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Connecting dryland fine-fuel assessments to wildfire exposure and natural resource values at risk

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Abstract

Background Wildland fire in arid and semi-arid (dryland) regions can intensify when climatic, biophysical, and land-use factors increase fuel load and continuity. To inform wildland fire management under these conditions, we developed high-resolution (10-m) estimates of fine fuel across the Altar Valley in southern Arizona, USA, which spans dryland, grass-dominated ecosystems that are administered by multiple land managers and owners. We coupled field measurements at the end of the 2021 growing season with Sentinel-2 satellite imagery and vegetation indices acquired during and after the growing season to develop predictions of fine fuel across the entire valley. We then assessed how climate, soil, vegetation, and land-use factors influenced the amount and distribution of fine fuels. We connected fine fuels to fire management points, past ignition history, and socio-economic vulnerability to evaluate wildfire exposure and assessed how fuel related to habitat of the endangered masked bobwhite quail (*Colinus virginianus ridgwayi*).

Results The high amount of fine fuel (400–3600 kg/ha; mean = 1392 kg/ha) predicted by our remote sensing model ($R^2 = 0.63$) for 2021 compared to previous years in the valley was stimulated by near-record high growing season precipitation that was 177% of the 1990–2020 mean. Fine fuel increased across the valley if it was contained within the wildlife refuge boundary and had lower temperature and vapor pressure deficit, higher soil organic content, and abundant annual plants and an invasive perennial grass ($R^2 = 0.24$). The index of potential exposure to wildfire showed a clustering of high exposure centered around roads and low-density housing development distant from fire management points and extending into the upper elevations flanking the valley. Within the Buenos Aires National Wildlife Refuge, fine fuel increased with habitat suitability for the masked bobwhite quail within and adjacent to core habitat areas, representing a natural resource value at risk, accompanied with higher overall mean fine fuel (1672 kg/ha) in relation to 2015 (1347 kg/ha) and 2020 (1363 kg/ha) means.

Conclusions By connecting high-resolution estimates of fine fuel to climatic, biophysical and land-use factors, wildfire exposure, and a natural resource value at risk, we provide a pro-active and adaptive framework for fire risk management within highly variable and rapidly changing dryland landscapes.

Keywords Altar Valley, Buenos Aires National Wildlife Refuge, Invasive plant species, Grassland, Masked bobwhite quail (*Colinus virginianus ridgwayi*), Sentinel-2 satellite imagery, Southern Arizona, Wildland fire

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Resumen

Antecedentes Los incendios de vegetación en regiones áridas y semiáridas pueden intensificarse cuando factores climáticos, biofísicos, y de uso de la tierra incrementan la carga de y continuidad de los combustibles. Para informar sobre el manejo del fuego bajo esas condiciones, desarrollamos estimaciones de alta resolución (10-m) de combustibles finos a lo largo del Valle de los Altares en el sur de Arizona, EEUU, que se extiende en una zona seca dominada por ecosistemas de que son administrados por múltiples dueños y manejadores de tierras. Acoplamos mediciones a campo tomadas al final de la estación de crecimiento del 2021 con imágenes satelitales Sentinel-2 e índices de vegetación adquiridos durante y luego de ocurrida la estación de crecimiento, para desarrollar predicciones de combustible fino a lo largo de todo este valle. Luego determinamos como el clima, suelo, vegetación y los factores de uso influenciaban la cantidad y distribución de los combustibles finos. Conectamos los puntos de combustibles finos con el manejo, la historia de las igniciones pasadas, y la vulnerabilidad socioeconómica para evaluar la exposición al fuego, y determinamos como el combustible se relacionaba con el hábitat de la codorniz cotuí (*Colinus virginianus* ridgwayi), especie en peligro de extinción.

Resultados Las altas cargas de combustibles finos (400–3.600 kg/ha; promedio = 1.392 kg/ha) predichas por nuestro modelo basado en el sensor remoto (R2 = 0,62) para 2021 comparado con años previos en el valle, fue estimulado por la precipitación casi récord registrada, que fue de un 177% más que la media de 1990 a 2020. Los combustibles finos se incrementaron a lo largo del valle si los mismos estaban contenidos dentro de los límites del refugio de fauna silvestre, tuvieron menor déficit de vapor de difusión y menor temperatura, mayor contenido de materia orgánica, abundante cantidad de plantas anuales y un pasto perenne invasor (R2 0,24). El índice de exposición potencial a incendios mostró un clúster de alta exposición centrado a los costados de caminos y con baja densidad en el desarrollo de casas distantes de los puntos de manejo del fuego, y extendiéndose hacia elevaciones más altas que flanquean el valle. Dentro del Refugio Nacional de Fauna Buenos Aires, los combustibles finos se incrementaron proveyendo un hábitat adecuado para la codorniz cotuí dentro y en las adyacencias del centro del hábitat, representando un riesgo para el recurso natural, acompañado por mayores cargas promedio de combustible fino (1.672 kg/ha) en relación a la media de 2015 (1.347 kg/ha) y 2020 (1.363 kg/ha).

Conclusiones Mediante la conexión de estimaciones de alta resolución del combustible fino con factores climáticos, biofísicos y uso de la tierra, la exposición al fuego y los valores de los recursos naturales en riesgo, proveímos de un marco proactivo y adaptativo para el manejo del riesgo de incendio dentro de un paisaje semiárido con alta variabilidad y rápidos cambios.

Background

While many studies have focused on increased wildfire activity and associated risk to human life, infrastructure, and natural resources in forest ecosystems (Abatzoglou and Williams 2016; Harvey 2016), non-forest ecosystems have also experienced increasingly severe wildfire activity in recent decades (Westerling et al. 2006; Fovell et al. 2022). Increases in fine-fuel load in arid and semi-arid (dryland) ecosystems are capable of rapidly carrying and spreading catastrophic wildfire and pose a serious management challenge in the western USA (Balch et al. 2013; Wilder et al. 2021). Grasslands, shrublands, savannas, and lower montane woodlands have experienced a growth of wildfire activity due to the spread of invasive grasses, woody plant encroachment, historical fire suppression, rapid drying of fuel, changes in fire weather, and changing land use (Brooks et al. 2004; Archibald et al. 2013; Squire et al. 2021). Dryland ecosystems in the southwestern USA exemplify these interacting stressors, and over the last several decades have undergone rapid warming and precipitation extremes due to climate change (Seager and Vechhi 2010; Abatzoglou and Kolden 2011). Intermittent extreme wet followed by dry years can elevate wildfire occurrence, size, and severity (Mueller et al. 2020). This region has also experienced rapid human population growth that is two to three times as fast as the rest of the country since the 1950s (USCB 2019), which has placed expanding urban areas at the interface of high wildland fuel hazard (WUI; Radeloff et al. 2018; Maranghides et al. 2021) and natural resource values at risk (Wilder et al. 2021).

Unlike forests, much of the fuel load in dryland ecosystems is composed of surface fine fuels (herbaceous grass and forb species) characterized by high spatial and temporal variability in both amount and continuity (Brooks and Matchett 2006). This variability in fine fuel is influenced by climatic (Mueller et al. 2020), biophysical (Levi and Bestelmeyer 2016), and land use (Wells et al. 2021) factors. Fine fuels fluctuate based on the timing and amount of precipitation, with high rainfall periods increasing plant productivity, and subsequent hot and dry periods reducing fuel moisture to levels that greatly enhances fire rate of spread, especially during high wind events. Invasion by dominant non-native grasses can lead to increased fine fuels and resultant fire intensity and spread (Brooks et al. 2004; McDonald and McPherson 2013; Livingston and Varner 2016). Soil properties, including texture, bulk density, and organic matter, can all affect soil moisture and nutrient availability in arid regions, which influences plant growth and fuel load (Noy-Meir 1973; Klemmedson 1989). Furthermore, land use in dryland ecosystems, including livestock grazing and urban growth can alter fuel loads and heterogeneity in fine-fuel structure. Contemporary wildfire events have increasingly made clear that these interacting factors can substantially alter the amount and distribution of hazardous fuels for drylands in the southwestern USA (Abatzoglou and Kolden 2011; Singleton et al. 2019).

To mitigate the high risks associated with the accumulation of fine fuel, fuel treatments and other management strategies are often implemented. These management actions may have secondary, often competing, long-term objectives including conserving wildlife habitat, reducing risk to endangered species, protecting infrastructure, sustaining ecosystem processes, and providing for livelihoods on working lands (Driscoll et al. 2010; Syphard et al. 2016). A fundamental step to meeting wildfire mitigation and these other management objectives is to provide updateable and reliable estimates of fine fuel over large cross-jurisdictional areas on a monthly to annual basis. Determining the amount and distribution of fine fuels at a high-spatial resolution can help connect hazardous fuel accumulation to wildfire exposure and values at risk such as human infrastructure, key watershed areas, and wildlife habitat. Quantifying fine-fuel abundance and distribution is also a prerequisite to integrated fire risk assessment (Chuvieco et al. 2012). Combining exposure (likelihood) with hazard (effect) to describe risk (Fairbrother and Turnley 2005; Atkinson et al. 2010; UNISDR 2018), as shown with the integral risk model (Miller and Ager 2013; Radeloff et al. 2018), requires spatially explicit fuel inputs to estimate potential fire activity. When coupled with factors influencing the likelihood of wildfire occurrence, an index can be created to assess exposure to wildland fire. Here, we sought to bridge the spatial distribution of fine fuels to exposure to wildfire across multiple firesheds (Ager et al. 2021) and WUIs in the Altar Valley that contains semi-arid grasslands, shrublands, savannas, and lower montane woodlands that are widespread across the southwestern USA.

To extend our remotely sensed fuel model to natural resources values at risk, we developed a case study of how fine fuels intersected habitat suitability for the endangered masked bobwhite quail (*Colinus virginianus ridgwayi*) that was historically found throughout the Altar Valley and for which the Buenos Aires National Wildlife Refuge (BANWR) within the valley was created (Engel-Wilson and Kuvlesky 2002). Not only does wildfire carried by fine fuel pose a direct threat of mortality to quail, but also the loss of vegetation for nesting, evading predators, and forage poses serious indirect threats to quail survival (Brown and Clark 2017). Additionally, indirect post-fire effects can reduce masked bobwhite population survival by habitat fragmentation, soil erosion, loss of hydrologic functioning, and expansion of invasive grass species (Kuvlesky et al. 2002). When more flammable invasive grasses proliferate, there is greater potential risk of more intense fire, habitat loss, and negative impacts to masked bobwhite quail demographics (Kuvlesky et al. 2000, 2012). Although resources have been dedicated to rearing, releasing, and monitoring masked bobwhite quail, and actively improving their habitat and providing fire protection (Brown and Clark 2017), questions remain on managing fine fuel in and around remaining suitable habitat. We hypothesized that risk to quail habitat and other natural resource values vary spatially by a combination of fuel hazard and biophysical factors that interface with human land use to influence wildland fire risk.

The objectives of our study were to (1) quantify the amount and distribution of fine fuel across multiple firesheds and land jurisdictions in dryland ecosystems, (2) determine how biophysical and land-use factors affect fine fuels, (3) integrate fuel, ignitions, and fire management activities to evaluate exposure to wildfire, and (4) assess natural resource values at risk such as wildlife and endangered species habitat. Combined, these objectives are aimed at improving short-term fuel management and long-term planning to prepare for present and future changes in wildland fire behavior and risk.

Methods

Study area

Our study area encompassed the Altar Valley (~250,000 ha) of southern Arizona, which extends from southwest of Tucson to the USA-Mexico border (Fig. 1). The valley is flanked to the west by the Baboquivari Mountains and the Tohono O'odham Reservation and to the east by the Cerro Colorado Mountains and is largely part of the Brawley Wash-Los Robles Wash watershed (USDA 2008). Land administration and ownership in the Altar Valley is diverse and includes U.S. Fish & Wildlife Service (USFWS), Bureau of Land Management, U.S. Forest Service, state, county, tribal, and private lands. The largest land parcel is the USFWS-managed BANWR, which covers 47,000 ha of the southern part of the valley (Fig. 1).

The Altar Valley has low human population density, apart from the northern part of the valley where rapid

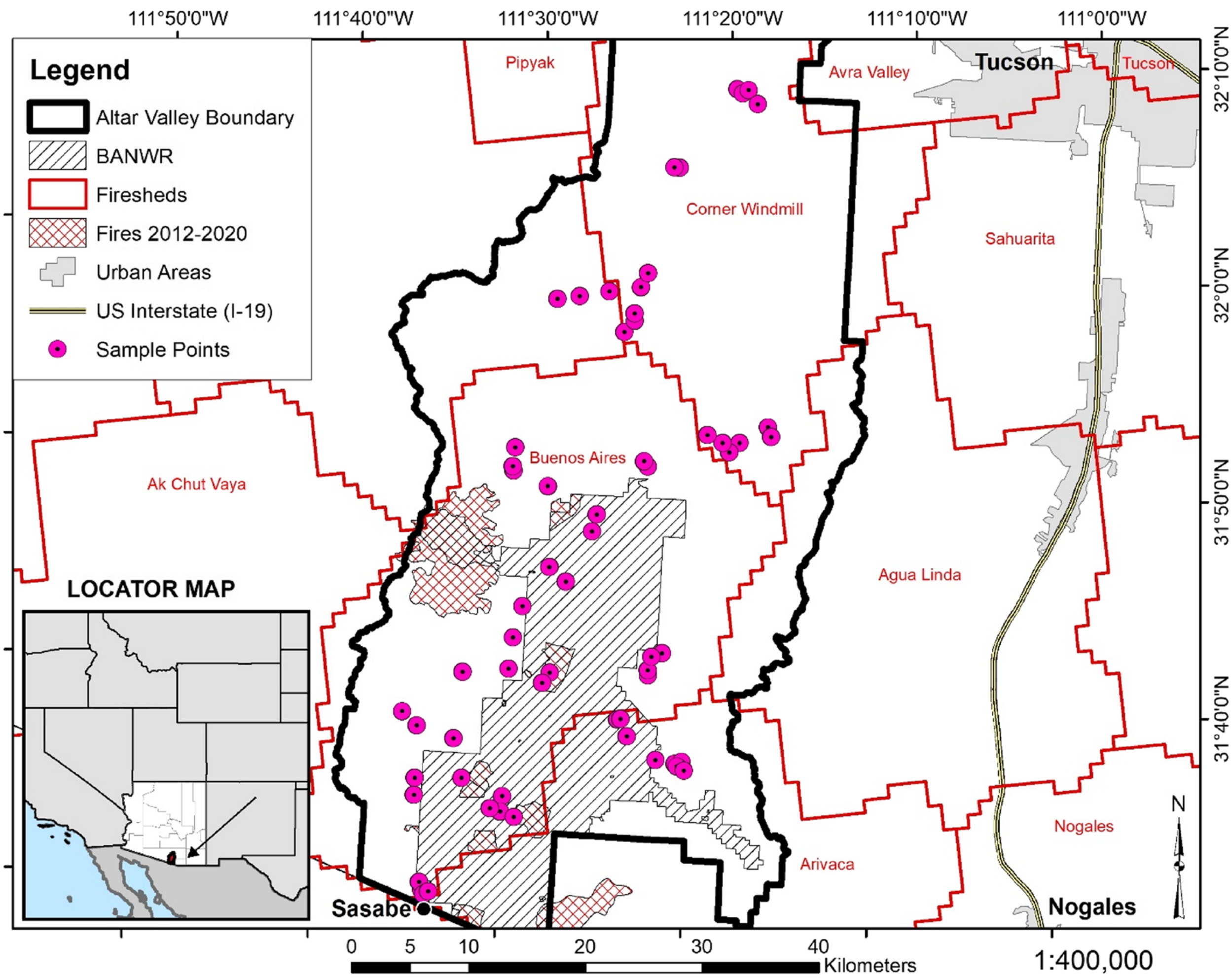

Fig. 1 Altar Valley study area, located southwest of Tucson, Arizona, USA, which includes multiple firesheds, recent fires, and the Buenos Aires National Wildlife Refuge (BANWR). Fine fuels were sampled (pink points) throughout the valley in 2021

urban expansion from southwestern Tucson can be classified as part of the WUI with low-medium density (Radeloff et al. 2018). The remaining rural areas support livestock grazing on private ranches and federal and state grazing allotments. The Altar Valley Conservation Alliance (AVCA 2022) is a collaborative land management and conservation partnership between local landowners and federal, state, county, and tribal agencies that coordinates wildland fire management and fuel treatments throughout the valley. While AVCA partners with BANWR fire managers on many fuel reduction operations, the private lands in the valley are grazed by livestock, in contrast to BANWR that excludes livestock grazing.

Historically, the Altar Valley was largely composed of semi-arid grasslands of native plant species (*Bothriochloa barbinodis, Digitaria californica, Bouteloua* spp., *Sporobolus* spp., *Aristida* spp.). A burgeoning cattle industry began with Euro-American settlement (Sayre 2002), and over time the grasslands have been encroached on by mesquite trees (*Prosopis velutina*), and invaded by non-native grass species (*Eragrostis lehmanniana*, *E. chloromelas*, and *E. superba*, *Pennisetum ciliare*). The semi-arid grasslands, savannas, and shrublands transition into Madrean oak woodlands in the higher elevations of the valley (Warshall 1995). Production of fine fuel across the Altar Valley is influenced by bimodal precipitation. Cool-moist winters followed by an increasing length of growing degree days throughout the early spring break plant dormancy and trigger plant growth. May and June are typically dry and are followed by localized heavy precipitation events from the North American Monsoon that spans July to September and promotes secondary plant growth. Cessation of monsoon rains into the warm-dry fall allows vegetation to senesce and cure into fine fuels.

Historically, frequent low-intensity fires were relatively common across the semi-arid grasslands of the region but overgrazing starting in the late nineteenth century disrupted the natural fire regime (Villarreal et al. 2020). Because of decreased animal stocking rates and contemporary changes to grassland fuels, the Altar Valley has experienced numerous fires over the past several decades (AVCA 2022), with most prescribed fire implemented by USFWS at BANWR. In adjacent woodlands and forests, wildfires are becoming more common despite decades of historical fire suppression (Villarreal et al. 2019). Humans are the most common ignition sources for wildfires in the Altar Valley and surrounding mountains, followed by ignitions from lightning strikes during the summer monsoon storms (Villarreal et al. 2022).

Quantifying and modeling fine fuel

To develop and quantify a remote sensing fine-fuel model, we field-sampled herbaceous plant structure and composition in the study area between 15 September to 16 October 2021 to establish ground truth information. We field-sampled structure and composition across grass-dominated plant communities and major land administration types (federal, state, county, and private) in the valley (Fig. 1). To direct field sampling, we stratified the study area into 9 classes based on vegetation production using the Normalized Difference Vegetation Index (NDVI) quantiles (-0.23–0.15, 0.15–0.27, and 0.27–0.71) from Sentinel-2 imagery (Drusch et al. 2012) captured in early August 2021, combined with quantiles of herbaceous cover (0–16%, 16–25%, and 25–70%) from previous mapping of the study area (Rigge et al. 2021). We generated and surveyed a random sample of points located between 50 and 400 m from a road to minimize road effects and travel time that were proportionally balanced across land ownerships.

At each sample point visited ($n=62$), we established a sample plot that contained nine evenly spaced 0.5 m $\times$ 0.5 m quadrats along three parallel transects, for estimation of biomass and cover, respectively. Within each quadrat, we visually estimated canopy cover and mean height of all forbs and grasses. We then destructively clipped the two plant functional groups at the ground level in two of the nine quadrats per sample plot and estimated biomass of the remaining seven quadrats using gradient boosted regression (see Supplemental Information for more detail). Along each transect, we measured line-point intercept at 4 height classes of (<0.025, 0.025–0.5 m, 0.5–2 m, and >2 m) above the ground at 0.5-m intervals (40 intercepts/transect) of substrate (<0.025 only), key plant species, and functional types (see Supplemental Information for more detail). To assess the contribution of invasive Lehmann lovegrass and annuals to fine fuel in the study area, we used density plots in program R (R Core Team 2022) to compare their proportional cover in relationship to biomass at the plot scale.

From the 62 sample plots visited (Fig. 1), we used the biomass estimates from all clipped ($n=124$) and modeled (non-clipped, $n=434$) 0.5 $\times$ 0.5 m quadrats to infer and spatially predict biomass with remotely sensed imagery. Estimates of quadrat biomass were iteratively pooled and average per plot by using circular neighborhood windows, 14 m in diameter, over the nine quadrats at each plot (Supplemental Fig. S1). Each circular window pooled 3 or 4 quadrats (Supplemental Fig. S2) for a total of 241 mean values of biomass parsed from the combined 558 weighed and estimated quadrat biomasses. This iterative process reduced bias from quadrat-pixel misregistration and helped randomize quadrats within the plot when averaging biomass estimates. These methods were applied to increase our training and testing sample size for development of the remote sensing model, while reducing spatial autocorrelation among samples.

To link these pooled estimates of quadrat and plot biomass to the entire Altar Valley, we used Sentinel-2A Multi Spectral Instrument remotely sensed imagery captured during leaf-on at the peak of plant production (Aug. 22, 2021) and leaf-off during plant dormancy (Nov. 10, 2021). Using the European Space Agency's Sentinel Application Platform (SNAP) with the Sen2Cor plugin v. 2.8 (Main-Knorn et al. 2018), we corrected level 1C images with the atmospheric, cirrus, and bidirectional reflectance distribution function, and performed topographic corrections with Shuttle Radar Topography Mission (SRTM) elevation models, to level 2A. We geometrically resampled all bands to 10 m and calculated biophysical parameters (Gianelle et al. 2009; Xie et al. 2019) and vegetation indices (Kross et al. 2015; Han et al. 2021) from leaf-on surface reflectance values including Fraction of Absorbed Photosynthetically Active Radiation (FAPAR; Senna et al. 2005), Fraction of Vegetation Cover (FVC; Kamenova and Dimitrov 2021), Leaf Chlorophyll Content (LCC; Gitelson et al. 2003), Canopy Water Content (CWC; Clevers et al. 2010), Leaf Area Index (LAI; Kross et al. 2015), Normalized Difference Vegetation Index (NDVI; Kross et al. 2015), and Soil-Adjusted Vegetation Index (SAVI; Xie et al. 2019). We used ENVI Classic 5.5.3 (Exelis Visual Information Solutions, Boulder, CO) to mosaic georeferenced scenes (R041_T12SVA & R04_T12RVV) with histogram matching over entire scenes. Pooled estimates of fine fuel were geospatially registered to remotely sensed imagery and image values were averaged by zonal statistic within each circular pool. Pooled estimates of fine-fuel quadrats were thus linked to reflectance, biophysical, and indices from remotely sensed imagery and used for subsequent modeling. Prior to further development of the remote sensing models of fine fuel, we used recursive feature elimination (RFE), a backwards selection method, to search and eliminate remote sensing variables on an internal cross-validation (tenfold) of minimum Root Mean Square Error (RMSE). Subsequently, after trying various data models and algorithmic models (Breiman 2001a), we then fit random forest (Breiman 2001b) regression models in the *caret* package (Kuhn 2008; Jain et al. 2020) using program R (R Core Team 2022) to diagnose and spatially predict a single remotely sensed model of fine fuel across the study area extent.

Prior to producing a final remote sensing model for spatial prediction, we diagnosed the remote sensing model performance by iteratively ($k=1000$) resampling and fitting our pooled plot biomass estimates ($n=241$) based on a 20–80% split into testing and training data, respectively. We trained (80%) a random forest model with each iteration ($k_1 \ldots k_{1000}$) and used the testing data (20%) to plot predicted versus observed estimates of biomass, reporting and tabulating individual linear fit of each iteration based on R^2. We fit the 1000 validation models using training controls, or hyperparameters, based on a tenfold cross-validation with 500 number of trees to grow (*ntree* = 500) and 20 randomly sampled predictors at each node (*mtry* = 20), using RMSE as the decision metric. We tabulated a mean, standard deviation, and general distribution of validation model fits (R^2 values). We compiled our data sample back together (100%) and generated a final remotely sensed model, based on a randomly selected iteration, with identical hyperparameter controls, for predicting the spatial distribution of fine fuels across the study area. This provided a basis for diagnosing overall expectations of model fit, while utilizing all sample data to capture the entire range of variability within the remotely sensed imagery and the field samples. The final remotely sensed model of fine fuel spatially predicted across the study area was used for the subsequent analysis, as described below.

Biophysical and land-use effects on fine fuel

We used a separate random forest regression tree model to assess the influence of climatic, biophysical, and land-use variables on the amount and distribution of fine fuels (*ntree* = 500, *mtry* = 20). Explanatory variables included past fuel treatments, plant community type, elevation, land ownership, elevation, soil, and climate variables. We extracted historical fuel treatments and wildfires from the U.S. Fish and Wildlife Service's Fire Management Information System and the Altar Valley Conservation Alliance GIS Portal (https://altarvalleyconservation.org/our-work/gis-portal). Plant community types were obtained from the SWReGap database (Lowry et al. 2005), land ownership from the BLM Arizona Surface Management (BLM 2022), and elevation from the NASA Shuttle Radar Topography Mission 30-m digital elevation model (NASA 2022). Soil texture, bulk density, and organic carbon density were derived from SoilGrids 2.0 (Poggio et al. 2021). To assess the influence of climate, we extracted 2021 annualized means of GridMet (Abatzoglou 2013) climate models over annual (Julian date 1–365), winter (Julian date 1–90), and summer (Julian date 182–273) time periods. Initially, we included the full suite of GridMet climate variables from each time period: maximum temperature, minimum temperature, precipitation accumulation, 100-h and 1000-h dead fuel moisture, downward surface shortwave radiation, wind speed, wind direction, maximum relative humidity, minimum relative humidity, specific humidity, reference evapotranspiration (from grass & alfalfa), energy release component, burning index, and vapor pressure deficit. We reduced Gridmet variables that were collinear by screening for correlations over annualized values followed by iteratively running RFE a hundred times to select important climate variables for further analysis in conjunction with all other non-climate predictor variables.

To understand individual variable effects, we estimated conditional variable importance with the *cforest* function in the *party* package (Strobl et al. 2008) in R (R Core Team 2022). With *cforest*, we regressed the random digital sample of point estimates (separated a minimum of 500 m from each other) of fine fuel ($n=1{,}691$) against all explanatory variables derived from the random forest model and derived mean and standard deviation of importance values per explanatory variable. We then used an ordinary least squares multivariate regression to fit the model derived from the random forest to test for overall fit and significance. Testing overall fit and significance with a general liner model protected univariate analysis of the effect of each significant explanatory variable of fine fuel. We then fit univariate linear models to each variable separately to test variable effect and significance.

Fire exposure

To assess wildfire potential, we calculated an exposure index across the study area that incorporated fine fuel, observed ignitions, fire management points, and socioeconomic vulnerability (Flanagan et al. 2011). Fire Management Points (FMP) were designated by AVCA for fire suppression activities that included fire departments, water sources, helipads, and staging areas (Fig. 2A). We calculated the Euclidean distances from each FMP across the study area and related the distance to the nearest FMP to fine fuels for a random sample of points ($n=1691$).

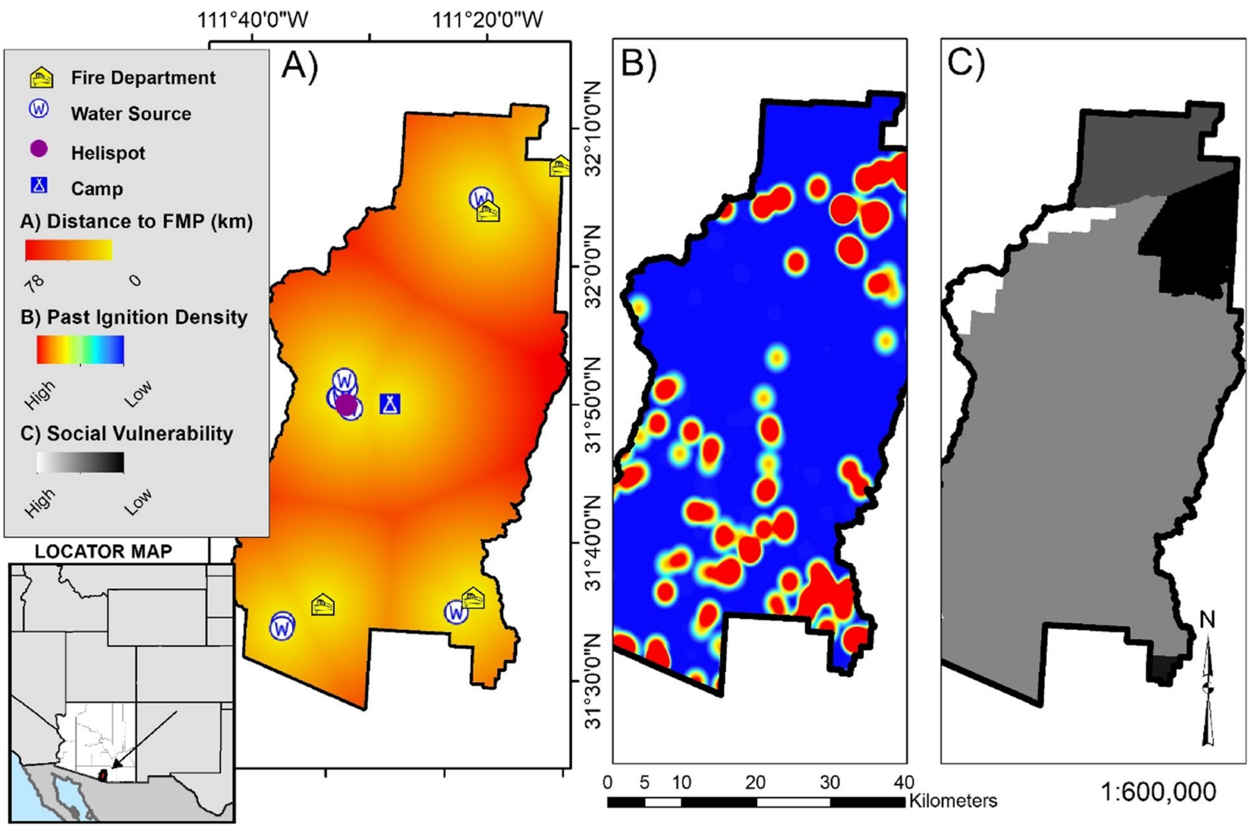

Fig. 2 Data layers used to create wildfire exposure index for the Altar Valley, Arizona, USA, in 2021, showing **A** Euclidean distance to Fire Management Point (FMP), **B** past ignition density, and **C** socio-economic vulnerability index based on data 2018 U.S. Census

We compared amounts of fine fuel among 0–25 km, 25–50 km, and more than 50 km distance classes from FMP that approximated different potential fire response times using ANOVA with a Bonferroni multiple-comparison adjustment. We also compared differences between fuel amounts inside and outside BANWR, and distance to FMP inside and outside BANWR. The exposure index also included past fire ignitions, represented as points in the national Fire Program Analysis fire-occurrence database from 1992 to 2018 (Short 2021). We used previous ignition to approximate probable ignition locations based on kernel density estimation (Fig. 2B) in ArcGIS Desktop 10.8.1 (ESRI, Redlands CA). We converted distance to FMP, fine fuels, and densities of past ignitions to Z-scores and summed the scores to normalize and merge the layers. Low-income, rural communities living within the WUI of the US-Mexico borderlands may lack the resources to prepare for or recover from wildfires (Davies et al. 2018). To represent community vulnerability to wildfire risks, we used the socio-economic vulnerability index generated from the 2018 U.S. Census data (CDC/ATSDR 2022), which was summarized in four themes (1) socio-economic status, (2) household composition and disability, (3) minority status and language, and (4) housing type and transportation. The percentile ranking (RPL) values of each theme were summed to create a social vulnerability layer (Fig. 2C), which was then multiplied by the summed Z-scores of FMP, fine fuels, and past ignitions.

At-risk natural resource values

We related our estimate of fine fuel to masked bobwhite quail habitat suitability. Mapped habitat suitability was developed from remotely sensed data combined with field assessments of forage, cover, and vegetation composition important to masked bobwhite survival and reproduction (Sesnie et al. 2022). To characterize the distribution of fine fuels in relation to habitat conditions, we defined a minimum mapping unit of 1 ha by casting a digital 100 m × 100 m (1 ha) fishnet (ESRI, Redlands CA) across 3 spatial extents, that of the entire refuge excluding suitable masked bobwhite quail habitat polygons, within suitable masked bobwhite quail habitat polygons, and in 250-m buffers around suitable masked bobwhite quail habitat polygons used to identify spatial units adjacent to areas with contiguous habitat appropriate for fuel treatments and at a scale shown to mirror bobwhite quail movement patterns and home range sizes (Simms 1989). We selected the largest masked bobwhite quail polygons ($n=101$) that exceeded the minimum mapping unit, and averaged suitability and fine fuels within coincident 1-ha fishnets. We related the distribution of fine fuels to masked bobwhite quail habitat suitability within core habitat areas, buffer zones, and outside these areas across the refuge based on mean values of fine fuel per 1-ha fishnet using a linear regression. We then extracted the slopes at each of the 3 spatial extents.

Results

Fine-fuel model

Along all line-point intercept transects at each of the four height classes in our field plots, substrate (< 0.025 m above ground) composition was mostly bare ground (56% mean cover), followed by litter (29%), basal plant cover (14%), and biological soil crust (1%). Ground-level (0.025–0.5 m) composition was annual grasses (31.1%), perennial grasses (12.4%), invasive Lehman lovegrass (24.7%), and herbaceous forbs (29.1%). Composition of taller plant species and functional groups in the subcanopy (0.5–2.0 m) was subshrubs and shrubs (4.5%), trees (7.0%), vines (1.4%), ocotillo (1.25%), cacti (0.98%), and yucca (0.04%), and in the canopy (> 2 m) were trees (4.7%) and ocotillo (1%).

Invasive buffelgrass (*Pennisetum ciliare*) was not detected along line-point intercept transects, although it has been reported within the study area. Lehman lovegrass and annual grasses accounted for a greater amount of fine fuel on average, with distributions that were more positively skewed, across all field plots relative to native perennial grasses (Fig. 3). Lehmann lovegrass occurred at 77% of field plots ($n=48$) across all height classes (0.025–2 m), with 7 of these plots containing over 99% cover of the invasive grass.

We predicted 0.5 m × 0.5 m quadrat ($n=434$) biomass (g) of non-destructively sampled quadrats ($n=124$) from clipped, dried, and weighed samples collected from 0.5 × 0.5 quadrats ($n=124$). Biomass of non-clipped plots estimated from clipped plots had a predictive accuracy of $R^2=0.65$ (Supplemental Fig. 3). Initial RFE internal cross-validation (tenfold) of the predictive quadrat biomass model had a similar amount of variance explained: $R^2=0.72$., showing a slight drop based on fitting of the gradient boosted regression model. The quadrat biomass model included total plant cover (relative variable importance [VI] = 29.4), percent grass cover (relative VI = 31.9), mean height (relative VI = 20.0), and forb cover (relative VI = 18.7). Estimates of fine fuel taken during 2021 on both destructively and non-destructively sampled quadrats had a mean of 139.2 g/m^2 (1392 kg/ha).

Validation diagnostics of the remote sensing model (Fig. 4) using random forest models, which were based

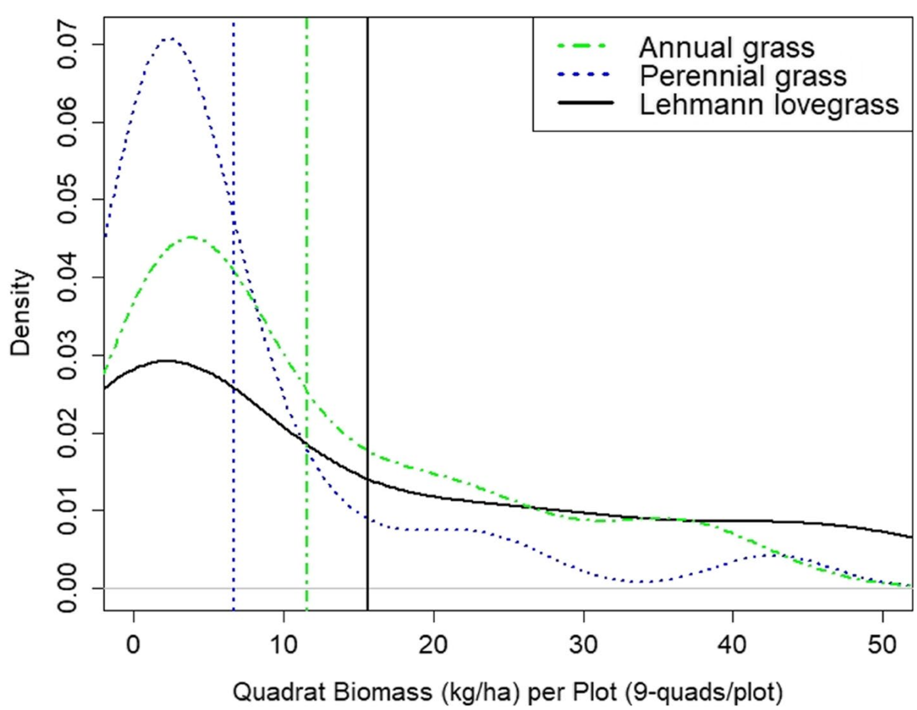

Fig. 3 Distribution of biomass and the mean biomass (vertical lines) of Lehmann lovegrass (*Eragrostis lehmanniana* Nees), perennial grasses, and annual grasses, in field plots ($n=62$) across the Altar Valley, AZ in fall 2021

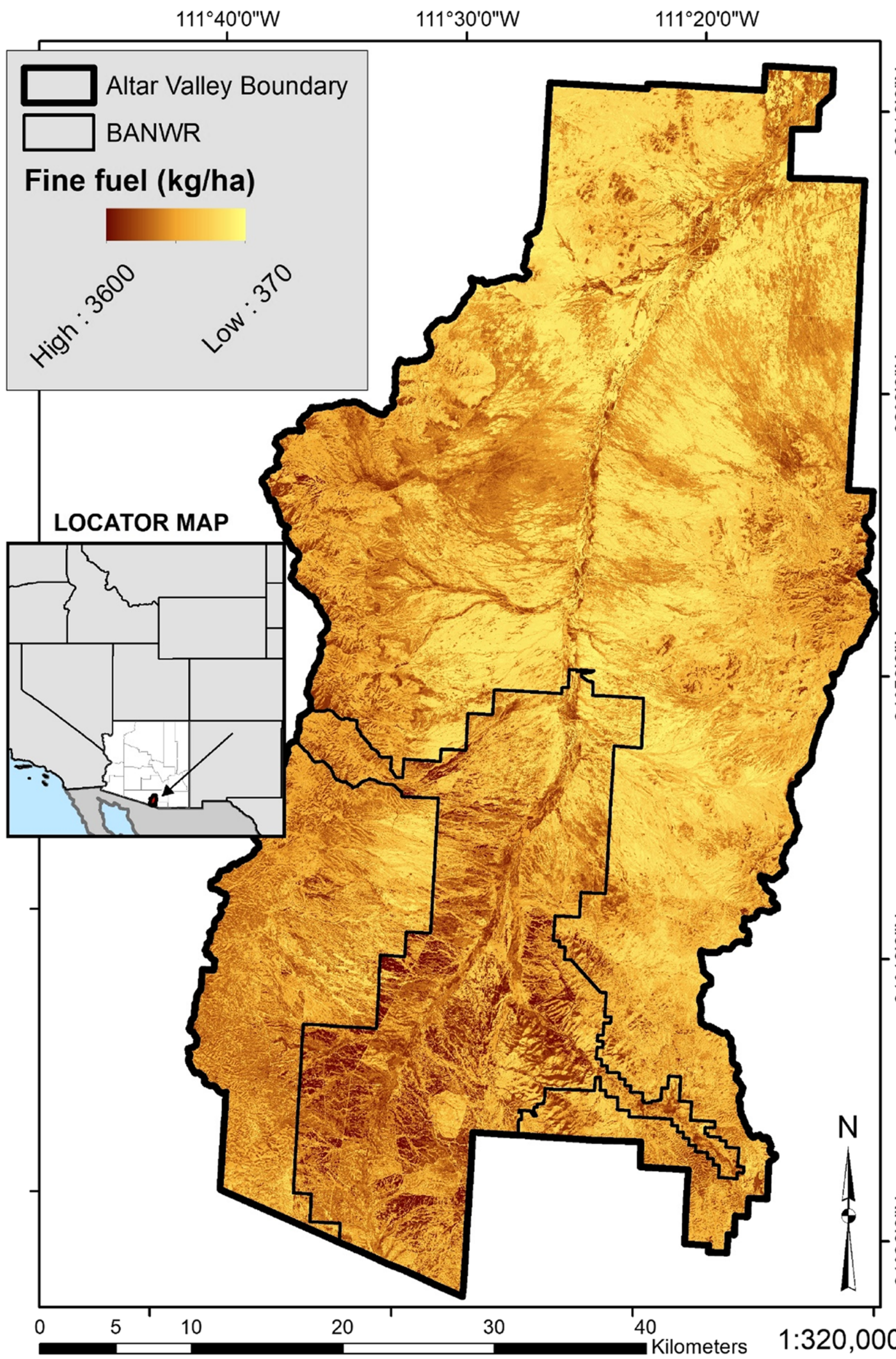

Fig. 4 Fine fuels (10-m resolution) across the Altar Valley, Arizona, USA, post-growing season of 2021and Buenos Aires National Wildlife Refuge (BANWR), based on Sentinel-2 remotely sensed imagery, field measurement and statistical estimation of fine fuel

on 1000 iterations of 20–80% of the pooled 241 sample frames (Supplemental Fig. S2), resulted in a distribution of R^2 values that ranged from 0.27 to 0.84, with a mean $R^2 = 0.63$. Final variables in the remotely sensed model of fine fuel included a mix of spectral bands and vegetation indices (Supplemental Table S1) derived from Sentinel 2 and were based on all 241 pooled sample frames. Spatial predictions of biomass (kg/ha) of fine fuel derived from the remote sensing-derived model ranged from 400 to 3600 kg/ha across the Altar Valley (Fig. 4), bounding the ranges of biomass previously reported by Cox et al. (1990) from the nearby Santa Rita Experimental Range in southern Arizona. In 2021, the mean amount of fine fuel across the whole Altar Valley was 1380 kg/ha, while just inside BANWR was 1672 kg/ha. Within BANWR, the 2021 mean amount of fine fuel exceeded estimates from 2014 and 2015 (Sesnie and Dickson 2018; Table 2a, 1363 kg/ha), as well as estimates from Wells et al. (2021) on BANWR in 2015 = 1347 kg/ha, 2016 = 1227, 2017 = 1460, 2018 = 1315, 2019 = 1504, and 2020 = 1575. The high amount of fuel in 2021 corresponded to near-record monsoon (summer) precipitation (July = 19.1 cm, August = 11.9 cm, September = 4.8 cm), which was 177% of the historical (1990–2020) mean (www.climateanalyzer.org, "Sasabe" ID # 27,619). This wet 2021 summer was preceded by a drier than average summer in 2020 (July = 4.5 cm, August = 4.0 cm, and September = 0.2 cm), which was 43% of the historical (1990–2020) mean.

Biophysical and land-use effects on fine fuel

Of the initial suite of 66 explanatory variables, we iteratively reduced the final model of biophysical and land-use effects to a set of 8 variables. Results from the ordinary least squares multivariate regression model (Supplemental Table S2; $R^2 = 0.24$, $F\,(8, 1682) = 67.69$, $p = < 0.2e-16$),) indicated that climatic, land-use, and biophysical factors (Fig. 6) explained variation in the amount of fine fuel with 6 of 8 variables significant at $p = 0.05$ (Supplemental Table S2). Land ownership by USFWS, representative of the BANWR boundary and relative absence of livestock grazing, had the highest variable importance on fine fuel, followed by annual vapor pressure deficit in 2021, soil organic carbon at 0–30 cm soil depth, maximum annual temperature in 2021 and elevation (Fig. 5). Bulk density, clay, and sand content at 0–30 cm soil depth were less important but retained in the final predictive model of biophysical and land-use effects.

We found a higher amount of fine fuel within the BANWR boundary (mean = 1672 kg/ha) compared to the rest of the Altar Valley (mean = 1274 kg/ha) ($F = 190.73$; $F\text{-}crit = 3.85$; $p < 0.00001$; $df = 1690$). Further univariate linear regression of biophysical factors indicated that fuels in the Altar Valley decreased with higher annual vapor pressure deficit (Fig. 6A), increased with higher soil organic carbon (Fig. 6B), clay content (Fig. 6C), elevation (Fig. 6D), and weakly decreased with increasing bulk density (Fig. 6E) and maximum annual temperature (Fig. 6E).

Fire exposure

Our index of potential exposure to wildfire (Fig. 7) indicated that the northern most area of the Altar Valley had low exposure due to the generally low estimates of fine fuel and proximity to multiple FMPs (Fig. 2A) within the greater Tucson WUI. Past ignitions, however, in the Tucson WUI highlight the clustering of ignitions (Fig. 2B) and the increased exposure to wildfire of areas associated with exurban development and roads in the northern part of the Altar Valley (Fig. 7). Within BANWR, in the southern Altar Valley, the central portion of the refuge shows

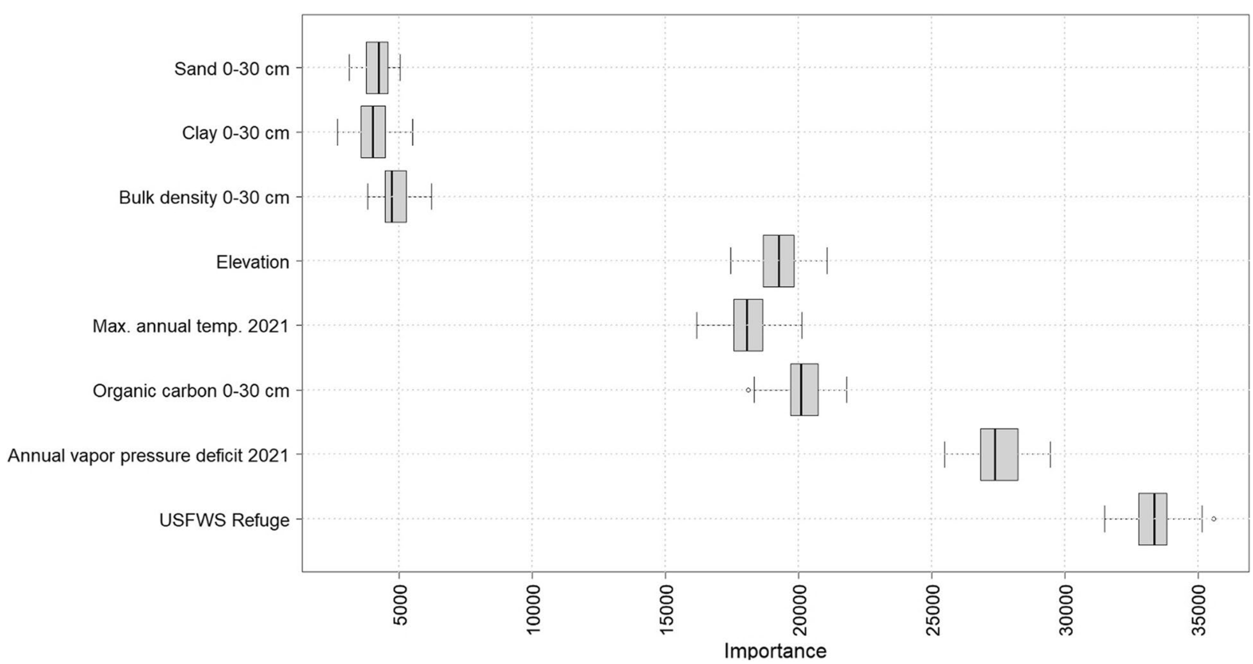

Fig. 5 Conditional variable importance of climatic, biophysical, and land-use factors influencing fine fuels in the Altar Valley, Arizona, USA, in 2021

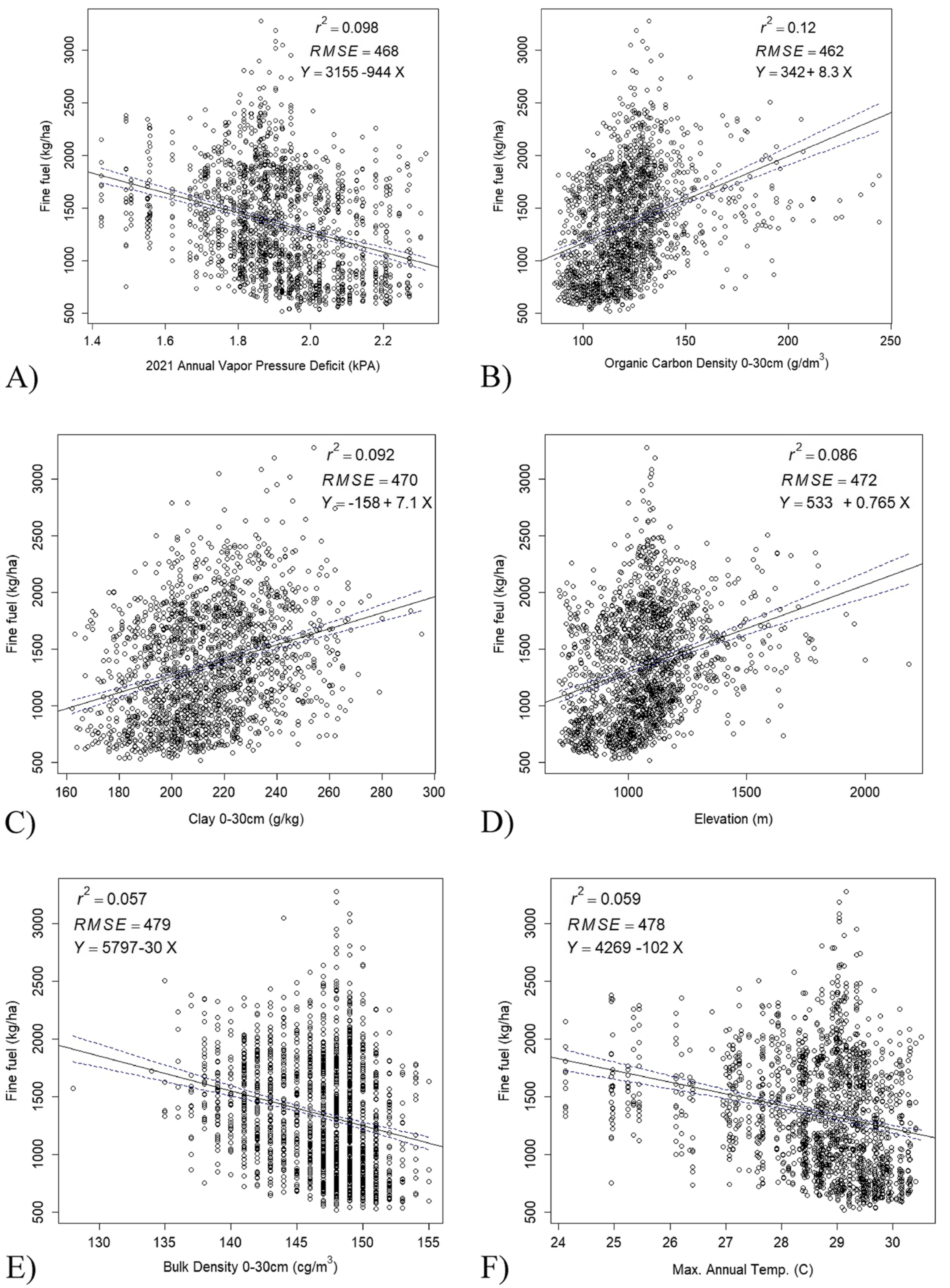

Fig. 6 **A**–**F** Relationships between individual climatic, biophysical, and land-use variables and the amount of fine fuel in the Altar Valley, Arizona, USA, in the 2021 growing season; variables included: **A** vapor pressure deficit, **B** soil organic carbon density, **C** soil clay content, **D** elevation, **E** soil bulk density, and **F** maximum annual temperature. All regressions have $P < 0.05$

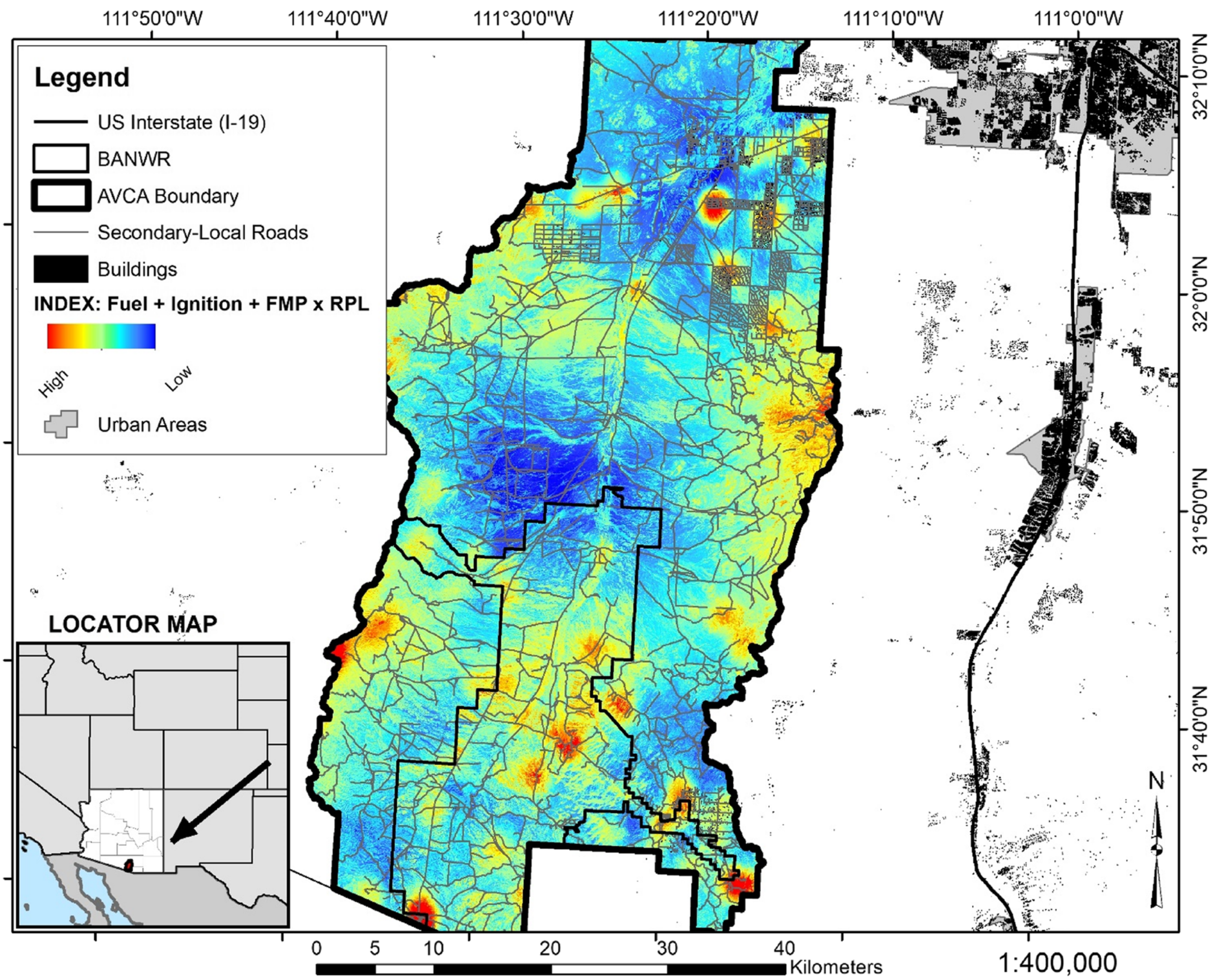

Fig. 7 Index of exposure to wildland fire across the Altar Valley, Arizona, USA, in 2021

high exposure to wildfire due to a long distance to FMP, high fine fuel, and a history of ignitions. The southern third of BANWR shows less exposure due to the proximity of the refuge fire department infrastructure, while the northern most reach of BANWR shows low exposure due to a decreasing amount of fine-fuel production as precipitation decreases from south to north on the refuge. The central portion of the greater Altar Valley shows the least exposure due to a combination of low fine fuel, proximity to FMPs, and few past ignitions. Heightened clusters of high exposure on the east and west edges of the valley are a result of increasing fuel at higher elevation, a steady history of ignitions, and generally long distances from FMPs. Likewise, the towns of Sasabe and Arivaca along the southern boundary of the Altar Valley show clustering of heightened exposure largely associated with previous fire ignitions. Areas in the most westerly region of the valley, with the high RPL or social vulnerability, (Fig. 2C), show elevated index of exposure to wildfire. Overall, we found a near significant difference in fine fuel among distance classes (0–25 km, 25–50 km, >50 km) to FMP ($F=2.81$; $F\text{-}crit=3.00$; $p=0.06$; $df=1690$), with a tendency for more fuel in the 0–25 km distance class. The distance to an FMP inside BANWR was significantly lower than outside the refuge ($F=41.15$; $F\text{-}crit=3.85$; $p=<0.0001$; $df=1690$).

At-risk natural resource values

When fine-fuel estimates were overlaid with a single core habitat polygon for masked bobwhite quail and an adjacent 250-m buffer zone in BANWR, several regions of high fuel and suitable habitat become evident (Fig. 8). However, the fuel is more contiguous to the north and south of the habitat buffer than inside the core habitat area. Across the entire refuge, the mean amount of fine fuel within the 9000 ha of all defined core habitat areas was 1651 kg/ha, which was significantly less than (t-stat$=12.46$; $df=40{,}733$, $p<0.001$) fine fuel within the

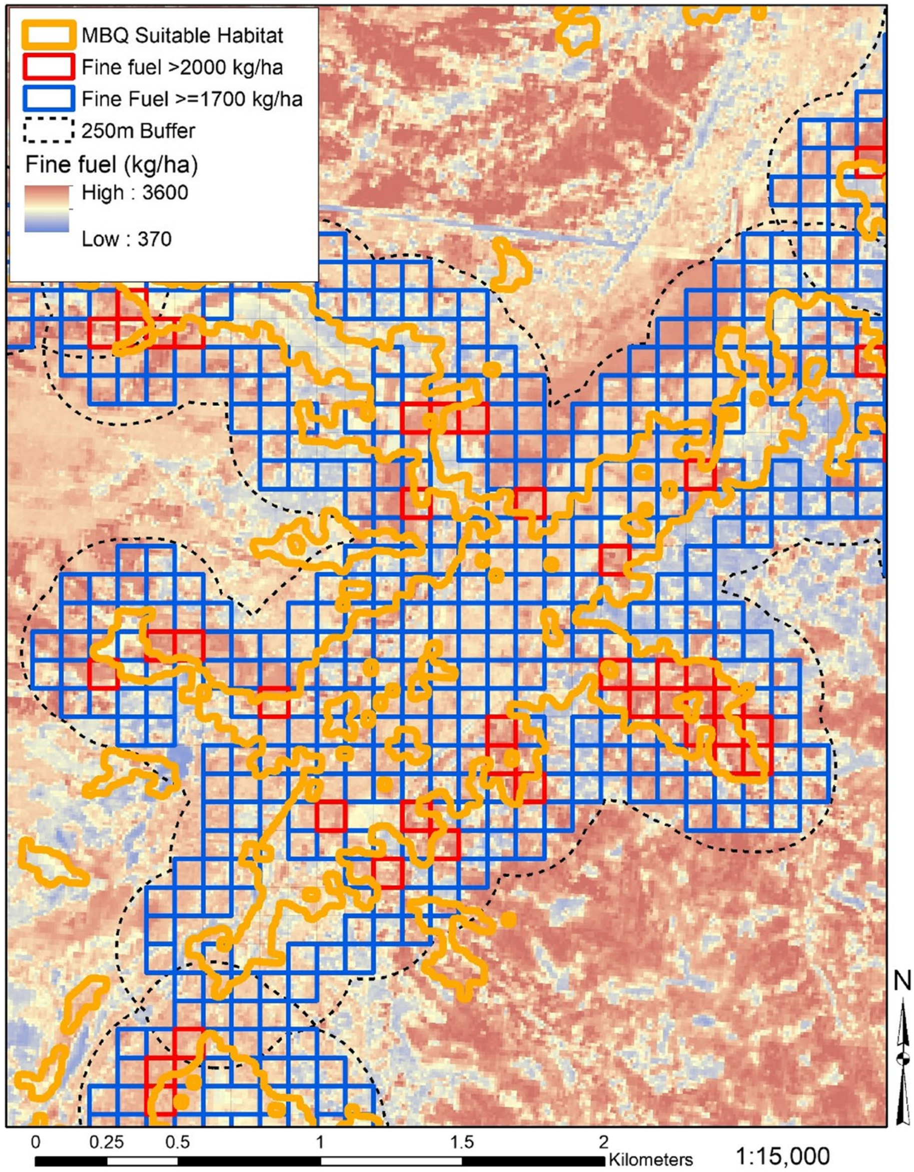

Fig. 8 Core habitat area of the federally endangered Masked Bobwhite Quail (MBQ), and a 250-m buffer zone, in relation to fine fuel (10 m) in 2021 shown with discrete grid patches of high > 1700 kg/ha and > 2000 kg/ha fuel for an area within the Buenos Aires National Wildlife Refuge, Arizona, USA. This example area shows the potential for devising a targeted fuel reduction plan to conserve key, high-value habitat components

5000 ha of 250-m habitat buffer of 1705 kg/ha and within the 31,000 ha of area outside of core habitat and the buffer zone of 1710 kg/ha.

Despite a lower mean amount of fuel in core habitat compared to buffer zones and the rest of the refuge, the amount of fine fuel within core habitat increased as habitat suitability increased ($y = 692.5x + 1355$; orange line in Fig. 9). Likewise, 250-m buffer zones surrounding core habitat areas show an increase in the amount biomass of fine fuel as habitat suitability increased ($y = 299.1x + 1597.2$; white line in Fig. 9), though this increase was not as high as within core habitat areas. Conversely, the 31,000 ha areas of BANWR outside of core habitat areas and buffer zones showed a slight decrease in the biomass of fine fuels as habitat suitability increased ($y = -689.7x + 1946.6$; yellow line in Fig. 9).

Discussion

We developed high-resolution estimates of fine fuel across multiple firesheds that span climatic, biophysical, and land-use gradients in the Altar Valley in southern Arizona to improve decision making in wildland fire

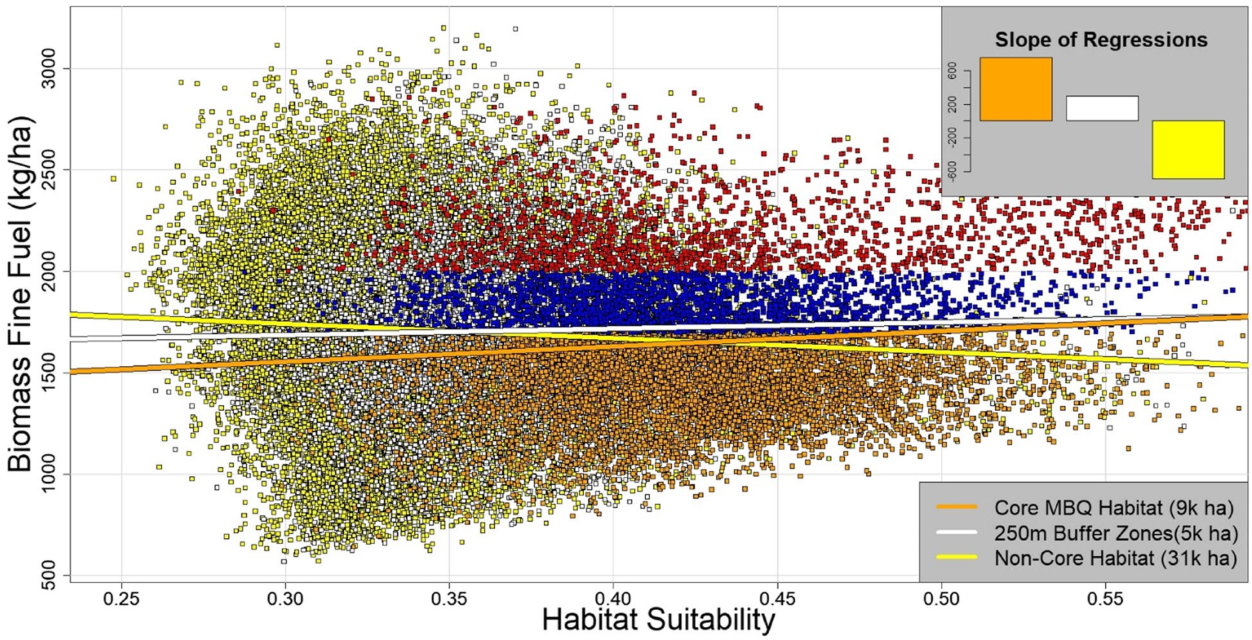

Fig. 9 Distribution of fine fuel (kg/ha) and habitat suitability for the masked bobwhite quail (MBQ), taken from 3 differing spatial extents: core habitat (orange; probability of zero slope < 0.0001), 250-m buffer zones surrounding core MBQ habitat (white; probability of zero slope < 0.03), and all other areas throughout the Buenos Aires National Wildlife Refuge (yellow; probability of zero slope < 0.0001). The comparison of slopes from regressions in the inset demonstrates increasing fine fuel with increasing habitat suitability in buffered and core habitat (fine fuel > 1700 kg/ha in blue; fine fuel > 2000 kg/ha in red; as shown in Fig. 8)

management. Fine fuel in the Altar Valley broadly represents the variation that exists across basin and range topography throughout the southwestern USA and its intersection with differing land jurisdictions and use including the wildland-urban interface south of Tucson, AZ. In 2021, fine fuel, composed primarily of herbaceous vegetation, was higher than in previous years in BANWR (Sesnie et al. 2018) and coincided with a high amount of summer monsoon precipitation, in stark contrast to near-record low monsoon precipitation in the previous 2020 growing season. Our explicit identification of fine-fuel amount, connectivity, and patterning provides a foundation for risk assessment and fire modeling that can vary substantially from year to year (Moloney et al. 2021). Wildland fire exposure indices enhanced fuel estimates to better assess fire risk to natural resource values that can help prioritize hazard mitigation activities.

Fine-fuel model

Our fine-fuel assessment, which combines field data, remote sensing, and algorithmic spatial modeling, provides a consistent, reliable, and flexible approach to map fine fuel in non-forest ecosystems on a regional scale, similar to recent models developed by D'Este et al. (2021) and Kearney et al. (2022). Our 1000-fold iteration of predicted versus observed quadrat biomass (Supplement Fig. 3) showed our quadrat model slightly over predicted biomass on the low end, but underpredicted at the high end of biomass. This underprediction suggests we provided a conservative estimate of fuel and that actual fuel amounts may be higher. Nonetheless, our results and those of previous studies (Sesnie et al. 2018; Wells et al. 2021) illustrate the utility of high-spatial resolution multitemporal and multispectral satellite imagery for assessing fine fuels in dryland ecosystems. Our validation of the remotely sensed model of fine fuels ($R^2 = 0.63$ with range of 0.27–0.85) had similar accuracy as Kearney et al. (2022; $R^2 = 0.75$–0.79) and Sesnie et al. (2018; 2015$R^2 = 0.65$–0.75), demonstrating the reliability and validity of our approach. Annual, field-based estimates of fine fuel can be updated with newer remotely sensed imagery for a reliable estimation of fine fuels, which represents an important step towards near real-time management of wildland fire (Elia et al.). Our approach was limited by a relatively small sample size, collected over a constrained time period, but can be modified and applied to the broader southwestern USA and beyond in grass-dominated ecosystems to meet fire management needs.

The relatively high contribution of annual plants and Lehmann lovegrass to the fuel load is consistent with previous studies in the region (Cable 1971; Van Devender 1997; Geiger 2006; McDonald and McPherson 2011; Sesnie et al. 2018), although 2021 was considerably wetter and more productive than average. Annuals have high inter-annual variability in production and can quickly respond to favorable precipitation, thereby increasing fire risk following wet years. Our field-based fuel composition estimates showed similarities to Sesnie et al. (2018), with a non-native grass accounting for a large amount of fuel. However, we found a larger contribution from annual plants than the previous study. Non-native lovegrasses contributing a higher amount of fuel than native perennial grasses are similar to findings by Cable (1971), McClaran (2003), and McDonald and McPherson (2011) at the nearby Santa Rita Experimental Range. Lehmann lovegrass was found throughout our study area and accounted for nearly as much cover as all other annual and perennial grasses combined. Together, our high estimates of fine fuel from Lehmann lovegrass and annuals in the Altar Valley suggests a faster fire return interval and elevated fire risk (Villarreal et al. 2016), as found when non-native species invade similar dryland ecosystems (Wilder et al. 2021). Lehmann lovegrass, introduced from South Africa, has high biomass on suitable sites and prolific seed production and increases continuity of fuel in semi-arid grasslands that historically supported sparse native plant cover (Anable et al. 1992). Van Devender (1997) indicated that Lehmann lovegrass can produce 2–4 times the annual biomass of native grasses. Although McDonald and McPherson (2011) experimentally showed that fire did not increase cover of Lehmann lovegrass 2–3 years after fire and surmised historic fire regimens bound the variability of fire intensity common to native plants, this supposition does not account for projected climate variability outside historical conditions.

Biophysical and land-use effects on fine fuel

We found a distinct high concentration of fine fuel within BANWR, although fuel was noticeably reduced in recently burned areas. Fine fuel generally increased as elevation increases along the outer perimeter of the valley into the lower foothills of adjacent mountain ranges. Throughout the entire Altar Valley, drainages clearly show high fine-fuel accumulations, especially within the centralized Brawley Rillito wash, with diminishing fuel amounts as it flows north into the more arid, low elevation reaches. Our fine-fuel assessment revealed elevated and connected fine-fuel loads near a developing WUI stemming from development in the greater Tucson area.

Climate, principally annual vapor pressure deficit, contributed to the variation of fine fuels throughout the Altar Valley. Vapor pressure deficit, as defined by the difference between water vapor pressure and saturation water vapor pressure, typically can identify a situation where water loss from a system limits plant productivity and, subsequently, fuels. In our study, as annual vapor pressure decreased, typically along the south to north increasing elevation gradient within the Altar Valley, we found a higher production of fine fuels. Vapor pressure deficit should be considered along with other traditional indicators of water loss when analyzing and modeling plant growth and fine fuel across semi-arid and arid grassland landscapes (Yuan et al. 2019; López et al. 2021). Similarly, increasing annual maximum temperature negatively influenced fuel amount, though the relationship was weak. Both vapor pressure deficit and annual maximum temperature are widely regarded as important factors for plant and biomass production (Hatfield and Prueger 2015). Vapor pressure deficit and maximum annual air temperatures can also contribute to lowering fuel moisture content in existing fine and coarse fuels and are expected to increase over time (Dannenberg et al. 2022), which will result in increased fire likelihoods and extreme fire behavior (Seager et al. 2015; Holden et al. 2018). The lack of precipitation driving variability in fine fuel countered our expectations as water input is generally assumed to be a primary driver of vegetation productivity and fine-fuel production. However, the above average precipitation received during the 2021 summer monsoon across the valley may have reduced the limitation of water input, and factors driving water output became more important in influencing primary production. Wet years that increase fine-fuel production, such as we observed in 2021, punctuate an expected continuation of drought-like conditions throughout the southwestern USA and are an important driver of increasing wildland fire occurrence.

Our results showed fine fuels were influenced, to a lesser degree, by the physical and chemical properties of soils, which have been previously shown to influence the spatial distribution of fires in the southwestern USA (Levi and Bestelmeyer 2016). Of the soil properties we investigated, increases in soil organic carbon explained the most variation in fine-fuel amount. Dryland ecosystems are typically limited in organic matter, which can constrain plant growth and fine-fuel production (Plaza et al. 2018). Soil organic carbon can markedly increase with encroachment of woody shrubs in dryland ecosystem (Throop et al. 2020) and can result in increases in fine fuels. An increase in clay content was weakly related to greater fine fuel, which is likely due to the high water-holding capacity of fine textured soils and the abundance of clay in low swales and depositional landforms, where plant production is typically high (Wondzell et al. 1996). Soil texture also has been shown to affect the growth of Lehmann lovegrass, which increases fuel load, though sandy soils typically provide more suitability for establishment and growth (Geiger 2006). Increased bulk density of the soil generally resulted in lower biomass of fine fuel, likely as result of low soil porosity and compaction that can reduce plant growth, or because of increases in runoff that decreased soil moisture input.

Exposure index

The high amount of fine fuel in 2021 represented an increase in wildfire hazard to the Altar Valley in 2022. This hazard was realized when the lighting caused Contreras Fire damaged human infrastructure and nearly destroyed the nearby Kitt Peak National Observatory (NIFC 2022). Our analysis showed that USFWS land ownership was related to a higher amount of fine fuel within BANWR relative to the rest of the study area. This is likely due to the absence of livestock grazing on the refuge over the last 30–40 years, unlike the rest of the Altar Valley, which is largely grazed. Together with a lack of grazing, invasion by non-native grasses have altered the composition of contemporary fine fuels and fire regimes within the refuge. Although mule deer (*Odocoileus hemionus*), white-tailed deer (*O. virginianus*), and pronghorn antelope (*Antilocapra americana*) occur on the refuge, they likely have a lower effect on reducing fine fuel than livestock, which have extensively lowered biomass throughout the region (McClaran and Van Devender 1995). The increasingly urbanized WUI adjacent to Tucson, AZ, which converts rangelands to developed and mixed use, may continue to alter fuel composition and amount.

Fuels, driven by the influence of climate, soils, and land use on vegetation, are only part of the equation of wildfire exposure. To expand on the potential exposure of the Altar Valley to wildfire, we incorporated ignition sources, which increase, and fire management points, which decrease fire exposure. This integration allowed us to identify hotspots of potential wildfire hazards, which in turn may be used to identify and prioritize areas for potential fuel treatment. The exposure index model shows some, but not all, of the interacting factors present in the Altar Valley. Generally, the higher densities of past ignitions in the valley were located along major travel corridors and growing developments and near rural community centers as expected in the WUI (Chas-Amil et al. 2015). Nearly half of the ignitions were of unknown cause (47%); however, ignitions with a known human cause (36%) were more than twice that of natural ignitions (17%). The heightened exposure in the more rugged mountains areas of the valley were likely due to elevated fuel load, greater instances of lighting, and a greater overall distance from any FMP. Fires in the mountainous regions of the study area are difficult to access and suppress, with the largest four wildfires recorded since 1985 occurring in the Baboquivari Mountains (AVCA 2022), yet likely had a less direct impact on human infrastructure. Building densities in the rural areas of the study area ranged from 0.006 to 0.20 structures/ha while the medium density WUI zones in the study area had a mean of 1.3 structures/ha. Catastrophic wildfire (Maranghides et al. 2021) in the WUI are extreme and costly events (Maranghides and Mell 2013) that require comprehensive analysis and planning for effective mitigation (Calkin et al. 2014). Hazardous fine-fuel development and connectivity due to invasive non-native grasses is expected to increase over time (Wilder et al. 2021) increasing the likelihood of wildfire occurrence. The effect of prescribed burning within BANWR showed that treatment effects to reduce fine fuels may only last 3–5 years depending upon climate and other conditions (Wells et al. 2021). Furthermore, other unaccounted for factors, such as humans crossing the USA-Mexico border by foot and vehicle, can influence the likelihood of wildfire in the study area. Our fire exposure index enhances fire mitigation and planning tools, comparable to other wildfire risk models such as Scott et al. (2020) and is based on readily available data sources in the Altar Valley. Strategic use of the index, such as identifying where high wildfire exposure and critical values overlap, can help allocate fuel treatments to key portions of the landscape to protect natural resource values and human infrastructure.

At-risk natural resource values

Habitat for the endangered masked bobwhite quail can be lost or degraded with increasing fire intensity resulting from areas of high fine-fuel concentration (Sesnie et al. 2022). Our study demonstrates how a fine-fuel assessment can be combined with a key value at risk, wildlife habitat, to prioritize management actions. The mean amount of fine-fuel load across the refuge were high enough (1697 kg/ha) to match experimental burning conditions demonstrated by McDonald and McPherson (2011), indicating potential for wildfire occurrence. Fine-fuel estimates across the largest masked bobwhite quail habitat patches were slightly lower but still high enough (1651 kg/ha) to carry fire. Many of the largest masked bobwhite quail habitat patches are areas aligned with drainages, which the refuge has historically tried to avoid burning. The middle of those drainages is often scoured resulting in low fuels; however, the higher fuels immediately adjacent to core habitat provide fuel connectivity for wildfire to threaten core habitat areas. Outside of buffered and core habitat areas, at the lower range of habitat suitability, trends in fine fuel showed a slight decrease in relation to increases in habitat suitability. However, this trend was offset, in relation to masked bobwhite quail population viability, by the increased fine fuels as suitability increased in core habitat areas and 250-m buffered zones. A plan to mitigate hazardous amounts of fine fuel within the 20% of the refuge that are composed of core habitat areas requires habitat and fine-fuel information at high resolution, as shown by our study. We chose a 1-ha minimum mapping unit (100 m × 100 m) as this unit area is management-relevant for planning treatments and prioritizing strategies to protect habitat. Based on our analysis, there is fine fuel within and around suitable habitat areas of the masked bobwhite quail at BANWR, which may pose a wildfire hazard. Limiting threat to core habitat and other natural resources at risk in relation to fine fuels will require balanced mitigation strategies and adaptive management based on updateable fine-fuel maps.

Conclusion

This study contributes to a growing body of knowledge seeking to encourage proactive and targeted fire and fuel management in fire-prone landscapes using estimates of wildfire exposure and risk. We quantified (400–3600 kg/ha), modeled (Fig. 4), and validated the spatial distribution of fine fuels across multiple land jurisdictions and firesheds in the Altar Valley, Arizona; a representative dryland ecosystem of the southwestern USA. We determined the biophysical and land-use factors contributing to the distribution of fine fuels and integrated the remotely sensed fine fuel model with ignition densities and fire suppression features to spatially assess exposure to wildfire (Fig. 7). We also show how the fine-fuel estimates can be used to assess natural resource values at risk, in this case habitat for the protected masked bobwhite quail. Our fine-fuel estimates can be incorporated into the fire operation and management plans for the Altar Valley, serially replicated, and spatially adapted to other dryland ecosystems where wildfire is driven by herbaceous biomass and fuel reduction efforts need to be prioritized. The temporal scalability of our remotely sensed model of fine fuel to annual time-steps allows for up-to-date adjustment of the exposure index, pliability to include additional risk factors, and serial analyses of fuel treatment effects. Integrated fire management, planning, and fuel monitoring frameworks such as those developed with this study can help target proactive responses to increased wildfire hazard and risk in dryland landscapes.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-023-00196-1.

Additional file 1: Supplemental Fig. S1. Plot design and layout used for field sampling in the Altar Valley, Arizona, USA, during September and October 2021 to estimate the biomass of fine fuels based on 0.5 m x 0.5 m quadrats and underlying remotely sensed pixel (10-m) data. **Supplemental Fig. S2.** Examples of different circular windows with 14-m diameters over laid on top of plot (large red square) and quadrat (small green squares) layout used for averaging field estimates of biomass (kg/ha) from the Altar Valley, Arizona, USA, post-growing season 2021. **Supplemental Fig. S3.** Linear relationships (solid black line) of predicted vs. observed biomass (g/0.25 m^2) of fine fuels in the Altar Valley of Arizona, USA, 2021. Relationships were based on field-based collection of herbaceous fine fuel and estimated using gradient boosted regression to predict quadrat biomass for subsequent analysis. **Supplemental Table S1.** Sentinel-2 remotely sensed predictor variables, show with their scaled, relative variable contributions to the random forest model used to predict fine fuels across the Altar Valley, Arizona, USA during fall 2021. Note abbreviations: Normalized Difference Vegetation Index (NDVI), Band (B), leaf-On (O), leaf-oFF (F), Soil Adjusted Vegetation Index (SAVI), Fraction of Vegetation Cover (FVC), Leaf-Area Index (LAI), Canopy Water Content (CWC), Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), Leaf Chlorophyll Content (LCC). **Supplemental Table S2.** Multivariate General linear model of biophysical factors selected by machine learning random forest showing combined variables effect of factors influencing the distribution of fine fuel in the Altar Valley, Arizona, USA during the Fall of 2021; significance codes: 0 = ***, 0.001 = **, 0.01 = *, . = 0.1.

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Authors' contributions

SM, SS, and MV conceived and developed support for the research project. KL collected field data for analysis. AW provided statistical and GIS analysis and compiled manuscript. SM also contributed significantly to manuscript refinement with intellectual and analytical support from SS, MV, and KL.

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Availability of data and materials

The data used and analyzed during this study are available from the corresponding author on reasonable request, and the 2021 Altar Valley fine-fuel model is publicly available through the USGS ScienceBase-Catalog (Wells et al. 2022; https://doi.org/10.5066/P9Q00PEY).

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests
The authors declare that they have no competing interests.

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References
Abatzoglou, J.T. 2013. Development of gridded surface meteorological data for ecological applications and modeling. *International Journal of Climatology* 33: 121–131. https://doi.org/10.1002/joc.3413.
Abatzoglou, J.T., and C.A. Kolden. 2011. Climate change in western US deserts: Potential for increased wildfire and invasive annual grasses. *Rangeland Ecology & Management* 64: 471–478. https://doi.org/10.2111/REM-D-09-00151.1.
Abatzoglou, J.T., and A.P. Williams. 2016. Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Science* 113: 11770–11775. https://doi.org/10.1073/pnas.1607171113.
Ager, A.A., M.A. Day, C. Ringo, C.R. Evers, F.J. Alcasena, R.M. Houtman, M. Scanlon, and T. Ellersick. 2021. *Development and application of the fireshed registry. Gen. Tech. Rep. RMRS-GTR-425, 47*. Fort Collins: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. https://doi.org/10.2737/RMRS-GTR-425.
Anable, M.E., M.P. McClaran, and G.B. Ruyle. 1992. Spread of introduced Lehmann lovegrass Eragrostis lehmanniana Nees. In southern Arizona, USA. *Biological Conservation* 61: 181–188. https://doi.org/10.1016/0006-3207(92)91114-8.
Archibald, A., J.L. Gomez-Dans, and R.A. Bradstock. 2013. Defining pyromes and global syndromes of fire regimes. *Proceedings of the National Academy of Science* 110: 6442–6447. https://doi.org/10.1073/pnas.1211466110.
Atkinson, D., M. Chladil, V. Janssen, and L. Arko. 2010. Implementation of quantitative bushfire risk analysis in a GIS environment. *International Journal of Wildland Fire* 19: 649–658. https://doi.org/10.1071/WF08185.
AVCA (Altar Valley Conservation Alliance). 2022. https://altarvalleyconservation.org.
Balch, J.K., B.A. Bradley, C.M. D'Antonio, and J. Gómez-Dans. 2013. Introduced annual grass increases regional fire activity across the arid western USA (1980–2009). *Global Change Biology* 19: 173–183. https://doi.org/10.1111/gcb.12046.
BLM (Bureau of Land Management). 2022. *Arizona surface management*. https://www.blm.gov/sites/default/files/docs/2022-05/BLM_AZ_SurfaceManagement_8x11_20220510_508_Optimized.pdf. Accessed 1 July 2022.
Breiman, L. 2001a. Statistical modeling: The two cultures. *Statistical Science* 16: 199–231. https://doi.org/10.1214/ss/1009213726.
Breiman, L. 2001b. Random forest. In *Machine learning*, ed. Robert E. Schapire, 5–32. the Netherlands: Kluwer Academic Publishers.
Brooks, M.L., and J.R. Matchett. 2006. Spatial and temporal patterns of wildfires in the Mojave Desert, 1980–2004. *Journal of Arid Environments* 67: 148–164. https://doi.org/10.1016/j.jaridenv.2006.09.027.
Brooks, M.L., C.M. D'Antonio, D.M. Richardson, J.B. Grace, J.E. Keeley, J.M. DiTomaso, R.J. Hobbs, M. Pellant, and D. Pyke. 2004. Effects of invasive alien plants on fire regimes. *BioScience* 54: 677–688. https://doi.org/10.1641/0006-3568(2004)054[0677:EOIAPO]2.0.CO;2.
Brown, D.E., and K.B. Clark. 2017. The saga of the masked bobwhite: Lessons learned and unlearned. *National Quail Symposium Proceedings* 8: 102. https://trace.tennessee.edu/nqsp/vol8/iss1/102.
Cable, D.R. 1971. Lehmann lovegrass on the Santa Rita Experimental Range, 1937–1968. *Journal of Range Management* 24: 17–21. https://doi.org/10.2307/3896058.
Calkin, D.E., J.D. Cohen, M.A. Finney, and M.P. Thompson. 2014. How risk management can prevent future wildfire disasters in the wildland-urban interface. *Proceedings National Academy Sciences* 111: 746–751. https://doi.org/10.1073/pnas.1315088111.
CDC/ATSDR (Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry). 2022. *Geospatial research, analysis, and services program. Social vulnerability index 2018*. Database Arizona. https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html. Accessed 20 Apr 2022**.**
Chas-Amil, M.L., J.P. Prestemon, C.J. McClean, and J. Touza. 2015. Human-ignited wildfire patterns and responses to policy shifts. *Applied Geography* 56: 164–176. https://doi.org/10.1016/j.apgeog.2014.11.025.
Chuvieco, E., I. Aguado, S. Jurdao, M.L. Pettinari, M. Yebra, J. Salas, S. Hantson, et al. 2012. Integrating geospatial information into fire risk assessment. *International Journal of Wildland Fire* 23: 606–619. https://doi.org/10.1071/WF12052.
Clevers, J.G.P.W., L. Kooistra, and M.E. Schaepman. 2010. Estimating canopy water content using hyperspectral remote sensing data. *International Journal of Applied Earth Observation and Geoinformation* 12: 119–125. https://doi.org/10.1016/j.jag.2010.01.007.
Cox, J.R., G.B. Ruyle, and B.A. Roundy. 1990. Lehmann lovegrass in southeastern Arizona: Biomass productions and disappearance. *Journal of Range Management* 43: 367–372.
D'Este, M., M. Elia, V. Giannico, G. Spano, R. Lafortezza, and G. Sanesi. 2021. Machine learning techniques for fine dead fuel load estimation using multi-source remote sensing data. *Remote Sensing* 13: 1658. https://doi.org/10.3390/rs13091658.
Dannenberg, M.P., D. Yan, M.L. Barnes, W.K. Smith, M.R. Johnston, R.L. Scott, J.A. Biederman, et al. 2022. Exceptional heat and atmospheric dryness amplified losses of primary production during the 2020 U.S. Southwest hot drought. *Global Change Biology* 28: 4794–4806. https://doi.org/10.1111/gcb.16214.
Davies, I.P., R.D. Haugo, J.C. Robertson, and P.S. Levin. 2018. The unequal vulnerability of communities of color to wildfire. *PLoS One* 13: e0205825. https://doi.org/10.1371/journal.pone.0205825.
Driscoll, D., D. Lindenmayer, A. Bennett, M. Bode, R.A. Bradstock, G. Cary, M.F. Clarke, et al. 2010. Resolving conflicts in fire management using decision theory: Asset-protection versus biodiversity conservation. *Conservation Letters* 3: 215–223. https://doi.org/10.1111/j.1755-263X.2010.00115.x.
Drusch, M., U. Del Bello, S. Carlier, O. Colin, V. Fernandez, F. Gascon, B. Hoersch, C. Isola, P. Laberinti, P. Martimort, et al. 2012. Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment* 120: 25–36. https://doi.org/10.1016/j.rse.2011.11.026.
Elia, M., R. Lafortezza, R. Lovreglio, and G. Sanesi. 2015. Developing custom fire behavior fuel models for Mediterranean wildland–urban interfaces in southern Italy. *Environmental Management* 56: 754–764. https://doi.org/10.1007/s00267-015-0531-z.
Engel-Wilson, R.W., and W.P. Kuvlesky Jr. 2002. Arizona quail: Species in jeopardy. In *Quail V: Proceedings of the fifth national quail symposium*, ed. S.J. DeMaso, W.P. Kuvlesky Jr., F. Hernández, and M.E. Berger, 1–7. Austin: Texas Parks and Wildlife Department.
Fairbrother, A., and J.G. Turnley. 2005. Predicting risks of uncharacteristic wildfires: Application of the risk assessment process. *Forest Ecology and Management* 211: 28–35. https://doi.org/10.1016/j.foreco.2005.01.026.
Flanagan, B.E., E.W. Gregory, E.J. Hallisey, J.L. Heitgerd, and B. Lewis. 2011. A social vulnerability index for disaster management. *Journal of Homeland Security and Emergency Management* 8: 0000102202154773551792. https://doi.org/10.2202/1547-7355.1792.
Fovell, R.G., M.J. Brewer, and R.J. Garmong. 2022. The December 2021 Marshall Fire: Predictability and gust forecasts from operational models. *Atmosphere* 13: 765. https://doi.org/10.3390/atmos13050765.
Geiger, E. 2006. *The role of fire and a nonnative grass as disturbances in a semi-desert grassland*. Ph.D. dissertation. University of Arizona. http://hdl.handle.net/10150/195861.
Gianelle, D., L. Vescovo, and F. Mason. 2009. Estimation of grassland biophysical parameters using hyperspectral reflectance for fire risk map prediction. *International Journal of Wildland Fire* 18: 815–824. https://doi.org/10.1071/WF08005.
Gitelson, A.A., Y. Gritz, and M.N. Merzlyak. 2003. Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves.

Journal of Plant Physiology 160: 271–282. https://doi.org/10.1078/0176-1617-00887.
Han, A., S. Qing, Y. Ba, L. Na, Y. Bao, X. Liu, J. Zhang, and C. Wang. 2021. Short-term effects of fire severity on vegetation based on Sentinel-2 satellite data. *Sustainability* 13: 432. https://doi.org/10.3390/su13010432.
Harvey, B.J. 2016. Human-caused climate change is now a key driver of forest fire activity in the western United States. *Proceedings of the National Academy of Sciences* 113: 11649–11650. https://doi.org/10.1073/pnas.1612926113.
Hatfield, J.L., and J.H. Prueger. 2015. Temperature extremes: Effect on plant growth and development. *Weather and Climate Extremes* 10: 4–10. https://doi.org/10.1016/j.wace.2015.08.001.
Holden, Z.A., A. Swanson, C.H. Luce, W.M. Jolly, M. Maneta, J.W. Oyler, D.A. Warren, R. Parsons, and D. Affleck. 2018. Decreasing fire season precipitation increased recent western US forest wildfire activity. *Proceedings of the National Academy of Sciences* 115: E8349–E8357. https://doi.org/10.1073/pnas.1802316115.
Jain, P., S.C.P. Coogan, S.G. Subramanian, M. Crowley, S. Taylor, and M.D. Flannigan. 2020. A review of machine learning applications in wildfire science and management. *Environmental Reviews* 28: 478–505. https://doi.org/10.1139/ER-2020-0019/ASSET/IMAGES/ER-2020-0019TAB3.GIF.
Kamenova, I., and P. Dimitrov. 2021. Evaluation of Sentinel-2 vegetation indices for prediction of LAI, fAPAR and fCover of winter wheat in Bulgaria. *European Journal of Remote Sensing* 54: 89–108. https://doi.org/10.1080/22797254.2020.1839359.
Kearney, S.P., L.M. Porensky, D.J. Augustine, R. Gaffney, and J.D. Derner. 2022. Monitoring standing herbaceous biomass and thresholds in semiarid rangelands from harmonized Landsat 8 and Sentinel-2 imagery to support within-season adaptive management. *Remote Sensing of Environment* 271: 112907. https://doi.org/10.1016/j.rse.2022.112907.
Klemmedson, J.O. 1989. Soil organic matter in arid and semiarid ecosystems: Sources, accumulation, and distribution. *Arid Soil Research and Rehabilitation* 3: 99–114. https://doi.org/10.1080/15324988909381194.
Kross, A., H. McNairn, D. Lapen, M. Sunohara, and C. Champagne. 2015. Assessment of RapidEye vegetation indices for estimation of leaf area index and biomass in corn and soybean crops. *International Journal of Applied Earth Observation and Geoinformation* 34: 235–248. https://doi.org/10.1016/j.jag.2014.08.002.
Kuhn, M. 2008. Building predictive models in R using the caret package. *Journal of Statistical Software* 28: 1–26. https://doi.org/10.18637/jss.v028.i05.
Kuvlesky, W.P., Jr., S.A. Gall, S.J. Dobrott, S. Tolley, F.S. Guthery, S.A. DeStefano, and N. King. 2000. The status of masked bobwhite recovery in the United States and Mexico. *National Quail Symposium Proceedings* 4: 8.
Kuvlesky, W.P., Jr., T.E. Fulbright, and R. Engel-Wilson. 2002. The impact of invasive exotic grasses on quail in the southwestern United States. *National Quail Symposium Proceedings* 5: 22.
Kuvlesky, W.P., Jr., L.A. Brennan, T.E. Fulbright, F. Hernandez, S.J. DeMaso, J.P. Sands, R.M. Perez, and J.B. Hardin. 2012. Impacts of invasive, exotic grasses on quail of southwestern rangelands: A decade of progress? *National Quail Symposium Proceedings* 7: 55.
Levi, M.R., and B.T. Bestelmeyer. 2016. Biophysical influences on the spatial distribution of fire in the desert grassland region of the southwestern USA. *Landscape Ecology* 31: 2079–2095. https://doi.org/10.1007/s10980-016-0383-9.
Livingston, A.C., and J.M. Varner. 2016. Fuel moisture differences in a mixed native and non-native Grassland: Implications for fire regimes. *Fire Ecology* 12: 73–87. https://doi.org/10.4996/fireecology.1201073.
López, J., D.A. Way, and W. Sadok. 2021. Systemic effects of rising atmospheric vapor pressure deficit on plant physiology and productivity. *Global Change Biology* 27: 1704–1720. https://doi.org/10.1111/gcb.15548.
Lowry, J.H., Jr., R.D. Ramsey, K. Boykin, D. Bradford, P. Comer, S. Falzarano, W.J. Kepner, et al. 2005. *Southwest Regional Gap Analysis Project: Final report on land cover mapping methods*. Logan: RS/GIS Laboratory, Utah State University. https://swregap.org/.
Main-Knorn, M., B. Pflug, J. Louis, V. Debaecker, U. Müller-Wilm, and F. Gascon. 2018. Sen2Cor for Sentinel-2. *Conference proceeding: Image and signal processing for remote sensing.* Available online: http://step.esa.int/main/third-party-plugins-2/sen2cor/. (Accessed 11 Aug 2021. http://step.esa.int/main/snap-supported-plugins/sen2cor/).
Maranghides, A., and W. Mell. 2013. *Framework for addressing the national wildland urban interface fire problem- determining fire and ember exposure zones using a WUI hazard scale. National Institute of Standards and Technology Technical Note 1748*. U.S. Department of Commerce.
Maranghides, A., E. Link, W. Mell, S. Hawks, M. Wilson, W. Brewer, C. Brown, B. Vihnaneck, and W.D. Walton. 2021. *A case study of the Camp Fire- Fire progression timeline. National Institute of Standards and Technology Technical Note 2135*. U.S. Department of Commerce. https://doi.org/10.6028/NIST.TN.2135.
McClaran, M.P., and T.R. Ven Devender. 1995. *The desert grassland*. Tucson: University of Arizona Press.
McClaran, M.P. 2003. A century of vegetation change on the Santa Rita Experimental Range. In *Santa Rita Experimental Range: 100 years (1903 to 2003) of accomplishments and contributions; conference proceedings; 2003 October 30-November 1; Tucson, AZ*, ed. Mitchel P. McClaran, Peter F. Ffolliott, Carleton B. Edminster, tech. cords., 16–33. Proc. RMRS-P-30. Ogden: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.
McDonald, C.J., and G.R. McPherson. 2011. Absence of a grass/fire cycle in a semiarid grassland: Response to prescribed fire and grazing. *Rangeland Ecology and Management* 64: 384–393. https://doi.org/10.2111/REM-D-10-00036.1.
McDonald, C.J., and G.R. McPherson. 2013. Creating hotter fires in the Sonoran desert: Buffelgrass produces copious fuels and high fire temperatures. *Fire Ecology* 9: 26–39. https://doi.org/10.4996/fireecology.0902026.
Miller, C., and A.A. Ager. 2013. A review of recent advances in risk analysis for wildfire management. *International Journal of Wildland Fire* 22: 1–14. https://doi.org/10.1071/WF11114.
Moloney, K.A., A. Fuentes-Ramirez, and C. Holzapfel. 2021. Climate impacts on fire risk in desert shrublands: A modeling study. *Frontiers in Ecology and Evolution* 9: 601877. https://doi.org/10.3389/fevo.2021.601877.
Mueller, S.E., A.E. Thode, E.Q. Margolis, L.L. Yocom, J.D. Young, and J.M. Iniguez. 2020. Climate relationships with increasing wildfire in the southwestern US from 1984 to 2015. *Forest Ecology and Management* 460: 117861. https://doi.org/10.1016/j.foreco.2019.117861.
NASA (National Aeronautics and Space Administration). 2022. *Shuttle radar topography mission*. https://www2.jpl.nasa.gov/srtm. Accessed 1 July 2022.
NIFC (National Interagency Fire Center). 2022. https://www.nifc.gov/fire-information/maps. Boise, ID.
Noy-Meir, I. 1973. Desert ecosystems: Environments and producers. *Annual Review of Ecology and Systematics* 4: 25–51. https://doi.org/10.1146/annurev.es.04.110173.000325.
Plaza, C., G. Gascó, A.M. Méndez, C. Zaccone, and F.T. Maestre. 2018. Chapter 2 – Soil organic matter in dryland ecosystems. In *The Future of Soil Carbon*, ed. Carlos Garcia, Paolo Nannipieri, Teresa Hernandez, 39–70. Academic. https://doi.org/10.1016/B978-0-12-811687-6.00002-X.
Poggio, L., L.M. de Sousa, N.H. Batjes, G.B.M. Heuvelink, B. Kempen, E. Ribeiro, and D. Rossiter. 2021. SoilGrids 2.0: Producing soil information for the globe with quantified spatial uncertainty. *The Soil* 7: 217–240. https://doi.org/10.5194/soil-7-217-2021.
R Core Team. 2022. *R: A language and environment for statistical computing*. Vienna: R Foundation for Statistical Computing. https://www.R-project.org/.
Radeloff, V.C., D.P. Helmers, H.A. Kramer, M.H. Mockrin, P.M. Alexandre, A. Bar-Massada, V. Butsic, T.J. Hawbaker, S. Martinuzzi, A.D. Syphard, and S.I. Stewart. 2018. Rapid growth of the US wildland-urban interface raises wildfire risk. *PNASS* 115: 3314–3319. https://doi.org/10.1073/pnas.1718850115.
Rigge, M., C. Homer, H. Shi, D. Meyer, B. Bunde, B. Granneman, K. Postma, P. Danielson, A. Case, and G. Xian. 2021. Rangeland fractional components across the western United States from 1985 to 2018. *Remote Sensing* 13: 813. https://doi.org/10.3390/rs13040813.
Sayre, N.F. 2002. *Ranching, endangered species, and urbanization in the Southwest: Species of capital*. Tucson: University of Arizona Press.
Scott, J.H., J.W. Gilbertson-Day, C. Moran, G.K. Dillon, K.C. Short, and K.C. Vogler. 2020. *Wildfire risk to communities: Spatial datasets of landscape-wide wildfire risk components for the United States*. Fort Collins: Forest Service Research Data Archive. https://doi.org/10.2737/RDS-2020-0016. Updated 25 November 2020.
Seager, R., and G.A. Vechhi. 2010. Greenhouse warming and the 21st century hydroclimate of southwest North America. *Proceedings of the National*

Academy of Sciences 107: 2127721282. https://doi.org/10.1073/pnas.0910856107.

Seager, R., A. Hooks, A.P. Williams, B. Cook, J. Nakamura, and N. Henderson. 2015. Climatology, variability, and trends in the U.S. vapor pressure deficit, an important fire-related meteorological quantity. *Journal of Applied Meteorology and Climatology* 54: 1121–1141. https://doi.org/10.1175/JAMC-D-14-0321.1.

Senna, M.C.A., M.H. Costa, and Y.E. Shimabukuro. 2005. Fraction of photosynthetically active radiation absorbed by Amazon tropical forest: A comparison of field measurements, modeling, and remote sensing. *Journal of Geophysical Research* 110: G01008. https://doi.org/10.1029/2004JG000005.

Sesnie, S., H. Eagleston, L. Johnson, and E. Yurcich. 2018. In-situ and remote sensing platforms for mapping fine-fuels and fuel-types in Sonoran semi-desert grasslands. *Remote Sensing* 10: 1358. https://doi.org/10.3390/rs10091358.

Sesnie, S.E., L. Johnson, E. Yurcich, T.D. Sisk, J. Goodwin, and R. Chester. 2022. Multisensor models for assessing recurrent fire compatibility with habitat recovery for a critically endangered species. *Remote Sensing of Environment* 269: 112824. https://doi.org/10.1016/j.rse.2021.112824.

Sesnie, S. and B.G. Dickson. 2018. Final report. In *Determining prescribed fire and fuel treatment compatibility with semi-desert grassland habitat rehabilitation for the critically endangered Masked Bobwhite Quail (Colinus Virginianus Ridgwayi)*. JFSP Project ID 13-1-06-16. Boise: Joint Fire Science Program.

Short, K.C. 2021. *Spatial wildfire occurrence data for the United States, 1992–2018 [FPA_FOD_20210617]*, 5th ed. Fort Collins: Forest Service Research Data Archive. https://doi.org/10.2737/RDS-2013-0009.5.

Simms, K.M. 1989. *Home range, habitat use and movements of reintroduced masked bobwhite.* Master's thesis, University of Arizona. http://hdl.handle.net/10150/277014.

Singleton, M.P., A.E. Thode, A.J.S. Meador, and J.M. Iniguez. 2019. Increasing trends in high-severity fire in the southwestern USA from 1984 to 2015. *Forest Ecology and Management* 433: 709–719. https://doi.org/10.1016/j.foreco.2018.11.039.

Squire, D.T., D. Richardson, J.S. Risbey, A.S. Black, V. Kitsios, R.J. Matear, D. Monselesan, T.S. Moore, and C.R. Tozer. 2021. Likelihood of unprecedented drought and fire weather during Australia's 2019 megafires. *npj Climate Atmospheric Science* 4: 64. https://doi.org/10.1038/s41612-021-00220-8.

Strobl, C., A.-L. Boulesteix, T. Kneib, T. Augustine, and A. Zeileis. 2008. Conditional variable importance for random forests. *BMC Bioinformatics* 9: 307. https://doi.org/10.1186/1471-2105-9-307.

Syphard, A.D., V. Butsic, A. Bar-Massada, J.E. Keeley, J.A. Tracey, and R.N. Fisher. 2016. Setting priorities for private land conservation in fire-prone landscapes: Are fire risk reduction and biodiversity conservation competing or compatible objectives? *Ecology and Society* 21: 2. https://doi.org/10.5751/ES-08410-210302.

Throop, H.L., S.R. Archer, and M.P. McClaran. 2020. Soil organic carbon in drylands: Shrub encroachment and vegetation management effects dwarf those of livestock grazing. *Ecological Applications* 30: e02150. https://doi.org/10.1002/eap.2150.

UNISDR. 2018. *UNISDR Annual Report 2017*. Geneva: United Nations Office for Disaster Risk Reduction.

USCB. 2019. https://www.census.gov/library/stories/2019/02/fast-growth-in-desert-southwest-continues.html.

USDA. 2008. *Brawley Wash - Los Robles Wash Watershed, (Altar Wash - Brawley Wash Watershed), Arizona, Rapid Watershed Assessment*. USDA Natural Resource Conservation Service, Arizona and University of Arizona Water Resources Research Center.

Van Devender, T.R. 1997. Exotic plants in the Sonoran Desert Region, Arizona and Sonora. In *California Exotic Pest Plant Council, 1997 Symposium Proceedings*.

Villarreal, M.L., L.M. Norman, S. Buckley, C.S. Wallace, and M.A. Coe. 2016. Multi-index time series monitoring of drought and fire effects on desert grasslands. *Remote Sensing of Environment* 183: 186–197. https://doi.org/10.1016/j.rse.2016.05.026.

Villarreal, M.L., S.L. Haire, J.M. Iniguez, C.C. Montaño, and T.B. Poitras. 2019. Distant neighbors: Recent wildfire patterns of the Madrean Sky Islands of southwestern United States and northwestern Mexico. *Fire Ecology* 15: 2. https://doi.org/10.1186/s42408-018-0012-x.

Villarreal, M.L., J.M. Iniguez, A.D. Flesch, J.S. Sanderlin, M.C. Cortés, C.R. Conrad, and S.L. Haire. 2020. Contemporary fire regimes provide a critical perspective on restoration needs in the Mexico-United States Borderlands. *Air Soil Water Research* 13: 1–18. https://doi.org/10.1177/1178622120969191.

Villarreal, M.L., L.M. Norman, E.H. Yao, and C.R. Conrad. 2022. Wildfire probability models calibrated using past human and lightning ignition patterns can inform mitigation of post-fire hydrologic hazards. *Geomatics, Natural Hazards and Risk* 13: 568–590. https://doi.org/10.1080/19475705.2022.2039787.

Warshall, P. 1995. The Madrean Sky Island Archipelago: A planetary overview. In *Biodiversity and management of the Madrean Archipelago: The Sky Islands of Southwestern United States and Northwestern Mexico*. *General technical report RM-GTR-264*. 1994 Sept. 19–23; Tucson, Arizona. Fort Collins: U.S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station.

Wells, A.G., S.M. Munson, S.E. Sesnie, and M.L. Villarreal. 2021. Remotely sensed fine-fuel changes from wildfire and prescribed fire in a semi-arid grassland. *Fire* 4: 84. https://doi.org/10.3390/fire4040084.

Wells, A.G., Munson, S.M., Villarreal, M.L., Sesnie, S.E. & Laushman, K.M. 2022. Predicted biomass of fine fuel for Altar Valley, Arizona, 2021., *U.S. Geological Survey data release*, https://doi.org/10.5066/P9Q00PEY.

Westerling, A.L., H.G. Hidalgo, D.R. Cayan, and T.W. Swetnam. 2006. Warming and earlier spring increase western US forest wildfire activity. *Science* 313: 940–943. https://doi.org/10.1126/science.1128834.

Wilder, B.T., C.S. Jarnevich, E. Baldwin, J.S. Black, K.A. Franklin, P. Grissom, K.A. Hovanes, et al. 2021. Grassification and fast-evolving fire connectivity and risk in the Sonoran desert, United States. *Frontiers in Ecology and Evolution* 9: 655561. https://doi.org/10.3389/fevo.2021.655561.

Wondzell, S.M., G.L. Cunningham, and D. Bachelet. 1996. Relationships between landforms, geomorphic processes, and plant communities on a watershed in the northern Chihuahuan Desert. *Landscape Ecology* 11: 351–362. https://doi.org/10.1007/BF02447522.

Xie, Q., J. Dash, A. Huete, A. Jiang, G. Yin, Y. Ding, D. Peng, et al. 2019. Retrieval of crop biophysical parameters from Sentinel-2 remote sensing imagery. *International Journal of Applied Earth Observation and Geoinformation* 80: 187–195. https://doi.org/10.1016/j.jag.2019.04.019.

Yuan, W., Y. Zheng, S. Piao, P. Ciais, D. Lombardozzi, Y. Wang, Y. Ryu, et al. 2019. Increased atmospheric vapor pressure deficit reduces global vegetation growth. *Science Advances* 5: eaax1396. https://doi.org/10.1126/sciadv.aax1396.

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