG funding have primarily focused on the program’s alignment with statutory goals and on its reach to low-capacity communities. The first round of grants was successful in prioritizing low-income and high-hazard communities ([Pohl et al., 2023](#)); subsequent

analyses found that this pattern held through the second and third rounds (Pohl, 2025, 2026). These analyses also find that the program has reached communities with low capacity. Capacity in these analyses was assessed using a Rural Capacity Index based on local government, institutional, and socioeconomic characteristics (Smith et al., 2026). However, capacity and vulnerability are conceptually distinct: a program that succeeds in reaching low-capacity communities is not necessarily reaching the most vulnerable ones. The distribution of program funding with respect to graduated measures of hazard and vulnerability, rather than the statutory criteria, remains under-investigated.

The operation of the scoring rubric in the first round of the program was investigated in Pohl et al. (2023), although the analysis was limited to assessing inter-reviewer consistency. This study found that reviewer scores were generally consistent — more so in applications for planning than implementation — but were more variable in the scoring of the Budget, Landscape Impacts, and Project Sustainability sections (Pohl et al., 2023). The relationship between application scores and award decisions, however, has yet to be addressed empirically. Additionally, little is known about the relative influence of each scoring component or the correlations between scoring elements.

3.1.5 The current study

This chapter investigates the operation of the CWDG scoring criteria and evaluates whether awards are reaching the communities facing the greatest wildfire hazard and social vulnerability. The analysis uses the full corpus of 1,416 applications from the first three rounds of the CWDG program. By linking application data to continuous measures of community-level wildfire hazard and social vulnerability, I assess the distributional outcomes of the program relative to need rather

than relative to the program’s statutory criteria.

The first part of the chapter examines the operation of the CWDG scoring rubric in practice through three linked questions: (1) What is the relationship between total application score and grant awards?, (2) Do the rubric elements measure distinct application characteristics?, and (3) How does each rubric component influence award receipt?

The second part of the chapter assesses whether CWDG awards reach communities facing high wildfire hazard and social vulnerability and is organized around three questions: (1) How are award dollars distributed across the joint hazard $\times$ SVI space?, (2) How are applicants distributed across hazard and SVI, relative to the national distribution of communities?, and (3) Among communities that apply for funding, how are hazard and SVI each associated with award receipt, net of the other and of application characteristics?

3.2 Methods

3.2.1 Data

Fig. 3.1 shows the flow of observations from the source datasets — applications and awards — to the samples used in the analyses. Sample 1 is composed of all CWDG applications and includes an indicator for whether each application was awarded based on the application’s inclusion or exclusion from the awards dataset. Sample 2 excludes applications that were not assigned scores. Sample 3 is constructed by matching applications to the places referenced by spatial data included in the applications and is used in the distributional analyses.

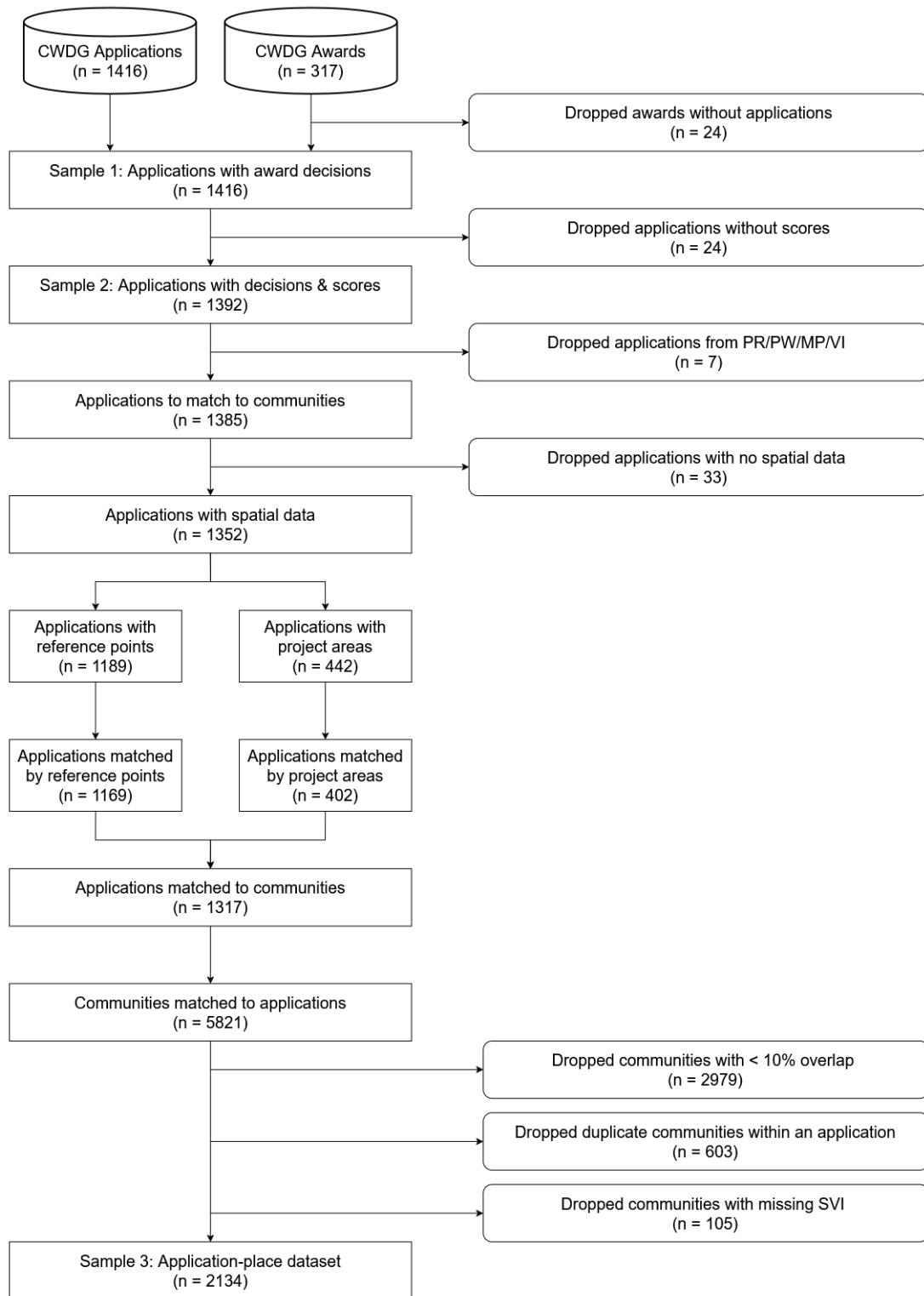


Figure 3.1: Construction of analytic samples. Sample 1 is used for the descriptive overview of CWDG program trends, Sample 2 is used for the scoring rubric analysis, and Sample 3 is used for the distributional analysis.

3.2.1.1 CWDG applications and awards

CWDG applications were downloaded from the Forest Service's [CWDG Grant Portal](#) on September 29, 2025. Applications include the full text submitted by applicants for each of the six qualitatively-scored grant sections, supporting documentation for the three binary scoring criteria, and spatial data representing the project location and/or treatment area. Each application is scored by three reviewers; the data include both per-reviewer and aggregate scores for each of the nine rubric items. A total of 1,416 applications are available for the first three rounds of the CWDG program. The application data from Round 2 includes 24 applications that were not assigned scores and are excluded from the scoring analyses.

CWDG awards data were downloaded from the Forest Service's website of [Funded Proposals](#). The data table lists 317 funded projects from the first three rounds of the CWDG program. Awards are matched to applications by exact project name; awards without an exact match were hand-matched to applications. All 218 funded projects from Rounds 2 and 3 matched to an application. Twenty-four of the 99 awards from Round 1 had no corresponding application in the Grant Portal; the source of this gap is unclear and these awards are excluded from analyses requiring application-level data.

Grant type (planning vs. implementation) is recorded in the awards dataset but is unavailable for denied applications. I therefore hand-code grant type from the application materials for all applications. For awarded grants, the hand-coding matches the grant type recorded in the awards dataset in all but one case, which I verified to be an error in the awards data.

3.2.1.2 Community hazard and social vulnerability

The analysis uses two community-level measures that reflect wildfire risk: hazard and social vulnerability. Communities are represented by place catchments, which encompass Census places and their surrounding areas. These spatial units were constructed in Humphrey (2026) by matching areas outside the boundaries of Census places to the nearest place. Both metrics were constructed and evaluated in Humphrey (2026) and are summarized only briefly here. The hazard measure aggregates Wildfire Hazard Potential (Scott, Dillon, et al., 2024) and Risk to Potential Structures (Scott, Dillon, et al., 2024) within Community Wildfire Risk Reduction Zones (Dillon et al., 2024). The social vulnerability measure is built from the fifteen American Community Survey variables used by the CDC’s Social Vulnerability Index (Flanagan et al., 2018). Each measure is expressed as a percentile computed across all Census place catchments in the United States. Hazard and SVI enter the analysis as separate percentiles rather than as a single composite risk index. Because applications may match to multiple place catchments, the measures are retained at the application-place level rather than aggregated to the application level.

3.2.1.3 Construction of application-place dataset

Unit of analysis CWDG applications include spatial data — reference points, project area polygons, or both — that allow each application to be matched to the communities that it serves. A given application may reference one or more spatial entries of either type and may therefore correspond to multiple places. Places referenced by an application can vary meaningfully in the wildfire hazard and social vulnerability that they face; this variation represents true within-application variability rather than uncertainty in a single underlying value. Aggregating place-

level characteristics to the application level would obscure this within-application variability: a project that serves both low-SVI and high-SVI communities cannot meaningfully be described as having medium social vulnerability. Rather than aggregating, the analysis is conducted at the application-place level, with each place catchment matched to an application treated as an observation nested within that application.

Matching Applications were matched to Census place catchments using the reference points and project areas provided in the application materials. Seven applications — four from Puerto Rico and one each from Palau, the Virgin Islands, and the Northern Mariana Islands — were excluded from matching because the hazard and SVI datasets do not extend to these jurisdictions. This left 1,385 applications eligible for matching, of which 1,189 provided at least one reference point and 442 provided at least one project area. The 33 applications that included no spatial data are excluded from the place-level analyses.

Coordinate-entry errors were common and were corrected automatically where possible. For each coordinate, the analysis tested whether swapping latitude and longitude, flipping the sign of one or both values, or some combination of these transformations would place the point within the boundary of the application's stated state; the unique transformation meeting this condition, if any, was applied. Coordinates that could not be resolved this way were left unchanged. After correction, 1,745 of 1,772 reference points fell within a state polygon, yielding matches for 1,169 applications.

Project area polygons were processed using the same coordinate-correction procedure applied vertex by vertex. 64 of the 649 areas either contained vertices that could not be corrected or had fewer than three distinct vertices and were excluded. Of the remaining areas, 86 were self-

intersecting or contained duplicate vertices as drawn. Because the source data does not consistently preserve a meaningful traversal order for polygon vertices, these areas were reconstructed as the convex hull of their vertex set. This yielded 585 usable project areas, all of which intersected at least one place catchment, producing matches for 402 applications.

A total of 1,317 applications were matched to place catchments by either reference points or project areas. Because many applications matched to more than one place catchment, this corresponds to 5,821 application-places. However, many of the application-places included in this count have only small overlaps with project areas. I exclude 2,979 applications-places with small overlaps — less than 10% of the project area — to limit the influence of places that are unlikely to receive significant benefit from mitigation projects. Additionally, I exclude 603 application-places that are duplicated within an application. For example, an application that provides two reference points that match to the same place catchment is de-duplicated to produce only a single application-place observation. Finally, 105 application-places that do not have SVI rankings are excluded from the distributional analysis.

Weighting Observations are weighted by the inverse of the number of unique places matched to the application, so that each application contributes equally to the analysis regardless of how many communities it references. This prevents applications referencing many communities from dominating the estimates and avoids imposing assumptions about within-project resource allocation that the application data do not support.

Two alternative weighting schemes were considered and rejected. Area-weighting based on the overlap between a project area and each catchment assumes that project resources are distributed uniformly across the area covered by the application. Population-weighting assumes

that resources are distributed in proportion to the population served. Neither assumption is documented in the applications, and neither is likely to hold uniformly across applicants. Some applications do speak to within-project allocation through narrative budget justifications, but these are inconsistently present and not in a structured form amenable to systematic extraction across more than 1,400 applications. Equal weighting applies a single rule to every application without imposing a distribution the applications themselves do not specify.

3.2.2 Analytical approach

Prior to addressing the chapter's main research questions, I conduct a descriptive overview that establishes the basic contours of CWDG funding across the program's first three rounds. The descriptive overview begins with an analysis of the geographic distribution of CWDG awards over time based on the raw awards data. Following this geographic analysis, I assess trends in grant types and amounts over time based on the matched applications-awards dataset (Fig. 3.1, Sample 1).

The main analyses are organized in two parts. The first part examines how the CWDG scoring rubric operates in practice: how total application scores relate to award decisions, whether the nine scoring criteria measure distinct characteristics, and how the scoring criteria influence award rates. The second part examines whether awards reach communities facing high wildfire hazard and social vulnerability. It begins by describing how award dollars are distributed across the joint hazard-SVI space, then examines two factors that shape that distribution: which communities apply and which applicants receive awards. Examining the applicant pool and the award relationship separately makes it possible to locate where any disconnect between wildfire risk

and funding arises: in who applies, or in who is funded among applicants.

3.2.2.1 Operation of the CWDG scoring rubric

The analyses of the CWDG scoring rubric use 1,392 applications from the first three funding rounds (Fig. 3.1, Sample 2). This sample excludes 24 applications that were not assigned scores, all of which were from Round 2 and were denied funding. Additionally, 24 Round 1 awards that did not have corresponding applications are not included in this analysis.

Score-to-award relationship The relationship between total application score and award receipt is characterized by examining the distribution of scores among awarded and denied applications within each combination of funding round and grant type, with attention to the range of scores where the two distributions overlap. Stratification by funding round and grant type is necessary because the award decision process was conducted separately across years, and different thresholds may have been applied for planning and implementation grants.

Uniqueness of scoring components The second stage assesses whether the scoring components capture distinct application characteristics. In particular, the six qualitative elements may represent a single underlying dimension. Pairwise correlations among the components are computed, and a principal component analysis of the qualitative scoring elements is conducted to assess dimensionality.

Influence of scoring components The third stage examines how each scoring component influences award receipt, and in particular whether the binary criteria function as eligibility gates. Conditional on the dimensionality analysis, the six qualitative components are either examined

individually or aggregated into a composite. Award rate is computed within each funding round across bins of the qualitative scores (or composite, if aggregated) and separately for applications that do and do not meet each binary criterion. For the binary criteria, award rates conditional on meeting each criterion, on meeting all three, and overall are computed by round to characterize the advantage each criterion confers and how it changes across rounds.

3.2.2.2 Allocation of funding to high-hazard and high-vulnerability communities

The analysis of the role of hazard and social vulnerability in grant funding is conducted using the application-place dataset described above, which contains 2,134 observations (Fig. 3.1, Sample 3).

Awards by hazard and vulnerability Awarded dollars are tabulated across the joint distribution of community-level wildfire hazard and social vulnerability to characterize whether CWDG funding has reached the communities facing the greatest wildfire risk. Because applications may match to multiple places, the awarded amount for each application is divided evenly across its matched catchments before aggregation. This preserves the total awarded amount across the grid: summing the values in all cells recovers the total dollars awarded through the program. The resulting distribution is presented as a heatmap on the joint hazard $\times$ SVI grid.

Applicant hazard and vulnerability Applications for funding are tabulated across the joint distribution of community-level wildfire hazard and social vulnerability to characterize whether high-risk communities are applying for funding. Applications matched to multiple catchments contribute to each catchment's bin, so an application spanning communities in different deciles contributes to multiple cells. The resulting distribution is presented as a heatmap on the joint hazard $\times$ SVI grid.

Logistic model of grant awards A Bayesian logistic regression of award receipt is fit to the application-place dataset using the brms software package (Bürkner, 2017) to quantify the association of hazard and vulnerability with the likelihood of award, controlling for grant year, grant type, and log funds requested (interacted with grant type), with a state-level random intercept. SVI and RPS are each mean-centered, and log funds requested is mean-centered separately for planning and implementation grants.

The model is described by

$$y_{ij} \sim \text{Bernoulli}(\pi_{ij})$$

$$u_{state} \sim \mathcal{N}(0, \sigma_{state}^2)$$

$$\begin{aligned} \text{logit}(\pi_{ij}) = & \alpha_{year_i} + u_{state_i} + \beta_1(SVI_j - \overline{SVI}) + \beta_2(RPS_j - \overline{RPS}) + \\ & \gamma type_i + \delta_{plan}(1 - type_i)(\log(req_i) - \overline{\log(req_{plan})}) + \delta_{imp}type_i(\log(req_i) - \overline{\log(req_{imp})}) \end{aligned}$$

where

- y_{ij} — indicator for whether community j received funding through application i
- π_{ij} — probability of community j receiving funding through application i
- u_{state} — set of state-level random intercepts
- $year_i$ — grant year for application i
- $state_i$ — state for application i
- SVI_j — SVI percentile (national) for community j
- RPS_j — RPS percentile (national) for community j
- $type_i = 0$ for planning, 1 for implementation
- req_i — funds requested for application i

The parameters of primary interest are β_1 and β_2 , which estimate the change in the log-odds of grant funding associated with a full-range increase in SVI percentile and RPS percentile, respectively. α estimates a set of year-specific intercepts, which correspond to the log-odds of funding associated with planning grants requesting the mean amount, submitted by a community with mean SVI and RPS. γ estimates the difference in log-odds between mean-request implementation and mean-request planning grants. δ_{plan} and δ_{imp} estimate the change in log-odds associated with a one-unit increase in $\log(req)$, estimated separately for planning and implementation grants. A final parameter of interest is σ_{state}^2 , which estimates between-state variance.

Each observation is weighted by the inverse of the number of unique place catchments matched to its application. Weakly informative priors were used throughout: $\text{Normal}(0, 2.5)$ on population-level coefficients, $\text{Normal}(0, 1.5)$ on the year-specific intercept terms, and $\text{Exponential}(1)$ on the state-level standard deviation.

Parameter medians and 95% credible intervals are estimated from 4000 total samples of the posterior distribution drawn from four independent chains, each discarding 1000 warm-up samples. Convergence is assessed using $\hat{R}$ and bulk and tail effective sample sizes, following the recommendations of Vehtari et al. (2021). Predicted award probabilities, with 95% credible intervals, are calculated across the range of each of the predictors, averaging across the empirical joint distribution of the remaining covariates, including state.

3.3 Results

3.3.1 Descriptive overview

3.3.1.1 Geographic distribution of CWDG awards

CWDG awards in the first three rounds clustered in the western states and the southern Appalachians, with sparse coverage elsewhere (Fig. 3.2). As reported in Tbl. 3.3, nearly half of all CWDGs overall were awarded to the top five states: California, Oregon, Washington, North Carolina, and New Mexico. However, the geographical distribution of awards has changed over time. Notably, the share of awards going to California decreased from one in three during the first round of awards in 2022 to just over 10% in 2024. The distribution of awards has become less concentrated over time; although a handful of states still account for most awards, a growing share has gone to states outside the top twelve (rising from 14% in 2022 to nearly 30% in 2024).

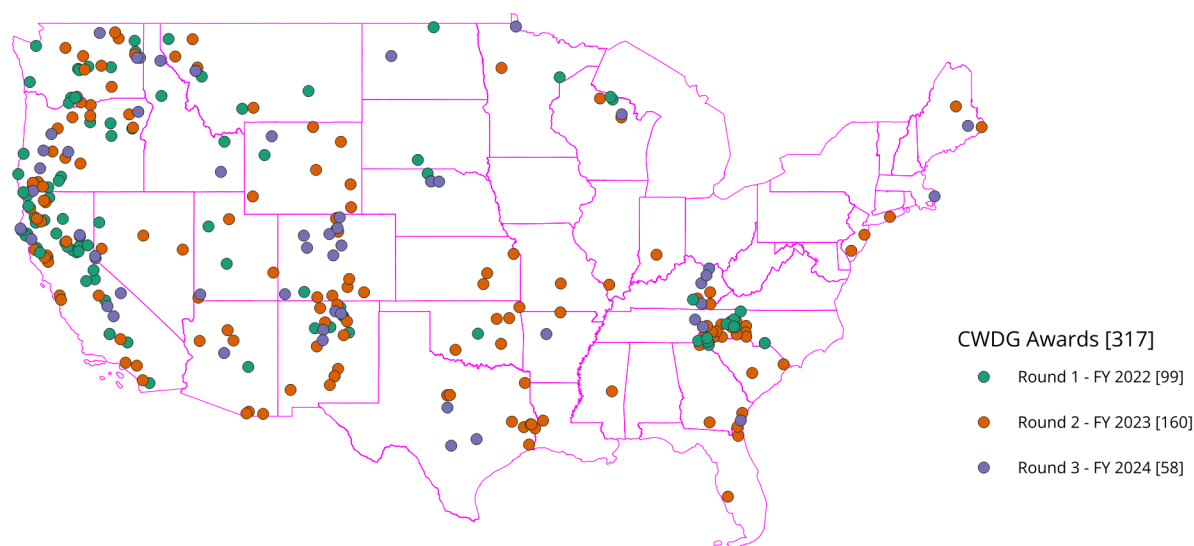


Figure 3.2: Locations of CWDGs awarded in the first three rounds, colored by funding round. 27 CWDG awards are not shown: 7 in Alaska, 17 in Hawaii, 2 in Puerto Rico, and 1 in Palau.

Table 3.3: CWDG awards by grant year for the ten states with the most total awards (including ties); remaining states are aggregated as “Other.” Percentages are within-column shares of that year’s awards.

State	2022 Awards	2023 Awards	2024 Awards	Total Awards
California	33 (33.33%)	17 (10.62%)	6 (10.34%)	56 (17.67%)
Oregon	10 (10.10%)	13 (8.12%)	6 (10.34%)	29 (9.15%)
Washington	13 (13.13%)	10 (6.25%)	4 (6.90%)	27 (8.52%)
North Carolina	11 (11.11%)	13 (8.12%)	0 (0.00%)	24 (7.57%)
New Mexico	5 (5.05%)	12 (7.50%)	4 (6.90%)	21 (6.62%)
Colorado	1 (1.01%)	9 (5.62%)	8 (13.79%)	18 (5.68%)
Hawaii	5 (5.05%)	9 (5.62%)	3 (5.17%)	17 (5.36%)
Texas	0 (0.00%)	10 (6.25%)	3 (5.17%)	13 (4.10%)
Montana	4 (4.04%)	5 (3.12%)	1 (1.72%)	10 (3.15%)
Arizona	1 (1.01%)	6 (3.75%)	1 (1.72%)	8 (2.52%)
Kentucky	1 (1.01%)	3 (1.88%)	4 (6.90%)	8 (2.52%)
Wyoming	1 (1.01%)	6 (3.75%)	1 (1.72%)	8 (2.52%)
<i>Other</i>	14 (14.14%)	47 (29.38%)	17 (29.31%)	78 (24.61%)
Total	99 (100.00%)	160 (100.00%)	58 (100.00%)	317 (100.00%)

The state-level distribution of funds requested and awarded shifted considerably across the program’s first three rounds (Fig. 3.3). Requested dollars far exceeded awarded dollars in every round, reflecting persistent oversubscription of the program. The clearest divergence is in California: requested dollars rose sharply over the three years, exceeding \$300M in FY2024, even as the state’s awarded dollars declined. Awarded dollars decentralized over time, mirroring the award-count trends: California’s awards fell while awards to other western states — particularly Colorado, New Mexico, and Texas — grew. Requested dollars, by contrast, grew across many western states and concentrated further in California, widening the gap between what the state sought and what it received.

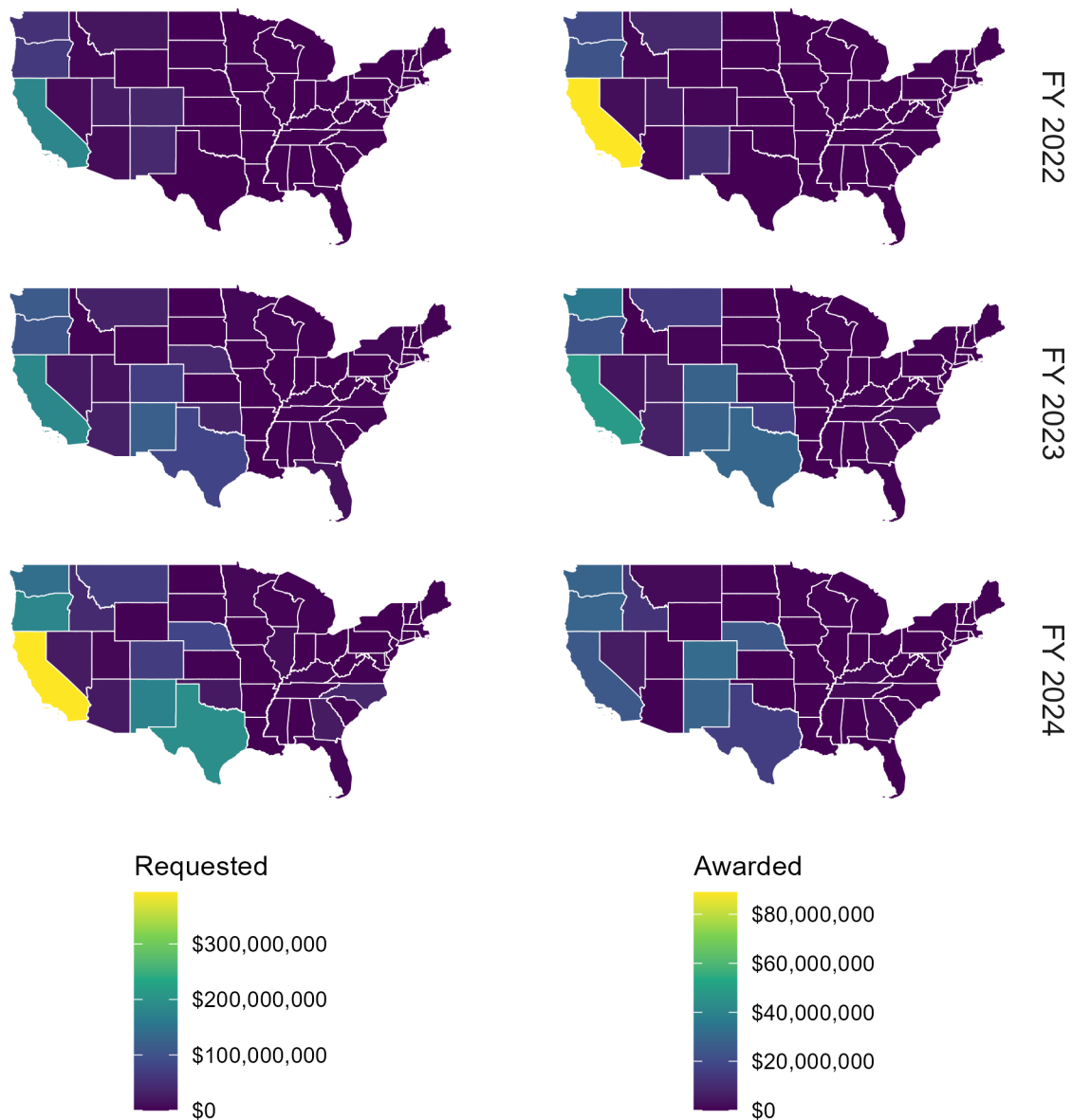


Figure 3.3: CWDG dollars requested (left column) and awarded (right column) by state, with one row per funding round (FY2022–FY2024). The two columns use independent color scales — requested dollars reach approximately \$300M, awarded dollars approximately \$80M. States with no applications or awards are shown at \$0.

3.3.1.2 Grant types and amounts over time

The program’s funding is concentrated in implementation grants, as illustrated by Tbl. 3.4. Although planning and implementation grants were awarded in comparable numbers, implementation grants account for the overwhelming majority of dollars disbursed. A total of \$608.84M, or more than 95% of all CWDG funding, went to implementation grants across the three years, against \$27.81M for planning grants. This disparity follows from the program’s structure: implementation grants may be awarded up to \$10,000,000, while planning grants are capped at \$250,000.

Table 3.4: CWDG applications, awards, success rate, median request, median award, and total awarded dollars for the three rounds of funding, separated by grant type (planning vs. implementation).

Grant type	Year	Apps	Awards	Success rate	Median request	Median award	Total awarded
Planning	2022	117	20	17.1%	\$103K	\$94K	\$2.76M
Planning	2023	220	110	50.0%	\$175K	\$185K	\$19.55M
Planning	2024	184	16	8.7%	\$235K	\$199K	\$3.10M
Implementation	2022	191	55	28.8%	\$993K	\$1.50M	\$159.48M
Implementation	2023	315	50	15.9%	\$1.5M	\$4.72M	\$239.10M
Implementation	2024	389	42	10.8%	\$2.8M	\$4.10M	\$204.78M

These funding totals mask considerable variation in the composition of awards across the three years of the program. Planning grants were a majority of awards in 2023 but a minority in the other two years. Over two-thirds of awards in 2023 were for the development of CWPPs, and half of the 220 planning applications submitted in 2023 were funded, compared to 17.1% in 2022 and 8.7% in 2024. Implementation award counts were stable across years, but success rates declined. The number of implementation awards was similar across the three years (55, 50, and 42), while the implementation success rate fell from 28.8% in 2022 to 15.9% in 2023 and 10.8% in

2024.

Requested amounts grew over time, and applicants increasingly requested at or near the program maximum. The median planning request more than doubled from 2022 to 2024, and the median implementation request nearly tripled during that period. Fig. 3.4 shows that this growth was accompanied by a shift in the shape of the request distribution: planning requests, which were roughly evenly distributed across amount bins in 2022, concentrated in the highest bins by 2024, while implementation requests shifted toward the \$1–5M and >\$5M bins. Although planning grants are statutorily capped at \$250,000, thirteen planning applications requested more than this amount, with requests ranging up to \$1.77M. Three of these requests were awarded amounts exceeding the cap, the largest being \$277,092; the basis for these exceptions is not documented in the available data.

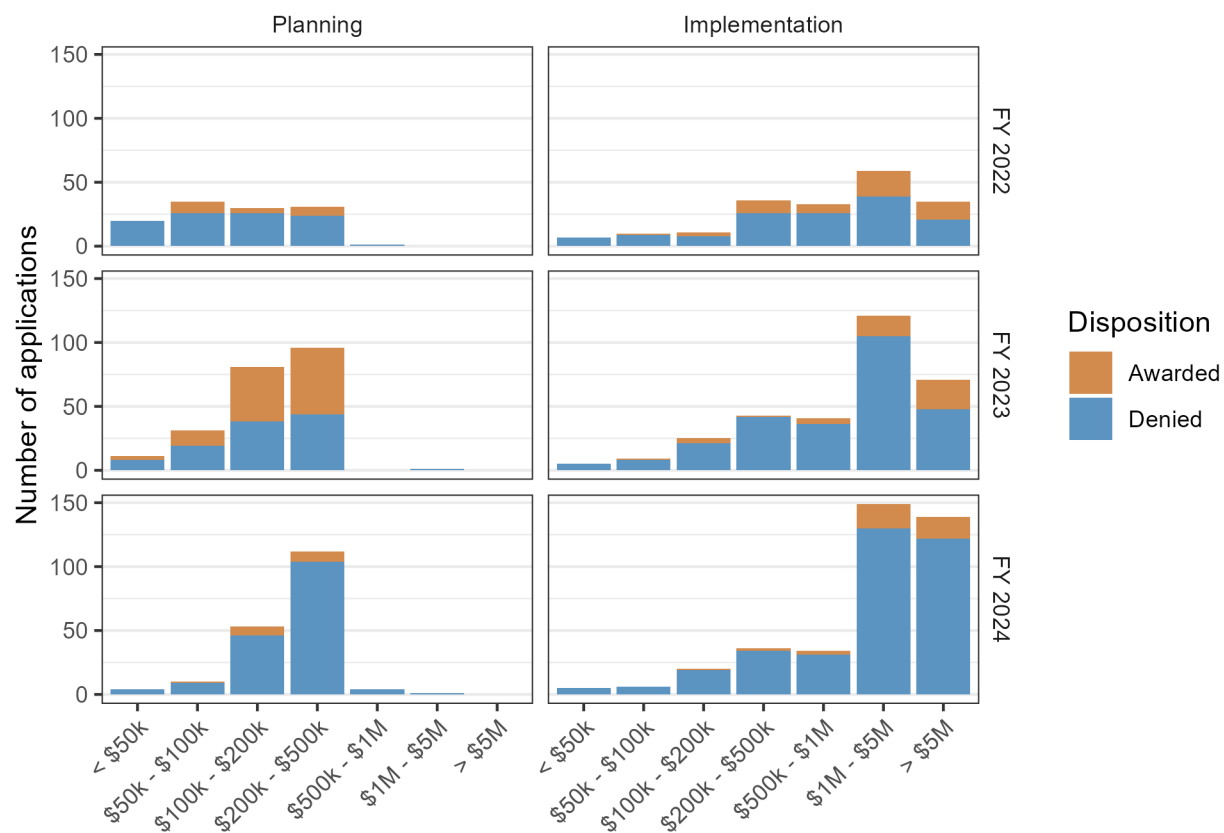


Figure 3.4: Distribution of CWDG application amounts by funding round and grant type. Each bar shows the number of applications requesting amounts within the indicated range, split by funding disposition (awarded vs. denied). Planning grant amounts (left column) are capped at \$250,000 by program rules; implementation grant amounts are capped at \$10,000,000.

3.3.2 Operation of the CWDG scoring rubric

3.3.2.1 Score-to-award relationship

The distribution of total application scores for awarded and denied applications (Fig. 3.5) shows that awarded applications are concentrated at the upper end of the score distribution across all six combinations of funding round and grant type. The lowest score associated with an award is 75. Awarded and denied applications overlap throughout the upper range of every panel, indicating that some selection occurs beyond what total score captures.

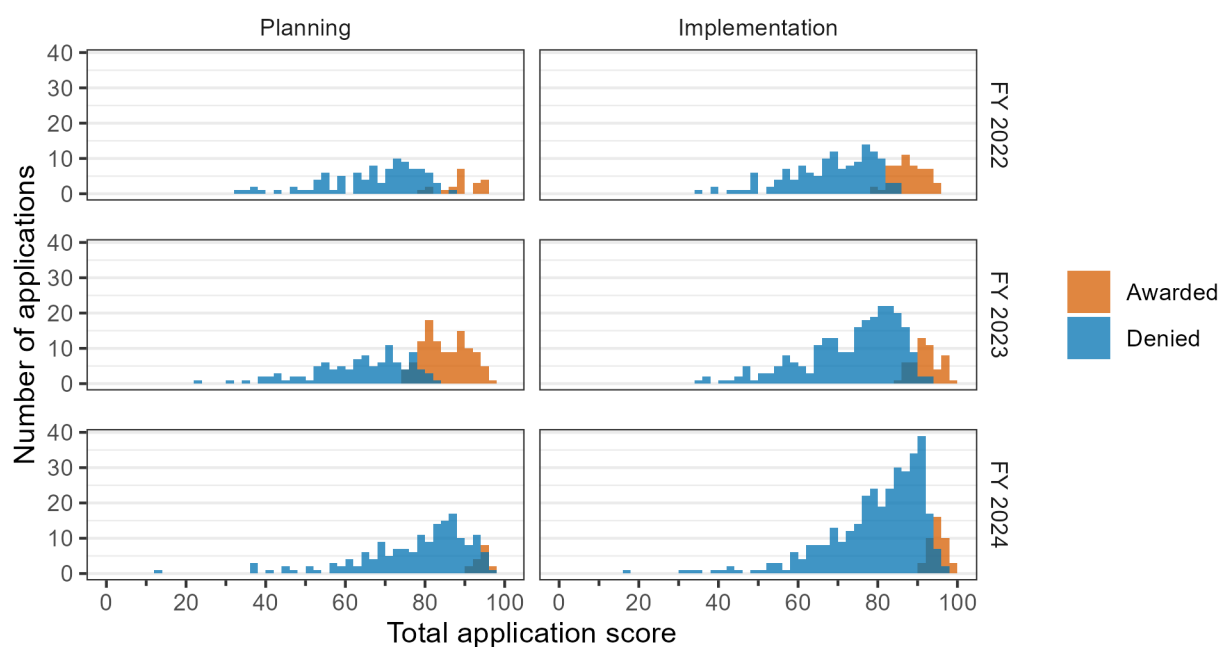


Figure 3.5: Distribution of total application scores by funding round and grant type. Each panel shows the distribution of total scores for awarded and denied applications. Awarded and denied distributions are plotted as overlapping histograms with two-point bins, so darker regions indicate score ranges in which both awarded and denied applications appear.

The presence of selection outside the scoring rubric raises the question of what criteria are being used for decisionmaking among applications that fall within this “overlap zone” — defined as applications with scores between the minimum awarded and the maximum denied, for each

funding round and grant type. Amount requested is one candidate: reviewers may favor the least expensive among similarly-scored applications. However, an examination of the disposition of these 312 applications alongside amount requested (Fig. 3.6) shows no clear separation between awarded and denied applications by amount requested, leaving the source of within-overlap selection unexplained.

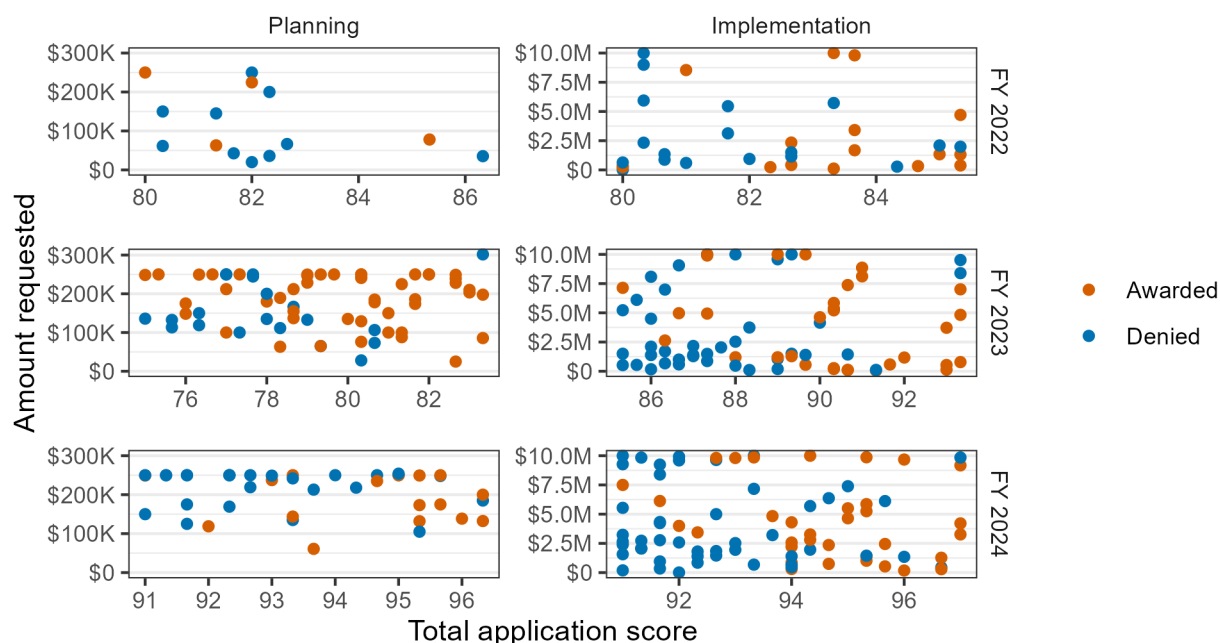


Figure 3.6: Amount requested vs. total application score for the 312 applications within the score overlap zone, by funding round and grant type, colored by disposition (awarded vs. denied). The overlap zone is defined per round and grant type as the range of scores between the minimum-scoring awarded application and the maximum-scoring denied application.

The increasing competitiveness of the program over time is visible as a shift in the scoring distributions shown in Fig. 3.5. Median total scores rose across rounds, from 73.3 (planning) and 76.3 (implementation) in 2022 to 83.3 and 84.7 in 2024. As applications concentrated at higher scores, award rates in 2024 fell at every score level, including the highest. Among 2024 applications scoring 90 or above, only 34.8% of Planning applications and 37.8% of Implementation applications were funded. High scores were thus necessary but not sufficient for funding in 2024.

3.3.2.2 Uniqueness of scoring components

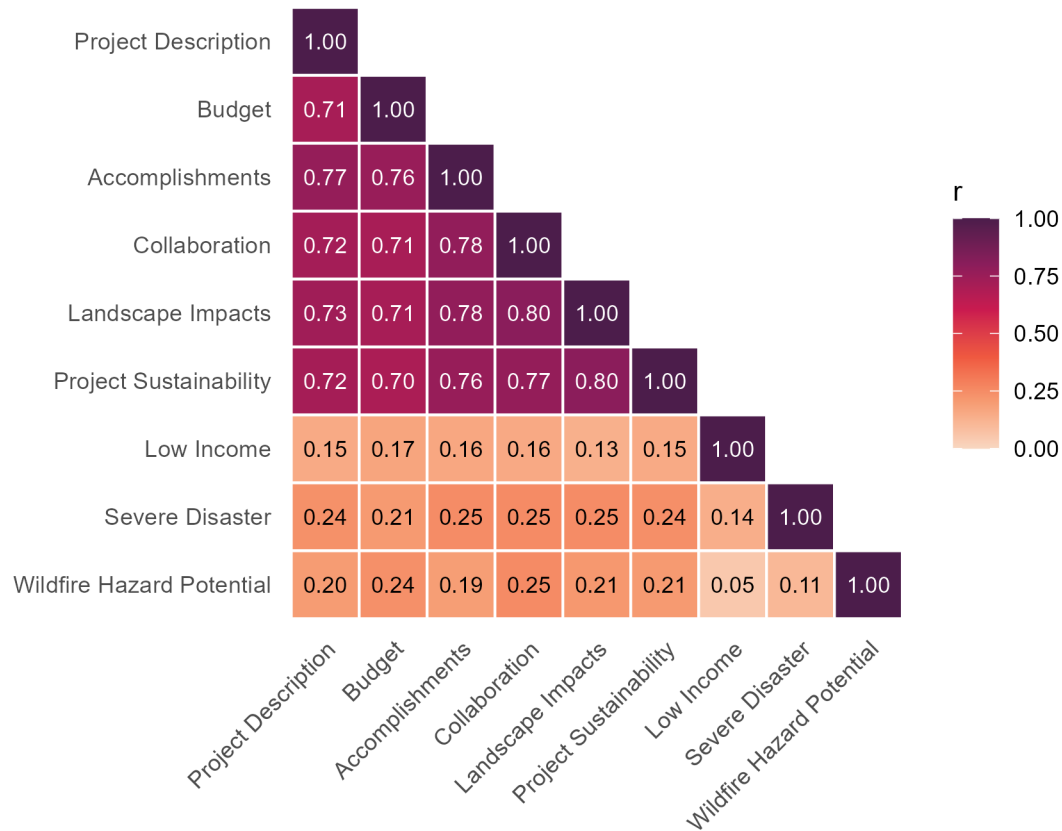


Figure 3.7: Pearson correlations among the nine CWDG scoring subcomponents: six qualitative components (Project Description, Budget, Accomplishments, Collaboration, Landscape Impacts, Project Sustainability) and three binary components (Low Income, Severe Disaster, Wildfire Hazard Potential).

The correlations between the nine scoring subcomponents show that the binary scoring components are less interdependent than the graded criteria (Fig. 3.7). The three binary scoring components — Low Income, Severe Disaster, and Wildfire Hazard Potential — are only weakly correlated with each other and with the qualitative scoring components. The six qualitative scoring components — Project Description, Budget, Accomplishments, Collaboration, Landscape Impacts, and Project Sustainability — are all strongly correlated with each other, with Pearson's r ranging from 0.70 to 0.80.

A principal component analysis of the six qualitative scores assesses whether they capture distinct dimensions. The first principal component explains 79.1% of the observed variance, with each of the six scoring measures receiving approximately equal weights (factor loadings range from 0.39 to 0.42). The second principal component explains only an additional 5.8% of the variance, indicating that it does not capture a meaningful additional dimension of variation. The statistical redundancy of the six qualitative components justifies collapsing them into a single measure in the assessment of the influence of scoring components on grant receipt. There are several potential explanations for this redundancy, which are addressed in the Discussion.

3.3.2.3 Influence of scoring components

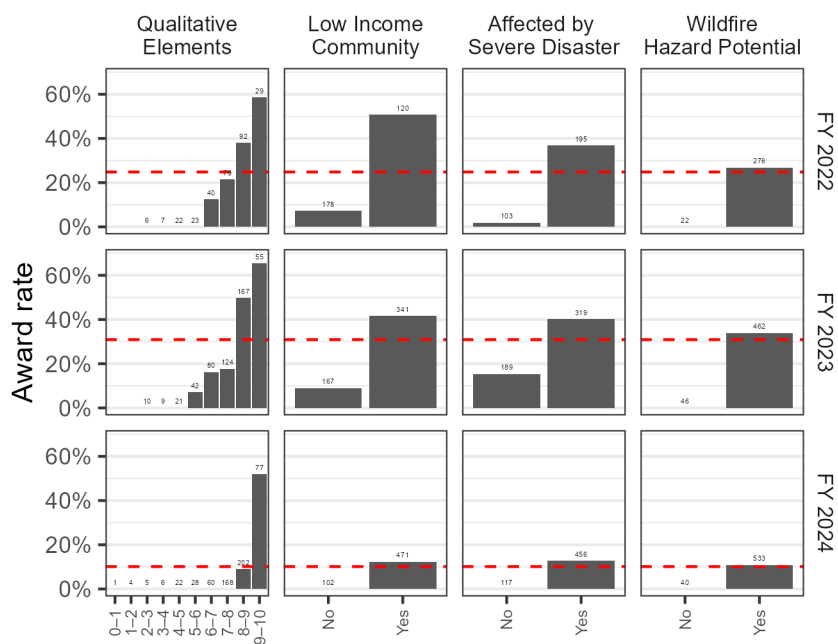


Figure 3.8: Award rates by funding round and rubric element. The leftmost column shows award rates by bin of the qualitative composite; the remaining columns show award rates for applications meeting versus failing each of the three binary criteria. Dashed lines indicate the overall award rate for each round. Numbers above each bar indicate the number of applications in that bin. Excludes 13 applications where the three reviewers did not agree on one or more of the binary criteria.

The relationship between award rates and criterion scores within each funding round shows increasing program competitiveness over time, as well as the strong influence of the binary scoring criteria (Fig. 3.8). The qualitative composite shows graded influence: award rate rises with score in every round, though the effective threshold tightens — grants were awarded in 2022 and 2023 to applications with composite scores in the 5–6 and 6–7 range, but no applications with composite qualitative scores lower than 8 were awarded in 2024. The three binary scoring criteria function more as gatekeepers. No application failing the high wildfire hazard potential criterion was awarded in any round, and meeting the low-income and severe-disaster criteria were de facto requirements for grant award in 2024.

Table 3.5: Award rates among CWDG applicants by funding round, conditional on meeting the program’s three binary scoring criteria (low income, severe disaster, high wildfire hazard potential). “N apps” is the total number of applications in the round and “Award rate” is computed across all of them; “N met all 3” is the count of applications meeting all three binary criteria and “Award rate, met all 3” is the rate among those applications. Excludes 13 applications where the three reviewers did not agree on one or more of the binary criteria.

FY	N apps	Award rate	N met all 3	% met all 3	Award rate, met all 3
2022	298	24.8%	77	25.8%	76.6%
2023	508	30.9%	200	39.4%	56.5%
2024	573	10.1%	360	62.8%	16.1%

As the number of applicants meeting all three binary criteria increased, the advantage conferred by that distinction decreased (Tbl. 3.5). The percentage of applicants that met all three criteria rose considerably across the three periods, from 25.8% to 62.8%. Simultaneously, the conditional award rate among applications meeting all three criteria dropped from 76.6% to 16.1%. In 2022, meeting all three criteria was nearly sufficient for award; by 2024, it had become only a necessary condition, with substantial additional selection occurring among gate-clearing applications.

3.3.3 Allocation of funding to high-hazard and high-vulnerability communities

Before addressing the distributional research questions, I briefly examine variation in the vulnerability of communities served by the same grant application (Fig. 3.9). Of the 413 applications that reference more than one community, 82 include communities in both the top and bottom quartile of vulnerability. This within-application heterogeneity is not limited to applications that matched to many communities — among the 212 applications that match to two communities, the average range in SVI is nearly 0.3. This degree of variation supports the methodological choice to analyze the distribution of CWDG funds at the application-place level.

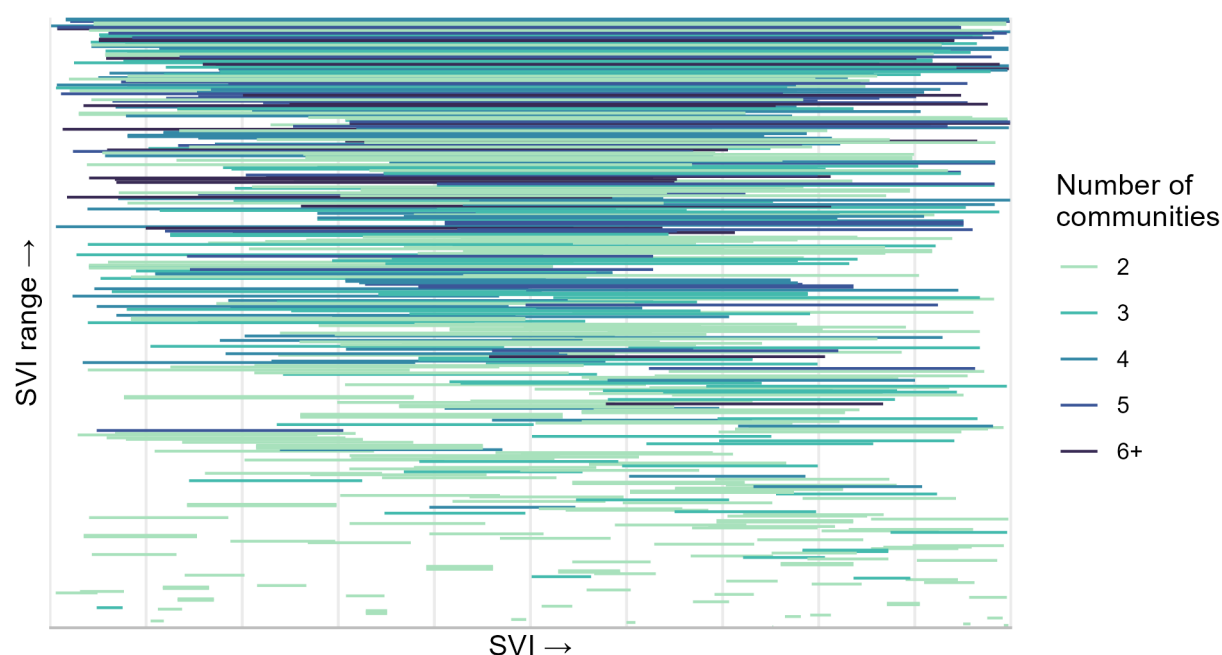


Figure 3.9: Variation in SVI among communities matched to the same application, for the 413 applications matched to more than one community. Each line spans from the minimum to maximum SVI of an application’s matched communities. Applications are sorted by SVI range, with the widest range at the top of the plot. Color indicates number of matched communities.

3.3.3.1 Awards by hazard and vulnerability

The distribution of awarded dollars across the joint hazard $\times$ SVI space shows that while grant funding was concentrated towards the top of the hazard distribution, the skew towards vulnerable communities was more modest (Fig. 3.10). The top decile of hazard alone captured over half of awarded dollars, and there were very few awards to communities with hazard below the 50th percentile. Communities that were in the highest decile of both hazard and SVI received the largest amount of funding overall. However, within the top hazard decile, only around 64% of awarded dollars went to above-median SVI communities.

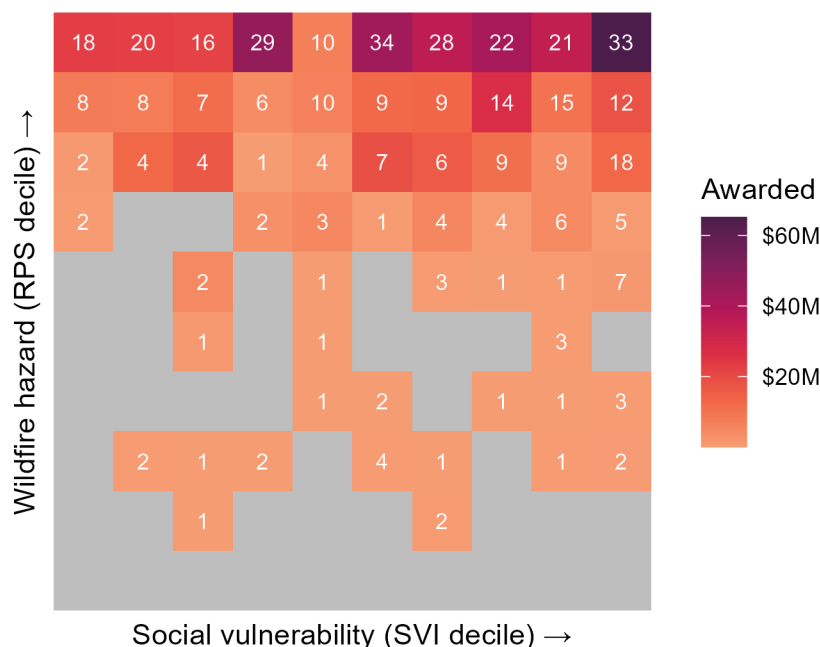


Figure 3.10: Total CWDG dollars awarded across the first three rounds (FY2022–FY2024), tabulated by joint decile of community-level wildfire hazard and social vulnerability. Awarded dollars are divided evenly across each application’s matched place catchments, preserving the total awarded amount when summed across the grid. Numbers in each cell indicate the count of communities. The heatmap represents 271 of 317 awarded applications, totaling \$587M of \$637M awarded across the first three rounds; the 46 omitted awards either lack a corresponding application in the Grant Portal or could not be matched to communities (see Methods). Gray cells contain no awarded applications.

3.3.3.2 Applicant hazard and vulnerability

The distribution of requested dollars across the joint hazard × SVI space is broadly similar to the distribution of awarded dollars (Fig. 3.11). Nearly half of the funding requested was intended to serve communities in the 90th percentile of the national hazard distribution, but just over 60% was directed towards communities with above-median SVI. The similarity between the applicant pool and the award pool is also apparent at the level of communities rather than grant amounts (Fig. 3.12). Within each decile of hazard, the distributions of SVI among all communities, communities that applied for funding, and communities that received grants are visually comparable.

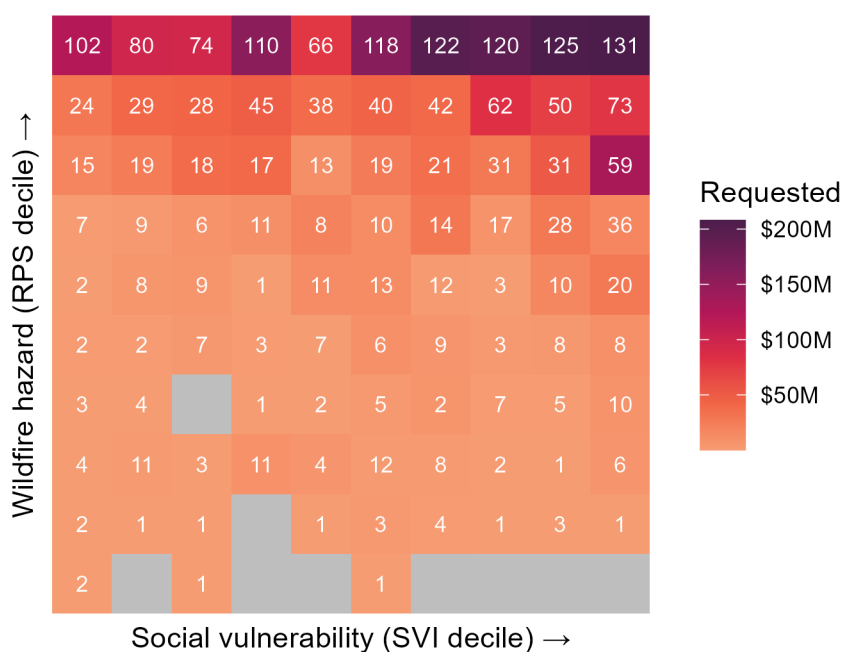


Figure 3.11: Total CWDG dollars requested across the first three rounds (FY2022–FY2024), tabulated by joint decile of community-level wildfire hazard and social vulnerability. Requested dollars are divided evenly across each application’s matched place catchments, preserving the total requested amount when summed across the grid. Numbers in each cell indicate the count of communities. The heatmap represents 1,282 of 1,416 applications, totaling \$2.75B of \$3.03B requested across the first three rounds; the 134 omitted applications either lacked application scores or could not be matched to communities (see Methods). Gray cells contain no applications.

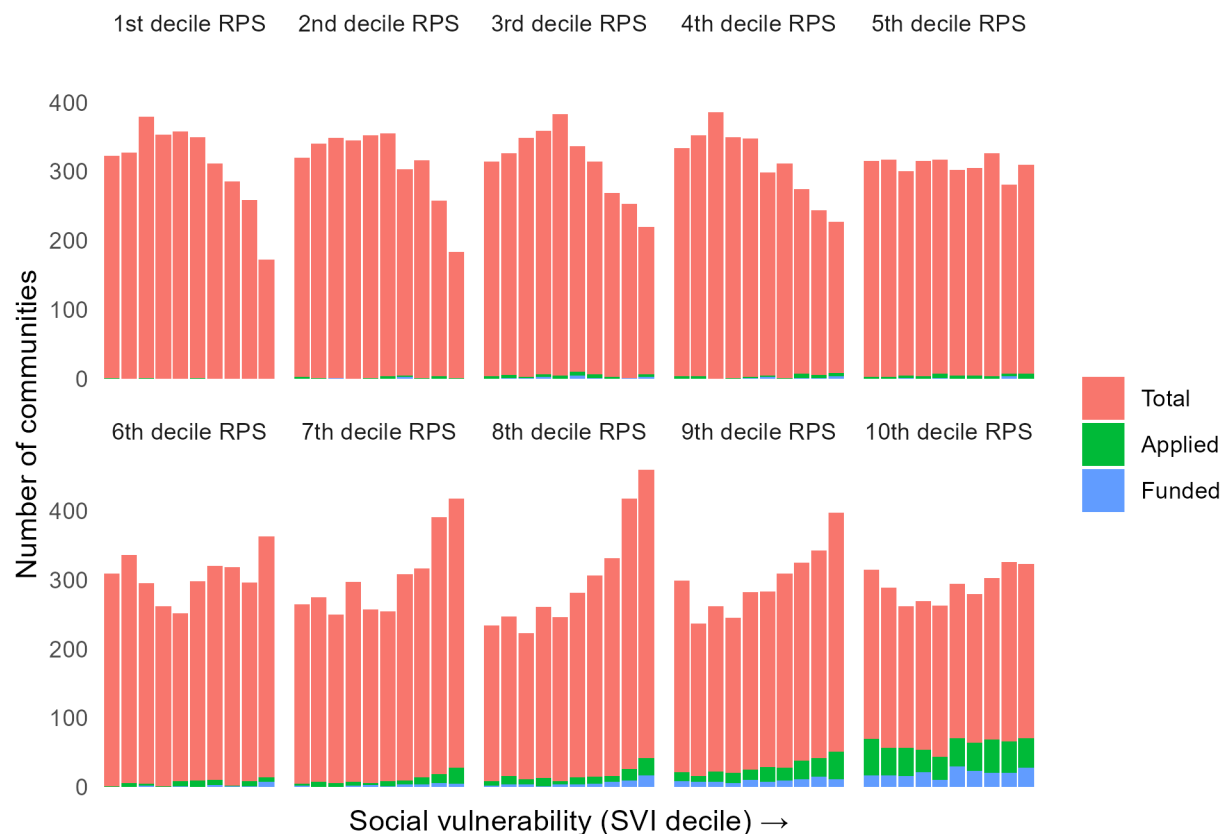


Figure 3.12: Distribution of social vulnerability, stratified by wildfire hazard, for communities that applied for and received CWDG funding. The heights of the green bars indicate the number of communities in each RPS-SVI decile that requested funding, while the blue bars represent the number of communities that received funding. The total number of communities in each RPS-SVI decile is shown in red.

3.3.3.3 Logistic model of grant awards

A Bayesian logistic regression of award receipt, controlling for grant type, requested amount, grant year, and state, quantifies the association of hazard and vulnerability with the likelihood of award. All parameters have $\hat{R} \leq 1.01$ and bulk and tail effective sample sizes above 2,000, indicating adequate convergence. The coefficient estimates (Tbl. 3.6) show that wildfire hazard percentile has a positive association with the likelihood of an application being awarded grant funding, consistent with prioritization of high-hazard applicants. In contrast, the credible interval for SVI spans zero, indicating that higher social vulnerability is not associated with greater odds of grant approval. The year fixed effects mirror the descriptive findings: the program was substantially more competitive in 2024 than in the prior two rounds. Funds requested has a positive relationship with likelihood of award for both planning and implementation grants, indicating that applicants who requested more funding were more likely to receive an award.

The predicted award probabilities express the marginal effect of a change in each predictor on the probability of grant approval, averaging over the empirical distributions of other covariates (Fig. 3.13). The positive slope on the WHP plot illustrates the higher probability of grant approval for communities facing higher wildfire hazard. The SVI slope is nearly flat, with median estimates ranging only about 3 percentage points between the highest and lowest vulnerability communities. The predicted probabilities for each year are similar to the observed probabilities shown in Tbl. 3.5. The funds requested slope for planning grants is steeper than that for implementation grants, suggesting that the disadvantage associated with smaller requests is more pronounced for planning grants.

Table 3.6: Coefficient estimates and 95% credible intervals from a logistic model of grant awards among the sample of 2,134 application-places. Observations are weighted by the inverse of the number of unique places matched to each application. Intercepts for each year correspond to the log-odds of funding associated with planning grants requesting the mean amount, submitted by a community with mean SVI and RPS. SVI and hazard coefficients estimate the change in the log-odds of grant funding associated with a full-range increase. The implementation grant coefficient estimates the difference in log-odds between mean-request implementation and mean-request planning grants. The two coefficients for log funds requested estimate the change in log-odds associated with a one-unit increase in log funds requested, estimated separately for planning and implementation grants. State-level random intercepts are estimated with a standard deviation of 0.49 (95% credible interval: 0.06–0.86).

	Median	2.5%	97.5%
Grant year 2022 intercept	-0.42	-0.84	0.02
Grant year 2023 intercept	-0.28	-0.60	0.08
Grant year 2024 intercept	-1.71	-2.11	-1.32
SVI percentile	0.21	-0.29	0.72
RPS percentile	1.17	0.25	2.12
Implementation grant (vs. planning)	-0.76	-1.07	-0.44
Log funds requested (planning)	0.52	0.16	0.88
Log funds requested (implementation)	0.32	0.18	0.48

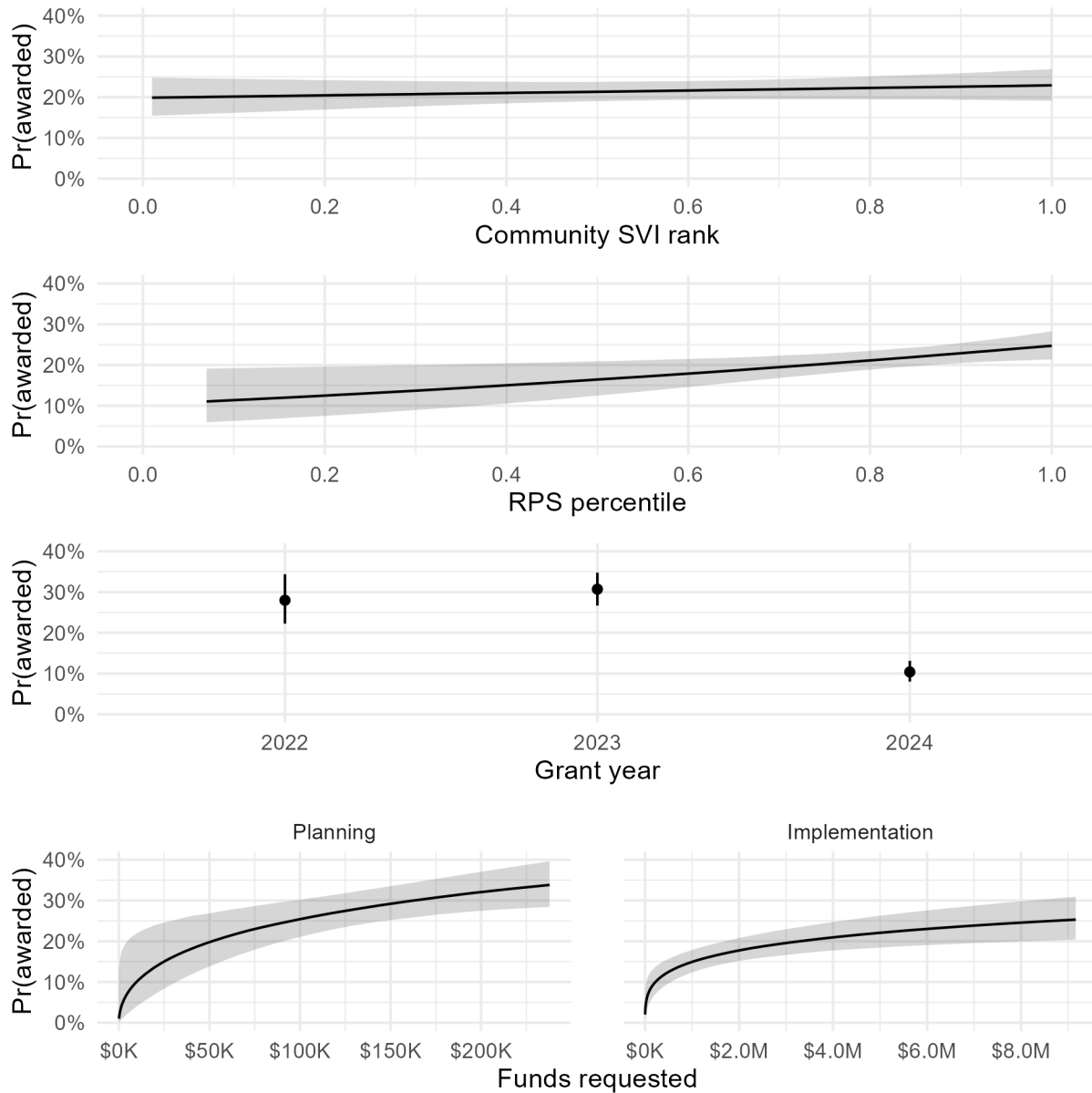


Figure 3.13: Predicted probability of award from a Bayesian logistic regression fit to the community-application dataset for the first three rounds of the CWDG program. Each panel shows the marginal effect of one predictor, averaged over the observed distribution of the others; shaded bands and vertical lines show 95% credible intervals. The funds-requested effect is shown separately by grant type, each restricted to its observed range.

3.4 Discussion

Three temporal patterns emerged across the program’s first three rounds: the geographic concentration of awards has loosened over time, the mix of planning and implementation grants has shifted substantially across rounds, and success rates have declined steadily even as median award amounts have grown. Importantly, increasing competition for funding has amplified the rubric’s influence on award decisions, making both the design and operation of the rubric more consequential over time.

The comparison of scoring distributions among approved and denied applications reveals that total score is highly predictive of grant awards, but that additional selection among marginal applications is occurring outside of the official scoring rubric. Within the rubric itself, the three binary scoring criteria — low income, disaster impacted, and high hazard — function as gatekeepers, and became increasingly necessary throughout the program. Simultaneously, the marginal benefit conferred by meeting the binary scoring criteria decreased over time due to increasing competitiveness across the three funding rounds. The six qualitative scoring criteria, by contrast, exhibit strong intercorrelations and functionally represent only a single dimension of variability.

The redundancy of nominally distinct scoring components mirrors the findings of Lindner et al. (2016). The low effective dimensionality of the qualitative scoring elements has several possible explanations. First, it is possible that reviewers are being influenced by halo effects: they assign high scores across the six qualitative components to applications that appear well-constructed. Second, the correlation may reflect the quality of the project itself: well-conceived projects naturally score higher on these elements. Third, the correlation between qualitative scoring elements may be due to the writing skills of applicants: sophisticated grant writers produce

compelling responses for each of the six sections. The second and third explanations — project quality and applicant skill — may both derive from applicant capacity. That is, applicants with more capacity both conceive better projects and are better at describing them. While each of these explanations is plausible, the data do not provide a mechanism for adjudicating between them.

Awarded dollars are overwhelmingly distributed to high-hazard communities, but the influence of social vulnerability is weaker. This pattern reflects selection of higher-hazard communities at two stages — the composition of the applicant pool and again at the awards stage — while socially vulnerable communities are not favored in either stage. At the application stage, higher-hazard communities are more likely to apply for funding and social vulnerability does not appear to serve as a barrier to application. Among submitted applications, hazard predicts awards but vulnerability does not. The vulnerability result aligns with Finucane et al. (2023), while the hazard result departs from their null finding for the role of hazard in FEMA’s BRIC program.

The strong influence of the binary scoring criteria suggests that the CWDG program is effectively prioritizing projects serving communities that meet the three statutory criteria, which supports the findings of prior studies of the program (Pohl et al., 2023; Pohl, 2025, 2026). However, the program performs less favorably when judged against vulnerability. Incorporating a measure of social vulnerability into the program’s scoring rubric would likely result in increased support to vulnerable communities. Specifically, including social vulnerability as a graded criterion avoids the need to define a threshold and confers an advantage to vulnerable communities during the scoring stage without categorically locking out less-vulnerable communities.

The approach used to match applications to communities has several limitations that complicate interpretation of the distributional findings. First, not all applications included valid refer-

ence points or project areas. If applications from better-resourced applicants are more likely to contain well-constructed geodata, the sample of application-places may systematically exclude communities with less technical proficiency. Second, applications that matched to multiple places do not provide usable information about the distribution of project funds between areas. The equal weighting approach implemented potentially obscures the relationship between funding and community characteristics if grants do not equally benefit all communities matched to an application. Additionally, mitigation projects may produce spillover effects for adjacent communities not necessarily matched to project areas. Future work exploring the impact of alternate matching strategies, including methods that apply spatial buffers to project areas, may better capture spillover effects.

3.5 Conclusion

This chapter examines the operation of the scoring rubric and the distributional outcomes of the first three funding rounds of the CWDG program. The analysis of the scoring rubric shows that meeting the three criteria prioritized in the program’s authorizing legislation — low income, disaster impacted, and high hazard — substantially increased the likelihood of award, and was effectively required by 2024. However, this gatekeeping mechanism did not produce distributional outcomes that strongly favored vulnerable communities. The analysis of distributional outcomes finds that, among applicants, wildfire hazard was predictive of grant awards, but higher levels of social vulnerability were not associated with increased likelihood of grant award. Explicitly including vulnerability as a scoring criterion, potentially as a graded measure to avoid thresholding issues, would likely produce distributional outcomes more favorable to vulnerable communities.

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