

Environmental justice and U.S. Forest Service hazardous fuels reduction: A spatial method for impact assessment of federal resource management actions

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ABSTRACT

Natural resource managers of federal lands in the USA are often tasked with various forms of social and economic impact analysis. Federal agencies in the USA also have a mandate to analyze the potential environmental justice consequences of their activities. Relatively little is known about the environmental justice impacts of natural resource management in rural areas. Quantitative environmental justice analyses have so far heavily favored urban populations, in part owing to the difficulty of quantitative analysis of rural U.S. Census data. We developed a spatial method for integrating rural U.S. Census data with natural resource management data to address this gap. The method learns from methodological advances in overcoming the spatial limitations of Census data, but prioritizes a simple, efficient technique that is applicable not only for identifying potential environmental justice problems, but also to a potentially broad spectrum of natural resource management activities and spatial scales. We pilot test the method by analyzing the hazardous fuels reduction activities of two national forests in central Oregon, USA. We find no evidence of systematic environmental justice issues on either forest, but identify local areas that warrant additional investigation.

1. Introduction

Natural resource managers in the USA are often tasked with projecting, monitoring, or retrospectively evaluating the economic and social impacts of their management activities. All U.S. federal agencies must also implement federal Executive Order 12898 on Environmental Justice (EJ), promulgated by President Clinton in 1994. The executive order directs agencies to undertake three analytical tasks: 1) identify EJ communities potentially impacted by the implementation of agency programs and policies; 2) determine which programs and policies may impose disproportionate adverse impacts on such communities; and 3) develop and execute a plan for mitigating any disproportionate impacts (59 FR 7629, 1994).

Multiple challenges confront these obligatory analyses. Most natural resource management (NRM) activities by federal land management agencies occur in rural areas, making rural populations the focus of impact assessments. U.S. Census data are typically used for these assessments, but because Census data geographies fit poorly with dispersed rural populations, quantitative analysis of EJ in the context of NRM activity is prone to serious selection bias and estimate error. Implementation of NRM policies and programs is not monolithic:

considerable discretion is delegated to unit-level administrators (e.g., a national forest), units are not equally funded, and local factors influencing implementation are variable. EJ assessment of NRM actions is needed at the scale where implementation occurs, but due to the small populations that neighbor individual units, only small numbers of Census data observations are likely to be relevant to the assessment, disqualifying many statistical procedures from consideration. The typical agency impact assessment, including for EJ, analyzes Census data but does not analyze NRM activity data in a way that allows for direct comparison with population characteristics. Such assessments could be significantly improved by doing so. However, this task encounters two further sources of potential error: the boundary problem, caused by NRM activity effects that cross Census unit boundaries; and, the modifiable areal unit problem (MAUP), where data observations are correlated with the physical size of the unit in which they are recorded. Social impact assessment, including for EJ, is usually performed by agency staff as part of National Environmental Policy Act (NEPA) analysis or land management plan revision. These staff may not possess advanced skills in spatial analysis and Geographic Information Systems (GIS), or specialized expertise in the limitations of Census estimates. Hence, there is a need for a quantitative analysis procedure that

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produces more insightful impact assessments while working within the limitations of the available data and managing the many causes of spatial and estimate error.

In response to these challenges, we developed a method for integrating NRM activity data and rural U.S. Census data into a GIS, and a series of analytical procedures to screen Census data units for possible EJ concerns. The method represents a compromise: between technically advanced solutions to the mismatches between Census data units and population, and Census data and NRM activity data; and the reality that agency personnel conducting EJ and related social impact analyses may lack the specialized research skills for advanced quantitative analysis. Our approach allows analysts to identify locations where some aspect of managing an entire unit (i.e., national park, national forest) is most likely to create potential EJ impacts. Agency managers can then prioritize locales for further investigation using complementary research methods. We pilot-tested our approach by analyzing the spatial location of wildfire hazard mitigation activities conducted by two national forests in central Oregon, USA, relative to the distribution of nearby low-income and minority populations. Our objective was to evaluate the range of options for data selection and analysis procedures by verifying results in national forests where knowledge of the social context of wildfire hazard reduction activities was current and thorough.

We chose wildfire hazard mitigation for our pilot test because wildfire is an urgent problem facing federal land management agencies in the USA. In the 11 western states, the fire season has lengthened by 78 days, and average wildfire size has doubled, since 1970 (USDAFS, 2015). Lands managed by the United States Forest Service (USFS) accounted for 45% of total burned area in these 11 states in 2015 (NIFC, 2016), above the ten-year average of 37%. Consequently, the USFS plays a lead role in western wildfire management. In 2015, more than half the USFS budget was allocated to fire-related activities, compared to 16% in 1995 (USDAFS, 2015). These trends seriously impair the agency's ability to carry out its many other management obligations, including hazardous fuels reduction.

Hazardous fuels reduction (HFR) activities are key to the USFS's effort to counteract these wildfire trends in the dry, high-fire frequency forests of the west. When effective, HFR can reduce the severity and minimize the spread of future fires within a treated area (Calkin, Cohen, Finney, & Thompson, 2014), and facilitate the re-establishment of historic fire regimes (Safford, Stevens, Merriam, Meyer, & Latimer, 2012). HFR may also reduce the cost of future fire suppression, though data do not yet confirm this. Any ecological or fiscal benefits that result from HFR accrue not only to national forest lands, but also to adjacent federal, state, tribal, or private lands. However, HFR activities cannot be applied uniformly to the vast acreage managed by a national forest.

The process of allocating limited HFR resources to a subset of priority treatment areas is influenced by numerous internal and external variables, including: the USFS's community protection, ecological restoration, and silvicultural objectives; land management allocations that may make treatments difficult to implement in some areas; and the social setting surrounding individual national forests (Charnley et al., 2015; Steelman & Burke, 2007; Stephens & Ruth, 2005). These influences may result in a spatial distribution of HFR activity that confers hazard reduction benefits on some populations adjacent to a national forest, but not others. If high proportions of minority or low-income households exist in the population that lacks access to HFR benefits, and populations benefitting from HFR have few such households, the agency may have created a disproportionate burden of wildfire risk for its neighboring EJ population, in violation of the executive order.

2. Literature review

Quantitative EJ research has evolved from its initial focus on locally unwanted land uses and stationary pollution sources (e.g. Saha & Mohai, 2005) to cover a broad range of topics. Recent efforts encompass

such diverse topics as: regional flood risk (Grineski, Collins, Chakraborty, & Montgomery, 2015; Maantay & Maroko, 2009); air pollution dispersion modeling (Bravo, Anthopoulos, Bell, & Miranda, 2016; Maroko, 2012); brownfield soil pollution (McClintock, 2012); fracking (Ogneva-Himmelberger & Huang, 2015); airport noise pollution (Most, Sengupta, & Burgener, 2004); and the interacting effects of multiple emissions sources (Lewis & Bennett, 2013). Environmental justice researchers have also increasingly measured the converse form of EJ impact: lack of equitable access to benefits such as parks (Boone, Buckley, Grove, & Sister, 2009), public beaches (Montgomery, Chakraborty, Grineski, & Collins, 2015), and safe walking and bicycling opportunities (Cutts, Darby, Boone, & Brewis, 2009); and exclusion from amenities caused by gentrification (Bullard, 2011). Some analysts seek to measure both amenity access and hazard exposure, drawing conclusions in terms of the relative balance of the two contrasting metrics (e.g. Johnson Gaither, 2015; Stewart, Bacon, & Burke, 2014).

Nearly all of these analyses focus on urban or metropolitan populations. Recent, novel methodological innovations such as rasterized population estimates (Seirup & Yetman, 2006), dasymetric mapping (Dmowska & Stepinski, 2014; Maantay & Maroko, 2009; Eicher & Brewer, 2001), and integrating household-level survey data into the traditional hazard event-and-Census-data model (Collins, Grineski, Chakraborty, Montgomery, & Hernandez, 2015), have all been tested in urban settings. Even the EJ literature pertaining to forests is almost exclusively concerned with urban forestry (e.g. Schwarz et al., 2015; Lawrence, 2013; Tooke, Klinkenberg, & Coops, 2010; Landry & Chakraborty, 2009). One research team has argued that Native Americans, a population that rarely exists in measurable concentrations in urban populations, are seriously underrepresented in EJ research (Vickery & Hunter, 2016), perhaps a side effect of the dominance of urban settings.

Quantitative analysis of rural populations using Census data is not scarce, but it tends to not be explicitly focused on EJ. Rather, many studies explore the spatial variability in association between social vulnerability characteristics and risk of environmental hazards, including wildfire (Paveglio, Prato, Edgeley, & Nalle, 2016; Poudyal, Johnson-Gaither, Goodrick, Bowker, & Gan, 2012) and smoke (Johnson-Gaither, Goodrick, Murphy, & Poudyal, 2015). These analyses are usually conducted at spatial scales where both rural and urban or suburban populations are present (e.g. Lewis & Bennett, 2013), or encompass broad multi-state regions (e.g. Ogneva-Himmelberger & Huang, 2015). Political ecology approaches to social inequities in rural landscapes sometimes include a quantitative component and may relate to NRM (e.g. Collins, 2008). However, we failed to identify any quantitative research that directly analyzes the social impact of a specific NRM agency action by a discrete management unit, in the manner envisioned by the executive order on EJ, where the affected population is almost exclusively rural.

Some qualitative research addresses this relationship much more directly. In two related studies, Norgaard analyzes the EJ consequences of fire suppression for the traditional culture of the Native American Karuk, and the differential risk perception of USFS herbicide applications held by forest managers, Karuk tribal members, and rural whites (Norgaard, 2014, 2007). Roberts (2013) offers a participant-observation critique of a single HFR project by the USFS. Macias (2008) and Pulido (1996) employ ethnographic methods in analyzing the complex relationship between traditional Hispano populations and national forest management. These analyses generate useful insights for the specific management units studied. However, a program of EJ analysis for an NRM agency could not feasibly be based on long-term, closely engaged, qualitative fieldwork such as these studies employ.

We conclude that there is a substantial knowledge gap that encompasses both documentation of the EJ consequences of NRM agency actions, and the appropriate research method for conducting such an analysis. The impacts of these agency actions are most often confined to a scale that matches closely with the individual NRM unit, such as a

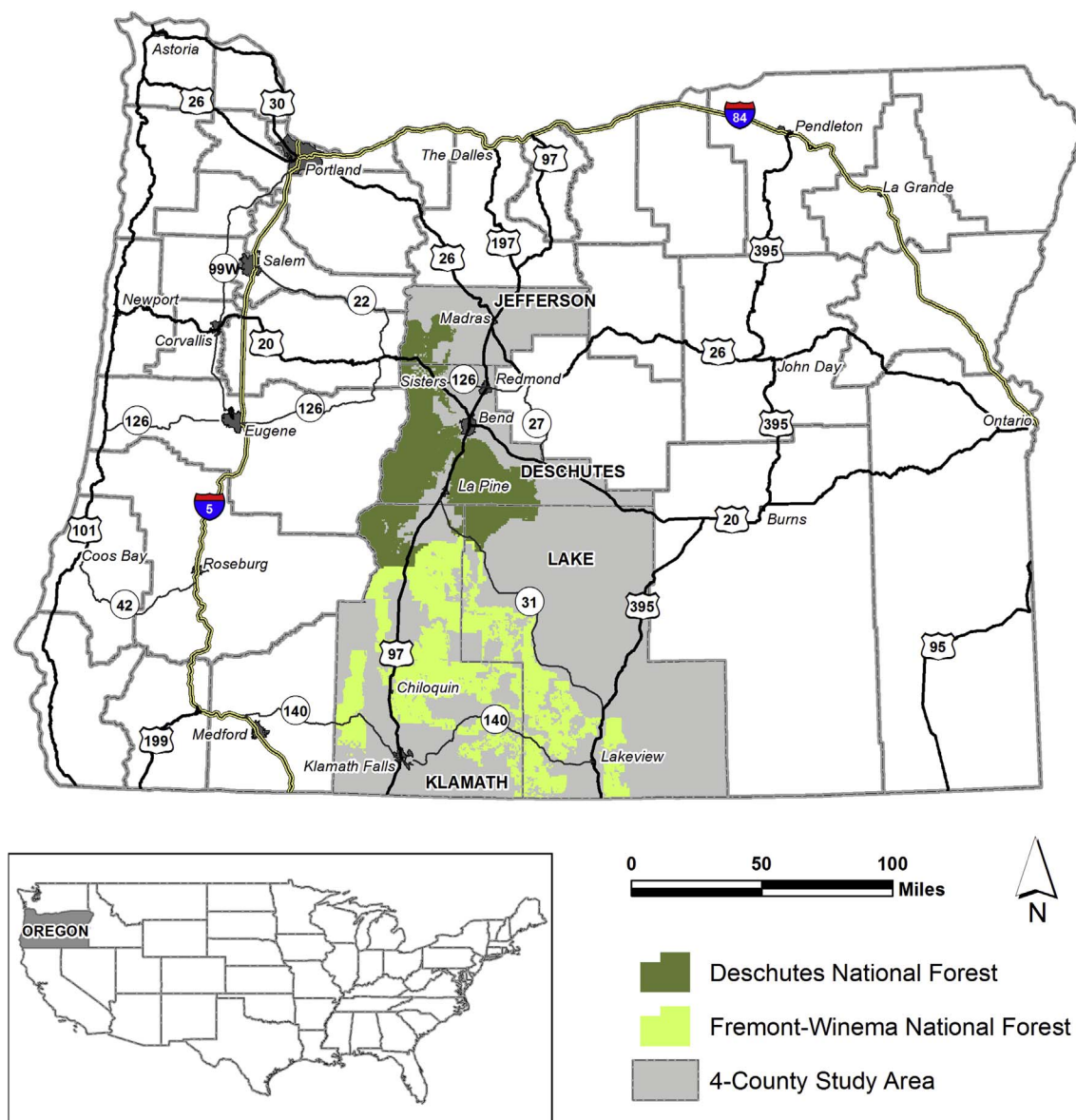


Fig. 1. Study area location in central Oregon, U.S.A.

national park or forest, rather than spanning broad regions. The rural population associated with a discrete NRM unit is typically small, and highly dispersed – characteristics that magnify the inherent error in Census data and may limit population datasets to relatively few observations. We sort through the options for managing this conundrum to arrive at a recommended best practice for analyzing integrated NRM and Census data within Census geographical units.

3. Methods

The principal appeal of quantitative EJ analysis is the prospect of generating statistically valid measurements of association, and possibly inferences of causality, between an environmental hazard and an at-risk population. However, the rural context of federal agency NRM requires careful attention to the limitations of Census data for such analyses. Our approach addresses three data issues that are particularly challenging for studying EJ in rural populations: 1) poor spatial fit between dispersed rural populations and Census data units; 2) the boundary problem; and 3) the MAUP. Responding to these issues while obtaining results relevant to fulfilling the direction of the executive order on EJ necessitates trade-offs that preclude a confirmatory approach. Instead,

our approach yields a spatially precise process for detecting localities where EJ is most likely to be a concern, somewhat analogous to “hot-pots” (e.g. Karimi, Brown, & Hockings, 2015). Additional investigation that can more effectively characterize the behaviors of NRM actors, confirm the characteristics of the affected population, and analyze the institutional and biophysical factors that drive NRM actions, can be efficiently targeted to a short list of hotspots where the potential for EJ impacts is highest.

3.1. Study location

We pilot-tested our method on two national forests in Oregon: Deschutes (DNF) and Fremont-Winema (FWNF) (Fig. 1). The management and ecology of these national forests have been well-examined by Forest Service scientists and their research partners (Charnley et al., 2015, 2017; Spies et al., 2017; Steen-Adams, Charnley, & Adams, 2017). They were chosen to capitalize on interviews about HFR practices conducted with agency field staff in 2012–2014 for the cited studies. Both forests contain large areas of frequent-fire forest ecosystems. Significant Native American populations reside adjacent to both (the Klamath Tribes near the FWNF and the Confederated Tribes of

Table 1

Comparison of estimate quality for 2000 SF3 and 2009–2013 ACS 5-year estimates of poverty in the FWNF data set.

Block group	Block group area (sq. miles)	Population 2000 SF1 data	Individuals in Poverty: 2000 SF 3 Data			Population 2010 SF1 data	Individuals in Poverty: 2009–2013 ACS 5-Year Estimate Data		
			Estimate	Margin of error ^a (90% CI)	Coefficient of Variation		Estimate	Margin of error (90% CI)	Coefficient of Variation
0359701001	947	362	24	(±) 32	<i>0.81^b</i>	531	97	(±) 99	<i>0.62^b</i>
0359701003	614	812	177	(±) 76	0.26	752	219	(±) 115	0.32
0359702001	1,285	765	90	(±) 45	0.30	828	221	(±) 200	<i>0.55^b</i>
0359702002	209	1021	323	(±) 96	0.18	970	106	(±) 115	<i>0.66^b</i>
0359702003	36	1437	195	(±) 73	0.23	1783	253	(±) 176	<i>0.42^b</i>
0359702004	204	1079	279	(±) 53	0.11	1142	191	(±) 120	<i>0.38^b</i>
0359703001	971	404	137	(±) 43	0.19	634	241	(±) 188	<i>0.47^b</i>
0359704001	218	1412	280	(±) 74	0.16	1418	249	(±) 132	0.32
0359705001	255	892	184	(±) 66	0.22	1012	365	(±) 206	0.34
0359705002	740	619	99	(±) 52	0.32	596	123	(±) 78	<i>0.39^b</i>
0379601001	2,990	1583	371	(±) 59	0.10	2010	382	(±) 46	0.23
0379601002	4,376	775	102	(±) 28	0.16	746	137	(±) 76	0.34
0379602001	750	692	33	(±) 25	<i>0.45^b</i>	1203	80	(±) 88	<i>0.67^b</i>
0379602006	230	723	55	(±) 45	<i>0.50^b</i>	611	31	(±) 43	<i>0.84^b</i>

^a Margins of error for SF3 data are not published by the Census bureau, but the Bureau publishes a method for user-estimation of error margins (US Census Bureau, 2002); we followed that direction to calculate values in this column.

^b Census Bureau user guidance states that estimates with a coefficient of variation near or exceeding 0.4 (*italicized*) should be considered highly unreliable; estimates with CV between roughly 0.15 and 0.4 are acceptable with some caution; **bold** estimates, with a CV of around 0.15 or less should be considered reliable.

Warm Springs near the DNF). The remaining neighboring population is racially and ethnically similar, with a small Hispanic component, and few other racial minorities. Communities adjacent to the DNF span a fairly wide household income spectrum, including both affluent resort home developments and low-income communities; the population near the FWNF is generally low-income.

3.2. Data

We analyzed variables describing race/ethnicity and housing stock characteristics, as a proxy for low income, from the 2010 decennial U.S. Census of Population and Housing. We tested the appropriateness of both block and block group data for EJ assessment of NRM activities. The USFS HFR activity data are from the Forest Service Activity Tracking System (FACTS) database.

3.2.1. Census data selection: balancing temporal accuracy with small-area estimate quality

The USFS interprets “protected populations” under Executive Order 12898 as ethnic/racial minorities, and individuals with incomes below the federal poverty level. Poverty is only available from the sample-estimate Census data. Up through Census 2000, the sample estimate data were published every ten years in release “SF3.” Since 2005, comparable sample data have been estimated in the American Community Survey (ACS). Both data sets have consequential error margins at the block group scale, but those of the ACS data are particularly wide, to the point where the estimates frequently have little or no practical meaning (see Spielman, Folch, & Nagle, 2014 or Bazuin & Fraser, 2013 for additional discussion). Table 1 illustrates the problems high error margins pose for using small-area poverty data. We conclude that neither dataset is appropriate. Instead, we rely on SF1 data from 2010 (also known as the “100% count” data), which contain selection error (e.g., a household that was missed), but not sample estimation error.

We limited our analysis to race/ethnicity and renter-occupied housing units from the 2010 Census SF1 data release. We combined nonwhite categories with Hispanic whites to form a single “nonwhite” variable – the term “nonwhite” used hereinafter includes both. Renter-occupied housing units are the best available proxy in the SF1 data for low incomes. We also examined seasonally-occupied housing units, presuming these might serve as a proxy for high household incomes,

but information from locally knowledgeable informants gave us reason to doubt this proxy assumption in our study locations. We report results only for nonwhite population and renter-occupied housing units. Our Census variables are profiled in Table 2.

3.2.2. Census data selection: data unit geography

Census data are available in three different sub-county geographic units: tracts, block groups, and blocks. In the limited EJ research that includes a substantive rural population, block groups are the standard unit of analysis. This may be an appropriate geographic scale for the higher-density rural populations in the eastern or southern U.S. In the west, however, block groups present major problems for analyses proximate to federal lands. Fig. 2 highlights an extreme example from our study area: a block group that is 20% larger than the state of Delaware (~2990 square miles), but has a 2010 population of 2010 – less than 0.7 persons per square mile. Maantay (2007) argues that “it is generally acknowledged that using the smallest practicable unit of analysis yields the most accurate and realistic results,” suggesting that blocks would be preferable units of analysis. However, distinct, even contradictory results may be found depending upon the scale of population data unit chosen for the analysis (e.g. Higgs & Langford, 2009). Bowen (2002) and Downey (2003) both strongly critique numerous studies reporting an EJ impact for using inappropriate population data units. In response, we tested both Census block groups and blocks as the base unit of analysis.

3.2.3. U.S. Forest Service data

The USFS has systematically recorded management activities in FACTS since 2005 (Thomas & Kiesz, 2015; personal communication). We selected all HFR activity records dated between 1/1/2006 and 12/31/2015 from the two pilot national forests, yielding 5949 total records (Table 3). Typically, HFR activities fall into three main categories: thinning (removing standing fuels by harvesting); other mechanical treatments (dispersing surface fuels such as logging slash or brush); and prescribed burns (removing surface fuels through intentional application of fire). The two primary quantifiable metrics for HFR in FACTS are “units accomplished” (in acres), and cost per unit. Significant non-random omissions exist in the cost field, so we exclusively used acres treated to measure HFR accomplishments. The FACTS data contained numerous errors and omissions in spatial attributes, and inconsistencies in the digitization of polygons. To manage these, we reduced all

Table 2
Primary and supplemental 2010 US Census variables included in the analysis.

Subpopulation variable	Universe population	Census data year/release	Census release table	Corresponding data release; table	Justification/precedent
Primary Variables					
1. Nonwhite population ^a	Total population: race reported	2010 SF1	P005	2000 SF1; P004 2015 ACS-5Y ^b ; B3002	- Protected population, EO 12898 - Nearly every published EJ study
2. Renter-occupied housing units	All occupied housing units	2010 SF1	H004	2000 SF1; H004 2015 ACS-5Y; B25003	- Paveglio et al., 2016 ; Poudyal et al., 2012 ; Collins, 2008 - Renting is associated with higher social vulnerability - Renter-occupancy is the best available proxy for low income households in the 2010 SF1 data
Supplementary Variable					
3. Vacant housing units seasonally occupied ^c	All housing units	2010 SF1	H005	2000 SF1; H005 2015 ACS-5Y; B25004	- Seasonal housing may be a proxy for households with higher incomes and educational attainment

^a Nonwhite population is calculated by subtracting values in the field “Only one race – white alone” from the field “total population.” Nonwhite in this analysis thus refers to all individuals who self-identify either as Hispanic, including Hispanic whites, or as a race other than white alone.

^b ACS-5Y is the 5-year rolling sample estimate version of the American Community Survey, the only release of ACS data that is published at the block group scale.

^c We analyzed vacant, seasonally occupied housing units alongside renter-occupied units and nonwhite population; however, supplemental investigation in our pilot study area showed that seasonal units may just as often be associated with low incomes as high, so we do not incorporate seasonal units into the identification of EJ concern.

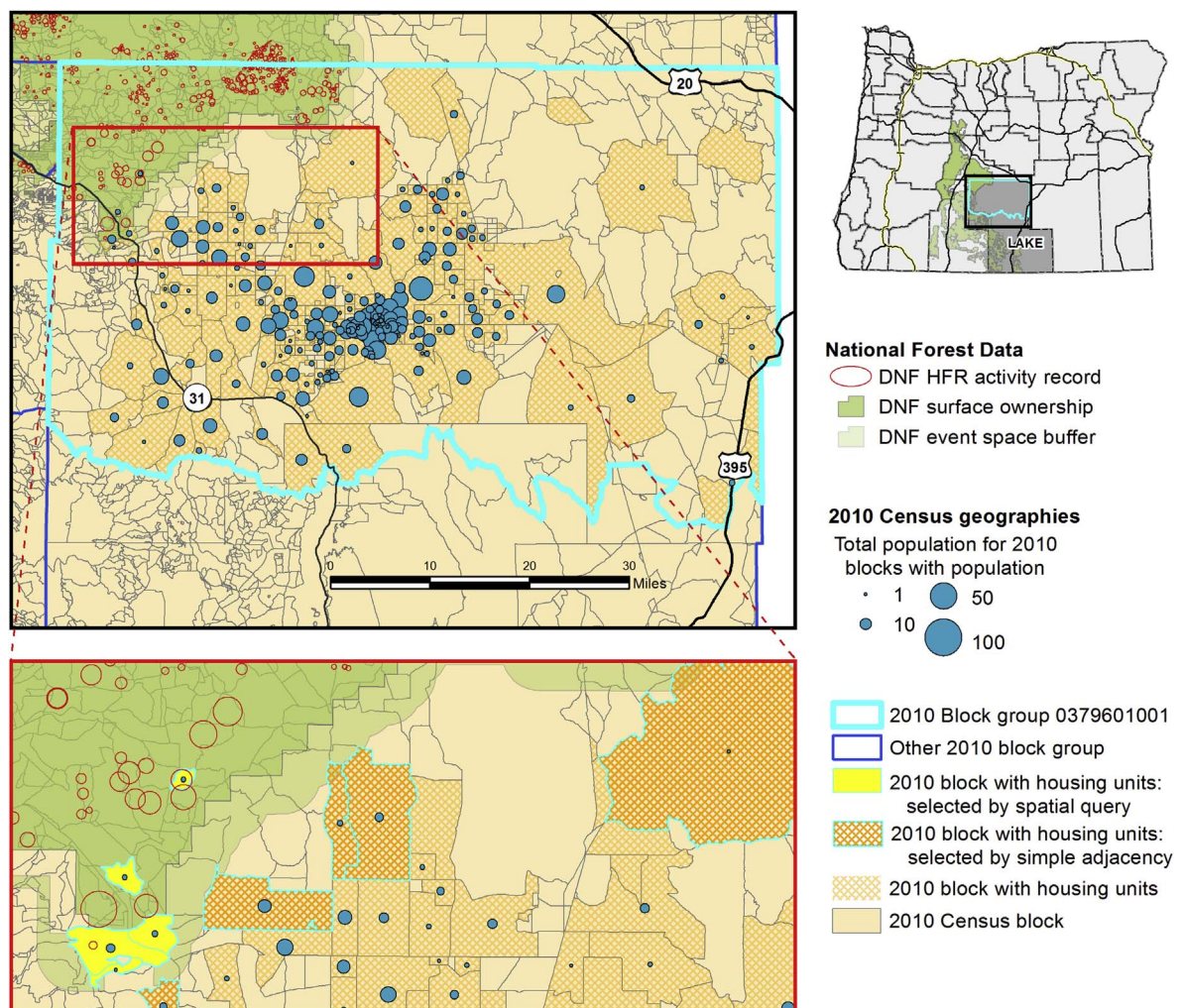


Fig. 2. Comparison of block group and block geography in rural Lake County, Oregon. Upper left: the complete extent of block group 0379601001, which covers 2,990 square miles and has a population of 2,010. Only 11% of the block group's area lies within the event space (dark and light green shading), but this portion of event space represents 10% of both the total land base that could receive HFR treatment benefits; and the total HFR activity of the DNF. Lower left: A total of 10 blocks with housing units intersect the event space for the HFR activities of the DNF. Only five of these blocks, with a total population of 16 – 0.7% of the block group's total population – have a sufficient area of intersection with the event space to justify inclusion in the affected population data set. This is an extreme example of a recurrent problem with the spatial configuration of Census data units relative to federal lands in the rural American West.

Table 3
HFR-related management activities recorded in FACTS used in the analysis.

Activity group	HFR activities (FACTS database code)	Deschutes NF ^a		Fremont-Winema NF ^a	
		Records	Acres treated	Records	Acres treated
Thinning	- Pruning to raise canopy height (1136) - Thinning for HFR (1160) - Fuel break (1180) - Commercial thin (4220) - Pre-commercial thin (4521)	2,916	160,333	2,334	133,522
Prescribed Burning	- Broadcast burning (1111) - Jackpot burning (1112) - Underburn (1113) - Understory vegetation control (4541)	287	29,399	156	94,422
Other	- Lop-and-scatter of fuels (1150) - Compacting / crushing of fuels (1152) - Chipping of fuels (1154)	1,154	66,174	595	36,670
TOTAL		4,357	255,906	3,085	264,614
		Deschutes NF ^a		Fremont-Winema NF ^a	
Total area of eligible ^b USFS land		1,609,615		2,254,111	
Ratio ^c of treated area to total eligible USFS land		0.159		0.117	

^a Records and acres treated are aggregate measures of HFR activity by DNF and FWNF for all activities completed between 1/1/2006 12/31/2015.

^b We define ‘eligible’ as national forest system lands that are located in an active management zone; wilderness, wild and scenic rivers, and other withdrawals that are essentially unmanaged by statutory directive are not included as areas eligible for HFR activity.

^c The ratio of HFR acreage treated to total USFS acreage is *not* equivalent to “percent of total national forest acres treated.” Many HFR treatments are sequential: e.g.: thinning is followed by lop-and-scatter, then underburn, on the same treatment area. The number shown here is the ratio of the total area of all treatments to total Forest Service land area that could be treated, to facilitate comparison of the two forests’ relative intensity of treatment activity.

polygon features to the centroid, then created a circular buffer feature derived from the units accomplished field, which was the most reliable data attribute. A similar approach to FACTS data has been employed by Schoennagel and Nelson (2011) and Schoennagel, Nelson, Theobald, Carnwath, and Chapman (2009).

3.3. Data processing

We devised three procedures to test for association between the relative distributions of HFR accomplishments and protected populations. First, we applied a spatial query in GIS to select either block groups or blocks as part of a subset containing “affected population” (3.3.1). Second, we devised a method for proportional allocation of HFR activity data into Census data units that mitigates the “boundary problem” (3.3.2). Third, in an effort to minimize the skew imposed by the MAUP on data collected in area units, we transformed Census estimates and HFR activity totals into unit-less ratios that can be validly compared and tested for association (3.3.3).

3.3.1. Spatial query selection of blocks or block groups containing the affected population

Defining the “affected population” of an EJ event when tabulating

the population in Census geographic units is a persistent challenge for analysts. Table 4 reviews the main alternative approaches that have been considered in quantitative EJ research. We approached these options intent to avoid re-processing published Census estimates or counts. Reprocessing violates calculation of estimate standard errors, and also requires difficult-to-verify procedures for sub-population characteristics such as race – the analysis by Dwomska and Stepinski (2016, p. 2) is an example. Because we settled on using 2010 SF1 Census data, error margin validity is not an issue. However, because our approach is exploratory rather than confirmatory, we believe the payoff from reprocessing by reference to external data would be insufficient to justify the effort. Instead, we conservatively adopted simple adjacency, but devised a spatial query to “adjust” the adjacency determination by eliminating units that border the NRM unit, but are unlikely to be relevant in the analysis.

Our query-selection procedure first identifies the area within a Census unit that can theoretically benefit from national forest HFR. Virtually all HFR activity is carried out on national forest lands, but its zone of impact is not limited to these lands because the policy intent of many HFR projects is to minimize the risk of wildfire spreading from national forests to adjacent private, tribal, or other lands (Calkin et al., 2014; Schoennagel et al., 2009). We term the combined area of national

Table 4
Alternative methods for determining the size and characteristics of the population that should be considered “affected” by an EJ hazard event.

Approach to defining affected population	Procedure	Examples
Unit-coincidence	A data unit is selected when an event (landfill, smokestack, HFR activity) is located within it; otherwise excluded	See Downey 2003 for examples with critique
Simple adjacency	A data unit is selected if a zone of exposure (floodplain, groundwater contamination plume, air quality non-attainment area) intersects it. The entire recorded estimate of population is included for all selected units even in cases of partial intersection.	Most et al. 2004
Proportional weighting (filtered areal weighting) Dasymetric estimation	Population estimates in units that are only partially within the exposure zone are modified by multiplying the estimate by the fraction of the unit’s physical area that intersects the exposure zone. Published Census data for all units that intersect an exposure zone are spatially re-apportioned within their respective unit by referring to secondary data such as land cover or cadastral data. Various methods are possible for apportioning the published value to better reflect the actual spatial pattern of housing units within the data unit.	Eicher & Brewer, 2001 Most et al., 2004 Dwomska and Stepinski, 2014 Maantay and Maroko, 2009

forest and adjacent non-national forest potentially benefiting from HFR the “event space.” We intersected the event space with the data units, and devised a query statement to remove units with very small proportions of total area within the event space, and also little or no national forest lands on which HFR can be conducted.

To define the extent of non-national forest event space, we followed the method used by [Radeloff et al. \(2005\)](#) to create the national wildland-urban interface (WUI) dataset. Their definition of WUI is Census block-based. A block is WUI if it has sufficient housing density and is located less than 1.5 miles from a 75% vegetated block on which wildfire can occur. The 1.5 mile threshold is the maximum distance a firebrand (burning branch or debris) launched from an active fire front can travel through the air and remain sufficiently aflame to cause a new ignition based on empirical observations of fire behavior in similar forested landscapes in California ([CFA, 2001](#); cited in [Radeloff et al., 2005](#)). A main goal of HFR is to reduce the forest fuels that increase the probability of crown fires with extreme propagation behavior, including firebrands ([Calkin et al. 2014](#); [Vaillant & Reinhardt, 2017](#)). The event space is thus the combined area of all national forest parcels where HFR takes place, plus a 1.5 mile buffer beyond their perimeter in which HFR activity could have the effect of minimizing the risk of uncontrollable fire spread via firebrand. The event space is delineated in [Fig. 2](#).

3.3.2. Split-allocation of the acres treated attribute across block group boundaries

In order to directly compare NRM activity with population, it is necessary to either allocate measurable NRM data attributes to Census data units, or allocate population to a unit reflecting the NRM activity. Because there is a single NRM unit – a national forest – the only option is allocating HFR treatment areas to Census data units. This runs afoul of the “boundary problem”: when a phenomenon that analysts want to measure (the risk-reduction benefits of HFR) crosses the boundaries of the units that are used to measure the phenomenon (the Census units) ([Griffith & Arnheim, 1983](#)).

We applied the firebrand behavior logic to mitigate the boundary problem. When a wildfire in a dry, high fire-frequency forest stand enters an effective HFR treatment, the fire's ability to “crown” and produce firebrands will be minimized ([Martinson & Omi, 2013](#)). Each HFR record thus has its own “benefit range” extending 1.5 miles beyond its perimeter, where the risk of a firebrand ignition tied to that activity record is reduced. To create the “benefit ranges” for HFR activities, we buffered the circular features representing HFR activities (see section 3.2.3) by 1.5 miles, intersected the resulting features with the Census units, and calculated the proportion of each “benefit range” (treated area + buffer) within each Census unit. The acres recorded in each record's attribute table were then proportionally allocated to each Census unit that the benefit range intersected. This process is depicted in [Fig. 3](#).

3.3.3. Ratio transformation of HFR and Census data

The preceding procedures generated raw counts of protected populations and HFR accomplishments for each block group or block, but these variables were enumerated in counts and acres, and also compromised by the MAUP – a source of statistical error that results when counts of spatial phenomena are correlated with the size and configuration of the areas in which they are aggregated ([Wong, 2009](#); [Openshaw, 1983](#)). The MAUP affects both HFR and Census data. In response, we standardized both sets of variables into unit-less ratios representing each Census data unit's *share* of the data set's total HFR treatment acres and population variables.

The standardized variables constitute a “concentration ratio” ([Fig. 4](#)). To form the numerator of the ratio, the observed value in each data unit is divided by the sum of all such observations. The denominator is the proportional relationship between a locally observed *universe variable* and the sum of all observations of the universe variable.

The universe populations for the primary Census variables are total population, and total occupied housing units. For HFR, the universe variable is the area of the event space that is theoretically eligible to receive the benefit of an actual HFR treatment.

The concentration ratio has a hypothetical “expected” value of 1.0 when all observed sub-populations are distributed in proportion to the distribution of their universe variables. For example: if a Census unit is allocated 500 acres of HFR treatments, out of a total of 50,000 acres of treatments; and there are 10,000 acres of event space in the unit out of a total of 1,000,000 acres; then the HFR ratio is 1.0. This unit has exactly the share of the total HFR activity that its share of the total event space would predict, assuming that HFR acreage is distributed in proportion to event space throughout the entire national forest area. Of course, there is no reason to assume HFR or population would be so uniformly distributed. But large deviations from 1.0 still have interpretive significance. If a concentration ratio value is significantly above 1.0, the variable in the numerator of the concentration ratio is over-represented relative to that in the denominator; the numerator variable is *concentrated* in that block group. Ratio values approaching zero indicate a disproportionate *absence* of the numerator variable. The impact of this transformation for the HFR data is shown in [Table 5](#): the raw count of HFR acres is extremely correlated with the area of event space, and strongly correlated with the area of the data unit in which it is recorded, but the HFR *ratio* is weakly or not at all correlated with either event space or unit size.

3.4. Why these data processing steps matter

The raw counts of nonwhite individuals and/or renter-occupied housing units identified by this procedure may often be very small, hardly remarkable compared to state or regional numbers. However, the executive order does not release agencies from the obligation to identify EJ populations just because the number of potentially impacted individuals is relatively small. The key question is whether the agency has identified any EJ population that appears to bear a disproportionate burden of the impact of an agency activity, or conversely, does not receive a proportionate share of the benefits of an activity, in comparison to the population that is reasonably subject to potential harm or benefit from agency actions. Some analysts have located affected EJ populations using pre-determined metrics – e.g., only data units where the percent of nonwhite population exceeds 25% could be considered as potential locations for EJ impacts (see [Lewis & Bennett, 2013](#) for a critique of this practice). Populations potentially protected by the EJ executive order could very easily be missed in such an approach.

The ratio approach to these data directly addresses this issue by expressing any concentration or disproportionate absence of a variable expressly in terms relative to the unit of analysis – an individual national forest, and its affected population for a specific action. Both high and low outliers of a ratio are salient to EJ assessment of HFR: high ratio values for nonwhite population or renter-occupied housing units indicate a relative concentration of EJ population as compared to the total study area; low ratio values for HFR indicate a relative absence of the risk-reduction benefits that HFR theoretically provides. If the two ratio values *always* exist in high-low opposition, and this association is confirmed by correlation analysis, then the data imply a national forest may be conducting its HFR program in a way that systematically deprives EJ populations of wildfire risk reduction benefits throughout the entire affected area. If a high-EJ, low-HFR ratio disparity exists in a few data units, a localized EJ problem may exist even in the absence of a general relationship. The result will not necessarily be relevant in a state or national context, but it will directly relate to the expectation of the EJ executive order.

3.5. Tests of association

We first tested the ratio form of each of the primary Census

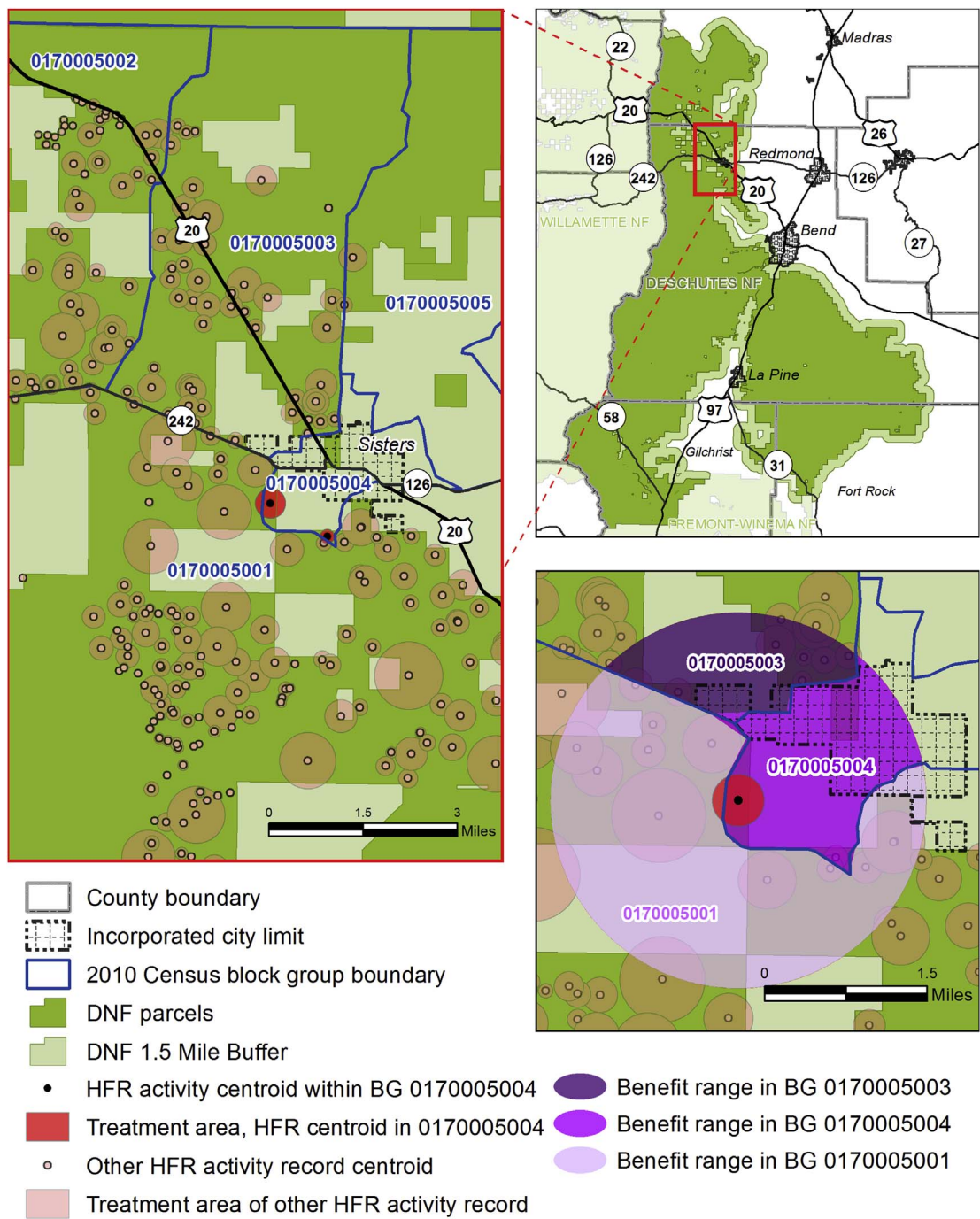


Fig. 3. Split-allocation of partial HFR record attribute values to multiple block groups. Many HFR projects have some capacity to influence wildland fire hazard in more than one block group. All 52 of the records with centroids in block group 0170005003, for example, have a “benefit range” that reaches at least one neighboring block group. The lower right inset illustrates the split-allocation procedure for one of the two HFR records with a centroid located in block group 0170005004. This block group is referenced in text Section 4.3, and Table 10.

$$\text{Relative share} = \frac{\left(\frac{\text{(area of HFR treatments located in block group } n)}{\text{(sum: all HFR area treated in all block groups } n_1 \dots n_x)} \right)}{\left(\frac{\text{(area of "event space" in block group } n)}{\text{(total "event space" area in all block groups } n_1 \dots n_x)} \right)}$$
$$\text{Relative share} = \frac{\left(\frac{\text{(subpopulation } x, \text{ (e.g. nonwhite persons) in block group } n)}{\text{(sum of all subpopulation } x, \text{ in all block groups)}} \right)}{\left(\frac{\text{(universe population } X \text{ (e.g., total population) in block group } n)}{\text{(sum: all universe population } X \text{ in all block groups,)}} \right)}$$

Fig. 4. “Concentration ratio” for total area treated by HFR activity (top) and for Census variables (bottom).

variables in Table 1 individually for correlation with the ratio form of HFR accomplishments. Correlation results are scale-dependent and should always be interpreted with caution (Lewis & Bennett, 2013). We agree. Thus the main emphasis of our method is not the general correlation test, but the identification of localities where HFR and protected populations are unusually low or high.

Our data sets precluded using formal statistical tests such as Anselin’s LISA (Anselin, 1995) to compare whether there are statistically significant local clusters of high and low HFR and EJ population, and the degree of overlap between them. However, because all of the ratios express the identical form of relative concentration/absence, an

Table 5
Effect of ratio transformation on correlation with total area and event space area.

	HFR – total acres treated	
	Correlation coefficient	
	Raw data	Ratio data
Deschutes NF		
Block group size (acres)	0.615	–0.224
Event space area (acres)	0.946	–0.272
Fremont-Winema NF		
Block group size (acres)	0.469	–0.038
Event space area (acres)	0.880	0.248

Note that in the DNF data set, the sign changes with the ratio transformed data, but not with the raw data. This reflects the tendency for HFR record centroids to be located near, but not within, the smallest block groups in the dataset.

alternative spatial assessment can be performed simply by identifying which data units have notable disparities between high shares of EJ population and low shares of HFR. We defined a ratio value of at least 1.5 (150% of the hypothetical expected value) and roughly 1 standard deviation or more above the mean as high. Low ratios have values of roughly 0.5 (50% of hypothetical expected value) or less and are approximately 2/3 standard deviation below the mean. We took a natural breaks approach to these thresholds to avoid arbitrarily eliminating observations that are more related to a group of high or low outliers than to the remaining observations. We also queried for units where either population ratio exceeded the HFR ratio by more than the difference between high and low – more than the value 1.0. This step guarded against missing observations where the HFR ratio value is not low, but the EJ ratio is extremely high, such that the disparity might still be meaningful.

4. Results

Each section of our results references the impact of one or more

Table 6
Impact of alternative combinations of data units and selection procedure on distribution of HFR ratio values.

	Block data		Block data – blocks with housing units only		Block data in block groups		Block group data	
	1. SA ^a	2. SQAA ^b	3. SA ^a	4. SQAA ^b	5. SA ^a	6. SQAA ^b	7. SA ^a	8. SQAA ^b
Deschutes National Forest								
# of data units	6,469	6,182	1,286	1,205	40	33	40	31
Total event space acres	1,811,905 (100%)	1,740,543 (96.1%)	351,139 (19.4%)	322,123 (17.8%)	1,811,927 (100%)	1,740,543 (96.1%)	1,811,927 (100%)	1,783,838 (98.4%)
Total HFR activity acres	291,125 (99.8%)	288,188 (98.8%)	56,794 (19.5%)	55,004 (18.9%)	291,636 (100%)	291,172 (99.8%)	291,636 (100%)	291,083 (99.8%)
Ratio: mean	1.25	1.20	1.46	1.34	1.79	1.26	1.79	1.33
Ratio: standard deviation	2.05	1.52	2.30	1.28	4.18	0.95	4.18	0.92
Ratio: minimum	0	0	0	0	0	0.11	0	0.10
Ratio: median	0.59	0.62	1.08	1.06	0.97	1.12	0.97	1.14
Ratio: maximum	55.03	9.71	50.48	7.44	26.80	3.69	26.80	3.68
Fremont-Winema National Forest								
# of data units	6,417	6,044	723	614	17	17	17	14
Total event space acres	3,385,292 (100%)	3,132,799 (92.5%)	866,061 (25.5%)	822,255 (24.2%)	3,385,292 (100%)	3,385,292 (100%)	3,385,292 (100%)	3,385,292 (100%)
Total HFR activity acres	300,386 (100%)	298,608 (99.4%)	60,699 (20.2%)	60,121 (20.0%)	300,488 (100%)	300,488 (100%)	300,488 (100%)	300,413 (100%)
Ratio: mean	1.05	1.02	0.61	0.53	0.69	0.69	0.69	0.82
Ratio: standard deviation	4.86	1.98	1.32	1.07	0.63	0.63	0.63	0.62
Ratio: minimum	0	0	0	0	0	0	0	0.07
Ratio: median	0.03	0.06	0.03	0.08	0.50	0.50	0.50	0.68
Ratio: maximum	310.82	15.34	12.5	9.49	2.43	2.43	2.43	2.43

Bold values are extreme outliers, indicators of highly skewed data distributions, or fatal selection biases, any of which make evaluating association between the distribution of HFR and EJ population ratio values difficult or impossible.

^a SA: simple adjacency selection procedure (refer to Table 4).

^b SQAA: spatial query-adjusted adjacency procedure developed for this analysis in section 3.3.1.

methodological steps in our analysis. Section 4.1 evaluates the effect of Census data unit choice (section 3.2.2) and selection procedure (simple or spatial query-adjusted adjacency) (section 3.3.1) on the distribution of ratio values. The impact of these decisions on tests of association between the ratios (section 3.5) is discussed in section 4.2. Section 4.3 illustrates how the split-allocation of HFR acreage data (section 3.3.2), and the concentration ratio (section 3.3.3) can affect the interpretation of local disparities between HFR and EJ.

4.1. Identifying appropriate Census data units – unit type and selection procedure

We tested eight combinations of Census data unit and selection procedure. Summary statistics for the eight versions of the HFR ratio and two primary Census data ratios are compared in Tables 6 and 7. The optimal set of ratio variables should exhibit the following characteristics: standard deviation is smaller than mean value, such that zero values are not treated as close to average; the data set is not strongly skewed towards one end of the distribution, as is indicated when mean and median values are highly disparate; and the data range permits a relatively small standard deviation so that interpretation of the maximum outlier has practical meaning. Problematic qualities of the ratio data generated by each combination of data unit and selection method are **bolded** in these two tables. Two findings are strongly indicated: blocks are a poor choice of geographic feature for conducting the comparative analysis; and selecting features with the spatial query-adjusted adjacency procedure minimizes undesirable qualities in the data distribution of both HFR ratios, and the nonwhite ratio for the DNF.

Blocks may allow for a higher degree of spatial precision in representing the population that can be affected by an EJ event, but we find two key reasons why they are not the best choice for the HFR data, and by implication, other NRM actions in rural settings. Blocks do not have a non-zero minimum housing count threshold; except in unusual circumstances, block groups do. In the rural American West, huge numbers of blocks contain only federal land, which by definition cannot

Table 7
Impact of alternative combinations of data units and selection procedure on distributions of population variable ratios.

	Block data		Block data – blocks with housing units only		Block data in block groups		Block group data	
	1. SA ^a	2. SQAA ^b	3. SA ^a	4. SQAA ^b	5. SA ^a	6. SQAA ^b	7. SA ^a	8. SQAA ^b
Deschutes National Forest								
Total non-white population	3,011	2,669	3,010	2,669	3,011	2,654	8,610	4,128
Ratio: mean	0.19	0.18	0.94	0.94	1.07	0.93	0.97	0.94
Ratio: standard deviation	0.91	0.91	1.87	1.87	1.47	0.37	1.58	0.27
Ratio: median	0.00	0.00	0.00	0.00	0.85	0.87	0.56	0.91
Ratio: minimum – maximum	0.0–13.18	0.0–13.13	0.0–13.19	0.0–13.13	0.39–9.89	0.39–1.87	0.23–7.72	0.37–1.53
Total renter-occupied housing	3,254	2,815	3,249	2,815	3,253	2,795	6,510	4,877
Ratio: mean	0.19	0.18	0.94	0.95	0.91	0.97	0.93	0.90
Ratio: standard deviation	0.68	0.69	1.27	1.30	0.59	0.47	0.47	0.44
Ratio: median	0.00	0.00	0.50	0.51	0.87	0.88	0.80	0.82
Ratio: minimum – maximum	0.0–5.03	0.0–5.12	0.0–5.03	0.0–5.12	0.0–3.09	0.30–2.38	0.25–2.08	0.26–2.05
Fremont-Winema National Forest								
Total non-white population	1,234	1,075	1,234	1,075	1,234	1,075	2,582	2,360
Ratio: mean	0.08	0.07	0.70	0.66	0.59	0.56	0.91	0.92
Ratio: standard deviation	0.48	0.43	1.27	1.18	0.51	0.48	0.49	0.48
Ratio: median	0.00	0.00	0.00	0.00	0.50	0.56	0.75	0.76
Ratio: minimum – maximum	0.0–4.90	0.0–4.45	0.0–4.90	0.00–4.45	0.0–1.82	0.0–1.68	0.39–2.32	0.50–2.22
Total renter-occupied housing	641	515	641	515	641	515	1,815	1,534
Ratio: mean	0.09	0.08	0.84	0.79	0.95	0.95	1.01	1.00
Ratio: standard deviation	0.51	0.47	1.30	1.26	0.61	0.63	0.34	0.29
Ratio: median	0.00	0.00	0.00	0.00	0.87	0.81	1.01	1.00
Ratio: minimum – maximum	0.0–4.27	0.0–4.27	0.0–4.27	0.00–4.27	0.0–2.04	0.0–2.17	0.61–1.88	0.63–1.74

Bold values are extreme outliers, indicators of highly skewed data distributions, or fatal selection biases, any of which make evaluating association between the distribution of HFR and EJ population ratio values difficult or impossible.

^a SA: simple adjacency selection procedure (refer to Table 4).

^b SQAA: spatial query-adjusted adjacency procedure developed for this analysis.

have housing units (note the outlines of blocks underlying DNF lands in Fig. 2.). The problem is quantified in columns 3 and 4 of Table 6: about 75–80% of the event space occurs in blocks that have no housing units; only about 20% of the HFR activity of both forests is allocated to a block with a housing unit. The preponderance of zero values creates extremely skewed distributions (columns 1 and 2). An association analysis comparing units in which 80% of observations are zero by default suffers from logical fallacy. Also, in rural landscapes such as these, many blocks have only 1 or 2 housing units. Extreme outliers in the population variable ratios can result. The outlier value of 13.19 in the DNF nonwhite ratio (Table 7) is generated when 100% of a block's population of either 1 or 2 individuals is nonwhite. Extreme outliers may affect the detection of correlation, and they present an interpretive problem: 20 blocks in the DNF data set have a population of 1 and the individual is nonwhite. No one could reasonably conclude that the EJ executive order requires managers to tailor the spatial impact of agency actions to the level of a single individual. Only the data in columns 5–8 of Tables 6 and 7 are mostly free of problematic observations. Both are based on block group features.

For block group data (columns 7 and 8), our query-adjusted adjacency procedure generates clearly preferred characteristics for the DNF nonwhite population ratio. The total nonwhite population of the DNF affected population is cut by half, though only 9 block groups containing 1.6% of the event space are eliminated. Fig. 5 illustrates how this happens. About 3500 Native Americans living on the Confederated Tribes of Warm Springs (CTWS) Reservation are counted by the simple adjacency selection procedure, though only very small portions of the block groups including this population intersect the event space. The maximum extent of the DNF event space is more than 5 miles from the actual physical location of the population. Eliminating these observations has two benefits. The distribution of nonwhite ratio values that results from query selection permits detection of subtle spatial variations in shares of nonwhites among the remaining block groups that might have management significance. Such variations would be undetectable by ratio value and z-score in the presence of such extreme outliers. Second, these CTWS block groups would produce a strong false

positive in the assessment of local HFR-EJ disparity, since both have nearly 8 times the 'expected' share of nonwhite population and HFR concentration ratio values of zero.

The query selection procedure is effective when the intersection area of event space and block group resembles the example in Fig. 5. It does not resolve dilemmas like the one shown in Fig. 2. Only 11% of the block group area lies within the event space. If the sole query criterion was percentage of block group area in the event space, this unit would be eliminated. Yet, this observation is essential to understanding the distribution of HFR by the DNF: the block group contains over 215,000 acres of national forest lands, on which nearly 30,000 acres of HFR were conducted. Eliminating it from the data set causes selection bias: 10% of the DNF's HFR records and 12% of its land base are thrown out. The query adjustment thus includes a term to prevent Census units with even small areas of national forest land on which HFR could be conducted from being eliminated in the selection procedure. However, retaining this block group's entire population count is also a problem: Only 0.7% of the population – 16 individuals – is located within range of HFR benefits. Characteristics typical of the other 99.3% will be arbitrarily projected onto those 16 people: more false readings are likely. Among the 57 block groups that comprise these two data sets, 10 exhibit this spatial relationship, and similar instances likely occur in proximity to federal lands throughout the west. We conclude that the preferred method of EJ analysis for NRM is to select blocks that are affected by a NRM event via the spatial query-adjusted adjacency procedure; aggregate the counts of the selected blocks to the block group feature they belong with; then calculate the population ratio values on the resultant sums: we term this the “block data-in-block groups” (hereinafter, “blocks-in-block group”) approach (columns 5–6, Tables 6 and 7).

4.2. Correlation analysis and significant local associations between high EJ and low HFR

The general correlation analysis was inconclusive on all eight combinations of data unit and selection procedure. Coefficients

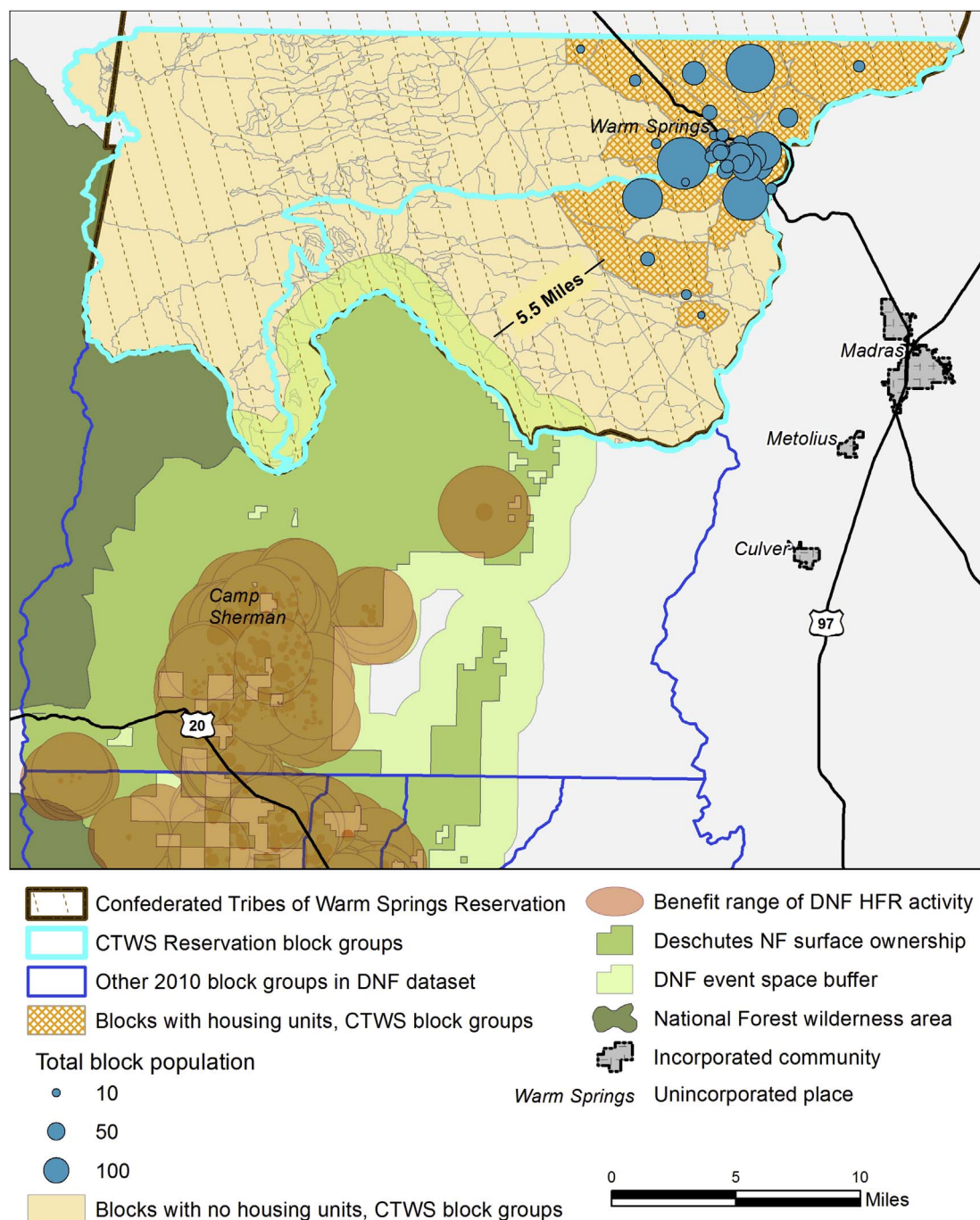


Fig. 5. Elimination by spatial query of block groups containing population of the Confederated Tribes of Warm Springs (CTWS) Reservation.

between 0.2 and 0.35 indicating weak association turned up in the block data. However, Pearson's correlation assumes that both data sets are relatively normally distributed: only the two query-selected data sets based on block group features (columns 5–8 in Tables 6 and 7) meet this standard. There were no coefficients of note for these datasets. The practical implication of this lack of correlation is that there is no evidence that either forest's spatial pattern of HFR activity is systematically favoring certain populations as defined by high or low proportion of nonwhites or renter-occupied housing units.

Table 8 compares the number of features with both low HFR ratios and high ratios for nonwhite population or renter-occupied housing units generated by the block group, and blocks-in-block group, datasets. The larger number of low HFR observations produced by the latter is caused by the inclusion of a few blocks within block groups that are not

part of the block group data set. These additions occur at the outer edge of the event space; all are remote from substantial HFR activity, so the resultant HFR ratios are either zero, or very low. In the DNF dataset, there are considerably more block groups with high ratios for nonwhites when using the blocks-in-block group data. Two of these, which do not have high nonwhite ratios in the block group dataset, also have very low HFR. They are thus identified as priority locations for EJ concern, whereas no block groups are so identified in the block group dataset. In the FWNF dataset, the features identified as potential EJ concern locations are nearly identical. Two block groups with high renter-occupied housing unit ratios are added in the blocks-in-block group data set. This forest's HFR activity is much more concentrated relative to its block group features than is the DNF, which causes more than half of the FWNF block groups to have low HFR ratios.

Table 8
Impact of data unit selection options on the detection of local association between HFR and EJ.

Data type	Total block groups	Low HFR ratio	High nonwhite population ratio	High renter-occupied housing units ratio	EJ Concern ^a
Deschutes NF					
Block group data	31	6	3	5	0
Block data in block groups	33	8	7	5	2
Units identified by both data sets ^b		6	2	4	0
Fremont Winema NF					
Block group data	14	7	3	2	3
Block data in block groups	17	11	2	3	5
Units identified by both data sets ^b		7	2	2	3

Bold observations indicate data units where further investigation of the EJ implications of HFR using complementary research methods is recommended.

^a EJ concern is indicated when the HFR ratio is classified as low and one or both of the population variable ratios are classified as high.

^b The two datasets use the same block group features. A block group feature with the same high or low classification in each of the two datasets is counted in this row.

Table 9 describes the characteristics of the two block group records from the DNF, and five from the FWNF, that meet the conditions for concern about potential EJ impacts. In the DNF data set, the relative importance of the two block groups changes substantially. The entire population of block group 0359701002 is 7% nonwhite; in the subset of blocks that actually intersect the event space, it is 14%. Using the blocks-in-block group data changes the nonwhite ratio value from 0.91 to 1.74, the largest change for any of the 31 observations; the z-score changes from near the mean to two standard deviations above the mean. Though the affected population is not large in absolute terms – 86 individuals out of 2654 – these two units now have the *most concentrated* nonwhite population relative to the entire DNF affected population, and also have among the lowest shares of HFR. No other combination of data unit and selection procedure identifies these units – which include the small unincorporated community of Gilchrist in Klamath County, OR, and rural subdivisions west of the town of La Pine in Deschutes County, OR (upper right panel, Fig. 3) – as having high potential for EJ impacts. This result illustrates the suitability of the blocks-in-block group approach for our analysis.

The FWNF results also clearly argue for the blocks-in-block group data assembly procedure. Block groups 0359702003 and 0359702004 are located in vicinity of the town of Chiloquin (Fig. 1), which is the main population center for enrolled members of the Klamath Tribes. The total nonwhite population adjacent to the FWNF is concentrated in

these two block groups, though the measurement of that concentration is very different depending on the data unit employed. In the block group dataset, 38% of the FWNF's neighboring nonwhite population is captured in these two block groups. The spatial query-adjusted adjacency selection of blocks eliminates at least some populated blocks from all 17 block groups (none is entirely within the FWNF event space). A substantial proportion of the total nonwhite population from the other 15 block groups is eliminated, but very little is eliminated from these two. In the blocks-in-block group dataset, the two block groups near Chiloquin thus contain 70% of the forest's nonwhite neighbors. The disparity between 1.9% of total HFR, and 70% of the forest's nonwhite neighbors – representing more than 700 people – strongly indicates the need to learn more about the relationship between the tribal population and FWNF management actions.

The last two records in Table 9 illustrate why the ratio value/z-score approach to inferring likely locations for EJ impacts needs to be verified by examining the underlying data count. We elected to use renter-occupied housing units as a proxy for low-income households given the large error margins for small-scale poverty estimates. In these two instances, however, there is too little data (e.g. one renter-occupied unit) for assuming that the proxy relationship between renting and low income is sound. The smaller the count in a Census unit, the more sensitive is the ratio to inflation, and this property of the ratio is one reason we argued against using the block as the base analysis unit. In this case,

Table 9
Block group features indicated as areas of local concern for EJ using block group or aggregated block data.

Unit ID	HFR acres	% total HFR	HFR ratio	Block group data ^a			Block data in block groups ^a		
Deschutes NF				Population (% total)	Nonwhite (% total)	Nonwhite ratio (Z-score)	Population (% total)	Nonwhite (% total)	Nonwhite ratio (Z-score)
0359701002	1,143	0.3%	0.16	1,755 (3.4%)	126 (3.1%)	0.91 (-0.13)	368 (1.1%)	49 (1.8%)	1.74 (2.21)
0170002004	34	0.0%	0.31	784 (1.5%)	72 (1.7%)	1.16 (0.81)	376 (1.1%)	37 (1.4%)	1.29 (0.97)
				Occupied housing units (% total)	Renter-occupied housing units (% total)	Renter-occupied ratio (Z-score)	Occupied housing units (% total)	Renter-occupied units (% total)	Renter-occupied ratio (Z-score)
none				–	–	–	–	–	–
Fremont-Winema NF				Population (% total)	Nonwhite (% total)	Nonwhite ratio (Z-score)	Population (% total)	Nonwhite (% total)	Nonwhite ratio (Z-score)
0359702004	4,859	1.6%	0.45	1,142 (8.0%)	417 (17.7%)	2.22 (2.78)	1,046 (21.9%)	394 (36.7%)	1.68 (2.39)
0359702003	806	0.3%	0.64	1,783 (12.4%)	482 (20.4%)	1.64 (1.54)	1,077 (22.5%)	360 (33.5%)	1.49 (1.98)
				Occupied housing units (% total)	Renter-occupied housing units (% total)	Renter-occupied ratio (Z-score)	Occupied housing units (% total)	Renter-occupied units (% total)	Renter-occupied ratio (Z-score)
0359701003	11,235	3.8%	0.43	354 (5.7%)	114 (7.4%)	1.31 (1.11)	59 (2.7%)	29 (5.6%)	2.10 (1.89)
0359704001	171	0.1%	0.07	541 (8.7%)	139 (9.1%)	1.04 (0.16)	3 (0.1%)	1 ^b (0.2%)	1.42 (0.78)
0359710001	74	0.0%	0.26	–	–	–	8 (0.4%)	3 ^b (0.6%)	1.60 (1.07)

Bold cell values correspond to ratios beyond the threshold values for high ($> \sim 1.5$, $Z > \sim 1.0$) EJ or very low ($< \sim 0.5$, $Z < \sim -0.67$) HFR ratios. Where at least one EJ ratio is high and the HFR ratio is very low, a strong disparity exists between concentrated EJ population and absence of HFR.

^a Both of these datasets are generated by the spatial query-adjusted adjacency procedure.

^b Note that the ratio values indicating EJ concern in these block group features are of dubious importance given the extremely small counts.

Table 10

Impact of split-allocation of HFR acreage and ratio transformation on the interpretation of EJ concern in a data unit with relatively high concentrations of EJ characteristics.

Block Group 0170005004, Town of Sisters, DNF	HFR acres (Z-score)	HFR ratio (Z-score)	Nonwhite population (Z-score)	Nonwhite ratio (Z-score)	Renter-occupied housing units (Z-score)	Renter-occupied units ratio (Z-score)
Split allocation and ratio transformation		2.25 (1.05)		1.29 (0.97)		2.38 (3.01)
Split allocation / <u>no</u> ratio transformation	808 (−0.48) ^a	–	181 (1.18) ^a		364 (3.22) ^a	
<u>No</u> split allocation / ratio transformation		0.39 (−0.48)		1.29 (0.97)		2.38 (3.01)
<u>No</u> split allocation / <u>no</u> ratio transformation	140 (−0.67) ^a	–	181 (1.18) ^a	–	364 (3.22) ^a	

Bold observations are at or above the threshold values that identify a block group as having a relative absence of HFR activity (low), and a concentration of either nonwhite population or renter-occupied units (high).

^a Mean values for these variables lack similar relevance to the EJ implications of HFR due to much larger data ranges and the MAUP, especially for HFR acres. Hence even the large z-score of 3.22 is not bolded because its significance to management of HFR by the DNF is not clear.

only about a dozen blocks contribute data to the block group ratio. Hence, we stress the importance of examining the underlying data for any finding of paired high EJ, low HFR ratios in order to confirm that inflation of the ratio values by extremely small counts is not the reason the observations are selected for EJ concern.

4.3. Impact of the split-allocation and ratio transformation procedures

The data in Table 10 use block group 0170005004, featured in Fig. 3, to illustrate how the presence/absence of the split-allocation (section 3.3.2) and ratio transformation procedures (section 3.3.3) can impact the interpretation of EJ concern. This block group, encompassing most of the town of Sisters (Fig. 1) has a relatively high concentration of nonwhite population, and the highest concentration of renter-occupied housing units, in the blocks-in-block group DNF dataset. When both split-allocation and ratio transformation are applied, the ratio values show that the block group has twice the share of HFR activity that its event space share would predict, and its rank in the data set is quite high – more than a deviation above the mean for the HFR ratio. In practical terms: the block group's relative concentration of HFR is roughly commensurate with its concentration of EJ characteristics; its significant EJ population is *not* disproportionately underserved by HFR. The opposite conclusion can be drawn in the absence of the split allocation procedure: the HFR concentration ratio is among the lowest in the dataset. The interpretation of simple counts and z-scores for HFR acres, nonwhite individuals, and renter-occupied housing units, is not structured by a metric equivalent to the hypothetical “exactly proportionate” meaning of the ratio value of 1.0. Consequently, it is not clear in the absence of the ratio transformation whether EJ concerns are warranted in this block group, though the negative z-score for HFR and large positive z-scores suggest they might be. We conclude that the two procedures are vital to the interpretation of patterns of relative concentration. A more complete assessment of the impact of these procedures is available from the authors.

5. Discussion and Conclusions

This research aimed to evaluate methodological options for quantitative EJ assessment in an NRM context and to develop an efficient and accurate quantitative technique for analyzing the EJ implications of federal NRM activities. Little quantitative research on EJ and rural populations applicable to the context of NRM exists, so the EJ implications of NRM activities are not well established. This is at least in part because standard methods used in the quantitative EJ literature are ill-suited to rural population data. There are several significant impediments to generating results relevant to the manner and spatial scale in which NRM activities are administered: small numbers of data observations form the typical data set; spatial distribution of rural populations is poorly represented by Census data units; and small area Census units have error margins for estimate data that are untenable for most analytical purposes. We perceived a need for an approach to the

task that accounted for these data limitations, could be standardized for application to a wide variety of NRM contexts, and could be executed with basic spatial analysis tools in GIS.

We developed four procedures for conducting such an analysis that appear to be novel in the quantitative EJ literature:

- 1) use of Census SF1 block data as the building blocks for an analysis conducted at the scale of the Census block group;
- 2) creation of an “event space” defined by the spatial behavior of the event that management actions are designed to address, and a spatial query process for selecting Census blocks based on the proportion of event space area in each block;
- 3) a procedure for allocating management activity data to Census block groups in a manner that acknowledges the boundary problem; and
- 4) transformation of the population and NRM event data into a unitless ratio that expresses the variables in terms of their relative proportional distribution within the data set, rather than in comparison to an externally applied absolute threshold.

Our pilot test of the options for evaluating EJ impacts in rural landscapes yielded key insights into how best to assemble Census data units to measure the relationship between NRM activities and EJ populations. Among the options we tested, only the blocks-in-block group dataset (procedures 1 and 2), coupled with the split-allocation and ratio transformation procedures (3 and 4) detected two indications of possible EJ concern on the DNF. It also most strongly indicated EJ concern for two block groups near the community of Chiloquin on the FWNF. Block groups have been the standard unit of analysis in quantitative analyses of EJ or social vulnerability that include rural areas. Ironically, our results strongly argue *against* the suitability of block group data for EJ assessments of NRM, but strongly *for* the suitability of the *features* themselves. Hence, assembling block data into block groups appears to be the best approach.

It should be emphasized that detecting indications for EJ concern does not mean we *determined* that an EJ problem exists in the execution of HFR by either the DNF or FWNF; nor was such determination our objective. Given the diverse social, economic, and ecological variables that influence implementation of NRM programs, the need to make findings relevant at the “unit” (national forest) rather than “global” (U.S. Forest Service) level, and the limitations of Census data, proposing a purely quantitative modeling approach to determine whether EJ impacts occurred would be misguided. The Chiloquin area illustrates this argument. Over half of the land that is now the Winema portion of the FWNF was formerly part of the Klamath Tribes' 1.8 million acre reservation. These lands were taken from the Tribes by Congressional passage of the Klamath Termination Act (P.L. 587) in 1954, which ended federal recognition of their tribal status. Tribal recognition was reinstated in 1986, but the reservation lands were not repatriated. The Klamath Tribes retain treaty rights to hunt, fish, gather, and trap on their former reservation lands, and have the right to be consulted about land management decisions affecting their treaty rights (USDAFS-

FWNF, 2017). Interviews with FWNF fire and fuels managers conducted in 2012–2014 indicated that tribal consultation regarding HFR activities in the vicinity of Chiloquin did occur, but numerous other factors also played a role in determining the scope and spatial extent of HFR work (Charnley et al., 2015). Quantitative analysis alone cannot account for these variables. An understanding of how consultations were conducted, any agreements about HFR implementation that were made, what the other factors were and how they were considered, is critical to determining whether an EJ impact to the Klamath Tribal peoples residing in the identified block groups actually occurred. Other data collection and analysis methods are needed to accomplish this goal, though quantitative assessments such as we developed here are an essential first step. In a subsequent paper, we demonstrate such a multi-method approach to EJ analysis of NRM, incorporating this method, in an analysis of HFR by 12 national forests in four western states.

Though we pilot-tested the method using the example of HFR activity by the USFS, the method is applicable to the EJ assessment obligation of several related NRM agencies and their actions. The “event space” in this example was delineated based on spatial aspects of wildland fire behavior that the agency action – HFR – was in part designed to mitigate, but other event spaces defined by the spatial behavior of other NRM activities are possible. Using the same spatial query-adjusted adjacency procedure based on a different event space could lead to a distinct selection set of Census blocks for another management activity – such as herbicide applications – on the same national forest. A chief virtue of our approach is that carefully defining an event space, using it to select block-level populations, then applying the ratio transformation, leads to clear spatial characterization of EJ population concentrations *relative* to the population that can be considered affected by the NRM action for which the event space is appropriate. This is the first key analytical task of the executive order on EJ: identify EJ communities potentially impacted by the implementation of agency programs and policies. The split allocation procedure for mitigating the boundary problem pertains to the second analytical task of the EJ order: determine which programs and policies may impose disproportionate adverse impacts on such communities. The allocation procedure also lends itself to redefinition by the spatial properties of other NRM events.

There is currently both a knowledge gap regarding the EJ impacts of NRM, and need for a quantitative analysis procedure that is adaptable to multiple analyses, can be integrated with other already mandated NRM impact assessments, and can be executed by agency analysts that may have less than highly advanced technical skills in spatial analysis. Our approach to NRM EJ assessment represents the key first step in a research process capable of filling this gap, and meets the needs of agencies that must conduct the analyses. Developing this method has also contributed substantial insights into the tradeoffs regarding data quality, spatial precision, and appropriate quantitative techniques that researchers must contemplate when conducting fine-scale quantitative analysis of rural U.S. populations.

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