Water Use Efficiency of California Evergreen Species from OCO-2 Satellite Data

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ABSTRACT

Forest evapotranspiration has the potential to affect climate and forests in other regions through "ecoclimate teleconnections." Climate models do not take into account species differences in water use efficiency (WUE), and research is currently conducted through time and labor-intensive field studies. This study attempts a unique method of detecting species differences in WUE using a combination of satellite data from the Orbiting Carbon Observatory-2 dataset and tree survey data from the Forest Inventory Analysis dataset. Only 13% of FIA data had overlapping summer satellite data. The study sites were three 0.6 x 0.6 degree forested areas in Northern California dominated by either Ponderosa Pine, Douglas Fir, or White Fir. A transpiration index was calculated for each major species to determine which of the species would have a non-negligible effect on atmospheric concentrations. The area dominated by Douglas Firs exhibited a very narrow unimodal distribution of low WUE index values, but there was a much wider distribution in the other two areas where Ponderosa Pine had a relatively large transpiration index. Because Ponderosa Pine is suspected to have a higher WUE, there is a possibility that this difference in graphs could be a visualization of the effects of species differences in WUE. Although not definitive, this study has provided a first step in revealing how we should approach quantifying species differences in WUE from space, which could guide climate change mitigation efforts and improve predictive climate models in the future.

KEYWORDS

remote sensing, climate, evapotranspiration, species differences, water vapor

INTRODUCTION

Terrestrial vegetation is one of the most significant contributors to the hydrologic cycle and the movement of water globally. Approximately 61% of terrestrial precipitation originates from land, around half of which is from plant transpiration (Schneider et al. 2017, Wei et al. 2017). Through "ecoclimate teleconnections," changing vegetation evapotranspiration in one region can cause significant effects on climate and forests in other regions (Swann et al. 2018). Modeling studies have shown that several changes to vegetation follow this trend, including large-scale tree mortality, afforestation, and increased water efficiency due to drought (Swann et al. 2018, Swann et al. 2012, Swann et al. 2016). Drought has one of the most impactful effects on vegetation because water is often the limiting factor of carbon uptake within terrestrial ecosystems (Polis 1999). Global climate change is expected to increase the frequency and intensity of droughts globally, as well as compound issues of water limitations in semi-arid and Mediterranean climates (IPCC 2013, Trenberth et al. 2014). Increasing water stress could drastically change the concentration of water vapor and CO_2 in the atmosphere as plants limit their growth and survival to adjust to limited water availability.

As forest compositions change and tree ranges shift with warming temperatures, one factor to consider is how dominant species differ from each other in their individual effects on climate (Rustad et al. 2018). These differences in water usage are largely caused by variations in tree physiology that result in differing reactions to water stress (Martinez-Vilalta et al. 2003). While informative of specific ecosystems, field studies of these vegetation factors are time consuming and can only be done over small areas. Modeling studies alone have also been limited because they incorporate most observations into broad forest functional classes, rather than capturing differences among tree species. Developing methods of studying how different evergreen trees respond to water stress on a regional and global scale using remote sensing has remained a challenge because standard vegetation indices such as NDVI are often not suited for use on evergreens and satellites are typically not high enough resolution to view species differences (Gamon et al. 1995).

One possible alternative method of studying how trees respond to water stress is to use a water use efficiency index calculated from satellite data. Water use efficiency (WUE) is the ratio between gross primary production (GPP) and evapotranspiration (ET). Conventionally, WUE has been measured at the leaf level using open gas exchange systems or at the canopy level using eddy-covariance flux towers (Field et al. 1983, Medrano et al. 2015). Leaf-level field studies conducted at the Jasper Ridge field site in Northern California have revealed evergreen species differences in WUE within Mediterranean climates (Field et al. 1983). When observing mixed conifer forests with eddy-covariance flux towers, Ponderosa Pine-dominated forests have 23% greater WUE on average than the White Fir-dominated forests (J. Battles, *personal communications*). Thus, it remains possible that the influence of an individual species on the atmospheric concentrations of water vapor and CO_2 could be seen from space by calculating a WUE index and determining what species are contributing to this value. This tool could be extremely useful in studying how drought affects vegetation and in turn, how climate will react to these changes.

The goal of this study is to better understand how the transpiration of different California evergreen species varies throughout the year. This approach is unique because it combines high-resolution satellite data observations from the Orbiting Carbon Observatory-2 (OCO-2) satellite with species survey data from the Forest Inventory Analysis (FIA) dataset to determine if there is a detectable species-specific vegetative signature in the WUE index. Using this information, I aim to address the scientific question of how the differing of WUE between evergreen forest species affects climate. This question can be addressed through the following objectives: (1) determine the amount of useful spatial overlap between the OCO-2 satellite data and the FIA data and find 0.6 x 0.6 degree plots where Douglas Fir, White Fir, and Ponderosa Pine-dominated areas overlap with OCO-2 summer coverage; (2) calculate a transpiration index of species >10% of all trees in each area to determine the magnitude of effect an individual species has on the atmospheric concentrations of CO_2 and water vapor; (3) generate histograms of WUE index values within each plot by month and compare WUE index distributions in areas dominated by different species.

Ultimately, I aim to determine whether or not this method is a viable way to generate global and seasonal distributions of WUE based on satellite observations, without assumptions of dependence on temperature or precipitation.

METHODS

Data sources

To calculate a satellite WUE index, I used the Orbiting Carbon Observatory-2's (OCO-2) CO_2 and water vapor dataset (NASA GES DISC). OCO-2 was launched on July 2, 2014 and employs grating spectrometers that measure at 0.76, 1.61, and 2.06 µm (Nelson 2016). Its primary use is to monitor global CO_2, but it also measures atmospheric water vapor in the process. The satellite takes daytime measurements at 1.3 x 2.3 km^2 resolution, and the concentrations are measured in units of $\frac{mol\ CO2}{mol\ air}$ and $\frac{mol\ water\ vapor}{mol\ air}$(Nelson 2016). Because the measurements are taken as the satellite moves 7 km/s, with 24 measurements per second, factors like wind can be disregarded, and the background water vapor and CO_2 concentrations can be assumed to be constant over each swath. The data from OCO-2 has been verified against validation data to have high accuracy (Nelson 2016).

To relate how the satellite WUE corresponds to different species, I used the Forest Inventory Analysis (FIA) dataset (U.S. Forest Service). The FIA dataset is an annual forest census that includes species, size, location, and health of individual trees, among other parameters. Within California, there were ~330,000 trees surveyed from 98 species (I. Fung, *personal communication*). The information from the FIA dataset is mapped using code received from Inez Fung and David Elvins at UC Berkeley, which returns the number of trees of each species within a selected latitude and longitude range (Figure 1).

Study site and species composition

The primary study system is evergreen forests within Northern California with a species dominance of Douglas Firs (*Pseudotsuga menziesii*), White Firs (*Abies concolor*), or Ponderosa Pines (*Pinus ponderosa*). The key time periods of satellite data were dry summer days in June, July, and August, where the effect of rain or precipitation would not have a large effect on the water vapor column measurements.

Modifying the code used to return the number of trees in an area, I generated maps of composition percentages for each of the three target species on a 0.1 x 0.1 degree grid of

California. From these maps, I handpicked 0.6 x 0.6 degree areas that appeared to have a large amount of a given species. To better understand the composition and structure of the forest in each area, I calculated the percentages of every present species to see what other species could potentially modify my interpretation of the results. For any trees making up >10% of the target area's total count, I used the FIA data to calculate the median size of trees for that species and calculated a transpiration index using the equation:

$$Transpiration\ Index = percent\ composition * average\ tree\ basal\ area.$$

This procedure allowed me to account for the possibility that larger trees may have a stronger influence on the measured WUE index.

Water use efficiency

After determining which areas were of interest and analyzing the species composition and structure within each area, I isolated the OCO-2 data to any points during the dry summer and calculated WUE using the following equation:

$$\text{WUE} = \frac{(CO2 - background\ CO2)}{(water\ vapor - background\ water\ vapor)}.$$

The background data is assumed to be the minimum value of a swath over California during the same day. I checked that there was a significant amount of satellite data within each of the target areas to ensure good overlap between the species coverage and the satellite coverage. For each of the target areas, I generated binned histograms of WUE index values for June, July, and August separately. These datasets were filtered for outliers greater than two standard deviations above and below the mean, and the graphs were restricted to a WUE index range of 0 to 20.

Other approaches

The first attempt to relate WUE with OCO-2 water vapor data involved dividing California into 0.1 x 0.1 degree grid spaces, finding grid spaces with over 40% of any species, and attributing any satellite pixels within these grid spaces to that species. On a grid that fine, there was no matching data for some species, and only 1 or 2 points for others, preventing this method from yielding any meaningful results. Furthermore, other attempts at parsing through each satellite point and matching to FIA data were unsuccessful due to computational limitations of equipment. Attempts to examine the differences between drought and non-drought periods also yielded no meaningful results resulting from a lack of overlapping data in the same area over several years.

RESULTS

Coincident Coverage: FIA data and OCO-2 summer data

13% of grid points with FIA data in California had at least one point of summer satellite coverage, amounting to 273 of the total 2,163 plots with FIA data coverage (Figure 1). This is an upper-bound estimation of usable overlap because it includes grid spaces that might only have a few points of satellite data along the edges that may not yield insight to the grid space as a whole.

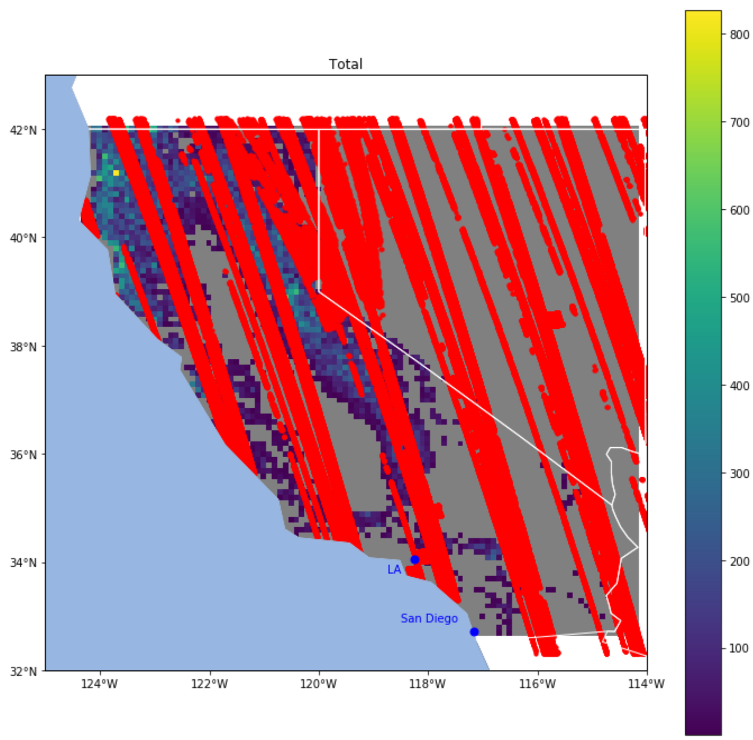

Figure 1: Map of total FIA coverage and OCO-2 coverage in California. The survey data consists of information about ~330,000 trees of 98 species and was documented by the U.S. Forest Service. The red dots indicate points of satellite coverage, while the color bar indicates number of trees in the grid space.

The percentage distribution of each target species revealed large areas of high species counts in Northern California, with many areas between 30-60% species dominance (Figure 2).

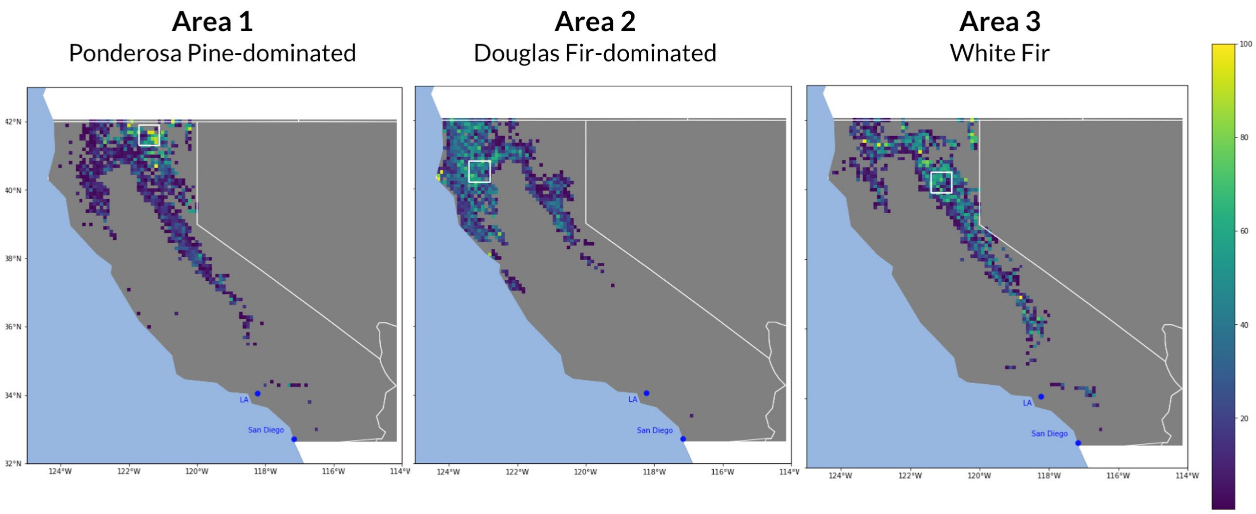

Figure 2. Percentage maps of Ponderosa Pine, Douglas Fir, and White Fir in California. I evaluated the percent distribution for each of the three species and plotted them on a map. For each species, I selected a 0.6 x 0.6 degree plot (shown as white boxes on each map) of high dominance that also overlapped with OCO-2 coverage.

Forest Composition

Within each target area, the difference in transpiration indices determines which species are making a substantial contribution to the measured WUE value. The transpiration index of Ponderosa Pine in Area 1, with a value of 0.0215, was 2.6 times larger than the transpiration index of White Fir in Area 1 of 0.0084. Within the same region, the transpiration index of Ponderosa Pine was 9.8 times larger than that of Lodgepole Pine, which had the smallest transpiration index of 0.0022. In Area 2, the transpiration index of Douglas Fir at 0.0326 was 6.3 times larger than the only other abundant species, Canyon Live Oak, which had a transpiration index of 0.0052. Finally, the transpiration indices in Area 3 for White Fir and California Red Fir were the largest at 0.0164 and 0.0169, respectively, while Ponderosa Pine and Douglas Fir had smaller transpiration indices of 0.0070 and 0.0088, respectively.

Table 1: Transpiration indices for species comprising over 10% of the area. I calculated the species percentages, average basal area, and transpiration indices for species that are >10% of (a.) Area 1, (b.) Area 2, or (c.) Area 3.

a.

Area 1: Ponderosa Pine dominated -Lat: [41.3 N, 41.9 N], Long: [121.7 W, 121.1 W]

Tree Species	Species Percentage (>10%)	Average tree basal area	Transpiration Index
Ponderosa Pine	37%	$\Pi * (0.272/2)^2 = 0.0581$	0.0215
White Fir	18%	$\Pi * (0.244/2)^2 = 0.0468$	0.0084
Lodgepole Pine	11%	$\Pi * (0.160/2)^2 = 0.0201$	0.0022

b.

Area 2: Douglas Fir dominated -Lat: [40.2 N, 40.8 N], Long: [123.3 W, 122.7W]

Tree Species	Species Percentage (>10%)	Average tree basal area	Transpiration Index
Douglas Fir	37%	$\Pi * (0.335/2)^2 = 0.0881$	0.0326
Canyon Live Oak	23%	$\Pi * (0.170/2)^2 = 0.0227$	0.0052

c.

Area 3: White Fir dominated- Lat: [39.9 N, 40.5 N], Long: [121.4 W, 120.8 W]

Tree Species	Species Percentage (>10%)	Average tree basal area	Transpiration Index
White Fir	36%	$\Pi * (0.241/2)^2 = 0.0456$	0.0164
Douglas Fir	12%	$\Pi * (0.305/2)^2 = 0.0731$	0.0088
Ponderosa Pine	12%	$\Pi * (0.273/2)^2 = 0.0585$	0.0070
California Red Fir	10%	$\Pi * (0.464/2)^2 = 0.1691$	0.0169

Water Use Efficiency

The WUE index values for June, July, and August were calculated and mapped to their respective coordinates (Figure 2). The data had sparse spatial coverage in many areas of California, leading to difficulty in picking areas of overlap between the datasets.

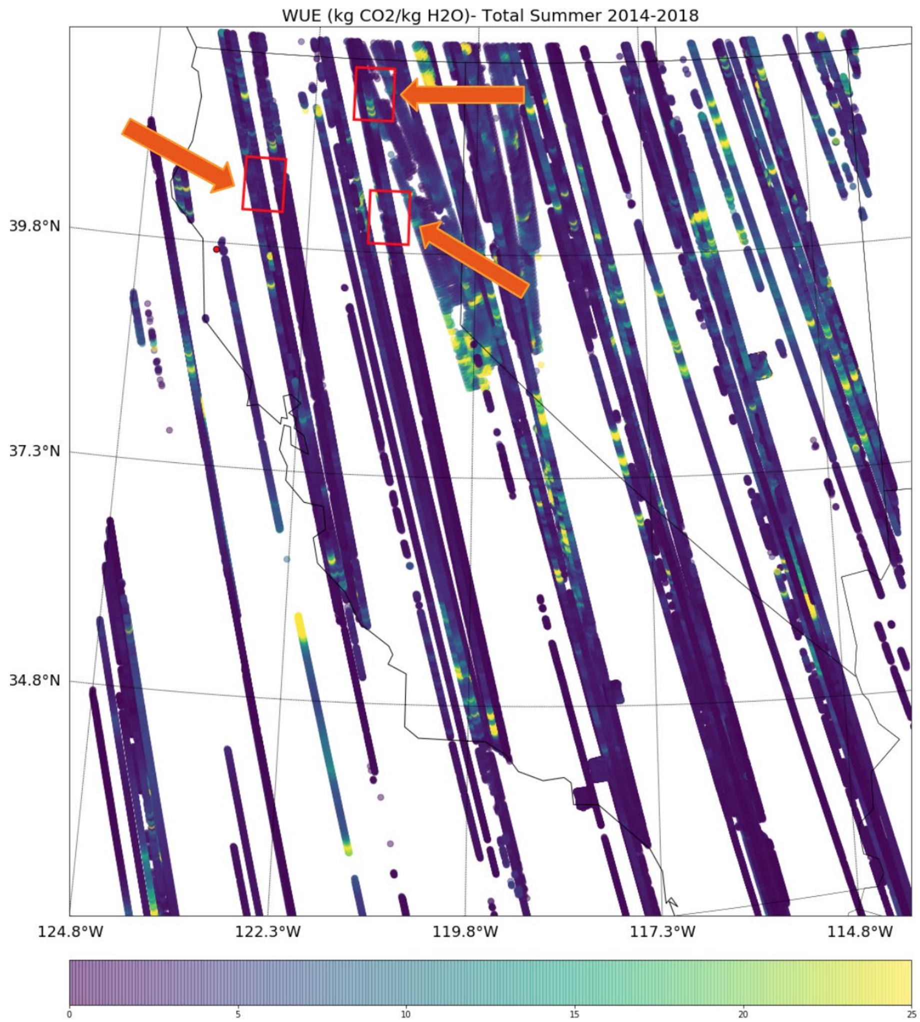

Figure 3 Distribution of WUE index values calculated for each satellite data point. The target areas of interest for each species are boxed in red.

After calculating the WUE index values, I isolated the values present within each of the three target areas by month (Figure 4) The WUE values in Area 1 appears to be closely clumped and unimodal at low WUE index values. In contrast, Area 1 and Area 3 have a much wider distribution than Area 2, and neither appears to be unimodal. The median WUE only increased in value throughout the summer for Area 3, but no trend in the median occurred in Area 1 and Area 2. The median values in Area 1, the Ponderosa Pine-dominated region, for June, July, and August were 2.206, 3.983, and 1.375, respectively. In Area 2, the Douglas Fir-dominated region, the median WUE values for June, July, and August were 1.817, 1.988, and 1.559, respectively. Finally, the median values for Area 3, the White Fir-dominated region, for June, July, and August were 2.243, 2.783, and 3.174, respectively.

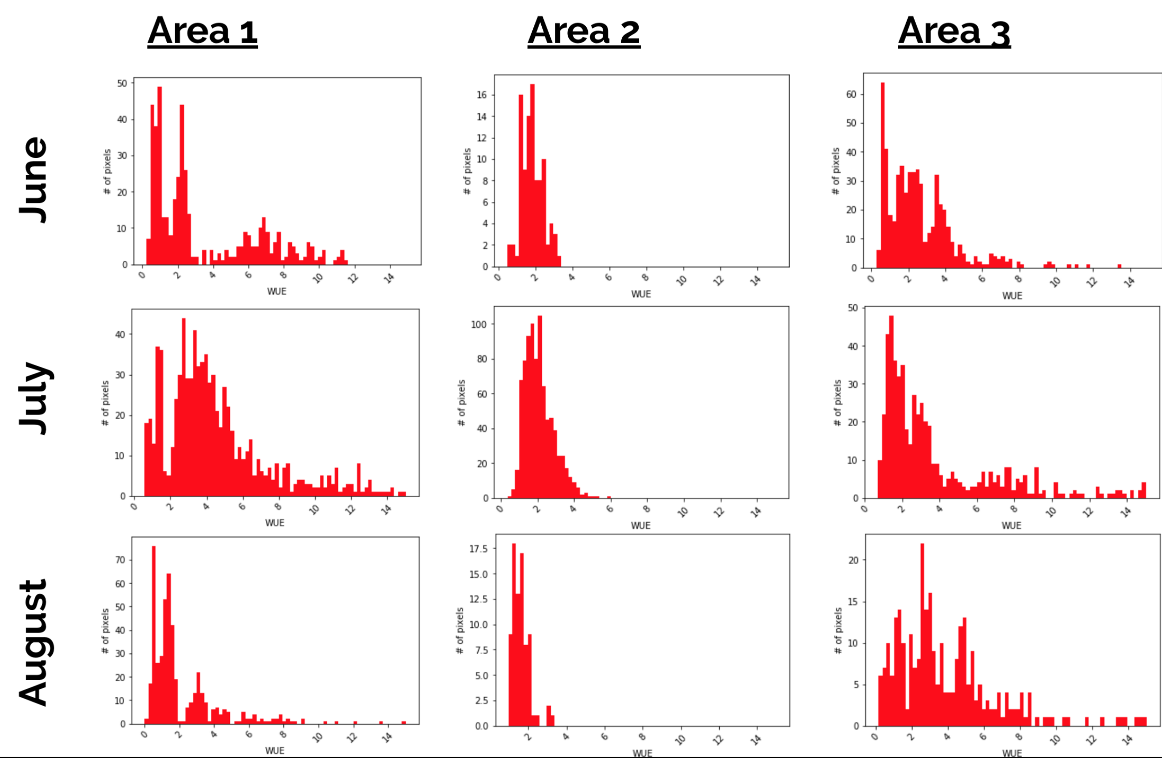

Figure 4: WUE index distributions for June, July, and August for each of the three target areas. Area 2 has a narrow distribution of low WUE index values, while Areas 1 and 3 have a wider distribution of WUE index values.

DISCUSSION

Exchange of CO_2 and water vapor between evergreen trees and the atmosphere could have a potentially significant influence on climate. The proper remote sensing tools to detect the variation of this exchange between species on a regional scale have yet to be developed to the extent necessary to enable proper studies on how WUE will change with a changing climate. By looking at three target areas to compare forest survey data and satellite data, this study uncovers potential problems with this method, as well as ways to move forward in creating a viable approach of measuring WUE of species from space.

Coincident Spatial Coverage

The FIA dataset and the OCO-2 satellite dataset have not been used together in studies. As a result, it was necessary to look at how much of the data is spatially overlapping. The study found that only 13% of the FIA data is covered by June, July, and August satellite data from OCO-2. This leads to difficulty in finding suitable study sites and areas. This issue may be improved upon by extending the OCO-2 satellite dataset from May to September. The main reason to avoid the non-summer months is to omit the presence of heavy clouds and rainfall that could cause the significantly smaller effect of tree species on water vapor to be masked. However, it may be possible to also tie in weather and cloud information to find clear days during other months.

Forest Composition and Structure

It was important to quantify the composition and structure of the forest by weighing the effects of both species percentage and average tree sizes. Although some species may have appeared to be more dominant due to a higher percentage of trees by tree count within a certain area, more accurate measurements of dominance require including basal area. Basal area is the cross-sectional area of a tree, giving weight to the fact that larger trees tend to have a larger effect on ecosystem functions and climate due to increased amounts of photosynthesis and evapotranspiration (Lindenmayer et al. 2012).

Based on the calculated transpiration index of each species, I can conclude that Area 2 likely has the best representation of one individual species— Douglas Fir. Only Douglas Firs and Canyon Live Oaks individually comprised over 10% of the population. The Douglas Firs had a significantly higher transpiration index of 0.0326 compared to the Canyon Live Oaks' transpiration index of 0.0052 within this area. Because of this difference, we can essentially attribute the WUE calculated over Area 2 as resulting from the presence of Douglas Firs. Area 1 presented a slightly more mixed region of species of interest. The three species that each made up over 10% of the population were Ponderosa Pine, White Fir, and Lodgepole Pine. Although this area was considered to be Ponderosa Pine-dominated due to its large transpiration index of 0.0215 and Lodgepole Pine had a negligible transpiration index of 0.0022, the White Firs had a non-negligible transpiration index of 0.0084 as well. Because their transpiration index was not very low in comparison to the Ponderosa Pines, I could not count out the effects of White Firs in this area and considered Area 1 to have a large effect due to Ponderosa Pines and a smaller effect due to White Firs. Finally, Area 3 presented the most mixed composition of the areas. Although this area was picked in order to be a sample of White Fir-dominated space, the species with a percentage over 10% included White Firs, Douglas Firs, Ponderosa Pines, and California Red Firs, several of which are other target species that could have an effect on the overall WUE of the ecosystem. While the White Firs and California Red Firs had large transpiration indices of 0.0164 and 0.0169, respectively, the presence of Douglas Fir and Ponderosa Pine, which had transpiration indices of 0.0088 and 0.0070, could have still had a contributing effect. All of these species effects within each area were taken into account when looking at the WUE index distributions.

Water Use Efficiency

With knowledge of the spatial limitations and the forest structures, I compared the distribution of WUE index values in an area to the local species composition. Area 2, which had only Douglas Firs dominating, yielded a very unimodal graph, with all the values at a relatively low WUE index for all three summer months. This result could be the WUE signature of the Douglas Fir species, and more comparisons with other Douglas Fir areas could generate a definitive answer. For areas 1 and 3, I was not able to definitively attribute the WUE index distributions of each graph to only one species in these two areas because of the species overlap. However, it is interesting to note that the two regions in which Ponderosa Pines have a larger transpiration index, resulting from both larger size and higher tree percentage, the WUE index values visually have a wider distribution. Ponderosa Pine has on average a larger WUE than White Fir and potentially other fir species. Thus, it is possible that we are seeing the effect of Ponderosa Pine when comparing the graphs from these two sites to Area 2, where Douglas Fir dominates and Ponderosa Pine is absent (J. Battles, *personal communication*).

Modeling Challenges

Because of the exploratory nature of this study, there were several challenges that came to light in the process of comparing satellite data and landscape information. The main issue I faced throughout this project was that, despite having very high spatial resolution along each individual swath, there was very limited spatial coverage from the satellite during the summer months. This deficit left very few areas to study the overlap between satellites and areas with one dominant species.

Another potential issue with using this methodology to study WUE arises from the difficulty scaling up ground data to use as comparison against satellite calculated WUE index values. Although it is possible to look at order of magnitude differences in species from ground measurements to compare, WUE at ground level does not necessarily scale up well to larger canopy and ecosystem WUE that is calculated from the satellite data, and vice versa (Medrano et al. 2015). Niu et al. 2011 found that a temperate steppe climate had increasing canopy and ecosystem WUE as the climate warmed, but leaf level WUE did not follow the same trend and actually decreased with warming. This study also functioned under the assumption that the calculated WUE will yield the same accuracy of results throughout the summer months. However, transitionary periods at the beginning and ending of plant growth periods could potentially cause problems. MODIS calculated WUE over croplands measured large uncertainties during these transitionary periods (Tang et al. 2015), and WUE from MODIS was lower than the ground calculated WUE for summer months, and overestimated during the transitionary periods (Tang et al. 2016).

Another important conclusion to be drawn from this result is that there are no notable trends between the months, meaning that any changes to WUE throughout the summer are not captured by this method of measurement. The expected result was that the WUE index peak would shift towards higher values as less water was available in the later summer because some trees will close their stomata and increase their WUE, while those with lower WUE and higher water demand may go dormant during periods of water shortage (Peters et al. 2018). However, this trend was not evident in all three study areas. Only Area 3 displayed an increased median WUE index as the summer progressed. This lack of a clear trend for all the areas could potentially be because of the limited scope of looking at just three months. If the study were extended to catch the transitionary periods between the wet and dry seasons (e.g. May to September), it is possible that this increase in detected WUE index and the start of dormancy for some tree species would be captured. Furthermore, looking at this data by month is also difficult because the satellite does not have the exact same pass over for every month, meaning that some months have significantly more data in our target area than others, depending on at what time of year it passed over that specific area.

Future Directions

This study provides the first step in determining WUE from satellites and can be built upon in several different ways. There is an inherent difficulty of analyzing species that are occurring in a mixed conifer forest, because it is nearly impossible to find large enough areas of forest where one species dominates, and the other species are completely absent. This lack of ability to analyze individual species pushes the need for a test that is able to account for the percentage effect that each species has. The main step that I am planning to execute over the next several months is to go through each individual OCO-2 satellite point and use the FIA data to weight the effect of species by the species percentage at that point. Because there are millions of data points in both datasets, this will require a computer that has more computational capabilities than my current computer is able to handle.

Another potential way of dealing with the issue of mixed conifer forests is by expanding beyond the borders of California. Although conifer evergreen forests tend to be mixed in California, there are other locations in the world where this study could be done with less effect of competing species. A site on Vancouver Island, British Columbia has an eddy-covariance tower located in an equally Douglas Fir-dominated area to my initial site, but without Ponderosa Pines and White Firs present (Ponton et al. 2006). Areas like these, in combination with mixed forest sites in the United States, could potentially be very useful for future satellite studies into species differences.

Because one of the main limitations is a lack of spatial coverage, another future study should use newer satellite instruments like TROPOMI, which measures both CO_2 and water vapor and has better spatial coverage than OCO-2. TROPOMI was launched in 2017 on the European Space Agency's Sentinel-5 Precursor satellite, and while it does not have enough data yet to perform this study, it could provide a more comprehensive understanding of species differences in the future using more reference points across California (Veefkind et al. 2011). Because of large variability in WUE by latitude and elevation, using these same strategies, similar studies should also be done globally to incorporate other ecosystem types.

Broader Implications

The need for a satellite-based method of accurately determining WUE remains both significant and necessary to society as a whole. Uncertainty in large scale water use efficiency necessitates validation from satellites. Within current predictive climate models, the increase in WUE over time that is predicted is not as large as the actual magnitude of WUE change over the past 20 years (Kennan et al. 2013). This finding within temperate and boreal forests in the Northern Hemisphere—both large components of the biosphere dominated by evergreens—displays the dire need for a method of studying WUE in this type of vegetation, if we hope to refine our climate models in the future.

Additional tools to measure water use efficiency from space have implications in the agricultural sector as well as for studying climate. Especially as water resources become more scarce, being able to study the WUE of crops in both California and across the country will become increasingly important. Satellites will be invaluable over the large spatial expanses of agricultural land, and this tool will also be important to study climate implications of changing forest compositions and structure resulting from drought (Clark et al. 2016). This study has shown the potential for a method of satellite-based WUE to show species differences. As this technology further develops, it will be able to guide climate mitigation response strategies concerning evergreen forests and improve climate model parameters to give more accurate predictions.

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