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A new remote sensing-based carbon sequestration potential index (CSPI): A tool to support land carbon management

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ABSTRACT

Integrating remote sensing into assessments of carbon stocks and fluxes has advanced our understanding of how global change affects landscapes and our capacity to support decision making about forest management. However, there remains a lack of detailed and actionable analyses conducted across widely ranging environmental conditions that are appropriate for tactical planning. We used airborne laser scanning data and multi-source satellite imagery to estimate forest aboveground carbon density and gross primary production, and to map forest cover across the main Hawaiian Islands. We used these measures to develop the Carbon Sequestration Potential Index (CSPI), which identifies where the potential for carbon sequestration following afforestation would be highest within a complex landscape of 304 management units. Variation in CSPI was high across islands and between ecosystems, with low values for cool, dry and largely intact forest systems and high values for warm, wet and largely non-forested systems. The CSPI provided a rapid, spatially-explicit and actionable assessment of Hawaiian forest reserves, which can help stewardship agencies contribute to state carbon neutrality goals through climate-smart and science-driven prescriptions that encompass conservation to restoration.

1. Introduction

Mitigating climate change requires reducing reliance on fossil fuels (emission reductions through reduced demand, increased efficiency, and a shift to renewables) paired with actions that offset emissions by sequestering carbon (C), typically in the natural and working land (NWL) sector (Cook-Patton et al., 2020). Actionable data products from the currently available suite of tools and approaches are underdeveloped for tropical environments, and demonstrations useful to resource stewards operating on landscape scales are rare. There are important remote sensing applications that can support decision making on carbon sequestration (Asner et al., 2011; Bastin et al., 2019). Satellite-based remote sensing has yielded high frequency and global-scale measurements critical to supporting climate policy and action, with data sources that have markedly improved capacity to estimate spatial variation and temporal change in terrestrial C dynamics. Gross primary production (GPP) and its spatiotemporal variation across the biosphere, in combination with detailed vegetation mapping, have particularly enhanced our understanding of complex eco-physiological patterns across changing environments (Asner et al., 2011; Running and Zhao, 2015; Hawbaker et al., 2017; Selmants et al., 2017).

Land managers are increasingly being asked to consider how management can be expanded to also achieve C related objectives, for example, protecting high carbon density areas or enhancing the amounts of C sequestered on stewarded lands. The required rapid and robust characterization of a site with respect to C sequestration potential requires accurate information on GPP, but also C stock attributes and information on the type and condition of vegetation within a management unit. From this intuitive set of measures, a decision support framework can be used to provide managers with an actionable description of current conditions. Sequestration potential of a site can then be achieved via the integration of highly resolved maps of: (*i*) Aboveground carbon density (ACD) including spatial variation in aboveground biomass of vegetation; (*ii*) GPP fluxes that account for temporal dynamics and

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spatial variation in C uptake rates; and (*iii*) the vegetation mosaic represented by management units being stewarded by land managers. A decision support framework is useful to users of these remotely sensed products as this approach translates geospatial data, well suited for strategic policy level planning and decision making, into information products that are appropriate for shorter-term tactical to operational scale planning. It is at regional to local scales that resource professionals can realize the value of remotely sensed information for the identification, design, planning, and implementation of C sequestration projects. This globally intensifying focus on C, for some geographies codified via policy mandates and public law, requires: (*i*) ready access to robust and verifiable estimates of GPP, ACD and forest cover; and (*ii*) support with data interpretation and with the tactical to operational scale design, implementation, monitoring and evaluation of C sequestration projects.

Gross primary production, the rate at which atmospheric carbon dioxide is fixed by photosynthesis, is the dominant C flux from the atmosphere to the terrestrial biosphere (Lieth, 1973; Chapin et al., 2011). Because this flux determines the amount of C available for the processes leading to sequestration, detailed temporal and spatial understanding of GPP and its partitioning (Litton et al. 2007; Litton and Giardina, 2008; Ise et al., 2010; Anav et al., 2015; Running and Zhao, 2015; Barbosa et al., 2017) is vital to planning-focused assessments (e.g., Selmants et al. 2017). To this end, satellite-driven models of GPP have been developed and now provide unprecedented temporal resolution of planetary-scale C process rates (Running and Zhao, 2015; Ellsworth et al., 2017). To date, the widely used Moderate Resolution Imaging Spectroradiometer (MODIS)-based GPP (MOD17) product provides data at a 500-m resolution (Running and Zhao, 2015). While the near weekly temporal resolution for GPP products is high, a coarse spatial resolutiond limits the utility of MOD17 data for operational scale planning for C management (Marvin et al., 2016a; Powell et al., 2017). Important technical and scientific developments in satellite image spectroscopy, however, are redefining what is possible via satellite based Earth mapping. Missions collecting fluorescence data (e.g., TROPOspheric Monitoring Instrument (TROPOMI), including the European Space Agency (ESA) FLuorescence Explorer to be launched in 2024, will enhance spatial resolution. Currently, Badgley et al., (2017) have developed a near-infrared reflectance of vegetation (NIR_V) index to drive a much higher-resolution (30-m) GPP product. Because this C flux co-determines maximum sequestration capacity for an ecosystem, accurate and spatially resolved estimates of GPP are critical for: contemporary forest monitoring, modeling the C benefits of climate mitigation actions, and evaluating options to support decision making about where and when to take such actions across landscapes (Cook-Patton et al., 2020). High spatial resolution GPP products also support the full integration of payments for ecosystem services (Ouyang et al., 2020) into financially credible C planning instruments.

The estimation of ACD has been supported by airborne laser scanning and satellite imagery (Asner et al., 2012; Marvin et al., 2016b) and is a reference variable critical to monitoring the status of forest ecosystems (Schimel et al., 2015; Huang et al., 2019). The use of laser echoes to define the 3D structure of forests results in wall-to-wall forest maps of tree crown height at the scale of a million-ha island (Asner et al. 2011) to whole nations (Asner et al. 2014). These, in turn, are used to model ACD data layers necessary for large scale C assessments (e.g., Selmants et al. 2017). The prediction of forest biophysical attributes relies on statistical inferences of area-based methods that link ground-based observations to data from lasers and images. Estimation of forest structure with airborne laser data is scientifically robust, widely applied, and highly suitable for deriving wall-to-wall estimates of ACD. Integration of high-quality ACD maps with existing cartographies of stewardship units allows managers to compute statistics and describe the present status of even remote and difficult to access forest areas. This integration also paves the way for evaluations of forest monitoring deliverables from Reducing Emissions from Deforestation and Forest Degradation (REDD+) or afforestation / reforestation / restoration projects (Cordell et al., 2017; Csillik et al., 2019).

Oceanic islands such as in the Hawaiian archipelago represent a compact yet complex mosaic of edaphic, climatic, and land-use conditions, resulting in a high diversity of biome types and dynamic ecological conditions. In particular, the invasion by non-native species into native dominated ecosystems presents important challenges to land managers seeking to enhance C sequestration (Asner et al., 2014; Friday et al., 2015; Selmants et al., 2017; Bastin et al., 2019). Here we describe an effort to integrate knowledge about vegetation cover, C stocks and C fluxes, all derived from remote sensing, into a simple but effective data product to support tactical to operational scale decision-making about the application of climate-smart practices to conservation landscapes of Hawai'i. The Hawai'i geography is particularly useful because there are rich C focused data sets (Selmants et al. 2017) and legislation requires State level C-neutrality by 2045 (Hawai'i State Energy Office, 2019). To achieve C-neutrality, the State of Hawai'i will need to implement natural and working land actions that offset C emissions by way of increased C uptake and storage (Cook-Patton et al., 2020; Kauppi et al., 2020). To better inform C sequestration planning and policies, we integrated ACD and GPP data products with existing data on Forest Cover (FC) for the State of Hawai'i. Accounting FC is important because sequestration planning is tied directly to achieving additional C, which in turn hinges on condition of the vegetation on a site. Here, knowledge of FC allows delineation of where afforestation activities are appropriate.

To support tactical to operational scale planning, we used GPP, ACD and FC data to develop the Carbon Sequestration Potential Index (CSPI), which can simultaneously inform resource managers on C uptake efficiency by forest vegetation while scaling index values according to FC defined restoration potential. We used ACD maps generated with airborne laser scanning data, GPP data estimated via the novel NIRv approach with Landsat-8 satellite data, and Land-Carbon vegetation type and condition maps (Jacobi et al. 2017) to assess sequestration potential of 304 State of Hawai'i administered land management units located across Hawaii's main islands. Specifically, we used the CSPI to rank forested reserves and parks with respect to ACD, FC and GPP and identify: 1) areas characterized by low ACD, low FC and high GPP, which indicate high potential to respond to restoration or afforestation; 2) high ACD and high native FC, which indicate high potential for protection; and 3) low GPP, low FC and low ACD, indicating low potential to respond to restoration / afforestation. For sites mapped as a low CSPI score (i.e., a low priority for restoration or afforestation), we examined native vegetation condition for high FC units to assess potential and prioritization for protection of stored C (e.g., category 2 units in native dominated, high ACD and high FC condition). Spatial patterns of GPP were also assessed to understand climatic, edaphic and ecological drivers (e.g., annual rainfall, vegetation type) affecting C uptake to provide general insights into landscape scale C management.

2. Material and methods

2.1. *Hawai'i as a model for understanding carbon sequestration*

The Hawaiian Islands examined here (Hawai'i, Maui, Lana'i, Moloka'i, Kāho'olawe, 'Ōahu, Kaua'i) are characterized by steep topographic relief, which leads to large climatic variation over short distances (Vitousek, 2004). A diversity of climatic gradients, land use management practices, the shaping human factor and the spread of invasive alien species have led to a highly heterogeneous land cover mosaic within a small geographic area (Asner et al., 2011; Barbosa et al., 2017). High-moisture content and orographic uplifting can bring up to 10000 mm of annual rainfall on the eastern, windward sides of islands while western leeward areas are consistently drier (200–2000 mm yr^{-1}). Mean annual temperatures range from 24 °C at sea level to single digits at 4200 m elevation on the summits of Hawaii's highest points. Even while Hawaii's sub-tropical geogrpahy limits seasonal temperature variation, prevailing weather patterns, orographic factors, and a highly active hot-spot geology result in a climatically, edaphically and vegetatively complex but constrained and so tractable study system for examining C sequestration questions. In this context, changing bio-physical conditions provide for a strong test of the capability of remotely sensing technology to highlight spatial patterns on C uptake across rich gradients of ecosystems (Selmants et al., 2017).

2.2. Aboveground carbon density (ACD) mapping

The estimation of ACD at a 30-m resolution was supported by: (*i*) airborne laser scanning surveys, (*ii*) ground-level measurements on forest structure, and (*iii*) NASA's Landsat-based vegetation cover imagery. The full description of the data generated for ACD is provided by Asner et al. (2016). Briefly, high-resolution laser data were collected over extensively sampled forest areas on Hawaii Island to derive top-of-canopy height (TCH) measurements. Relationships between TCH measurements, ground measured bio-physical attributes, and satellite derived vegetation metrics were identified in the sampling design prior to wall-to-wall estimation of TCH across the state of Hawaiʻi. Estimates of ACD were then derived from the TCH raster map using species-specific allometries before comparing the results to 2011–2012 ground records available in US Forest Service Forest Inventory and Analysis (FIA) dataset. The 30-m wall-to-wall ACD raster map reached a maximum of 69.8 kg C m^{-2}. The prediction of ACD using only TCH as predictor variable was statistically robust ($R^2 = 0.82$; RMSE 78.7 Mg C ha^{-1}) under applied Random Forest Regression Modelling.

The publicly available 2015–2016 ACD raster map (Asner et al., 2021) was used to compute the distribution of ACD within management units and to compute their FC by counting the number of 30-m cells within each management unit. This raster map was also used to mask estimates for GPP (Fig. 1). The accuracy of the ACD raster map and its alignment with the irregular and patchy layout of forest vegetation is high; diverse expertise was assembled for surveying campaigns across Hawaiʻi, with the goal of using airborne laser technology for a wide range of estimation and prediction focused applications (Asner et al., 2011, 2016). The spatial variability of ACD estimates and their overlay over existing management units across the Hawaiian Islands represent valuable new applications to support C focused restoration, especially when integrating GPP estimates.

2.3. MODIS based estimates of gross primary production

Large-scale estimation of GPP has relied on MODIS reflectance data (MOD17A2H V6), which is hosted and freely available on Google Earth Engine (GEE) (Running and Zhao, 2015; Gorelick et al., 2017). Global MOD17 estimates of GPP, computed over 8-day cumulative periods at a 500-m spatial resolution, represent the flux of C from the atmpshere into vegetation during photosynthesis. We selected the period 2015–2019 to assess C uptake monthly across the state of Hawaii. We relied on standard MODIS assumptions, versus climate and vegetation values derived

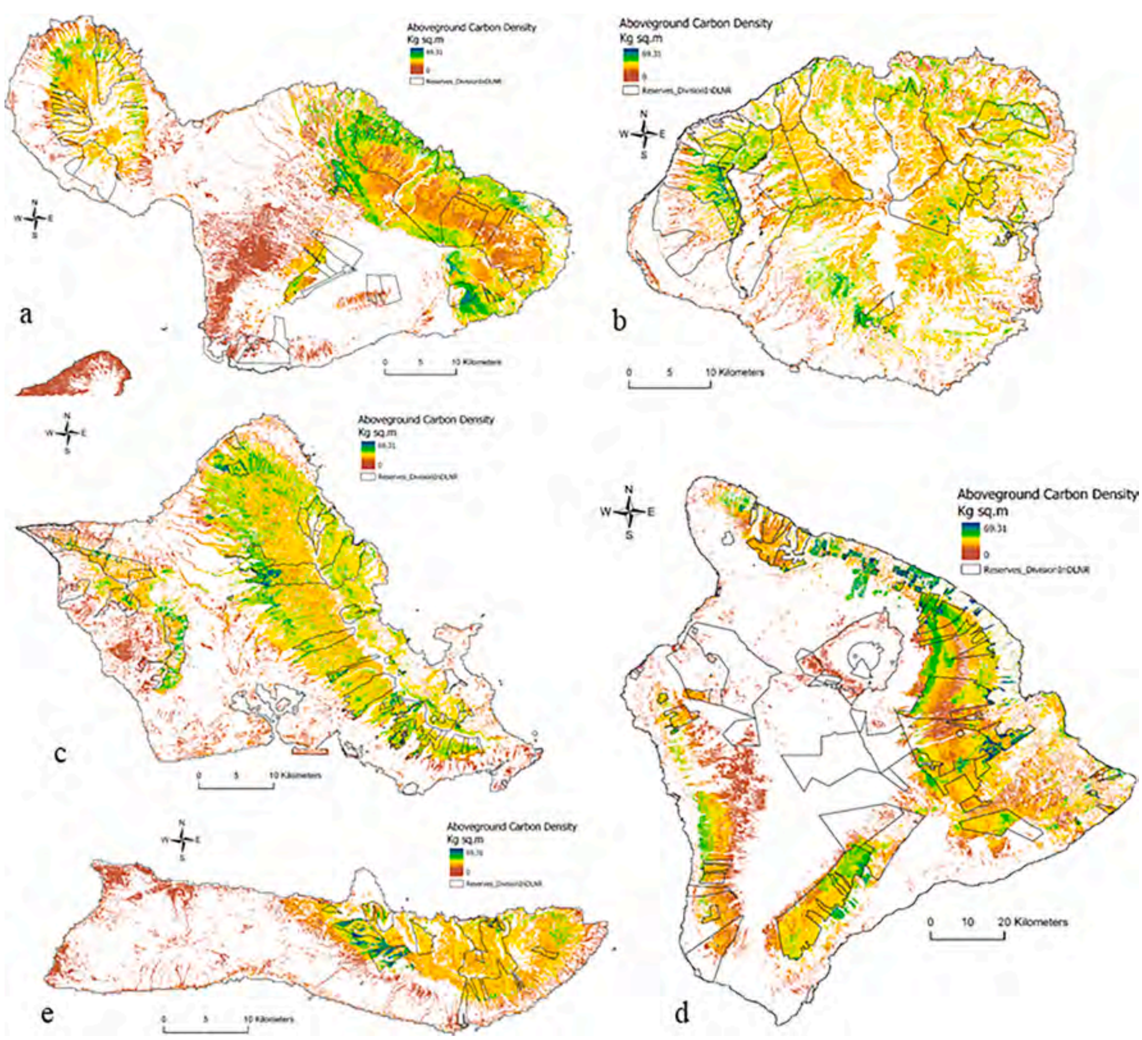

Fig. 1. Distribution of aboveground carbon density (ACD, expressed in Kg C m^{-2}) predicted with airborne laser scanning and satellite images collected across five main Hawaiian Islands: Maui (a), Kauaʻi (b), Ōʻahu (c), Hawaiʻi Island (d) and Molokaʻi (e) (data from Asner et al. 2016).

specifically for Hawai'i (Kimball et al. 2017). The median value of all available 8-day composite imagery at a 500-m scale were computed monthly, annually, and then across the 4-year period of this study. The filtering between forest vegetation and other NWL land uses was done using the ACD raster extent. The upper bound for GPP across the islands was 2.98 kg C m^{-2} $year^{-1}$. The maps for MOD17 GPP are presented in Supplementary A. The coarser resolution but widely used MOD17 product was integrated into our analyses to evaluate the finer-grained (30-m resolution) GPP estimates derived from the newer multi-temporal Landsat-8 satellite mission, which we also used to create cloud-free image mosaics.

2.4. Landsat-8 satellite images

Landsat-8 is a wide-swath, high-resolution, open-access, multispectral imaging mission with a global 16-day revisit frequency. The LC08/C01/T1_SR collections of GPP data are available in GEE, and were used to develop cloud-free satellite image mosaics for the 2015–2019 period. The removal of cloudy pixels and shadow effects was based on quality assessment information. The operations of retrieving, masking and mosaicking images was done in GEE (see Supplementary C). Cloud-masking and QA band-based filtering allowed us to derive NIR reflectance values and the normalized difference vegetation index (NDVI) at the same 30-m spatial resolution as the ACD map product.

2.5. Prediction of gross primary production (GPP) using NIRv

We also estimated GPP using the near-infrared reflectance of terrestrial vegetation (NIRv), which represents the proportion of pixel reflectance attributable to the vegetation in the pixel (Badgley et al 2017). We chose to pair the MOD17 GPP product with NIRv because NIRv has been shown to be a robust predictor of GPP while providing a higher spatial resolution. It also minimizes both the effects of soil contamination and variable viewing geometry on the image spectrum. Consequently, NIRv serves as a comprehensive index of energy capture efficiency (Badgley et al., 2019). The agreement between NIRv values and MOD17 GPP estimates is consistently strong across a range of biomes (Badgley et al 2017). We calculated NIRv as the product of monthly median NDVI and monthly median NIR reflectance, excluding all values less than or equal to zero under the assumption that NIR and so NIRv cannot equal zero. The resulting monthly raster maps were aggregated for each island to conform the 2015–2019 annual mosaic of

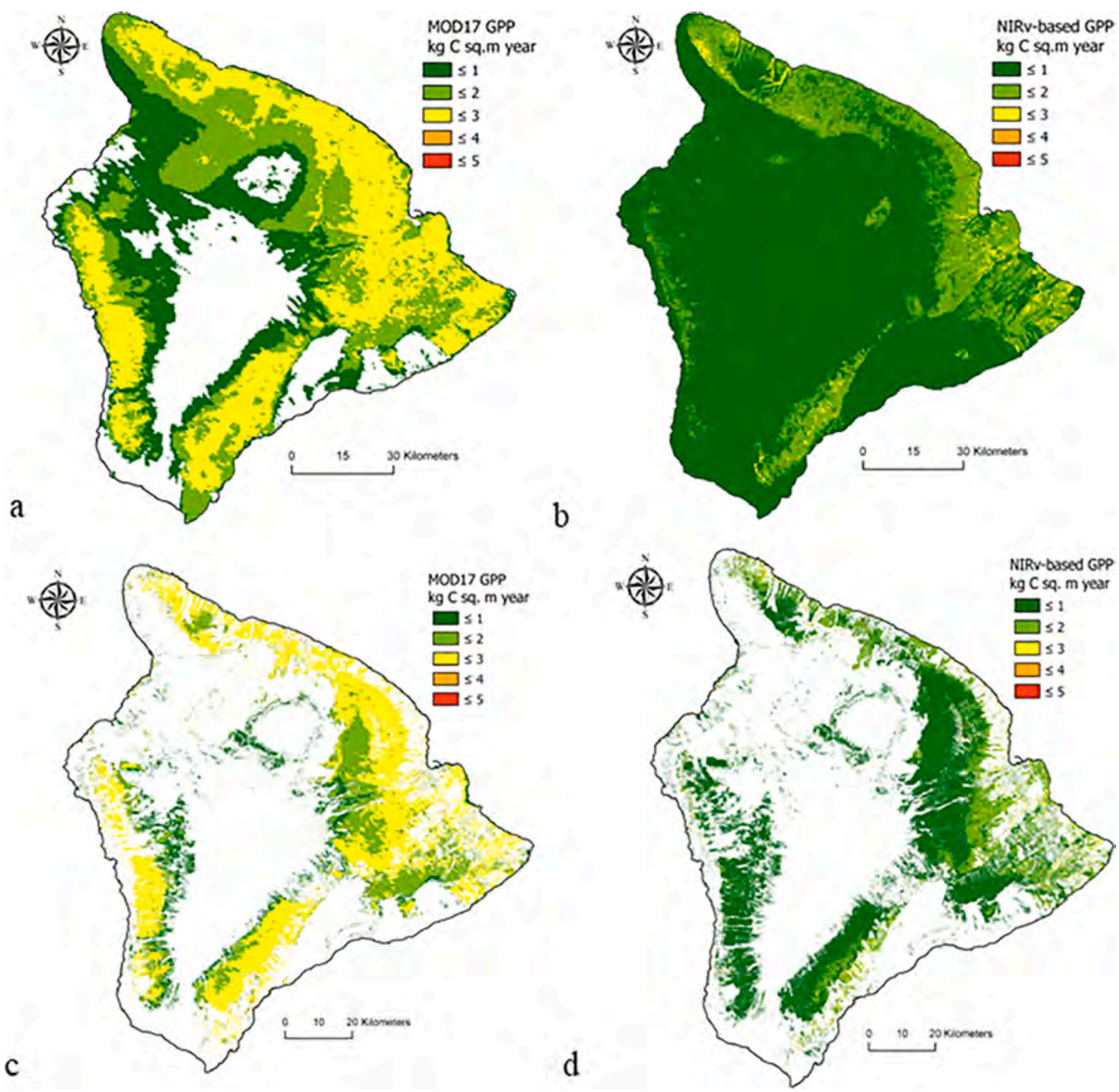

Fig. 2. Focusing on Hawai'i Island, the spatial distribution of gross primary production (GPP) derived from MOD17 data at 500-m resolution (left, a, c), and the near-infrared reflectance of terrestrial vegetation (NIRv)-based GPP product with a 30-m resolution (right, b, d). Cells completely contained under areas classified as forests were used for the assessment (c and d).

NIRv using the extent of ACD map for masking forested areas (Fig. 2).

The package RStoolbox (Leutner et al., 2019), available in the R statistical software (R Development Core Team, 2020), was used to derive NDVI maps and produce the raster maps for NDVI, NIR and NIRv. The annual NIRv mosaic was used with the one-predictor regression model provided by Badgley et al. (2017). The model was applied considering the three cover types categorized during model fitting (Table 1). The Evergreen cover type is the most representative case across Hawaiian forests (Selmants et al., 2014; Asner et al., 2016). Most 30-m cell predictions of GPP corresponded to Evergreen class after masking NIRv using the ACD map. The NIRv-based GPP estimates reached a maximum of 4.74 kg C m^{-2} yr^{-1} on ʻŌʻahu.

2.6. Drivers of spatial variability of GPP estimates

The NIRv and MOD17 based GPP estimates were compared across a gradient of 7 moisture zones and 20 main forest types, including ecosystems with a strong presence of invasive/alien species in addition to native dominated forests, as described in the Hawaii Land Carbon Assessment (Jacobi et al., 2017; Selmants et al., 2017) and supported by previous research (Selmants et al., 2014; Barbosa et al., 2017). These comparisons of MOD17 and NIRv-based estimates of GPP across the sizable spatial variability of Hawaiʻi Island allowed us to integrate ACD variability (Asner et al., 2016) and spatial patterns in GPP. Finally, we conducted this comparison to validate the use of the higher resolution NIRv product for calculating and mapping C sequestration potential of land units administered by the State of Hawaiʻi.

2.7. Assessment of carbon sequestration potential

The set of 304 State of Hawaiʻi administered management units, 256 of which contained ACD estimates, were provided by the Hawaiʻi Division of Forestry and Wildlife (DOFAW), whose function is to manage and protect watersheds and native ecosystems. These units included Forest Reserves, Game Management Areas and State Parks (Supplementary B), and were used as training areas with which to calculate CSPI, an area-level index we introduce here and which was developed to inform managers about the potential of a given management unit to sequester C where:

$$CSPI = GPP_{NIR_v} \times ACD^{-1} \times (1 - FC_{ACD}) \tag{1}$$

In Equation (1), GPP_{NIR_v} is the mean predicted value for GPP using the NIRv method and considering all 30-m pixels within the boundaries of a management unit, ACD is the mean value of the ACD raster map, and FC_{ACD} is the forest cover computed as the area of ACD divided by the total area of the given management unit. The role of CSPI is to inform C related aspects of unit management. The first ratio represents GPP over the vegetation biomass in the unit (ACD). The product scales the opportunity of restoration or afforestation accounting for the available space in the unit not occupied by forest vegetation. High values for CSPI are indicative of high C assimilation rates, low ACD and low FC. The value of CSPI approaches zero under full FC, indicating low potential for afforestation to reestablish forest vegetation for the purposes of C sequestration. For example, sites characterized by high GPP, low ACD, and low FC are associated with high CSPI values because such sites have a high potential to sequester C via increased FC and ACD. Conversely, sites characterized by high FC and ACD, and variable GPP are associated with low CSPI but may be candidates for protection. The 30-m resolutions maps for GPP supported the ranking of forest reserves using the CSPI index, with results presented for each management unit on each of the six main islands.

Table 1
Regression model coefficients for predicting gross primary production (GPP) using the near-infrared reflectance of terrestrial vegetation (NIRv) as predictor variables.

Parameter	Cover Type	Posterior Mean Estimate
Intercept		−110.762
Slope	Crop	0.083
Slope	Deciduous	0.080
Slope	Evergreen	0.104

3. Results

3.1. Benchmark of NIRv-based estimation of GPP and MOD17

The assessment of GPP estimates considering moisture gradients, habitat status and the management units showed two consistent tendencies: 1) mean MOD17 values were systematically higher than NIRv values; and 2) NIRv was able to increase the range of GPP distribution towards higher values (Supplementary Table C). The correlation of both GPP methods with respect to means and coefficients of variations (CV) was high while showing an average difference of ~1 kg C m^{-2} yr^{-1} across sites (Table 2), with small differences in dry ecosystems and larger differences in wet ecosystems. The trend for CV showed distributions that became progressively similar with increasing rainfall. Importantly, both methodologies captured the higher performance of invasive species on C uptake across ecosystem type (Table S2). Across forest type, the 30-m resolution GPP maps showed strong spatial variability (Fig. 3), which we illustrate by comparing resolution differences between GPP methods; the coarser scale MOD17 product showed a strong smoothing effect across management units (Fig. 4).

We found one of the most efficient sites for C uptake to be located in the northern portion of Hilo District on Hawaiʻi Island, where ACD values ranged from 60 to 70 kg C m^{-2}. The results showed the alignment of ACD and GPP and the high spatial variability of ACD across the landscapes but also the covariation of ACD and GPP at management unit level. High-resolution maps for all islands using MOD17 and the NIRv-method are presented in the Supplementary B data.

3.2. Assessment of forest reserves by islands

Most management-unit CSPI scores fell below 0.5, with 90.3% of units showing annual GPP estimates that were half or less of ACD in the unit (Fig. 5). For simplicity and clarity, we used a keycode to display the values of the CSPI index representing the ratio GPP to ACD on the Y and X axes while FC is depicted via color coded labelling (Supplementary B). The results were summarized for each island to highlight priority areas for conservation and restoration on each island, often managed by the same agency but with different teams of professionals. Management units located in the top-right zone of each panel tend to be associated with high ACD, high GPP, and high FC (label color = red) because most high ACD sites are typically forested. This combination of features then indicates low potential for sequestration but could indicate a high potential for protection of high ACD. Conversely, low FC values (=blue) are much more common on the left hand side (low ACD) of the figure, and when combined with high GPP, point to strong opportunities for enhanced sequestration via investments into planting and expanding FC. The results showed substantial heterogeneity on each island when comparing reserves of similar ACD stocking (codes and the names of management units can be found in Supplementary B data Table S1). To better explain the CSPI, we highlight some contrasting management scenarios from across Hawaiʻi Island:

- Unit #28 (EWA FOREST RESERVE - WAIMANO SEC) or Unit #294 (KAOHE MITIGATION) showed very high GPP but low ACD paired with low FC, indicating high potential for investments into afforestation actions to yield high rates of C sequestration.
- Unit #61 (WEST MAUI FOREST RESERVE) and Unit #307 (KULA FOREST RESERVE) both showed similar ratios of GPP to ACD, but the FC value for Unit #61 approaches 100%, greatly reducing the

Table 2
Summary statistics for aboveground carbon density (ACD) and Gross Primary Production (GPP) under MOD17 and the NIRv method considering habitat status and moisture gradient across Hawai‘i.

Habitat status	**ACD (kg C sq.m)**			**MOD17 GPP (kg C sq.m yr^{-1})**			**NIRv GPP (kg C sq.m yr^{-1})**		
	Mean	**CV**	**Max**	**Mean**	**CV**	**Max**	**Mean**	**CV**	**Max**
Heavily Disturbed	6.83	1.09	50.27	2.03	0.33	2.98	1.09	0.66	4.00
Native / Alien Mix	7.66	0.74	69.31	1.96	0.34	2.98	1.07	0.72	4.36
Native Dominated	6.74	0.62	52.65	1.85	0.32	2.95	0.56	0.94	4.75
Bare or < 5% Forest	1.83	1.24	43.36	0.94	0.76	2.98	0.10	3.24	2.96
Moisture gradient									
Arid	0.77	1.27	12.43	0.69	0.49	2.38	0.11	3.14	2.75
Very Dry	0.67	1.45	15.03	1.54	0.49	2.98	0.58	1.05	3.62
Moderately Dry	2.04	1.20	27.59	0.90	0.58	2.93	0.17	2.24	3.09
Seasonal Mesic	7.30	0.67	34.13	2.03	0.23	2.92	0.81	0.81	4.59
Moist Mesic	8.62	0.61	57.92	2.06	0.15	2.70	0.85	0.60	3.91
Moderately Wet	8.47	0.51	69.31	1.94	0.37	2.98	0.98	0.80	4.28
Very Wet	7.75	0.63	55.38	2.08	0.27	2.98	0.94	0.83	4.75

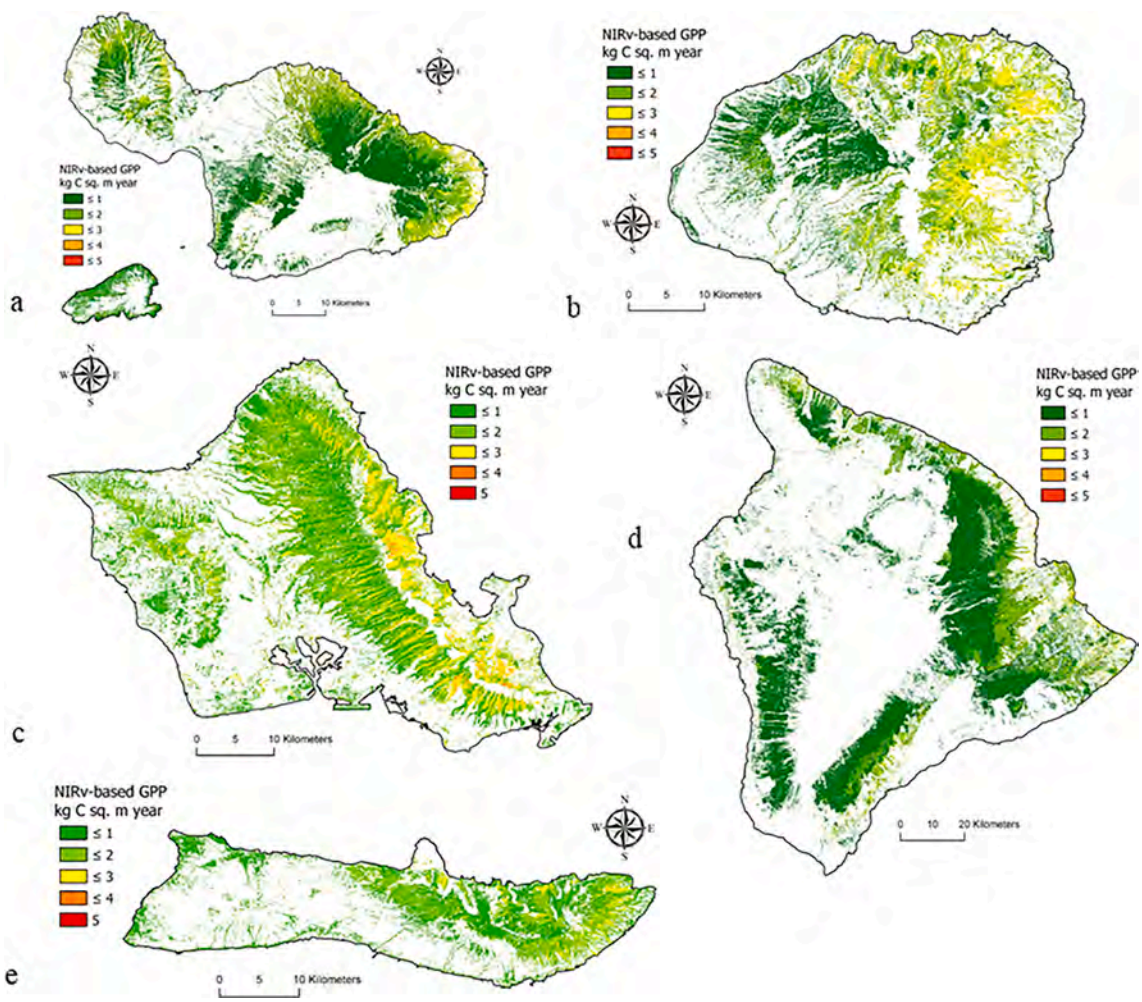

Fig. 3. Maps for gross primary production (GPP) when predicted using the near-infrared reflectance of terrestrial vegetation (NIRv) across Hawai‘i: ‘Ō‘ahu (a), Hawai‘i Island (b), Maui (c), Moloka‘i and Kāho‘olawe (d) and Kaua‘i (e). The maps were masked using the ACD carbon map derived with airborne laser scanning and Landsat-8 satellite images.

possibility to increase FC, while Unit #307 shows low FC, indicating potential for investment into afforestation for C sequestration.

- Unit #244 (POHAKULOA TRAINING AREA RESERVATION / MAUNA KEA FR) had low GPP, moderately high ACD and very high FC, indicating high potential for implementing forest protection measures that maintain high ACD.
- Unit #132 (PUU WAAWAA FOREST BIRD SANCTUARY) is associated with low GPP, low ACD but high FC, indicating that the unit might have limited capacity to accrue C from active forest management.

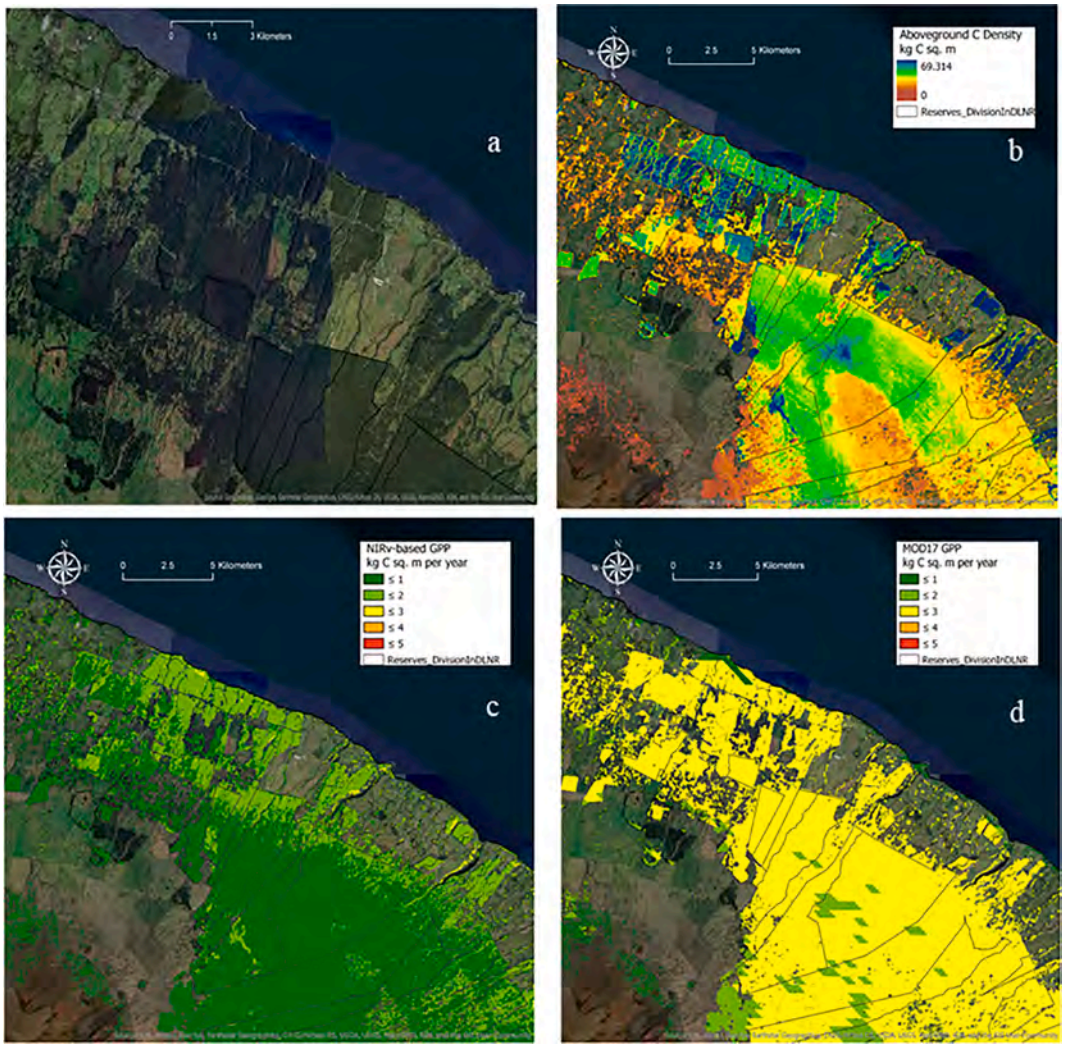

Fig. 4. Showcase scene of forest reserves along the Hilo and Hāmākua districts showing: (a) the spatial layout of aboveground carbon density; (b) maps for gross primary production (GPP); (c) the 500-m resolution MOD17 GPP product; and (d) the 30-m resolution near-infrared reflectance of terrestrial vegetation-based (NIRv) GPP estimates.

4. Discussion

We used the CSPI to conduct a high resolution assessment of the C sequestration potential of 304 management units administered by the State of Hawai'i across the main Hawaiian Islands. This index integrates: GPP as a measure of total C input by vegetation into an ecosystem; ACD as a measure of ecosystem carbon standing stock that can be influenced by management over short time periods; and FC as a measure of forest cover, which can be used to distinguish between strong and weak opportunities for C focused afforestation. We found that this intuitive and practical index was highly effective for graphically describing stewardship opportunities for sequestration outcomes at the level of individual forest reserves (relevant for tactical planning) while also providing high-resolution wall-to-wall information at the 50 to 500 ha level of typical management projects (relevant for operational planning). For example, this index could be used to support planning directed at meeting policy goals, including legislated C neutrality targets, by examining the full distribution of units administered by the State of Hawai'i. By examining clustered CSPI values at finer resolution, for example at the scale of 50–500 ha contiguous projects, this index can support operational scale land-use planning. As with any index, the CSPI could be used in a way that inadvertently elevates C sequestration above other important management factors, such as biodiversity. This can be avoided if CSPI is integrated into a decision support framework where multiple variables are assessed and prioritized together, and through which synergies can be identified.

We aimed to develop a simple but accurate and highly resolved decision-making metric that could be directly computed from existing and available data and that could be used to assess forest stewardship opportunities for mitigating climate change. The CSPI scales the possibility of action for restoration by integrating fine-grained estimates of FC that realistically describe the horizontal distribution of forest vegetation within management units often showing patchy or irregular distribution. In this way, CSPI is an informative area-based indicator that is amenable to tactical scale planning, including prioritizing units for stewardship investment, but also smaller scale operational planning because the data (Fig. 5) are easy to assimilate into a rapid assessment of potential C sequestration projects including afforestation. At the other end of the CSPI spectrum, forest reserves with high ACD and FC might be better managed under forest protection guidelines including fencing or invasive species control as a mean to protect C stocks (Paul et al., 2016). The linking of CSPI to REDD+ objectives supports prioritizing the prevention of C loss and resulting emissions from the highest ACD areas – a valuable outcome of some remote sensing-based C monitoring (Asner et al., 2011; Csillik et al., 2019).

The presented methodology relies on the conversion of NIRv to GPP

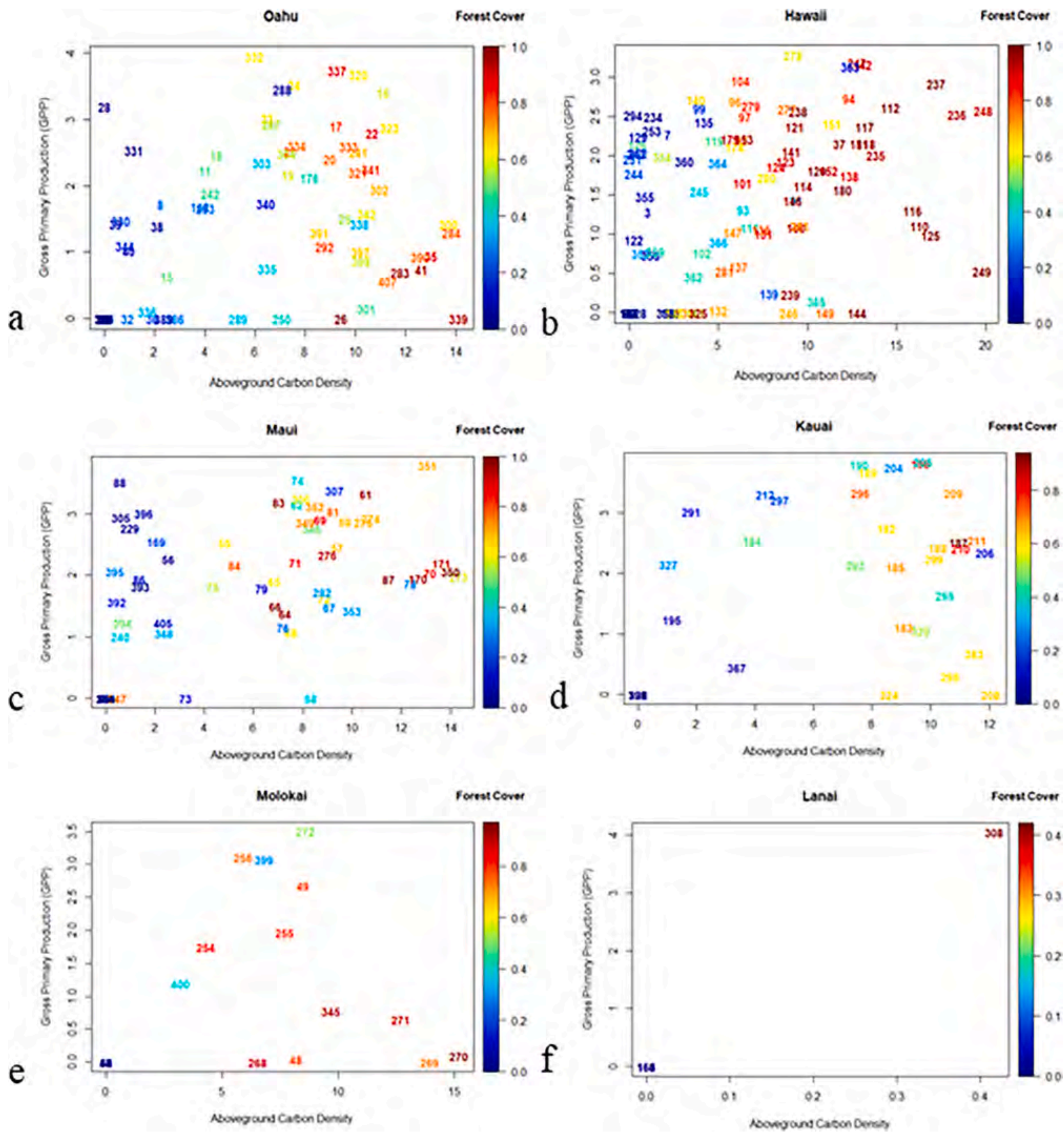

Fig. 5. Relationship between the three components of the CSPI index for four of the main Hawaiian Islands showing aboveground carbon density (ACD, kg C m^{-2}) on the x-axis, NIRv-based annual gross primary productivity (GPP, kg C m^{-2} yr^{-1}) on the y-axis, and the forest cover (FC) depicted with symbol color. Supplementary Table S1 links numerical codes to named management units.

estimates to upgrade the spatial prediction of C uptake across heterogenous ecosystems. The models and findings from Badgley et al. (2017, 2019) suggest that the NIRv method provides a robust proxy of GPP that is reliable across the diverse biomes tested here, while improving on the coarser resolution of the MOD17-based GPP product (Ise et al., 2010; Marvin et al., 2016b, Kimball et al., 2017). The detection of fine scale spatial variation across and within management units via NIRv also allows for operational scale planning, especially where integration of NIRv-based GPP with ACD and FC can be complimented with high resolution species and/or forest type-specific data layers to allow for improved accuracy of the CSPI index.

In the context of C sequestration planning, NIRv derived GPP provides the CSPI with a strong theoretical foundation while representing a straightforward computational process based on many remote sensing missions, and yielding reflectance-based observational data, thus facilitating the study of GPP controls on C sequestration at clobal scales (Anav et al., 2015; Marvin et al., 2016b; Huang et al., 2019). The coming development of satellite mission based on advanced image spectroscopy will eventually replace the laborious and non-error-free calibration process required to obtain the GPP estimates used to compute CSPI here. For example, the decision to manage a given reserve unit for restoration (C sequestration) or conservation (C protection) could be made by using these area-based indicators to accurately describe vegetation cover and C fluxes at 30-m resolution. Interestingly, the greatly enhanced spatial resolution of NIRv derived GPP also support ecosystem models that could integrate stand level processes such as C allocation (e.g., Binkley et al., 2004; Litton et al., 2007).

The Hawaiian Islands provide a unique laboratory for integrating ACD, FC and GPP products, for synthesizing information at management-relevant scales, and for supporting actionable mapping of spatial and temporal patterns in C storage and flux across a wide range of ecosystem types and condition (Asner et al., 2012; Marvin et al., 2016b; Selmants et al. 2017). The status of C pools as the relationship among volume, biomass and carbon have been well established using allometries in Hawaiʻi (Asner et al., 2012). Species-specific estimates for ACD, FC and GPP enhance the robustness of the CSPI, especially with respect to management efforts addressing for example invasive species impacts on C stocks and stand dynamics in native forests. And so while allometries for diverse species are available for Hawaiʻi (Asner et al., 2016), the spatial location of trees within the management units requires laser-based remote sensing. In future work, image spectroscopy will provide valuable insights on species-specific statistics within unit boundaries (Sommers and Asner, 2013), adding value to CSPI focused methods. Another application would be to use standard fine-grained resolution images (widely available and supported by Planet) to delineate canopies and tree clusters within large management units (Csillik et al., 2019) to refine CSPI estimates. In Hawaiʻi, the CSPI could be split into at a minimum native versus alien/invasive, the main challenge for forest managers across the archipelago. Indeed, the research was supported by DOFAW in Hawaiʻi, the agency responsible for converting decisions into actions over most of the management units assessed in this study. The close cooperation between authors and DOFAW also facilitates implementation of the CSPI in data interpretation and decision making. Further research will target how spatially explicit optimization can be developed for forest reserves focusing on the joint achievement of economic, ecological and spatial goals.

5. Conclusions

The CPSI is a promising local-to-regional indicator for rapid assessment of forest landscapes restoration and protection. The work fills a niche at the interface between forest mapping and stewardship decision-making for tactical to operation scale decision making, with a focus on prioritizing reserves or management units within reserves for climate-smart actions. The work also serves the planning process by enhancing the quality of information needed for implementing site-specific management plans. Where high resolution ACD and vegetation cover maps are available, the CSPI is intuitive, highly practical, straightforward, and so easy to implement methodology. Further, the CSPI can be scaled to new locations, with high potential for refinement given current developments in satellite image spectroscopy and rapidly expanding capacity to derive ecological variables from remotely sensed data. Finally, the CSPI provides a link between C management and meeting the needs of conservation planning at large scales within an ecosystem services framework.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foreco.2021.119343.

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