Monitoring changes in ecosystem services in key biodiversity areas in the Western Ghats biodiversity hot-spot

Technical Report Submitted to the Critical Ecosystems Partnership Fund

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Contents

List of Figures

List of Tables

List of Abbreviations

APAR	Absorbed Photosynthetically Active Radiation
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CEPF	Critical Ecosystems Partnership Fund
DEM	Digital Elevation Model
DLM	Dynamic Linear Models
ET	Evapotranspiration
GPP	Gross Primary Productivity
GRASS	Geographical Resource Analysis Support System
HANTS	Harmonic ANalysis of Time Series
INR	Instantaneous Net Radiation
IUCN	International Union for Conservation of Nature and Natural Resources
KBA	Key Biodiversity Area
LST	Land Surface Temperature
LUE	Light Use Efficiency
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalised Difference Vegetation Index
NIR	Near Infra Red
NPP	Net Primary Productivity
PAR	Photosynthetically Active Radiation
SLC	Scan Line Corrector
TRMM	Tropical Rainfall Measuring Mission
USGS	United States Geological Survey
fPAR	Fraction of Photosynthetically Active Radiation

Executive Summary

The Critical Ecosystems Partnership Fund (CEPF), since 2007, has directed investments to the tune of $6 million towards conservation initiatives in the Western Ghats biodiversity hot spot. Projects supported by CEPF covered direct conservation interventions, research and documentation of biodiversity and conservation challenges, and awareness raising regarding conservation.

In late 2013 a study was commissioned to determine whether there were any measurable changes in ecosystem services as a result of these interventions in the Western Ghats. These were to be measured in terms of 1) Extent of improvement in habitat as a proxy for biodiversity services, 2) Extent of improvement in hydrological services, and 3) Extent of improvement in carbon services. Findings are presented both as an overall analysis of trends across the Western Ghats as well as a comparison between key biodiversity areas (KBA) selected by the CEPF for interventions (priority KBA) and those where interventions were not undertaken (non-priority KBA). This study also aimed to develop a scientifically valid and replicable framework for monitoring impacts of CEPF interventions on ecosystem services.

We used two principal sources of data namely, MODIS and Landsat for analysis. We used dynamic linear models to remove the effect of climatic variables (rainfall and temperature) on the observed trends in the three ecosystem services studied. Thus the reported trends are largely impacts of conservation interventions and other non-climatic processes.

Key results showed no significant change in any of the three ecosystem services in nearly half of the Western Ghats. In the remaining region, results showed a declining trend in NDVI as a proxy for biodiversity, but an increasing trend was observed in carbon storage and hydrologic services. When priority KBAs were compared with non-priority KBAs, a decreasing trend in NDVI was seen in a larger proportion of priority KBAs than non-priority KBAs. However, results from the carbon services indicate a greater proportion of area with increase in carbon sequestration in both priority and non-priority KBAs. The total amount of carbon sequestered by priority KBAs was almost twice that of non-priority KBAs. Results of the hydorlogical services show a greater proportion of area with increase in blue water services (streamflow, soil moisture and ground water recharge) for both priority and non-priority KBAs. The total amount of blue water provided by priority KBAs was almost twice that of non-priority KBAs.

It is not possible to attribute the observed trends to interventions made by a single programme. Hence our results represent a combination of conservation actions by different players. Our study suggests that freely available remotely sensed products like MODIS and Landsat can be used efficiently to analyse trends in ecosystem services as a response to conservation/anthropogenic factors at a given site. The framework provided in this study can be improvised to monitor impact of climate change on ecosystem processes and services, and in predicting future changes in the ecosystem.

Background

Goal and Objectives

This study aimed to develop a scientifically valid and replicable framework for monitoring impacts of CEPF interventions on ecosystem services. The objectives of this study were to measure trends in three ecosystem services using remotely sensed proxy's or indices namely

1. Biodiversity
2. Hydrologic and
3. Carbon.

This technical report describes the data spanning the period 2000 to 2013, analytic procedure and results of the analysis. We also present an interpretation of the results along with a brief discussion on the way forward.

The study had two major deliverables. 1) A complete technical write-up (this report) and 2) the source code used for the analysis along with associated documentation[*]. The results have been presented in terms of overall trends in the ecosystem services and trends across priority KBA in comparison to non-priority KBA, the latter providing the control. The script used for the analysis will facilitate replication of this exercise in other regions with minimal expert intervention.

Study Design

The design of this study needed to meet the following major requirements:

1. The analysis presented could be re-run on data for different regions with minimal modification of the script.
2. Data requirements were to be limited to existing monitoring procedures at CEPF and the use of freely available satellite imagery. No field work or additional field based data was to be used.
3. The methods used were to rely on established protocols for analysis which had been published in high ranked peer reviewed journals and tested in production environments.
4. Results of the analysis were to be presented in terms of percentage change as well as graphs. Additional detailed results of the analysis were to be provided in this technical report.
5. Open source software was to be used throughout this study. The code written to do the analysis was to be released under a Creative Commons open source license to facilitate peer review and improvement.

The required outputs of this study were:

- Maps showing trends in change of the normalised difference vegetation index (NDVI) as a proxy for biodiversity services[45], hydrologic services as blue and green water and carbon services, covering the period 2000 to 2013.

[*] Published on GitHub https://github.com/feralindia/CEPF_monitoring and https://github.com/feralindia/CEPF_monitoring/wiki

- A comparison between CEPF invested key biodiversity areas (priority KBA) and areas without CEPF investment (non-priority KBA) for these services.
- A documentation of the script used for the analysis, along with relevant citations.

Overview of Methods

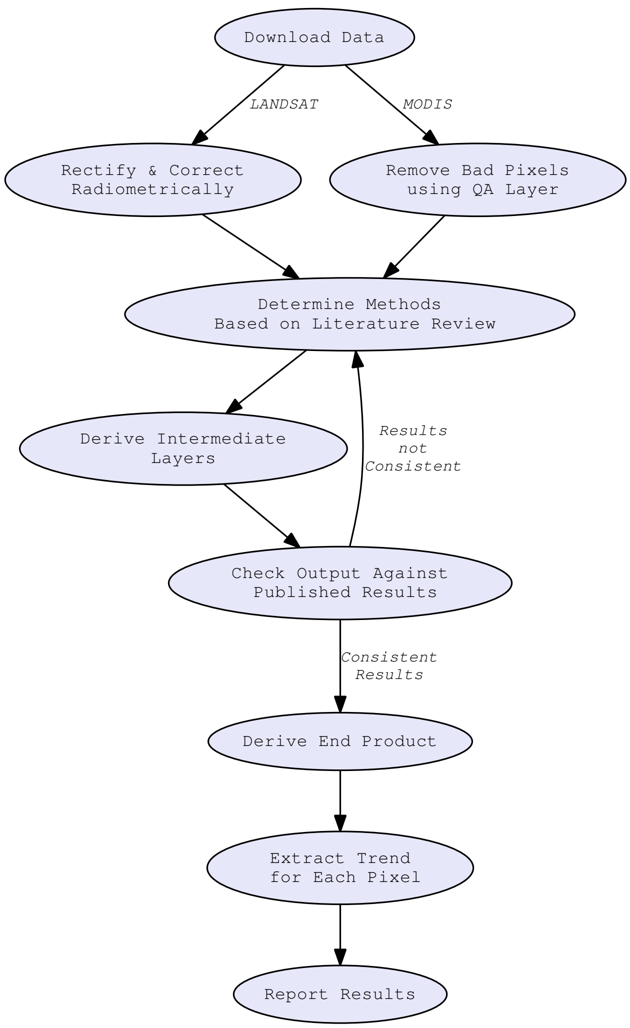


Figure 1: Simplified flowchart of steps used for analysing the imagery.

The methods adopted in this study were significantly influenced by the recent publication of global maps of forest cover loss between the period 2000-2012 [31,32]. The work of Hansen et al. [31] was based on a time series of Landsat images and training data from Quickbird imagery validated through existing percent tree cover layers based on Landsat and MODIS. Their approach was based on estimating forest loss / gain using decision trees and the trends using ordinary least squares slope of the regression of annual loss versus year. To validate the modelled outputs, the authors use MODIS NDVI data. As acknowledged by the authors to fully characterise these dynamics, such efforts should extend beyond estimating forest cover loss to identifying causes of forest cover loss and to estimate recovery rates. Other issues with the paper included the categorisation of forests which did not differentiate between plantations and native species (all vegetation taller than 5m was classified as forest) and the definition of gain and loss of forests which was categorical and coarse in terms of time scales.

We used a non-parametric regression based approach which provides more information than a simple image subtraction procedure [16]. A continuous non-parametric linear regressions was used to quantify change as a trend [48,96] broadly along the approach used by Reymondin et al. [76] for integrating data from the Tropical Rainfall Measuring Mission (TRMM) into the analysis to account for changes in NDVI due to rainfall.

The non-parametric Sen slope [88] was used to quantify the magnitude of the monotonic trend in the time-series of vegetation quality, carbon services and hydrological services. This approach involves computing slopes for all the pairs of ordinal time points and then using the median of these slopes as an estimate of the overall slope. Unlike linear regression, it is not greatly affected by data errors, outliers, or missing data. Results from the vegetation quality, carbon services and hydrologic services analysis were used to analyse the spatial variability of trends for the period 2000 – 2013 for all pixels within the Western Ghats. The overall procedure that was followed comprised of six steps, namely:

1. Downloading data after checking for quality.

Images were first screened using quality control documentation on the respective sites. For Landsat, we discarded images with more than 10% cloud cover and only downloaded images which had been corrected for terrain. For MODIS we used pixel reliability or quality layer provided along with the product to remove pixels which were affected by cloud, sensor and aerosol effects. Automated scripts were used to download MODIS data. Scripts were written to batch process the original HDF file, they were re-projected to WGS 84 datum and converted to geo-tiffs. The output files were renamed to indicate the row path, date and product.

2. Performing radiometric corrections.

   For Landsat images cloud assessment and removal through masking was done followed by radiometric normalisation using the dark object subtraction method (DOS4).

3. Identifying procedures for processing images.

   An extensive literature review was undertaken ahead of the study to identify the broad framework for analysis. This was refined to specific procedures after assessing the pros and cons of alternative methods.

4. Derive intermediate products.

   A number of intermediate products were derived prior to the final output, at each stage the output was validated against published literature. On occasion, results had to be rejected and alternative procedures adopted based on additional review of literature.

5. Derive index for the respective ecosystem service.

   The final annual measure of each ecosystem service was validated against published literature and other comparable data-sets.

6. Run trend analysis.

   Finally trends in the three ecosystem services were determined for the period 2000 to 2013. First "raw" trend, not corrected for effects of temperature and rainfall, was derived. The trend analysis was then repeated after these effects were removed, to approximate the impact of non-natural processes on trends.

We used four principal sources of data namely, MODIS [43], Landsat 7 ETM [14], TRMM: 3B43 [39] and ASTER [1]. Methods used for analysis are presented below.

The following datasets were downloaded from relevant sites:

- MODIS (2000–2013)
  - MOD13Q1[version5]: NDVI
  - MOD11A2[version 5]: Land Surface Temperatures
  - MOD17A3[version5.5]:Net Primary Productivity
  - MOD16A2[version 5]: Evapotranspiration
  - MOD16A3[version5]: Potential Evaopotranspiration
  - MOD44B[version 5.1]: Tree-cover
  - MCD12Q1[version 5]: Landcover
- Landsat 7 ETM (1999–2013): Multispectral (8 band) imagery

- TRMM: 3B43 [version 7]: Potential rainfall
- ASTER: Digital Elevation Model (DEM)

All these datasets are available free of cost from web portals. Each dataset was screened for quality prior to downloading. The Landsat 7 ETM datasets used were L1T corrected prior to distribution [57], implying they were geometrically corrected and had been corrected for terrain effects.

Radiometric correction of images

Pre-processing of images to correct radiometric and geometric errors is a prerequisite to image processing. We encountered three major types of errors:

- Atmospheric interference - this is caused by aerosols, moisture and dust which alter the reflectance at the sensor. All images were corrected for top of atmosphere reflectance and at surface radiance using dark object subtraction.
- Instrumentation errors - errors which creep in due to malfunctioning of the sensors such as the scan line corrector malfunction for Landsat 7. Available techniques for gap filling often introduced artefacts in the data which would have influenced our results. Our approach was therefore to reduce the gap by merging multiple images from the same season and year by extracting the maximum digital numbers.
- Cloud cover - obscuring of scenes due to cloud cover was dealt with by identifying clouds and masking them out of the image. A merger of the same season/year images as described earlier was then done which reduced the gaps in the final product.

Techniques we used for pre-processing of images were based on methods followed in peer reviewed literature. Relevant publications include Hansen et al. [31] and Potapov et al. [69] both of who performed top of atmosphere correction based on Chander et al. [14]. Other relevant literature includes Hansen et al. [33] for pre-processing Landsat data, Hansen et al. [30] for MODIS and Hansen and DeFries [29] for selecting cloud free images and forest change metrics. The latter procedure is also illustrated in Broich et al. [10].

The approach used by Hansen et al. [31] involved a mix of Landsat and MODIS products and they normalised the images using dark object subtraction method. Systematic differences across Landsat scenes due to variations in scan angles were rectified using a linear relationship described in Hansen et al. [33]

Various techniques have been employed for cloud removal which includes the use of classification trees based on two-band ratios as inputs [33,68,69]. A different approach was followed by Reymondin et al. [76] who used the Harmonic ANalysis of Time Series (HANTS) algorithm [42].

Filling of gaps created due to the failure of the scan line corrector on Landsat 7 has been dealt with differently. Among the most common techniques is to use compositing between different periods [10] which is also used to fill in gaps created by clouds.

Top of atmosphere correction

The Geographical Resource Analysis Support System (GRASS) is a comprehensive open source package for GIS and remote sensing. The GRASS module “i.landsat.toar” was used to perform atmospheric correction using the dark object subtraction (DOS4) method and for calculating top of atmosphere radiance values which were subsequently utilised for the cloud detection and masking operations.

Cloud detection

The Landsat automatic cloud cover assessment module “i.acca” uses the algorithm from Irish et al.[40]. The algorithm is “an unsupervised classifier for clouds, which takes advantage of known spectral properties of clouds, snow, bright soil, vegetation, and water”[40]. The GRASS module “i.acca” uses reflectance values of images processed with the module “i.atcorr”. Other approaches used for cloud filling include the use of Fourier analysis of time series[79].

De-striping

Striping is caused by the failure of the Scan Line Corrector (SLC) in Landsat 7 ETM on May 31, 2003, as described on the United States Geological Survey (USGS) web page† and led to a wedge shaped area appearing on the image edge leading to the loss of about 22% of the total pixels per scene.

De-striping methods There are two common approaches within which different algorithms can be used for removing stripes from images.

Statistical techniques for filling in from existing image edges This technique requires an interpolation of neighbouring (edge) pixels to fill in gaps. Examples of algorithms used include:

1. gdal_fillnodata.py‡ uses a four directional conic search and an inverse distance weighting to interpolate values from neighbouring edge pixels of gaps described by a MASK file[23].
2. Interpolation using a neighbourhood filter wider than the maximum size of the void (14 pixels).

This method has the following advantages:

1. It uses pixel values from the existing scene and not from a referenced scene. The latter method would result in repetitions of pixels for a series of images in the same tile leading to a flattening of the NDVI slope during the analysis.
2. It uses fewer assumptions than some of the more involved statistical approaches.

On the down side this method may introduce artefacts from the interpolation which would have otherwise been corrected. For example, an abrupt change in land cover from a building or small water body will not be detected, instead pixel values interpolated from the edges will be used. Another disadvantage is that it causes smudging of the resulting raster as shown in figure 2. This smudging can be reduced by lowering the width of the neighbourhood filter.

Mosaicking of images and extraction of pixel values from reference images Mosaicking requires the reference image to be filled in by one or more “reference” image set. The latter is a SLC-on image, i.e. before the SLC failed. This image is typically the closest anniversary date image to the SLC-off image. Other properties desired from a reference image are listed in the USGS page§

1. Image segmentation where NxN pixel windows from a source raster nearest in year-date are used to replace same sized windows in the gap.

† http://landsat.usgs.gov/products_slcoffbackground.php
‡ http://www.gdal.org/gdal_fillnodata.html
§ https://landsat.usgs.gov/images_will_work_best_to_fill_in_the_gaps.php

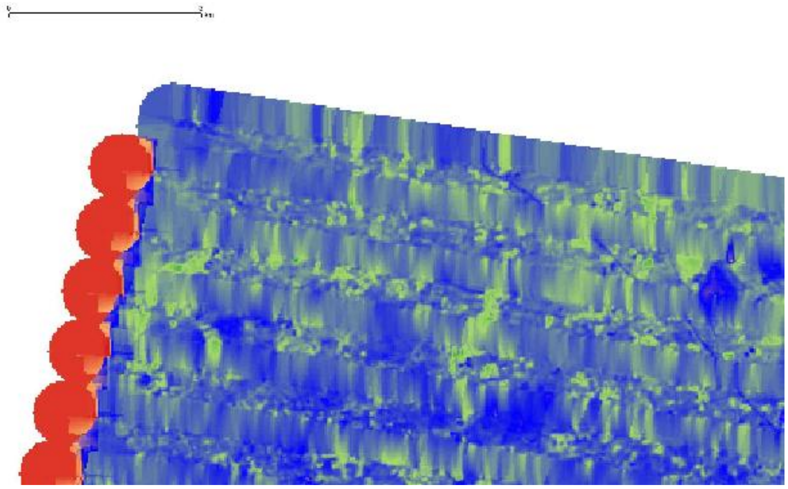


Figure 2: Results of running the gdal_fillnodata.py algorithm on a striped image (left). The results show a smudging of the image for the entire width defined in the gap-filling routine.

2. The USGS approach [87], similar to the one above, where a no-gap image closest in terms of the anniversary date of the SLC-off image is used to fill in the void pixel by pixel. Values used are based on bias corrections and standard deviates of pixel brightness. The method is computationally efficient and is utilised by numerous commercial packages.

3. A statistical approach where no-gap images are used alone or in time-series to predict the value of the missing pixels in the gap.

Procedure adopted We first ran the analysis without filling in the SLC gaps as initial runs showed that overlay of three or more scenes from the same tile acquired close together in time resulted in a substantial filling of the SLC gap. Given that our analysis required images taken from seasonal time periods, it was assumed that we could fill in gaps from the SLC error simply by taking values from temporally adjacent images. While this may not totally replace the gap, it would reduce it substantially as demonstrated in figure 3. Further, as we are detecting change based on a statistical slope derived from images spanning over a decade, it was felt that a few missing points due to gaps in data are unlikely to affect the overall results obtained.

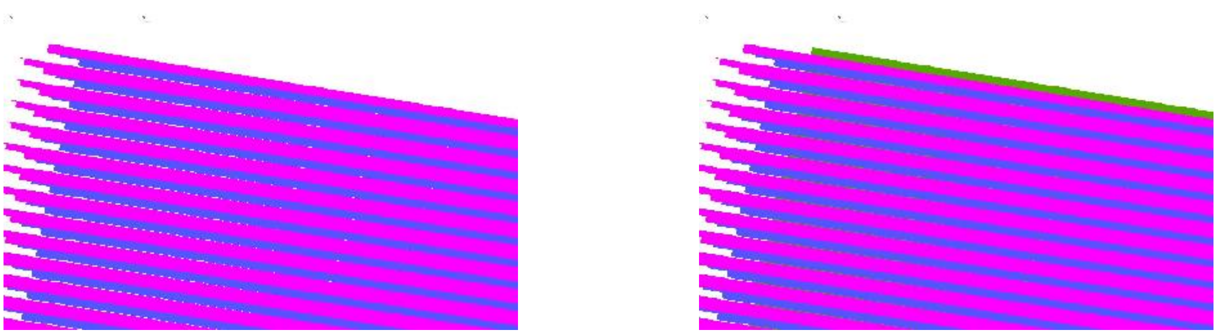


Figure 3: Reduction of the gap due to SLC errors by overlaying temporally adjacent images. Two adjacent images (left) and three adjacent images (right).

However, on analysing the final product we found that the SLC gaps were distinct from the other regions of the image on account of varying NDVI values in the images used to fill in the missing pixels. Therefore we reverted to the interpolation method provided by the GDAL libraries for the gap filling of images for this exercise.

For the MODIS images a different approach was used. We first removed the pixels affected by cloud, aerosols, sensor artefacts etc., using pixel reliability or quality assessment layer provided along with the product. We then corrected for bad pixels and filled the gaps in the MODIS layers (NDVI and LST), by performing Harmonic ANalysis of Time Series (HANTS) algorithm on original time series data [79] in GRASS 7 (r.hants module).

Analytic approach

We used a statistical or "soft" approach to measure the extent of change observed in the study area. This provides a number of specific advantages over "hard" approaches where the data is categorised into fixed and often arbitrary groups.

1. Statistical approaches are less sensitive to data gaps, provided there are sufficient number of points available to determine a trend. This can play an important role in areas where successive imageries may not be available due to atmospheric disturbances (cloud cover) or where the data itself has gaps such as the SLC error in Landsat 7 images after 2003.

2. Statistical measurements allow us to derive confidence intervals for the reported change. This is crucial when using such information for decision support where different degrees of confidence may be appropriate according to the given application.

3. Unlike approaches where responses are reported in hard classifications, statistical results are reported on a continuous scale.

Removing the effect of climatic variables

Dynamic linear models (DLM) have been used in different scientific disciplines to study trends over time and these include stream hydrology and population ecology [11,47,49] and more recently to analyse changes in vegetation greenness in response to climate change [48]. In a linear regression, the regression coefficients do not change over time. However, in a dynamic linear model the regression coefficients, the intercepts and slopes can vary as a function of time. Thus allowing us to capture the time-varying nature of the relationship. In a DLM the regression coefficients are generated for each time step, the trend in the intercept can be interpreted as variability in the response variable that is not captured by the co-variates alone. In this case the response variables are biodiversity services, hydrologic services and above ground carbon sequestration and the co-variates used are rainfall and temperature. The monotonic trends in the regression coefficient can be estimated using a non parametric bootstrap estimate of the median values or by fitting a non-parametric Sen slope.

We used data from the TRMM (TRMM3B43 dataset) to derive monthly rainfall estimates for each of MODIS and Landsat layers used in the analysis. Remotely sensed Land Surface Temperature was used to characterise ambient temperature. To improvise computational efficiency we restricted the analysis to annual time series of MODIS and Landsat data. However the same approach can be used to work with the original 16 day MODIS data and 3 hourly TRMM3B42 datasets.

We then ran a dynamic linear model to extract the intercept for each response layer (biodiversity services, hydrologic services and above ground carbon sequestration) with rainfall and temperature as climatic variables which influenced the response variable. The monotonic trends derived from the Sen's slope of the intercept can be interpreted as variability in the response variable that is not captured by the co-variates, and can be attributed to anthropogenic sources.

Challenges and Opportunities

There were a number of challenges which had to be overcome during this study, some of which considerably delayed our progress. The most serious of these was the difficulty in building a seasonal or annual time series of gap filled Landsat images. This is owing to persistent cloud cover, particularly during the monsoons, and the increasing scan line gap from 2003 to 2013. The computational requirements imposed by the large datasets and the limited computational power at our disposal was another challenge. The dataset comprised hundreds of images, all of which needed to go through many intermediate steps prior to the results. Consequently, computational times were very large. Most scripts ran for days to deliver each intermediate result. An additional cause for added computational times was "false starts", where weeks to months of efforts had to be discarded in favour of a different approach.

The inclusion of Landsat images in the analysis, on the suggestion of earlier reviewers of the proposal, was a major challenge. The Landsat dataset had three major advantages, its resolution is 30m (60m for the period prior to year 1999) compared to 250m for the MODIS dataset. Landsat bands cover a wide range of the electromagnetic spectrum allowing the extraction of more features than MODIS. Finally, the Landsat products go back to 1970 as compared to the MODIS data which is available from 2000. On the down-side, the Landsat required far more processing than the MODIS dataset. This was not just in terms of the large number of pixels to be processed, but more so because the original proposal envisaged the use of available MODIS products which had already been processed and were useable directly for the trend analysis. Furthermore, all of the MODIS products have been validated through comprehensive field testing and modelling. Therefore for every MODIS product, for example net primary productivity (NPP) we had to derive a product from Landsat images going through numerous steps and cross checks with other published results.

Another major challenge was the validation of the results which could not be done both due to the absence of historical datasets and the lack of resources for field validation. We therefore relied on available literature. For projects where literature was not available, for instance the land surface temperature outputs, we compared with the station level air-temperature data and obtained the relationship. All results presented in the study are therefore indices or approximations of actual values and error margins or uncertainties vary by each output.

Future Work

This study has led to new avenues of research being opened up. For instance, the existing analytic framework can easily be extended to determine trends across other ecological processes such as how the change in vegetation cover is impacting carbon or hydrologic services. The relationship between aerosols and rainfall as reported by recent literature [(50)] is another avenue which remains to be explored. Aerosols are produced largely due to anthropogenic activities such as burning of biomass, fuel and industrial processes.

The large baseline and derived datasets which have been created by this project can be used elsewhere.

In terms of further work, there is a good case for re-writing the code for speed optimisation: Creating small, independent sub-routines and replacing repetitive tasks and loops with functions where possible would make the code far more efficient and re-useable. Using multi-core features built into R so it can be run on large server clusters is another task which would greatly improve the performance of the existing scripts.

Layout of the Report

This technical report comprises of this introductory chapter which provides an overview of the study and broad description of the methods and challenges faced. This is followed by three major chapters, each dealing with one of the ecosystem services studied. These three chapters are largely self contained and comprise of three sections each. The first introduces the context and state of the science with respect to the ecosystem service being covered. The methods section covers details of the data used, analytic process and refers to relevant literature where appropriate. The results are presented at the end of each chapter along with discussions on the relevance of the findings.

Trends in Biodiversity Services

Introduction

Tropical forests support the highest concentration of biodiversity, with a few hotspots supporting a large number of endemics [55]. However, tropical forests are in turn seriously threatened by habitat destruction, leading to large scale biodiversity loss [17,22]. Historical analysis of extinctions, for a few groups of organisms, reveal extinction rates for the last three centuries which are several hundred times higher than the rate expected on the basis of the geological record [17]. Projections of biodiversity loss also indicate that continued land-use change is the most important driver which will push several species towards extinction [63]. Adding to this global crisis is the loss of biodiversity due to habitat fragmentation [20,35,44].

Understanding trends in forest cover loss [2,31,34,67,76,89] and fragmentation [77] has gained significant importance in the last few decades. Studies analysing these trends have only been possible with the advancement in remotely sensed products and software to analyse large volumes of data [5,25,26,65,95]. Currently it is estimated that nearly 1.71 million km^2 [77] to 2.3 million km^2 [31] of forest has been lost between 2000 and 2012. Riitters et al. [77] found that rate of loss of forest interior compared to the rate of loss of all forest area was 3.1 times higher on the global scale, with a net loss of 3.76 million km^2 of interior forest areas between 2000 and 2012. Further studies on trends in biodiversity loss indicate that, land-use change will probably have the largest effect, followed by climate change, nitrogen deposition, biotic exchange, and elevated carbon dioxide concentration [85].

In India, it is estimated that nearly 0.89 to 0.63 million km^{2}of forest was lost between 1880 and 2010. More recently, decadal trends between 1985 and 2005 shows that nearly 0.36 million km^{2}of forest cover was lost across the country, with deciduous broad leaf forest showing the highest percentage of loss during the above mentioned time period [81]. In the Western Ghats, one of the 36 global biodiversity hotspots [55], nearly 40,000 km^2 of forests was lost during the period 1973 -1995. During the same period dense forest was reduced by 33.2% and open forests decreased by 33.2%, also degraded forest increased indicating high levels of fragmentation [41].

Associations between habitat loss, land-use change and biodiversity loss have contributed towards the development of remotely sensed indices to characterise biodiversity [6,18,45,94]. Remotely sensed indices or surrogates of biodiversity provides a rigorous and comparable basis for understanding vegetation heterogeneity–diversity relationships, and offer a powerful tool for monitoring and understanding the responses of biodiversity and ecosystems to the changing environment. Recent studies have shown that monitoring productivity and land-cover changes through time has the potential to identify not only areas undergoing forest cover loss but also to indicate areas where potential biodiversity change may be occurring [18,74]. Studies have also shown the utility of using automated analysis of multi-date NDVI data in the real time monitoring of vegetation change. These assist in identifying areas where biodiversity losses can be expected [76].

Studies in the Western Ghats have shown the utility of using NDVI, a remotely sensed product of greenness, to characterise areas of high and low species richness of trees in tropical forests [6]. Krishnaswamy et al. [45] demonstrated the utility of using multi-date NDVI data to quantify variability in forest types across a moisture gradient and also its ability to capture floristic diversity. Additionally their multi-date NDVI distance measure provides a continuous ecological scale, which complements existing forest classification systems. While this is seen as a superior approach [78] as compared to using single date NDVI as a surrogate for biodiversity, the procedure followed requires a reference set of sites to develop a surrogate for tree diversity. Implementing this approach might be constrained to landscapes where ground truth data is available.

As a surrogate for trends in biodiversity we studied trends in habitat quality measured by NDVI in the Western

Ghats for the period 2000 to 2013. Our main objective was to analyse the changes in NDVI, a proxy for biodiversity services, as a response to conservation and management interventions undertaken in the Western Ghats key biodiversity areas by CEPF and other organisations. We make use of a time series of satellite images, remove the influence of climatic variable like temperature and rainfall and then derive trends to estimate observed changes in the quality of habitat due to anthropogenic factors.

Methods

We used remotely sensed data for analysing trends in habitat quality from two sources, Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat. NDVI is a measure of greenness and therefore changes in NDVI represent an alteration in quality of the habitat which can be associated with biodiversity services [(6)]. Earlier studies have shown that the NDVI and heterogeneity in NDVI can be used to characterise tree species richness [(6,45)]. To explore the relationship between NDVI and faunal diversity we calculated species richness of mammals, reptiles and amphibians from the IUCN redlist data set at a spatial resolution of 5 km^2 for the entire Western Ghats. We plotted this data against the median NDVI calculated for each pixel from monthly maximums across the years 2000 to 2013.

MODIS dataset

We used MOD13Q1 product from MODIS for this study. MOD13Q1 provides the average NDVI data at 250m resolution, every 16 days. This product also includes two quality assessment layers, Quality detailed QA layer (unit- Bits) and pixel reliability summary QA layer (unit- Rank), which can be used to evaluate the quality of each pixel. We found that the outputs generated by considering pixel ranks 0 –Good data and 1 –Marginal data, available in pixel reliability layer, were highly comparable with outputs generated using flags good and highest quality from detailed QA layer. As pixel reliability layer was rank based and simpler to use, we preferred this over detailed quality layer for removing pixels with bad quality such as those affected by cloud and aerosols from MOD13Q1 product. The resulting 16 days product was gap filled using Harmonic Analysis of Time Series (HANTS) algorithm [(42,79)] implemented in the r.hants module in GRASS7. Monthly maximum NDVI tiles were then generated for all the years from 2000 to 2013. Further, we generated annual tiles from 16 day NDVI tiles with the median NDVI values for each year. Land Surface Temperature (LST) during day time was obtained from the MOD11A2 product, which is characterised by a temporal resolution of 8 days and spatial resolution of 1km. Using quality control layer available with the product only the pixels with good quality algorithm results were retained for further analysis. Quality assessed eight day products were then gap filled using r.hants module. Further, we developed annual median temperature tiles from these eight day products for each year.

The TRMM data set was used to estimate the amount of rainfall received. We used the 3 hourly product 3B43 (V7) to generate, daily, monthly and annual totals.

Landsat dataset

The pre-processed (see section 2.2 for additional details) Near Infra Red (NIR) and Red (R) bands from Landsat for the period 2000-2013 were used to derive the NDVI layer using the formula:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{1}$$

We derived the maximum NDVI for each year using the tiles from post-monsoon season (October, November and December).

Analysis

The monotonic trends in NDVI for the period 2000 to 2013 were estimated across the Western Ghats using Sen slope [88]. A dynamic linear model (DLM) [64] was fitted to remove the influence of climatic variables on the levels of NDVI data. To do this we ran a regression of the time varying annual median NDVI against annual median land surface temperature and rainfall. The LST was derived from MODIS LST product and annual rainfall from the TRMM product. We then used the Sen slope on the time varying intercepts from the resulting DLM model to characterise the trends after removing the influence of temperature and rainfall,

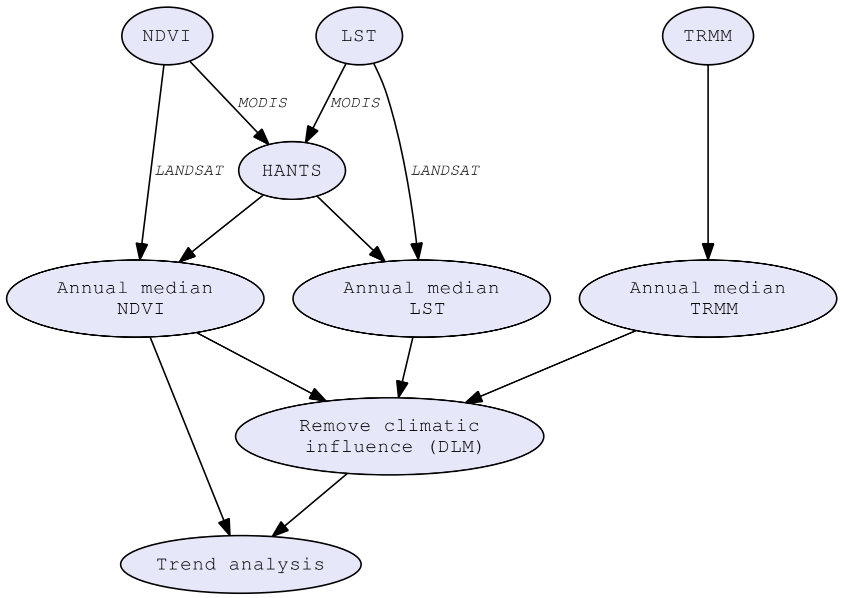


Figure 4: Procedure followed for deriving NDVI values as proxies for biodiversity services.

Results and Discussion

In the Western Ghats, areas with high NDVI also house higher diversity of amphibians, reptiles and mammals. However this relationship is not linear, as NDVI tend to saturate at higher values. On the other hand, areas with low NDVI correspond to areas with low biodiversity, whereas areas with high NDVI correspond to areas with higher (Fig. 5). Earlier studies had demonstrated the utility of using NDVI to map biodiversity of trees in the Western Ghats [6]. Our results further strengthens the use of NDVI to monitor faunal diversity as well as monitoring vegetation quality [96].

Our results show that when the trends are not corrected for climatic factors, biodiversity change was noticed in only 15% of the Western Ghats (Table 1). However when corrected for temperature and rainfall nearly 50% of the Western Ghats shows significant trend in biodiversity during the period 2000-2013 and 28% of the Western Ghats showed decline for the same period. Spatial patterns in the trends are shown in Figure 6. Analysis of trends at level of Key Biodiversity Areas identified by CEPF reveals that priority KBA's showed greater decline in biodiversity than those identified as non priority KBAs (Fig. 7).

Krishnaswamy et al. (2009) show that spatial variability in NDVI is a better approach to monitor biodiversity using remotely sensed products. They develop an "eco-climatic" distance as a distance measure from the wettest vegetation formations in the Western Ghats, adopting such an approach would require ground truth data. While this approach of developing an index of eco-climatic distance might be better than using NDVI to monitor biodiversity trends, it would require collecting ground information from reference plots representing

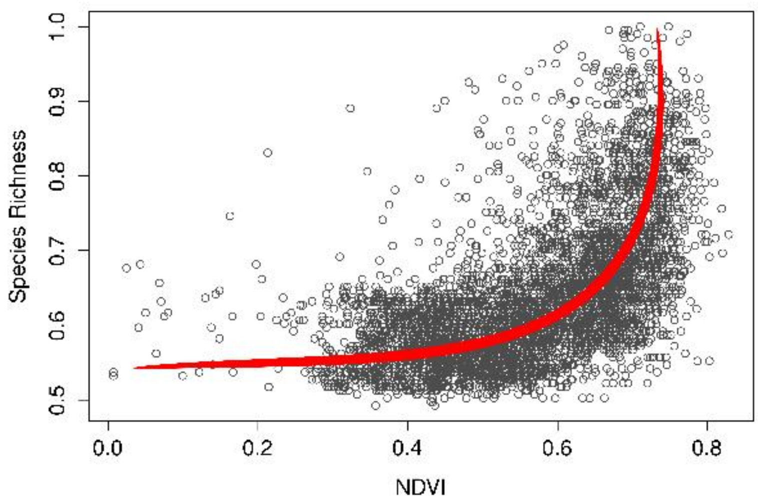


Figure 5: Relationship between NDVI and faunal richness (mammals, amphibians and reptiles). The richness index is derived by dividing total richness in each pixel by the maximum richness estimated across all the pixels. Greater the index higher is the faunal diversity.

the wettest vegetation type in each landscape and this acts as a limiting constraint within the overall objective of developing a monitoring framework.

Table 1: Gains and losses in NDVI within priority and non-priority KBAs. Raw gains/losses are without correcting for climate effects. Gains/losses corrected for climate effects are reported for statistically significant trends at $p \leqq 0.1$.

Type of KBA	Raw Gain	Raw Loss	Corrected Gain	Corrected Loss
Priority (sq. km.)	4711	10227	3118	5246
Non-Priority(sq. km.)	4098	7175	2884	3554
Priority (% area)	32%	68%	37%	63%
Non-Priority (% area)	36%	64%	45%	55%

We compared the performance of MODIS NDVI with Landsat derived NDVI data. It was not possible to develop a monthly time-series across all the years using Landsat files, hence we developed layers showing the maximum NDVI that is accumulated in a year by using the NDVI values from post-monsoon season. A comparison of maximum NDVI for a priority KBA, Haliayal, showed similar positive trends in NDVI for both MODIS and Landsat datasets (Fig. 8) in the period 2000-2013. Although the trends followed a similar pattern, the slopes were not the same between MODIS and Landsat NDVI for Bondla, a non-priority KBA (Fig. 9). This could be attributed to the data loss we observed for a few pixels in Landsat images in Bondla during the post-monsoon season due to extensive cloud cover for a few years. The results suggest that, although Landsat can be used along with MODIS data for monitoring changes in NDVI, it is not possible to use them for large-scale monitoring, especially in tropical forests, which experience high cloud cover.

In the Western Ghats several studies have been carried out, across varying time scales and spatial extents, to assess the loss of forest cover [41,81]. However our results not only capture loss of forest/vegetation cover it also captures decline in the quality of the cover. We choose to present the results in terms of declines and increases as our main objective was to link habitats and biodiversity. To demonstrate the utility of using MODIS tree cover

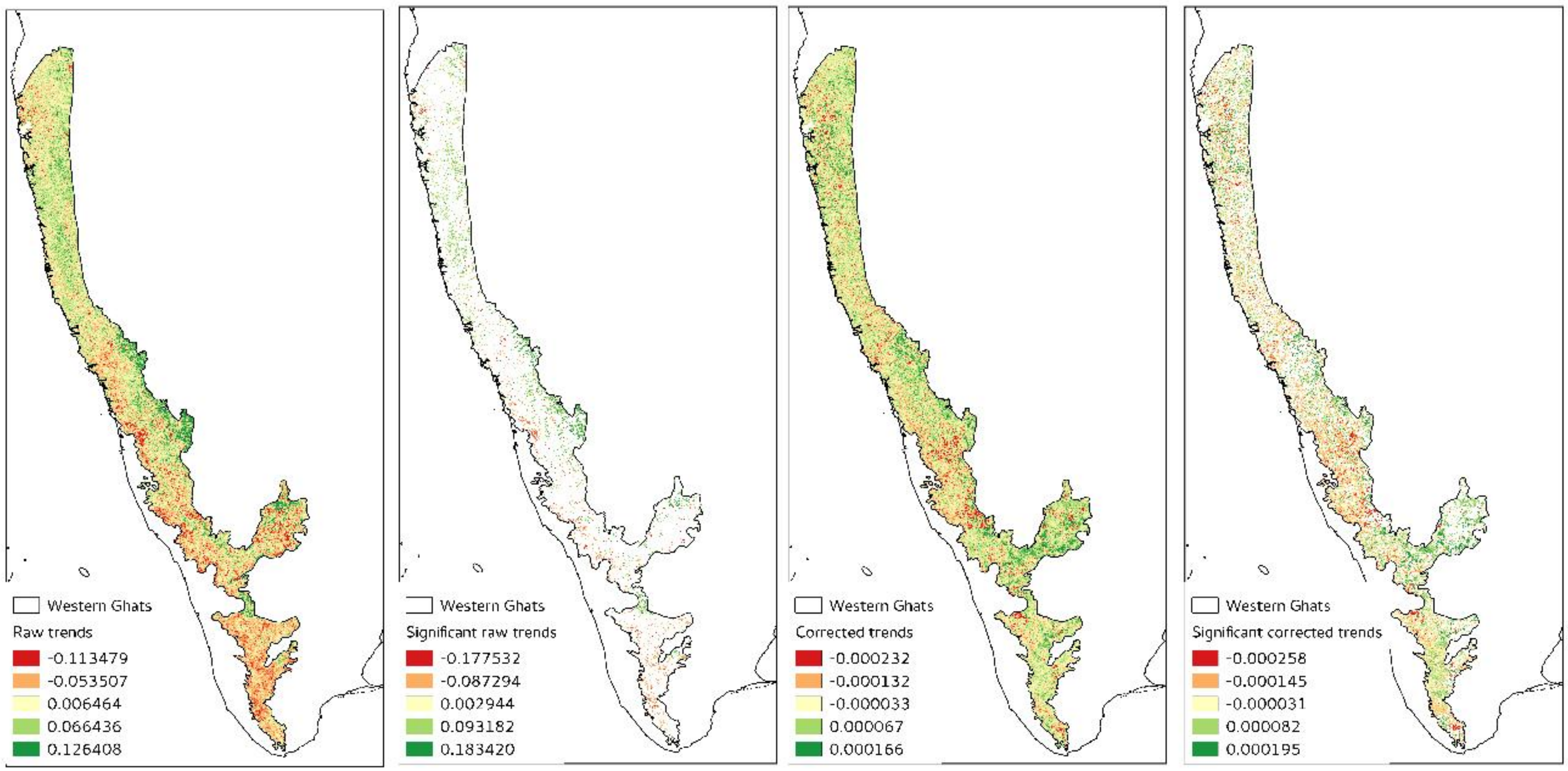
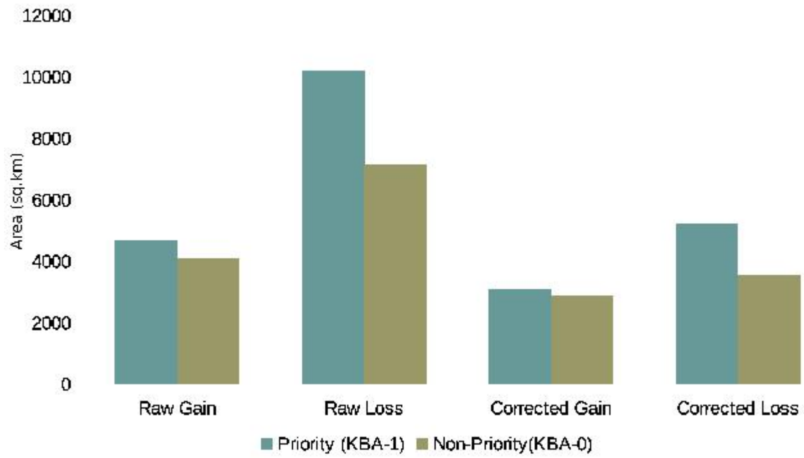
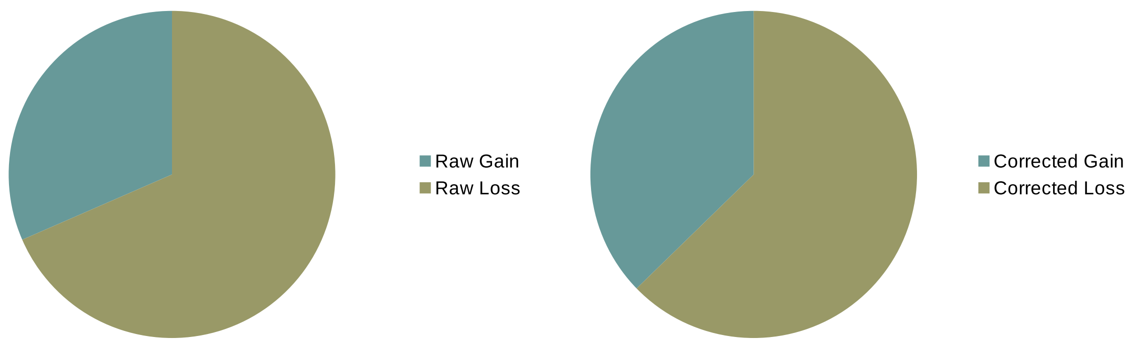


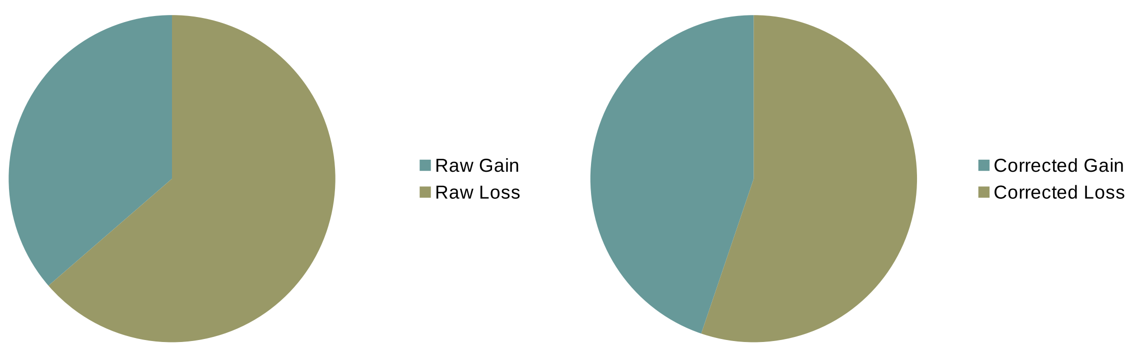
Figure 6: The map show how the vegetation cover has changed in the period between 2000 and 2013. The maps highlighted in red show pixels where the change is statistically significant at p<=0.1. Those in blue show all pixels.



(a) Statistically significant raw (uncorrected for climate effects) and corrected trends in NDVI within priority KBA and non-priority KBAs reported as area in sq.km.



(b) Statistically significant raw (uncorrected for climate effects) and corrected trends in biodiversity services in priority KBAs reported in proportions.



(c) Statistically significant raw (uncorrected for climate effects) and corrected trends in biodiversity services in non-priority KBAs reported in proportions.

Figure 7: Priority KBAs showed a greater loss and smaller gains in biodiversity services than non-priority KBA regions. Raw gains/losses are without correcting for climate effects. Gains/losses corrected for climate effects are reported for statistically significant trends at $p \leqq 0.1$.

product (MOD44B) to monitor change in tree cover we compared the significant trends in tree cover with results from Hansen et al.[34]. Our results (Fig. 10) show a higher tree cover loss across the entire Western Ghats when compared to Hansen et al.[34]. Reddy et al. also show higher forest losses in India when compared to Hansen et al.[31]. Hansen et al define loss within a 30 meter pixel if the average amount of tree cover lost is 50% to 100%. In our analysis we do not use any such criteria to report increasing or decreasing trends in tree cover and it

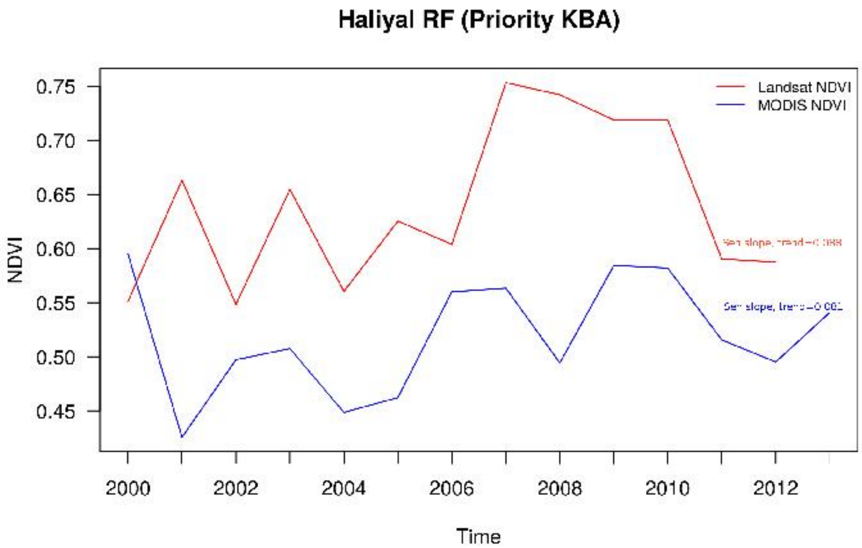


Figure 8: A similar trend in NDVI was observed between Landsat and MODIS data for priority KBA Haliyal, Western Ghats. Analysis of Sen slope suggested a similar positive trend with a slope of 0.08 to 0.09 over the period 2000-2013. While the patterns were similar, the trends in both Landsat (p=0.59) and MODIS (p=0.38) were non-significant at p<0.1.

captures not only loss but also deterioration in the quality of tree cover. Table 2 compares the Hansen tree cover analysis and the MODIS tree cover analysis for priority and non priority KBA's identified by CEPF.

Table 2: Hansen and MODIS tree cover datasets showed a similar gain in tree cover in KBAs. Whereas, Hansen dataset showed greater losses in tree cover compared to MODIS data.

Type of KBA	Hansen Tree Cover Analysis		Modis Tree Cover Analysis	
	Corrected Gain	Corrected loss	Corrected Gain	Corrected loss
Priority (% area)	0.16	0.40	0.16	0.15
Non-Priority (% area)	0.09	0.22	0.11	0.16

In conclusion, using NDVI to monitor biodiversity change is a better approach when field data is not available. It not only shows potential areas undergoing biodiversity changes, it also indicates areas where vegetation changes are occurring. The trends we report are due to non climatic variables and can be directly attributed to anthropogenic interventions and reveal both loss/gain and deterioration/improvements. Our results also show that high resolution Landsat data can be used for a similar trend analysis, however temporal coverage of Landsat is a major constraint in large scale applications. Both high spatial and high temporal resolution imageries are needed to accurately discern trends in forest fragmentation and degradation. Neither Landsat nor MODIS meet both these requirements.

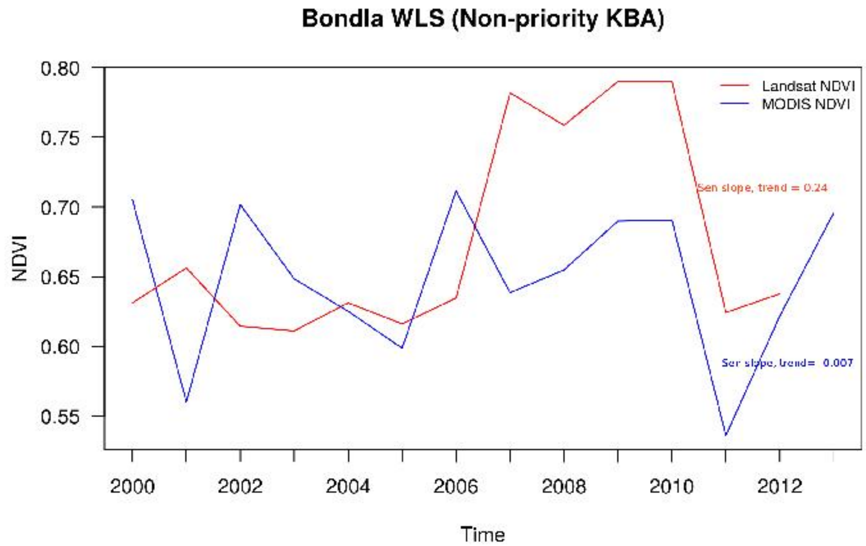


Figure 9: A similar trend in NDVI was observed between Landsat and MODIS data, however, the Sen slope values for NDVI trend across the years were different for non-priority KBA Bondla, Western Ghats. The differences could be a result of data loss in Landsat tiles due to high cloud cover for some of the years in post-monsoon season. While the patterns were similar, the trends in both Landsat (p=0.21) and MODIS (p=0.9) were non-significant at p<0.1.

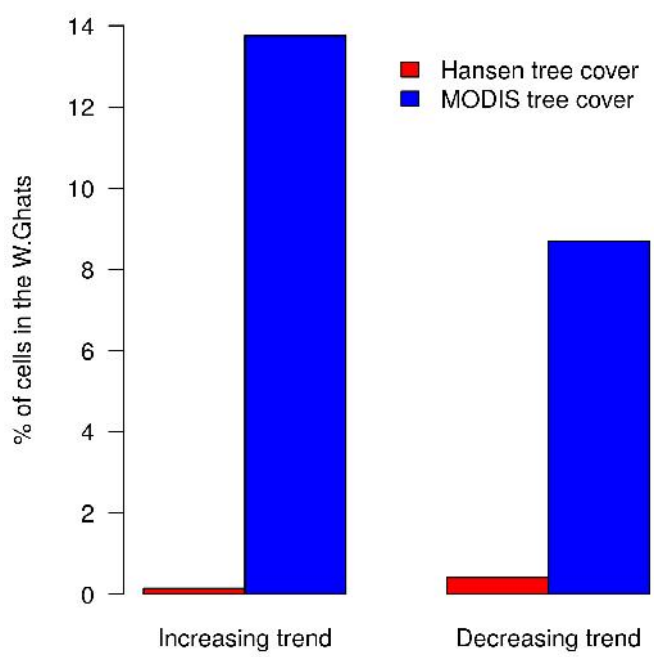


Figure 10: Trends in tree cover derived using MODIS product (MOD44B) showed a higher tree cover loss in the Western Ghats compared to Hansen tree cover data.

Trends in hydrologic services

Introduction

Hydrologic services refer to a gamut of regulatory as well as provisioning services offered by ecosystems with respect to water. This includes its retention as soil moisture, recharge of ground water, discharge as streamflow or evapotranspiration. Determining the impact of restoration and conservation efforts on provisioning of water can provide the basis of a convincing economic argument in favour of protecting catchments in their natural forms. Recent research in the Western Ghats shows that forests converted to plantations or degraded tend to show an overall increase in discharge [46] and reduction in hydrologic conductivity, or recharge [9]. While most hydrologic services are associated with quantum, duration and quality of stream flow, green water fluxes are also recognised as an important component in the overall water budget and are known to sustain a range of ecosystem services [21,45].

Hydrological services are arguably the most valued services from natural ecosystems. This is more so for agricultural societies, such as India. The widespread impression that forests provide us clean and continuous supplies of water oversimplifies complex interactions between vegetation, geomorphology and climate. Land cover plays a significant role in determining the quantity of fresh water discharge and its quality, even if geomorphology and climatic conditions remain similar.

However, measuring discharges across large and difficult terrain poses huge financial and logistic challenges. Much like other parts of the country, the Western Ghats are poorly gauged and field measurements of hydro-meteorological parameters are sparse.

The Western Ghats are important from the perspective of hydrological services forming the headwaters of six major river basins [97]. Recent estimates suggest that the region "will have 81 million people with insufficient water by 2050" [51].

Discharge or streamflow, re-charge and soil moisture together form the blue-water component of the water balance. The other component - green-water, refers to the proportion of precipitation which is circulated back into the atmosphere through evapotranspiration. This can be further broken down into a non-productive component of evaporation and a productive component of transpiration through plants. Non-productive green water or evaporation is the sum of water lost through surface evaporation from water bodies and soil as well as canopy interception.

The question we pose in this section is, what are the trends in hydrological services in terms of blue water during the period from 2000 to 2013 across the Western Ghats? We further ask what proportion of these trends can be attributed to non-climatic processes, i.e. factors other than temperature?

Methods

Remote sensing has long been used to derive indices and estimates of hydro-meteorological parameters such as precipitation, actual and potential evapotranspiration heat flux and soil moisture. While this does not replace field measurements, it provides us a handle on large scale trends across numerous parameters and can be tied to changes in land cover, such as modification of natural forest to other land uses.

There are a number of approaches to measure evapotranspiration from remote sensing. Most of these are based on measurements of heat flux from the thermal bands of imageries. We utilised an approach proposed in 2001 by Zhang et al. [98] wherein a proxy for soil moisture is used as a parameter to derive evapotranspiration [19].

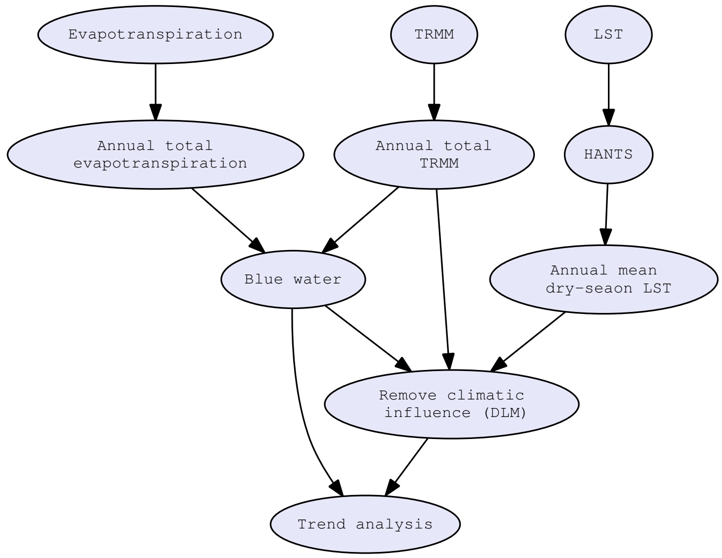


Figure 11: Procedure followed for deriving blue water values as proxies for hydrologic services.

Three specific estimates are required in order to estimate trends in green and blue water from a catchment:

1. Approximation of actual evapotranspiration.
2. Approximation of soil moisture at the root zone and
3. Approximation of at-surface temperatures and emissivity which is a prerequisite to the above two derivations.

The overall framework for the analysis is the water balance equation:

$$P = ET + R + D + \Delta S \tag{2}$$

where P is precipitation, ET is evapotranspiration, R is surface runoff or streamflow, D is ground water recharge and ΔS is change in soil water storage. This can be simplified to

$$P = ET + Q + \Delta S \tag{3}$$

where, $Q = R + D$ or total runoff which includes surface, base flows and interflow [(99)]. The latter term is assumed to be a constant over annual time periods leading to the simplified equation:

$$P = ET + Q \tag{4}$$

Therefore, if we can derive the term ET (or green water) and assume the term ΔS to be a constant, we are in a position to determine the proportion of blue water Q. Zhang et al. [98] demonstrated that *ET* can be calculated based on measurements of potential evapotranspiration (E_o) and a parameter *w* which is a coefficient for plant available moisture at the root zone as per the equation:

$$\frac{ET}{P} = \frac{1 + w\frac{E_o}{P}}{1 + w\frac{E_o}{P} + \left(\frac{E_o}{P}\right)^{-1}} \tag{5}$$

We used Landsat imageries and a modules and calculations using the raster package in R and GRASS GIS to derive the blue and green water for each year. E_o values were taken from available MODIS based products. The value for the w parameter was estimated by deriving the Temperature Vegetation Dryness Index (TVDI) based on publications by Sandholt et al. [86] and Son et al. [92]. In order to proceed with the analysis a number of intermediate layers were derived. These were based on remotely sensed measurements of surface temperature and emissivity which can be calculated directly from the thermal band of satellite imageries as per Chander et al. [14]. Trends for these were then calculated using Sen slopes as described in the methods presented earlier.

An independent set of blue water estimates was derived using MODIS monthly evapotranspiration products, MOD16A2, available at 1km resolution, and TRMM rainfall data. We calculated annual total evapotranspiration for each year from 2000 to 2013 and subtracted this from annual total rainfall to obtain blue water for each year. This was later expressed as percentage of total rainfall and analysed for trend using Sen slopes and DLM.

Results and Discussion

Our results suggest that there has been a 43% increase in area where blue water, i.e. discharge and recharge, has increased. 48% of the Western Ghats remains unchanged and 8% of the area shows a declining trend. The spatial patterns in the trends are shown in Fig. 12.

Table 3: Gains and losses in blue water trends in priority and non-priority KBAs. Raw gains/losses are without correcting for climate effects. Gains/losses corrected for climate effects are reported for statistically significant trends at $p \leqq 0.1$.

KBA	Raw Gain	Raw Loss	Corrected Gain	Corrected Loss
Priority KBA (sq. km.)	12030	5182	5503	608
Non-Priority KBA (sq. km.)	8498	4509	2922	208
Priority (% area)	69.89%	30.11%	90.05%	9.95%
Non-Priority (% area)	65.33%	34.67%	93.35%	6.65%

The observed trends were validated against field measurements of stream discharge from four catchments in the Western Ghats. These were from different regions, Anjanari representing the northern Western Ghats in the state of Maharashtra, Ganjim central Western Ghats in the state of Goa, Santeguli and Sakleshpur in the southern state of Karnataka. They also represented different rainfall regimes. While the comparison shows a consistent bias, the trends shown by the blue water estimates are consistent with field observations. This validates our approach (Fig. 15).

We compared Landsat derived blue water values with blue water values derived using MODIS. Both data sets showed a strong significant correlation with each other, with R^2 values ranging from 0.44 to 0.68 ($p < 0.001$) (Fig. 16). However, the temporal coverage by Landsat images was poor compared with MODIS data. Hence we used MODIS derived blue water data for trend analysis.

Results presented here indicate an increase in blue water availability from a large proportion of both priority KBA (89%) and non-priority KBA (93%) (Fig. 13). However, the total amount of blue water provided by priority KBAs was almost twice that of non-priority KBAs across the Western Ghats (Fig. 14). This implies additional water was available through streamflow into reservoirs and rivers, soil moisture and recharge of ground water. Given the importance of the Western Ghats as headwaters of important rivers, our results indicate a positive trend. There are two major processes that could contribute to the increased blue water flows. 1) The increase in total precipitation in the region over the study period and 2) a decrease in the green water component of the annual water budget. The latter would indicate a reduction in the total amount of “productive green water” or reduction in transpiration implying reduced green forest cover. However our observations on trends in NDVI over the same period show that there has been an increase in overall productivity in the Western Ghats. Further

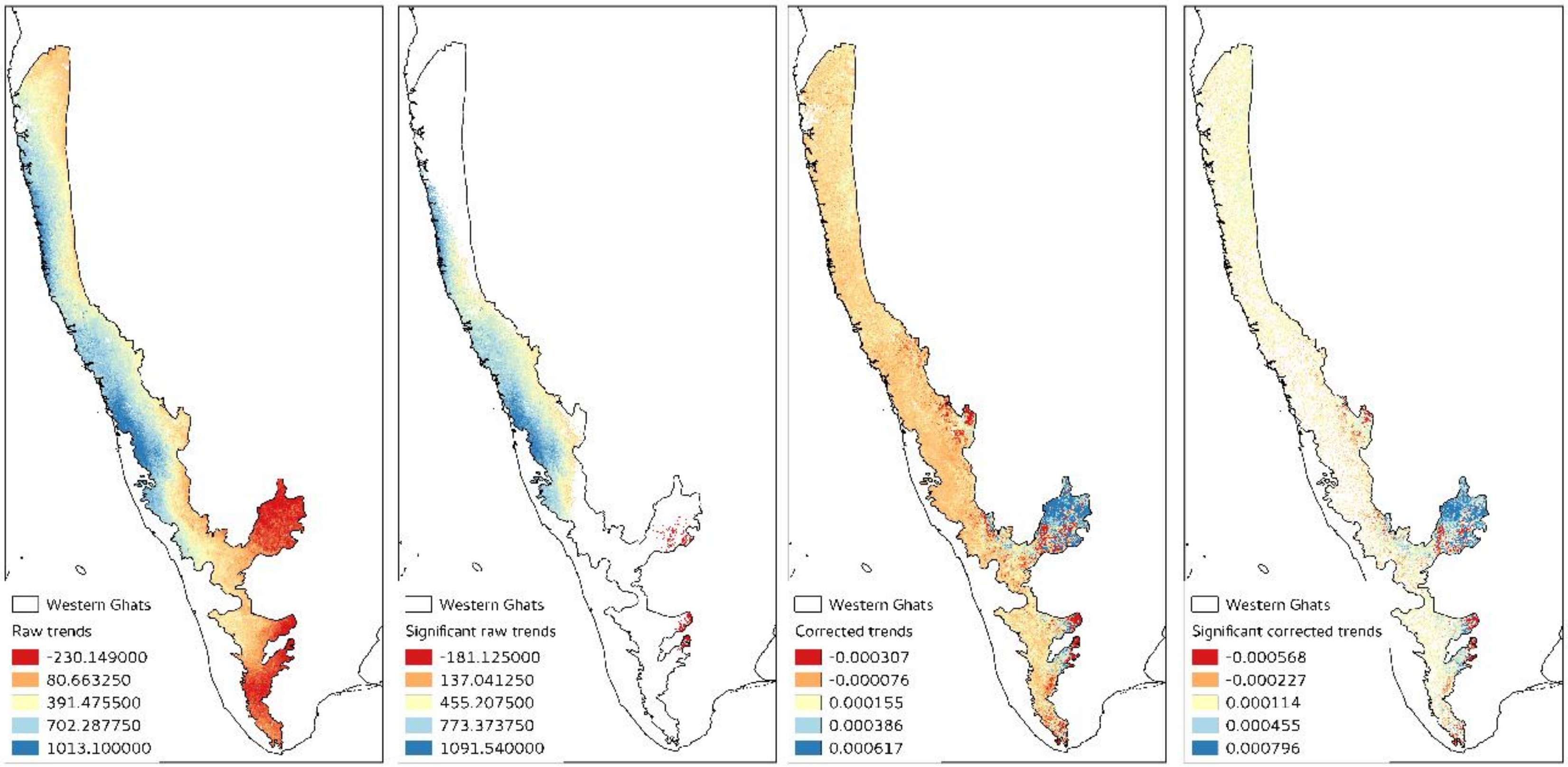
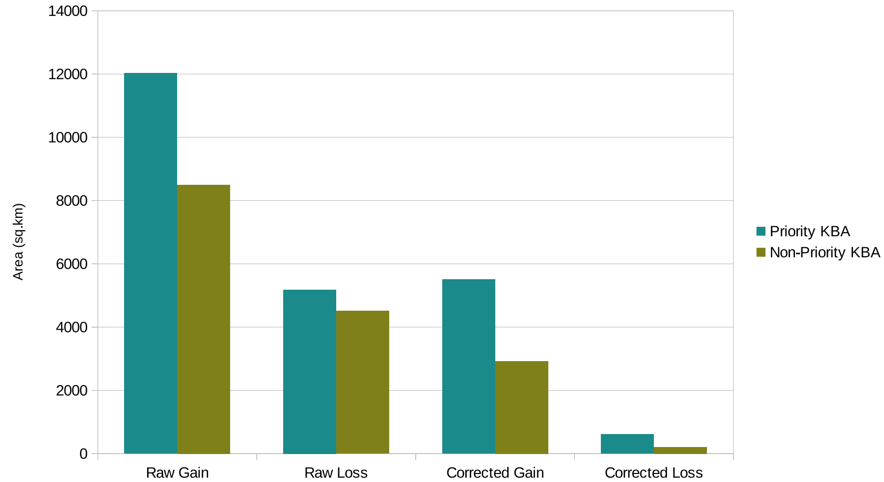
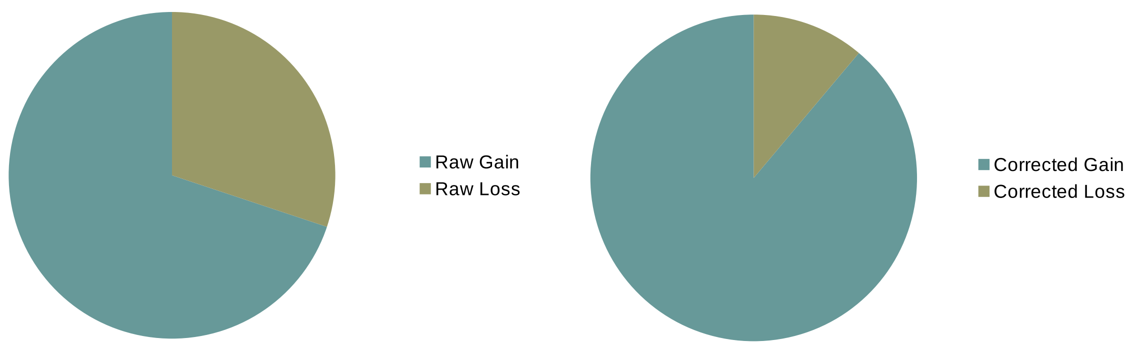


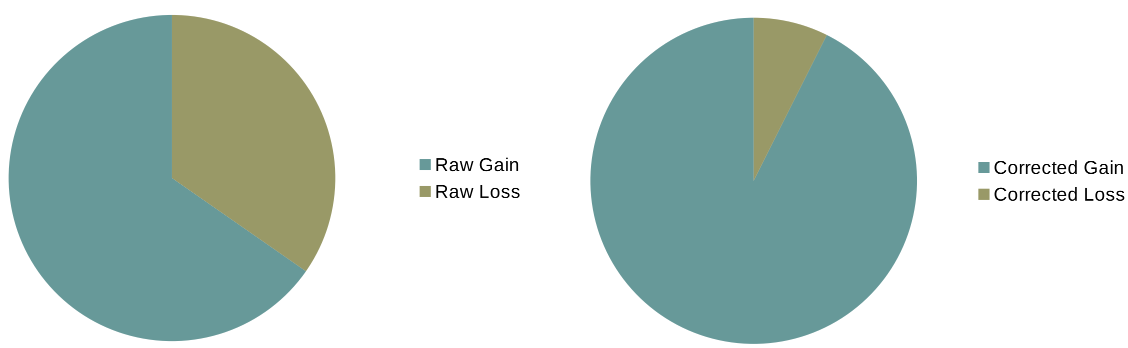
Figure 12: Trends in blue water in the period between 2000 and 2013. The maps highlighted in red show pixels where the change is statistically significant at p<=0.1. Those in blue show all pixels.



(a) Statistically significant raw (uncorrected for climate effects) and corrected trends in priority KBA and non-priority KBAs reported as area in sq.km.



(b) Statistically significant raw (uncorrected for climate effects) and corrected trends in blue water in priority KBAs reported in proportions.



(c) Statistically significant raw (uncorrected for climate effects) and corrected trends in blue water services in non-priority KBAs reported in proportions.

Figure 13: Priority KBAs showed a greater increase in hydrologic services than non-priority KBA regions. Raw gains/losses are without correcting for climate effects. Gains/losses corrected for climate effects are reported for statistically significant trends at $p \leqq 0.1$.

work is required to determine the extent to which changes in precipitation have contributed to the increased blue water trends observed in the region.

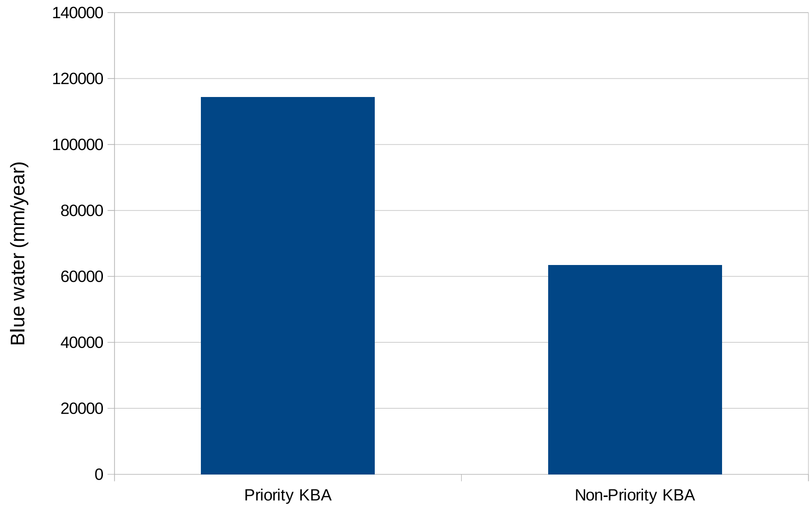
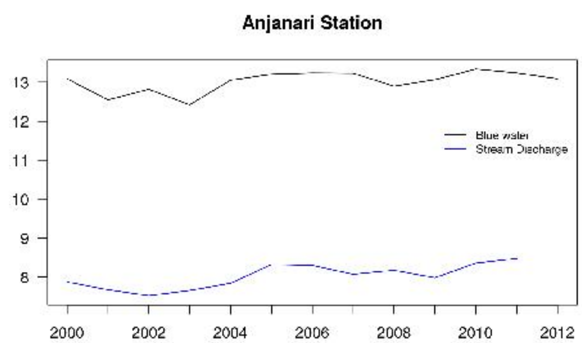
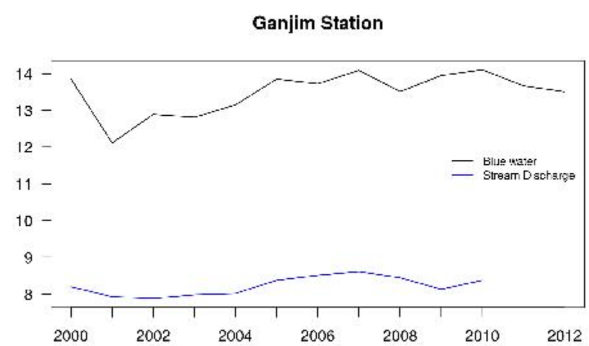


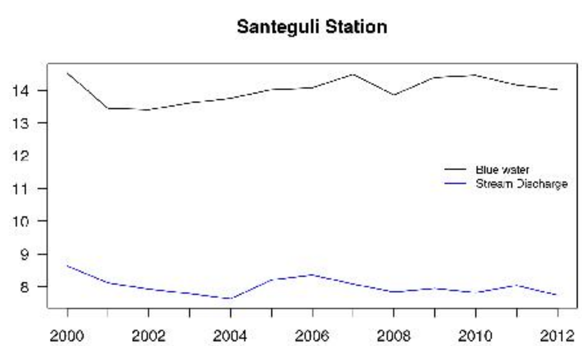
Figure 14: Priority KBAs had greater amounts of blue water than non-priority KBAs. The blue water is shown as average (mm) per year across the period 2000 to 2013.



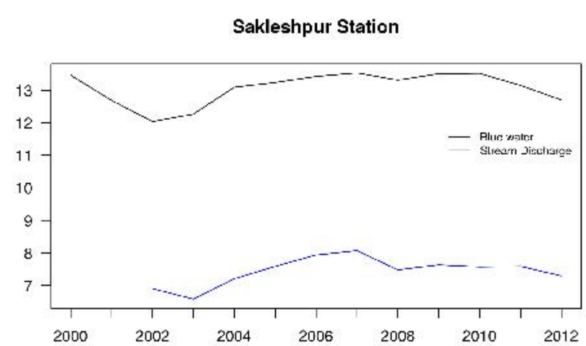
(a) Trends were statistically significant at $p<0.1$ for both MODIS ($p=0.024$) and for field measurements ($p=0.013$)



(b) Trends were statistically significant at $p<0.1$ for both MODIS ($p=0.047$) and for field measurements ($p=0.10$)



(c) Trends were statistically significant at $p<0.1$ for MODIS ($p=0.011$) but not for field measurements ($p=0.84$)



(d) Trends were not statistically significant at $p<0.1$ for MODIS ($p=0.59$) and neither for field measurements ($p=0.19$)

Figure 15: Validation of blue water trends based on MODIS, against field measurements of discharge at four catchments in the Western Ghats.

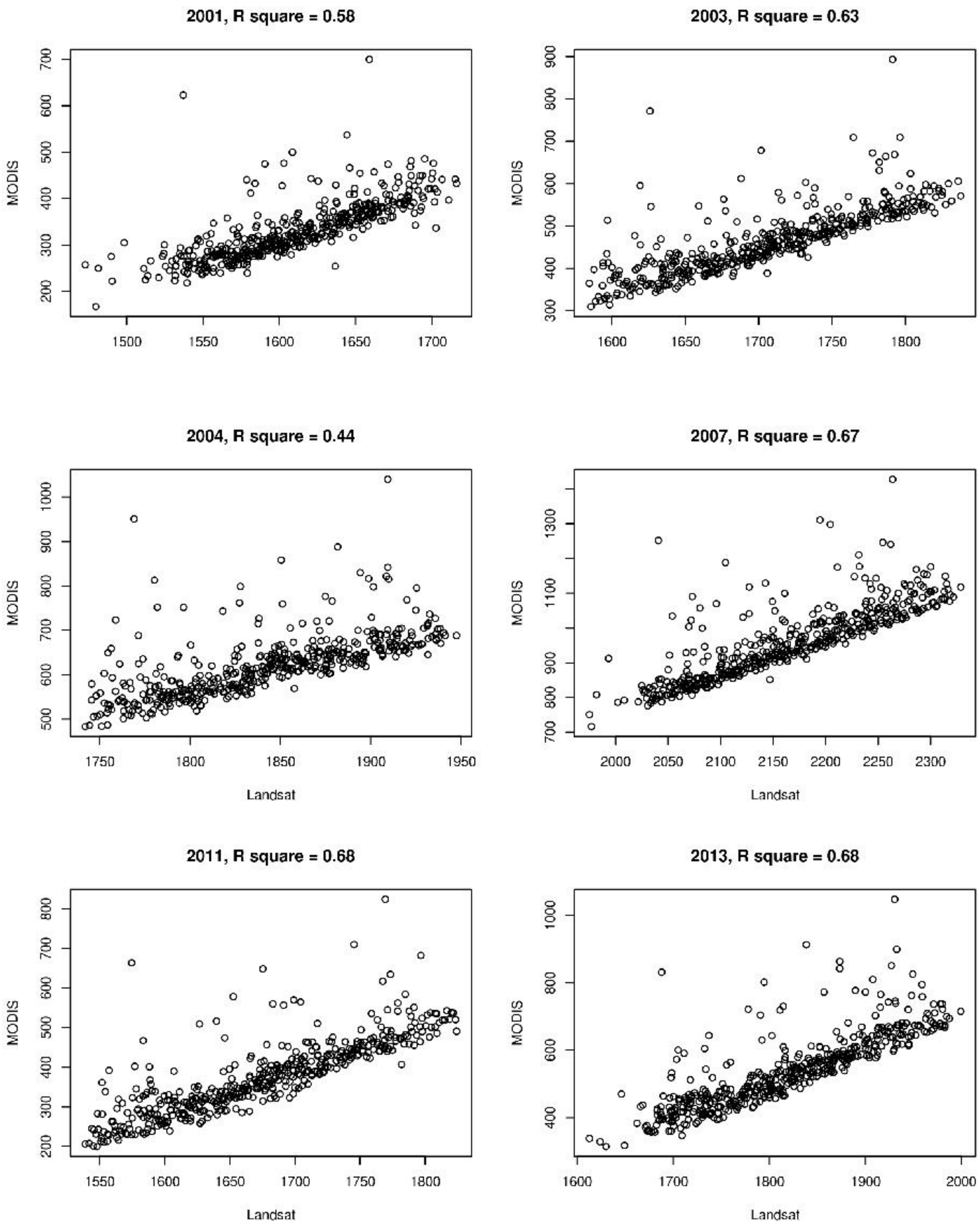


Figure 16: A very strong correlation was observed between MODIS derived blue water and Landsat derived blue water.

Trends in Carbon Services

Introduction

Tropical forests have been recognised as significant sinks of carbon [62,66] with the current carbon stock estimated to be 471 Pg with a stock density of 242 Mg C ha^{-1} [62]. Pan et al. [62] estimated an average annual carbon sequestration rate of 1.2 Pg C yr^{-1} for tropical forests between the years 1990 and 2007. However, they observed 23% reduction in carbon sink between 2000 and 2007 which reduced from 1.3 Pg C yr^{-1} for 1990 to 1999 to 1.0 Pg C yr^{-1} for 2000–2007. They attributed this reduction to deforestation and fragmentation of intact forests between 2000 and 2007. Over the last few decades tropical forests have experienced rampant deforestation and conversion of forests to non-forestry activities [4,24,41,91]. This significantly contributes to emission of CO_2, reduced carbon stock, reduced soil carbon assimilation, and global warming [38,60,90]. There is an immediate need to understand CO_2 dynamics in terrestrial ecosystems for developing global as well as regional policies for climate change mitigation and carbon sequestration [73].

Primary productivity is a term used in ecology to refer to CO_2 that gets assimilated as biomass in an ecosystem. Net Primary Productivity (NPP) is considered as a measure of total carbon sequestered/ assimilated after accounting for the maintenance losses [12]. Increase in NPP suggests a higher rate of CO_2 sequestration in a system in which case that system acts as a major carbon sink. Similarly, a decrease in NPP suggests reduced rate of sequestration in an ecosystem. Hence, NPP trend analysis is an important step in understanding the ecosystem carbon dynamics and effect of deforestation or management interventions [73].

We studied carbon sequestration trends, using NPP, in the Western Ghats landscape for the period 2000 to 2013. Our main objective was to analyze the changes in carbon services, mainly carbon sequestration, as a response to conservation and management interventions undertaken in the sWestern Ghats key biodiversity areas by CEPF and other organisations.

The methodology used here and results obtained, can be extended further to evaluate the effects of climate change, and to identify areas that act as sources and sinks of CO_2 in the Western Ghats. NPP is very sensitive to CO_2 concentrations [100]. Increased CO_2 removes the light related photosynthesis constraint experienced by plants resulting in increased NPP [52]. However, this relationship is not linear. Increase in air temperature and droughts, which are the resultants of increase in CO_2 /global warming, can result in higher respiration losses from forests, and thus change the nature of forests from carbon sinks to carbon sources [13,101]. Under these circumstances a study of CO_2 dynamics in terrestrial ecosystems with respect to changes in other climatic and anthropogenic variables, and knowing the source and sinks of CO_2 can help in better management of these ecosystems and in policy formulation.

Methods

We used remotely sensed data, which is among the only sources of temporal information needed to analyse trends in carbon sequestration. Data from both MODIS and Landsat was used and the performance of each was compared in terms of spatial and temporal resolution and accuracy.

MODIS dataset

The MOD17A3 product was used from the MODIS dataset for this study. MOD17A3 provides NPP data at 1km resolution which is estimated on yearly basis. This product has been validated using field data and found to be accurate in measuring NPP at global and regional scales [61,83]. We estimated the monotonic trends in NPP

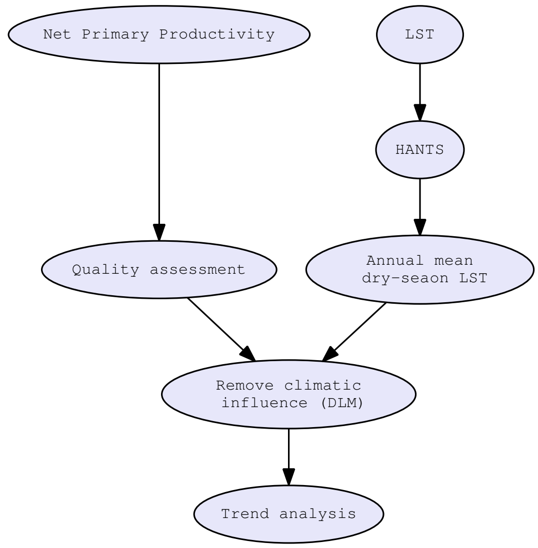


Figure 17: Procedure followed for deriving net primary productivity values as proxies for carbon services.

for the period 2000 to 2013 across the Western Ghats using Sen slope [88]. A dynamic linear model (DLM) was fitted to remove the influence of climatic variables on the levels of NPP data by regressing the time varying NPP against annual summer temperature (March, April, May) derived from MODIS LST (MOD11A2) day time layers. We used summer temperature as it is known to increase the respiration rate dramatically and thereby reduce NPP [93].

Estimating Net Primary Production (NPP) from Landsat

Estimation of NPP from Landsat is largely based on the light use efficiency (LUE) model [53,54]. In this model, gross primary productivity (GPP) is a function of absorbed photosynthetically active radiation (APAR) and a LUE coefficient (ε), and NPP is calculated from GPP after deducting the respiration losses (Γ) for maintenance;

$$\begin{aligned} GPP &= \varepsilon * APAR \\ NPP &= GPP - \Gamma \end{aligned} \tag{6}$$

The LUE model is conceptually simple and can be easily parameterised with remote sensing data [3,27,28,82,84].

APAR is often represented as a product of fraction of photosynthetically active radiation (fPAR) as shown below,

$$APAR = fPAR * PAR \tag{7}$$

where, PAR is the total incident photosynthetically active radiation.

Several studies have shown that fPAR can be estimated from remotely sensed images and it is correlated to spectral vegetation indices. fPAR is considered approximately equal to the normalised difference vegetation index (NDVI) [27,56,58,84]. And hence equation 7 can be rewritten as,

$$\begin{aligned} APAR = NDVI * PAR \quad & \quad therefore \\ GPP = \varepsilon * NDVI * PAR \end{aligned} \tag{8}$$

We used maximum NDVI value observed in the study area to estimate NPP. Maximum NDVI was calculated by extracting maximum pixel value across post-monsoon season (October, November and December), which is the peak period for biomass production in plants. We calculated instantaneous net radiation (INR) for the post-monsoon season using i.eb.netrad module in GRASS. PAR was calculated as 0.45 of INR [36,84]. We multiplied maximum NDVI with maximum PAR estimated to obtain highest possible APAR in that season in the landscape.

MODIS derived landcover maps (MCD12Q1) were used to identify vegetation types in each year. We restricted our NPP analysis to the period from 2001 to 2012 which corresponds to the availability of the MODIS landcover maps. We developed a APAR conversion efficiency (ε) map by using the ε values described in MODIS NPP products (MOD17) for each vegetation type [36]. ε was then multiplied with APAR to obtain GPP for each year. We then analysed the trend in these estimated maximum possible GPP values to know trends in CO_2 sequestration across the Western Ghats.

Results and Discussion

The estimated range of MODIS NPP for the entire Western Ghats for the period 2000 to 2013 ranged between 0.01 and 1.38 kg C m^{-2} with a median of 0.6 kg C m^{-2}. Field measurements of NPP in the Western Ghats range between 0.03 and 2.2 kg C m^{-2} [7,8]. Comparison of estimates from remotely sensed MODIS product and field measurement from Bhat et al. [7], Bhat and Ravindranath [8] shows that remotely sensed data estimates, 0.04 to 0.6, are within acceptable ranges obtained from field studies.

Our results show that if not corrected for temperature, the overall trend appears to be negative. However when corrected for climatic variables the trend is significantly positive for nearly 40% of the Western Ghats (Fig. 18).

Table 4: Gains and losses in NPP trends within priority and non-priority KBAs. Raw gains/losses are without correcting for climate effects. Gains/losses corrected for climate effects are reported for statistically significant trends at $p \leqq 0.1$.

Type of KBA	Raw Gain	Raw Loss	Corrected Gain	Corrected Loss
Priority KBA (sq.km)	6828	7773	7029	1390
Non-Priority KBA (sq.km)	5604	5478	6576	664
Priority KBA (% area)	47.00%	53.00%	83.00%	17.00%
Non-Priority KBA (% area)	51.00%	49.00%	91.00%	9.00%

Several other studies have also found an increase in NPP globally as well as in tropical ecosystems [37,58,72]. A strong correlation has been found between increase in NPP carbon sink and enhancement in global carbon pool [15,59,71]. This suggests the importance of green vegetation in mitigating the effects of climate change. However, we found that when not corrected for effects of temperature there was a negative trend in NPP. An increase in air temperature is known to induce higher respiration losses in plants which leads to reduced NPP [93,100]. Thus both enhanced carbon and temperature might be playing a role in determining NPP carbon sink in the Western Ghats. With finer level data and images, this study design adopted by us could be useful in monitoring climate change and its influence on tropical ecosystems.

Priority KBAs identified by CEPF showed greater increase in carbon services than those identified as non-priority KBAs (Fig. 19). The total amount of carbon sequestered in priority KBAs was almost twice that of non-priority KBAs (Fig. 20). Better protection to priority KBAs under various conservation projects and management interventions could be one of the factors that contributed towards increased carbon sequestration. About 56% of carbon is stored in biomass in tropical forests [62]. The reduced rate of removal of biomass in the form of fuel-wood, timber, litter etc., could have facilitated greater carbon storage in the form of biomass in these priority sites. It is also

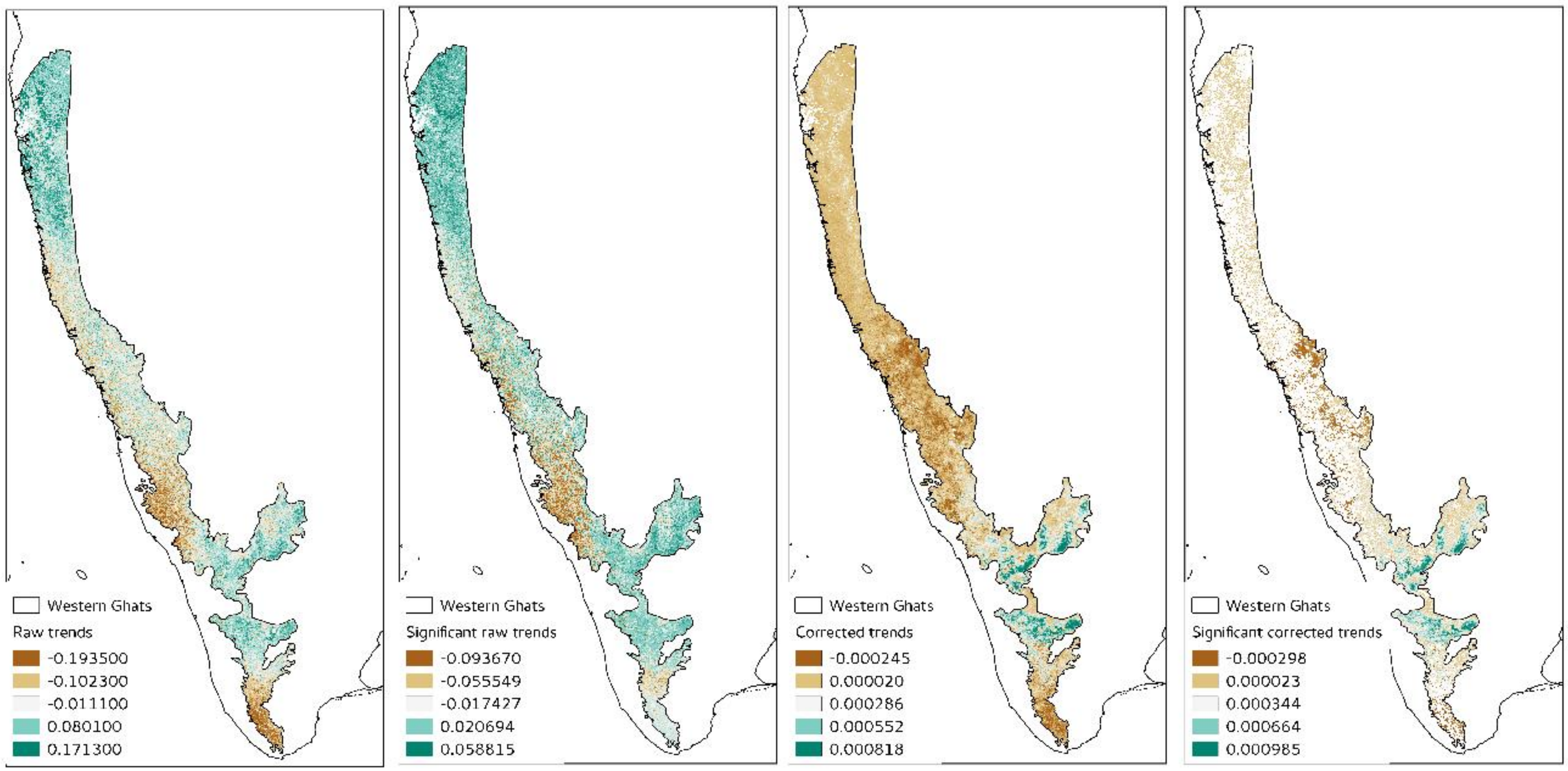


Figure 18: The map show how trends in net primary productivity as an index of carbon sequestration over the period from 2000 to 2013. The maps highlighted in red show pixels where the change is statistically significant at p<=0.1. Those in blue show all pixels.

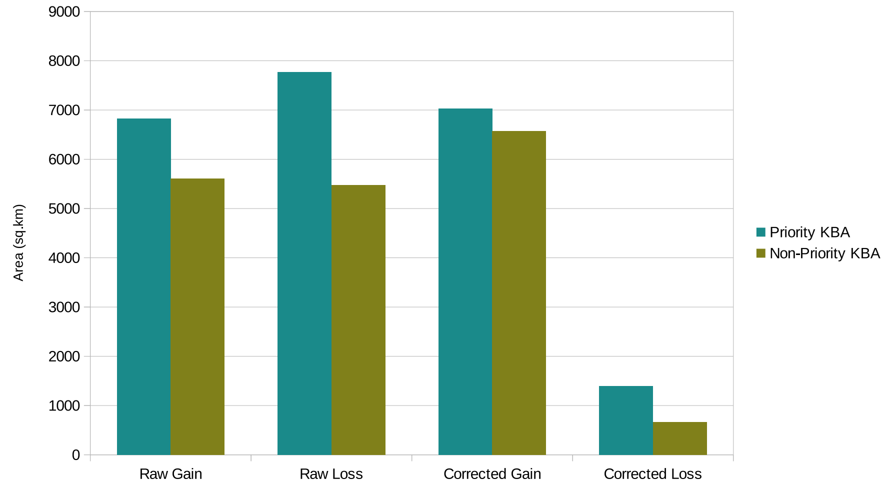
important to note that, majority of the forests in the Western Ghats are relatively younger forests. The younger forests have a greater potential to sequester carbon compared to old forests [62].

We found a correlation between MODIS annual NPP and Landsat derived potential maximum GPP (Fig. 22). Although higher than MODIS the estimates of GPP from Landsat shows similar trends across years. The higher Landsat estimates are probably because GPP is the total carbon sequestered and does not account for the respiration losses associated with tissue maintenance and growth. A general assumption is that 40% of the GPP is converted into NPP annually [80]. However, the NPP conversion efficiency varies largely with vegetation type and the age of the stand. Hence, we did not convert Landsat GPP into NPP. A fine scale land-cover map and standardisation of correlation between GPP and NPP at field level can help in improving the efficiency of Landsat images in estimating NPP.

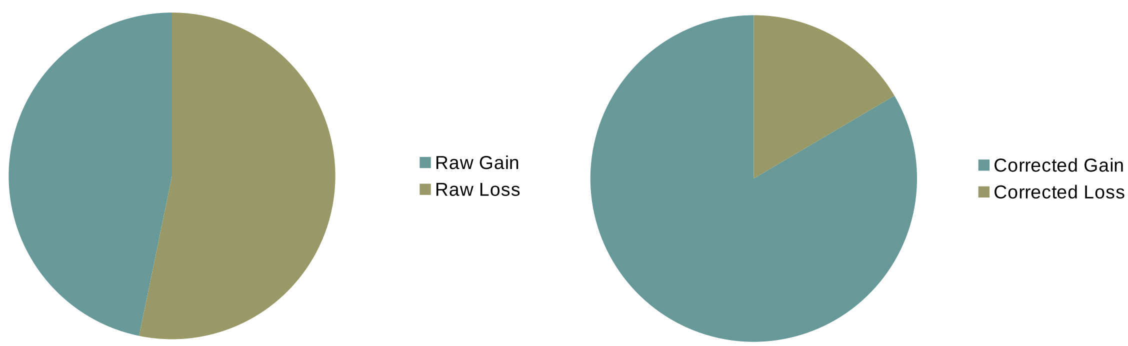
Although MODIS images cannot capture spatial details as well as Landsat, availability of MODIS product throughout the year at regular intervals makes it a superior product in estimating average annual productivity of a site. Additionally the MODIS product includes loss of carbon due to various climatic factors [36]. While Landsat provides superior spatial resolution the temporal coverage is very poor; for the entire Western Ghats temporal data loss was nearly 26%, whereas for few sites the loss was as high as 92% (h146,v50). Further there was loss in information due to cloud cover and striping due to SLC failure. Other studies also have established the usefulness of MODIS products in estimating annual productivity and inter-annual variability in NPP [70,93].

We conclude that MODIS NPP products can be used to monitor improvements in carbon sequestration in ecosystems as a response to conservation/anthropogenic factors at a given site. These monitoring tools are cost effective and perform better over other freely available remotely sensed products, including Landsat. The study design and methodologies adopted can also be used effectively to monitor impact of climate change on ecosystem processes and services. Further data and monitoring of priority sites studied here, will be crucial in predicting future changes and developing strategies to mitigate the effects of climate change in the Western Ghats.

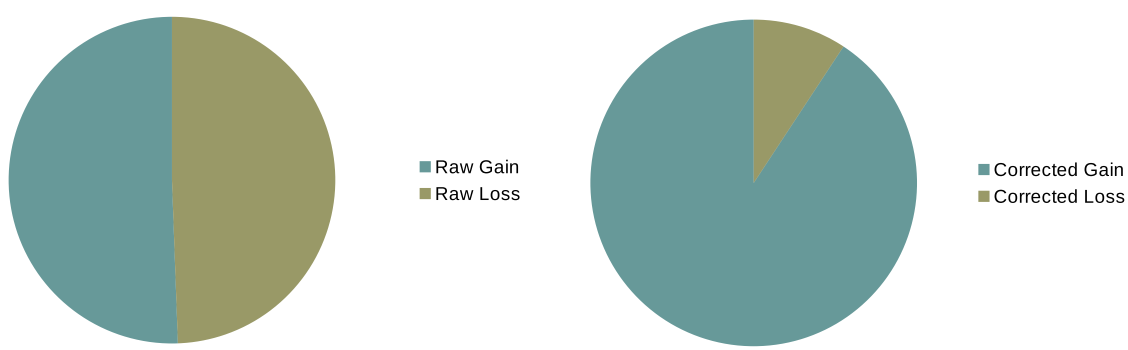
The analysis presented in this report could be further refined by including phenological datasets, additional covariates like aerosols and high resolution rainfall, all these can be derived from MODIS products. The current approach sets up a frame work for advanced analysis to look at lagged response in three services as covariates evolve in time. It also provides the inputs required to detect break points, or points in time where drastic shifts in trends have been observed .



(a) Statistically significant raw (uncorrected for climate effects) and corrected trends in priority KBA and non-priority KBAs reported as area in sq.km.



(b) Statistically significant raw (uncorrected for climate effects) and corrected trends in carbon services in priority KBAs reported in proportions.



(c) Statistically significant raw (uncorrected for climate effects) and corrected trends in carbon services in non-priority KBAs reported in proportions.

Figure 19: Priority KBAs showed a greater increase in carbon services than area under non-priority KBA. Raw gains/losses are without correcting for climate effects. Gains/losses corrected for climate effects are reported for statistically significant trends at $p \leqq 0.1$.

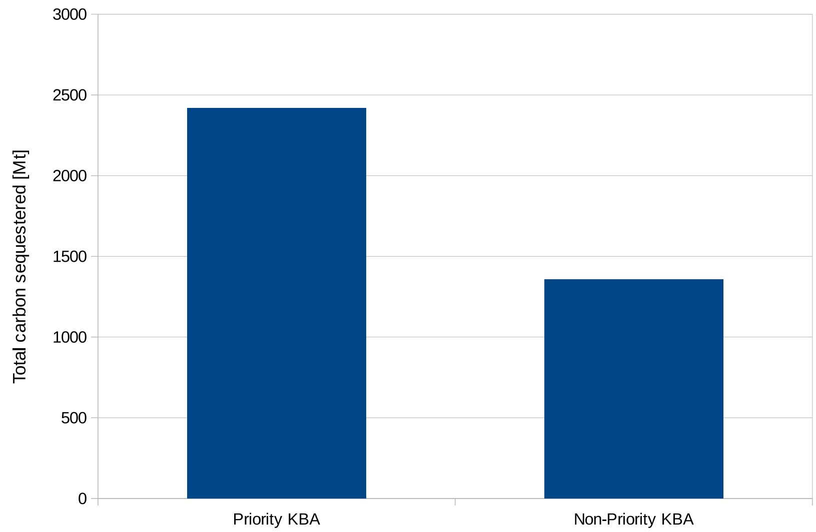


Figure 20: Priority KBAs showed greater amounts of carbon sequestered compared to non-priority KBAs. Total amount of carbon sequestered is shown in megatons (Mt) summed across the period 2000 to 2013.

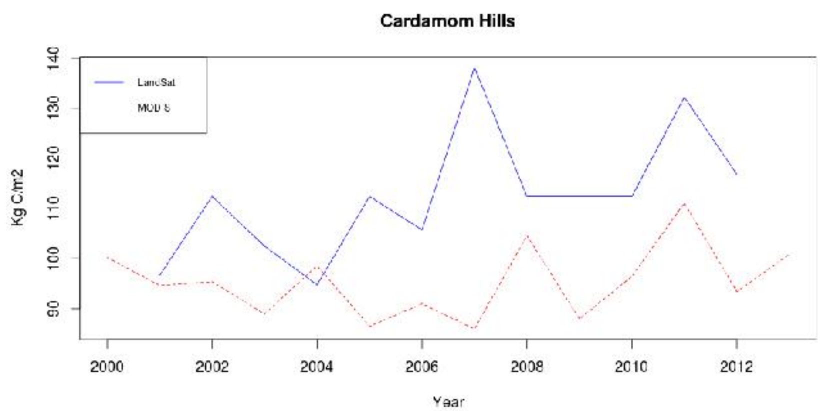


Figure 21: Comparison of trends in carbon services in the Cardamom hills priority KBA measured by MODIS and Landsat. Landsat data for Cardamom hills has 5 missing years, and 3 consecutive years with no data.

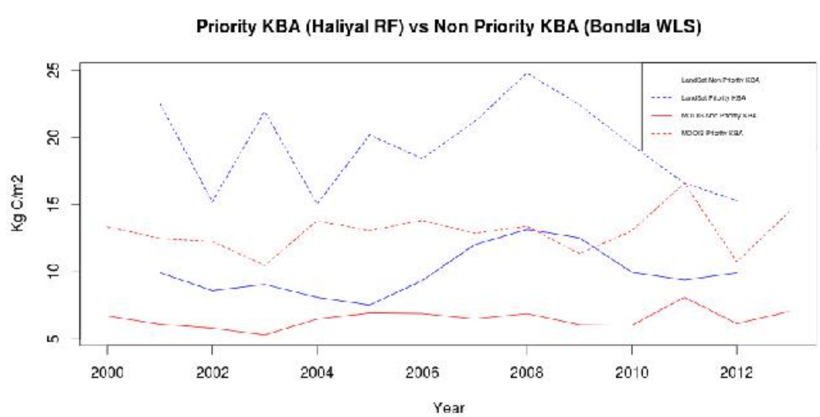


Figure 22: Comparison of trends in carbon services in a priority (Haliyal RF) and a non-priority KBA (Bondla WLS) measured by MODIS and Landsat. The Landsat dataset for Haliyal RF and Bondla WLS has only one missing year (2010).

Bibliography

[1] Abrams M. 2000. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER): data products for the high spatial resolution imager on NASA's Terra platform. *International Journal of Remote Sensing* **21**: 847–859.
URL http://www.tandfonline.com/doi/abs/10.1080/014311600210326

[2] Achard F, Eva HD, Stibig HJ, Mayaux P, Gallego J, Richards T, Malingreau JP. 2002. Determination of deforestation rates of the world's humid tropical forests. *Science* **297**: 999–1002. ISSN 0036-8075, 1095-9203.
URL http://www.sciencemag.org/content/297/5583/999

[3] Ahl DE, Gower ST, Mackay DS, Burrows SN, Norman JM, Diak GR. 2005. The effects of aggregated land cover data on estimating NPP in northern Wisconsin. *Remote Sensing of Environment* **97**: 1–14.
URL http://www.sciencedirect.com/science/article/pii/S0034425705000817

[4] Alencar A, Asner GP, Knapp D, Zarin D. 2011. Temporal variability of forest fires in eastern Amazonia. *Ecological Applications* **21**: 2397–2412.
URL http://www.esajournals.org/doi/abs/10.1890/10-1168.1

[5] Asner GP. 2014. Satellites and psychology for improved forest monitoring. *Proceedings of the National Academy of Sciences* **111**: 567–568.
URL http://www.pnas.org/content/111/2/567.short

[6] Bawa K, Rose J, Ganeshaiah KN, Barve N, Kiran MC, Umashaanker R. 2002. Assessing biodiversity from space: an example from the Western Ghats, India. *Conservation Ecology* **6**: 7.
URL http://www.researchgate.net/profile/Narayani_Barve/publication/42763983_Assessing_Biodiversity_from_Space_An_Example_from_the_Western_Ghats_India/links/02bfe5148a8bc5994b000000.pdf

[7] Bhat DM, Murali KS, Ravindranath NH. 2003. Carbon stock dynamics in the tropical rain forests of the Uttara Kannada district, Western Ghats, India. *International Journal of Environment and Pollution* **19**: 139–149.
URL http://www.inderscienceonline.com/doi/abs/10.1504/IJEP.2003.003746

[8] Bhat DM, Ravindranath NH. 2011. Above-ground standing biomass and carbon stock dynamics under a varied degree of anthropogenic pressure in tropical rain forests of Uttara Kannada district, Western Ghats, India. *Taiwania* **56**: 85–96.
URL http://tai2.ntu.edu.tw/taiwania/pdf/tai.2011.56.85.pdf

[9] Bonell M, Purandara BK, Venkatesh B, Krishnaswamy J, Acharya HAK, Singh UV, Jayakumar R, Chappell N. 2010. The impact of forest use and reforestation on soil hydraulic conductivity in the Western Ghats of India: Implications for surface and sub-surface hydrology. *Journal of Hydrology* **391**: 47–62.
URL http://www.sciencedirect.com/science/article/pii/S0022169410004178

[10] Broich M, Hansen MC, Potapov P, Adusei B, Lindquist E, Stehman SV. 2011. Time-series analysis of multi-resolution optical imagery for quantifying forest cover loss in Sumatra and Kalimantan, Indonesia. *International Journal of Applied Earth Observation and Geoinformation* **13**: 277–291.
URL http://www.sciencedirect.com/science/article/pii/S0303243410001340

[11] Calder C, Lavine M, Müller P, Clark JS. 2003. Incorporating multiple sources of stochasticity into dynamic population models. *Ecology* **84**: 1395–1402.
URL http://www.esajournals.org/doi/abs/10.1890/0012-9658(2003)084%5B1395:IMSOSI%5D2.0.CO%3B2

[12] Cao M, Prince SD, Small J, Goetz SJ. 2004. Remotely sensed interannual variations and trends in terrestrial net primary productivity 1981–2000. *Ecosystems* **7**: 233–242.
URL http://link.springer.com/article/10.1007/s10021-003-0189-x

[13] Cao M, Woodward FI. 1998. Net primary and ecosystem production and carbon stocks of terrestrial ecosystems and their responses to climate change. *Global Change Biology* **4**: 185–198.
URL http://onlinelibrary.wiley.com/doi/10.1046/j.1365-2486.1998.00125.x/full

[14] Chander G, Markham BL, Helder DL. 2009. Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment* **113**: 893–903.
URL http://www.sciencedirect.com/science/article/pii/S0034425709000169

[15] Ciais P, Reichstein M, Viovy N, Granier A, Ogée J, Allard V, Aubinet M, Buchmann N, Bernhofer C, Carrara A, others. 2005. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. *Nature* **437**: 529–533.
URL http://www.nature.com/nature/journal/v437/n7058/abs/nature03972.html

[16] De Beurs KM, Henebry GM. 2005. A statistical framework for the analysis of long image time series. *International Journal of Remote Sensing* **26**: 1551–1573.
URL http://www.tandfonline.com/doi/abs/10.1080/01431160512331326657

[17] Dirzo R, Raven PH. 2003. Global state of biodiversity and loss. *Annual Review of Environment and Resources* **28**: 137–167.
URL http://dx.doi.org/10.1146/annurev.energy.28.050302.105532

[18] Duro DC, Coops NC, Wulder MA, Han T. 2007. Development of a large area biodiversity monitoring system driven by remote sensing. *Progress in Physical Geography* **31**: 235–260. ISSN 0309-1333.
URL http://ppg.sagepub.com/cgi/doi/10.1177/0309133307079054

[19] Elmqvist T, Tuvendal M, Krishnaswamy J, Hylander K. 2010. Ecosystem services: managing trade-offs between provisioning and regulating services. In Kumar P, Wood M (eds.) *Valuation of regulating services of ecosystems: methodology and applications*. London: Routledge.

[20] Fahrig L. 2003. Effects of habitat fragmentation on biodiversity. *Annual Review of Ecology, Evolution, and Systematics* **34**: 487–515.
URL http://dx.doi.org/10.1146/annurev.ecolsys.34.011802.132419

[21] Falkenmark M, Rockström J. 2006. The new blue and green water paradigm: Breaking new ground for water resources planning and management. *Journal of Water Resources Planning and Management* **132**: 129–132.
URL http://ascelibrary.org/doi/10.1061/(ASCE)0733-9496(2006)132%3A3(129)

[22] Gaston KJ, Blackburn TM, Goldewijk KK. 2003. Habitat conversion and global avian biodiversity loss. *Proceedings of the Royal Society B: Biological Sciences* **270**: 1293–1300. ISSN 0962-8452, 1471-2954.
URL http://rspb.royalsocietypublishing.org/cgi/doi/10.1098/rspb.2002.2303

[23] GDAL Development Team. 2014. GDAL: GDAL - Geospatial Data Abstraction Library.
URL http://www.gdal.org/index.html

[24] Geist HJ, Lambin EF. 2002. Proximate causes and underlying driving forces of tropical deforestation. *BioScience* **52**: 143–150.
URL http://bioscience.oxfordjournals.org/content/52/2/143.short

[25] Gillespie TW, Foody GM, Rocchini D, Giorgi AP, Saatchi S. 2008. Measuring and modelling biodiversity from space. *Progress in Physical Geography* **32**: 203–221.
URL http://ppg.sagepub.com/content/32/2/203.abstract

[26] Gillespie TW, Willis KS, Ostermann-Kelm S. 2015. Spaceborne remote sensing of the worlds protected areas. *Progress in Physical Geography* **39**: 388–404.
URL http://ppg.sagepub.com/content/39/3/388.abstract

[27] Gitelson AA, Peng Y, Masek JG, Rundquist DC, Verma S, Suyker A, Baker JM, Hatfield JL, Meyers T. 2012. Remote estimation of crop gross primary production with Landsat data. *Remote Sensing of Environment* **121**: 404–414.
URL http://www.sciencedirect.com/science/article/pii/S0034425712001101

[28] Gower ST, Krankina O, Olson RJ, Apps M, Linder S, Wang C. 2001. Net primary production and carbon allocation patterns of boreal forest ecosystems. *Ecological Applications* **11**: 1395–1411.
URL http://www.esajournals.org/doi/abs/10.1890/1051-0761(2001)011%5B1395:NPPACA%5D2.0.CO%3B2

[29] Hansen MC, DeFries RS. 2004. Detecting long-term global forest change using continuous fields of tree-cover maps from 8-km Advanced Very High Resolution Radiometer (AVHRR) data for the years 1982–99. *Ecosystems* **7**: 695–716.
URL http://link.springer.com/article/10.1007/s10021-004-0243-3

[30] Hansen MC, DeFries RS, Townshend JRG, Carroll M, Dimiceli C, Sohlberg RA. 2003. Global percent tree cover at a spatial resolution of 500 meters: First results of the MODIS vegetation continuous fields algorithm. *Earth Interactions* **7**: 1–15.
URL http://journals.ametsoc.org/doi/abs/10.1175/1087-3562(2003)007%3C0001%3AGPTCAA%3E2.0.CO%3B2

[31] Hansen MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Thau D, Stehman SV, Goetz SJ, Loveland TR. 2013. High-resolution global maps of 21st-century forest cover change. *Science* **342**: 850–853.
URL http://www.sciencemag.org/content/342/6160/850.short

[32] Hansen MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Thau D, Stehman SV, Goetz SJ, Loveland TR. 2013. Supplementary Materials for .
URL http://www.yadvindermalhi.org/uploads/1/8/7/6/18767612/hansen_2013_sm.pdf

[33] Hansen MC, Roy DP, Lindquist E, Adusei B, Justice CO, Altstatt A. 2008. A method for integrating MODIS and Landsat data for systematic monitoring of forest cover and change in the Congo Basin. *Remote Sensing of Environment* **112**: 2495–2513.
URL http://www.sciencedirect.com/science/article/pii/S0034425707004774

[34] Hansen MC, Stehman SV, Potapov PV. 2010. Quantification of global gross forest cover loss. *Proceedings of the National Academy of Sciences* **107**: 8650–8655.
URL http://www.pnas.org/content/107/19/8650.short

[35] Hanski I. 2005. Landscape fragmentation, biodiversity loss and the societal response. *EMBO Reports* **6**: 388–392. ISSN 1469-221X.
URL http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1299308/

[36] Heinsch FA, Reeves M, Votava P, Kang S, Milesi C, Zhao M, Glassy J, Jolly WM, Loehman R, Bowker CF, others. 2003. GPP and NPP (MOD17a2/A3) products NASA MODIS land algorithm. *MOD17 User's Guide* : 1–57.
URL http://www.researchgate.net/profile/Joseph_Glassy/publication/252523420_Users_Guide_GPP_and_NPP_(MOD17A2A3)_Products/links/550b4a790cf290bdc111e18f.pdf

[37] Hicke JA, Asner GP, Randerson JT, Tucker C, Los S, Birdsey R, Jenkins JC, Field C, Holland E. 2002. Satellite-derived increases in net primary productivity across North America, 1982–1998. *Geophysical Research Letters* **29**: 69–1–69–4.
URL http://onlinelibrary.wiley.com/doi/10.1029/2001GL013578/pdf

[38] Houghton RA. 2007. Balancing the global carbon budget. *Annual Review of Earth and Planetary Science* **35**: 313–347.
URL http://www.annualreviews.org/doi/abs/10.1146/annurev.earth.35.031306.140057

[39] Huffman GJ, Bolvin DT. 2013. TRMM and other data precipitation data set documentation. *NASA, Greenbelt, USA* : 1–40.
URL ftp://rsd.gsfc.nasa.gov/pub/trmmdocs/3B42_3B43_doc.pdf

[40] Irish RR, Barker JL, Goward SN, Arvidson T. 2006. Characterization of the Landsat-7 ETM+ automated cloud-cover assessment (ACCA) algorithm. *Photogrammetric Engineering & Remote Sensing* **72**: 1179–1188.
URL http://essential.metapress.com/index/A4G0927Q78254713.pdf

[41] Jha CS, Dutt CBS, Bawa KS, others. 2000. Deforestation and land use changes in Western Ghats, India. *Current Science* **79**: 231–237.
URL http://tejas.serc.iisc.ernet.in/currsci/jul252000/RESEARCH%20COMMUNICATIONS2.pdf

[42] Jun W, Zhongbo S, Yaoming M. 2004. Reconstruction of a cloud-free vegetation index time series for the Tibetan Plateau. *Mountain Research and Development* **24**: 348–353.
URL http://www.bioone.org/doi/abs/10.1659/0276-4741(2004)024%5B0348:ROACVI%5D2.0.CO%3B2

[43] Justice CO, Vermote E, Townshend JR, Defries R, Roy DP, Hall DK, Salomonson VV, Privette JL, Riggs G, Strahler A. 1998. The Moderate Resolution Imaging Spectroradiometer (MODIS): Land remote sensing for global change research. *Geoscience and Remote Sensing, IEEE Transactions on* **36**: 1228–1249.
URL http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=701075

[44] Krauss J, Bommarco R, Guardiola M, Heikkinen RK, Helm A, Kuussaari M, Lindborg R, Ockinger E, Partel M, Pino J, Poyry J, Raatikainen KM, Sang A, Stefanescu C, Teder T, Zobel M, Steffan-Dewenter I. 2010. Habitat fragmentation causes immediate and time-delayed biodiversity loss at different trophic levels. *Ecology Letters* **13**: 597–605. ISSN 1461-023X.
URL http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2871172/

[45] Krishnaswamy J, Bawa KS, Ganeshaiah KN, Kiran MC. 2009. Quantifying and mapping biodiversity and ecosystem services: Utility of a multi-season NDVI based Mahalanobis distance surrogate. *Remote Sensing of Environment* **113**: 857–867.
URL http://www.sciencedirect.com/science/article/pii/S0034425708003696

[46] Krishnaswamy J, Bonell M, Venkatesh B, Purandara BK, Lele S, Kiran MC, Reddy V, Badiger S, Rakesh KN. 2012. The rain-runoff response of tropical humid forest ecosystems to use and reforestation in the Western Ghats of India. *Journal of Hydrology* **472-473**: 216–237.
URL http://www.sciencedirect.com/science/article/pii/S0022169412008190

[47] Krishnaswamy J, Halpin PN, Richter DD. 2001. Dynamics of sediment discharge in relation to land-use and hydro-climatology in a humid tropical watershed in Costa Rica. *Journal of Hydrology* **253**: 91–109.
URL http://www.sciencedirect.com/science/article/pii/S0022169401004747

[48] Krishnaswamy J, John R, Joseph S. 2014. Consistent response of vegetation dynamics to recent climate change in tropical mountain regions. *Global Change Biology* **20**: 203–215.
URL http://onlinelibrary.wiley.com/doi/10.1111/gcb.12362/full

[49] Krishnaswamy J, Lavine M, Richter DD, Korfmacher K. 2000. Dynamic modeling of long-term sedimentation in the Yadkin River basin. *Advances in Water Resources* **23**: 881–892.
URL http://www.sciencedirect.com/science/article/pii/S0309170800000130

[50] Lau KM, Kim KM. 2006. Observational relationships between aerosol and Asian monsoon rainfall, and circulation. *Geophysical Research Letters* **33**: n/a–n/a. ISSN 1944-8007. L21810.
URL http://dx.doi.org/10.1029/2006GL027546

[51] McDonald RI, Green P, Balk D, Fekete BM, Revenga C, Todd M, Montgomery M. 2011. Urban growth, climate change, and freshwater availability. *Proceedings of the National Academy of Sciences* **108**: 6312–6317. ISSN 0027-8424, 1091-6490.
URL http://www.pnas.org/content/108/15/6312

[52] Melillo JM, McGuire AD, Kicklighter DW, Moore B, Vorosmarty CJ, Schloss AL. 1993. Global climate change and terrestrial net primary production. *Nature* **363**: 234–240.
URL http://www.nature.com/nature/journal/v363/n6426/abs/363234a0.html

[53] Monteith JL. 1972. Solar radiation and productivity in tropical ecosystems. *Journal of Applied Ecology* **9**: 747–766.
URL http://www.jstor.org/stable/2401901

[54] Monteith JL, Moss CJ. 1977. Climate and the efficiency of crop production in Britain. *Philosophical Transactions of the Royal Society B: Biological Sciences* **281**: 277–294.
URL http://rstb.royalsocietypublishing.org/content/281/980/277.short

[55] Myers N, Mittermeier RA, Mittermeier CG, da Fonseca GAB, Kent J. 2000. Biodiversity hotspots for conservation priorities. *Nature* **403**: 853–858. ISSN 0028-0836.
URL http://dx.doi.org/10.1038/35002501

[56] Myneni RB, Williams DL. 1994. On the relationship between FAPAR and NDVI. *Remote Sensing of Environment* **49**: 200–211.
URL http://www.sciencedirect.com/science/article/pii/0034425794900167

[57] NASA. 2011. *Landsat 7 Science Data Users Handbook*. NASA.
URL http://landsathandbook.gsfc.nasa.gov/inst_cal/prog_sect8_2.html(7).

[58] Nemani RR, Keeling CD, Hashimoto H, Jolly WM, Piper SC, Tucker CJ, Myneni RB, Running SW. 2003. Climate-driven increases in global terrestrial net primary production from 1982 to 1999. *Science* **300**: 1560–1563.
URL http://www.sciencemag.org/content/300/5625/1560.short

[59] Norby RJ, Hanson PJ, O'Neill EG, Tschaplinski TJ, Weltzin JF, Hansen RA, Cheng W, Wullschleger SD, Gunderson CA, Edwards NT, others. 2002. Net primary productivity of a CO2-enriched deciduous forest and the implications for carbon storage. *Ecological Applications* **12**: 1261–1266.
URL http://www.esajournals.org/doi/abs/10.1890/1051-0761(2002)012%5B1261:NPPOAC%5D2.0.CO%3B2

[60] Osuri AM, Kumar VS, Sankaran M. 2014. Altered stand structure and tree allometry reduce carbon storage in evergreen forest fragments in India's Western Ghats. *Forest Ecology and Management* **329**: 375–383.
URL http://www.sciencedirect.com/science/article/pii/S0378112714000632

[61] Pan Y, Birdsey R, Hom J, McCullough K, Clark K. 2006. Improved estimates of net primary productivity from MODIS satellite data at regional and local scales. *Ecological Applications* **16**: 125–132.
URL http://www.esajournals.org/doi/abs/10.1890/05-0247

[62] Pan Y, Birdsey RA, Fang J, Houghton R, Kauppi PE, Kurz WA, Phillips OL, Shvidenko A, Lewis SL, Canadell JG, others. 2011. A large and persistent carbon sink in the world's forests. *Science* **333**: 988–993.
URL http://www.sciencemag.org/content/333/6045/988.short

[63] Pereira HM, Leadley PW, Proenca V, Alkemade R, Scharlemann JPW, Fernandez-Manjarres JF, Araujo MB, Balvanera P, Biggs R, Cheung WWL, Chini L, Cooper HD, Gilman EL, Guenette S, Hurtt GC, Huntington HP, Mace GM, Oberdorff T, Revenga C, Rodrigues P, Scholes RJ, Sumaila UR, Walpole M. 2010. Scenarios for global biodiversity in the 21st century. *Science* **330**: 1496–1501. ISSN 0036-8075, 1095-9203.
URL http://www.sciencemag.org/cgi/doi/10.1126/science.1196624

[64] Petris G, Petrone S, Campagnoli P. 2009. Dynamic linear models. In *Dynamic Linear Models with R*, Use R. Springer New York. ISBN 978-0-387-77237-0 978-0-387-77238-7, 31–84.
URL http://link.springer.com/chapter/10.1007/b135794_2

[65] Pettorelli N, Vik JO, Mysterud A, Gaillard JM, Tucker CJ, Stenseth NC. 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology & Evolution* **20**: 503–510.
URL http://www.sciencedirect.com/science/article/pii/S016953470500162X

[66] Phillips OL, Malhi Y, Higuchi N, Laurance WF, Núnez PV, Vásquez RM, Laurance SG, Ferreira LV, Stern M, Brown S, others. 1998. Changes in the carbon balance of tropical forests: evidence from long-term plots. *Science* **282**: 439–442.
URL http://www.sciencemag.org/content/282/5388/439.short

[67] Potapov P, Hansen MC, Stehman SV, Loveland TR, Pittman K. 2008. Combining MODIS and Landsat imagery to estimate and map boreal forest cover loss. *Remote Sensing of Environment* **112**: 3708–3719. ISSN 0034-4257.
URL http://www.sciencedirect.com/science/article/pii/S0034425708001764

[68] Potapov P, Turubanova S, Hansen MC. 2011. Regional-scale boreal forest cover and change mapping using Landsat data composites for European Russia. *Remote Sensing of Environment* **115**: 548–561. ISSN 0034-4257.
URL http://www.sciencedirect.com/science/article/pii/S0034425710003056

[69] Potapov PV, Turubanova SA, Hansen MC, Adusei B, Broich M, Altstatt A, Mane L, Justice CO. 2012. Quantifying forest cover loss in Democratic Republic of the Congo, 2000–2010, with Landsat ETM+ data. *Remote Sensing of Environment* **122**: 106–116.
URL http://www.sciencedirect.com/science/article/pii/S0034425712000430

[70] Potter C, Gross P, Genovese V, Smith ML. 2007. Net primary productivity of forest stands in New Hampshire estimated from Landsat and MODIS satellite data. *Carbon Balance and Management* **2**.
URL http://www.biomedcentral.com/content/pdf/1750-0680-2-9.pdf

[71] Potter C, Klooster S, Genovese V. 2012. Net primary production of terrestrial ecosystems from 2000 to 2009. *Climatic Change* **115**: 365–378.
URL http://link.springer.com/article/10.1007/s10584-012-0460-2

[72] Potter C, Klooster S, Steinbach M, Tan PN, Kumar V, Shekhar S, Carvalho CRd. 2004. Understanding global teleconnections of climate to regional model estimates of Amazon ecosystem carbon fluxes. *Global Change Biology* **10**: 693–703.
URL http://onlinelibrary.wiley.com/doi/10.1111/j.1529-8817.2003.00752.x/full

[73] Potter CS. 1999. Terrestrial biomass and the effects of deforestation on the global carbon cycle results from a model of primary production using satellite observations. *BioScience* **49**: 769–778.
URL http://bioscience.oxfordjournals.org/content/49/10/769.short

[74] Powers RP, Coops NC, Morgan JL, Wulder MA, Nelson TA, Drever CR, Cumming SG. 2013. A remote sensing approach to biodiversity assessment and regionalization of the Canadian boreal forest. *Progress in Physical Geography* **37**: 36–62.
URL http://ppg.sagepub.com/content/37/1/36.abstract

[75] Reddy CS, Jha CS, Dadhwal VK, Krishna PH, Pasha SV, Satish KV, Dutta K, Saranya KRL, Rakesh F, Rajashekar G, others. 2015. Quantification and monitoring of deforestation in India over eight decades (1930–2013). *Biodiversity and Conservation* : 1–24.
URL http://link.springer.com/article/10.1007/s10531-015-1033-2

[76] Reymondin L, Jarvis A, Perez-Uribe A, Touval J, Argote K, Rebetez J, Guevara E, Mulligan M. 2010. A methodology for near real-time monitoring of habitat change at continental scales using MODIS-NDVI and TRMM, 2010. *Submitted Remote Sensing of Enviroment* .

[77] Riitters K, Wickham J, Costanza JK, Vogt P. 2016. A global evaluation of forest interior area dynamics using tree cover data from 2000 to 2012. *Landscape Ecology* **31**: 137–148.
URL http://link.springer.com/article/10.1007/s10980-015-0270-9

[78] Rocchini D. 2009. Commentary on Krishnaswamy et al. - Quantifying and mapping biodiversity and ecosystem services: Utility of a multi-season NDVI based Mahalanobis distance surrogate. *Remote Sensing of Environment* **113**: 904–906. ISSN 0034-4257.
URL http://www.sciencedirect.com/science/article/pii/S0034425709000248

[79] Roerink GJ, Menenti M, Verhoef W. 2000. Reconstructing cloudfree NDVI composites using Fourier analysis of time series. *International Journal of Remote Sensing* **21**: 1911–1917.
URL http://www.tandfonline.com/doi/abs/10.1080/014311600209814

[80] Roy J, Mooney HA, Saugier B. 2001. *Terrestrial global productivity*. Academic Press.

[81] Roy PS, Roy A, Joshi PK, Kale MP, Srivastava VK, Srivastava SK, Dwevidi RS, Joshi C, Behera MD, Meiyappan P. 2015. Development of decadal (1985-1995-2005) land use and land cover database for India. *Remote Sensing* **7**: 2401–2430.

[82] Running SW, Justice CO, Salomonson V, Hall D, Barker J, Kaufmann YJ, Strahler AH, Huete AR, Muller JP, Vanderbilt V, others. 1994. Terrestrial remote sensing science and algorithms planned for EOS/MODIS. *International Journal of Remote Sensing* **15**: 3587–3620.
URL http://www.tandfonline.com/doi/abs/10.1080/01431169408954346

[83] Running SW, Nemani RR, Heinsch FA, Zhao M, Reeves M, Hashimoto H. 2004. A continuous satellite-derived measure of global terrestrial primary production. *Bioscience* **54**: 547–560.
URL http://bioscience.oxfordjournals.org/content/54/6/547.short

[84] Running SW, Thornton PE, Nemani R, Glassy JM. 2000. Global terrestrial gross and net primary productivity from the earth observing system. In *Methods in Ecosystem Science*. Springer, 44–57.
URL http://link.springer.com/chapter/10.1007/978-1-4612-1224-9_4

[85] Sala OE, Stuart Chapin F, III, Armesto JJ, Berlow E, Bloomfield J, Dirzo R, Huber-Sanwald E, Huenneke LF, Jackson RB, Kinzig A, Leemans R, Lodge DM, Mooney HA, Oesterheld M, Poff NL, Sykes MT, Walker BH, Walker M, Wall DH. 2000. Global biodiversity scenarios for the year 2100. *Science* **287**: 1770–1774.
URL http://www.sciencemag.org/content/287/5459/1770.abstract

[86] Sandholt I, Rasmussen K, Andersen J. 2002. A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status. *Remote Sensing of Environment* **79**: 213–224.
URL http://www.sciencedirect.com/science/article/pii/S0034425701002747

[87] Scaramuzza P, Micijevic E, Chander G. 2004. SLC gap-filled products phase one methodology. *Landsat Technical Notes* .
URL http://landsat7.usgs.gov/documents/SLC_Gap_Fill_Methodology.pdf

[88] Sen PK. 1968. Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association* **63**: 1379–1389.
URL http://amstat.tandfonline.com/doi/abs/10.1080/01621459.1968.10480934

[89] Sexton JO, Song XP, Feng M, Noojipady P, Anand A, Huang C, Kim DH, Collins KM, Channan S, DiMiceli C, Townshend JR. 2013. Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS vegetation continuous fields with lidar-based estimates of error. *International Journal of Digital Earth* **6**: 427–448. ISSN 1753-8947.
URL http://www.tandfonline.com/doi/abs/10.1080/17538947.2013.786146

[90] Shukla J, Nobre C, Sellers P, others. 1990. Amazon deforestation and climate change. *Science* **247**: 1322–1325.
URL https://dlc.dlib.indiana.edu/dlc/handle/10535/2838

[91] Skole D, Tucker C. 1993. Tropical deforestation and habitat fragmentation in the Amazon. Satellite data from 1978 to 1988. *Science* **260**: 1905–1910.
URL http://www.researchgate.net/profile/David_Skole/publication/6003334_Tropical_deforestation_and_habitat_fragmentation_in_the_Amazon_satellite_data_from_1978_to_1988/links/0912f509915d63f5a9000000.pdf

[92] Son NT, Chen CF, Chen CR, Chang LY, Minh VQ. 2012. Monitoring agricultural drought in the Lower Mekong Basin using MODIS NDVI and land surface temperature data. *International Journal of Applied Earth Observation and Geoinformation* **18**: 417–427. ISSN 0303-2434.
URL http://www.sciencedirect.com/science/article/pii/S030324341200058X

[93] Tang G, Beckage B, Smith B, Miller PA. 2010. Estimating potential forest NPP, biomass and their climatic sensitivity in New England using a dynamic ecosystem model. *Ecosphere* **1**: art18.
URL http://www.esajournals.org/doi/abs/10.1890/ES10-00087.1

[94] Tuanmu MN, Jetz W. 2015. A global, remote sensing-based characterization of terrestrial habitat heterogeneity for biodiversity and ecosystem modelling. *Global Ecology and Biogeography* **24**: 1329–1339. ISSN 1466-8238.
URL http://dx.doi.org/10.1111/geb.12365

[95] Turner W, Rondinini C, Pettorelli N, Mora B, Leidner A, Szantoi Z, Buchanan G, Dech S, Dwyer J, Herold M, Koh L, Leimgruber P, Taubenboeck H, Wegmann M, Wikelski M, Woodcock C. 2015. Free and open-access satellite data are key to biodiversity conservation. *Biological Conservation* **182**: 173–176. ISSN 0006-3207.
URL http://www.sciencedirect.com/science/article/pii/S000632071400473X

[96] Vaidyanathan S, Krishnaswamy J, Samba Kumar N, Dhanwatey H, Dhanwatey P, Ullas Karanth K. 2010. Patterns of tropical forest dynamics and human impacts: Views from above and below the canopy. *Biological Conservation* **143**: 2881–2890.
URL http://www.sciencedirect.com/science/article/pii/S0006320710001710

[97] WRIS Project Team. 2015. Basins.
URL http://india-wris.nrsc.gov.in/wrpinfo/index.php?title=Basins

[98] Zhang L, Dawes WR, Walker GR. 2001. Response of mean annual evapotranspiration to vegetation changes at catchment scale. *Water Resources Research* **37**: 701–708.
URL http://onlinelibrary.wiley.com/doi/10.1029/2000WR900325/full

[99] Zhang L, Hickel K, Dawes WR, Chiew FH, Western AW, Briggs PR. 2004. A rational function approach for estimating mean annual evapotranspiration. *Water Resources Research* **40**.
URL http://onlinelibrary.wiley.com/doi/10.1029/2003WR002710/full

[100] Zhao M, Running SW. 2010. Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. *Science* **329**: 940–943.
URL http://www.sciencemag.org/content/329/5994/940.short

[101] Zhao M, Running SW. 2011. Response to comments on "drought-induced reduction in global terrestrial Net primary production from 2000 through 2009". *Science* **333**: 1093–1093.
URL http://www.sciencemag.org/content/333/6046/1093.5.short