

Article

Soil Respiration and Related Abiotic and Remotely Sensed Variables in Different Overstories and Understories in a High-Elevation Southern Appalachian Forest

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Abstract: Accurately predicting soil respiration (R_s) has received considerable attention recently due to its importance as a significant carbon flux back to the atmosphere. Even small changes in R_s can have a significant impact on the net ecosystem productivity of forests. Variations in R_s have been related to both spatial and temporal variation due to changes in both abiotic and biotic factors. This study focused on soil temperature and moisture and changes in the species composition of the overstory and understory and how these variables impact R_s . Sample plots consisted of four vegetation types: eastern hemlock (*Tsuga canadensis* L. Carriere)-dominated overstory, mountain laurel (*Kalmia latifolia* L.)-dominated understory, hardwood-dominated overstory, and cinnamon fern (*Osmundastrum cinnamomeum* (L.) C. Presl)-dominated understory, with four replications of each. Remotely sensed data collected for each plot, light detection and ranging, and hyperspectral data, were compiled from the National Ecological Observatory Network (NEON) to determine if they could improve predictions of R_s . Soil temperature and soil moisture explained 82% of the variation in R_s . There were no statistically significant differences between the average annual R_s rates among the vegetation types. However, when looking at monthly R_s , cinnamon fern plots had statistically higher rates in the summer when it was abundant and hemlock had significantly higher rates in the dormant months. At the same soil temperature, the vegetation types' R_s rates were not statistically different. However, the cinnamon fern plots showed the most sensitivity to soil moisture changes and were the wettest sites. Normalized Difference Lignin Index (NDLI) was the only vegetation index (VI) to vary between the vegetation types. It also correlated with R_s for the months of August and September. Photochemical reflectance index (PRI), normalized difference vegetation index (NDVI), and normalized difference nitrogen index (NDNI) also correlated with September's R_s . In the future, further research into the accuracy and the spatial scale of VIs could provide us with more information on the capability of VIs to estimate R_s at these fine scales. The differences we found in monthly R_s rates among the vegetation types might have been driven by varying litter quality and quantity, litter decomposition rates, and root respiration rates. Future efforts to understand carbon dynamics on a broader scale should consider the temporal and finer-scale differences we observed.

Keywords: carbon flux; hardwood forest; soil moisture; soil temperature; vegetation indices; vegetation types



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1. Introduction

Forests play a critical role in the global carbon cycle. In the northern hemisphere alone, forests sequester about 7×10^8 metric tons of carbon annually [1]. Forested ecosystems capture carbon dioxide (CO_2) through photosynthesis and lose CO_2 through respiration

which includes soil respiration (R_s). R_s is a significant carbon flux back to the atmosphere and even small changes can have significant impacts on CO_2 concentrations in the atmosphere. Therefore, forests are being investigated extensively as they likely will play a large role in the management of global CO_2 emissions [2]. In fact, U.S. forested land offsets about 12% of the annual greenhouse gas emissions [3]. Recent research has suggested that if the globe were forested to its potential, forests could reduce the atmospheric carbon pool by 25% [4]. R_s makes up 30%–80% of total ecosystem respiration. Variations in R_s have been identified both spatially and temporally by researchers, and these variations are affected by both biotic and abiotic factors [5]. The biotic factors can include canopy cover, leaf area, and litter deposits. Biotic and abiotic factors can directly influence each other and often interact. Soil moisture and soil temperature are considered the two most influential abiotic factors influencing soil respiration [6]. Soil moisture and soil temperatures' effect on R_s varies depending on climate and soil conditions. Among different ecosystems, a study found the soil temperature sensitivity of R_s per 10°C temperature change at a global scale to be between 1.43 and 2.03 [7]. In most studies investigating both soil temperature and moisture, soil temperature has the most influence on R_s when soil moisture is not limiting or in excess [8].

As of now, we have a relatively good understanding of R_s under managed forest ecosystems such as pine plantations. In the present study, R_s was examined under different overstories and understories in a high-elevation Southern Appalachian forest in order to get a better understanding of R_s under a natural hardwood system. Vegetation has been found to affect the soil microclimate, the quantity and quality of litter deposited, as well as the rate of root respiration [9]. Studies have not examined in-depth the comparison of R_s across the overstories and understories in Appalachian forests. In particular, the high-elevation Appalachian forests are biologically very complex, and thus understanding how they cycle carbon under the smaller spatial scales could help us scale up to the landscape.

In 1974, the National Academy of Sciences challenged the forestry and remote-sensing sectors to come together, observe, and overcome any obstacles in their way of integrating [10]. In these areas of study, it is neither practical nor economically feasible to gather all the data needed using field measurements. Remotely sensed data can build upon existing data sets to fill in gaps in the landscape. Currently, remote sensing's applications in forestry cover a wide range of subjects, including terrain analyses, forest management, updating forest inventories, forest cover type delineation, and mapping burned areas [10]. This study will also investigate its application in estimating R_s .

Relating R_s to easily obtained remotely sensed variables has several advantages. It is cheaper, allows estimations of R_s at regional, continental, and global scales, and can be used to view remote locations [11]. Several studies have found relationships between R_s and remotely sensed temperature or plant cover [12,13]. Vegetation reflectance can give us further insight into plant phenology by examining the variation in near-infrared and visible bands. We can determine canopy photosynthesis from vegetation indices (VIs) derived from more than one band of reflectance, and since they have a possible relationship with the substrate supply to R_s we can gain more insight into the R_s of the area [14]. Examples of indices include the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) [15].

For this study, we used light detection and ranging (LiDAR) data, which use a laser to measure variable distance to the earth's surface [16]. In addition to vegetation indices, remote sensing can also provide information on the canopy height, density, and change over time through the use of LiDAR or other related technologies. In this study, we use LiDAR data to calculate canopy height and hyperspectral data to calculate vegetation indices (VIs), which were compared to ground data. We calculated canopy height from LiDAR. Hyperspectral data were used to calculate VIs to compare to our ground data. We examined, using regression analysis, whether the amount of variability in the R_s data set gathered from the ground was explained by the remotely sensed data collected over our study area.

The main objectives for this study were to characterize how fine-scale differences in dominant understory or overstory plant communities affect total R_s and the relationship of R_s to soil temperature and moisture. Also, we wanted to determine whether remotely sensed data can predict R_s directly or improve on models using fine-scale land-based measures of R_s .

2. Materials and Methods

2.1. Study Area

The study took place on the Mountain Lake Biological Station in Giles County, VA owned and operated by the University of Virginia, as well as near the site of the National Ecological Observatory Network (NEON) tower. The area is considered a Southern Appalachian northern red oak forest based on the natural communities of Virginia: Classification of ecological groups and community types by the Virginia Department of Conservation and Recreation [17]. The distinction of species within this ecological group includes deciduous holly (*Ilex montana* Torrey and A. Gray), white oak (*Quercus alba* L.), black cherry (*Prunus serotina* Ehrh.), and striped maple (*Acer pensylvanicum* L.), with occasional small patches of pitch pine (*Pinus rigida* Mill.) and eastern hemlock (*Tsuga canadensis* L. Carriere). The topography across our specific study area can be described as generally flat terrain. The average annual rainfall is 96.5 cm, and the average annual snowfall is 66 cm per year. The high temperature in July is 28.9 °C and January's low temperature is −5 °C [18]. The soil is mapped as a combination of Lily–Bailegap complex (Fine-loamy, siliceous, semiactive, mesic Typic Hapludults), as well as generic Fluvaquents described as poorly drained, and on nearly level surfaces [19]. Over relatively short distances, abrupt changes in overstory and understory vegetation occur. We worked in four distinct vegetation types. Type 1 (hardwood) were areas dominated by an overstory of hardwood species (*Quercus* spp., *Acer* spp.) with little to no understory. Type 2 (cinnamon fern) was a similar overstory but with a heavy understory of cinnamon fern (*Osmundastrum cinnamomeum* (L.) C. Presl). Type 3 (mountain laurel) was a similar hardwood overstory but with a heavy mountain laurel (*Kalmia latifolia* L.) understory. Type 4 (hemlock) were areas dominated by an eastern hemlock overstory. Four replications of each of the different vegetation types were identified in the landscape, which resulted in a total of sixteen plots.

2.2. Site Characterization and R_s Measurement

In a 1/50th ha (200 m²) circular fixed radius plot, all trees and shrubs greater than 2 cm diameter at 1.37 feet above the ground were identified and measured for diameter in September of 2018. We waited until February of 2019, for the absence of leaves, to collect tree heights to obtain better accuracy using a TruPulse 200 (Laser Technology, Inc., Centennial, CO, USA). In February, about 3% of the trees measured in September were snapped or broken by an ice storm. In order to obtain an estimate of their previous heights before the storm we created a simple linear regression based on the height and DBH data already gathered for undamaged trees of that species. Basal area, trees per acre, relative average dominance (basal area of a given species expressed as a percentage of the total basal area of all species present) and volume per hectare for all the species in each plot were calculated. Volume was estimated using the equations from Clark and Schroeder [20]. Species-specific equations were used for the following species: blackgum (*Nyssa sylvatica* Marshall.), red maple (*Acer rubrum* L.), black oak (*Quercus velutina* Lam.), northern red oak (*Quercus rubra* L.), and white oak (*Quercus alba* L.). We used either a hard hardwood or soft hardwood equation for the other hardwood species' in the plots. Species-specific equations were used for our two conifer species, hemlock and eastern white pine (*Pinus strobus* L.) from Hahn [21]. Biomass of herbaceous understory plants such as ferns was measured using a 1 m² clip plot in each 1/50th ha plot collected on 14 August 2018 and later dried and weighed. The clip plot was taken 1 m distance from the plot center, aimed towards the first tree that we measured for DBH. Soil was sampled (0 to 10 cm) at three randomly selected locations in each 1/50th ha plot using a soil push tube (2 cm diameter).

The subsamples were well mixed on site and the composite sample was used for analysis. The 16 soil samples were sent to the Virginia Tech Soil Testing Laboratory to be tested for nutrients, pH, and organic matter content. We also tested for C:N ratio of the soil using a vario MAX CNS analyzer (Elementar Americas Inc., Ronkonkoma, NY, USA).

In each of the vegetation types, we measured R_s , and soil temperature and moisture in each plot monthly, spanning a full year, in order to get a wide range of soil temperatures and plant phenologies. Three random subsamples were collected in each plot. A Li-Cor 8100-103 gas analyzer (LI-COR Inc., Lincoln, NE, USA) with a survey chamber diameter of 20 cm was used to measure R_s . In the same subsample locations during each visit, a digital thermometer, the AcuRite 00641, (Chaney Instrument Co., Lake Geneva, WI, USA) was used to measure soil temperature at a depth of 12 cm. A hydrosense II soil -water sensor (Campbell Scientific USA, Logan, UT, USA) was used to measure percent volumetric soil moisture from 0 to 11 cm.

2.3. Remote-Sensing Calculations

We retrieved hyperspectral and LiDAR data of our plots from NEON (neonsciences.org accessed on 12 March 2018) for the year 2015. We used a Trimble Geo 7X handheld GPS (Trimble Inc., Sunnyvale, CA, USA) to find accurate plot centers and extracted data for all 16 areas. The image analysis software ENVI (Harris Geospatial Solutions Inc., Broomfield, CO, USA) was used to calculate various VIs for the plot areas, including normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), Atmospherically Resistant Vegetation Index (ARVI), photochemical reflectance index (PRI), normalized difference nitrogen index (NDNI), and Normalized Difference Lignin Index (NDLI). We examined the differences between the VIs' averages among the vegetation types. We then examined the VIs and the annual average R_s for each plot, the average growing season (May to September) R_s of each plot, the average R_s of each plot for each date sampled, and the average dormant season (October to April) R_s for correlation. We found the average canopy height of each of the sixteen plots from LiDAR data and then examined the relationship of these values to the overall annual average R_s for each plot, the average growing season R_s , average dormant season R_s , and the average R_s of each plot for each date sampled. We incorporated the VIs individually into our base model and observed any changes statistically to assess if they improved the predictability of R_s .

2.4. Statistical Analyses

The statistical software JMP[®] 14 (SAS Institute, Cary, NC, USA) was used for all analyses. The experiment was performed as a randomized complete block design with four replications. The experimental units were the treatment plots per vegetation type and the average of any subsamples collected in each plot. For R_s , we measured one set of each vegetation type at a time and used time as the block variable in order to remove variation based on daily temporal differences. Variables were transformed as needed in order to meet assumptions of analysis of variance and regression. Vegetation treatment characteristics such as biomass (volume, basal area, and DBH), annual means of R_s , soil temperature, and soil chemistry parameters were analyzed using analysis of variance. Statistical exploration of the variables was performed, including scatterplots and determining Pearson's correlation coefficient to look at the relationship of the variables and R_s as well as the relationships between the variables themselves. Tukey's HSD Post Hoc test was used to compare the vegetation indices, soil chemistry values, R_s , soil moisture, and soil temperature between the vegetation types. Regression analysis was used to measure the relationships between R_s , soil temperature, soil moisture, soil chemistry parameters, and remotely sensed variables. Parameter estimates of the vegetation type-specific models were examined for any significant differences using the indicator parameterization estimates table.

3. Results

3.1. Soil Temperature, Soil Moisture, Vegetation Type, and R_s

Simple linear regression indicated a strong positive relationship between soil temperature and R_s ($R^2 = 0.82$, $p < 0.0001$) while a weak negative relationship between soil moisture and R_s was found ($R^2 = 0.01$, $p < 0.0260$). On average, the cinnamon fern vegetation type had statistically higher soil moisture than the other three vegetation types (Table 1). On average, for all seasons, both soil temperature and R_s were not significantly different across all four vegetation types.

Table 1. Average soil respiration (R_s), average soil temperature (12 cm), and average soil moisture (0 to 11 cm) and standard errors across all the sampling dates for hardwood, cinnamon fern, hemlock, and mountain laurel vegetation types.

Vegetation Type	R_s ($\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$)	Soil Temperature at 12 cm ($^{\circ}\text{C}$)	Soil Moisture at 0 to 11 cm
Hemlock	2.29 ± 0.28	10.5 ± 0.87	$33.8 \pm 0.83 \text{ B}^1$
Cinnamon Fern	3.02 ± 0.34	11.0 ± 0.92	$36.5 \pm 0.63 \text{ A}$
Mountain Laurel	2.72 ± 0.27	11.0 ± 0.95	$33.3 \pm 0.59 \text{ B}$
Hardwood	2.63 ± 0.27	11.1 ± 0.95	$33.3 \pm 0.58 \text{ B}$

¹ A different letter signifies a significant difference ($p < 0.05$) between vegetation types using Tukey's HSD Post Hoc test.

3.2. General R_s Patterns

R_s was higher in the growing season and lower in the cooler, dormant months across all vegetation types. No strong patterns between vegetation types were evident. However, April, August, and December had R_s values that differed significantly between two or more of the vegetation types. R_s was highest in the cinnamon fern plots during the warmer months. Hemlock plots had higher rates in the cooler months (Figure 1).

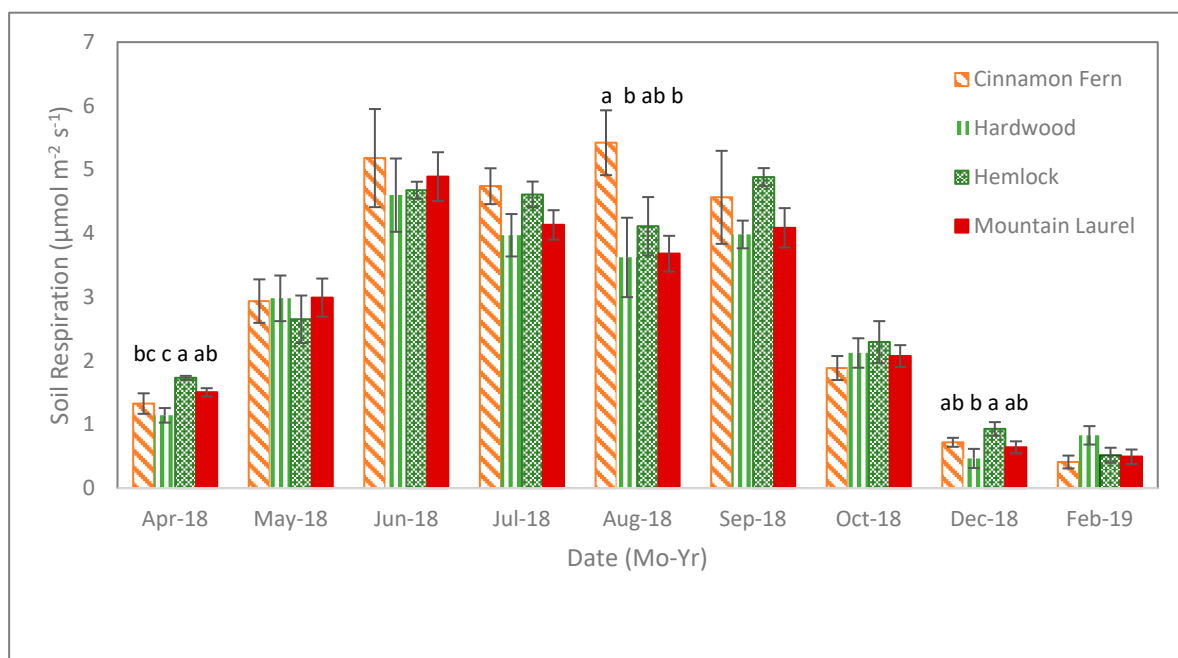


Figure 1. Average soil respiration (R_s) for all sampling dates for hardwood, cinnamon fern, hemlock, and mountain laurel vegetation types. A different letter signifies a significant difference ($p < 0.05$) between vegetation types for that sampling date.

R_s in our data did not meet the assumptions of normality; therefore, a natural logarithmic transformation was used on R_s . The model also showed unequal variance. The square

root of soil temperature and the natural log of soil moisture provided the best resolution for this. Soil temperature alone explained 81% of the variation observed. R_s was best explained by a model that included soil moisture and soil temperature ($R^2 = 0.87$) (Table 2). There was no significant interaction between soil temperature and soil moisture. Standard characterizations, such as basal area, volume, and trees per ha, as well as soil chemical properties (e.g., nutrients, pH, and organic matter content), did not add any significance to our model.

Table 2. Multiple linear regression parameter estimates for soil respiration (R_s) in the form: $\ln(R_s) = \text{Intercept} + A [\text{sqrt}(\text{Soil Temperature})] + B [\ln(\text{Volumetric Soil Moisture})]$ for the vegetation type-specific models for hardwood, cinnamon fern, hemlock, and mountain laurel ($n = 108$).

Model	Intercept	A	B	RMSE	R^2	R^2 Adjusted
General	−0.0741	0.8209	−0.5011	0.32	0.86	0.86
Hardwood	3.2047	0.7359	−1.386	0.34	0.85	0.85
Cinnamon Fern	3.1809	0.8637	−1.437	0.31	0.90	0.89
Hemlock	−0.7283	0.8221	−0.2858	0.30	0.87	0.86
Mountain Laurel	−3.1951	0.8316	0.3678	0.30	0.88	0.88

When comparing the parameter estimates of our vegetation-type specific models, we found significant differences (Table 3). Holding certain parameters to an average for the growing season allowed us to examine how each of the vegetation type models responded to soil temperature (Figure 2) and soil moisture (Figure 3) separately. The soil moisture slope is significantly more negative for the cinnamon fern plots than the hemlock or mountain laurel plots. For every unit increase in soil moisture, the cinnamon fern plots' R_s lower at a faster rate than both the hemlock and mountain laurel R_s rates. The intercept in the cinnamon fern model was significantly higher than the mountain laurel model's intercept. The soil temperature slope values did not significantly differ between the vegetation types' models (Figure 2).

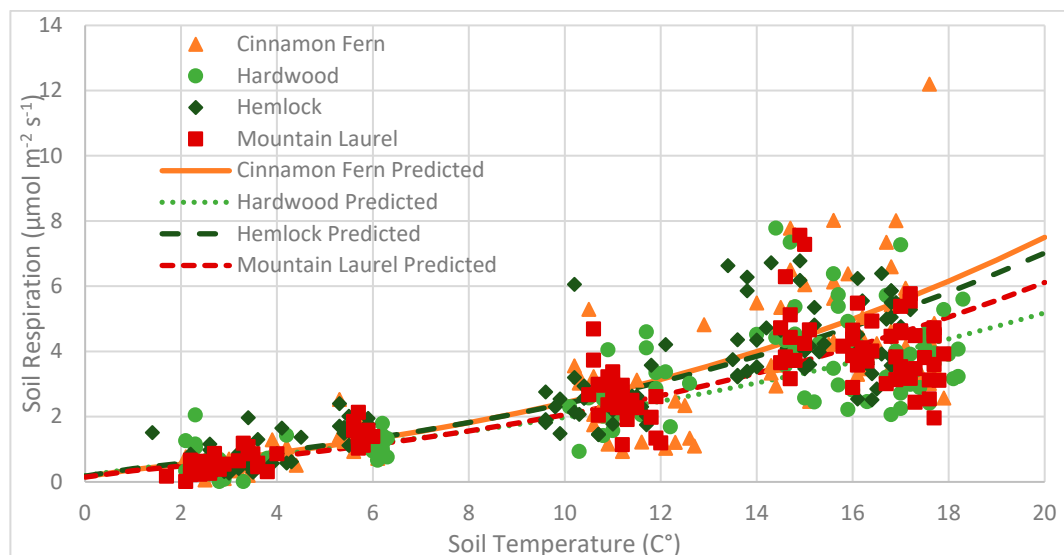


Figure 2. Soil respiration (R_s) in a high-elevation southern Appalachian forest (Giles County, VA, USA) as influenced by soil temperature for each vegetation type: hardwood, cinnamon fern, hemlock, and mountain laurel. Predicted lines were generated using the formulas from Table 2 while holding soil moisture at a value of 33.07 (the average soil moisture for the months of May–September).

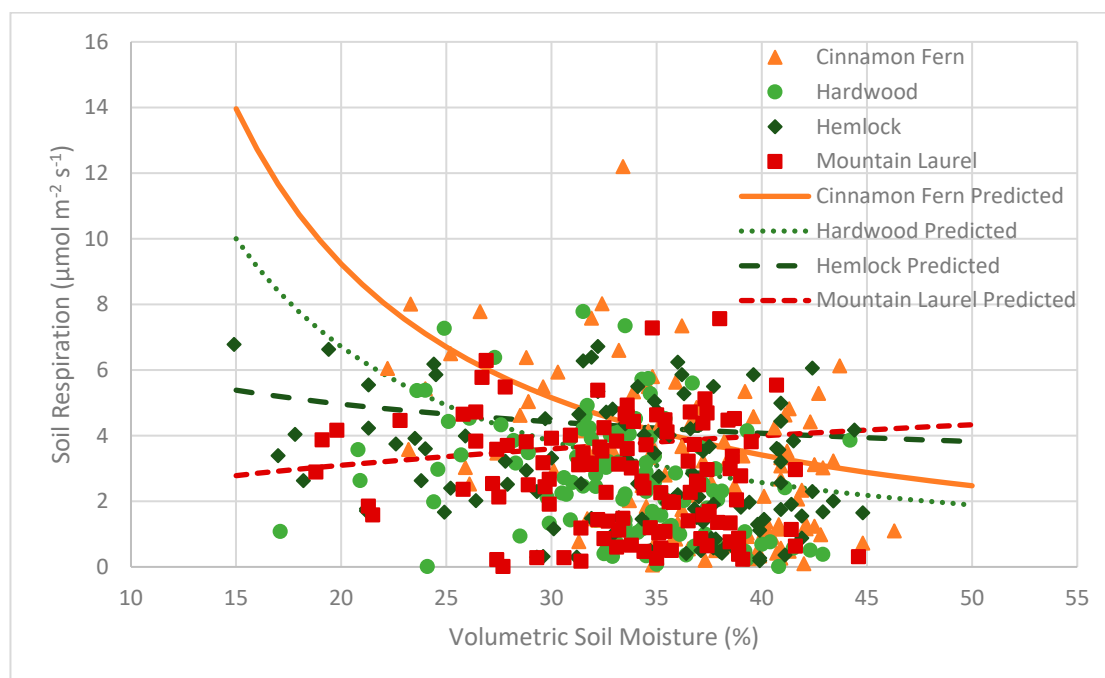


Figure 3. Soil Respiration (R_s) in a high-elevation southern Appalachian forest (Giles County, VA, USA) as influenced by soil moisture for each vegetation type: hardwood, cinnamon fern, hemlock, and mountain laurel. Predicted lines were generated using the formulas from Table 2 while holding soil temperature at a value of 15.02 °C (the average soil temperature for the months of May to September).

Table 3. p -values for the comparison of parameter estimates of the vegetation-type specific models.

Vegetation Type Comparisons	Intercept	A	B
Hardwood vs. Cinnamon Fern	0.9933	0.1371	0.9466
Hardwood vs. Hemlock	0.0993	0.3170	0.0873
Hardwood vs. Mountain Laurel	0.0173 *	0.2414	0.8176
Cinnamon Fern vs. Hemlock	0.1074	0.6394	0.0749
Cinnamon Fern vs. Mountain Laurel	0.0201 *	0.7036	0.0149 *
Hemlock vs. Mountain Laurel	0.2073	0.9108	0.2844

* Values are statistically significant at the $\alpha = 0.05$ level.

3.3. Remotely Sensed Variables and R_s

3.3.1. Vegetation Indices

With the exception of NDLI, none of the VIs differed between vegetation types. For NDLI, cinnamon fern (-0.0154) differed significantly from mountain laurel (-0.0144) which had the highest NDLI of all vegetation types. The annual average R_s value, the average growing season R_s , the average non-growing season R_s , and all VIs were not significantly correlated. When we examined the correlation between the VIs and the average R_s by date sampled, we found some statistically significant relationships (Table 4). Our R_s under each of the sixteen plots for the sample date of August showed a significant correlation ($p = 0.0214$, $R^2 = 0.324$) to the NDLI. For the R_s for the sample date of September, we found a correlation between several VIs including NDLI ($p = 0.0462$, $R^2 = 0.25$), NDVI ($p = 0.02$, $R^2 = 0.329$), PRI ($p = 0.0285$, $R^2 = 0.30$), and NDNI ($p = 0.025$, $R^2 = 0.31$). For all significant correlations, the first cinnamon fern plot acted as a high leverage data point. When removed, the relationship between August's R_s and NDLI was stronger ($R^2 = 0.64$); however, all other significant correlations drastically decreased in strength when the high leverage value was removed. We found no reason to remove the value as the number was still an accurate representation of the site. Accounting for soil temperature and soil

moisture variation, adding our vegetation indices individually into our base model did not explain any additional variation of R_s .

Table 4. p -values and R^2 values for the VIs and R_s sampling dates that were found to have significant correlations.

Sampling Date	Vegetation Index	p -Value	R^2
August	NDLI	0.0214	0.32
September	PRI	0.0285	0.3
September	NDVI	0.02	0.33
September	NDLI	0.0462	0.25
September	NDNI	0.025	0.31

3.3.2. Mean Canopy Height

We found no significant relationship between mean canopy height calculated from LiDAR data and average growing season R_s . We also found no significant relationship between average nongrowing season R_s and mean canopy height. Mean canopy height correlated with the September sample date ($p = 0.0254$, $R^2 = 0.30$).

4. Discussion

4.1. Soil Temperature, Moisture and R_s

As is well-established in the literature, soil temperature is the main driver of R_s and alone, and explained 75% of the variation in our model. A study by Yu et al. in a 50-year-old oriental arborvitae (*Platycladus orientalis* (L.) Franco) plantation in China found soil temperature to explain 82% of the variation in R_s in the overall annual cycle. It was the main determinant for R_s when soil moisture was not limiting [8]. This is just one of many studies that found soil temperature to be the strongest driver of R_s . Another example is Inclán et al., who reported that soil temperature was the main driver of R_s variation unless soil moisture reached levels below 15%, in which case it then became the better predictor [22].

We know R_s varies both spatially and temporally. Temporal variation of R_s includes diurnal, weekly, seasonal, or annual changes [23]. When we examined R_s seasonally, we found significant differences among the vegetation types. The cinnamon fern's R_s was significantly higher in the month of August, most likely due to its sheer abundance at that time of the year. We expected to see significantly higher R_s rates for hemlock on our cooler sampling dates than the other vegetation types, which was the case for our study. As an evergreen, when there are mild winter days, hemlocks continue photosynthesizing, and in some cases with approximately the same photosynthetic capacity as in the summer [24]. We know R_s is influenced by substrate availability and thus strongly linked to photosynthesis, litterfall, and plant metabolism, and, therefore, higher activity aboveground in evergreens in the cooler months can lead to higher activity belowground [25].

Though we found differences in our soil moisture levels, with cinnamon fern occupying the wetter sites, this did not provide a large enough influence on R_s rates to observe any differences between sites. Soil moisture usually explains less of the variation in R_s than soil temperature. Our results were not unlike those of the study by Akburak and Makineci [9]. They explored the temporal changes of soil respiration under different tree species. They found monthly R_s to be statistically different between the tree types; however, there was no significant difference between the mean annual R_s rates among the tree types. R_s followed their soil moisture trend. Despite no significant difference for the annual mean R_s between vegetation types, we still encountered monthly differences. We would need to explore the root respiration rates, quality and quantity of litter, and more soil characteristics to see if perhaps these monthly differences could be due to the influence of vegetation type, perhaps as a secondary effect.

When comparing our vegetation-type specific models, there were statistically significant differences in the response of R_s to soil moisture (Table 2). Cinnamon fern's model

for predicting R_s was the most sensitive to soil moisture changes (Figure 3). The response of R_s to soil temperature between all of the vegetation types did not differ (Figure 2). It is important to note that the spatial variation in R_s is usually driven by soil characteristics as well as biological processes, while temporal variation is usually driven by climatic variables [26]. We found few differences in the soil's chemical properties between the vegetation types. Perhaps the soil environment was similar enough across the vegetation types that the vegetation's effect on annual mean R_s was minimal. A study by Martin and Bolstad examined R_s and its influences, such as moisture and site characteristics for five different forest types. They noted an apparent lack of effect of dominant vegetation type on R_s [27]. Similar to our study, the site conditions were relatively homogenous. Our topography did not significantly differ, nor did site characteristics or soil chemical properties. In our case, vegetation type may have minimal utility in predicting R_s on a spatial scale. Bilal compared R_s across cover types in a southern Appalachian hardwood forest. Their model included soil temperature and soil moisture as the two drivers of variation. Our R_s rates were similar to those reported by Bilal [28] at the same soil temperature. Their sites were located on either foot or shoulder slopes and at lower elevation than ours and they found slight but significant differences due to changes in overstory species composition. Differences in site quality correlated with the differences they saw in R_s between the cover types [26,28]. Perhaps similar to the study by Martin et al. [29], they experienced topographically induced soil moisture regimes which may have contributed to changes in R_s between cover types. Our sites were much wetter overall. The average soil moisture values at our sites were higher than highest soil moisture value found by Bilal [28] suggesting soil moisture is not driving differences in R_s between our vegetation types.

There has been controversy in the past with some studies saying the influence of vegetation on soil microclimate is sufficient enough to explain differences in R_s among vegetation types [30]. Others say the correlation between climate characteristics, net primary productivity, and R_s has caused scientists to speculate which factors are truly driving the differences in R_s between different vegetation types [31]. In the future, we should focus on developing models that try to isolate vegetation effects and partition the R_s into its autotrophic and heterotrophic components in order to get a better picture of species' influence on R_s .

4.2. The Use of Remotely Sensed VIs to Predict R_s

Very few significant correlations were found between VIs and R_s , and most of the correlations we did find between R_s and the six different VIs were relatively weak. Seasonally, it may be difficult to correlate R_s with greenness VIs due to soil temperature or moisture limitation which may limit the influence of substrate supply from photosynthesis to R_s [32]. NDVI was negatively correlated with R_s for September and August. The negative correlation may be related to the fact that litter with higher lignin content is more difficult to break down by heterotrophic organisms, lowering R_s [33]. The reason we may have found correlations with the R_s rates for September and August may simply be because that time of the year has high R_s , as seen in Figure 1.

Remotely sensed VIs, in the past, have been more closely correlated with gross primary production (GPP) than with respiration components [34]. However, Chen et al. [35] found significant correlations between EVI, GPP, LAI, and NDVI and R_s in subtropical forests. Wu et al. [36] found strong growing season correlations between R_s and NDVI ($R^2 = 0.82$) and between R_s and nighttime surface temperature ($R^2 = 0.80$) in Canadian black spruce. Wylie et al. looked at estimating daytime and nighttime carbon flux using an integrated NDVI (iNDVI). Linear relationships between the iNDVI and daytime carbon flux were strong, with R^2 values of 0.72 to 0.92 for the three years observed. The iNDVI even correlated better with their nighttime carbon flux ($R^2 = 0.34$) than NDVI correlated with our values of R_s ($R^2 = 0.07$) in our study [37]. It is important to note that NDVI tends to saturate at high vegetation densities and can be sensitive to background reflectance [38]. Our sites, therefore, could have been too highly vegetated for the use of NDVI, or there

was little change in GPP across our fine-scale changes in vegetation types. The above-cited studies are generally at a much broader scale than our study.

VIs can be estimators of changes in biophysical parameters such as green leaf area index (GLAI), and canopy chlorophyll content ($\text{Chl}_{\text{canopy}}$). GLAI and $\text{Chl}_{\text{canopy}}$, in turn, can explain most of the variation in R_s , much like in the study by Huang et al. [15]. Huang et al. saw the potential to investigate how VIs may directly relate to R_s due to the strong relationship between VIs and biophysical parameters. They found strong correlations between daily mean R_s and EVI, as well as daily mean R_s and $\text{CI}_{\text{red edge}}$. The study was looking at maize and winter wheat fields and the indices were calculated from hyperspectral reflectance data taken by a portable spectroradiometer [15]. The differences in land use types between our study and the one mentioned above as well as the difference in capturing the hyperspectral data, may explain the differences we saw in the ability of VIs to estimate R_s . In fact, the study mentioned that sites with evergreen species might not exhibit as drastic a seasonal change in vegetation greenness as crop fields which may make the estimation of R_s by VIs more difficult.

In our study, it is important to consider the difference between the spatial scale of the data collected on site versus the spatial scale of the remotely sensed indices. In turn, this could have explained the few weak relationships we found between the two. Perhaps, our vegetation types were at too fine of a scale compared to the satellite data. A study by Hogrefe et al. explored the use of NDVI as an estimator of biomass and nutritional value of forage plants in Alaska. They wanted to explore the differences in NDVI's ability as an estimator when it was collected in two different spatial scales, from moderate resolution satellite data (250×250 m) and from a handheld spectrometer (20 cm diameter area). The NDVI derived from the handheld spectrometer performed better in the model ($R^2 \geq 0.67$) than the NDVI from the satellite data ($R^2 < 0.40$). This study showed the importance of considering scale in modeling in order to increase accuracy of predictions [39]. Remotely sensed variables from satellite data may do a better job predicting factors such as GPP, R_s , or biomass on a broader spatial scale where there may be more obvious variation in these factors. Many processes may appear homogenous at a local scale but as the observation scale becomes larger may start to appear heterogenous. Therefore, processes may seem important at one scale but remain trivial in another scale [40]. Further research into the accuracy and the spatial scale of VIs could provide us with the information needed to know whether they will have the ability to predict R_s on the landscape scale in the future.

5. Conclusions

In agreement with many studies, most of the variation in R_s was explained by soil temperature. More significant are the differences in R_s we saw among the vegetation types when observed by sampling date and not for the annual mean. This demonstrates the importance of looking at R_s under various temporal and spatial scales, including weekly, monthly, and yearly, in order to achieve a better understanding of variation. Conducting the study over a number of years may provide us with more insight into vegetation's influence on R_s . The vegetation may still have driven the differences we saw in monthly R_s by their influence on litter decomposition rates, soil microbiology, and other soil microclimate characteristics. Future studies may want to gather more data on litter differences, partition the R_s into its autotrophic and heterotrophic components, and take the LAI under each vegetation type.

The ability of remotely sensed VIs to predict R_s was limited in our study. NDLI was the only VI to show a significant difference between vegetation types, as well as correlate with certain monthly R_s rates. The lack of relationships we found otherwise may have been due to a scale discrepancy between our ground data and the VIs calculated from satellite data.

Studies may want to focus on examining VIs, ability to predict processes under broader spatial scales as well as achieve a better understanding of VIs' spatial accuracy. Perhaps our vegetation types were at too fine of a scale compared to the satellite data.

In conclusion, R_s was mainly driven by soil temperature and moisture, but this relationship was significantly impacted by the vegetation types. That being said, our model may provide the basis for future models estimating R_s in natural hardwood systems in the Appalachian Mountains. Remotely sensed VIs had very limited relationships with our fine-scale R_s measurements.

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