Quantifying the Effects of Environmental Covariates on Leaf Area Index (LAI) in Riparian Reforestation in Western Oregon, USA

by

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THESIS ABSTRACT

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Title: Quantifying The Effects of Environmental Covariates on Leaf Area Index (LAI) in Riparian Reforestation in Western Oregon, USA

Riparian reforestation projects are projected to have high potential for increasing Leaf Area Index (LAI) after planting, but this benefit is not yet well quantified. Riparian forests are adjacent to a stream, wetland, lake, or other body of water. These areas have an abundance of ecosystem services, such as providing habitat and corridors to wildlife, filtering water, stabilizing streambanks, and providing shade and cooling for the adjacent water body. Western Oregon, USA contains an array of river systems surrounded by riparian habitat within temperate forest ecosystems, but many of these forests have been historically degraded. To restore some of these degraded ecosystems, over 2,000 riparian reforestation plantings have occurred in Oregon since 1995 to achieve goals such as providing wildlife habitat, streambank stability, and mitigating water temperature. Measuring the LAI outcomes of these projects can improve strategies for maximizing leaf output as a co-benefit in future plantings. We hypothesize that a combination of edaphic, climatic, geomorphic, and stand properties can be used to predict the LAI values from riparian plantings over time and space. To understand reforestation trajectories, we measured LAI using Digital Hemispherical Photography (DHP) at 37 riparian sites in western Oregon, which ranged in their environmental and planting conditions. Using these measured values, we created linear regression models to predict LAI values across the most significant predictor variables. Our models predict that both total LAI and canopy LAI increase with years since planting, proximity to streambank, tree stem density, decrease with fine particle content, with two, three, and four-way interactions, and decrease with slope as an independent effect. A unique set of predictors were important for understory LAI, which increased with understory species richness, distance from streambank, years since planting, lower temperatures, with two, three, and four-way interactions, with stream size as an individual effect. By quantifying the LAI of past riparian reforestation projects and the variables that impact it the most, we can understand strategies to optimize future projects, and therefore maximize their environmental benefits.

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CHAPTER I - INTRODUCTION

Riparian restoration projects are projected to increase leaf area, but predicting the growth rate of the plants within these projects can be difficult because of their different environmental and planting variables at local scales (Parker, 2020). One form of restoration that is commonly used to improve degraded riparian areas is reforestation, a promising natural climate solution that is projected to be an effective strategy to capture carbon from the atmosphere (Marvin et al., 2023; Silva et al., 2022). Riparian reforestation is the conversion of a non-forested area to a forested area within a riparian zone next to a body of water (Graves et al., 2020). Riparian reforestation is a promising strategy in climate change mitigation for its positive impacts on biodiversity, wildlife habitats, erosion control, and stream health (Dybala et al., 2018; Mitchell et al., 2022). Carbon sequestration is a strong co-benefit of reforestation that should be maximized (Dybala et al. 2019). Riparian areas are especially important to study because freshwater ecosystems are less resilient to climate change, so they must be carefully monitored over time (Rusnák et al., 2022). Reforested riparian areas are more resilient to climate change than degraded riparian areas (Peroni et al., 2023). Theoretical models show that riparian reforestation can mitigate annual emissions more efficiently than most other forms of restoration, land management, and avoided conversion, coming second to deferred timber harvest (Graves et al., 2020). Despite this potential for mitigated emissions, there is a lack of empirical evidence quantifying plant growth over time after riparian reforestation.

LAI is a commonly used measurement throughout ecological studies, defined as the total surface area of leaves per unit of ground area (Parker, 2020). Differences in LAI are key to the health of riparian ecosystems, as a high LAI provides shade for the river and upland area, and allows more energy to be captured by the leaf's surface (Hoek van Dijke, 2020). One study located in a tropical rainforest found that open pasture had an average LAI of 1.74, while old growth forests had an average LAI of 5.62 (Tang et al., 2012). LAI quantification includes essential information about the productivity in a forest, and can be compared across different environmental factors between forests. LAI can also serve as a proxy for radiation and rain interception, photosynthesis, respiration, and is an essential variable for recording vegetation-atmosphere interactions (Fang et al., 2019; Rasti et al., 2022). Along with these essential direct ecosystem functions, LAI can also indirectly serve as a proxy for potential carbon storage, which is a method that researchers have used in the past (Naidoo et al., 2019).

LAI can be measured using a variety of methods, including destructive sampling, litter traps, digital hemispherical photography (DHP), and remote sensing (Fang et al. 2019). For the purposes of this study, DHP was used because of its ability to capture detailed images of a small area (Figure 1). Using DHP also allows researchers to have a permanent trace of data, which can be used for future comparisons and analyses (Fang et al., 2019; Chianucci and Cutini, 2012). Many different satellite models are currently used for LAI, but their spatial resolution (pixel size) and temporal resolution (how often the images are taken) can drastically change their outputs. One study found that their remotely sensed data slightly underestimated the LAI values compared to the hemispherical images (Alexandridis et al. 2013). LAI results among satellite-derived products are generally not comparable, leading to significant uncertainty in research outcomes and when comparing across products, especially in broadleaf and shrubland ecosystems (Alexandridis et al., 2013). This can especially be an issue within riparian areas, as they can be so small that they get lost in satellite data if the grain is too large, and the pixels will include other areas of habitat within their data. When delineating the spatial scale of a study, it has been shown the scale should be smaller than the heterogeneity of a landscape so that differing variables can be accounted for (Houghton et al., 2009). These LAI images contain detailed data of riparian habitats, and can help validate other models that have more coarse resolution in future research.

Figure 1. Example of an LAI image taken at a 20 year old planting with low water stress and fine soil texture.

In Oregon, USA, there have been over 2,000 riparian reforestation projects with plantings of native trees and woody shrubs since 1995 (OWEB, 2023). However, the rate of LAI accumulation of these projects has not yet been quantified. **To study reforestation outcomes, we asked: How does the Leaf Area Index of native trees and shrubs within riparian reforestation projects in western Oregon, USA change over time within different planting conditions?** We investigated this question by measuring LAI at riparian reforestation sites across western Oregon, and comparing LAI to 25 covariates within edaphic, climate, geomorphic, biophysical, image, and planting strategy groupings (Appendix, Supplementary table 1). This is the first known study quantifying the LAI of riparian reforestation empirically within western Oregon. With this data, we can inform on how to increase LAI in future riparian reforestation projects, and understand which variables impact it most. The research team for this study includes members of the Soil Plant Atmosphere (SPA) research lab at the University of Oregon and The Nature Conservancy (TNC).

CHAPTER II - METHODOLOGY

Study area/ Site selection

This study was conducted in 37 riparian sites in temperate forests across western Oregon, USA planted on both public and private land. We sampled at both reforested (31) and unplanted reference sites (6), with planted sites being at least 5 years post-planting and 0.5 hectares or larger. To cover a range of soil textures and climates, we focused on the Willamette Valley, Coastal Range, and Klamath Mountain ecoregions. Riparian zones were delineated using various sources including the National Hydrography Dataset (NHD)Plus V2 stream reach network (U.S. Geological Survey, 2022), 20-year floodplain maps (Wing et al., 2017), and 10-digit Hydrologic Unit Codes (HUC) boundaries (Cybercastor, 2024). The sampling design was stratified by soil texture and climate-water deficit, the average 30-year difference between potential and actual evapotranspiration in mm (The Nature Conservancy and Resilient Forestry 2023). Mapped soil texture was gathered from the Natural Resources Conservation Service (NRCS) National Cooperative Soil Survey dataset, and classified based on the NRCS Soil Survey Handbook (NRCS 2017, 2023). This allowed us to group our sites based on their predicted soil texture and climate. We used the Oregon Watershed Restoration Inventory (OWRI) database to locate sites, and obtained landowner permission to sample at the selected sites (Oregon Watershed Enhancement Board, 2023).

For final site selection we aimed to have an even number of sites between fine and coarse soil texture, low (<225mm) and high (>225 mm) water deficit, and within the binned age groups of 0 (control), 5-9, 10-14, 15-19, and 20+ years. We also screened for accessibility factors including distance from access roads, slope, and blackberry cover. To be able to randomly select three circular plots with an 8 meter radius at each site, we only selected sites with a minimum planting width of 16m. The sampled sites represented a diversity of riparian habitats in western Oregon, ranging from small creeks on farm properties to large areas of protected forest along major rivers (Figure 2).

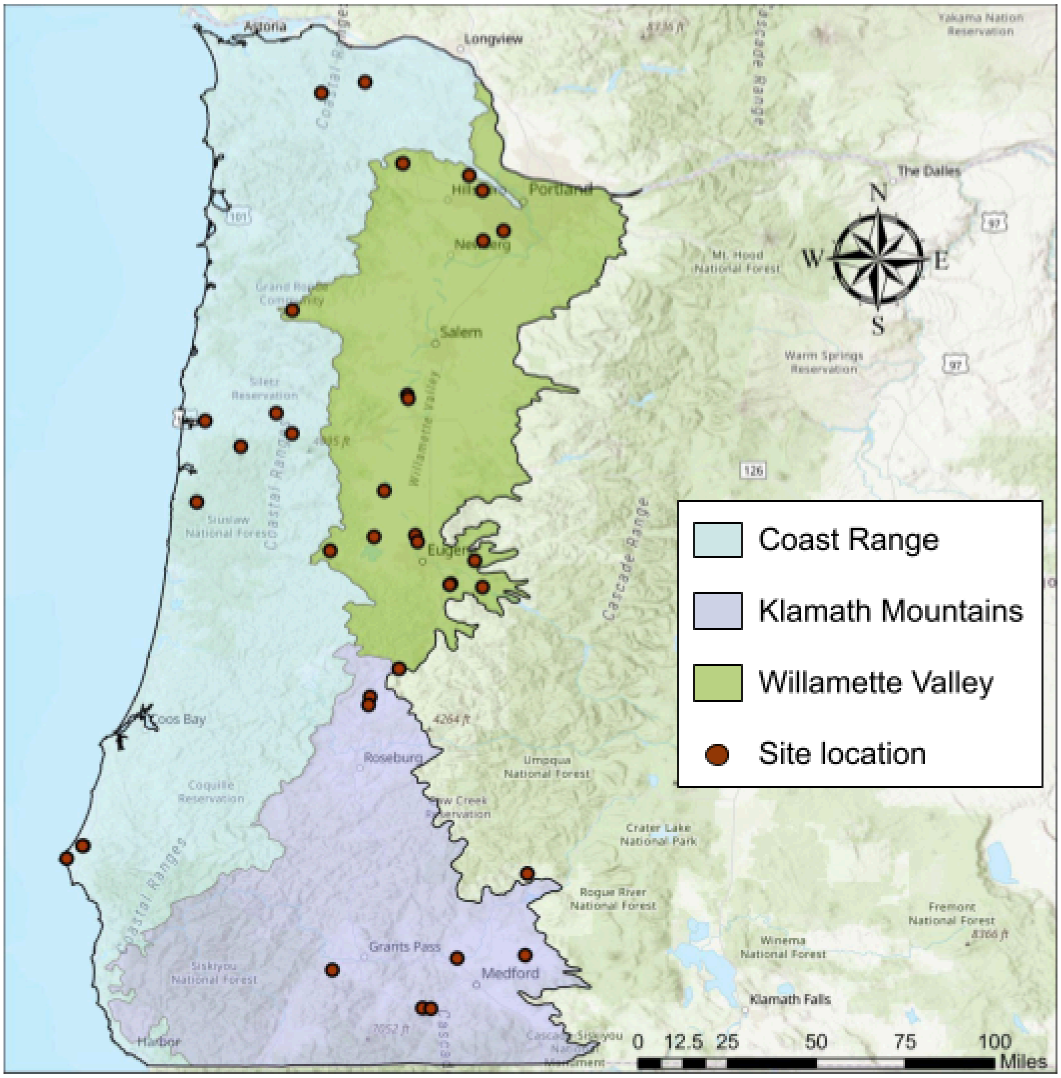

Figure 2. A map of western Oregon showing the Coast Range, Klamath Mountain, and Willamette Valley EPA level 3 ecoregions in three different colors, along with the site locations. Site locations represent riparian reforestation sites where LAI measurements were taken. ArcGIS Pro, 2024. Scale: 1: 2,206,676 Spatial reference: WGS 1984.

Data collection

At each site we randomly selected three circular plots, each with an 8 meter radius. We quantified LAI by taking images of the riparian canopy from below with a Nikon Coolpix 4500 camera and a fisheye converter lens, at each plot center and its adjacent streambank. We captured 4 images per plot and 12 per site (Figure 3). At each photo point, the images were taken with the camera facing north with the lens facing directly upwards at two different lens heights of 0.7 and 1.24 meters. The lower height allowed us to capture the forest understory, as many of the sites had shorter vegetation from both young plantings and shrubs. For soil texture analysis, two soil samples were taken at two random azimuths 8 meters from each plot center, and the two samples were homogenized. These samples were taken at depths up to 45cm, in three 15cm increments. To gather species richness and density data (stand variables), we identified and measured the volume of every plant with a DBH > 5cm within each plot. For plants with a DBH < 5cm, every shrub > 15 cm tall or tree > 1.3 m tall was recorded within 4m of the plot center.

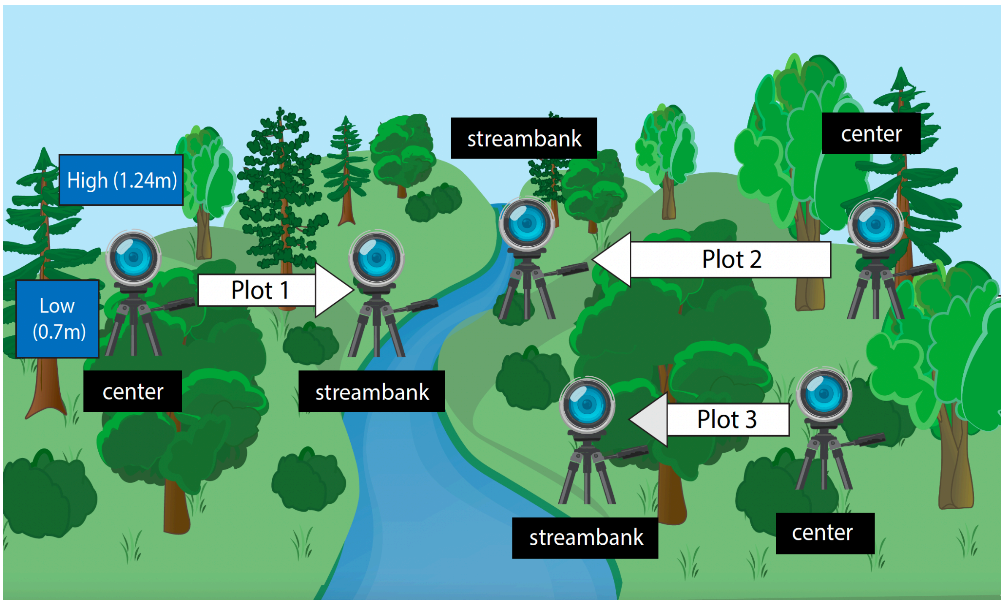

Figure 3. LAI image taking sampling scheme at each sampled site for the riparian reforestation survey. Each site contained three plots where images would be taken, at high and low heights at two locations within each plot (center and streambank). (Adobe Inc., 2025).

LAI editing

The methods used for editing and analyzing LAI are adapted from the State of Washington Department of Ecology Standard Operating Procedure (Stohr, 2019). Images were edited in Adobe Photoshop to ensure strong contrast between sky and vegetation pixels before analyzing. Of the initial 424 DHP images taken, 43% of them needed manual editing because of flaws such as bright sunspots, glare, front lit vegetation, man made structures, and other influencing factors. After editing, we binarized the images into black and white pixels, where black pixels are vegetation, and white are sky, and then performed analyses to calculate the LAI and canopy cover % using Gap Light Analyzer (GLA).

Soil texture analysis

Soil samples were dried in an oven directly after being brought back from the field, and sieved through a 2mm sieve once dry. Soil texture was analyzed using the adapted pipette method (Burt R Soil Survey Staff, 2014). This allowed us to use the natural settling times of sand and silt particles to get the percentages of sand, silt, and clay, and place our sites into soil texture classes.

Data analysis

We analyzed the resulting LAI data in RStudio (R Core Team, 2025), to see how the chosen environmental predictors influenced the LAI values. We first did exploratory analysis by using correlation tests to see where the significant paired correlations were within the data using the ggpairs function in GGally (Schloerke et al., 2024), and a Pearson correlation test to show the statistics along with the correlation values. We did not include predictors that were strongly correlated ($R > 0.7$) in the same model to avoid multicollinearity (Akoglu, 2018), and studied which predictors were highly correlated with the response variable to test first in our models. Some other initial data exploration revealed that the canopy and understory fractions of LAI were correlated with different predictors, therefore LAI was separated into total, canopy, and understory bins for three separate models. Canopy LAI was taken from the high DHP images (1.24m lens height), total from the low images (0.7m lens height), and understory LAI was calculated from subtracting the high image LAI value from the low image value, to leave a ring of understory data. Each model was checked for normality and was found to not be normally distributed when looking at its residuals, due to the model being zero inflated from the control sites. We therefore used a Tweedie distribution (Dunn, 2022) to improve model normality, since this distribution works with zero inflated models. We centered and scaled the data, and then used the glmmTMB RStudio package (Brooks et al., 2017), to perform linear mixed effects models with plot nested within site as a random variable, and multiple climate, edaphic, planting strategy, and geomorphic variables as fixed effects. For model building, we used forward selection and checked for decreased model AIC with each added effect, using a decreased AIC of 2 or more as a significant improvement of the model (Burnham and Anderson, 2002). After each added effect, we checked its significance, the significance between interactions, and checked for multicollinearity.

CHAPTER III - RESULTS

Distribution of sites

We found that our sites generally fell into the category of siltier sand, rather than falling equally around the spectrum of possible textures (Figure 4). Site selection aimed to equally spread sites between high and low water deficit, but because of access and abundance, we ended up sampling 29 low water deficit sites, and 8 high water deficit sites. Floodplains generally have finer soil texture in our study area, and are generally within ecosystems that have lower water deficit, therefore those characteristics are more likely to be abundant within this ecosystem in western OR (USGS, 2013; OSU, 2007). This left us with sites that varied across our soil texture and water deficit groups less evenly than planned, but still gave us a variation which was representative of western Oregon and its riparian ecosystems.

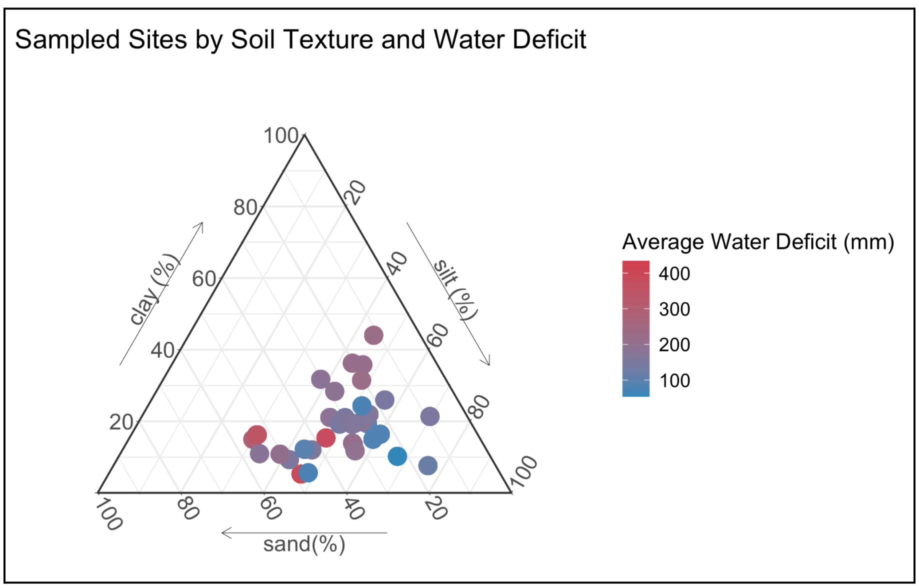

Figure 4. Soil texture triangle (Hamilton and Ferry, 2018), showing where sites fell in terms of soil texture and average water deficit (potential - actual evapotranspiration (mm)) for sampled sites in riparian reforestation survey.

Leaf Area Index over planting age, soil texture, and water deficit

Further investigation of the correlation between LAI and the original three strata of planting age, soil texture, and water deficit through a Pearson correlation test, uncovered that LAI generally increased with time and coarser soil, but was not significantly driven by water deficit. The average LAI by site was most significantly correlated with time ($r = 0.701$, 95% CI [0.65, 0.75] $p < .001$). The unplanted sites had an average LAI of 0.38, the 5-9 years since planting age class had an average LAI of 1.12, the 10-14 years age class had an average LAI of 1.62, the 15-19 years age class had an average LAI of 1.94, and the 20+ years age class had an average LAI of 2.14 (Figure 5.a). LAI was significantly negatively correlated with fine soil texture content (clay + silt%), (r = -0.224, 95% CI [-0.31, -0.13] p < .001). A site with < 70% clay + silt content had an average LAI of 1.67, while a site with > 70% silt + clay content had an average LAI of 1.22 (Figure 5.b). LAI was not found to be correlated with water deficit (Figure 5.c).

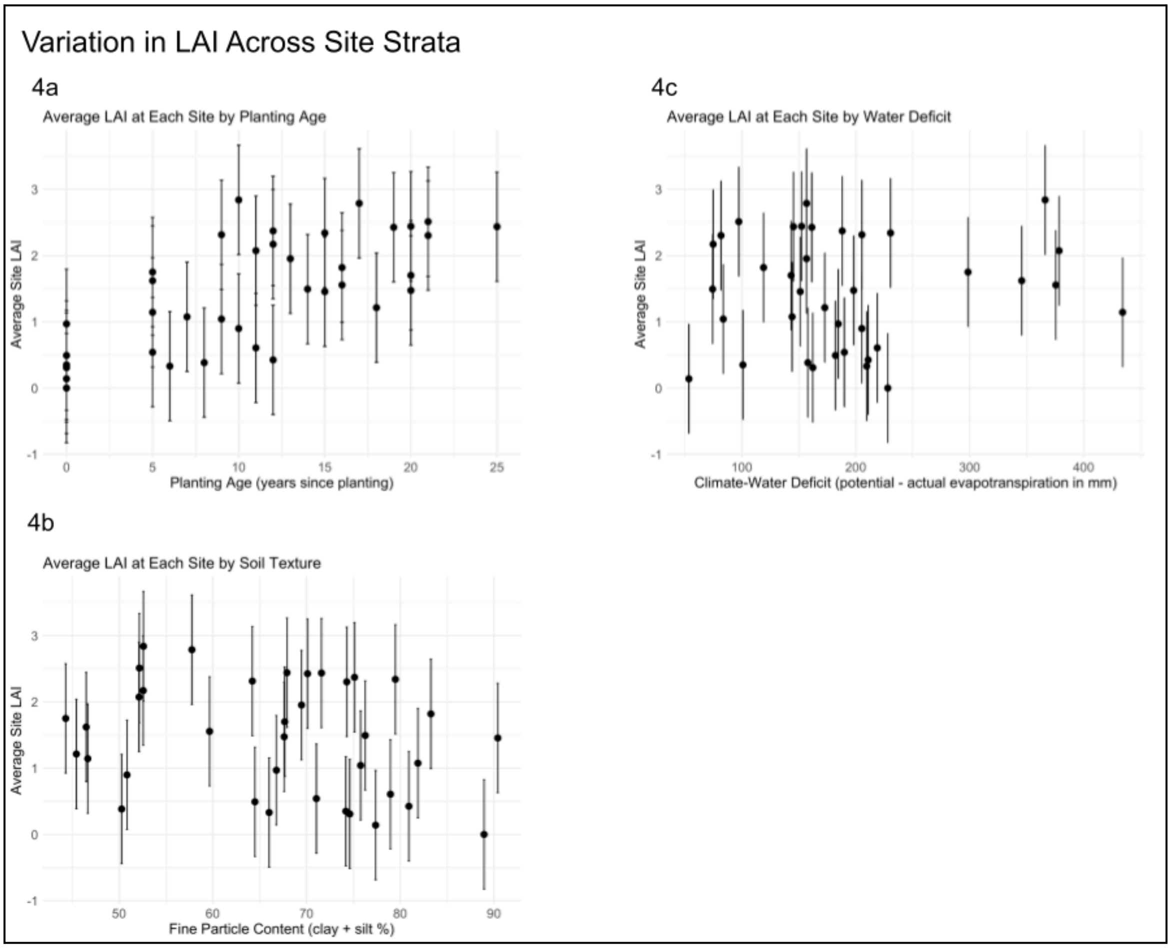

Figure 5. LAI total site average in 37 reforested riparian areas in Oregon vs. a) planting age b) fine soil particle content (clay + silt %) and c) water deficit (potential - actual evapotranspiration(mm)).

Total LAI model

The final total LAI model included plot nested within site as a random effect, total LAI as the response variable, and center/streambank position, years since planting, fine particle content, and tree stem density as fixed effects with two, three, and four way interactions, as well as slope as an individual effect. Our final total LAI model had an R^2m value of 0.73, R^2c value of 0.91, telling us that a high proportion of the variance in LAI is explained by the fixed and random effects. The significance of each significant fixed effect on the response variable is as follows; Time since planting (β =0.77, p < .001), center/streambank position (β =0.19, p < .001) with increasing LAI for streambank images, tree stem density (β =0.49, p < .001), fine particle content (β = -0.17, < .05) and their interactions, and slope as an independent effect (β = -0.16, < .05) (Figure 6).

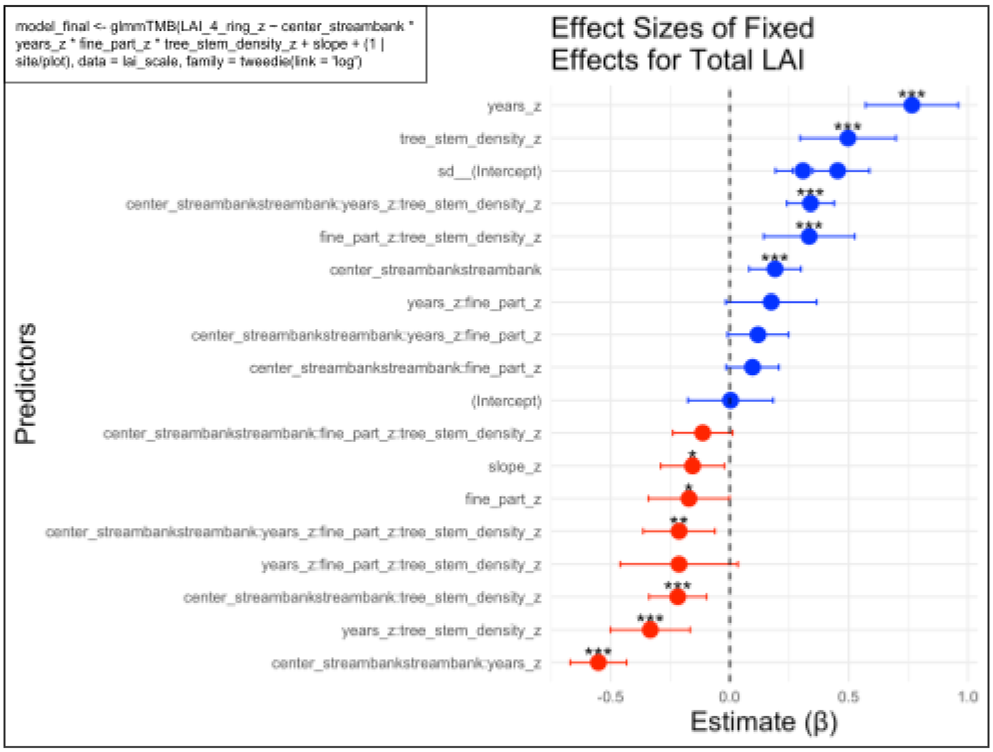

Figure 6. Effect sizes from tweedie model for total LAI at riparian reforestation sites in western Oregon. Shows positive effects in blue, negative effects in red, with a dotted vertical line representing neutral. Significance strengths shown with stars above each effect point.

LAI functions differently in canopy and understory

To understand if understory LAI and canopy LAI were driven by different predictors, we investigated the proportion of the total LAI that they each contributed towards. Understory LAI was shown to contribute less over time to the overall LAI within each age class, as canopy LAI makes up more of the proportion over time (Figure 7). The canopy LAI had the same random and fixed effects as total LAI, with slightly different effect sizes. This model had an R^2m value of 0.74, R^2c value of 0.92. Linear mixed effect models with a tweedie distribution uncovered that canopy LAI was influenced by time since planting (β =0.85, $p < .001$), center/streambank position (β =0.28, $p < .001$) with increasing LAI for streambank images, tree stem density (β =0.55, $p < .001$), fine particle content (β = -0.22, < .05), and their interactions, and slope as an individual effect (β = -0.15, < .05) (Figure 8).

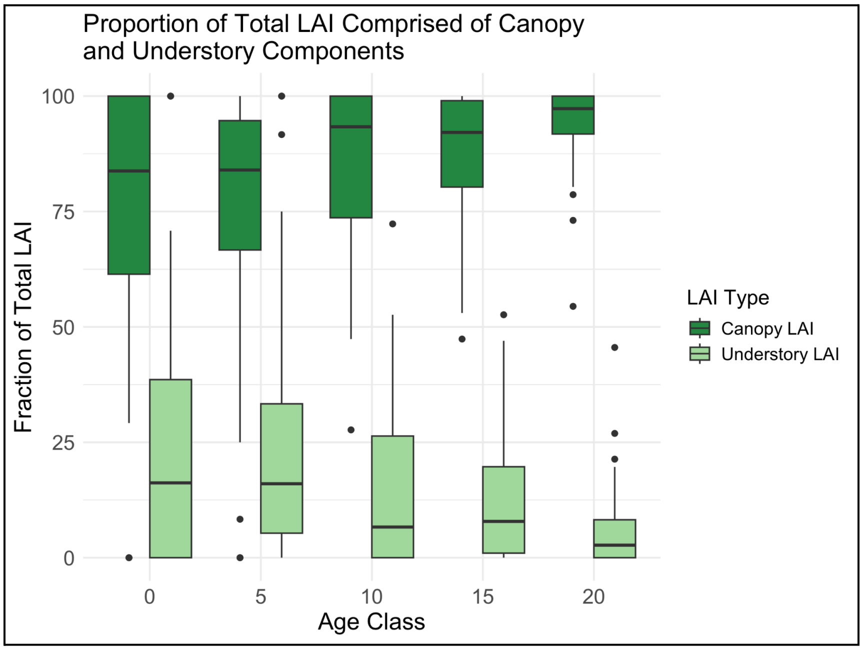

Figure 7. Proportion of canopy and understory LAI within total LAI in riparian reforestation sites in Western Oregon across age classes grouped by 5 year increments (0 is unrestored sites). Canopy LAI is in dark green, and understory is in light green.

Understory LAI has its own driving influences. Understory LAI did not have the site as a random effect alone, as the other two models included both site, and site/plot combination, understory only included the unique combination of each site and plot. This model had an R^2m value of 0.33, R^2c value of 0.76. By using linear mixed effect models with a tweedie distribution, it was found that the most influential predictors of understory LAI are understory species richness (β =0.77, $p < .001$), distance from streambank (β =-0.13, p = ns), years since planting (β = 0.61, $p < .001$), temperature (β = -0.06, p = ns), and their interactions, with stream size as an individual effect (β = 0.30, $p < .05$). Although distance from streambank and temperature are not significant on their own, their interactions with other effects are highly significant such as understory richness:center/streambank:temp (β = 0.31, $p < .01$), which tells us that the strength of the relationship between understory LAI and understory richness, is mediated by both the image position and temperature. (Figure 9).

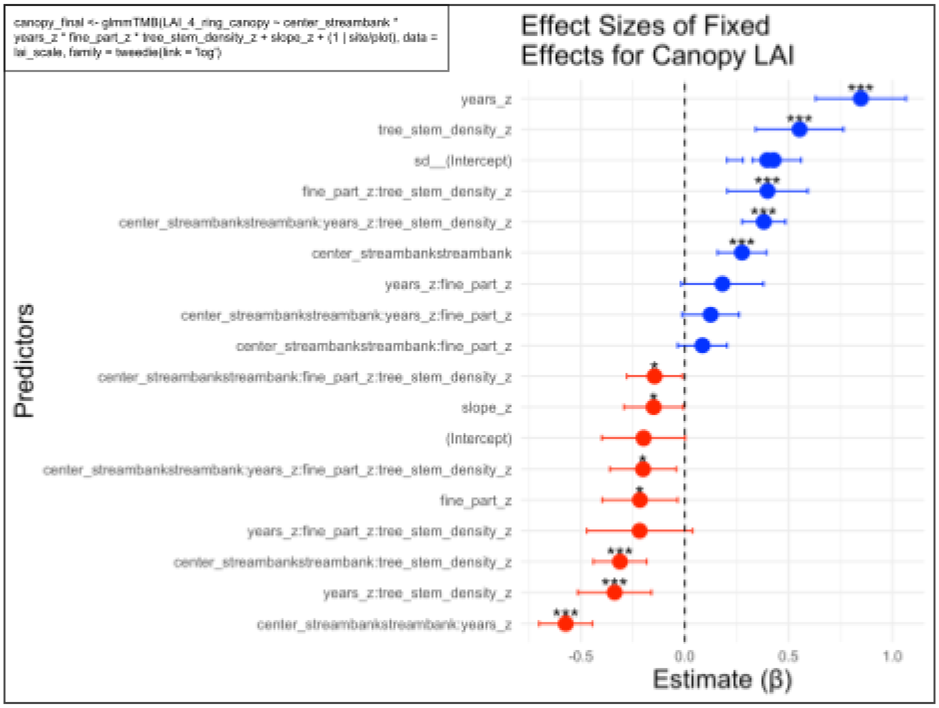

Figure 8. Effect sizes from tweedie model for canopy LAI at riparian reforestation sites in western Oregon. Shows positive effects in blue, negative effects in red, with a dotted vertical line representing neutral. Significance strengths shown with stars above each effect point.

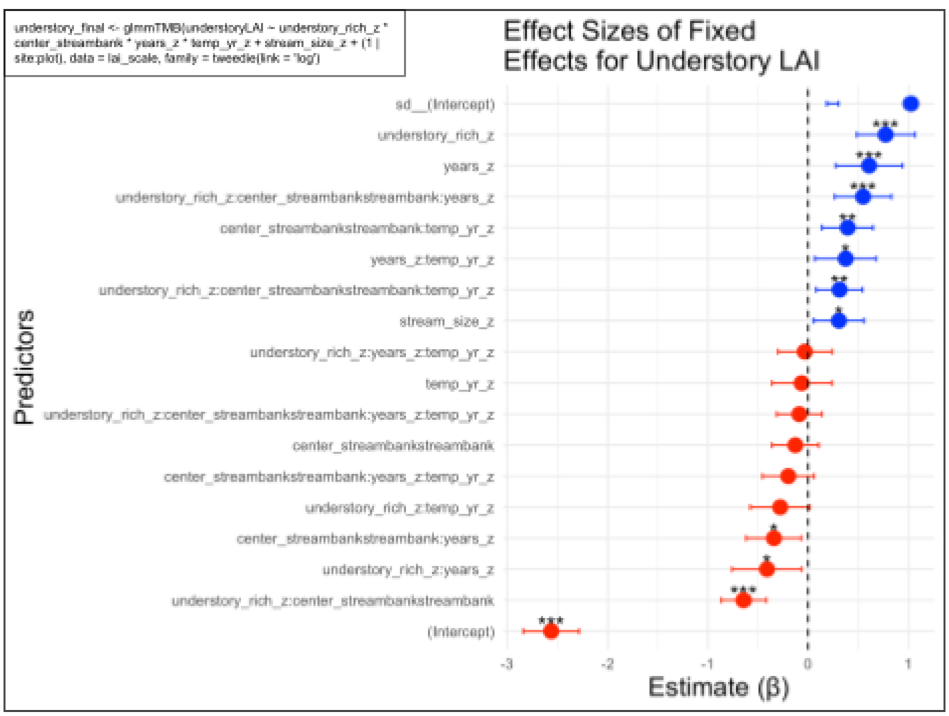

Figure 9. Effect sizes from tweedie model for understory LAI at riparian reforestation sites in western Oregon. Shows positive effects in blue, negative effects in red, with a dotted vertical line representing neutral. Significance strengths shown with stars above each effect point.

CHAPTER IV - DISCUSSION

By measuring the LAI in reforested riparian areas, we gain an understanding of the potential for essential ecosystem processes in these habitats such as radiation and rain interception, photosynthesis, and respiration (Fang et al., 2019; Rasti et al., 2022). We studied the most significant predictors that contribute to high LAI values in riparian reforestation sites across western Oregon. Studying existing sites gives us insights on how to plan future reforestation projects, and gives us knowledge about which variables may have the largest impact on the success of these plantings. This data can also give us insights into predicting the LAI potential of a riparian area that is unrestored, if it were restored in the future. By addressing these questions and gathering data about these essential ecosystems, we are able to provide research detailing the ideal conditions to increase LAI in riparian ecosystems. Our data supports the finding that riparian reforestation is a promising natural climate solution (Graves et al., 2020), as we found that a reforested site that is at least 20 years old on average will have almost 6x the total LAI than an unrestored riparian site.

Total and canopy LAI and their influences

Total and canopy LAI functioned identically in their ecosystem drivers, with only slight differences in the magnitude of their fixed effects. Time was the strongest predictor of total and canopy LAI values across the sites, supporting our hypothesis that the biomass would increase over time. Fine particle % was hypothesized to be positively correlated with LAI, as finer soil particles retain water better than sandier soils typically leading to more plant growth (Weil and Brady, 2017). The opposite was found from this research, where on average, as the soil got sandier, the LAI values increased. This may be because although finer textured soils are better at retaining water, sandier particles are necessary for proper drainage and aeration (Weil and Brady, 2017). Water deficit was shown to not be significant, which was also an unexpected finding, as lower water deficit was hypothesized to be more beneficial for LAI. This lack of significance could be due to the fact that most of our sites fell into the low water deficit category, with fewer sites representing high water deficit. Since water deficit was shown to not be significant, the climate variables of temperature and precipitation were further investigated. Total and canopy LAI were correlated to average yearly temperature (correlation of 0.141** and 0.109* respectively), but the effects were not found to be important enough to include in the final models. Both total and canopy LAI also had no relationship to average yearly precipitation, which we expected to increase with higher precipitation values. These riparian areas may be less prone to stress from climate variables because they have water access from the floodplain. Trees also typically have longer roots than shrubs, and can therefore reach deeper groundwater more easily (Maeght et al., 2013). Tree stem density was found to be a major contributor to total and canopy LAI. This is likely due to the initial planting density making it so that there was a higher chance of a dense canopy, and therefore a higher LAI. Tree stem density was more impactful than total stem density, understory stem density, or any species richness variables. The center images had a larger range of LAI compared to the streambank images, which could allude to the fact that often the streambank images often fell outside of the actual planting boundary, or resided far from the planting itself, which would explain the differences between the two groups of values. Finally, a decrease in slope was shown to significantly increase LAI values independently of the other fixed effects, possibly due to more stable soil conditions.

Understory LAI

The exploration into understory LAI emphasized the difference of this variables' predictors from the total or canopy LAI models. Understory LAI does not relate to planting density or soil characteristics, while both canopy and total LAI do. This follows our ecological understanding because trees take much longer to grow than shrubs, and when trees are very tall, there is not much light left over for shrubs (Götmark et al., 2016). Understory LAI was also more correlated with temperature and stream size compared to the total and canopy LAI values, suggesting that the understory is more sensitive to climate conditions and water availability. Our model tells us that temperature is mediating the relationship between understory LAI and the strength of the center streambank image position. Being closer to the stream increases LAI more when the temperatures are higher. This may be due to an understory thriving more when there is a higher potential for river water reaching the roots of the riparian planting mixed with warmer temperatures (Maeght et al., 2013). The younger sites that we visited were filled with dense shrubs and young trees, compared to tall trees with space underneath in older plantings, and this is shown in these significant differences when parsing out the understory LAI. Ultimately, the main factor driving understory LAI was the understory species richness ($\beta = 0.77$), even more so significantly than years since planting. The more shrub species present, the higher the understory

LAI values, which are especially important for the contribution to younger plantings (Figure 7). This tells us that the shrub biodiversity is a primary contributor to LAI in the first few years after planting, with trees taking over with time. This means that planting more shrub species can support multiple restoration goals of high understory LAI, habitat, shade and carbon sequestration. This finding highlights the importance of planting a diverse mix of shrub species if there is a goal for high understory LAI early in restoration projects. Doing so can accelerate the visible benefits of restoration, making it especially effective for those aiming to see positive outcomes in the near future.

CHAPTER V - CONCLUSION

The upper mainstream of the Willamette River has lost 85% of its riparian forests since 1850, and many other parts of Oregon have followed this pattern (Gregory, 2004). By quantifying the impacts of riparian restoration projects that have been conducted so far, we have shown that the reforestation of these areas is essential for ecosystem function through increase in LAI. Studying these projects and recording their successes will allow us to continue maximizing the potential of natural climate solutions through restoration efforts in the future. In this study we learned that some management decisions drive LAI values in these riparian projects. Shrub biodiversity was the main driver for understory LAI, and tree stem density was the main driver of total and canopy LAI, which are both variables that managers have control over. The data from this study will allow project managers to make informed decisions for future projects, and be able to assess the amount of LAI accumulation they can expect a degraded riparian area to have over time after replanting. This data can also be used by policymakers when determining what areas of land are essential to protect because of their potential for climate change mitigation. Finally, these LAI images provide permanent data of reforested riparian areas that can be referenced in the future to see how these projects change over time. This kind of data is essential in our changing world, and can help guide us towards a future of healthy riparian ecosystems.

APPENDIX

Supplementary Table 1. Definitions, sources, and predictor groups for predictors included in at least one global generalized linear mixed models for Leaf Area Index (LAI). Climate data were obtained from (Parameter-elevation Regressions on Independent Slopes Model) (PRISM), geomorphic data from US Geological Survey DEMs, and using the Riverscapes Consortium (RC) data exchange and models.

Predictor	Definition	Source	Predictor Group
Planting age	Years since site was planted when sampled	Project records	Stand
Total stem density	Number of stems planted per acre	Field data	Stand
Tree stem density	Number of tree stems planted per acre	Field data	Stand
Understory stem density	Number of shrub stems planted per acre	Field data	Stand
Total species richness	Total number of species in a plot	Field data	Stand
Tree species richness	Total number of tree species in a plot	Field data	Stand
Understory species richness	Total number of shrub species in a plot	Field data	Stand
Fine particle content	Proportion of silt and clay-sized particles in soil	Lab analysis	Edaphic
pH	pH of soil sample in 1:1 soil:water	Lab analysis	Edaphic
Precipitation	Mean annual precipitation (mm)	PRISM	Climate
Temperature	Mean annual temperature (C°)	PRISM	Climate
Solar radiation	Annual sloped solar radiation	PRISM	Climate
Climate-water deficit	average 30-year difference between potential and actual evapotranspiration	The Nature Conservancy and Resilient Forestry	Climate

Supplementary table 1, continued

Predictor	Definition	Source	Predictor Group
Floodplain width	Mean width of floodplain	RC	Geomorphic
Stream gradient	Mean slope along valley bottom center line (%) within IGO* analysis window.	RC	Geomorphic
Confinement ratio	Proportion of channel abutting a confining margin	RC	Geomorphic
Channel complexity	Ratio of channel length to valley bottom length	RC	Geomorphic
Stream size	Categorical classification of stream size from 0 (small, headwater streams) to 4 (large continental rivers)	RC	Geomorphic
Slope	Slope at plot center (%)	USGS	Biophysical
Elevation	Plot elevation (m)	USGS	Biophysical
Aspect	Aspect at plot center (º)	USGS	Biophysical
Latitude	Plot center latitude d.d.	Field data	Biophysical
Longitude	Plot center longitude d.d.	Field data	Biophysical
Image height	Lens height that the image was taken	Field data	Image
Center streambank position	Image was either taken at plot center, ot it's adjacent streambank	Field data	Image

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