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Matching the scales of planning and environmental risk: an evaluation of Community Wildfire Protection Plans in the western US

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Abstract

Theory predicts that effective environmental governance requires that the scales of management account for the scales of environmental processes. A good example is community wildfire protection planning. Plan boundaries that are too narrowly defined may miss sources of wildfire risk originating at larger geographic scales whereas boundaries that are too broadly defined dilute resources. Although the concept of scale (mis)matches is widely discussed in literature on risk mitigation as well as environmental governance more generally, rarely has the concept been rigorously quantified. We introduce methods to address this limitation, and we apply our approach to assess scale matching among Community Wildfire Protection Plans (CWPPs) in the western US. Our approach compares two metrics: (1) the proportion of risk sources encompassed by planning jurisdictions (sensitivity) and (2) the proportion of area in planning jurisdictions in which risk can originate (precision). Using data from 852 CWPPs and a published library of 54 million simulated wildfires, we demonstrate a trade-off between sensitivity and precision. Our analysis reveals that spatial scale match—the product of sensitivity and precision—has an n-shaped relationship with jurisdiction size and is maximal at approximately 500 km². Bayesian multilevel models further suggest that functional scale match—via neighboring, nested, and overlapping planning jurisdictions—may compensate for low sensitivity. This study provides a rare instance of a quantitative framework to measure scale match in environmental planning and has broad implications for risk mitigation as well as in other environmental governance settings.

Keywords Scale matching · Wildfire · Community Wildfire Protection Plans · US West

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Introduction

Environmental management outcomes are mediated by social-ecological processes that vary across scalar dimensions (Cumming et al. 2006). This variability complicates efforts to achieve desired outcomes by making it difficult to define the scale at which to take management actions and monitor results (Abrams et al. 2015; Schultz et al. 2019). In turn, incorrect assumptions about the appropriate scales for planning can lead to inefficiencies and management failures (Crowder et al. 2006; Folke et al. 2007; Galaz et al. 2008; Cumming and Dobbs 2020). When planning is conducted at too small of a scale, managers may be limited in their capacity to address the full extent of ecological processes. Planning at too large of a scale may cause resources to be diluted or inefficiently deployed.

Reconciling the spatial scale of planning with the scale of environmental variation is challenging in part because it is difficult to identify the proper scale for environmental management. For example, environmental stochasticity

contributes to uncertainty about the scale of planning needed to encompass key ecological processes (Wilson et al. 2009; Bolam et al. 2019). Moreover, while jurisdictional boundaries are commonly distinct, ecological “boundaries” are typically fuzzy and span multiple scales, which contributes to the challenge of specifying management jurisdictions that are congruent with ecological processes (Moss 2012; Baggio et al. 2019; Koontz 2021). Polycentric environmental governance presents another dimension of complexity: in landscapes characterized by multiple overlapping jurisdictions of institutions with different mandates and management objectives, the appropriate spatial scales for management depend not only on scales of environmental variation but also on patterns of interactions among interdependent institutions (Powell 2010; Wiegant et al. 2022). These realities highlight the value of approaches for evaluating spatial scale match to provide robust scientific guidance to policymakers and land managers. However, there have been limited attempts to rigorously quantify spatial scale mismatch despite broad recognition of its implications (Cumming and Dobbs 2020).

This paper provides a rare case in which the appropriate scales for planning are measured using a framework that quantitatively evaluates scale match for a large number of risk mitigation planning jurisdictions. Within the broad domain of environmental management, risk mitigation planning offers an ideal context to evaluate the coherence between the spatial scales of management and environmental variability. Hazard events such as floods, heatwaves, and wildfires vary considerably in scale. Additionally, because risk can be transmitted from one place to another, risk management jurisdictions can be exposed to hazard events that originate outside their boundaries (Huntjens et al. 2012; Ager et al. 2017; Lubell et al. 2021). Moreover, the uncertainty associated with when and where hazard events will occur further challenges planners’ ability to contain risk within a given risk management boundary.

Our method for quantifying spatial scale match conceptualizes spatial scale match as the product of sensitivity and precision. *Sensitivity* measures how adequately an intervention captures all true instances of phenomenon (reducing false negatives; i.e., is the scope of intervention sufficiently broad?). By contrast, *precision* measures how well an intervention targets only true instances (reducing false positives; i.e., is the scope of intervention sufficiently focused?). This approach is commonly used to assess diagnostic measures when there are costs associated with false negatives and with false positives. For example, medical tests must not only avoid failing to detect a disease but must also avoid mistakenly diagnosing individuals without a disease (Akobeng 2007). Similarly, assessments that guide interventions designed to prevent social or behavioral outcomes (e.g., dropping out of high school; Bowers et al. 2012) must not only correctly identify individuals at high

risk of the outcome, but should also ideally exclude those who are not at risk, given the limited resources available for interventions. Such approaches commonly compare sensitivity with *specificity*, which accounts for true negatives (Enøe et al. 2000). However, identification of true negatives is commonly not feasible when considering the appropriate spatial scale of an environmental management area because the area outside any particular jurisdiction is potentially limitless. Consequently, our approach focuses on the comparison of true positives with false positives and of true positives with false negatives by evaluating sensitivity and precision, respectively (Fig. 1). In the context of environmental planning for mitigation of wildfire risk—the empirical focus of this paper—“positives” and “negatives” correspond to the presence and absence of sources of exposure, e.g., ignitions that result in wildfires that burn towards human communities.

We apply this approach to evaluate spatial scale match in Community Wildfire Protection Plans (CWPPs), which are voluntary hazard management plans that are used extensively across the USA to guide wildfire risk mitigation activities (Palsa et al. 2022). Because CWPPs have few formal requirements (Jakes et al. 2011), they provide an excellent context to study the multiple scales at which communities have chosen to address local risks from wildfire, ranging from specific neighborhoods to multi-county regions. This variation reflects the multi-scale issue of wildfire risk in addition to the diversity of motivations for communities to engage in such planning. Specifically, we examine the spectrum of different spatial scales that CWPPs encompass by evaluating each plan with respect to sensitivity and precision, whether there is a trade-off between the two metrics, and how spatial scale match—the product of the two metrics—varies as a function of the level, size, and other characteristics of CWPPs. At the same time, the scale matching strategy used by a given CWPP will likely take into account nearby plans, given that plans may benefit from the fact that they are adjacent to, overlap with, or are enclosed within the boundaries of other CWPPs. Accordingly, for each CWPP, we examine the degree to which sources of exposure to wildfire are contained within other CWPPs that also share planners with the focal CWPP (a measure of functional scale match), to explore whether higher functional scale match can compensate for lower spatial scale match.

Methods

Study system

We evaluated scale match in Community Wildfire Protection Plans (CWPPs) developed within 11 states of the western US (Fig. 2). Within this region, over one thousand CWPPs have

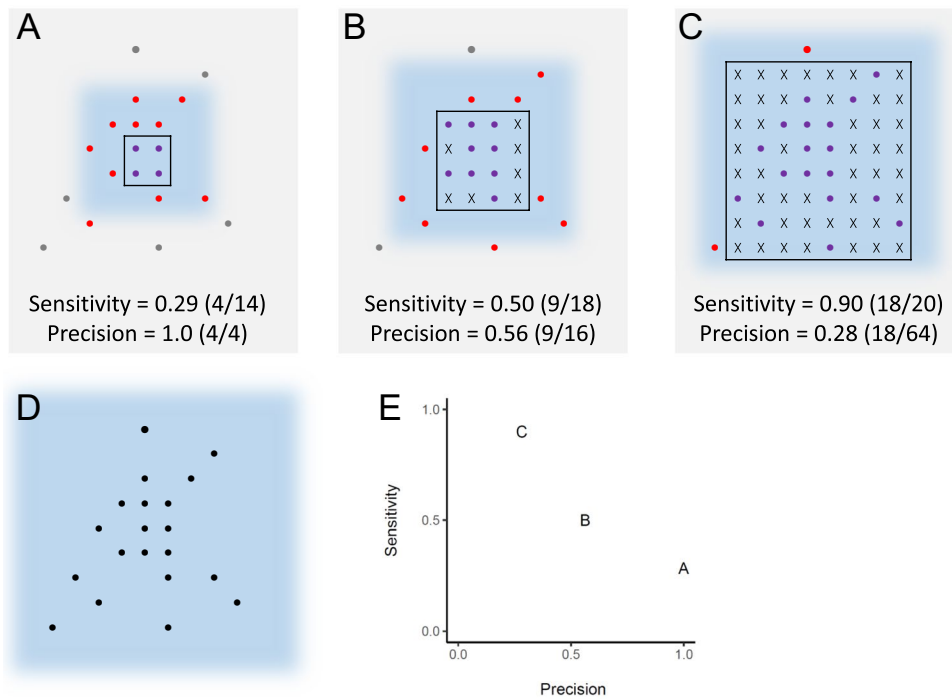


Fig. 1 Metrics of spatial scale match. Panels A–C depict different strategies for delimiting a boundary for managing wildfire risk, based on the hypothetical spatial distribution of sources of exposure (i.e., ignitions; black points) depicted in panel D. Purple points represent sources of exposure to values at risk (e.g., housing units) that lie within the management boundary. Red points represent ignitions outside the management boundary but within a zone (shaded blue region) where ignitions result in wildfires that can present risk within the boundary; gray points represent ignitions that result in wildfires

that do not spread to the management area. Black Xs indicate regions within the boundary without sources of exposure. Sensitivity is calculated as the proportion of sources of exposure that lie within a management boundary. Precision is calculated as the proportion of a management area that contains sources of exposure. Panel E illustrates how the strategy depicted in panel A has low sensitivity but high precision, while the strategy in panel C has high sensitivity but low precision, and the strategy in panel B has intermediate values of both metrics

been developed over the last two decades (Palsa et al. 2022). CWPPs are one of several models for local-level wildfire risk mitigation; other frameworks include county-level Hazard Mitigation Plans, as well as multi-stakeholder decision-making processes such as projects supported through the Collaborative Forest Landscape Restoration Program (Monroe and Butler 2016; Kooistra et al. 2022). Among this broad set of wildfire risk mitigation processes, we examine CWPPs because they are among the most extensively used planning tools for community-level wildfire risk mitigation. While not a formal requirement, most CWPPs have well-defined boundaries within which wildfire risk mitigation actions are planned and implemented. These boundaries are generally delineated based on existing administrative and ownership jurisdictions, rather than the scale of wildfire risk to which communities are exposed (Ager et al. 2015). Many CWPPs adopt county or fire protection district boundaries as their planning jurisdictions. Plans developed at the community-level define boundaries that may be specific to the CWPP. Such flexibility at the community level, as well as the variation in spatial scales of planning (i.e., ranging from community plans that encompass single neighborhoods to

county-level plans that are orders of magnitude larger), is reflective of the vagueness of the federal statute that introduced CWPPs; planners were left to define “community” as they saw fit (Jakes et al. 2011; Williams et al. 2012), and further that such flexibility reflects the broad scale across which communities are understood and governed (Flint et al. 2010; Wilkinson 2023). We use “community” to refer to one of the administrative levels at which CWPPs are developed (along with the fire protection district- and county-level plans).

Data

Our data include spatial boundaries and basic attributes of 852 CWPPs as well as estimates of wildfire exposure to communities within CWPP jurisdictions.

As described in Palsa et al. (2022), we mapped CWPP jurisdictions using spatial data associated with the plan or that had been previously assembled when possible. When such data were not available, we digitized plan boundaries using maps included in the plan. Several CWPPs lacked maps but included written descriptions of jurisdictional boundaries (e.g., references to surrounding highways or

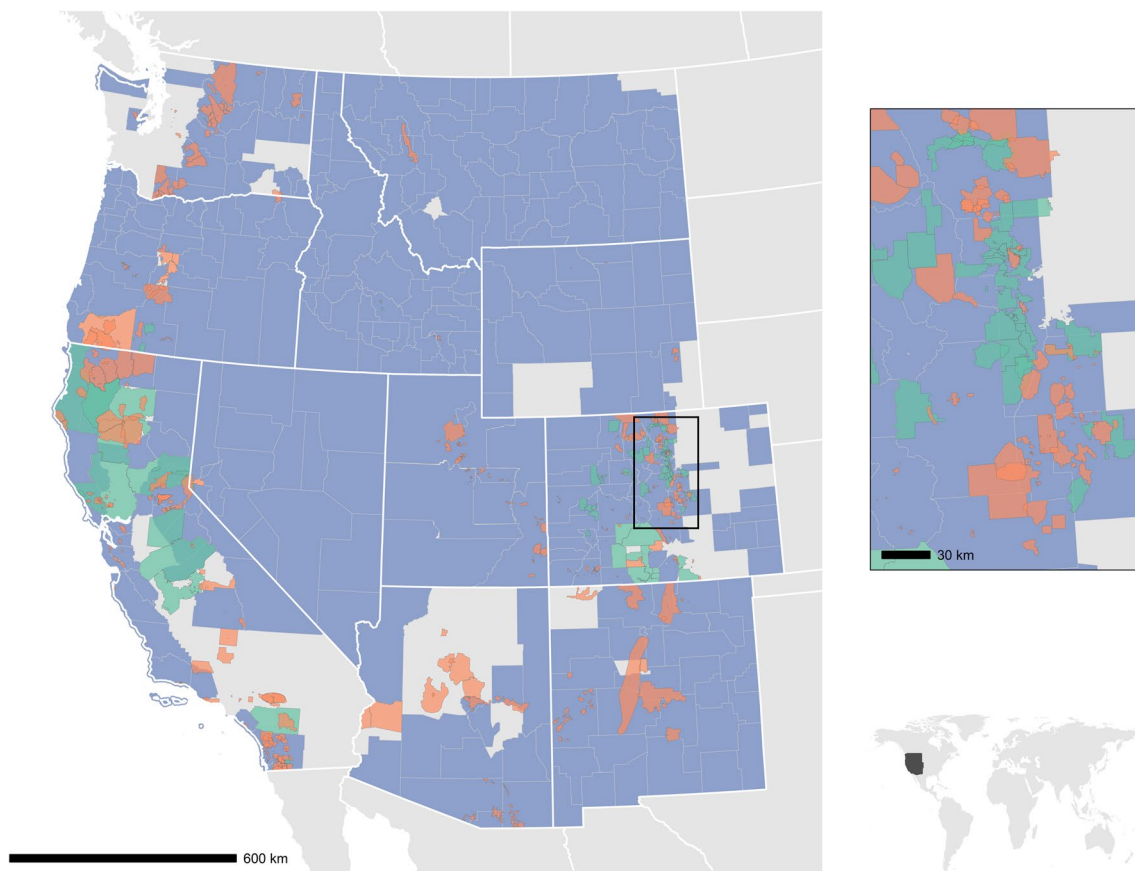


Fig. 2 Map of Community Wildfire Protection Plan boundaries in the western US. Blue polygons represent county-level plans; green represents fire protection district-level plans; orange represents commu-

nity-level plans. The inset map of Colorado's Front Range shows how a large number of plans may be nested or overlapping within a given region

other landmarks), which we used to delineate jurisdictions. For the 20 plans that lacked maps or descriptions of jurisdictional boundaries, we delineated their jurisdictions using census-designated place boundaries.

We categorized plans based on the state in which they were developed, and we distinguished between plans developed at the community, fire protection district, and county level (Table 1). Table 1 also shows the distribution of sizes of plans, the dates when plans were published, and the number of housing units exposed to simulated wildfires per year. These latter three variables are binned in Table 1 but were included in models as continuous variables. Table S1 presents a cross-tabulation of states and the other variables.

We also recorded the individuals who participated in each plan, using rosters of planners, core team members, and other individuals who meaningfully contributed to the development of plans (i.e., beyond serving as a funder or signatory).

Community wildfire exposure was estimated using fire perimeters simulated in FSIM, a large-fire simulator based on a quasi-empirical fire growth model used extensively in

national quantitative wildfire risk assessments (e.g., wildfire-risk.org). Simulated wildfires are based on historical fire size and frequency, fire weather data (e.g., wind, aridity), and ignition patterns (see Finney et al. 2011). Tens of thousands of potential wildfire seasons are simulated; the resulting data provides a probabilistic estimate of fire activity across large landscapes by creating a large enough sample to estimate probabilities of fire while accounting for the inherently stochastic aspect of low-probability, high-consequence events.

Like other studies (e.g., Evers et al. 2019; Ager et al. 2019), we define community exposure as the overlap between simulated wildfire boundaries and populated census blocks derived from 2010 census housing unit counts (Radeloff et al. 2018). All populated blocks were assigned to one or more CWPP boundaries that they intersected. We then intersected all FSIM fires with populated census blocks and calculated the associate exposure amount as the area of the intersection multiplied by the housing density. Total exposure was then summed for each fire and attributed to its point of ignition. Using this technique, exposure is extended outward from populated areas to the surrounding landscape

Table 1 Summary statistics of variables included in models

Variable	Number (%)
State	
Arizona	31 (4)
California	181 (21)
Colorado	251 (29)
Idaho	47 (6)
Montana	53 (6)
New Mexico	58 (7)
Nevada	19 (2)
Oregon	62 (7)
Utah	63 (7)
Washington	61 (7)
Wyoming	26 (3)
Level	
County	331 (39)
Fire protection district	85 (10)
Community	436 (51)
Area	
Less than 100 km ²	295 (35)
100 km ² –1000 km ²	181 (21)
1000 km ² –10,000 km ²	286 (34)
Greater than 10,000 km ²	90 (11)
Year published	
2005 and earlier	201 (24)
2006–2010	355 (42)
2011–2015	183 (22)
2016 and later	112 (13)
Housing units exposed per year	
Less than 0.1	144 (17)
0.1–1	189 (22)
1–10	284 (33)
10–100	173 (20)
Greater than 100	62 (7)

where the fire originates. In the next section, we describe how these tagged ignition points were assessed relative to the CWPP boundary in order to quantify metrics for spatial and functional scale match.

Measurement of spatial and functional scale match

Sensitivity and the precision provide a means for quantifying spatial scale match that accounts for the realities managers face in navigating the need for plan boundaries that are large enough to account for key areas of risk but not so large as to make it difficult to prioritize mitigation actions. The sensitivity of the plan to exposure represents the proportion of exposure coming from within the plan boundary based on the wildfire ignition location (Fig. 3). The precision of

the plan describes the proportion of the area covered by the CWPP that contains ignitions leading to exposure.

An appropriately scaled CWPP jurisdiction will ideally have high sensitivity and high precision given that neither external exposure nor internal dead space is desirable. We quantify this balance by taking the product of both measures, which ranges from 0 (minimal scale match) to 1 (maximal scale match). Planners may emphasize one measure more than the other (for example, due to levels of risk aversion or the availability of resources for risk mitigation) with implications for the characteristics of an “optimal” jurisdiction from the perspective of spatial scale match. Although our analysis weights sensitivity and precision equally as a necessary simplification, we reflect, in the “Discussion” section, on research methods that could account for unequal weighting of the two metrics.

A secondary objective of this study is the evaluation of interdependence between spatial and functional scale match, and specifically the question of whether higher functional scale match may compensate for lower spatial scale match. We measured functional scale match by assessing sources of exposure relative to other CWPP boundaries and the potential for coordination between CWPPs via shared participants (i.e., individuals). Given that CWPP boundaries frequently abut or overlap one another, the logic of our approach is that CWPPs can perform complementary functions in responding to the same source of wildfire risk. For example, some CWPPs emphasize integration of planning efforts but not the implementation of specific risk mitigation projects, and vice versa. However, without mechanisms for coordination among risk mitigation jurisdictions, these complementary functions may not develop (or inefficiencies may arise). Accordingly, for each CWPP, we calculated functional scale match as follows:

$$\text{Functional scale match} = \text{exposure}_j / \text{exposure}_i$$

where exposure_j is the number of housing units in a focal CWPP’s jurisdiction that are exposed to fires that ignited within the jurisdictions of CWPPs with which the focal CWPP shared at least one participant, and exposure_i is the total number of housing units within the focal CWPP’s jurisdiction exposed to fire (Fig. 4).

Analysis

We used Bayesian mixed effects models to predict spatial and functional scale match using the following fixed effects: plan level (community, fire protection district, county), plan jurisdiction size (log km²), year published (2001 to 2021), and exposure to wildfire (log total housing units exposed within simulated fire-years). We included the state in which plans were developed as a random intercept in both

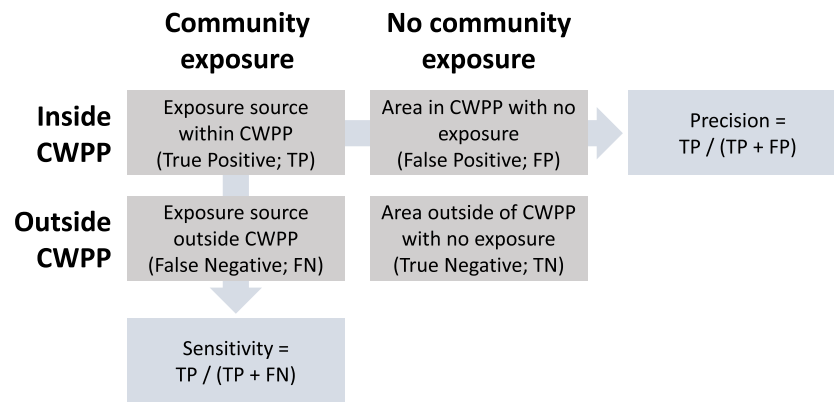


Fig. 3 How measurement of metrics of spatial scale match (sensitivity and precision) are determined based on the location of ignitions (inside versus outside a planning boundary) that represent potential sources of exposure and whether community exposure results from ignitions. Ignitions outside plan boundaries that did not result in

exposure (i.e., True Negatives) were not incorporated into our evaluation of spatial scale match due to the impracticality of objectively identifying the extent of area that might have been included in each plan

models to account for state-level variation in factors that influence CWPP development (Abrams et al. 2016; Palsa et al. 2022). In our model of functional scale match, we also included sensitivity and precision as fixed effects, to test for interdependence between spatial and functional scale match. We also ran models that included state as a fixed effect (Table S3), which show that, while spatial and functional scale match do vary by state, 95% credibility intervals include 0 for the effects of most states. We additionally fitted separate models of sensitivity and precision using level, jurisdiction size, year published, exposure to wildfire, and

state as a random intercept (Table S4); these models indicate that several variables have opposing effects on sensitivity and precision, including exposure to fire and the size of planning jurisdictions.

Models were estimated using the brms package (Bürkner 2017). The spatial scale match model used a beta distribution, and the functional scale match model used a zero–one-inflated beta distribution (Figure S1); both models used uninformative priors. Both models were run for 2000 iterations following a burn-in period of 2000 iterations and were thinned at a rate of 1. Model diagnostics showed adequate mixing (Figure S2) and all Gelman–Rubin (Rhat) statistics were below 1.05 (Table S2), providing indication of model convergence (Cowles and Carlin 1996).

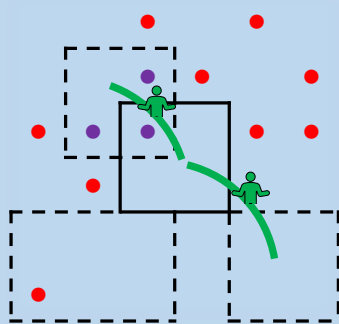


Fig. 4 Illustration of functional scale match calculation. In the focal CWPP (solid polygon), housing is exposed to fire from 12 ignitions (points). Three of these ignitions (purple points) fall within the jurisdiction of a CWPP boundary with which the focal CWPP shares at least one planner (green links and icons). Accordingly, the focal CWPP's functional scale match value is 3/12 or 0.25

Results

Spatial scale match in Community Wildfire Protection Plans

Figure 5 indicates a trade-off between sensitivity and precision, the two components of spatial scale match—plans with greater sensitivity tend to have lower precision and vice versa. The trade-off is weak in the sense that the majority of points lie above and to the right of the solid line (which delineates a linear trade-off; i.e., an increase in one measure would translate into a commensurate decrease in the other). Correspondingly, there is potential for moderately high values of both metrics. Nevertheless, a relatively large number of plans have extreme values (i.e., maximum precision but minimum sensitivity or vice versa), which suggests that by choice or chance, plan focus tends towards either large or small. This trend is particularly striking with county-level

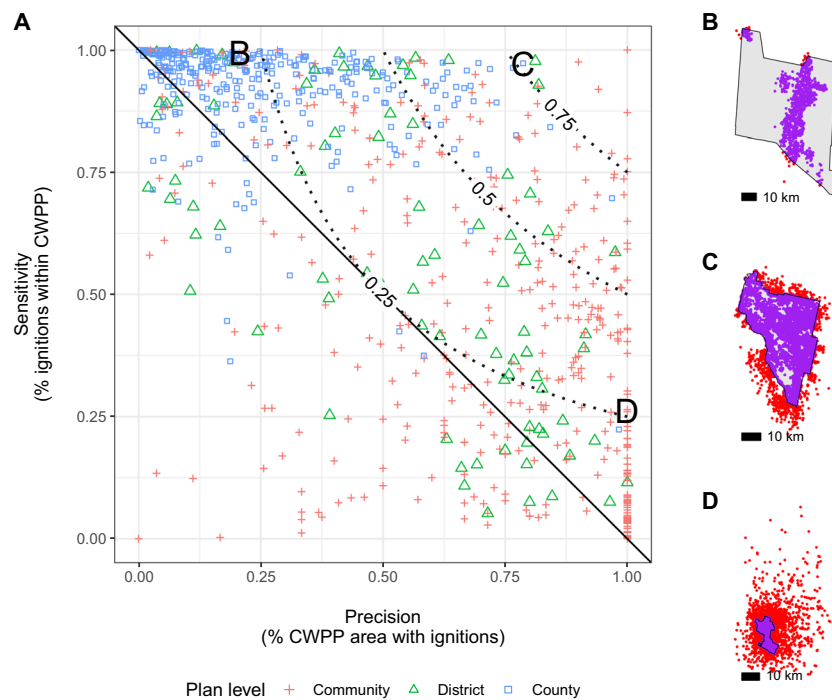


Fig. 5 Relationship between sensitivity and precision. Panel A: Points represent Community Wildfire Protection Plans (CWPPs) in the western US. The majority of points lie above and to the right of the solid line (which delineates a linear trade-off), indicating a weak trade-off between the two metrics of spatial scale match. The dotted isolines indicate equivalent combinations of the two metrics, resulting in overall spatial scale match values of 25%, 50%, and 75%. The plot also depicts variation in sensitivity and precision across the three levels of plans: community, fire protection district, and county. CWPPs with high sensitivity (which tended to be county-level plans) captured

a greater proportion of wildfire ignition sources while plans with high precision (most commonly community-level plans) avoided areas with little community wildfire exposure. The three labeled CWPP jurisdictions from different regions of panel A illustrate high sensitivity and low precision (panel B; Valencia County, New Mexico), high sensitivity and high precision (panel C; Canyon County, ID), and low sensitivity and high precision (panel D; Outer Jamul Community, CA). In panels B–D, points represent ignitions that expose housing units; color indicates whether ignitions are external (red) or internal (purple) to CWPP jurisdictions

plans clustered in the top-left of Fig. 5, where nearly 75% of plans have a sensitivity greater than 0.9 (yet note an equivalent, though lesser clustering of community-level plans in the bottom right). Note that in both instances, these clusters have relatively low-scale match scores (i.e., <0.25), which we address below.

Factors that shape spatial and functional scale mismatch

Figure 6 presents results of Bayesian mixed effects models that evaluate spatial and functional scale match. Because the functional scale match model includes three submodels, and the model mainly serves to explore the possibility that higher functional scale match can compensate for lower values of sensitivity and precision, we only include the effects of these two variables in Fig. 6 (full model results are presented in Table S2). Turning to the model of spatial scale match (Fig. 6A), we observe that spatial scale match is higher in plans developed at the community and fire protection district levels (relative to the county level), although the

effect of fire protection district plans is not credibly different from zero. Spatial scale match is higher in plans with more housing units exposed to wildfire.

Model results for area (log km²) and area squared (log km² squared) indicate that the relationship between plan jurisdiction size and spatial scale match is n-shaped, i.e., that match increases with area up to a certain size before declining. As a reminder, we understand scale match as a plan that is neither too large nor too small; a scale that captures sources of community exposure while avoiding surrounding regions that pose no threat. Figure 7 shows that spatial scale match peaks at approximately 500 km² (50,000 ha), a scale that might be described as that of the community fireshed. Interestingly, this maximum is approximately the upper limit in size of community level plans, the lower limit in size for county level plans, and the scale least represented among the CWPP jurisdictions surveyed.

Turning to the question of whether functional scale match can compensate for low spatial scale match, results indeed reveal a negative relationship between sensitivity and functional scale match (Fig. 6B), which means that jurisdictions

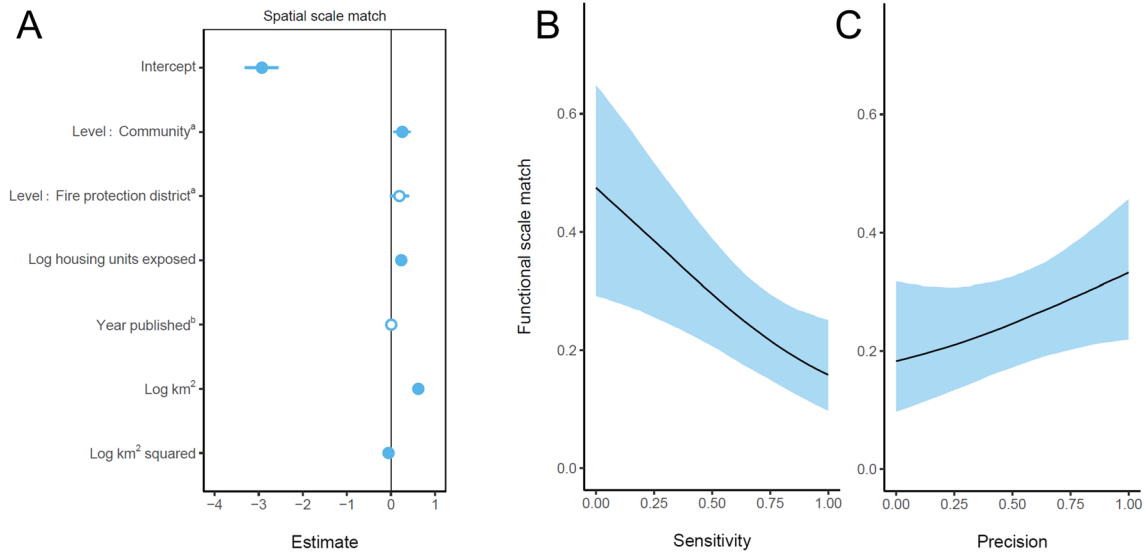


Fig. 6 Results from Bayesian multilevel statistical models of spatial scale match (panel A) and functional scale match (panels B and C) of CWPPs. Both models included a random intercept for the state in which CWPPs were developed. Points in panel A indicate posterior mean estimates of the effects of variables on spatial scale match and whiskers indicate 95% credibility intervals. Estimates with open points are not significantly different from zero based on their cred-

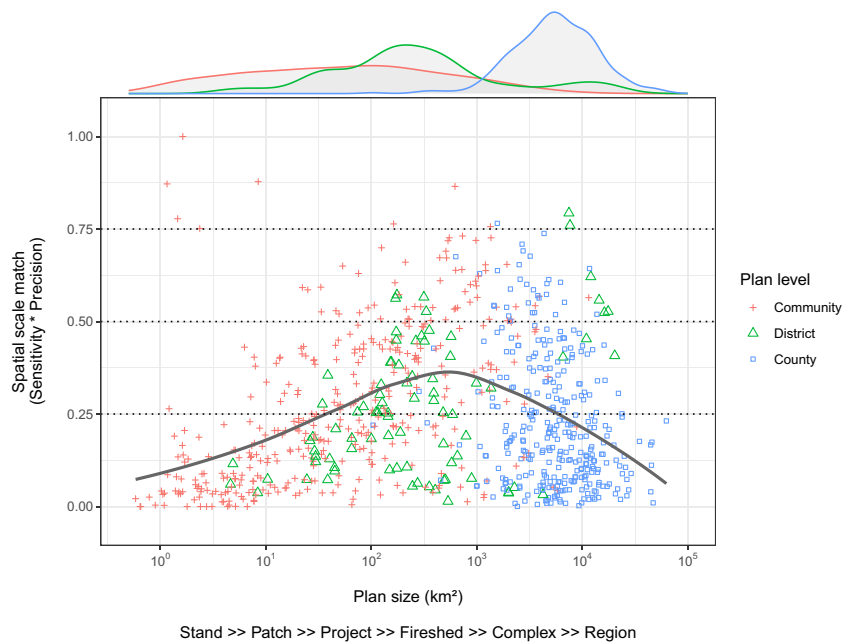
ibility intervals (i.e., whiskers overlap with zero). Notes: ^areference=Level: County; ^brescaled so that values begin at 0=2001. Using the submodels of the zero–one inflated beta model of functional scale match, panels B and C plot predicted values of functional scale match at different levels of sensitivity and precision, demonstrating a strong negative relationship with sensitivity and a slightly positive relationship with precision

in which a higher proportion of exposure stems from fires that ignite externally tend to have higher exposure to fires that ignite within other planning jurisdictions. However, the relationship between functional scale match and precision is positive, though the size of the effect is marginal compared with the range of the uncertainty interval (Fig. 6C).

Discussion

Although a large body of literature focuses on scale *mismatch*, there are several advantages to a conceptual and analytical focus on scale *match*. In particular, it is rarely possible for risk management jurisdictions to perfectly

Fig. 7 Relationship between spatial scale match (the product of sensitivity and precision) and the size of CWPP jurisdictions. Density plots indicate how the distribution of plan size varies across the three levels of plans (community, fire protection district, and county)



overlay sources of environmental risk. Consequently, rather than asking “is there a mismatch between environmental management jurisdictions and ecological processes” (yes, always, at least somewhat), we examine the *degree* to which jurisdictions capture sources of social-ecological risk interdependence. Our analysis reveals substantial variation in spatial scale match, ranging from complete misalignment to nearly complete alignment. We further show that the scale at which plans perform best was the same scale at which wildfire planning was least likely. The plans with the highest scale match were those that avoided strictly delineating plan boundaries to county or municipal limits. This finding supports the argument for geography-specific hazard planning.

Our approach demonstrates the utility of decomposing spatial scale match into measures that capture fundamental characteristics of the concept: management jurisdictions should be extensive enough to internalize sources of environmental risk but restrictive enough to avoid allocating resources to areas without risk. While the concept of sensitivity is consistent with prior research that characterizes spatial scale mismatch in terms of management jurisdictions that are not large enough to include the extent of key ecology processes, including sources of environmental risk (Birkmann and von Teichman 2010; Ager et al. 2015), the complementary concept of precision is consistent with the reality that planners and managers have limited resources. Accordingly, there are rewards for restricting jurisdictions to areas in which management can make a difference. Our focus on whether jurisdictions are “not too large” (precision) as well as “large enough” (sensitivity) recognizes that planners and managers must navigate different sets of costs and benefits: higher precision is beneficial in the sense that resources can be allocated more efficiently (i.e., by focusing on areas where risk is most elevated) but is costly in the sense that the jurisdiction may be more exposed to external risk. By contrast, higher sensitivity can minimize external risk, but potentially at the expense of efficiency (i.e., allocating resources to regions with relatively low risk).

Compounding the challenge of navigating these sets of costs and benefits is the high uncertainty about the spatial and temporal distribution of large wildfire events. For example, the likelihood that a particular neighborhood will be exposed to wildfire each year is very low. Consequently, even if precision is prioritized, given a sufficiently short window of observation, a substantial proportion of a planning area may not appear warranted. In this sense, different CWPP scales may inadvertently focus on different degrees of wildfire risk, which vary by expected return interval. Prediction efforts in other natural hazards focus on these extreme events by estimating expected magnitudes for different return intervals (e.g., a 1 in 100-year flood event). Despite the long-tailed distribution of wildfire events, wildfire disturbance in CWPPs continue to be described in terms that suggest

mean behavior (e.g., fire return interval). Likewise, it is difficult to completely prioritize sensitivity because if a jurisdiction is expanded to capture external points of exposure, the peripheral region will likely be exposed to additional sources of risk. Against the backdrop of these complexities and realities, we found evidence of a weak trade-off between sensitivity and precision, which indicates the possibility that wildfire risk mitigation jurisdictions can be delineated in ways that balance these two contrasting components of spatial scale match.

We emphasize that our approach for conceptualizing and measuring spatial scale mismatch has diagnostic as well as prescriptive value. In a prescriptive application, decision-makers can compare spatial scale match among multiple alternative jurisdictions designs. However, many planning jurisdictions (e.g., county boundaries) are fixed or are meaningful for political or cultural reasons (Koontz 2021). In these contexts, there is diagnostic value in assessing spatial scale match, not only to gain awareness of exposure to risk, but to potentially compensate for undesirable risk profiles. Managers have multiple options for compensating for low spatial scale match. For example, they may reallocate resources within a jurisdiction based on the spatial configuration of risk transmission within and external to its boundaries (Ager et al. 2014). They may also coordinate with other risk mitigation planning areas nested within, adjacent to, or overlapping their own jurisdiction (Hamilton et al. 2019). With respect to the latter, our findings highlight the possibility that risk mitigation planners may compensate for poor spatial scale match (low sensitivity) by relying on functional scale match, measured in terms of the potential for other neighboring, nested, or overlapping jurisdictions to mitigate risk in areas where fires ignite and subsequently spread to a particular planning jurisdiction. The potential for functional scale match to compensate for spatial scale mismatch highlights the importance of understanding how collaborative networks shape polycentric and multilevel governance systems (Wyborn and Bixler 2013; Guerrero et al. 2015; Berardo and Lubell 2016; Huber-Stearns et al. 2021; Hamilton et al. 2023).

Our findings also have implications for policy initiatives that aim to re-scale wildfire risk governance. In particular, recent US federal efforts to address and mitigate wildfire exposure to communities have focused on regional “fire-sheds” to delineate and prioritize wildfire mitigation efforts over the coming decade (USDA Forest Service 2022). Defined as contiguous regions with shared wildfire risks, fire-sheds used in these efforts averaged 100,000 ha in size (Evers et al. 2020; Ager et al. 2021). By comparison, we found the spatial match for CWPP boundaries peaked at around 50,000 ha. Interestingly, plans of this scale were among the least common. These findings suggest an “optimal” scale for intervention somewhat smaller than most

counties in the western US, but substantially larger than most individual communities. The plans most common at this scale were typically based on rural fire protection districts. A range of explanations could account for the relative scarcity of plans at this scale, including the potential challenge of identifying existing jurisdictions at this scale within which wildfire risk mitigation actions can be based. This gap also suggests the need for improved methods for systematically linking regional fire to development patterns at the appropriate scale of the fireshed (Ager et al. 2021; Moritz et al. 2022). CWPPs tend to focus on fuels reduction in strategic locations, such as areas designated as Wildland Urban Interface (WUI), which may be delineated based on a 1.5 mile (2.4 km) boundary around communities (Radeloff et al. 2005). Despite evidence that this scale is inadequate to address wildfire risk (Paveglio et al. 2009; Ager et al. 2015; Steelman 2016), communities may lack the tools to decide how to prioritize the limited time, efforts, and resources in order to effectively mitigate risk. Addressing these challenges represents an important new frontier in hazard management and community planning.

Similarly, while new funding mechanisms at both US federal and state levels provide funding for communities to develop, revise, and implement CWPPs (Charnley et al. 2023), these mechanisms continue to focus on CWPPs in isolation, rather than as part of a cohesive strategy for managing wildfire hazard. An underexplored function of CWPPs is the degree to which these plans can and should contribute to both horizontal and vertical integration of broader resiliency efforts. Some scholars have called for regional planning around managing wildfire that more explicitly addressed the network of underlying drivers leading to intensifying wildfire risks (Moritz et al. 2022). Likewise, wildfires are not the only natural hazard for which communities must plan and extreme hazard events can precipitate a sequence of interrelated post-events hazards (de Ruiter et al. 2020).

Reflecting both the scale at which people understand community as well as existing jurisdictions and authorities, hazard planning will always exist across a gradient of spatial scales. In fact, as CWPPs became increasingly common following enabling legislation in the early 2000s, newer planning efforts presumably took into account planning boundaries that were already established. The “community” in Community Wildfire Protection Plans suggests that these plans necessarily exist on a single spatial scale (i.e., the community). Not only does this fail to reflect the huge range in spatial scale found in CWPPs that have been developed over the past decades, but it also misses the opportunity for understanding how nesting and overlapping may provide opportunities to address focus-based or breadth-based strategies. This suggests that in addition to the typical guidance provided towards developing CWPPs, more attention

should be placed on how CWPPs integrate with adjacent plans, as well as with larger plans within which they exist or smaller plans within their own jurisdictions. In addition, functional matching also requires integration with other hazard management plans, some of which are highly developed or otherwise integrated with comprehensive land use plans (Kappes et al. 2012).

Our study is not without limitations. In particular, our analysis is narrowly focused on one specific element of the plan: the jurisdictional boundary. CWPPs were conceived in part as a mechanism by which communities could identify and define the wildland urban interface, and in doing so, streamline federal efforts to address high wildfire hazard potential. These linkages were loosely conceived, and some have argued that the vagueness of these objectives aided in the widespread adoption of these voluntary planning efforts (Jakes et al. 2011). If these plans are meant to promote coordinated risk mitigation actions, these boundaries will likely need to be defined explicitly and consistently. CWPPs of course accomplish much more than merely identifying the area surrounding a community targeted for fuel management projects and many have called for a more comprehensive approach to wildfire hazard planning that facilitates adaptation and resilience, for example, through more extensive modifications to the built environment (Moritz et al. 2022). More importantly, CWPPs provide a forum for key stakeholders in wildfire management to convene prior to a fire event and plan how they can coordinate staff, resources, and attention to minimize adverse outcomes (Lachapelle and McCool 2012; Jakes and Sturtevant 2013). Likewise, CWPPs focus on more than risk to houses themselves and often include extensive analysis of other values at risk including critical community infrastructure (e.g., power lines, municipal water sources, transportation corridors), recreational areas, or key public or private resources (e.g., forest timber). We specifically focused on houses in this study in part because the data is readily available, but also because structures/houses are often the most immediate concern of wildfire managers. Other values at risk from wildfire are often found in areas far from where people live, such as municipal water supplies. Our examination of CWPP boundaries did not consider these elements, but a similar approach to ours in estimating exposure could be applied to other spatially explicit values of social concern.

Similarly, it is important to acknowledge that our measure of spatial scale match weighted sensitivity and precision equally. However, levels of risk aversion may vary considerably among stakeholders (e.g., planners, community members), with important implications for prioritization of sensitivity. Likewise, communities vary in risk mitigation capacity, which suggests that prioritization of precision may vary as well. Consequently, the degree to which planners prioritize sensitivity versus precision has important implications

for the characteristics of an “optimal” planning jurisdiction. For example, prioritizing sensitivity would generally increase the spatial scale match of larger planning jurisdictions (and would shift the peak of the dark solid curve in Fig. 7 to the right). Furthermore, the resources required for risk mitigation may vary considerably within a prospective risk mitigation planning jurisdiction, for example, as a function of land use, population density, or other factors. As a result, inclusion of certain areas may not present significant costs and may well merit inclusion as part of a risk mitigation jurisdiction even if they do not present significant sources of exposure. Indeed, considering the social complexity of wildfire-prone landscapes, extending jurisdictions to low-risk areas may also enable the engagement of stakeholders who may otherwise not participate in collaborative planning processes. Given the trade-off between sensitivity and precision, approaches such as multi-objective optimization can leverage data on characteristics of stakeholders and communities to identify prospective management jurisdictions with scale matching strategies that fit the preferences and capabilities of a given community.

Furthermore, it is important to note that in our measure of functional scale match, the participation of at least one individual in a pair of CWPPs was considered indication of a mechanism for coordination. In focusing on how these individuals provide a mechanism (i.e., the potential) for coordination, our analysis assumes that shared participants indeed increase the likelihood for coordination. This assumption follows prior research that evaluates coordination based on relationships among people and/or decision-making processes (e.g., Nowell et al. 2017; Vantaggiato and Lubell 2023). However, it is important to evaluate the degree to which our findings bear out in studies that rely on more concrete indicators of coordination. For example, studies could retrospectively assess consultation about risk mitigation measures across plans or could evaluate records of resource pooling, joint implementation of activities, or other forms of coordination between planning processes.

Conclusions

This paper introduced a framework for qualifying spatial scale matching in environmental management that can be broadly applied in risk governance settings. A large literature discusses mismatches between the scales of environmental processes and the scales at which those processes are managed, which can lead to inefficiencies and management failures. However, there have been limited attempts to rigorously quantify scale (mis)match despite broad recognition of its implications. In addressing this gap, we focused on wildfire risk mitigation planning, which is an ideal context given plans’ well-defined jurisdictions and the strong

spatial signature of wildfire events. The key element of our approach is our joint consideration of (1) the proportion of risk sources encompassed by planning jurisdictions (i.e., sensitivity, a measure of how well jurisdictions capture the breadth of their risk exposure) and (2) the proportion of area in planning jurisdictions in which risk can originate (i.e., precision, a measure of how well jurisdictions focus on risk). We argued that combining sensitivity and precision to measure scale match is consistent with the reality of environmental management, in which scarce resources must be allocated across large areas of land to address objectives under considerable uncertainty. Although we focused on wildfire risk, our approach can be applied in any hazard-prone setting in which risk can be transmitted from one area to another.

In applying our approach to quantify scale match, we leveraged data on Community Wildfire Protection Plans (CWPPs), one of the most extensively used planning tools for community-level wildfire risk mitigation in the USA. The delineation of each plan’s boundary is a fundamental factor that affects planners’ strategies for mitigating wildfire risk, and CWPP jurisdictions vary in size by several orders of magnitude. Accordingly, despite the “community” in its name, CWPPs represent planning efforts at a variety of scales—from neighborhood to multiple counties—and likewise reflect an implicit choice in each case regarding the most appropriate scale at which to address community wildfire risk. Small plans are geographically focused but also more exposed to dynamics that play out within the larger landscape; large plans may provide greater protection but with less efficient allocation of resources if risk is unevenly distributed within plan jurisdictions. While this trade-off is inherently scale dependent (all else equal), knowledge of the spatial configuration of risk exposure can enhance how planners and managers are able to improve scale match.

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Data availability Data (<https://doi.org/10.6084/m9.figshare.23672355>) and code (<https://doi.org/10.6084/m9.figshare.23672379>) are available via figshare.

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