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Mapping site index and volume increment from forest inventory, Landsat, and ecological variables in Tahoe National Forest, California, USA

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1 **Mapping site index and volume increment from forest inventory,**
2 **Landsat, and ecological variables in Tahoe National Forest,**
3 **California, USA**

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Abstract

High-resolution site index (SI) and mean annual increment (MAI) maps are desired for local forest management. We integrated field inventory, Landsat, and ecological variables to produce 30m SI and MAI for the Tahoe National Forest (TNF) where different tree species coexist. We converted species-specific SI using adjustment factors. Then, the SI map was produced by (1) intensifying plots to expand the training sets to more climatic, topographic, soil, and forest reflective classes, (2) using results from a stepwise regression to enable a weighted imputation that minimized the effects of outlier plots within classes, and (3) local interpolation and strata median filling to assign values to pixels without direct imputations. The SI (reference age is 50 years) map had an R^2 of 0.7637, a root-mean-square error (RMSE) of 3.60, and a mean absolute error (MAE) of 3.07 meters. MAI was similarly produced with an R^2 of 0.6882, an RMSE of 1.73, and a MAE of 1.20 cubic meters per hectare per year. Spatial pattern and trend of SI/MAI were analyzed to be related to elevation, aspect, slope, soil productivity, and forest type. The 30m SI and MAI maps can be used to support decisions on fire, plantation, biodiversity, and carbon.

Key words: site index, mean annual increment, timber productivity, remote sensing, Sierra Nevada

1. Introduction

Forest productivity is an important indicator of diverse applications such as biofuels supply, carbon sequestration, and forest growth projection. In the western United States (US), potential productivity is assessed by the Forest Inventory Analysis (FIA) program whereby site trees are selected to produce a site index (SI) for forest field plots (Latta *et al.*, 2009). SI is a common species-specific approach in forestry for assessing forest site productivity; it is defined as the height of dominant trees of a stand projected to some particular reference age, using specific tables and equations for each forest species differing by region (Curt *et al.*, 2001). Mean annual increment (MAI), defined as the increment (increase in volume) of a timber stand averaged over the period between age zero and the age at which MAI culminates (i.e., reaches its maximum value), is used in economic analysis and determinations of forest policy because it can be associated with value and rate of return on investment. From different aspects, both SI and MAI can help evaluate the quality of the land and predict timber productivity, wood volume, and potential rate of forest growth, important for local forest management such as silviculture, ecological restoration, and habitat conservation. Ideally, spatially continuous maps, including SI and MAI, at detailed to moderate resolutions (e.g., 1-30 m) are needed for tactical planning and operational forest management (Falkowski *et al.*, 2009). The maps at this detail provide the greatest flexibility for meeting the widest variety of forest information needs by allowing researchers and forestry practitioners to tailor analyses to meet particular objectives (Brososke *et al.*, 2014). However, high resolution spatially-explicit SI and MAI products are usually not available.

Historically, spatial site productivity data have been based on soil maps from the Natural Resource Conservation Service (NRCS) that lacked the accuracy required for project level planning or site studies. In particular, the FIA program collects forest information in the field; however, to preserve confidential information for private land owners, the U.S. Farm Bill specifically requires that the reported positions of FIA plots be perturbed from their actual coordinates. To greatly enhance the utility of FIA data, one of the proposed alternatives is to provide a variety of model-based maps of forest attributes that users could access via the Internet (McRoberts *et al.*, 2005). However, it is difficult to map forest growth potential across regions with different environmental conditions from limited field measurements of productivity (Waring *et al.*, 2006; Weiskittel *et al.*, 2011). Despite the difficulties, several different methods have been used to map SI and MAI. Correlating SI with site types according to a local or regional site classification system was reported (Curt *et al.*, 2001). Parametric regression and statistical models have been commonly used to predict SI and MAI from biophysical factors related to climate, soil, and topography (e.g., Brandl *et al.*, 2014; Fries *et al.*, 2000; Hamel *et al.*, 2004; Monserud *et al.*, 2006; Sharma *et al.*, 2012; Wang and Klinka, 1996). Nonparametric random forest models have been developed to relate SI as a function of climate variables (Crookston *et al.*, 2010; Jiang *et al.*, 2015; Weiskittel *et al.*, 2011), and random forest was also combined with regression models for predicting plantation loblolly pine (*Pinus taeda* L.) SI from biophysical variables (Sabatia and Burkhart, 2014). Geostatistical techniques such as simplified universal kriging (UK) were also adopted to predict SI for six major tree species in the German state of Baden-Württemberg based on large data sets from forest inventories (Nothdurft *et al.*, 2012). A biophysical SI method, which obtains the SI of a given site by making adjustments to a mean provincial SI using multipliers

according to site climatic, edaphic, and stand structural properties, was proposed by Ung *et al.* (2001) and applied by Beaulieu *et al.* (2011) to predict SI for seven plantation-grown conifer species in Quebec. Modeling approaches such as the Physiological Processes to Predict Growth (3-PG) model were used to generate estimates of SI and potential productivity (Coops *et al.*, 2011; Swenson *et al.*, 2005). Based on spatially-explicit climate data and point-specific productivity data, Latta *et al.* (2009) evaluated four possible imputation methods (nearest neighbor, multiple linear regression, thin plate spline functions, and a spatial autoregressive model) to produce culmination potential MAI for all of Oregon and Washington timberland at 800m resolution. Waring *et al.* (2006) used the mid-summer Moderate Resolution Imaging Spectroradiometer (MODIS) Enhanced Vegetation Index (EVI) values to generate a 1 km resolution map predicting spatial variation in SI of Douglas-fir over 630,000 km² in the Pacific and Inland Northwest, U.S.A.

All these previous efforts provide different solutions to SI and MAI mapping, but they have three drawbacks. First, high resolution remote sensing data, such as 30m Landsat, have been rarely used, although Ma *et al.* (2006) ignored the biophysical factors and predicted the spruce-dominant forest-ecosystem site index from Landsat vegetation index based on a simple linear correlation. Second, very few studies were reported for a landscape where many trees species coexist but a specific species is only found in a limited area. Third, although there are many methods (e.g., regression, random forest, and nearest neighbor) to map and predict inventory attributes for operational forest management, each method has its own advantage and disadvantage, as reviewed by Brososke *et al.* (2014). For example, parametric regression approach relies on data assumptions and cannot easily handle missing values. Nearest neighbor approach is sensitive to the spatial mismatch caused by poor georeferencing of

remotely sensed imagery and positional errors associated with ground reference points (McRoberts, 2010). Recently, Huang *et al.* (2016) demonstrated a nonparametric imputation approach that extrapolates plot-level aboveground live biomass to a wall-to-wall map by using satellite images and environmental datasets. This approach is nonparametric and accounts for spatial mismatch; however, it has not been applied to SI and MAI predictions, which are dependent on tree species and forest type.

Given that the existing FIA site index (SI) data have been rarely used for creating high resolution (e.g., 30m) spatially-explicit products, the objective of this paper is to explore the new approach of Huang *et al.* (2016) to predict SI and MAI on a scale that is relevant for local forest management. To achieve this goal, we integrated forest inventory, Landsat satellite images, ecological variables, and Integrated Biosphere Simulator (IBIS) modeling to map 30m SI and MAI in the Tahoe National Forest (TNF).

2. Study area

Our study area is the TNF located in northern California's Sierra Nevada with a total area of 3526.82 km² (**Figure 1**). This area is renowned for its rugged extremes, ranging from an elevation of 457 m on the western edge of the forest to over 2865 m on mountain tops along the Sierra Crest. The western third of the area is dominated by deeply incised canyons that are separated by long, narrow, gently sloping ridges; however, the eastern third is featured by low foothills and broad valleys. The study area is a temperate ecosystem with many tree species that coexist in a heterogeneous environment. The study area generally experiences warm dry

summers and cold wet winters, but elevation plays a major role in distribution of weather conditions. Winter temperatures below zero and summer temperatures above 37.8 °C indicate the normal seasonal spread. Temperatures range from very warm in the canyons in the western part during summer to very cold in the high areas and eastern parts in the winter. The precipitation falls mainly from October through April, but it typically comes in the form of snow at higher elevations. The soils on the TNF were formed under the combining properties of physiography, topographic relief, hydrology, vegetation, and geomorphology. The TNF has a variety of soil types with productivity ranging from very low to very high, according to “Soil Survey Tahoe National Forest Area California” (http://www.nrcs.usda.gov/Internet/FSE_MANUSCRIPTS/california/tahoeNFCA2002/tahoeNFCA2002.pdf). TNF also has some of the most productive forest lands in the US and it is home to a large variety of conifer and deciduous trees. The dominant species include red and white fir (*Abies magnifica* and *Abies concolor*), ponderosa pine (*Pinus ponderosa*), sugar pine (*Pinus lambertiana*), incense-cedar (*Calocedrus decurrens*), and California black oak (*Quercus kelloggii*). Local managers requested a high-resolution SI and MAI map to capture the heterogeneous landscape for forest management.

Insert figure 1 around here

3. Methodology

3.1 Datasets

3.1.1 Landsat data

A Landsat 5 Thematic Mapper (TM) image with path 43 and row 33 acquired on September 27, 2011 was collected. The data were processed into surface reflectance data with LEDAPS algorithm (Masek *et al.*, 2006).

3.1.2 SI and MAI from FIA

The FIA program has established field plot centers in permanent locations. The inventory plots consist of four 7.32-m fixed-radius subplots spaced 36.6 m apart in a triangular arrangement with one subplot in the center and three peripheral subplots located at 36.58 m from the center of the central subplot with azimuths of 0°, 120°, and 240°. In each plot, the field crew selected and measured the site trees according to field protocol. A total of 225 homogeneous plots with the site tree species were selected (**Figure 1**). These plots were collected in different years ranging from 2003 to 2015. In this study, 205 of the 225 FIA plots were randomly used to produce maps and the remaining 20 plots were withheld for accuracy assessment. The actual plot locations were used rather than the perturbed locations. We retrieved plot level SI (with reference age of 50 years) from the FIA database. In addition, in each plot all the survey trees were used by the FIA program to determine the forest type of the plot (**Figure 2**). We calculated the MAI for each plot from the plot SI with different equations that were derived from yield data found in published normal yield tables (**Table 1**).

Insert figure 2 around here

Insert table 1 around here

For a regional SI mapping, SI measurements covering different landscape are desired. However, a specific species may only be found in a limited area (e.g., most of the California red fir site trees were located in the center portion of our study area, as shown in **Figure 1**), and the SI from different species cannot be combined directly because SI is species specific.

Nevertheless, the SI for different species are correlated (Keyser *et al.*, 2008), and a reasonable relationship exists to convert the SI of different species to a regional site index (RSI, equation 1) so that they can be comparable to reflect site quality:

$$RSI = SI / F_s \tag{1}$$

where RSI is the regional site index adjusted from species-specific SI (height in meters with reference age of 50), and F_s is the species-specific adjustment factor (**Table 2**). F_s was determined by Keyser *et al.* (2008) to convert the 50-year SI of individual species in the western Sierra Nevada to reflect the site quality, ranging from 0.45 to 1.0. The adjustment resulted in a new RSI for each plot, which can be comparable and applied to a spatially continuous regional mapping.

Insert table 2 around here

3.1.3 Climate, topography, and soil zones

SI and MAI are affected by ecological factors such as climate, topography, and soil; therefore, we compiled three ecological classifications to represent these factors (**Figure 3**). For climate, four raster datasets of 270m Actual Evapo-Transpiration (AET), climatic water deficit (CWD), January mean temperature (T_{jan}), and July mean temperature (T_{jul}) over the entire California were obtained (Flint *et al.*, 2013). A Random Forest technique (Breiman, 2001), which is a classification method that operates by constructing a multitude of decision trees at training time and then outputting the mode of the classes of the individual trees, was used to classify California into 100 zones and the portion of our study area was clipped, resulting in 52 zones (**Figure 3a**). For topography, we used the Landscape Management Unit (LMU) tool version 2

(North, 2012) to divide the study area into 6 types based on a 4m Digital Elevation Model (DEM). These 6 zones represented distinctions in slope, aspect, and relative position (e.g., canyon and ridge) (**Figure 3b**). The soil productivity information was compiled from the forest survey site class of Soil Survey Geographic (SSURGO) database (<http://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx>), resulting in 9 zones (**Figure 3c**).

3.1.4 Integrated Biosphere Simulator (IBIS) productivity

The Integrated Biosphere Simulator (IBIS) (Foley *et al.*, 1996; Kucharik *et al.*, 2000) is a physically consistent modeling framework that follows basic rules of physics, plant physiology, and biogeochemistry. Through another project, a 1km resolution, 1901-2010 IBIS simulation was performed. The simulation was driven by PRISM monthly precipitation and temperature data (<http://prism.oregonstate.edu>) and the SSURGO soil data. We then summarized the mean of the simulated total biomass carbon (unit: kg C m⁻²) between year 70 and year 110 (**Figure 3d**). This gives the general spatial distribution of forest productivity. We classified the productivity into 3 zones of “<5”, “5~10”, and “>10”.

Insert figure 3 around here

3.2 Extrapolating SI and MAI

3.2.1 Overview

To extrapolate field SI and MAI to a spatially continuous map, we assigned the SI and MAI value for each 30m pixel with a new computer tool called “Field And Satellite for Ecosystem MAPping” (FastEmap, Huang *et al.*, 2016). The tool assimilates measured point-specific

estimates of forest biophysical characteristics, satellite images, and auxiliary datasets to map forest parameters at a 30m resolution. The tool consists of four major modules, which are defined below, including: a) intensifying plots; b) conducting a stepwise regression; c) imputation with regression as weights, and d) local interpolation and strata median filling. In general, the first step of “intensifying plots” assigns the attribute of a field plot to those pixels that are “extremely similar” so that the training sets can be expanded to more climatic, topographic, soil, and forest reflective classes (see section 3.2.2). The second step of “stepwise regression” provides a map prediction on measured metrics to capture the general distribution of forest attributes, enabling a subsequent weighted imputation (see section 3.2.3). The third step of “imputation” is to divide the study area into many groups composed of similar pixels. The weighted mean of plots falling within a specific group is assigned to the group; weighting is inversely proportional to the differences between measurement and regression for minimizing the effects of outlier plots within groups (see section 3.2.4). The last step of “local interpolation and strata median filling” is to assign values to pixels without direct imputations (see section 3.2.5). This flowchart was applied to SI and MAI separately and in this section, we have taken SI to illustrate the procedure (**Figure 4**).

Insert figure 4 around here

3.2.2 Intensifying plots by creating additional “virtual” plots

Imputation methods usually require a lot of field data, which is confirmed by the simulation study of Nilsson (1997) who showed that at least one plot per 26 km² was required for his study. However, in many cases the plot spatial sampling frequency may be too sparse to provide adequate reference data for a typical project area extent (Hudak *at al.*, 2014); therefore, the main purpose of creating additional “virtual” plots from existing FIA plots was

to solve potential problems stemming from insufficient field plot numbers (Huang *et al.*, 2016). A plot intensification methodology was adopted by previous studies to address similar problems. For example, Breidenbach *et al.* (2012) created 580 artificial sample plots and then aggregated them with 154 measured sample plots to improve above-ground biomass predictions.

Intensifying plots was accomplished by assigning a SI of an FIA plot to those “extremely similar” pixels as follows. Assuming a) an FIA plot is falling in climate zone X, topography zone Y, and soil zone Z; b) The reflectances of Landsat bands 3, 4, 5 and 7 of this plot are R1, R2, R3 and R4, respectively; and c) the SI of this plot is V, then a SI of V was assigned to those pixels that met the following criteria: a) they were in the same climate zone X, topography zone Y, and soil zone Z; b) their reflectances of Landsat bands 3, 4, 5, and 7 fell within “ $R1 \pm \alpha$ ”, “ $R2 \pm \alpha$ ”, “ $R3 \pm \alpha$ ”, and “ $R4 \pm \alpha$ ”, respectively, where α , an empirical threshold value defining “closeness”, was set as 0.01. All original FIA plots and the new pixels that were assigned a SI value (virtual plots) were combined as “intensified plots”. This step of “intensifying plots” resulted in 5590 intensified plots, 27 times the original number of 205 plots. One should be aware that the procedure of “intensifying plots” simply duplicates the attribute from the existing plots and cannot enhance the variation, so there was no additional information being created; however, it creates more plots distributed in spatial domain.

3.2.3 Stepwise regression

Regression is a traditional analysis approach to predict inventory attributes from limited field plots, so a regression was conducted to create a SI map. To do this, the 205 FIA plots were overlaid with AET, CWD, T_{jul} , T_{jan} , soil productivity (SP), and Landsat bands 1, 2, 3, 4, 5, and

7 to extract the values, and a SI map (**Figure 5**) was produced from the stepwise regression (equation 2).

$$SI = (1.58T_{jan} + 0.0028B_4 - 0.052B_1 - 0.56T_{jul} + 0.034B_3 - 0.018B_7 + 0.51SP + 0.0088B_5 - 8.41) \quad (2)$$

The R^2 of this regression was 0.29, indicating a low accuracy. However, the general distribution of SI was reasonable: high SI tended to be located in warmer areas and in the low foothills while areas of low SI were typically found in the colder regions and in the high mountain tops. This indicated that the stepwise regression could capture the general pattern of SI, which led us to use it for calculating weights in the following imputation process.

Insert figure 5 around here

3.2.4. Group imputation weighted by regression

In forestry, the “stratum/stand mean” technique has been used for mapping. For example, in estimating forest stand characteristics, Muinonen *at al.* (2001) superimposed the stand boundaries on the field plots and calculated stand results from plots falling within stand boundaries. Within the study area of McRoberts (2008), the boundaries of 12 representative stands were delineated and stand-level means for each variable were estimated as means over plots within stands. A similar concept was adopted in our following group imputation process but in an iterative manner.

After intensifying plots (section 3.2.2) and stepwise regression analysis (section 3.2.3), the study area was divided into many groups through two steps. First, Landsat bands 3, 4, 5, and 7 were each equally binned into 15 classes. Second, we used the ArcGIS “combine” function to combine these Landsat classes with 52 climate zones (**Figure 3a**), 6 topography zones (**Figure 3b**), and 9 soil zones (**Figure 3c**) to create $15 \times 15 \times 15 \times 15 \times 52 \times 6 \times 9 = 142\,155\,000$

unique groups. In this way, each group is composed of similar pixels having similar remote sensing metrics and environmental conditions. In each group, the intensified plots falling within a group were identified, and then equation (3) was used to calculate the SI for all the pixels in this group:

$$SI_{group} = \sum_{k=1}^n W_k \times SI_{m-k} \quad (3)$$

where n is the number of intensified plots located within the group, and SI_{m-k} indicates the SI for the k^{th} plot. W_k is the weighting coefficient for the k^{th} plot, which is inversely related to its absolute difference between field SI (SI_{m-k}) and regression predicted SI (SI_{p-k}) (equation 4):

$$W_k = \frac{(|SI_{m-k} - SI_{p-k}|)^{(-t)}}{\sum_{k=1}^n (|SI_{m-k} - SI_{p-k}|)^{(-t)}} \quad (4)$$

where t was set as 2 and k was set as > 3 , which means at least 4 plots were required to fall in the group in order to perform imputation. The main reason for adopting weighting was that there were possible spatial mismatches between field plots and remote sensing images (e.g., the coordinates of our FIA plots had errors ranging from less than 10.1 m to larger than 30.8 m, if only assessed from the Global Position System instrument), thus creating possible outliers within each group. For example, a high-biomass forest plot may fall in an adjacent low-biomass shrubland due to its Global Position System error. In this case, the falsely-located plot would cause the shrubland biomass to be overestimated if not properly handled. However, regression prediction can capture the general distribution of high biomass in forest and low biomass in shrubland. If the weighting was calculated as the inverse absolute difference between measured biomass and regression predicted biomass, a low weighting will

be assigned to this falsely-located plot for shrubland biomass prediction, thus reducing the influence of spatial mismatch. See more details in Huang *et al.* (2016).

When there was an insufficient number of plots within a specific group, we ignored the soil zone and then conducted the imputation again. If the number of plots was still insufficient, we ignored the topography zone. This iteration was repeated until the climate zone was ignored. In other words, we chose which environmental characteristics were most important and dropped them from the imputation process in reverse order of importance. Even after all of climate, topography, and soil constraints were ignored, it was still possible that insufficient plots were located within a group. In this case, we reduced the number of Landsat bins from 15 to 10 and repeated the above steps.

From the aforementioned context, we can see the SI was imputed in an iterative manner. It started with a high bin number and many condition constraints for imputation, then iteratively proceeded to impute the remaining pixels with fewer condition constraints and fewer bins. Clearly, if an area was imputed earlier in iteration, the imputation result was intrinsically more accurate because the area is more similar to the plots falling within the area. During this iteration, intensified plots serve an important role: the intensification was done in a way that all the environment variables were considered and the remote sensing value was very close, thereby assuring the pixels were “extremely similar”. If there was no plot intensification, there might be no sufficient suitable plots for a group to be imputed in an earlier iteration stage; therefore, the intensification allows a group without sufficient actual FIA plots to be associated with sufficient intensified plots to improve the imputation.

3.2.5. Filling the remaining empty pixels

If there were still insufficient plots falling within the group, we finished all remaining pixels through three steps. First, we interpolated the missing value using a local window mean value starting from a small window size 3x3 and gradually increasing the window size to 9x9. Second, we divided the regression predicted SI map (i.e., **Figure 5**) into 20 bins and then combined them with 52 climate zones (**Figure 3a**), 6 topography zones (**Figure 3b**), and 9 soil zones (**Figure 3c**), and 3 IBIS zones (**Figure 3d**), resulting in $20 \times 52 \times 6 \times 9 \times 3 = 168\,480$ strata. In each stratum, those pixels that had never been imputed were filled with the median value of the already-imputed pixels that were within the same stratum. Third, these two datasets (i.e., location interpolation and strata median) were averaged to fill the remaining empty pixels.

3.3 Accuracy assessment

To evaluate the SI and MAI accuracy, we used 40 plots for accuracy assessment. Twenty of these plots were the FIA plots that were withheld for validation; addition 20 plots were surveyed in August 2016 specifically for the validation purpose with the FIA protocol (i.e., selecting and boring the site trees) followed by the same SI and MAI determination. We compared the field and estimated SI and MAI. The root-mean-square error (RMSE) (equation 5) and the mean absolute error (MAE) (equation 6) were computed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad (5)$$

$$MAE = \frac{\sum_{i=1}^n |y_i - \hat{y}_i|}{n} \quad (6)$$

where n is equal to 40, y_i is field value, and $\hat{y}_i$ is prediction.

4. Results

Site Index for TNF was produced from climate, topography, soil, Landsat, and FIA data (Figure 6). The comparison between FIA field SI and predicted SI (Figure 7) shows that the dots are distributed along line 1:1 and the R^2 is 0.7637 with an RMSE of 3.60 and a MAE of 3.07 meters, indicating that the 30m SI is accurate. Generally the low elevations on the west side of the study area were characterized by high SI, indicating the good site quality in the foothills and along the valley due to optimum moisture and temperatures for the associated conifer species. In the high elevation Sierra crest (central portion of the TNF), the SI was frequently low, indicating the poor site quality of mountain tops from their shallow soils. Moving east of the Sierra crest increased SI as elevation decreased, but generally didn't reach west side SI values due to more xeric conditions. However, on the east side, there was a relatively lower elevation area (compared to surrounding high mountains, see Figure 1), where the SI was unexpectedly high when compared to neighboring areas of similar bioclimatic conditions. Further investigation revealed that there was a congregation of plots that were within an intensively managed (fertilized, terraced, multiple herbicide applications) plantation that most likely inflated surrounding SI values.

Insert figure 6 around here

Insert figure 7 around here

We calculated SI mean in different ecological zones (Table 3). When the elevation was lower than 700~900 m, the mean regional site index (RSI) was around 25~26, indicating that trees

may grow up to 25~26 m at the age of 50 years without competition. However, when the elevation was above 700~900 m, the SI consistently decreased from 24 to 11, implying that elevation plays an important role in tree growth. For topography in terms of ridge, canyon, and slope, the SI ranged from 17 to 20 without obvious difference, indicating that influence of aspect and slope on SI was negligible or that their influence was overwhelmed by elevation change. For soil productivity, the SI was generally lower in the poor areas (ranking 1~4) but higher in the good areas (ranking 5~9) with an exception (SI was 17 in the area ranking 6). This indicates soil productivity had an effect on tree growth, but a consistent trend could not be observed.

Insert table 3 around here

A similar approach was used to produce the MAI map (**Figure 8**). The comparison between field and predicted MAI (**Figure 9**) shows the dots are generally distributed along line 1:1. The regression equation is $y=0.9592x$ with an R^2 of 0.6882, an RMSE of 1.73, and a MAE of 1.20 cubic meters per hectare per year. These results indicate the 30m MAI was 4.1% underestimated, but the accuracy was satisfactory. Several interesting patterns can be observed. First, the lower elevation west side of the study area was generally characterized by high MAI with a pattern similar to SI, indicating the high timber productivity in the foothills and along the valley. Second, in the high elevation Sierra crest, despite the low SI (around 6~15, see **Figure 6**), most of the MAI was not low, especially in the northern portion. The main reason was that the forest types were mainly California red fir, white fir, and California mixed conifer (see **Figure 2** for the forest distribution), and their MAI was relatively high when the SI was 6~15 (see **Figure 10**, which is another expression form of **Table 1**). Third, in the east side of the study area, the SI was relatively high (around 24~37, see **Figure 6**);

however, the MAI was low (around 4~8 cubic meters per hectare per year, see **Figure 8**). The main reason was that the forest types were ponderosa pine and Jeffrey pine (see **Figure 2** for the forest distribution), and their MAI was relatively low when the SI was 24~37 (see **Figure 10**). These indicate that timber productivity is related to site quality, and forest type plays an important role as well.

Insert figure 8 around here

Insert figure 9 around here

Insert figure 10 around here

5. Discussion

In this study, we used a new approach to produce the SI and MAI maps. This method is a nonparametric approach independent of data assumptions. This method can reduce the influence of plot location errors. It can also address the potential issue of insufficient plots. However, this method has two disadvantages that are related to SI and MAI mapping.

First, the method requires that field plots are a representative sample of the landscape, which means the SI and MAI from field measurements need to be collected in different areas to capture the heterogeneity. This was also the reason why we chose 205 of 225 plots to create maps: we wanted the training plots to cover the landscape and its inherent heterogeneity. Nevertheless, SI is species dependent and must be calculated by species. If the species of interest can only be found in a limited extent (e.g., site trees of California red fir were not found in the west side of our study area, as shown in **Figure 1**), then the prerequisite of

“representativeness” is broken, which creates a barrier to producing a continuous SI map over a large area. Although SI value is not usually equivalent between species, some relationship exists among species: the adjustment factors (F_s) as shown in **Table 2** can be used to convert different species into a common reference. It should be pointed out that species-specific site indices can then be obtained by multiplying the regional SI (as shown in **Figure 6**) and their corresponding adjustment factor (as shown in **Table 2**), which can provide useful information for species management. If our approach is applied to other regions that are heterogeneous in terms of environment and tree species, the adjustment factors for additional species may need to be found in order to complete a regional mapping effort.

Second, the method needs to select the variables that significantly correlate with SI and MAI for imputation. There are typically a large number of readily available covariates in the form of remotely sensed and geospatial data. Many previous studies (e.g., Mohamed *et al.*, 2014; Sabatia and Burkhart, 2014) chose the variables related to topography (elevation, aspect, and slope), soil (pH, sand, and silt), and climate (temperature and precipitation zones) as the major determining factors of SI and MAI. In this study, we selected AET, CWD, T_{jul} , T_{jan} , topography, and soil for imputation. Additionally, we adopted Landsat remote sensing for imputation. As expected, the correlation between Landsat pixel metrics and SI of FIA plots is low. However, Landsat uses an optical sensor that captures the plant spectrum features, which are not a directly determining factor of SI and MAI. Nevertheless, land surface, especially vegetation distribution, is a result of the combined effect of the determining factors such as climate, soil, and moisture. Landsat imagery is sensitive to chlorophyll which can indicate prevailing conditions in the forest site, and the amount of chlorophyll is closely related to forest growth and plant spectrum traits (Ma *et al.*, 2006; Ung *et al.*, 2001); therefore, Landsat

427 reflectance was used in our study. The 30m Landsat allowed us to map SI and MAI at 30m,
428 which cannot be accomplished with the climate, soil, and topography alone at coarser
429 resolution.

430 In addition to the quantitative validation from 40 plots, the 30m SI and MAI products that we
431 created were also qualitatively evaluated by local foresters having intimate knowledge of the
432 landscape. Their feedback showed our products were very promising and deemed important
433 for local forest management in the TNF regarding fuels management to reduce fire severity,
434 plantation, biodiversity, and carbon. For fuels management, local managers use these products
435 to understand where fuels accumulate the fastest which could then target those areas for
436 potential fuel reduction. For plantation, our products are used to locate the optimal site and
437 species combinations for tree planting to aid post-fire ecosystem recovery. For biodiversity,
438 the TNF is about to embark on its forest plan revision where part of that plan is to manage the
439 California Spotted Owl (*Strix occidentalis occidentalis*). Wildlife biologists use SI and MAI
440 to locate those more mesic areas that can sustain more trees around Owl nests for retention
441 and those more xeric environments for potential tree density management. For carbon
442 sequestration, local managers can use SI and MAI to identify the poor and productive areas to
443 make decisions related to carbon cap-and-trade and carbon taxes. More potential applications
444 are currently being explored to take full advantage of the high-resolution SI and MAI products.

445 The products created from this study were produced with an automated tool (Huang *et al.*,
446 2016). Three research directions are warranted. First, in our current study, we used limited 20
447 FIA plots plus extra 20 plots for validation; however, cross-validation may be preferred for a
448 more convincing accuracy assessment. Second, our method is a nonparametric approach
449 similar to the nearest neighbor method. The only assumption is that the explanatory variables

(e.g., climate) have a strong relationship to the response variable (e.g., SI); a complete knowledge of the complicated relationships between them is not needed (Eskelson *et al.*, 2009). When the number of explanatory variables increases, selecting the critical and important variables for forest attributes prediction is a challenging and time-consuming task, which still remains daunting for the widely-used nearest neighbor approach (McRoberts, 2012; Brososke *et al.*, 2014). Stepwise regression analysis, correlation analysis, neural network, and feature extraction approaches may be used to identify the suitable variables (Lu, 2006). We have incorporated the stepwise regression (e.g., equation 2) into an automation line of FastEmap to aid variable selection (Huang *et al.*, 2016); however, stepwise model selection has deficiencies (Flom and Cassell, 2007). Therefore, in our study on SI and MAI, we identified the variables and their importance based on additional expert judgement, which plays an important role in landscape ecology (Perera *et al.*, 2012). The number of explanatory variables for SI and MAI in our study was limited (i.e., only Landsat bands, climate/topography/soil zones, and IBIS productivity). When our method is applied to future studies and there are many variables to choose from, the procedure of selecting the critical and important variables still needs to be automated somehow. Third, the present study was conducted only in TNF. With the availability of SI and MAI in the FIA database, the next step is to apply the methodology to a broader area (e.g., entire California) so that 30m SI and MAI maps can be accessed by the public without releasing the actual plot locations.

6. Conclusion

Over a heterogeneous mountain, the U.S. FIA program has been collecting point-specific site index (SI), but SI is species-specific and a tree species may be only found in a limited extent, so directly putting different species site indices together to predict continuous SI is not feasible. However, a relationship exists among different species, which can lead to a conversion by an adjustment factor so that all species can be simultaneously combined for SI mapping. This adjustment factor could be used to convert different species site indices into a region SI, a common reference independent upon site tree species.

In extrapolating point-specific SI data to a heterogeneous TNF, the common stepwise regression approach could capture the general distribution pattern of SI, but the accuracy (with a low R^2 of 0.29) was not sufficiently satisfactory. Our new approach consists of four major modules “intensifying”, “regression”, “imputation” and “filling”. The 4-step methodology resulted in an improved SI prediction, with an R^2 of 0.7637, an RMSE of 3.60, and a MAE of 3.07 meters. Plot-level MAI could be modelled from FIA site index and could be similarly extrapolated to landscape level at 30m resolution using the same 4-step approach, resulting in a MAI map with an R^2 of 0.6882, an RMSE of 1.73, and a MAE of 1.20 cubic meters per hectare per year. These SI and MAI results indicate our new approach is effective enough to map SI and MAI at 30m resolution over a complex landscape. The SI and MAI maps can be applied to fire, plantation, biodiversity, and carbon management.

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637

638 **Tables**

639 **Table 1.** Mean annual increment (MAI, in cubic meters per hectare per year) calculation for
 640 forest type

Forest type (COND_FORTYPCD code)	MAI Equation*	References
Douglas-fir forest (201)	$-4.20 + 0.39 \times \text{SI}$ (SI < 22.86) $-5.69 + 0.46 \times \text{SI}$ (22.86 ≤ SI ≤ 39.62) $1.60 + 0.28 \times \text{SI}$ (SI > 39.62)	McArdle <i>et al.</i> (1961)
California red fir forest (262)	$3.38 + 0.017 \times \text{pow}(\text{SI} \times 3.28, 1.6)$	Schumacher (1928)
White fir forest (261)	$0.0088 \times \text{pow}(\text{SI} \times 3.28, 1.561) + 1.66$	Krumland (2004)
Ponderosa pine forest (221)	$\exp(0.702695 \times \text{pow}(\text{SI} \times 3.28, 0.42) -$ $0.51367) \times 0.070$	Meyer (1961)
Jeffrey pine forest (225)	$\exp(0.702695 \times \text{pow}(\text{SI} \times 3.28, 0.42) -$ $0.51367) \times 0.070$	Meyer (1961)
Western white pine forest (241)	$1.04 + 0.40 \times \text{SI}$	Brickell (1970)
Lodgepole pine forest (281)	$0.20 \times \text{SI} - 1.56$	Dahms (1975)
California mixed conifer (371)	$\exp(0.578265 \times \text{pow}(\text{SI} \times 3.28, 0.4) +$ $1.8108) \times 0.70$	Dunning and Reineke (1933)
Hardwoods forest (922,931,933,962)	$0.39 \times \text{SI} - 3.72$	Worthington <i>et al.</i> (1960)

641 * exp is natural exponent and pow is power function; the equations were revised from original
 642 equations due to the unit difference; SI is in unit of meters with reference age of 50 years;
 643 MAI is in unit of cubic meters per hectare per year.

644

645 **Table 2.** Site tree species and the adjustment factor

Site tree common name (SITE_SPCD)	Scientific name	F _s
Douglas-fir (202)	<i>Pseudotsuga menziesii</i>	1.0
California red fir (20)	<i>Abies magnifica</i>	1.0
White fir (15)	<i>Abies concolor</i>	1.0
Ponderosa pine (122)	<i>Pinus ponderosa</i>	1.0
Jeffrey pine (116)	<i>Pinus Jeffreyi</i>	1.0
Sugar pine (117)	<i>Pinus lambertiana</i>	0.9

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648 **Table 3.** Mean regional site index (RSI) in elevation, topography, and soil productivity zones

Elevation			Soil		
(m)	RSI	Topography	RSI	productivity*	RSI
<500	26	Ridge	18	Rank 1	18
500-700	25	Canyon/drainage	19	Rank 2	17
700-900	26	Middle slope northeast < 30% slope	18	Rank 3	17
900-1100	24	Middle slope northeast > 30% slope	17	Rank 4	17
1100-1300	24	Middle slope southwest < 30% slope	20	Rank 5	22
1300-1500	22	Middle slope southwest > 30% slope	18	Rank 6	17
1500-1700	20			Rank 7	27
1700-1900	18			Rank 8	21
1900-2100	15			Rank 9	24
2100-2300	13				
2300-2500	11				
>2500	11				

649 * Soil productivity increases from rank 1 to 9

650

Figure captions

Figure 1. Study area of Tahoe National Forest in California, USA encircled by the white polygon. The background is a Digital Elevation Model (DEM) ranging from 200m in black to 2800m in white. Site index for different site tree species were surveyed in Forest Inventory Analysis (FIA) plots. Note the plot locations were perturbed according to law and this is for demonstration only.

Figure 2. The plot forest type determined by the Forest Inventory Analysis (FIA) program. The background is a Landsat normalized difference vegetation index (NDVI) ranging from 0.3 (black) up to 0.9 (white). Note the plot locations were perturbed according to law and this is for demonstration only.

Figure 3. The map of 52 climate zones (a), 6 topography zones (b), 9 soil productivity zones (c), and continuous modeling productivity (d).

Figure 4. Flowchart and conceptual modeling framework of site index.

Figure 5. Regional site index (SI) map predicted from stepwise regression analysis.

Figure 6. Region site index (SI) prediction in the Tahoe National Forest.

Figure 7. The comparison between field and predicted site index from 40 validation plots.

Figure 8. Mean annual increment (MAI) prediction in the Tahoe National Forest.

Figure 9. The comparison between field and predicted mean annual increment (MAI) from 40 validation plots.

670 **Figure 10.** Mean annual increment (MAI) prediction curve from site index (SI) for different
671 forest type.

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