FINAL REPORT

Low-cost UAS platforms to quantify and predict post-fire recovery in arid shrublands

JFSP PROJECT ID: 21-1-01-43

December 2022

Andrii Zaiats
Boise State University

Trevor Caughlin
Boise State University

FIRESCIENCE.GOV
Research Supporting Sound Decisions

Table of Contents

List of Tables ………………………………………………………………………………. ii
List of Figures ……………………………………………………………………………… ii
Keywords ……………………………………………………………………………………ii
Acknowledgements ………………………………………………………………………… ii
Abstract ……………………………………………………………………………………… 1
Objectives …………………………………………………………………………………… 2
Background ………………………………………………………………………………….. 3
Materials and Methods ……………………………………………………………………… 4
Results and Discussion ……………………………………………………………………… 8
Conclusions and Implications for Management/Policy and Future Research ………………… 11
Literature Cited …………………………………………………………………………….. 12
Appendix A: Contact Information for Key Project Personnel ……………………………….. 19
Appendix B: List of Completed/Planned Scientific/Technical Publications/Science Deliveries 19
Appendix C: Metadata ……………………………………………………………………… 20

List of Tables

The report contains no tables.

List of Figures

Figure 1: Study sites …………………………………………………………………… 6

Figure 2: Study design on the example of Cold wildfire, ID ………………………………….. 6

Figure 3: Wildfire effect on shrubland structural heterogeneity ………………………………. 8

Figure 4: Scale dependent wildfire effect across sites ………………………………………… 9

Figure 5: Scale dependent predictive power of structural heterogeneity for recruit abundance . 10

Keywords

structural heterogeneity, scale dependence, arid ecosystems, ecosystem resilience, shrublands, recruitment, UAS

Acknowledgements

We thank Anna Roser for collecting the UAS data and data management; Valorie Marie for her help with UAS image processing and data organization; Ryan Wickersham, Cana Foncannon, Amy Johnson, Ian Lambrecht, Cayden Whipkey, Lena Griffith, and Shyam Batchu for their help in data collection. We thank Peter Olsoy and Caughlin Lab for their feedback and support during all stages of the project.

Abstract

Monitoring ecosystem status and recovery potential is critical for natural resource management. Recent evidence in ecological studies suggest a fundamental link between ecosystem physical structure and function, including resistance and recovery. Resistance and recovery properties of the imperiled Great Basin ecosystems are of critical utility in management with direct ties to abiotic and biotic site characteristics. Our work demonstrates that UAS surveys can provide novel insights into community resistance and resilience by measuring physical structure across a range of spatial scales. Specifically, we investigated how vegetation structure, measured as structural heterogeneity, responds to wildfire effects and recovery processes and whether the response is scale-dependent. We conducted a survey of a representative set of shrub stands that partially burnt between 1996 and 2015, and span a wide range of abiotic conditions. We found that shrubland structural heterogeneity was sensitive to wildfire effects and shrub recruit abundance, but this sensitivity was scale-dependent and different for the two ecological processes. Wildfire effects were most prominent at the intermediate scale resolutions (2.34 m), while the abundance of shrub recruits required higher resolution structural information (0.29 m). Surprisingly, structural heterogeneity at the very fine resolution (< 0.30 cm) was superfluous and did not provide additional value to the predictive models of recruit abundance. Our project demonstrates a low-cost monitoring framework for quantitative measures of shrubland resistance and recovery potential. We demonstrate how UAS platforms can provide landscape-level data while optimizing the resolution and extent of the survey for the ecological process of interest.

Objectives

The original project objectives underwent minor conceptual changes during the course of the project. These changes were motivated by recent developments in the ecological literature and more directly address management-oriented research questions and methodologies. The original set of objectives included:

- Constructing UAS-based demographic monitoring and modeling framework, including quantifying growth, survival, and reproduction of big sagebrush individuals.
- Improving landscape predictions of big sagebrush recovery by incorporating detailed UAS data into demographic models, including subspecies, size structure, and environmental heterogeneity.

The updated objectives simplify the assumptions and data requirements of the original objectives, and approach the ecological recovery more comprehensively. Specifically, we investigate the relationship between the physical structure, disturbance effects, and recovery in post-wildfire landscapes. We answer the following questions to guide UAS applications for ecological monitoring and assessment:

- What is the most sensitive spatial scale of vegetation structure to wildfire effects and stand-level changes?
- Can the physical structure of vegetation community predict the abundance of shrub recruits, and what is the optimal spatial scale of structure for such predictions?

Background

Anthropogenic pressures increasingly threaten the integrity of dryland ecosystems (Berdugo et al., 2022; Requena-Mullor et al., 2019). The Great Basin of the Intermountain Western US exemplifies arid land degradation, motivating management action to improve ecosystem integrity (Davies et al., 2011; Pilliod et al., 2021). The Great Basin shrublands from low and high elevations face functionally distinct challenges, from intensified grass-fire cycles to conifer encroachment (Davies et al., 2011). Across these environments, a decline in the shrub component is a common feature that dramatically changes vegetation structure. Therefore, the establishment of new shrubs is a critical ecological process representing the opposing force to disturbance pressures. Importantly, shrub establishment may show feedbacks with the spatial structure of vegetation (Mahood, Koontz, et al., 2021; Miriti, 2006; Urza et al., 2019). Understanding these feedbacks as drivers of recovery may inform restoration treatments with long-lasting effects on ecosystem trajectory (Arkle et al., 2022; Shriver et al., 2019). Overall, structural complexity directly relates to two key challenges in the region. First, as an indicator of key ecosystem health metrics, including the detection of transient demographic shifts (Shriver et al., 2019) and invasion status (Pilliod et al., 2021; Reinhardt et al., 2020). Second, structure-recovery feedbacks may inform management strategies to increase resilience and recovery potential that will help overcome major bottlenecks in Great Basin conservation efforts (Arkle et al., 2014; Pyke et al., 2020; Shriver et al., 2018).

Recent advances in remote sensing further illuminate the relationship between structure and function (Atkins et al., 2022; Ilangakoon et al., 2021; LaRue et al., 2019). Unoccupied aerial systems (UAS) enable a novel, detailed view of vegetation structure at spatial extent exceeding those using field methods (Cunliffe et al., 2016; Gillan et al., 2020; Howell et al., 2020). Nevertheless, analyzing the pathways between structural complexity and ecosystem function will often require a multi-scale approach (Wu, 2004). The problem of identifying appropriates scales of heterogeneity emerges in both theoretical and practical aspects of ecology. Specifically, disturbance effects and ecological indices that measure ecosystem shifts are scale specific, and management response may depend on the perceived ecosystem state and the need for an intervention (Standish et al., 2014). In addition to a growing recognition for standardizing UAS survey protocols (Cunliffe et al., 2022), an explicit approach to scale decisions would further benefit UAS applications and knowledge exchange. Identifying an optimal grain and spatial extent for a specific monitoring objective currently represents a knowledge gap, with potential resource and time costs for researchers and managers (Mahood, Joseph, et al., 2021). Here, we demonstrate a multi-scale approach to UAS data and identify optimal scales for wildfire and effects and recovery process with implications for research and management of the Great Basin ecosystems.

Materials and Methods

Overview

We combined a comprehensive dataset of UAS and field data in South-Western Idaho, USA to capture a range of environmental and post-wildfire stages using the space-for-time since wildfire approach. We surveyed 10 sites with a consumer-grade UAS along the edge of a wildfire line followed by extensive, randomized ground surveys of shrub abundance totaling > 22,000 shrub locations (Figures 1 and 2). We mapped all shrubs within 729 plots of 25 m^2 using a high-precision GPS system, and stratified the individuals into juvenile (< 25 cm) and adult (> 25 cm) categories. Next, we quantified the structural heterogeneity at discrete spatial scales using a UAS-derived canopy height model and a discrete wavelet transform (DWT). To identify the optimal scales of heterogeneity for the stand- and individual-plant levels, we quantified the heterogeneity-wildfire and recruit abundance-heterogeneity relationships using a combination of generalized linear models (GLMs). We used k-fold cross-validation to quantify how well structural heterogeneity can predict juvenile abundance. Lastly, we explored the interactive effect of structural heterogeneity and adult density on the abundance of juvenile shrubs using a GLM with a log-link and negative binomial error distribution.

Field surveys

Field sites were distributed across south-western Idaho, USA to include a range of elevation and time-since wildfire site conditions. This space-for-time substitution approach in site selection allowed us to increase the spatiotemporal representation of disturbance effects and recovery stages in our dataset (Adler et al., 2020). Each site follows a sampling design where approximately half of the rectangular footprint surveyed with a UAS was intact shrubland, while the other half was previously burnt (Figure 2). This design allowed us to measure the state of reference vegetation for each post-wildfire landscape. Because our sites spanned a wide range of environmental conditions, shrublands had different species composition, including the predominant species of canopy formation. In proportional representation, approximately 75% of the data were represented by *Artemisia tridentata*, 17% of *Artemisia arbuscula*, 1-2% *Chrysothamnus viscidiflorus*, *Ericameria nauseosa*, *Purshia tridentata*, and < 1% of *Eriogonum sphaerocephalum*, *Ribes aureum* and *Rosa woodsii*. Within each 25 m^2 plot we exhaustively mapped all shrubs, placing the GPS unit in the middle of the shrub crown. We used a survey-grade RTK GPS unit (Topcon HiPer V, Topcon Positioning Systems Inc., Livermore, CA, USA) that allowed us to collect geospatial data with ~ 2 cm accuracy (Rayburn et al., 2011). Each plant was assigned a binary index to indicate whether the plant was above or below 25 cm. We considered the plants below the 25 cm threshold as recent recruits, based on the relationship between small size and lower probabilities of survival and fecundity in the dominant shrub *Artemisia tridentatas* (Shriver et al., 2019). Once the geospatial field data was collected, a post-processing correction was necessary to reduce the positioning errors. We used Online Positioning User Service (OPUS) and a proprietary software *MagnetTools* (Topcon Positioning Systems Inc., Livermore, CA, USA) to correct the data points.

Data processing

We used UAS products surveyed at our sites to obtain spatially explicit structural metrics of vegetation communities. Each UAS product included a raster and a point cloud representing a digital surface model (DSM) of the site, that follows a vegetation and topography footprint of the landscape. We restricted our focus to the structural characteristics composed only by the vegetation component, and therefore removed the topographic variation from the DSM by subtracting the digital terrain model (DTM). We generated the DTM by applying existing software tools and fine-tuned filtering of the DSM, aiming to remove large and small vegetation from the dense point cloud, using open-source tools *CloudCompare* and 'lidR' package (https://github.com/andriizayac/uas_data_preprocess). We then used the resulting canopy height model (CHM) as an input to quantify scale-dependent structural variability.

Structural heterogeneity

To quantify structural heterogeneity from the CHM and decompose it into scales of variability, we used a mathematical technique: Discrete Wavelet Transform (DWT). Wavelet transform is an operation that decomposes a signal (*e.g.*, canopy height) into a series of scale resolutions from low- and high-frequency changes. For example, low- and high-frequency changes may correspond to variability created by large and small plants or branches, respectively. In ecology, wavelet transformation is used to investigate the scales of variability in spatial or temporal processes, *e.g.*, forest spatial structure, temporal and spatial synchrony in communities (Bradshaw & Spies, 1992; Keitt & Fischer, 2006; Walter et al., 2017). We used wavelet transform from the 'wavethresh' package to decompose spatial variability in the CHM into discrete scales of variation, from fine to coarse, and tested the relationship of each scale to the effect of wildfire and shrub recruit abundance. For each 25 m^2 plot we quantified a total amount of variability at each scale by summing the squared difference coefficients of the wavelet transform. Difference coefficients characterize changes in the canopy structure by comparing the values at neighboring pixels, where a high wavelet difference coefficient at a coarser resolution would correspond to very different neighborhood pixels at a finer resolution, and the finest resolution corresponds to the canopy height in the original raster.

Data analysis

Wavelet transformation of the CHM resulted in characteristic variability of the canopy across nine scales. Therefore, we ran nine linear mixed models where we used heterogeneity as response and wildfire as a predictor, while controlling for site differences via the random effect. The wildfire effect was quantified using a binary variable indicating whether the plot was within the burnt or the reference area. We used 'brms' package and ran the linear models in the Bayesian framework with default priors (Bürkner, 2017). To evaluate the predictive potential of a structural heterogeneity we iteratively fit nine models with recruit abundance within each plot as a response and a single scale of heterogeneity as a predictor. Each time, we replaced the predictor, *i.e.*, scale of heterogeneity, with the next, coarser scale and evaluated the predictive power by calculating Bayesian version of R^2 and mean absolute error (MAE) as metrics of predictive power. We calculated the MAE as $e = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$, where N is the number of field plots, y is the observed data, and $\hat{y}$ is the predicted count of shrub recruits. For all data manipulation and analysis we used *R* software v4.2.2 (R Core Team, 2021), including 'sf', 'terra', 'ggplot2' packages (Hijmans et al., 2022; Pebesma, 2018; Wickham, 2011; Wickham et al., 2019).

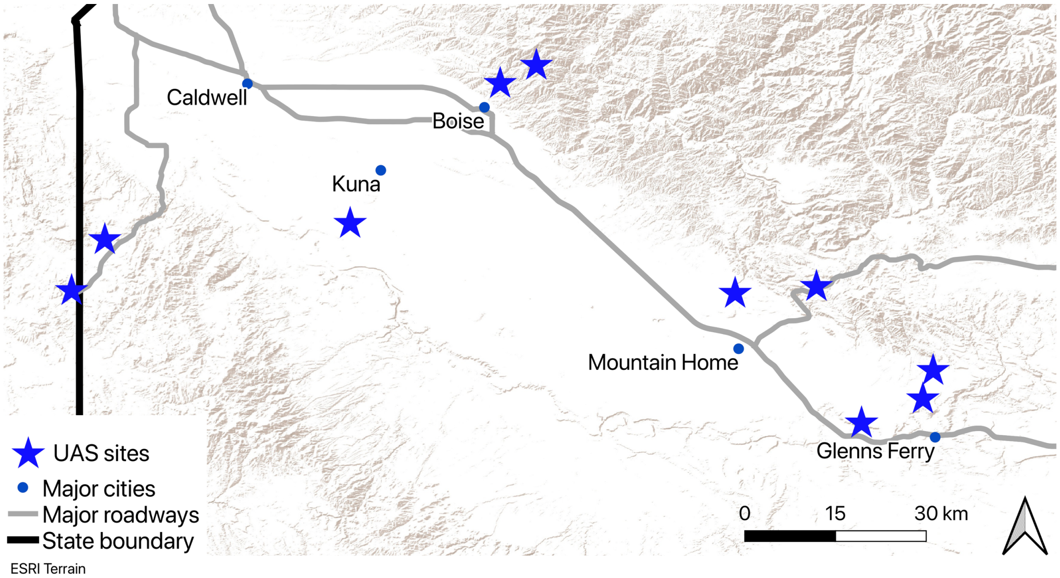

Figure 1: The distribution of the study sites in SW Idaho, USA. Each site includes UAS data combined with an extensive field survey documenting the location of individual shrubs. The UAS sites span a range of elevation conditions and time-since-wildfire.

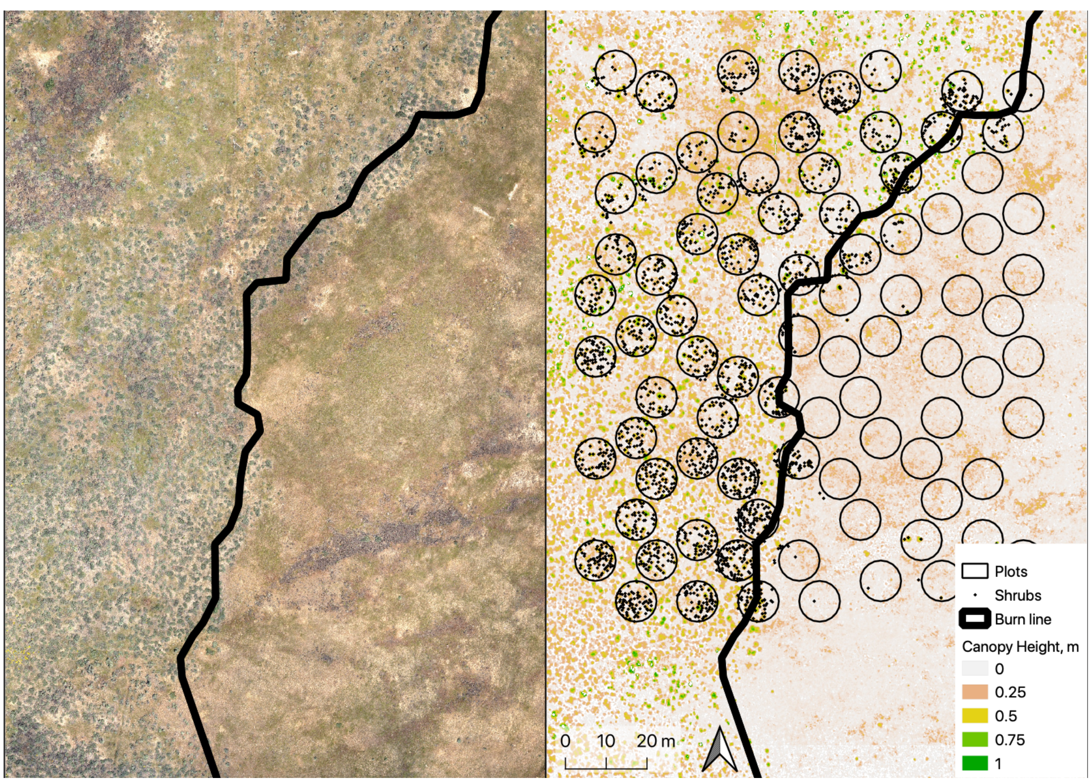

Figure 2: Sampling design on the example of Cold wildfire, Idaho, USA. The figure shows a combination of the products from remotely sensed (canopy height) and field-based data. Field data includes randomly distributed field plots (25 m^2), circular boundaries with the centroid indicated by black points, exhaustively surveyed to map individual shrubs.

Results and Discussion

The relation of structural heterogeneity to the two ecological processes, disturbance and recovery, revealed markedly different scale dependence (Figure 3). Namely, structural heterogeneity was most sensitive to wildfire effects at intermediate scales (2.34 m, Figure 4), while the recovery processes measured as the abundance of shrub recruits was most associated with a finer scale (0.29 m, Figure 4). Despite the differences among sites, this trend was consistent across the range of elevation (867 – 1514 m) and time-since-fire (7 – 26 years) gradients. Disturbance and recovery also showed a varying degree of scale dependence. Wildfire effects had a negative, unimodal pattern of scale dependence, with a single optimal scale most sensitive to structural changes. In contrast, scales of heterogeneity showed a combination of positive and negative effects on recruit abundance (Figure 2).

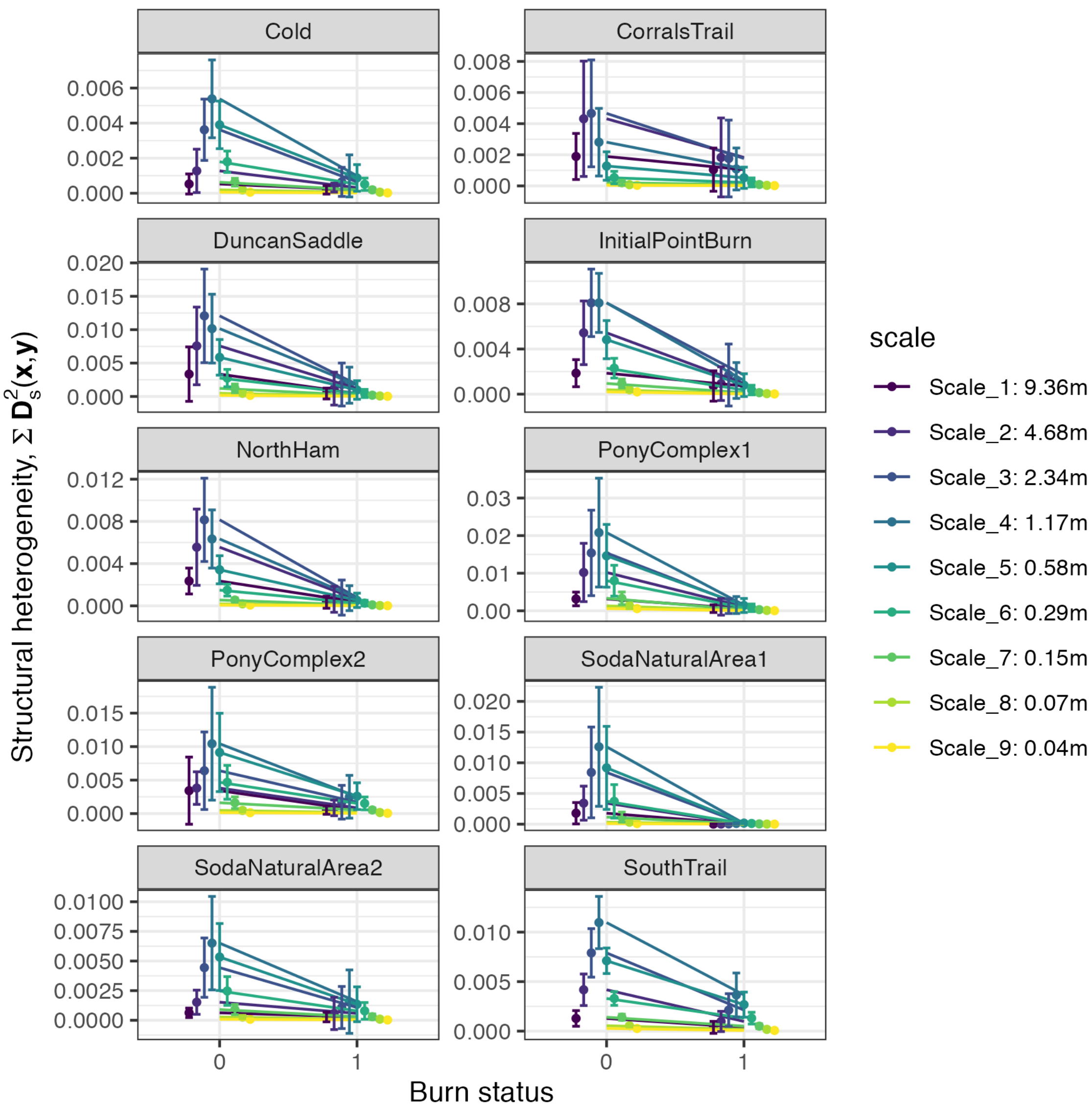

Figure 3: Wildfire effects on the structural heterogeneity of shrublands of the Great Basin, USA. Each plate shows a single site surveyed across the range of elevation and time-since-fire, where the disturbed and undisturbed field plots are compared as an average change in structural

heterogeneity across scales. The difference between the burnt and reference structural metrics is shown on the y-axis. The units correspond to raw wavelet difference coefficients summarized at 25m² plots and divided by the total amount of heterogeneity. The points and the error bars indicate the means and 2 SD of structural variation, respectively.

Shrubland structure at very small and large scales was less sensitive to the effects of a wildfire. The unimodal pattern of scale dependence points to the generality of the structure-function relationship in our study system (Maestre et al., 2016). Wildfires in the Great Basin may equally remove large and small shrubs from the landscape (Mahood, Koontz, et al., 2021; Miller et al., 2013; Requena-Mullor et al., 2019), but our results emphasize that the structure created large plants can be a sensitive indicator of the wildfire effects. The sensitivity of intermediate scales highlights structural heterogeneity as a metric of stand-level wildfire effects that do not require fine-scale structural accuracy. The result is relevant for assessing wildfire severity and monitoring the Great Basin shrublands, suggesting that excessively fine-scale resolutions of remotely sensed data will have diminishing returns. This finding contrasts with biomass and cover estimates from canopy structure that typically require very high resolution UAS data (Cunliffe et al., 2022; Gillan et al., 2020). Focusing on coarser spatial resolution (*e.g.*, 2.34 m) remote sensing products could be an adequate approach to monitor low-structure arid vegetation at larger spatial extents. In particular, applications of UAS in natural resource management face an inherent trade-off between the grain of the structural data and the spatial extent of the survey (Koontz et al., 2022). Matching the monitoring goal with the scale of observation will optimize resource investment and contribute to the standardization of UAS in ecological applications (Cunliffe et al., 2022). Overall, we show that a single, optimal scale of observation could be operationalized for ecosystem monitoring as an efficient and sensitive metric of ecosystem states across a range of environments and ecosystem states (Spake et al., 2022).

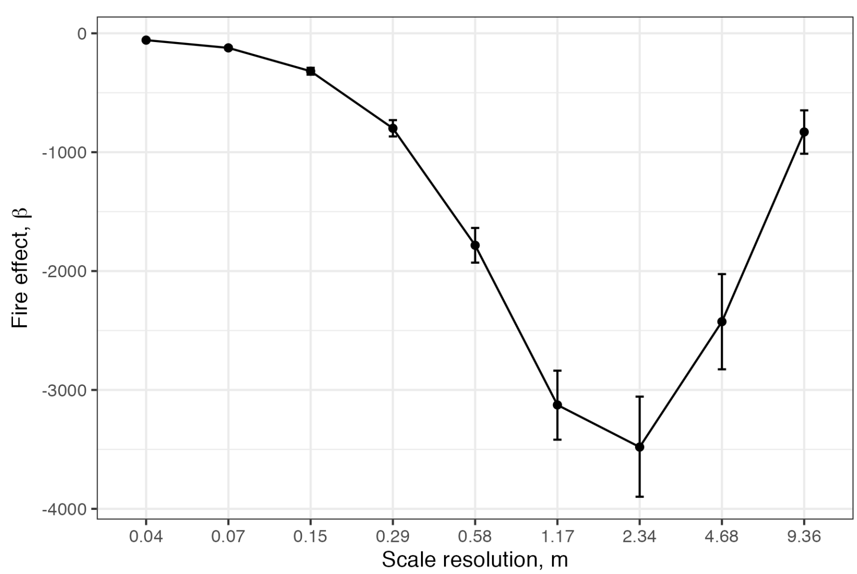

Figure 4: The effect size of wildfires on Great Basin shrublands measured by changes in canopy structure across the range of scale resolutions. Distance from zero indicates the deviation of a disturbed shrubland in reference to the adjacent intact vegetation surveyed along the wildfire boundary with unoccupied aerial systems (UAS). The effect size shows the decline in canopy

structural heterogeneity at discrete scales (x-axis). The points indicate the means and the error bars correspond to 2 SD of the posterior distribution.

The predictive power of structural heterogeneity for recruit abundance also depended on the scale of measured heterogeneity. Specifically, structure at fine scales (0.04 – 0.15 m) brings little predictive power for small individuals (Figure 3). A combination of structural heterogeneity from 9.36 - 0.29 m scales showed high predictive capacity using k-fold cross-validation: R^2 = 0.43 (95%CI: 0.39-0.48) with a mean absolute error (MAE) of 24.7 juvenile individuals. This pattern of predictive errors reiterates that the process is structurally most pronounced at the scale of 0.26 m, in contrast to the stand-level disturbance effect at a coarser resolution. This threshold is particularly surprising because small shrub recruits are often smaller in diameter than the size of a single pixel at this resolution. Therefore, our results contribute to the growing evidence of ecosystem structure being a powerful predictor of ecosystem function (LaRue et al., 2019). Adapting UAS surveys for ecological applications could thus incorporate spatial scales explicitly into the project objectives (Lines et al., 2022; Spiers et al., 2021).

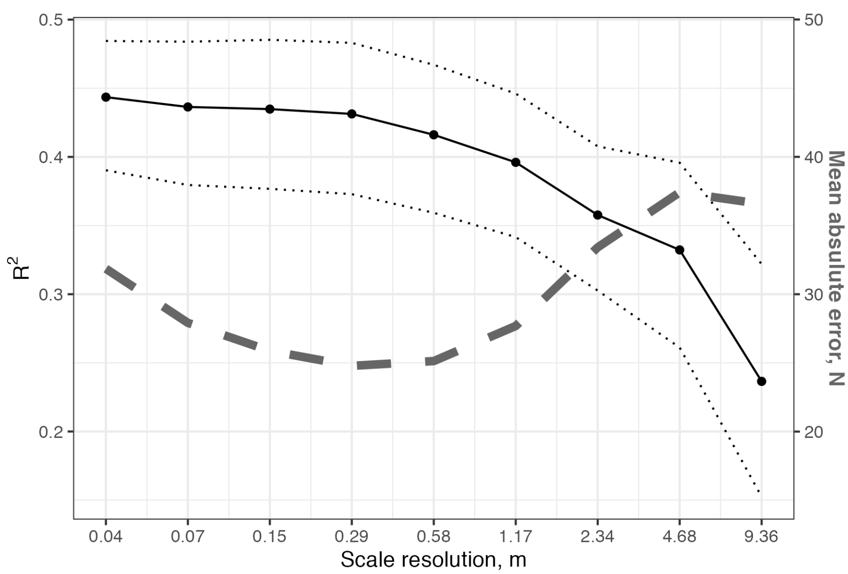

Figure 5: The predictive power of canopy structural heterogeneity to forecast juvenile shrub abundance. The predictor variables included site elevation and canopy structural heterogeneity using 10-fold cross validation with individual sites left out for each fold. Scale resolutions correspond to individual scales of structural variation with the rest of the scales removed from the predictor list. Finer dotted lines indicate 95% credibility interval of R^2 propagated through parameter uncertainty to juvenile count predictions.

Conclusions and Implications for Management/Policy and Future Research

Our study demonstrates the importance of scale in monitoring Great Basin shrublands with UAS. We found that structural heterogeneity is a sensitive metric for disturbance and recovery processes but this sensitivity is scale dependent (Spake et al., 2022). The sensitivity of structure to wildfire effects at intermediate scales (~2 m) suggests that the extent of surveyed Great Basin shrublands with UAS can be dramatically increased compared to high-resolution data. While monitoring vegetation structure at the scale that is predictive of recruit abundance is higher (~ 0.30 m), compared to ultra-high resolution surveys the extent of UAS surveys could be considerably expanded as well. Optimal scales of structural heterogeneity show promise as a predictive tool to assess the recovery trajectory of a degraded ecosystem. In agreement with the recent findings of a strong structure-function relationship (LaRue et al., 2019), we found that the structural composition of a Great Basin shrublands directly ties disturbance and recovery processes. We conclude that scale decomposition of vegetation structure will be fruitful for future studies aiming to link ecosystem structure and functional metrics like resistance and recovery, with direct utility for natural resource management.

Literature Cited

Adler, P. B., White, E. P., & Cortez, M. H. (2020). Matching the forecast horizon with the relevant spatial and temporal processes and data sources. *Ecography*, *43*(11), 1729–1739. https://doi.org/10.1111/ecog.05271

Arkle, R. S., Pilliod, D. S., Germino, M. J., Jeffries, M. I., & Welty, J. L. (2022). Reestablishing a foundational species: Limitations on post-wildfire sagebrush seedling establishment. *Ecosphere*, *13*(8), e4195. https://doi.org/10.1002/ecs2.4195

Arkle, R. S., Pilliod, D. S., Hanser, S. E., Brooks, M. L., Chambers, J. C., Grace, J. B., Knutson, K. C., Pyke, D. A., Welty, J. L., & Wirth, T. A. (2014). Quantifying restoration effectiveness using multi-scale habitat models: Implications for sage-grouse in the Great Basin. *Ecosphere*, *5*(3), art31. https://doi.org/10.1890/ES13-00278.1

Atkins, J. W., Stovall, A. E. L., & Alberto Silva, C. (2022). Open-Source tools in R for forestry and forest ecology. *Forest Ecology and Management*, *503*, 119813. https://doi.org/10.1016/j.foreco.2021.119813

Berdugo, M., Gaitán, J. J., Delgado-Baquerizo, M., Crowther, T. W., & Dakos, V. (2022). Prevalence and drivers of abrupt vegetation shifts in global drylands. *Proceedings of the National Academy of Sciences*, *119*(43), e2123393119. https://doi.org/10.1073/pnas.2123393119

Bradshaw, G. A., & Spies, T. A. (1992). Characterizing Canopy Gap Structure in Forests Using Wavelet Analysis. *Journal of Ecology*, *80*(2), 205–215. https://doi.org/10.2307/2261007

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*, 1–28.

Cunliffe, A. M., Anderson, K., Boschetti, F., Brazier, R. E., Graham, H. A., Myers-Smith, I. H., Astor, T., Boer, M. M., Calvo, L. G., Clark, P. E., Cramer, M. D., Encinas-Lara, M. S., Escarzaga, S. M., Fernández-Guisuraga, J. M., Fisher, A. G., Gdulová, K., Gillespie, B. M., Griebel, A., Hanan, N. P., … Wojcikiewicz, R. (2022). Global application of an unoccupied aerial vehicle photogrammetry protocol for predicting aboveground biomass in non-forest ecosystems. *Remote Sensing in Ecology and Conservation*, *8*(1), 57–71. https://doi.org/10.1002/rse2.228

Cunliffe, A. M., Brazier, R. E., & Anderson, K. (2016). Ultra-fine grain landscape-scale quantification of dryland vegetation structure with drone-acquired structure-from-motion photogrammetry. *Remote Sensing of Environment*, *183*, 129–143. https://doi.org/10.1016/j.rse.2016.05.019

Davies, K. W., Boyd, C. S., Beck, J. L., Bates, J. D., Svejcar, T. J., & Gregg, M. A. (2011). Saving the sagebrush sea: An ecosystem conservation plan for big sagebrush plant communities. *Biological Conservation*, *144*(11), 2573–2584. https://doi.org/10.1016/j.biocon.2011.07.016

Gillan, J. K., Karl, J. W., & van Leeuwen, W. J. D. (2020). Integrating drone imagery with existing rangeland monitoring programs. *Environmental Monitoring and Assessment*, *192*(5), 269. https://doi.org/10.1007/s10661-020-8216-3

Hijmans, R. J., Bivand, R., Forner, K., Ooms, J., Pebesma, E., & Sumner, M. D. (2022). Package 'terra.' *Maintainer: Vienna, Austria*.

Howell, R. G., Jensen, R. R., Petersen, S. L., & Larsen, R. T. (2020). Measuring Height Characteristics of Sagebrush (Artemisia sp.) Using Imagery Derived from Small

Unmanned Aerial Systems (sUAS). *Drones*, *4*(1), Article 1. https://doi.org/10.3390/drones4010006

Ilangakoon, N., Glenn, N. F., Schneider, F. D., Dashti, H., Hancock, S., Spaete, L., & Goulden, T. (2021). Airborne and Spaceborne Lidar Reveal Trends and Patterns of Functional Diversity in a Semi-Arid Ecosystem. *Frontiers in Remote Sensing*, *2*, 743320. https://doi.org/10.3389/frsen.2021.743320

Keitt, T. H., & Fischer, J. (2006). Detection of Scale-Specific Community Dynamics Using Wavelets. *Ecology*, *87*(11), 2895–2904. https://doi.org/10.1890/0012-9658(2006)87[2895:DOSCDU]2.0.CO;2

Koontz, M. J., Scholl, V. M., Spiers, A. I., Cattau, M. E., Adler, J., McGlinchy, J., Goulden, T., Melbourne, B. A., & Balch, J. K. (2022). Democratizing macroecology: Integrating unoccupied aerial systems with the National Ecological Observatory Network. *Ecosphere*, *13*(8), e4206. https://doi.org/10.1002/ecs2.4206

LaRue, E. A., Hardiman, B. S., Elliott, J. M., & Fei, S. (2019). Structural diversity as a predictor of ecosystem function. *Environmental Research Letters*, *14*(11), 114011. https://doi.org/10.1088/1748-9326/ab49bb

Lines, E. R., Fischer, F. J., Owen, H. J. F., & Jucker, T. (2022). The shape of trees: Reimagining forest ecology in three dimensions with remote sensing. *Journal of Ecology*, *110*(8), 1730–1745. https://doi.org/10.1111/1365-2745.13944

Maestre, F. T., Eldridge, D. J., Soliveres, S., Kéfi, S., Delgado-Baquerizo, M., Bowker, M. A., García-Palacios, P., Gaitán, J., Gallardo, A., Lázaro, R., & Berdugo, M. (2016). Structure and functioning of dryland ecosystems in a changing world. *Annual Review of Ecology,* *Evolution, and Systematics*, *47*, 215–237. https://doi.org/10.1146/annurev-ecolsys-121415-032311

Mahood, A. L., Joseph, M. B., Spiers, A., Koontz, M. J., Ilangakoon, N., Solvik, K., Quarderer, N., McGlinchy, J., Scholl, V., Denis, L. S., Nagy, C., Braswell, A., Rossi, M. W., Herwehe, L., Wasser, L., Cattau, M. E., Iglesias, V., Yao, F., Leyk, S., & Balch, J. (2021). *Ten simple rules for working with high resolution remote sensing data*. OSF Preprints. https://doi.org/10.31219/osf.io/kehqz

Mahood, A. L., Koontz, M. J., & Balch, J. (2021). *Fuel connectivity, burn severity, and seedbank survivorship drive ecosystem transformation in a semi-arid shrubland.* EcoEvoRxiv. https://doi.org/10.32942/osf.io/6x3as

Miller, R., Chambers, J., Pyke, D., Pierson, F., & Williams, C. (2013). A review of fire effects on vegetation and soils in the Great Basin region: Response and site characteristics. *Gen. Tech. Rep. RMRS-GTR-308. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station*.

Miriti, M. N. (2006). Ontogenetic shift from facilitation to competition in a desert shrub. *Journal of Ecology*, *94*(5), 973–979. https://doi.org/10.1111/j.1365-2745.2006.01138.x

Pebesma, E. J. (2018). Simple features for R: Standardized support for spatial vector data. *R J.*, *10*(1), 439.

Pilliod, D. S., Jeffries, M. A., Welty, J. L., & Arkle, R. S. (2021). Protecting restoration investments from the cheatgrass-fire cycle in sagebrush steppe. *Conservation Science and Practice*, *3*(10), e508. https://doi.org/10.1111/csp2.508

Pyke, D. A., Shriver, R. K., Arkle, R. S., Pilliod, D. S., Aldridge, C. L., Coates, P. S., Germino, M. J., Heinrichs, J. A., Ricca, M. A., & Shaff, S. E. (2020). Post-fire growth of seeded and planted big sagebrush – strategic designs for restoring Greater Sage-grouse nesting habitat. *Restoration Ecology*. https://doi.org/10.1111/rec.13264

R Core Team. (2021). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Rayburn, A. P., Schiffers, K., & Schupp, E. W. (2011). Use of precise spatial data for describing spatial patterns and plant interactions in a diverse Great Basin shrub community. *Plant Ecology*, *212*(4), 585–594. https://doi.org/10.1007/s11258-010-9848-0

Reinhardt, J. R., Filippelli, S., Falkowski, M., Allred, B., Maestas, J. D., Carlson, J. C., & Naugle, D. E. (2020). Quantifying Pinyon-Juniper Reduction within North America's Sagebrush Ecosystem. *Rangeland Ecology & Management*. https://doi.org/10.1016/j.rama.2020.01.002

Requena-Mullor, J. M., Maguire, K. C., Shinneman, D. J., & Caughlin, T. T. (2019). Integrating anthropogenic factors into regional-scale species distribution models—A novel application in the imperiled sagebrush biome. *Global Change Biology*, *25*(11), 3844–3858. https://doi.org/10.1111/gcb.14728

Shriver, R. K., Andrews, C. M., Arkle, R. S., Barnard, D. M., Duniway, M. C., Germino, M. J., Pilliod, D. S., Pyke, D. A., Welty, J. L., & Bradford, J. B. (2019). Transient population dynamics impede restoration and may promote ecosystem transformation after disturbance. *Ecology Letters*, *22*(9), 1357–1366. https://doi.org/10.1111/ele.13291

Shriver, R. K., Andrews, C. M., Pilliod, D. S., Arkle, R. S., Welty, J. L., Germino, M. J., Duniway, M. C., Pyke, D. A., & Bradford, J. B. (2018). Adapting management to a changing world: Warm temperatures, dry soil, and interannual variability limit restoration success of a dominant woody shrub in temperate drylands. *Global Change Biology*, *24*(10), 4972–4982. https://doi.org/10.1111/gcb.14374

Spake, R., Barajas-Barbosa, M. P., Blowes, S. A., Bowler, D. E., Callaghan, C. T., Garbowski, M., Jurburg, S. D., van Klink, R., Korell, L., Ladouceur, E., Rozzi, R., Viana, D. S., Xu, W.-B., & Chase, J. M. (2022). Detecting Thresholds of Ecological Change in the Anthropocene. *Annual Review of Environment and Resources*, *47*(1), 797–821. https://doi.org/10.1146/annurev-environ-112420-015910

Spiers, A., Scholl, V., McGlinchy, J., Balch, J., & Cattau, M. E. (2021). *UAS for Forest Inventory Traits: A Review*. https://ecoevorxiv.org/repository/view/4052/

Standish, R. J., Hobbs, R. J., Mayfield, M. M., Bestelmeyer, B. T., Suding, K. N., Battaglia, L. L., Eviner, V., Hawkes, C. V., Temperton, V. M., Cramer, V. A., Harris, J. A., Funk, J. L., & Thomas, P. A. (2014). Resilience in ecology: Abstraction, distraction, or where the action is? *Biological Conservation*, *177*, 43–51. https://doi.org/10.1016/j.biocon.2014.06.008

Urza, A. K., Weisberg, P. J., Chambers, J. C., & Sullivan, B. W. (2019). Shrub facilitation of tree establishment varies with ontogenetic stage across environmental gradients. *New Phytologist*, *223*(4), 1795–1808. https://doi.org/10.1111/nph.15957

Walter, J. A., Sheppard, L. W., Anderson, T. L., Kastens, J. H., Bjørnstad, O. N., Liebhold, A. M., & Reuman, D. C. (2017). The geography of spatial synchrony. *Ecology Letters*, *20*(7), 801–814. https://doi.org/10.1111/ele.12782

Wickham, H. (2011). Ggplot2. *Wiley Interdisciplinary Reviews: Computational Statistics*, *3*(2), 180–185.

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., & Hester, J. (2019). Welcome to the Tidyverse. *Journal of Open Source Software*, *4*(43), 1686.

Wu, J. (2004). Effects of changing scale on landscape pattern analysis: Scaling relations. *Landscape Ecology*, *19*(2), 125–138. https://doi.org/10.1023/B:LAND.0000021711.40074.ae

Appendix A: Contact Information for Key Project Personnel

Andrii Zaiats

Department of Biological Sciences

Boise State University

Email: andriizaiats@u.boisestate.edu

Phone: (208) 426-3262

Dr. Trevor Caughlin

Department of Biological Sciences

Boise State University

Email: trevorcaughlin@boisestate.edu

Phone: (208) 426-3262

Appendix B: List of Completed/Planned Scientific/Technical Publications/Science Deliveries

1. PhD Dissertation chapter, expected Spring 2022

2. Refereed publication: "Scale-dependent structural heterogeneity – an insight into wildfire effects and recovery in arid shrublands". In prep. Target journal: PNAS

3. Conference presentations:

    Zaiats, A., Cattau, M.E., Delparte, D., Caughlin, T.T. "Scale-dependent shifts in structural characteristics of sagebrush stands before and after wildfire events". Idaho NSF EPSCoR Annual Meeting, 26-28 October, Boise, ID. Invited Poster Presentation.

    Zaiats, A., Cattau, M.E., Delparte, D., Caughlin, T.T. "Scale-dependence of structure-function relationships: optimal scales of shrubland structural heterogeneity measured using unoccupied aerial systems (UAS)". Planned presentation at IALE – North America 2023 Annual meeting, March 19-23, Riverside, California.

    Zaiats, A. "Interactive effects of structural heterogeneity and density on shrub recruitment in post-wildfire landscapes". Planned presentation at SER Great Basin 2023 Annual Meeting, March 21-23.

4. Protocols:

    Marie, V., Zaiats, A., Caughlin, T.T. "Open Drone Map: Structure-from-Motion Worklow". A hands-on protocol to process UAS data using open-source software.

Appendix C: Metadata

See final project page in JFSP database for project metadata. Data products used in the analysis will be archived in the Northwest Knowledge Network (NKN) upon publication of results in peer reviewed journals.

The unoccupied aerial systems (UAS) data will be permanently archived on the NKN public repository, including the processed products, as well as raw imagery and ground control points that will allow reproducibility or reprocessing using any structure-from-motion software.