Title of the grant: Consequences of changing mangrove forests in South Asia on the provision of global ecosystem goods and services

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1. Project description

Our three-year project examines mangrove cover change from 1985 to the present in Bangladesh, India, Myanmar, Pakistan, and Sri Lanka, and it assesses the consequences for two globally important ecosystem services, carbon sequestration and biodiversity conservation. It has four objectives:

Objective 1: to develop an operational methodology for annual monitoring of mangrove cover changes

Objective 2: to create a comprehensive database of annual mangrove cover changes from 1985 to the present at 30 m resolution

Objective 3: to quantify the impacts of mangrove cover changes on carbon stock changes and species extinction risks on an annual basis from 1985 to the present

Objective 4: to analyze the effectiveness of existing mangrove protection programs, and prospective cost-effective expansions of them, in reducing carbon emissions and species extinctions.

Research to achieve the first two objectives emphasizes analysis of Landsat data. For the third objective, we will estimate carbon stock changes by combining area data from the mangrove cover change database with carbon densities per unit area. We are using meta-analysis to estimate the latter, and we will value carbon stocks changes using published estimates of the social cost of carbon. We will investigate mangroves’ role in biodiversity conservation by using data from the mangrove cover change database to assess how much original forest remains and
how fragmented it is, and down-scaled species range maps to determine which areas have the most endemic species facing the greatest extinction risks as a result of habitat loss and fragmentation.

For the fourth objective, we will build on the other research and conduct three types of economic studies: (i) conventional retrospective evaluations of the impacts of protection programs on avoided mangrove deforestation and degradation in all five countries; and, for Bangladesh and India, (ii) novel retrospective evaluations of the impacts of protection on carbon sequestration and biodiversity conservation and (iii) prospective analyses of new protected areas to cost-effectively enhance carbon sequestration and biodiversity conservation.

In accordance with the timeline in our proposal, our work during the first year has focused on three activities:

1. Develop and test methodology for annual mapping and monitoring
2. Estimate carbon stocks and changes in carbon stocks
3. Species mapping

We have gotten an early start on a fourth activity, compile land-value data for the protection cost analysis. We report progress on each of these activities in turn.

2. Develop and test methodology for annual mapping and monitoring

We have collected ancillary data needed for annual mapping and monitoring, prepared a preliminary classification of mangrove/non-mangrove areas for the years 2017, 2005, 2000, 1990, and 1970, and developed an NDVI differencing change analysis technique. Ancillary data collected include SRTM 90 m and 30 m DEM data, existing mangrove/non-mangrove maps for the countries, and global land cover datasets such as Globcover.

To classify mangrove/non-mangrove areas, we used Landsat satellite data at 30 m spatial resolution available from Google Earth Engine (GEE) (https://explorer.earthengine.google.com). The GEE leverages cloud computing services to provide analysis capabilities on over 40 years of Landsat data. We used Top of Atmosphere (ToA) Reflectance annual Landsat mosaics. The ‘raw’ scenes available from USGS contain imagery with digital numbers (DNs) that represent scaled radiance. The conversion of DNs to at-sensor radiance was performed using a linear transformation using coefficients stored in scene metadata (Chander et al. 2009). The ee.Algorithms.Landsat.calibratedRadiance method (available from GEE) performs this conversion. Conversion to TOA (or at-sensor) reflectance is a linear transformation that accounts for solar elevation and seasonally variable Earth-Sun distance.

Training data were selected based on the Landsat mosaic and very high resolution satellite data (less than 5 m). We classified only true mangroves, defined as having all or most of the following features: (i) occurring only in a mangrove environment and not extending into
terrestrial communities; (ii) morphological specialization (aerial roots, vivipary); (iii) physiological mechanisms for salt exclusion and/or salt excretion; and (iv) taxonomic isolation from terrestrial relatives. A Random Forest classifier was used for the classification. Random Forest is an ensemble of unpruned classification or regression trees created by using bootstrap samples of the training data and random feature selection in tree induction. Prediction is made by aggregating (majority vote or averaging) the ensemble predictions. Our analysis shows that this technique is suitable for mangrove mapping in South Asia.

For the change analysis, we have been testing two approaches: post-classification change analysis and spectral change analysis. Fig. 1 is an example of post-classification change analysis showing persistent mangroves of South Asia with forest gain and loss from 2000 to 2012.

![Figure 1. Persistent mangroves of South Asia with forest gain and loss from 2000 to 2012.](image)

One of the change analysis techniques we are exploring is NDVI differencing. Fig. 2 shows an example of NDVI differencing using annual time series data from 1985 to 2014. The graph shows that around 2001, mangrove forest changed from healthy forest to non-forest and never recovered. This technique will be used for all five countries, and both deforestation and forest re-growth will be measured.
3. Estimate carbon stocks and changes in carbon stocks

Data compiling

We have already completed the compilation of the basic carbon stock data for South Asia. The data we compiled came from three main sources: 1) Web of Science literature search; 2) unpublished data obtained by contacting local collaborators in South Asia; and 3) a recently published global synthesis of mangrove soil carbon stocks. To be included in our dataset, a paper or data source must meet the following two criteria. First, it must report at least one measure of carbon stock, either aboveground biomass carbon, belowground biomass carbon (or biomass), soil carbon (30 cm deep), and soil carbon (100 cm deep). A few studies that reported debris carbon stock and non-tree vegetation carbon stock were included in our data set but are not analyzed here. Second, reports of soil carbon stock had to estimate soil carbon (carbon stock per unit area, percent organic carbon, and loss on ignition) in soil cores of > 20 cm in length to be
included in our 30cm deep soil carbon stock estimates and > 60 cm in length to be included in our 100cm deep soil carbon stock estimates. Estimates using soil cores of < 20cm long were excluded.

Reports of biomass, soil percent organic carbon, and loss on ignition were converted into carbon stock per unit area, using established formulas (Atwood et al. 2017 Nat Clim Change). Studies containing soil depth profiles <30cm and <100cm were extrapolated to 30 cm and 100 cm long soil cores.

In total, we collected 221, 176, 175, and 132 estimates of aboveground biomass carbon, belowground biomass carbon, soil carbon (30 cm deep), and soil carbon (100 cm deep), respectively. Along with these carbon estimates, several covariates were also extracted, including country, site, latitude, longitude, estuarine or oceanic mangroves, land use type (natural, planted, cleared, aquaculture, or agriculture), mangrove species, mixed or monospecific stands, number of mangrove species (if available), and soil bulk density (if available). Most of the available data were on natural or planted mangroves, while studies that simultaneously measured carbon stock in natural mangroves and deforested areas, such as cleared mangroves, aquaculture, or agriculture, were only a few. A map of mangrove sites with available carbon estimates is given in Fig. 3.

Figure 3. Map showing sites with available mangrove carbon stock data. A) all sites; B) sites for each carbon stock category.

Data analysis and findings

We have performed preliminary analyses. The grand mean estimates of aboveground biomass carbon, belowground biomass carbon, soil carbon (30 cm deep), and soil carbon (100 cm deep) in mangroves in South Asia were 68.74 (±4.34; SE), 34.16 (±1.92), 38.34 (±1.02), and 123.49 (±3.08) Mg C/ha (Fig. 4A). Our estimates represent the most inclusive and robust that are currently available for South Asia. Comparing our estimates with other published estimates (Fig.
4B), we found that while our soil carbon (100cm deep) estimate was comparable to multiple other less-inclusive estimates, it was only ~50% of the estimate for South Asia (254.49 ± 7.94) in Atwood et al. (2017 Nat Clim Change). Why Atwood et al. (2017) evidently substantially overestimated mangrove soil carbon stock in South Asia (and potentially globally) is unclear, although they appear to have estimated soil carbon stock by extrapolating surface soil cores (even just 5 cm deep) to soil profiles of 100 cm deep.

![Figure 4](image.png)

**Figure 4.** Overall summary of carbon stock estimates in South Asian mangroves. A) carbon stock in aboveground biomass, belowground biomass, and soils (up to 30cm and 100cm deep, respectively); B) soil carbon stock (100cm deep) estimated in this study compared to other estimates including the most recent estimate in Atwood et al. (2017 Nat Clim Change). Data are means ± SE.

Our analysis further showed that among South Asia countries with available data, mangroves in Bangladesh had the highest average aboveground biomass, belowground biomass, and soil carbon stock per unit area (Fig. 5). Although no relationship between aboveground biomass carbon stock and latitude was found, we found belowground biomass carbon, soil carbon (30 cm deep), and soil carbon (100 cm deep) all increased significantly with increasing latitude ($P < 0.001$) (Fig. 6). Although this region-scale latitudinal pattern is contrary to global-scale latitudinal patterns in mangrove carbon stock, it is consistent with the view that mangroves in northern South Asia, such as the Sundarbans, represent a highly valuable carbon stock. As a next step, we will develop multivariate predictive models by incorporating climate and GIS data, such as temperature, precipitation, mangrove cover, and land-use history.
Figure 5. Carbon stock estimates in mangroves in different countries in South Asia. Data are means + SE. NA indicates not available. No mangrove carbon stock estimates were available for Myanmar. Note that estimates of soil carbon stock (30 cm deep) in Sri Lanka and Pakistan should be interpreted with caution due to small sample size (1 and 3, respectively).

Figure 6. Mangrove soil carbon stock (30 cm deep) as a function of latitude as detected in a linear regression. Similar relationships were detected between latitude and mangrove belowground biomass carbon/soil carbon stocks (100 cm deep).
4. Species mapping

To date, we have mapped all avian species across the globe that BirdLife International classifies as using mangroves as a major habitat (Fig. 7). Of the five countries in the scope of this study, the areas with the highest richness of mangrove-dependent species are the Sundarbans between India and Bangladesh and the south coast of Myanmar. Not all of these species are endemic, however. Most use other habitat types such as inland wetlands and lowland forests. Of the species that have ranges in the countries of interest, we have identified the following as endemic to mangrove habitat: the brown-winged kingfisher (*Pelargopsis amauroptera*), collared kingfisher (*Todiramphus chloris*), mangrove whistler (*Pachycephala cinerea*), and the mangrove pitta (*Pitta megarhyncha*).

![Figure 7](image.png)

**Figure 7.** Global and South Asian maps of avian species that use mangroves as a major habitat.

Assessing threats to biodiversity

So far we have refined species ranges for *P. amauroptera* and *P. megarhyncha*. While the more accurate annual maps of mangrove classification are being developed, we have used the Hansen tree cover dataset to determine mangrove habitat for the years 2000-2015. We then identified potential individual metapopulations from the resulting maps. A single metapopulation was defined as any cluster of habitat patches that was more than 70 km away from the next nearest habitat patch. We set this distance threshold since there is a less than a 1% chance of an individual dispersing this distance in a single flight as given by the results of Van Houtan et al. (*Ecology Letters*, 2007). For each metapopulation, we calculated the landscape’s capability to
support a species, also known as the metapopulation capacity ($\lambda$), using the model as provided by Schnell et al. (PLOS One, 2013). A central feature of metapopulations is that there is a balance between local colonization and extinction, with local extinction likely in small habitat patches and colonization infrequent in distant ones. Even if suitable habitat remains, there is a threshold number of patches below which a set of habitat fragments can support the species. A heuristic interpretation of metapopulation capacity is that it represents how far above the threshold are the existing habitats.

Additionally, since this metric is heavily reliant on total area remaining, we also calculated the metapopulation density ($\Lambda$; Schnell et al. 2013). This informs us of the level of fragmentation independent of total habitat loss (i.e. how much a decrease in likelihood of persistence is due to the total amount of habitat removed versus the manner by which it is removed). The summary of results can be found in Table 1.

**Table 1.** Calculated metapopulation capacities ($\lambda$) and metapopulation densities ($\Lambda$) for the years 2000 and 2015 as well as the percent change over the years.

<table>
<thead>
<tr>
<th>Species</th>
<th>Metapop.</th>
<th>2000 $\lambda$ ($\Lambda$)</th>
<th>2015 $\lambda$ ($\Lambda$)</th>
<th>$\Delta \lambda$ (%)</th>
<th>$\Delta \Lambda$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>P. megarhyncha</em></td>
<td>1</td>
<td>6.8E+12 (1564)</td>
<td>6.8E+12 (1564)</td>
<td>-0.048</td>
<td>-0.0028</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2.3E+11 (253)</td>
<td>1.8E+11 (290)</td>
<td>-27.867</td>
<td>12.826</td>
</tr>
<tr>
<td><em>P. megarhyncha</em></td>
<td>3</td>
<td>1.3E+11 (523)</td>
<td>1.3E+11 (525)</td>
<td>-0.049</td>
<td>0.435</td>
</tr>
<tr>
<td><em>P. megarhyncha</em></td>
<td>4</td>
<td>1.8E+12 (515)</td>
<td>1.7E+12 (522)</td>
<td>-1.357</td>
<td>1.350</td>
</tr>
<tr>
<td><em>P. amauroptera</em></td>
<td>1</td>
<td>6.8E+12 (819)</td>
<td>6.8E+12 (857)</td>
<td>-0.048</td>
<td>4.453</td>
</tr>
</tbody>
</table>

In all metapopulations analyzed so far, we have not only observed a decrease in metapopulation capacity, but the decrease has exceeded changes in metapopulation density. This suggests that the overall extent of habitat fragmentation has been increasing in these areas and that large continuous patches of mangroves are being broken up into smaller fragmented patches as opposed to the preferential removal of smaller patches. This is supported by cumulative distribution plots that illustrate that a larger proportion of the landscape in 2015 is comprised of smaller patches than in 2000 (Fig. 8).
Figure 8. Cumulative distribution plot of fragment areas for the second metapopulation of *Pitta megarhyncha* for the years 2000 and 2015.

5. Compile land-value data for protection cost analysis

Opportunity costs—the agricultural or other economic values that are forgone if mangroves are protected—are usually the largest component of protection costs. These costs are not the same at all sites, for the simple reason that some land is more valuable for agriculture (or development) than other land due to location (e.g., proximity to market), elevation, soil quality, and so on. Our analysis of protection costs focuses on India and Bangladesh.

In the proposal, we wrote that we would base our estimates of opportunity costs on assessed land values in the vicinity of mangroves. The process of obtaining these data from government offices in the two countries is underway and is farthest along in India. We used a 2000 digital mangrove map (http://sedac.ciesin.columbia.edu/data/set/lulc-global-mangrove-forests-distribution-2000) and more recent government reports to identify the ten districts in India containing the most substantial mangrove areas:

<table>
<thead>
<tr>
<th>State</th>
<th>District</th>
</tr>
</thead>
<tbody>
<tr>
<td>West Bengal</td>
<td>South 24 Parganas</td>
</tr>
<tr>
<td>Gujarat</td>
<td>Kachchh</td>
</tr>
<tr>
<td>Andaman &amp; Nicobar</td>
<td>Andaman</td>
</tr>
<tr>
<td>Andhra Pradesh</td>
<td>East Godavari</td>
</tr>
<tr>
<td>Odisha</td>
<td>Kendrapara</td>
</tr>
<tr>
<td>Gujarat</td>
<td>Jamnagar</td>
</tr>
<tr>
<td>Andhra Pradesh</td>
<td>Krishna</td>
</tr>
<tr>
<td>Maharashtra</td>
<td>Raigarh</td>
</tr>
<tr>
<td>Andhra Pradesh</td>
<td>Guntur</td>
</tr>
<tr>
<td>Maharashtra</td>
<td>Thane</td>
</tr>
</tbody>
</table>
These districts include about 90% of the mangrove area in the country. We are currently using the digital map to identify subdistricts within them that are adjacent to mangroves. Those are the locations for which we will obtain data on assessed land values.

We identified several additional potential sources of land value data in India. The most promising is the National Sample Survey conducted by the Ministry of Statistics and Programme Implementation. Three rounds of that survey have collected land value data for a large number of households across India: the 48th Round (1992; 57,031 households), the 59th Round (2003; 143,285 households), and the 70th Round (2013; 110,800 households). We initiated the process of ordering the data in October and were informed on January 3 that the Ministry had mailed them to us. (The Ministry does not provide a digital download option.) These data will provide an important cross-check of the data on assessed land values, which our local collaborators have informed us are prone to underestimation.

Lead authors of this report by section are: Chandra Giri, develop and test methodology for annual mapping and monitoring; Qiang He and Brian Silliman, estimate carbon stocks and changes in carbon stocks; Ryan Huang and Stuart Pimm, species mapping; and Jeffrey Vincent, Brian Murray, GP Shukla, and Wumeng He, compile land-value data for protection cost analysis.