

Article

Temporal and Spatial Upscaling with PlanetScope Data: Predicting Relative Canopy Dieback in the Piñon-Juniper Woodlands of Utah

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Highlights

What are the main findings?

- NDVI from PlanetScope imagery significantly explains the sitewide mean of relative canopy dieback in the study area, and this relationship remains robust when upscaled spatially or temporally, even from a modest ground-truthing dataset.
- Model outputs indicate that relative canopy dieback has remained stable, with little evidence of substantial regreening in the four years following the 2017–2018 drought.

What are the implications of the main findings?

- This approach provides a cost-effective, scalable framework for monitoring canopy dieback and regreening, facilitating forest health assessments without extensive field sampling.
- We also identified hotspots of severe canopy dieback in the piñon-juniper forests of Utah, which represent priority areas for further study and management intervention.



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Abstract

Drought-induced forest mortality threatens biodiversity globally, particularly in arid, and semi-arid woodlands. The continual development of remote sensing approaches enables enhanced monitoring of forest health. Herein, we investigate the ability of a limited ground-truthed canopy dieback dataset and satellite image derived Normalised Difference Vegetation Index (NDVI) to make inferences about forest health as temporal and spatial extent from its collection increases. We used ground-truthed observations of relative canopy mortality from the *Pinus edulis-Juniperus osteosperma* woodlands of southeastern Utah, United States of America, collected after the 2017–2018 drought, and PlanetScope satellite imagery. Through assessing different modelling approaches, we found that NDVI is significantly associated with sitewide mean canopy dieback, with beta regression being the most optimal modelling framework due to the bounded nature of the variable relative canopy dieback. Model performance was further improved by incorporating the proportion of *J. osteosperma* as an interaction term, matching the reports of species-specific differential dieback. A time-series analysis revealed that NDVI retained its predictive power for our whole testing period; four years after the initial ground-truthing, thus enabling retrospective inference of defoliation and regreening. A spatial random forest model trained on our ground-truthed observations accurately predicted dieback across the broader landscape. These findings demonstrate that modest field campaigns combined with high-resolution satellite data can generate reliable, scalable insights into forest health, offering a cost-effective method for monitoring drought-impacted ecosystems under climate change.

Keywords: defoliation; forest health; PlanetScope; relative canopy dieback; satellite remote sensing; beta regression; spatial random forests; piñon-juniper woodlands; ecological monitoring

1. Introduction

Global forest coverage is experiencing an alarming decline [1], driven predominantly by anthropogenic factors, with climate change emerging as a particularly significant threat [2]. This trend has profound implications for tree mortality due to physiological stresses such as hydraulic failure and the loss of suitable climatic conditions for the continued survival of existing trees, reducing the health of forest ecosystems [3,4]. Forests create their own micro-climates [5], and consequently also the ecological niches that allow numerous other species to thrive, often in the world's biodiversity hotspots [4]. Additionally, forests offer vital ecosystem services, including carbon sequestration, water regulation, and soil conservation, making their preservation essential for environmental health and biodiversity.

The threats facing forest communities can have deleterious and cascading effects throughout their ecosystem. As the climate continues to warm, seasonal rainfall patterns continue to change [6,7]. This leaves many established forests globally at increasing risk from higher temperatures, reduced water intake, and hydraulic stress leading to physiological damage [8–10]. Of the various strategies used by trees in response to prolonged heat stress, premature canopy defoliation is a widely observed behavioural coping mechanism critical to a tree's survival. It is also observable from gross inspection alone, making it an accessible and near real-time indicator of the severity of heat stress that any given tree has endured. Early defoliation can be beneficial for overall tree survivability as it reduces transpiration, thereby conserving water [3]. The reallocation of available resources towards other behaviours like root growth enhance a tree's ability to access water and nutrients from elsewhere in the environment [11]. Moreover, reducing the leaf area helps prevent hydraulic stress and cavitation, maintaining the integrity of the tree's vascular system. However, despite its immediate benefits, early defoliation (defoliation which occurs before typical times of leaf loss in the autumn) often leads to an overall reduction in tree health, as evidenced by increased mortality rates in the years following a drought [10].

Aerial remote sensing tools, such as Earth observation satellites and Unmanned Aircraft Systems (UAS), offer a promising avenue for monitoring defoliation (a well-established proxy for tree health) [12], as they typically offer cost-effective and globally accessible data to assess environmental and biotic forest conditions with minimal temporal lag. The past decade has witnessed a blossoming of research demonstrating the inferential power these technologies have [13–18]. Of particular relevance for researchers studying forest health, aerial remote sensing research has been successfully used to monitor the health of floral ecosystems using Normalised Difference Vegetation Index (NDVI) reflectance, track land use change, and map invertebrate biodiversity in forests [12,19–23]. However, the inferential scope of remote sensing tools is necessarily limited to that which can be reasonably extrapolated by the ground-truthing data available. This poses a challenge as there remains a considerable gap in the availability of recent ground-truthing datasets with comprehensive, spatiotemporally precise, tree mortality data [24,25]. Though initiatives like the “Global Tree Mortality Database” are valuable initial steps in pursuit of systematically making metrics of tree mortality available for subsequent study, some shortfalls remain. For example, few studies tracked binary mortality (i.e., dead or alive) among their sample populations [25]. Most studies instead opted to use a proxy for tree health, such as relative canopy dieback. Despite the widespread use of this metric, there does not seem to be a standardised way to measure it, with each study taking a different approach [26–30]. Consequentially, mortality data and its proxy metrics can seldom

be compared across studies. So despite the rapid advancement of remote sensing tools, recent ground-truthing data is rarely available to fully utilise them.

Given the significant implications of premature defoliation to tree health and mortality, it is worth investigating whether the timing of defoliation events inferred by aerial remote sensing can be used as a predictor for future defoliation events and, by extension, the future health of forest ecosystems. Understanding this relationship could provide practical benefits for forest management, enabling mitigation strategies to be implemented earlier. As climate change continues to worsen the health of woodland ecosystems, the relevance of being able to predict premature defoliation events becomes increasingly relevant. This paper aims to test whether tree stand phenology (as measured by NDVI) can establish a relationship with subsequent health of the trees in the stand (measured by the aggregate of recent canopy defoliation). Furthermore, we assess whether defoliation timing can serve as a phenological indicator for predicting canopy dieback and thus overall tree health. By evaluating the viability of the PlanetScope satellite networks' almost daily and relatively high resolution (3 m × 3 m) imaging, this study seeks to provide a novel approach to inferring forest health throughout an extensive woodland region in southeastern Utah which experienced drought induced defoliation in 2018.

In particular, we analyse the following:

1. Whether the piñon-juniper (*Pinus edulis* and *Juniperus osteosperma*) forest stands of south-eastern Utah, USA, exhibit a relationship between recent, drought-induced canopy dieback and NDVI, and characterise any such relationship.
2. Whether controlling for the proportion of *J. osteosperma* enhances our ability to make NDVI-based predictions of relative canopy dieback.
3. Whether an NDVI time series can serve as a predictor for future defoliation events.
4. Whether the relationship between field-based canopy dieback data and NDVI can be upscaled to predict the extent of canopy dieback throughout the piñon-juniper forest ecosystem following the drought.

2. Materials and Methods

2.1. Study Area

The study sites for this analysis were selected based on relevant datasets from the Global Tree Mortality Database [24]. To be considered for inclusion, studies were required to meet several criteria: they needed to contain mortality data from a minimum of three sites, with each site focusing primarily on a single species. Additionally, only studies which conducted ground-truthing after 2014 were considered, as this is when PlanetScope remote sensing data became available. If there were sufficient, separate studies examining the same features of the same species, the data from these studies would be combined to achieve the minimum threshold of three ground-truthed replicates. However, no suitable combination of separate studies in the Global Tree Mortality Database met this requirement.

Ultimately, three studies met the selection criteria for inclusion in this analysis: two based in Europe and one in North America. However, only the dataset from Kannenberg et al. [8] examining multiple piñon-juniper woodland sites in southeastern Utah, USA, was made available for further analysis. Kannenberg et al. [8] selected these sites to serve as a representative microcosm of the drought afflicted piñon-juniper woodland ecosystem. These woodlands have also been studied in Campbell et al.'s [31] remote sensing research. Both studies establish the ecological relevance of this ecosystem in the literature, and are a valuable foundation upon which to conduct further research.

Kannenberg et al.'s [8] study included 12 sites, each defined as a 15-metre radius circle situated on broadly level terrain. Figure ?? illustrates the region where Kannenberg et al.'s [8] study took place, alongside the sites' location within western North America. Figure 2 illustrates Kannenberg et al.'s [8] 12 study sites at a very fine spatial resolution. The

image makes clear the dry environs typical of southeastern Utah and serves to visualise the size and density of trees in each forest ecosystem. Even though PlanetScope offers a class leading combination of temporal and spatial resolution compared to other satellite imagery providers, PlanetScope's spatial resolution of $3\text{ m} \times 3\text{ m}$ is not suitable for tree crown delineation or the calculation of leaf area index values, elucidating why it was necessary to make inferences at the scale of forest stands, rather than of individual trees.

2.2. Defoliation Data

We used defoliation data collected by Kannenberg et al. [8] as part of their study. Kannenberg et al. [8] measured recent defoliation for each tree as a percentage of its previous full crown. This was achieved by two observers each estimating the extent of dead leaves on the branches of a tree, and determining how much of the total branch length this was equivalent to. Both observers were found to have very similar estimates of recent defoliation. Mean recent defoliation was calculated at the stand level, and for each species within each stand, as described in Kannenberg et al. [8].

2.3. PlanetScope Data

Satellite image data were acquired from Planet's PlanetScope satellite network. We opted to use data spanning from the start of PlanetScope's availability (the 27/06/2016) until the present day (the 17/09/2023). We specified that the data be harmonised to Sentinel-2 (as recommended by PlanetLabs' technicians [32]), and selected their standard 4-band (blue, green, red, and Near Infra-Red (NIR)) orthorectified image output. The data was processed by removing any images which had only partial coverage of the site, which had any cloud cover, or were otherwise marked as having "bad pixels" by the datum's corresponding quality mask. All the data were downloaded via Planet's Orders API (version 2.0.0) using a Python (version 3.11.4) script.

2.4. Data Preprocessing

To efficiently, reproducibly, and reliably process this quantity of data, we used R to prepare our data. Data processing was conducted in R version 4.5.0 [33], utilising the R packages TidyVerse [34], sp [35], sf [36], terra [37], and spatialRF [38], among others. Site-level attributes were extracted from the data's associated manifest files using R. To ensure data quality, any sites with any amount of cloud coverage were removed, resulting in a refined dataset containing 2243 unique dates with data that were used in subsequent analyses. Table 1 summarises each site, including the number of times data were downloaded and the number of observations retained after removing sites with clouds or other "bad" pixels. The NDVI value of each pixel was calculated and then used to calculate the sitewise mean of NDVI for that site (as per the formula below).

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \quad (1)$$

$$\overline{\text{NDVI}}_s = \frac{1}{n_s} \sum_{i=1}^{n_s} \text{NDVI}_i \quad (2)$$

where

- S is the site
- $\overline{\text{NDVI}}_s$ is the mean NDVI value for the site
- n_s is the number of valid (non-cloudy) pixels within site S on a given date
- NDVI_i is the NDVI value of the i^{th} pixel within the site S

This was calculated for each site, each time it was downloaded. The output of this process was a timeseries of the sitewise means of NDVIs. An explanation of our choice to use NDVI can be found in Table A1 of the Appendix A.

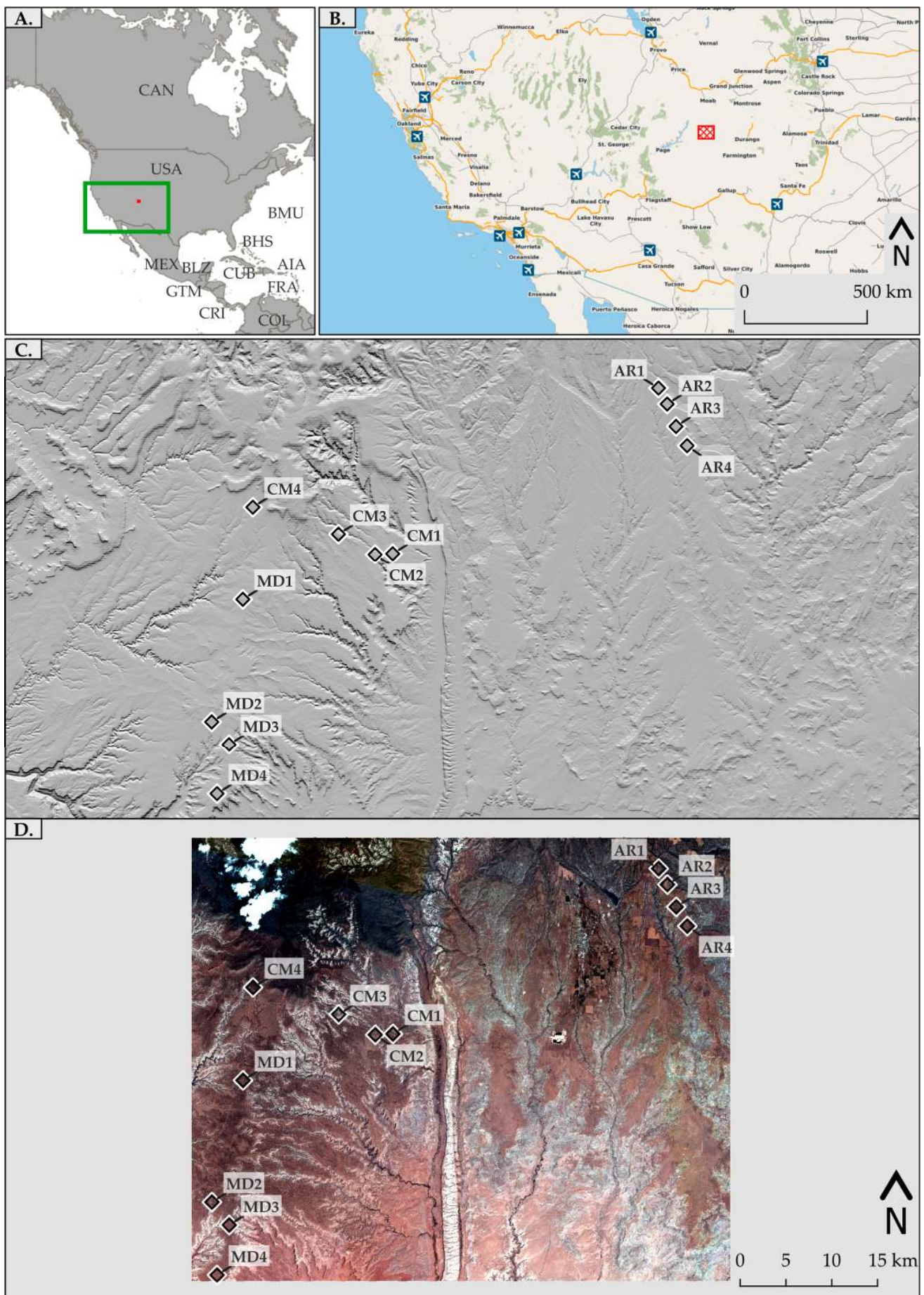


Figure 1. (A) A subset of the world map illustrating the national boundaries in a subset of north America. The green rectangle indicates the area presented in (B). A map illustrating the study sites' location within the western United States (the red cross-hatched square within the map). The map's base layer is courtesy of ÖPNV-Karte. (C) A hillshade map illustrating the topography of the region of south-eastern Utah in which our study takes place (source: Prizren Global Terrain). (D) An RGB map covering the same geographic extent as panel C, with Kannenberg et al.'s 12 study sites marked [8]. The panel's RGB base layer is from PlanetScope's Dove-2 satellite network, harmonised to Sentinel-2's image output. The image was captured on the 29/05/2019.

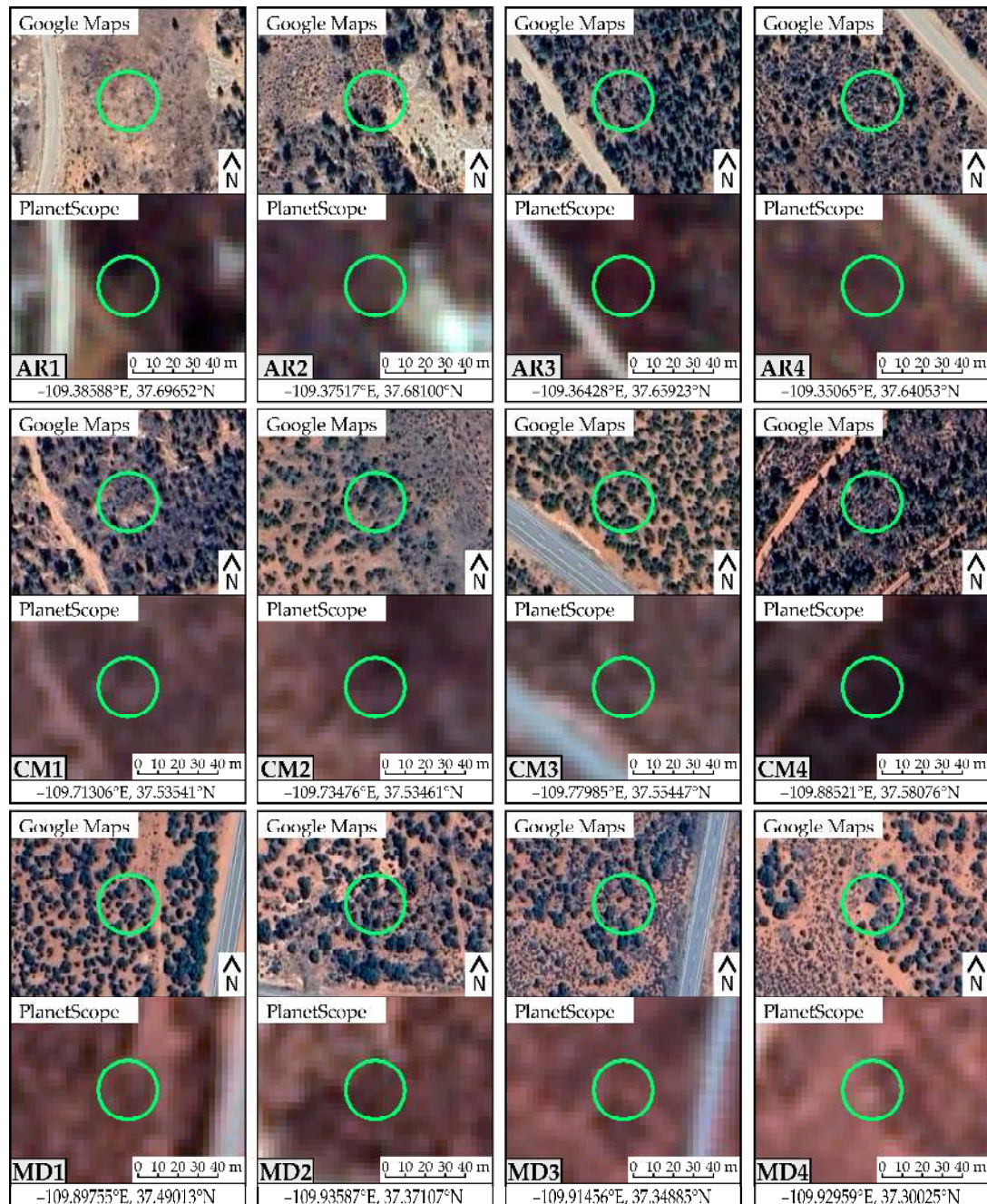


Figure 2. A series of satellite-derived RGB images illustrating the 12 study sites from Kannenberg et al. [8]. Each panel's green ring indicates the exact boundaries of the study site within its surrounding environs. Each panel's label (bottom left of the bottom panel) indicates the study site. All panels are presented at the same spatial scale, with north facing the top of the image. Each study site has a high resolution image from Google Maps (top), with a coarser image from PlanetScope below. The co-ordinates below each panel pair indicate the centre of the study site (CRS: EPSG:4326).

Table 1. Number of unique images downloaded from the PlanetScope Satellite Network for each study site and number of images that remained after Quality Control (QC) for subsequent analyses.

Site	AR1	AR2	AR3	AR4	CM1	CM2	CM3	CM4	MD1	MD2	MD3	MD4
N^o of images	3968	3974	4014	4020	4131	4127	4024	3933	3990	4099	4111	4137
N^o after QC	1979	1967	2005	2034	2029	2031	1972	1957	1986	2049	2054	2062

2.5. Data Analysis

2.5.1. Can a Relationship Between Relative Dieback and NDVI Be Found?

Determining the presence of a relationship between our ground-truthing data and remote sensing data, and quantifying any such relationship, is the fundamental prerequisite for justifying the use of remote sensing data to analyse this dataset. Therefore, we tested whether the piñon-juniper forest stands in the study area exhibit a relationship between recent drought-induced canopy dieback and NDVI.

As our remote sensing data is unable to discern individual tree crowns (see Figure 2), we used each sampled tree in the site to calculate a sitewide mean value of relative canopy dieback. We calculated the sitewide mean of relative canopy dieback for all 12 sites using the ground-truthing data from the May 2019 sampling round, and then again for the October 2019 sampling round. This gave us a total of 24 ground-truthed mean sitewide relative canopy dieback datapoints. We calculated the sitewide mean NDVI for each site using values extracted from the most temporaneous PlanetScope GeoTIFF imagery. For each of the 12 sites sampled for canopy dieback in May 2019, we identified the closest-in-time PlanetScope image and used it to calculate the sitewide mean NDVI, aligning these values with the ground-truthed sitewide mean canopy dieback measurements. For each site, we calculated the sitewide mean NDVI once for May 2019 and again for October 2019 to correspond to the May and October 2019 sampling rounds [8]. To minimise the influence of any potential edge effects and ensure construct validity, only pixels that were wholly within the boundaries of the sites were used to calculate the sitewide mean NDVI value.

To statistically determine whether a relationship between the sitewide mean of NDVI and the sitewide mean of relative canopy dieback exists, simple linear regressions were conducted. The response variable was the sitewide mean of relative canopy dieback, and the predictor was the sitewide mean of NDVI. We conducted three linear models, one using the May data, another the October data, and finally, a linear regression which included both May and October data.

The model was fitted using the Ordinary Least Squares (OLS) method using the ‘lm()’ function in R. Model assumptions were evaluated by inspecting residual diagnostics, including normality (via the Shapiro-Wilk test [39]), homoscedasticity (using residual vs. fitted plots), and linearity. Statistical significance was assessed at a threshold of $\alpha = 0.05$. To evaluate model performance, we reported the R^2 , adjusted R^2 , and p values for predictor significance.

2.5.2. What Is the Optimal Way to Model This Relationship?

Whilst the prior statistical approach using a simple linear model is a robust and readily understood method to determine and compare relationships, its performance may be limited when used to describe the relationship between our ground-truthing data and remote sensing data. As the response variable (the sitewide mean of relative canopy dieback) is a bounded variable (i.e., a site could never have more than 100% or less than 0% of relative canopy dieback), linear modelling approaches could predict biologically impossible values of relative canopy dieback. Therefore, we also compared the previous

linear model to a beta regression model with a logit link function to see whether the latter can better describe the relationship [40]. The beta regression model is described below:

$$\log\left(\frac{Y}{1-Y}\right) = \beta_0 + \beta_1 X + \epsilon \quad (3)$$

where

- Y represents the mean sitewide relative canopy dieback for both species combined (rescaled to a decimal value)
- X represents sitewide mean NDVI
- β_0 represents the intercept
- β_1 represents the slope coefficient
- ϵ represents the residual error

The extent of relative canopy dieback differs significantly between *J. osteosperma* and *P. edulis* [8]. This was reconfirmed statistically by us using Student's t-test. As *J. osteosperma* experienced more severe canopy dieback than co-dominant *P. edulis*, it is possible that the proportion of *J. osteosperma* may confound NDVI-based predictions of relative canopy dieback. Therefore, we compared the performance of another beta regression model which includes the proportion of *J. osteosperma* in the sites as an additional interaction term. We assessed this model's performance by identifying significant interaction terms (again using $\alpha = 0.05$ as our threshold) and through comparison to the performance of previous models. The model is described as follows:

$$\log\left(\frac{Y}{1-Y}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 (X_1 \times X_2) + \epsilon \quad (4)$$

where

- Y represents the mean sitewide relative canopy dieback for both species combined (rescaled to a decimal value)
- X_1 represents sitewide mean NDVI
- X_2 represents the proportion of *J. osteosperma* in the given site
- β_0 represents the intercept
- β_1 and β_2 represent the main effect coefficients
- β_3 represents the interaction coefficient
- ϵ represents the residual error

Given the differences in relative canopy dieback between *J. osteosperma* and *P. edulis*, it might follow that an NDVI-based assessment of relative canopy dieback is more accurate when used to model only *J. osteosperma* or *P. edulis*, as each species reacted differently to drought. Modelling both in one model may be less effective as it combines two distinct biological effects into one output variable. Therefore, we reparametrized a beta regression model to predict the relative canopy dieback of only *J. osteosperma*, followed by *P. edulis*. The subsequent models were as follows:

$$\log\left(\frac{Y}{1-Y}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 (X_1 \times X_2) + \epsilon \quad (5)$$

where

- Y represents the mean sitewide relative canopy dieback for either *J. osteosperma* or *P. edulis* (rescaled to a decimal value)
- X_1 represents sitewide mean NDVI
- X_2 represents the proportion of *J. osteosperma* in the given site

- β_0 represents the intercept
- β_1 and β_2 represent the main effect coefficients
- β_3 represents the interaction coefficient
- ϵ represents the residual error

The performance of these models was compared to ascertain whether NDVI can better model one species or the other.

2.5.3. Can NDVI Be Used to Predict Defoliation and/or Assess Regreening of the Canopy?

To assess whether an NDVI time series can serve as a predictor for future defoliation events, a series of beta regressions were conducted to test the relationship between the sitewise mean of relative recent defoliation and the mean of sitewise means of NDVI, aggregated into 10-day intervals spanning the length of time for which satellite image data was available. As this analysis made temporally informed predictions, only May's ground-truthing data was used. Each beta regression included the proportion of *J. osteosperma* in the study area to account for the more severe relative canopy dieback *J. osteosperma* experienced. So overall, the beta regressions sequentially tested the interaction between the sitewise mean of relative canopy dieback for each site, and the mean of sitewise mean NDVIs from each 10-day period for each site, with each 10-day test period assessed with its own beta regression. Each regression was conducted independently of the preceding and succeeding one. The models' equation is as follows:

$$\log\left(\frac{Y}{1-Y}\right) = \beta_0 + \beta_1 \overline{X_{\text{NDVI}}} + \beta_2 X_2 + \beta_3 (\overline{X_{\text{NDVI}}} \times X_2) + \epsilon \quad (6)$$

where

- Y represents the mean sitewise relative canopy dieback of *J. osteosperma* and *P. edulis* combined (rescaled to a decimal value)
- $\overline{X_{\text{NDVI}}}$ represents the mean of sitewise mean NDVIs for the time period being tested
- X_2 represents the proportion of *J. osteosperma* in the given site
- β_0 represents the intercept
- β_1 and β_2 represent the main effect coefficients
- β_3 represents the interaction coefficient
- ϵ represents the residual error

Each model's performance metrics, such as significance and pseudo- R^2 value, were considered to determine whether the relationship between NDVI and prior canopy dieback remains biologically relevant as temporal distance from the ground-truthing date increases. These results were used to discuss the extent to which NDVI can be used to contextualise the current level of foliage at the study sites.

2.5.4. Can NDVI Predict Relative Canopy Dieback Elsewhere in the Ecosystem?

To evaluate whether remotely sensed vegetation indices can reliably predict drought-induced relative canopy dieback beyond the original sample sites (spatial upscaling), we developed a spatial random forest regression model [38,41]. The spatial random forest model enables non-parametric modelling of non-linear relationships and variable interactions whilst accounting for the spatial structure of the forest ecosystem [41].

The model was trained using the site level mean of relative canopy dieback, although not the relative proportions of *J. osteosperma* as this data was not available for the wider forest. We used the ground-truthing data from May and October 2019. For each site, we extracted satellite-based reflectance data and multiple different vegetation indices (listed below) from the most temporally aligned PlanetScope imagery. All remote sensing

covariates were spatially averaged within the boundaries of each site using only fully enclosed pixels to avoid edge effects.

The final model incorporated both raw spectral reflectance values (blue, green, red, and NIR), and five commonly used vegetation indices: NDVI, Green NDVI (GNDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), and Modified Soil-Adjusted Vegetation Index 2 (MSAVI2). These indices were also suitable for use with PlanetScope's red, green, blue, and NIR image bands. This combined approach was selected to maximise model performance by capturing both processed index-based metrics and raw spectral information that can provide complementary insights into canopy structure and health.

Model training was performed on all 12 ground-truthed sites using both the May and October data, thus giving 24 observations in total. The spatialRF package's default parameters were generally sufficient for model construction. Thus, our grid search created 64 models. The number of trees in each iteration of the random forests model could be either 100, 200, 500, or 2500, the predictor subset size (mtry) could be either 2, 3, 4, or 5, and the minimum node size could be either 1, 5, 10, or 15. We then found the best performing of these models. Model performance was assessed using out-of-bag and full prediction accuracy metrics, including the coefficient of determination (R^2), and Root Mean Squared Error (RMSE). Pseudo- R^2 residuals were tested for normality using the Shapiro-Wilk test [39], and for spatial autocorrelation using Moran's I [42].

We then used the best model for spatial upscaling. Predictions were calculated for a series of hexagonal pseudo-sites spanning an expanded area. The footprint of our predicted area was a subset of San Juan county's piñon-juniper woodlands which were used by Campbell et al. [31]. This region comprised the same semi-arid piñon-juniper woodland, which was comparable to the drought-affected ecosystems Kannenberg et al. [8] originally sampled. The region selected extended beyond the original ground-truthed sites while maintaining similar forest composition and structure. Application of the model to this significantly expanded area allowed us to evaluate the spatial generalisability of the approach and explore its capacity for landscape-scale defoliation inferences.

3. Results

Table 2 presents stand composition statistics derived from the May and October 2019 sampling periods, describing the stand composition of the 12 study sites [8]. This table includes both the count and proportion of *J. osteosperma* and *P. edulis* in each site, in addition to the mean extent of canopy dieback for each species. The total tree count and mean canopy dieback extent for both species across all sites is also provided. As the area of each field site is constant, the broad range of the count of trees per site is indicative of heterogenous stand density (range = $23 \leq X \leq 99$, mean = 50, median = 48). Though not included in the table, the sitewide mean NDVI indicated the relatively close clustering of NDVI values during both ground-truthing rounds (range = $0.2260767 \leq X \leq 0.3668071$).

3.1. The Relationship Between the Mean of Sitewide Relative Canopy Dieback and the Sitewide Mean of NDVI

To evaluate whether the piñon-juniper forest stands of southeastern Utah exhibit a relationship between recent drought-induced canopy dieback and remotely sensed vegetation indices, we fitted a linear regression model using sitewide mean NDVI as a predictor of ground-truthed sitewide mean relative canopy dieback ($N = 24$ observations from May and October 2019).

The model identified a significant negative relationship between NDVI and observed canopy dieback ($\beta = -236.63$, $SE = 87.84$, $p = 0.013$, $N = 24$). The intercept was also

significant ($\beta = 91.24$, $SE = 25.76$, $p = 0.0018$). The model explained approximately 25% of the variance in observed dieback ($R^2 = 0.25$, adjusted $R^2 = 0.21$), indicating a moderate but statistically meaningful relationship. Residuals ranged from -25.89 to 34.27 , with no evidence of extreme outliers.

Table 2. Stand composition statistics derived from the fieldwork Kannenberg et al. [8] conducted during May and October of 2019.

Site	Count of Junipers in Site	Junipers as a Proportion of the Site (%)	Mean of Junipers' Canopy Dieback (%)	Count of Piñons in Site	Piñons as a Proportion of the Site (%)	Mean of Piñons' Canopy Dieback (%)	Total Count of Trees in the Site	Mean of Sitewide Canopy Dieback (%)
May 2019 sampling round								
AR1	57	58	8	42	42	4	99	6
AR2	22	88	18	3	12	0	25	16
AR3	46	67	73	23	33	28	69	58
AR4	19	83	31	4	17	1	23	26
CM1	39	91	54	4	9	54	43	54
CM2	22	88	58	3	12	36	25	55
CM3	34	65	4	18	35	0	52	3
CM4	9	26	3	26	74	1	35	2
MD1	36	77	8	11	23	2	47	7
MD2	25	48	13	27	52	3	52	8
MD3	35	78	18	10	22	18	45	18
MD4	52	83	32	11	17	1	63	27
Mean	33	71	27	15	29	12	48	23
October 2019 sampling round								
AR1	54	57	9	41	43	5	95	7
AR2	20	87	16	3	13	1	23	14
AR3	51	65	68	27	35	30	78	55
AR4	19	83	30	4	17	0	23	25
CM1	43	90	56	5	10	62	48	57
CM2	24	86	46	4	14	53	28	47
CM3	39	66	3	20	34	2	59	3
CM4	9	26	6	26	74	0	35	2
MD1	37	74	6	13	26	2	50	5
MD2	26	47	13	29	53	3	55	8
MD3	35	76	13	11	24	13	46	13
MD4	59	84	31	11	16	1	70	26
Mean	35	70	25	16	30	14	51	22

This result demonstrates that NDVI serves as a useful proxy for recent canopy dieback in this semi-arid woodland, with higher NDVI values generally associated with lower levels of drought-induced damage. A scatterplot of the relationship is shown in Figure 3.

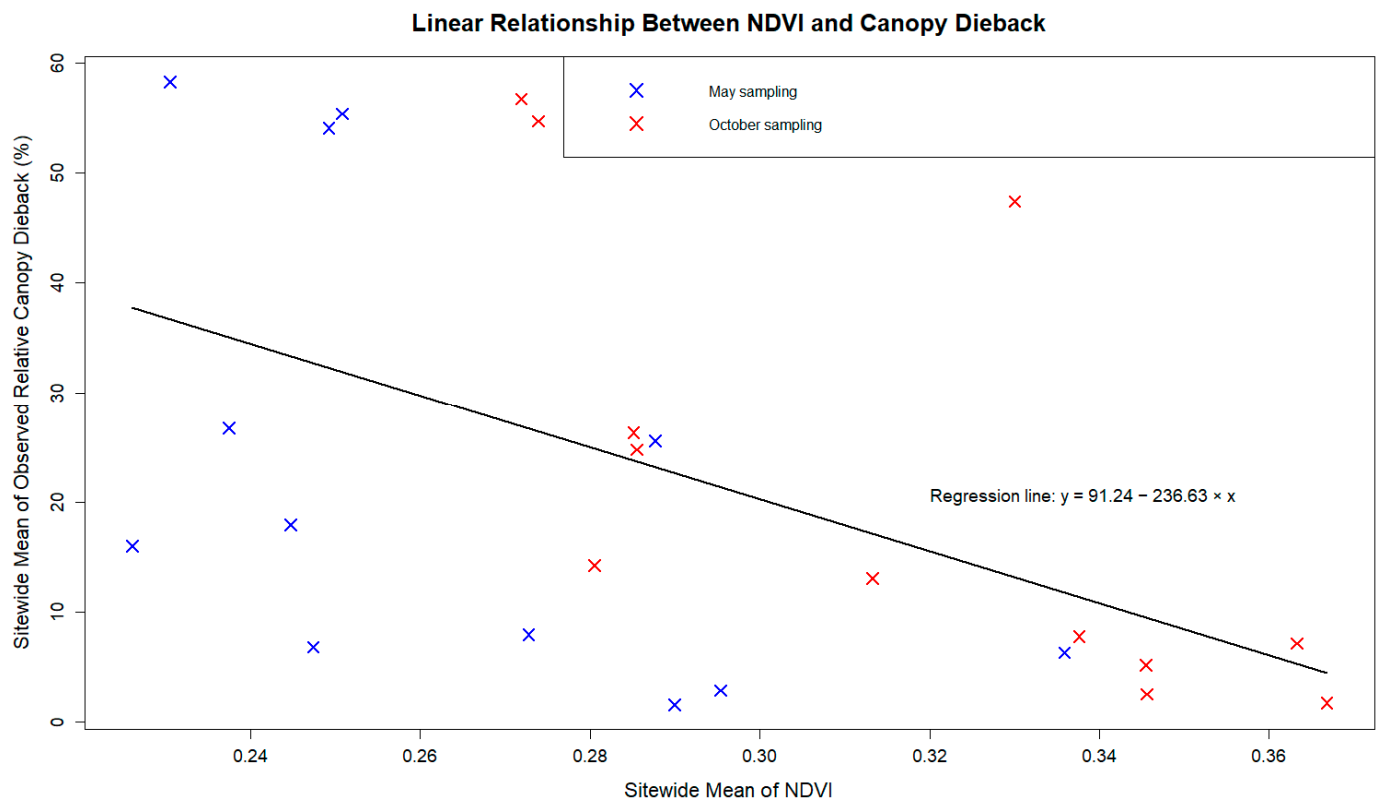


Figure 3. The linear relationship between the sitewide means of relative canopy dieback from Kannenberg et al.'s [8] ground-truthing data, and the sitewide mean of NDVI from the date closest to the site's ground-truthing date.

3.2. The Optimal Modelling Approach

3.2.1. The Improved Efficacy of Beta Regressions Compared to Simple Linear Regressions

The beta regression model indicated a statistically significant negative relationship between sitewide mean NDVI and relative canopy dieback. Specifically, NDVI was a significant predictor of dieback ($\beta = -11.97$, $SE = 4.39$, $z = -2.73$, $p = 0.0064$, $N = 24$), suggesting that higher NDVI values are associated with lower levels of drought-induced canopy damage (pseudo- $R^2 = 0.32$). The model converged after 22 iterations of the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm and two Fisher scoring steps, and precision (phi, hereafter denoted as " ϕ ") was estimated at 5.405 ($SE = 1.533$, $p < 0.001$).

Quantile residuals ranged from -1.78 to 1.80 , indicating acceptable dispersion and no extreme outliers. Together, these diagnostics suggest that the beta regression provided a statistically sound and biologically appropriate model for predicting relative canopy dieback from NDVI.

3.2.2. Species-Specific Disparity in the Mean of Relative Canopy Dieback Observed with Ground-Truthing Data

A Welch Two-Sample t-test was conducted to compare the relative canopy dieback between *P. edulis* and *J. osteosperma* in May. The results indicate a highly significant difference in dieback between the two species ($t(511.55) = -8.58$, $p < 2.2 \times 10^{-16}$). On average, *J. osteosperma* experienced substantially higher levels of canopy dieback (mean = 28.59%) compared to *P. edulis* (mean = 7.99%).

3.2.3. Species-Specific Disparity in the Mean of Relative Canopy Dieback Observed with NDVI

To assess whether species composition improves the modelling of canopy dieback, we fitted a beta regression model that included an interaction between mean NDVI and the proportion of *J. osteosperma* at each site.

In this model, none of the predictors were statistically significant at $\alpha = 0.05$, including the main effects of NDVI ($\beta = -12.07$, $p = 0.504$) and juniper proportion ($\beta = 0.0058$, $p = 0.939$), nor their interaction ($\beta = 0.0746$, $p = 0.763$). Confidence intervals for all coefficients included zero, indicating high uncertainty in their individual effects.

Nevertheless, the model achieved a pseudo- R^2 of 0.54, which is substantially higher than the simpler NDVI-only beta regression model (pseudo- $R^2 = 0.32$). This suggests that including species composition improved the model's overall explanatory power, even if the terms did not meet the threshold for statistical significance. The precision parameter was significant ($p < 0.001$, $\phi = 7.135$, $SE = 2.052$), indicating stable residual dispersion. The estimated coefficients for the predictors are summarised in Table 3.

Table 3. Beta regression predictor performance metrics.

Predictor	Estimate	Std. Error	z value	p value
Intercept	0.267	5.651	0.047	0.962
Mean NDVI	−12.069	18.058	−0.668	0.504
Junipers' Proportion in Site	0.006	0.075	0.077	0.939
Mean NDVI $\times$ Proportion of Junipers in the Site	0.075	0.247	0.302	0.763

Taken together, these findings suggest that while species composition may not significantly modulate NDVI-dieback relationships in this dataset, incorporating it improves the model's performance. This implies a potential benefit to including ecologically relevant covariates, such as species ratios, when using NDVI to predict drought-induced canopy dieback at landscape scales.

3.3. Species-Specific Relative Canopy Dieback Does Not Significantly Improve Model Performance

Given the previously established discrepancy in drought-induced canopy dieback between *J. osteosperma* and *P. edulis*, we tested whether species-specific modelling would enhance the performance of NDVI-based predictions. To this end, two additional beta regression models were constructed: one to predict relative canopy dieback in *J. osteosperma* and one for *P. edulis*, each using mean NDVI, juniper proportion, and their interaction as predictors. These were compared to the earlier model predicting sitewide mean dieback across both species combined.

None of the three models yielded statistically significant coefficients for their predictors at the $\alpha = 0.05$ level. In the combined-species model, the interaction term between NDVI and juniper proportion was not significant ($\beta = 0.075$, $p = 0.763$), and the main effects of NDVI and juniper proportion were also non-significant ($p = 0.504$ and $p = 0.939$, respectively). Similarly, in the juniper-only model, neither NDVI ($\beta = -11.81$, $p = 0.515$) nor the interaction ($\beta = 0.051$, $p = 0.838$) contributed significantly. The piñon model also lacked significant effects, including the NDVI predictor ($\beta = -23.74$, $p = 0.275$) and interaction term ($\beta = 0.394$, $p = 0.195$).

However, model performance metrics showed notable differences across models. The combined-species model had the highest pseudo- R^2 value (0.54), suggesting a moderate degree of explained variance. The juniper-only model had a pseudo- R^2 of 0.40, while the piñon-only model had the lowest explanatory power (pseudo- $R^2 = 0.072$). Log-likelihood

values followed a similar trend: 18.98 (combined), 14.13 (juniper), and 59.19 (piñon). Although none of the species-specific models outperformed the combined model in terms of pseudo- R^2 , the juniper-only model achieved a residual distribution and convergence behaviour comparable to the combined-species model, with a significantly estimated dispersion parameter ($\phi = 5.98$, $p < 0.001$).

3.4. The Predictive Power of NDVI and an Assessment of Canopy Regreening

To determine whether NDVI can serve as a reliable predictor of drought-induced canopy dieback over time, we ran a sequence of beta regression models linking ground-truthed sitewide mean relative canopy dieback (recorded in May 2019) to temporally binned NDVI values averaged across 10-day intervals from July 2016 to September 2023. Each model included an interaction term between NDVI and juniper proportion to account for species-level variation in dieback response.

The results show that the relationship between NDVI and observed canopy dieback was statistically significant across nearly the entire time series (Figure 4). Specifically, most models returned p values below the conventional $\alpha = 0.05$ threshold (red points), indicating consistent statistical significance. Moreover, pseudo- R^2 values (blue points) remained largely above 0.5 throughout the seven-year interval, suggesting strong explanatory power in nearly all temporal windows.

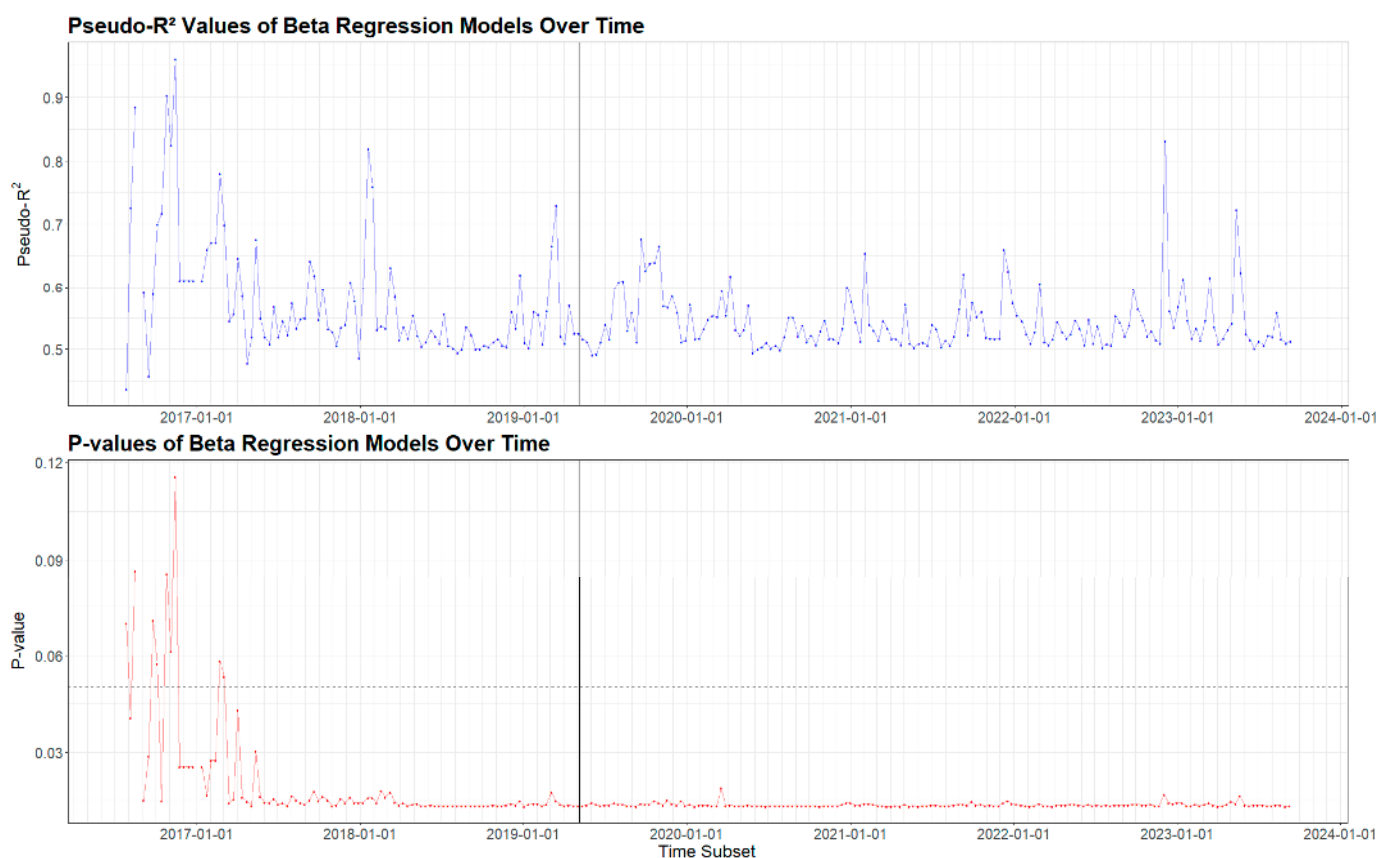


Figure 4. This chart illustrates the ability of satellite remotely sensed NDVI to predict the sitewide mean of canopy dieback, whilst accounting for the proportion of *J. osteosperma* present, as temporal distance from the ground-truthing date increases. Each point represents a beta regression model of a given temporal interval (the mean of mean sitewide NDVI was calculated for each 10-day interval for each site), and the sitewide mean of relative canopy dieback observed during the May ground-truthing. The black dashed horizontal line at $p = 0.05$ indicates the threshold for statistical significance. The vertical black line indicates when ground-truthing data were collected.

Figure 5 illustrates our predictions of relative canopy dieback at the level of our fieldsites throughout the same temporal intervals as above. It indicates that relative canopy dieback fluctuates in accordance with the seasons, forming yearly cycles with similar peaks and troughs throughout our study period. Notably, within each regional field site cluster (e.g., AR1, AR2, AR3, and AR4), all the field sites exhibit a marked disparity in the severity of sitewide mean relative canopy dieback, but a temporally aligned and similar intensity of seasonal fluctuations in sitewide mean relative canopy dieback. This may indicate that predictions of relative canopy dieback are not strongly spatially autocorrelated in this ecosystem.

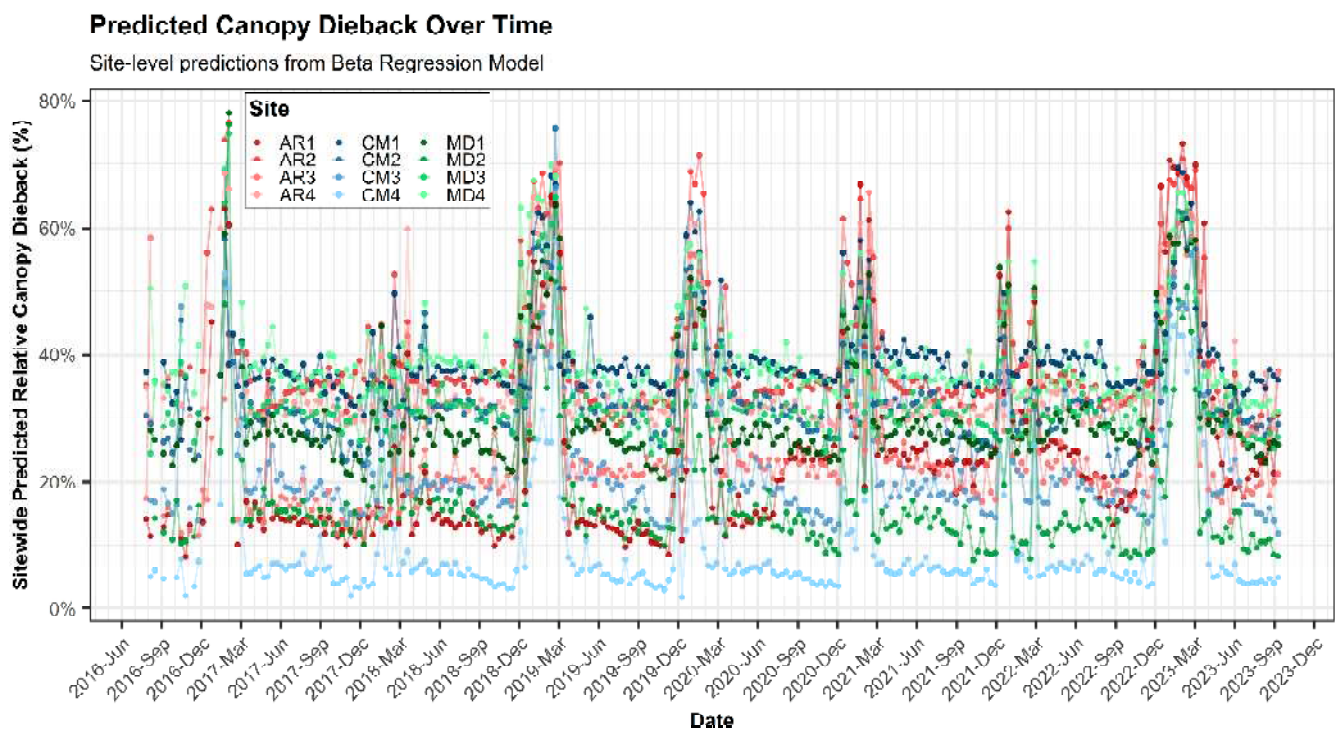


Figure 5. Predicted relative canopy dieback (%) over time for 12 piñon-juniper woodland field sites in southeastern Utah. Values were predicted using a beta regression model with NDVI and species composition (juniper proportion) as interacting predictors. Each point represents a 10-day time interval, with lines connecting values within each site to illustrate trends. An interactive and scalable version of this figure is available in this project's associated GitHub repository, and as a separate downloadable file in the Supplemental Files section of the article's webpage.

3.5. Our Forest-Wide Prediction of Relative Canopy Dieback

To evaluate whether NDVI and other remotely sensed indices can predict relative canopy dieback beyond the originally sampled sites, we trained a spatial random forest regression model on May and October 2019 data from 12 ground-truthed sites ($N = 24$ observations). The best-performing model, selected via grid search, incorporated raw spectral reflectance bands (blue, green, red, and NIR) and five vegetation indices (NDVI, GNDVI, EVI, SAVI, and MSAVI2). Model performance metrics indicated strong predictive capacity, with an out-of-bag R^2 of 33.48% and out-of-bag RMSE of 16.65. Residual diagnostics confirmed normality (Shapiro-Wilk $W = 0.967$, $p = 0.5986$) and no spatial autocorrelation (Moran's $I = 0.058$, $p = 0.179$).

The final model was then applied to a grid of pseudo-field sites across a subset of San Juan County's piñon-juniper woodlands. This area, ecologically similar to the original sampling sites, allowed for robust spatial upscaling. The overall distribution of sitewide means of relative canopy dieback for all pseudo-sites is illustrated in Figure 6. Predicted sitewide mean relative canopy dieback values ranged from 5.11% to 53.97%,

with a mean of 23.98% ($SD = 8.75\%$). The interquartile range ($IQR = 7.53\%$) indicates moderate spatial variability in predicted dieback, while a coefficient of variation of 0.36 reflects a substantial spread in canopy condition across the region. Notably, the most frequently predicted value was 25.64%, aligning closely with the median. This and Figure 6 indicate a clear, unimodal distribution skewed toward moderate dieback levels.

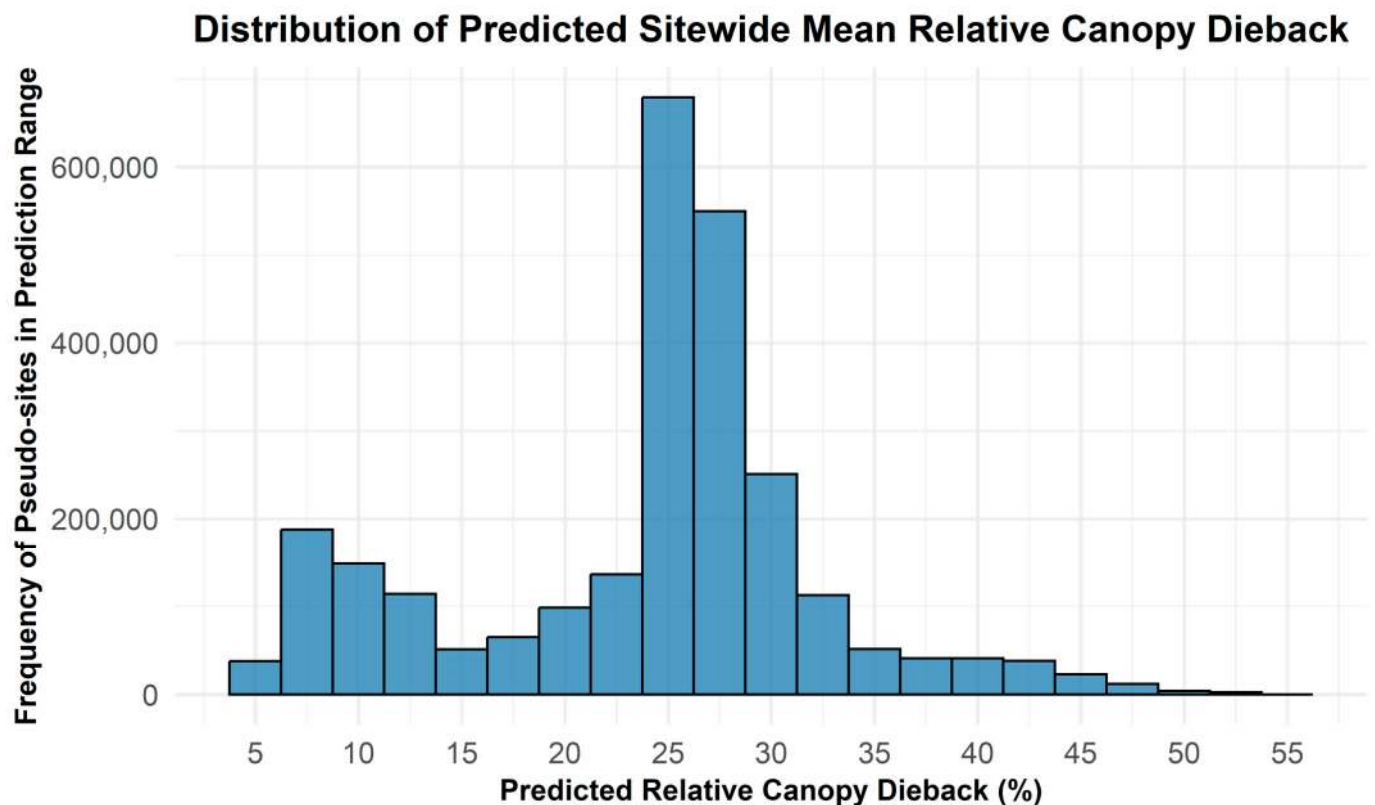


Figure 6. Distribution of predicted sitewide mean relative canopy dieback across pseudo-field sites within a subset of the piñon-juniper woodlands in San Juan County, Utah. Predicted values were generated using a spatial random forest regression model trained on ground-truthed data from May and October 2019 [8]. The model incorporated raw spectral reflectance values (red, green, blue, and NIR) and vegetation indices (NDVI, GNDVI, SAVI, MSAVI2, and EVI) derived from PlanetScope satellite imagery. Dieback predictions were aggregated across hexagonal pseudo-sites spanning an ecologically comparable piñon-juniper woodland.

A map of predicted relative canopy dieback (Figure 7) revealed clear spatial gradients, with certain areas consistently exhibiting higher predicted dieback. These results support the model's utility for extrapolating local field-based observations across broader landscapes using remotely sensed vegetation data.

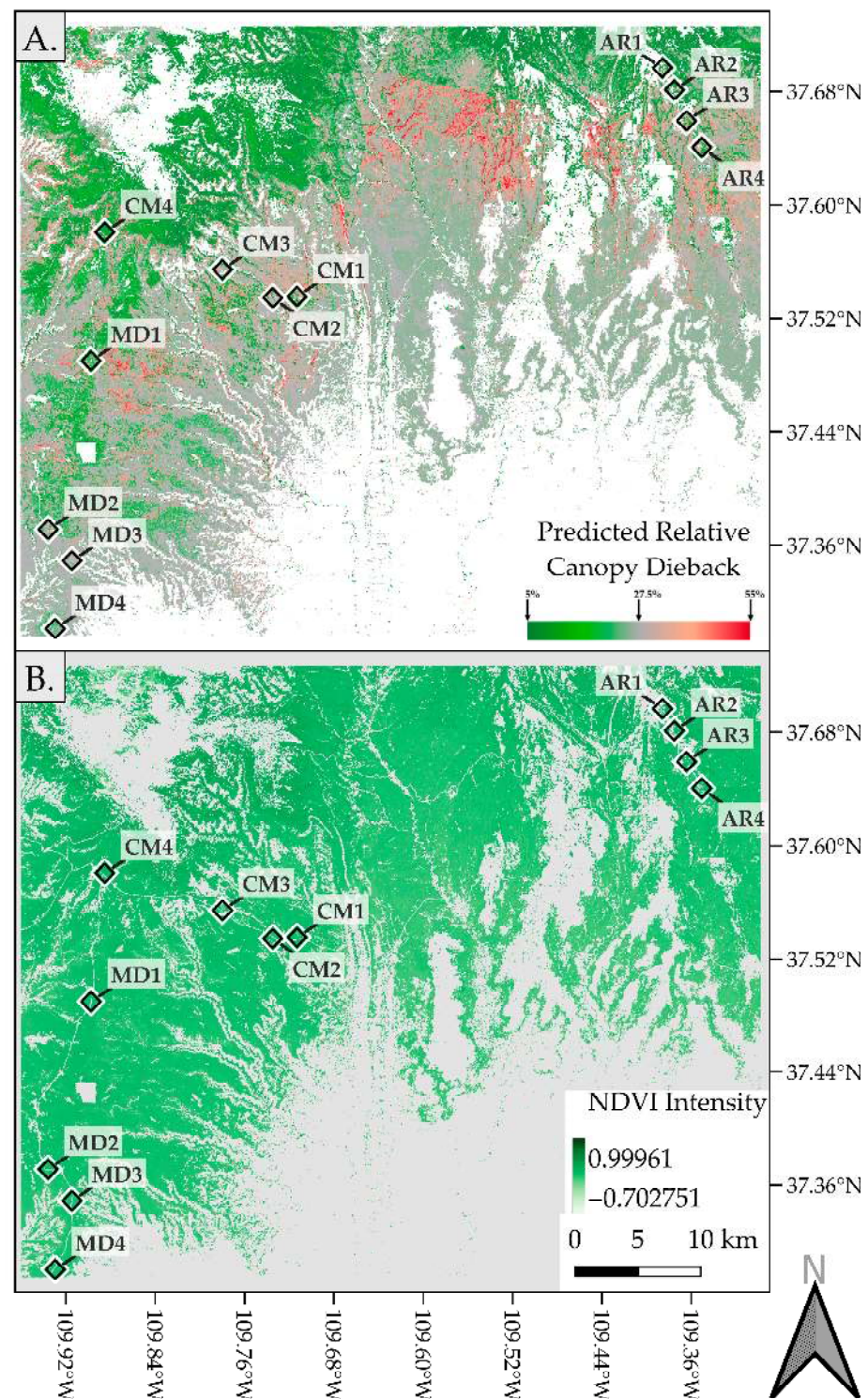


Figure 7. Spatial predictions of sitewide mean relative canopy dieback across pseudo-fieldsites in southeastern Utah. (A) This map shows our predicted canopy dieback values generated by a spatial random forest regression, overlaid on a pale blue background. Each hexagonal pseudo-fieldsite represents a prediction unit, with dark green tones indicating lower predicted dieback, grey tones indicating moderate predicted dieback, and dark red indicating higher predicted dieback levels. The model was trained on ground-truthed data from 12 sites sampled in 2019 and includes both raw spectral reflectance and vegetation indices as predictors. The mapped area corresponds to a piñon-juniper woodland ecosystem, comparable in heterogeneity and composition to the original field sites (which are labelled in white). (B) This map shows the varying NDVI intensity of the piñon-juniper woodlands in the studied area. Each pixel is a 9 m² area of the forest.

4. Discussion

This study set out to investigate the potential of using satellite-derived vegetation indices, specifically NDVI from PlanetScope imagery, to detect and predict drought-induced canopy dieback in piñon-juniper woodlands of southeastern Utah. By aligning remote sensing data with field-verified defoliation metrics, we sought to answer four core research questions:

1. Whether NDVI can detect patterns of recent canopy dieback,
2. How different modelling approaches can maximise inferential ability,
3. Whether accounting for species composition enhances predictive accuracy, and
4. Whether spatially/temporally upscaled predictions of relative canopy dieback are effective with these data.

These questions are increasingly relevant as climate-driven disturbances become both more frequent and severe [6,7]. Our findings elucidated the potential of PlanetScope data as a tool to monitor the health of forests, particularly when constrained by ground-truthing data availability, sensor resolution, and the complex interactions between spectral signals and species-specific drought responses. The following sections sequentially discuss the implications of this research for each objective, contextualising the results in light of broader ecological monitoring efforts and highlighting key implications for future research and remote sensing applications in forest ecosystems.

Although NDVI is already a well established proxy for forest health [12], this requires empirical revalidation for every environment it is used in. Since each forest ecosystem is unique, confounding environmental variables, such as understory vegetation or changes in the weather, have the potential to obfuscate the relationship. Thus, our initial assessment establishes a baseline, and also facilitates comparisons with other datasets.

Our results nevertheless made clear that there is a significant explanatory relationship between the mean of sitewide relative canopy dieback and NDVI, as indicated by our linear regression's significant p value (for the model overall, $p = 0.013$, $N = 24$). Despite establishing a clear relationship between the sitewide means of canopy dieback and NDVI, the low R^2 of the relationship ($R^2 = 0.25$) indicates that this somewhat simplistic approach can only describe a small amount of observed variation, so the inferential power of this relationship is limited.

We contend that this is likely due to confounding variables which were not included in this preliminary model, such as the bimodal distributions of relative canopy dieback for each species (*J. osteosperma*'s mean and range of relative canopy dieback were both larger than for *P. edulis*, see Table 2) or the absence of meteorological data (the ecosystem had experienced a drought in the years prior to ground-truthing). Furthermore, though we have established the relationship between the means of sitewide relative canopy dieback and NDVI, we lacked the necessary data to establish the relationship between this and absolute sitewide defoliation. Basing our analyses upon a relativistic value may have limited the subsequent results' explanatory power as relative dieback values likely deviate from the theoretical value of absolute sitewide defoliation. However, Kannenberg et al.'s [8] ground-truthing approach was an efficient approach to sample many trees and infer the health of forest stands thereof, and has been used by others studying this ecosystem [31]. Since measuring relative canopy dieback is already established in studies of this ecosystem, we assert that it remains a relevant metric for use in related research like ours, and justifies our decision not to resample the ecosystem to gain an absolute measure of defoliation.

The first amendment to our modelling approach was to use a beta regression model instead of an OLS linear model. As the dependent variable in our analysis (the mean values of sitewide relative canopy dieback) is bounded, our *a priori* prediction was that a beta

regression model would be more effective at characterising the relationship between the mean values of sitewide relative canopy dieback and NDVI [40]. As previously stated, a field site can never have relative canopy dieback exceeding 100%, or less than 0%, although linear modelling does not account for this biological reality. In contrast, our beta regression was able to explain a greater proportion of the variation observed in our dataset, yielding a modest improvement in explanatory power (pseudo- $R^2 = 0.32$). This reinforces Geissinger et al.'s [40] assertion that bounded data can be modelled better by beta regressions.

Our t-test confirmed that *J. osteosperma* experienced more severe canopy dieback than neighbouring *P. edulis*. To account for potential noise from these mixed-species stands, we incorporated the proportion of *J. osteosperma* at each site into our models. This substantially improved performance (pseudo- $R^2 = 0.54$), indicating that accounting for species composition enhances predictive accuracy. However, when modelling species-specific dieback, performance declined. Neither model met the threshold for statistical significance, and pseudo- R^2 values decreased. These results suggest that, within the constraints of our dataset, modelling species separately does not necessarily improve predictive power over combined-species models. The marginally better fit of the juniper-only model compared to the piñon-only model implies that *J. osteosperma* dieback may be more strongly linked to NDVI-based canopy structure signals, perhaps stemming from its lower drought tolerance. Ultimately, given the equivocal benefits of species-specific modelling, we retained the combined-species approach in subsequent analyses while continuing to include *J. osteosperma* proportion as a covariate.

The relationship between NDVI and sitewide mean values of relative canopy dieback broke down prior to the reported drought-induced defoliation (see Figure 4). As PlanScope data were less consistently available in 2016 and 2017, many of the models were constructed with incomplete satellite coverage of the field sites, thereby reducing the representativeness of the data used in model development, and the models' subsequent decrease in reliability. Alternatively, it may indicate that the canopy structure of the field sites had changed so substantially after the drought-induced defoliation event, that the prior state of the canopies could not be modelled using post-defoliation ground-truthing data. As our results (Figures 4 and 5) did not indicate a clear pattern prior to the drought-induced defoliation event, we therefore cannot use the sitewide mean values of NDVI to predict a future mass defoliation event in the study area examined.

However, these findings do indicate that the sitewide mean values of NDVI can be used to assess the contemporaneous state of the canopy, and that a single ground-truthing campaign can remain useful to predict relative canopy dieback multiple years after the initial ground-truthing campaign, even accounting for seasonal fluctuations in foliage (see Figure 5). Furthermore, the sustained statistical significance of these models over time suggests that the sitewide mean values of NDVI can be used to assess defoliation and monitor regreening in this piñon-juniper ecosystem. As previously postulated, if the canopy structure of our field sites had been substantially altered by the dieback event recorded in 2017 to 2018, then this may explain why our approach remains viable many years after the initial ground-truthing campaign. Inspection of Figure 5 indicates that relative canopy dieback has neither increased nor decreased overall since ground-truthing was conducted, implying that substantial regreening has not occurred. Thus, the models' predictive power remains because the canopy structure is generally unchanged. Perhaps when the 2019 ground-truthing data and the contemporaneous sitewide mean values of NDVI become unable to predict sitewide means of relative canopy dieback, it will be indicative of either substantial regreening or further mass diebacks having taken place. In Kannenberg et al.'s [8] discussion, they posed the question 'Is this a one-time dieback event [...], or the start of a widespread disappearance of low elevation piñon-juniper woodlands?'

The absence of detected canopy regreening suggests the latter, with the notable caveat that previous studies found that the piñon-juniper woodlands can take decades to recover from drought [43]. Whether they have this time to recover will largely depend on our ability to halt, or at least mitigate, the effects of climate change.

Our findings also highlight both the strengths and current limitations of optical satellite indices for assessing canopy dieback. While PlanetScope-derived NDVI was effective for site-level upscaling, the inability of optical imagery at this resolution to resolve individual crowns or species-specific dynamics constrains ecological inference. Recent advances in remote sensing offer potential avenues to overcome these limitations. Drone-based photogrammetry and Light Detection And Ranging (LiDAR) are increasingly capable of tree-level crown delineation, mortality detection, and above-ground biomass detection [25,31,44,45], although this can add substantial cost and complexity. Emerging satellite-based platforms, including Synthetic Aperture Radar (SAR), can penetrate canopy layers and provide structural information that complements optical indices [19]. Measurements of NDVI signal are susceptible to interference from soil [46]. Therefore, whilst we unequivocally assert the veracity of the inferences presented in this study, we suggest that the inclusion of some of these additional technologies with our approach to yield higher fidelity assessments of drought impacts, and enable clearer modelling of the relationships of the canopy structure's drought response. Cost-conscious researchers and forest managers should explore hybrid workflows that combine moderate-resolution optical indices like ours with pre-existing canopy height models and digital elevation models to better capture species-specific and demographic forest responses to drought [25].

We further determined that our map of predicted dieback amongst piñon-juniper woodlands of south-eastern Utah has meaningfully described the patterns of relative canopy dieback, despite some limitations. Notably, even though Campbell et al.'s [31] study used Sentinel image data from October (our PlanetScope image data was captured at the end of May), our model's predictions are broadly concordant with theirs. For example, our model also predicted that the most severe defoliation was clustered in relatively small areas, such as in the woodlands surrounding and east of Blanding, Utah, and also in the woodlands surrounding site CM1 (see Figure 7) (Campbell et al. [31] also identified a 3rd canopy dieback hotspot, although it is situated outside of our study area). However, Campbell et al. [31] predicted that most of the forest outside these pockets of severe relative canopy dieback were minimally affected. In contrast, our model predicted a higher average value of relative canopy dieback overall (see Figure 6). This may be explained by two factors: the propensity of the model used in Campbell et al. [31] to somewhat underestimate relative canopy dieback, or (as illustrated in Figure 5) the cyclical pattern of predicted relative canopy dieback to be higher at the end of spring, before decreasing as the summer continues.

However, our spatially upscaled predictions include some artefacts stemming from the satellite imagery. Despite PlanetScope data undergoing a standardisation and quality assurance process prior to publication [32], a small stripe at the north-western edge of the map appears darker than the rest of the map, without any apparent environmental explanation. Commensurately, the predicted relative canopy dieback in this area is much lower, which we consider unlikely to reflect reality. Although our model performance is considerably lower than Campbell et al.'s [31], it has still produced results which are broadly concurrent with those produced by the subset of Campbell et al. [31] which we compared it to, with the benefit of substantially reduced cost, commitment, and complexity involved.

Nevertheless, the results of our spatial upscaling highlight an interesting direction for further research. As our map of predicted canopy dieback also identified the defoliation hotspots Campbell et al. [31] found, we contend that these hotspots require examination.

The tree stands in these hotspots may have additional burdens affecting their response to drought stress, such as a localised outbreak of bark beetles [47], or the presence of a microclimate which prior to European colonisation of the Americas, would not have supported infilling by piñon-juniper woodlands [43,48]. Further study of these dieback hotspots may therefore shed light on the root cause of the ‘rapid and surprising’ canopy dieback observed by Kannenberg et al. [8].

The apparent preference of *P. edulis* saplings to germinate in shade [49] leads us to question how the identified canopy dieback hotspots might affect ecosystem succession. Gottfried [49] explained that in areas being newly colonised or infilled following an ecosystem disturbance, junipers often establish first, creating the shaded microhabitats that later facilitate piñon recruitment. However, the relatively higher mortality of *J. osteosperma* observed during this drought raises uncertainty over whether this pattern will continue. Increased juniper dieback not only reduces canopy cover, but also elevates ground-level temperatures, diminishes available shade, and may promote the expansion of grasses at the expense of *P. edulis* regeneration. These dynamics raise the possibility that canopy dieback hotspots could shift towards juniper-dominated stands, but equally that they might become increasingly open, grassy areas prone to further disturbance. These unknowns identified by our study prompt further research to elucidate the next chapter of the piñon-juniper woodlands’ continually fluctuating ecosystem succession story [48].

Importantly, the accumulation of dead woody material and leaf litter, with an expanded, potentially grassier understory, likely increases the local fire risk [43]. For this reason, areas identified as dieback hotspots warrant particular attention from land managers, as they also represent critical zones of ecological transition where successional trajectories, regeneration potential, and disturbance regimes are actively being reshaped by drought legacies.

Beyond methodological considerations, we reiterate that our approach demonstrates a compelling value proposition for cost-conscious conservationists and land managers needing to monitor forest health. Whilst drone-based photogrammetry and LiDAR surveys produce superior detail and facilitate more complex modelling approaches [25,31,44,45], their logistical and financial demands often limit their practicality outside well-funded and staffed research programmes [50]. By contrast, our use of widely available PlanetScope imagery combined with modest ground-truthing demonstrates that robust inferences about canopy dieback can be generated with relatively little labour or expense. Our approach is particularly relevant for semi-arid, open-canopy systems globally, such as woodlands and savannas in African countries wherein the economic trade-offs between protecting forests through conservation programmes and extracting forest resources is already much starker and unevenly felt [51–53]. In these contexts, the ability to detect canopy stress and track regreening dynamics at broad scales could provide critical information for adaptive management, fire risk assessment, and conservation planning. Whilst local calibration is essential, our results suggest that a modest ground-truthing campaign combined with just PlanetScope image data inexpensively provides a sufficient framework to monitor large woodlands, and precisely identify and respond to areas of greater concern.

5. Conclusions

This study demonstrates that remotely sensed vegetation indices, particularly NDVI derived from high-resolution PlanetScope imagery, can meaningfully predict relative canopy dieback in piñon-juniper woodlands affected by drought, even when using a ground-truthing dataset multiple orders of magnitude smaller than the upscaled predictions derived from it. Though the ecological utility of NDVI is well established, its performance in tracking relative dieback, a metric influenced by intra-site variation and species

composition, was not a given. That our models consistently captured this relationship strengthens confidence in NDVI as a scalable proxy for canopy stress in semi-arid systems.

Incorporating the proportion of *J. osteosperma* improved model performance, highlighting the bimodal species-specific responses to drought. However, species dominance alone is insufficient to wholly predict canopy outcomes across drought cycles. For instance, the cause of *J. osteosperma*'s markedly more severe dieback remains unknown, nor do we know why *P. edulis* was the species to experience more severe dieback during the early 2000s drought. Whilst these confounding drought responses are still equivocally explained, another future forest disturbance could confound our model. Thus, further research into the physiological responses of trees to drought could improve our ability to model forest health, and additional data, such as forest-wide microclimate characterisation, could inexpensively improve modelling performance in the future.

The ability to extrapolate dieback predictions across large spatial extents with high fidelity, despite the use of just 24 ground-truthed observations, underscores the power of spatial machine learning approaches. Nonetheless, while our results suggest that relative dieback levels have remained stable in recent years, this should not be interpreted as an ecological recovery. Stability in NDVI-derived metrics does not capture potential delayed mortality or broader functional impacts on regeneration, faunal habitat availability, or soil biotic integrity. These remain unknown and warrant further study.

Finally, our findings point to an important limitation in current satellite remote sensing workflows: the inability to resolve individual tree crowns constrains the ecological resolution of defoliation assessments. Drone-derived RGB images are already suitable for tree crown delineation using photogrammetry and machine learning is already yielding interesting new datasets for more granular analysis of forests. Future efforts such as satellite based SAR may achieve more accurate, species-specific, and demographically resolved forest health monitoring.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs17193323/s1>.

Author Contributions: Conceptualisation, E.S.S. and D.Z.; methodology, E.S.S. and D.Z.; software, E.S.S.; validation, E.S.S.; formal analysis, E.S.S.; investigation, E.S.S.; resources, E.S.S.; data curation, E.S.S.; writing—original draft preparation, E.S.S.; writing—review and editing, E.S.S. and D.Z.; visualisation, E.S.S.; supervision, D.Z.; project administration, E.S.S. and D.Z.; funding acquisition, E.S.S. and D.Z. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: A GitHub repository sharing the R script we used and some exemplar data to demonstrate our workflow was established. You may access it from: <https://github.com/Samuel-Green/PlanetScope-Upscaling.git> from the 23/09/2025, 2025 onwards.

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conducted, and assistance in drafting the published text. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

In our research, we considered a variety of different vegetation indices, before proceeding with NDVI for our parametric tests. This is because NDVI is a very widely used and understood index [54], whilst also being almost as performant as our top performing index, SAVI. We tested each index by running a beta regression between the sitewide mean value of each index and the sitewide mean values of relative canopy dieback, akin to Equation (3). Full performance figures of each tested index are presented below in Table A1.

Table A1. Summary of beta regression model performance for different vegetation indices tested as predictors of sitewide mean canopy dieback. Reported metrics include Pseudo- R^2 , p values for the predictor term, coefficient estimates, and model log-likelihood. Indices are ordered by model performance, with NDVI, SAVI, and MSAVI2 showing the strongest explanatory power.

Index	Pseudo- R^2	p value	Estimate (X)	Log-Likelihood
SAVI	0.3160	0.00639	−7.996	15.94
NDVI	0.3154	0.00637	−11.97	15.93
MSAVI2	0.3129	0.00652	−9.97	15.91
EVI	0.2799	0.0159	−5.19	15.33
GNDVI	0.2082	0.0232	−9.99	14.78

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