Tropical biodiversity assessments: predicting species richness, habitat structure, and tiger habitat connectivity in Thailand

Introduction

Biodiversity loss due to human activities and climate change is a global crisis, with tropical regions experiencing the worst declines [1]. Timely and accurate assessment of biodiversity at local to regional scales is important for conservation biology, policy making, and sustainable socioeconomic development [2]. Remotely sensed data are imperative to understand and monitor biodiversity at relevant scales of time and space [3]. However, there are no standardized remotely sensed indices designed specifically for broad-scale biodiversity assessments in the tropics [4]. Recently, high-spectral and spatial satellite data from space-borne systems have gained importance as effective approaches for detecting individual species or assemblages, but such data are not widely available. Alternative approaches to biodiversity assessment use environmental parameters as proxies. Spectral-temporal reflectance signatures, or indices available in remotely sensed data, and biophysical variables such as Leaf Area Index (LAI), and fraction of Photosynthetically Active Radiation (fPAR), can predict species diversity patterns and habitat requirements indirectly [5]. Such approaches work well in temperate areas, but less so in tropical ecosystems where complex habitat types support over two-thirds of all known species on earth. Due to the complexity of biodiversity in the tropics, quantifying diversity patterns at broad scales using remotely sensed data is challenging [6].

The overarching goal of my proposed research is to improve biodiversity and habitat assessments in Thailand's tropical ecosystems. I propose to integrate multitemporal MODIS and Landsat data to model species richness patterns, species distributions, and habitat connectivity. Thailand provides an ideal study site for this work because Thailand is a global biodiversity hotspot [7] facing rapid habitat loss and species extinction [8]. Better understanding of the current status of biodiversity and habitat patterns in Thailand will ultimately determine the fate of its biodiversity. Specifically, I will:

Objective 1: Develop a Dynamic Habitat Index (DHI) across Thailand using fPAR, LAI, EVI, and NDVI derived from MODIS sensors from 2002-2014, and test the utility of the DHI in predicting terrestrial vertebrate species richness patterns for different taxa.

Objective 2: Quantify habitat structure using image texture measures derived from dense time stacks of Landsat satellite data to understand tropical forest bird distributions.

Objective 3: Model habitat suitability and assess habitat connectivity for the Indochinese tiger by modeling tiger habitat based on remotely sensed measures of habitat heterogeneity (Obj. 1 and 2).

My research addresses NASA Earth Science's fundamental question of how the Earth's ecosystems are changing by describing changes in terrestrial productivity and habitat structure in a dynamic and imperiled ecosystem, the tropics. Further, I provide a framework for predicting the consequences of these changes for species richness and distributions. My project will rely heavily on NASA assets, especially MODIS and Landsat data, to develop indices for biodiversity assessments in the tropics, and I will advance the understanding of the patterns and drivers of biodiversity, characterize habitat quality, and construct biodiversity maps for conservation efforts.

Study area

Thailand is rapidly losing wildlife habitat to commercial forestry, economic development, urbanization, and plantations (rubber, oil palm, and eucalyptus) [9]. Emerging international free market policies in 2015 (i.e., ASEAN Economic Community) may cause further agricultural clearing and the transformation of subsistence agricultural to cash crops [10]. The loss of forest cover from 53% in 1961 to 33% in 2010 [11] led to the extinction of several of Thailand's native species, such as the giant ibis (*Pseudibis gigantean*) and Schomburgk's deer (*Cervus schomburgki*) [12]. I will study terrestrial vertebrate species richness, as well as forest bird and tiger distributions. These species diversity data are ideal to conduct measures of biodiversity assessment using multiresolution remotely sensed data (*Fig. 1*) because species richness and distribution patterns positively associate with productivity [13] and habitat structure [14]. Moreover, the rapid loss of habitat in high biological diversity ecosystems of Thailand demands timely and consistent assessment of biodiversity to protect endangered species such as the Indochinese tiger (*Panthera tigris*).

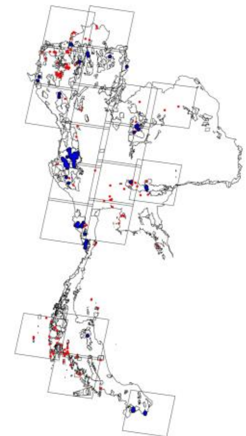

***Figure 1*. The 19 sample Landsat footprints in Thailand. Red and blue points represent bird and tiger occurrence data.**

Approach

Objective 1: Develop a Dynamic Habitat Index across Thailand and test its utility in predicting terrestrial vertebrate species richness patterns.

Vegetation productivity strongly influences species diversity patterns [15]. The Dynamic Habitat Index (DHI, [16-17]) is a measure of vegetation productivity designed for biodiversity assessments and summarizes: (1) annual cumulative productivity (areas with high productivity to support higher species richness); (2) annual minimum productivity (lower minima support fewer species); and (3) seasonal variation in productivity (less intra-annual variability supports more species). NASA's MODIS products provide a suite of routinely updated vegetation indices, the fraction of Photosynthetically Active Radiation (fPAR), and Leaf Area Index (LAI) [18-19]. The DHI derived from MODIS provides a unique opportunity to develop relevant, consistent, and applicable measures for biodiversity assessments in the tropics, because they are grounded in the biogeography of biodiversity patterns [20]. I propose to determine which MODIS vegetation metric is best suited for calculating the DHI and predicting biodiversity patterns.

I will develop DHI measures across Thailand during 2002-2014 for each of four productivity variables: fPAR and LAI, and NDVI and EVI, obtained from 1-km MOD15A2 and MOD13A3 data respectively (LP DAAC, [21]). I propose to fill gaps and smooth the fPAR, LAI, NDVI, and EVI datasets by fitting a double logistic curve with TIMESAT [22]. For each variable, I will calculate DHI measures for the 15th of each month from average monthly values based on fitted TIMESAT curves. The subsequent DHI values will be calculated for each year, averaged from 2002-2014 (*Fig. 2a*), and compared between the four MODIS productivity products. To depict regional variability, I will summarize the means, coefficients of variance, and ranges of the DHI measures for each land-cover type and compare them across 15 terrestrial ecoregions [23]. I expect the DHI to differ among land cover types, such as moist evergreen forest versus mixed deciduous forest and agriculture. I will categorize land cover types using a land cover map (2000) from the Thailand Department of National Parks, Wildlife, and Plant Conservation. Additionally, I will compare the VIIRS Vegetation Index product (VIIRS-VI-EDR) available since 2012 with the MODIS-based DHI. This comparison will allow me to identify a suite of DHI measures which best predict species richness and increase the robustness of the DHI analyses.

After calculating the DHI, I will test its utility for species richness prediction. For species richness data, I will refine distribution maps derived from IUCN range maps [12] by excluding habitat types that are unsuitable for the species [24]. I will remove elevations outside the suitable range for the species using Shuttle Radar Topography Mission (SRTM) data [25], compile potential habitat types for each species from the literature, identify those based on the 2000 Thai land cover map, then sum the species present in each grid cell, excluding grid cells with less than 50% land area (*Fig. 2b*) [26]. To minimize the effects of spatial autocorrelation, I will randomly sample 5000 grid cells with a minimum distance of 5 km, the typical dispersal distance of the largest terrestrial mammal in Thailand (i.e., tigers, [27]). I will also calculate collinearity among DHI variables (r >0.8 as a threshold).

To assess the relationships between species richness and the DHI, I will inspect scatter plots (*Fig. 2c*), and model the richness of functional guilds (i.e., feeding guild, food type, foraging habit, and nesting) [28] and IUCN threat levels as a function of the DHI measures using best-subsets [29] and hierarchical partitioning regressions [30].

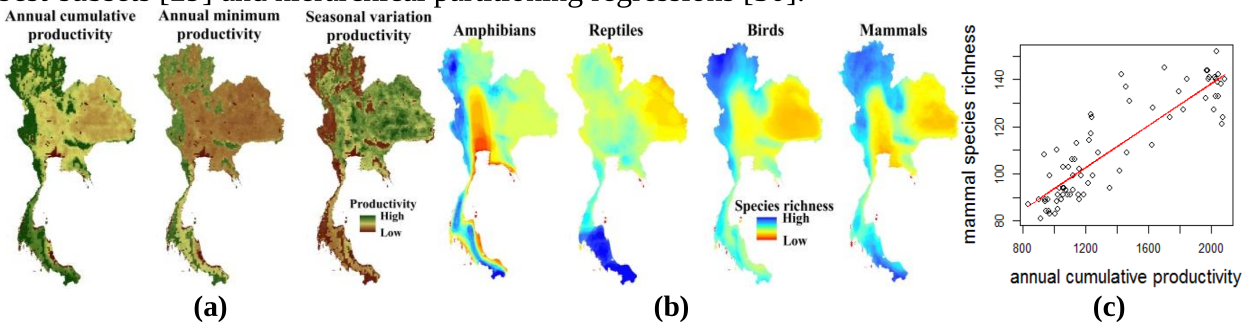

Figure 2. **DHI and species richness: (a) three DHI measures: annual cumulative productivity, annual minimum productivity, and seasonal variation in productivity derived from 2002-2012 MODIS fPAR data. Green areas have high productivity and brown areas indicate low productivity; (b) species richness for amphibians, reptiles, birds, and mammals. Blue indicates high species richness. Red indicates low species richness; (c) scatter plot of mammal richness and annual cumulative productivity.**

Lastly, I will test the synergies of the DHI and other environmental variables that affect species richness patterns. Specifically, I will add landscape composition and configuration [31], topography [32], and climate variables [33] to the models. For landscape composition metrics, I will use the proportion of land cover classes, the total number of land cover classes, and the Shannon diversity index [34] of land cover classes. To quantify landscape configuration, I will characterize core areas and edges of different forest types, grassland, and wetland using Morphological Spatial Pattern Analysis (MSPA) with the GUIDOS tool. The MSPA allows an automated per pixel classification and description of the geometry, pattern, fragmentation, and connectivity of a landscape [35-36]. I will obtain topographic data from the SRTM data [25] and climate data, including temperature and precipitation from WorldClim [37].

The results from Objective 1 will be a quantitative measure of the sensitivity of the DHI to a suite of MODIS vegetation products in explaining nationwide terrestrial vertebrate species richness patterns, and how functional guilds respond to geographical and climate variables.

The dynamic ranges of the DHI measures and maps in different land cover types and ecoregions will provide a tool for monitoring productivity changes and highlighting biodiversity hotspots for species conservation. I will submit this work to *Remote Sensing of Environment*.

Objective 2: Quantify habitat structure using image texture for tropical forest bird distributions.

Land-cover classifications from satellite data are commonly used to assess habitat patterns [38]. However, this ignores habitat heterogeneity within a given land-cover class [39]. An alternative solution is to consider texture measures of habitat, which capture finer-scale habitat structure [40-41]. I propose to use texture measures from Landsat imagery to characterize forest habitat for birds. Birds are ideal study taxa, because bird species differ significantly in migratory behavior, nesting requirements, feeding and mating habitats, and other life history traits [42]. I am specifically interested in (1) whether image texture measures can predict forest bird species distributions, and (2) the relative importance of measures of habitat structure, productivity (Obj.1), and other environmental variables for predicting bird distributions.

For this objective, I selected 19 Landsat TM/ETM+ scenes (*Fig. 1*) covering the predominantly forested areas across Thailand from 2000 to 2010 during the growing season to temporally coincide with the bird occurrence data. Cloud and shadow will be masked using FMask [43], and atmospheric corrections applied using LEDAPS [44].

For each image, I will calculate first- and second-order texture measures [45] using ENVI [46]. First-order texture measures will include mean and standard deviation for bands 2, 3, 4, and 5 using 3x3, 5x5, 7x7, and 11x11 30-m pixel windows. Second-order measures will include angular second moment (ASM), contrast, correlation, entropy, homogeneity, and sum of squares variance. These window sizes represent the approximate territory sizes of bird species in this study [42]. I excluded Landsat bands 1 and 7 due to their high correlation with texture from other bands [47].

To evaluate the performance of image texture in modeling tropical forest bird distributions, I will use logistic regression models based on presence data [48]. I will use birds' occurrence data from Global Biodiversity Information Facility (GBIF) (*Fig. 1*) for 20 forest bird species. I selected 20 bird species as habitat indicator species based on their strong association with evergreen forest, mixed deciduous forest, and secondary forest. I will randomly sample forested areas within the terrestrial range of each species, and select pseudoabsence points [49]. Then I will fit univariate logistic regression models using image texture measures as predictors. Lastly, I will model bird distributions as a function of image texture measures, productivity (Obj.1), and other environmental variables, in multivariate models with best-subsets regression models and an AIC ranking [29]. For model evaluation, I will compute the area under the curve (AUC) [50] using 5-fold cross-validation [51], and apply Bayesian model averaging of the set of best models to predict forest bird distributions [48].

For further model validation, I will use an independent bird dataset by Dr. Phillip D. Round at Mahidol University, Thailand (see letter), that includes species richness, abundance, and habitat of birds for each major protected area across Thailand. I will calculate the area predicted as suitable habitat based on my species distribution models for each bird species in each protected areas. Then, I will compare my predicted habitat areas with the independent field data to estimate model prediction errors. The results from Objective 2 will be a set of habitat structure measures derived from Landsat data for modeling tropical bird species distributions. I plan to submit this work to *Ecological Applications*.

Objective 3: **Assess habitat connectivity for the Indochinese tiger**.

Intensive forest loss and degradation in Thailand have led to extirpations of species with fragmented populations because of dispersal limitations [52]. I will use the Indochinese tiger (*Panthera tigris*) as a focal species for a habitat connectivity analysis because tigers are listed as globally endangered (IUCN) and serve as an umbrella species in conservation planning [27]. Recent estimates indicate that only 250-350 tigers remain in Thailand, in 15 disjunct subpopulations, each with a high risk of extirpation [53]. The subpopulations are isolated due to intensive land-use change, and by areas of rapid development (i.e., economic corridors in the Greater Mekong Subregion) lending urgency to the connectivity analysis.

To map habitat suitability for tigers, I will develop ensemble species distribution models using the BIOMOD2 package in R [54-55]. BIOMOD2 requires both species occurrence data and data on habitat attributes and prey availability. For occurrence data, I will use a large dataset of tigers and their prey species such as Sambar deer (*Rusa unicolor*), Eurasian wild boar (*Sus scrofa*), red muntjac (*Muntiacus muntjac*), and gaur (*Bos gaurus*) from collaborators A. Lynam, Wildlife Conservation Society-Asia Programs; R. Sumasuang and N. Pongpattananurak, Kasetsart University, Thailand; R. Steinmetz, World Wildlife Fund Thailand; W. McShea, Smithsonian Institution; D. Ngoprasert and W. Chutipong, King Mongkut's University of Technology Thonburi, Thailand; and S. Kitamura, Ishikawa Prefectural University, Japan (see letter). These collaborations have given me access to camera trap data across Thailand (*Fig. 1*) that I will use to develop habitat suitability maps using biophysical, geographical, and land cover variables from Objective 1 and 2.

The second part of my proposed work is to assess tiger habitat connectivity. I will integrate least-cost path analysis [56] and graph theory [57], where the edges of the graphs are least-cost travel routes. For least-cost modeling, I will add dispersal barriers, such as highways, economic corridors, and human settlements to the habitat suitability maps [59]. I will also calculate dispersal ability and home range obtained from camera trap data using the Minimum Convex Polygons function [58]. Least-cost paths will be constructed by accumulating cost surface values [56], which will be the inverse of my habitat suitability map. To estimate relative importance of habitat patches and corridors, I will use Conefor Sensinode 2.6 software, which performs removal operations of habitat patches and corridors to assess the importance of each of them [60]. Knowing current habitat suitability and tiger habitat connectivity, I will identify priority areas for tiger conservation, such as sites for reintroductions, with the aim to facilitate movement among subpopulations and mitigate impacts of environmental change.

The results of Objective 3 will be a tiger habitat suitability map for Thailand, an evaluation of habitat connectivity, and the ranking of habitat patches and corridors for the overall connectivity networks of tiger habitats. This will help to support tiger conservation efforts that facilitate tiger dispersal. I plan to submit this work to *Biological Conservation.*

Overall significance

"To study Earth from space to advance scientific understanding and meet societal needs" is the NASA strategic goal 3A, and the proposed study will contribute to that goal by developing and testing the Dynamic Habitat Index and image textures that are specifically designed to characterize habitat and biodiversity patterns. My proposed research will contribute to the science, methodology, and application of remote sensing, biodiversity science, and conservation biology.

Improved biodiversity assessments in tropical regions are urgently needed for governments, policy-makers, and conservation biologists, given concerns about global biodiversity loss and the impacts of rapid environmental changes. My research provides such assessments, and makes use of consistent and well-calibrated NASA's Earth Observing System data to predict species distributions and richness patterns. My proposed research represents a major step towards the ultimate goal of understanding and predicting the consequences of global ecosystem changes on biodiversity. Specifically, I will test and improve methods of characterizing complex forest habitat in Thailand, which will serve as a model for other tropical studies. My research will advance remote sensing science by assimilating MODIS data in order to produce consistent and accurate productivity measures into habitat indices for predicting species richness patterns. Moreover, I will incorporate pre-processing of Landsat data in order to overcome atmospheric and topographic spectral differences. Synergistic remotely sensed data will enhance the ability to quantify habitat quality and habitat biodiversity values. The most important contribution of my work on the ground is its direct application to conservation and management in Thailand. I will use the Dynamic Habitat Index and image texture measures to highlight priority areas for sustaining biodiversity, thus providing tools to monitor habitat quality over broad scales. Lastly, this work will support tiger conservation efforts in the region.

My interdisciplinary research will contribute to biodiversity science, and will have broad societal relevance by advancing global efforts to protect biodiversity and the ecosystem services that sustain human well-being.

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Timeline of the research

Research part		2014	2015				2016				2017		
		IV	I	II	III	IV	I	II	III	IV	I	II	III
I	DHI from MODIS fPAR,LAI, NDVI, EVI	■	■										
	DHI by land cover class			■									
	Terrestrial vertebrate species richness				■								
II	Image texture measures					■	■						
	Bird data acquisition					■							
	Forest bird species distribution modeling							■	■				
III	Tiger data acquisition							■					
	Tigers' habitat suitability map								■	■			
	Tigers' habitat connectivity										■	■	
Output	Planned submission of publication				■				■				■

Anticipated milestones of the applicant's degree program

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