Estimating spatial and temporal beta-diversity of plant communities from spaceborne hyperspectral data

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With thanks to: Kerry Cawse-Nicholson, Chris Ware, Karel Mokany, Tom Harwood, Andrew Hoskins, Mike Harfoot
Biodiversity crisis is now attracting significant attention
Essential Biodiversity Variables

Redefining and standardizing biodiversity and ecosystem services (e.g. for IPBES) projections

High-level indicators of biodiversity & ecosystem services (e.g. for CBD)

Ancillary attributes (slow changing)

Ecosystem-service valuation & other data

Observations of drivers & pressures

Observations of policy & management responses

Essential Biodiversity Variables

Genetic composition

Species populations

Species traits

Community composition

Ecosystem structure

Primary observations of change in state of biodiversity

In-situ monitoring

Remote sensing

Ecosystem function

GEO BON
Group on Earth Observations
Biodiversity Observation Network

Policy Forum

ECOLOGY

Essential Biodiversity Variables

A global system of harmonized observations is needed to inform scientists and policy-makers.

Global biodiversity loss is astounding. But it is hard to assess progress towards the Aichi Biodiversity Targets for 2011-2020 set by the Convention on Biological Diversity (CBD). Target 5, for instance, aims to have global deforestation rates by 2020, but reliable indicators for deforestation that can be monitored remotely have not been developed or agreed upon. National biodiversity monitoring programs differ widely, many data sets are inconsistent, and few data are shared openly.

Scientists have proposed classes of ‘essential biodiversity variables’— including species traits, populations, and ecosystem function and structure. But measuring these on the ground is laborious and limited. Satellite remote sensing is crucial to gathering long-term global coverage. It can rapidly reveal where to reverse the loss of biodiversity on a wide range of scales, to address conservation targets. However, no agreement on how to translate these measurements into metrics that are relevant to biodiversity monitoring.

We call on conservation and space agencies to agree on a defined set of biodiversity variables and how these will be tracked from space, to address conservation targets. Methods to derive these variables and the set of satellites needed to observe them will also need to be developed, to ensure continuous monitoring.
Essential Biodiversity Variables

Scenarios for biodiversity & ecosystem services (e.g. for IPBES)

High-level indicators of biodiversity & ecosystem services (e.g. for CBD)

Ancillary attributes (slow changing)

Ecosystem-service valuation & other data

Observations of policy & management responses

Essential Biodiversity Variables

Genetic composition

Species populations

Species traits

Ecosystem structure

Ecosystem function

Primary observations of change in state of biodiversity

In-situ monitoring

Remote sensing

Agree on biodiversity metrics to track from space

Ecosystem and species agencies must forge a global monitoring strategy, say Andrew K. Skidmore, Nathalie Pettorelli and colleagues.
Broad approaches to monitoring biodiversity change

Direct observation of biological change

Data acquisition strategies

Indirect habitat-based approaches
- intersecting remotely observed change in habitat condition with mapping of...

Individual species distributions

Discrete community (or ecosystem) classes

Continuous variation in community composition

LIVING PLANET INDEX

The Global Living Planet Index shows a decline of 58 per cent (range: -48 to -66 per cent) between 1970 and 2012.

Key

- Global Living Planet Index
- Confidence limits
Broad approaches to monitoring biodiversity change

Data acquisition strategies

Direct observation of biological change

Individual species distributions

Indirect habitat-based approaches

Discrete community (or ecosystem) classes

Continuous variation in community composition

EXPLORING APPROACHES FOR CONSTRUCTING SPECIES ACCOUNTS IN THE CONTEXT OF THE SEEA-EEA

Modelling and mapping of continuous patterns in collective properties of biodiversity

Local richness (\textit{alpha diversity}) at location \( A \) is a function of \( f(\text{abiotic environment, biogeographic history, human disturbance, etc}) \).

Compositional dissimilarity (pairwise \textit{beta diversity}) between locations \( A \) and \( B \) is a function of differences in abiotic environment, biogeographic isolation, etc.

Local richness (\textit{alpha diversity}) at location \( A \) is a function of \( f(\text{abiotic environment, biogeographic history, human disturbance, etc}) \).
Biodiversity Habitat Index (BHI)

- Combines remotely monitored habitat condition with modelled spatial variation in biodiversity composition
- Derived at 1km grid resolution across the entire land surface of the planet

Local habitat condition (intactness) - statistical downscaling of land-use change using MODIS remote sensing

Biologically-scaled environments (ecosystems) - modelling of spatial variation in biodiversity composition (beta diversity) using data for > 400,000 species
The BHI is recalculated, using remote-sensing inputs from different years, to report change in habitat retention across all biologically-scaled environments occurring within any given spatial unit (e.g. country, ecoregion, the entire planet).
Broad approaches to monitoring biodiversity change

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Indirect habitat-based approaches

- Intersecting remotely observed change in habitat condition with mapping of...

Individual species distributions

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Continuous variation in community composition

Mapping tropical forest canopy diversity using high-fidelity imaging spectroscopy

Jean-Baptiste Féret and Gregory P. Asner
The coarser pixel resolution of spaceborne imaging spectroscopy presents a major challenge.
Can pairwise beta-diversity (across space and/or time) be estimated directly from composite spectral profiles?
Modelling and mapping of continuous patterns in collective properties of biodiversity

Local richness (alpha diversity) at location \( A = f \) (abiotic environment, biogeographic history, human disturbance, etc)

Compositional dissimilarity (pairwise beta diversity) between locations \( A \) and \( B = f \) (differences in abiotic environment, biogeographic isolation etc)
Generalised dissimilarity modelling (GDM)
Ferrier, S et al (2007) *Diversity & Distributions*

Compositional dissimilarity

\[ d_{ij} = 1 - e^{-\eta} \]

Ecological distance

\[ \eta = \alpha + \sum_{p=1}^{n} (f_p(x_{pi}) - f_p(x_{pj})) \]
Measuring β-diversity by remote sensing: A challenge for biodiversity monitoring

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Abstract

1. Biodiversity includes multiscalar and multitemporal structures and processes, with different levels of functional organization, from genetic to ecosystemic levels. One of the most-used methods to infer biodiversity is based on taxonomic approaches and community ecology theories. However, gathering extensive data in the field is difficult due to logistic problems, especially when aiming at modelling biodiversity changes in space and time, which assumes statistically sound sampling schemes. In this context, airborne or satellite remote sensing allows for the information to be gathered over wide areas in a reasonable time.

2. Most of the biodiversity maps obtained from remote sensing have been based on the inference of species richness by regression analysis. On the contrary, estimating compositional turnover (β-diversity) might add crucial information related to relative abundance of different species instead of just richness. Presently, few studies have addressed the measurement of species compositional turnover from space.

3. Extending on previous work, in this manuscript, we propose novel techniques to measure β-diversity from airborne or satellite remote sensing, mainly based on: (1) multivariate statistical analysis, (2) the spectral species concept, and (3) self-organizing maps.
Mapping beta diversity from space: Sparse Generalised Dissimilarity Modelling (SGDM) for analysing high-dimensional data

Pedro J. Leitão1,2, Marcel Schwieder1, Stefan Suess1, Ines Catry2, Edward J. Milton3, Francisco Moreira2, Patrick E. Osborne4, Manuel J. Pinto5, Sebastian van der Linden1 and Patrick Hostert1

**Figure 3.** Example of species compositional turnover mapping in the study area with Sparse Generalised Dissimilarity Modelling based on Landsat time series. The predicted dissimilarities between the sample plots were transformed with Non-metric Multi-Dimensional Scaling. The resulting three axes were applied to the image and visualised on the red, green and blue channels. Roads are represented by the grey lines, the limits of the Castro Verde Special Protection Area by the yellow line and the Castro Verde town by black circle.

**Figure 3.** Above (in yellow) the location of the sampled pixels with a sample cover of at least 75% in PESA, Parque Estadual da Serra Azul (A) and PNCV, Parque Nacional da Chapada dos Veadeiros (B). Below, RGB maps of the main axes of variation in species turnover in PESA (C) and PNCV (D) woody plant communities. Each of the first three NMDS axes (A1 to A3 for PESA and B1 to B3 for PNCV) were, respectively, plotted in the R, G and B channels, so that, for example, a bright turquoise pixel would mean high loadings on axes 2 and 3 (high values on both the G and B channels).
Mapping Cerrado woody plant community turnover with spaceborne imaging spectroscopy data

Pedro J. Leitão,
Marcel Schwieder, Fernando Pedroni, Maryland Sanchez, José R. R. Pinto,
Mercedes Bustamante, Patrick Hostert
Motivation & Aims:

• Mapping and monitoring **spatial patterns** of community composition and turnover using spaceborne imaging spectroscopy

• Develop an **operational method** capable of dealing with high-dimensional and high-collinear remote sensing data

The EnMAP is one of several forthcoming spaceborne imaging spectroscopy missions
Methods:

- Sparse Generalized Dissimilarity Modelling (SGDM)
Methods:

- Sparse Generalized Dissimilarity Modelling (SGDM)
  - Generalized Dissimilarity Modelling (GDM)
    - A statistical technique for analysing and predicting patterns of turnover in community composition
    - Fits non-linear functions on the environmental variables to predict compositional dissimilarity
    - Affected by data collinearity
Methods:

• Sparse Generalized Dissimilarity Modelling (SGDM)
  • Sparse Canonical Correlation Analysis (SCCA)

  • Supervised transformation approach
  • Used in genetic research, where typically number of features is much greater than number of samples
  • Transforms two matrices in order to maximise the correlation between them
  • Based on penalised (Lasso) regression, thus downweighting redundant data
  • Capable of (and designed for) dealing with high-dimensional and high-collinear datasets
Methods:

- Sparse Generalized Dissimilarity Modelling (SGDM)

- 2015, Description of the SGDM method

- 2017, Description of the sgdm R package

- 2018, Mapping Cerrado woody plant communities
Data:

- Woody plant inventory data following a systematic sampling scheme (RAPELD adapted to the Cerrado)

PESA:
- 65 samples
- 184 species

PNCV:
- 29 samples
- 94 species

Floristic gradients
Data:

- Hyperion (hyperspectral) data

  - Pre-processing:
    - Radiometric correction
    - Correction for pixel shift, striping, keystone & smile
    - Atmospheric correction
    - Geometric correction
    - Spectral smoothing

  - Post-processing:
    - Data quality screening > 81 spectral bands remaining per image

From sample to pixel: multi-scale remote sensing data for upscaling aboveground carbon data in heterogeneous landscapes

Pedro J. Leitão, Marcel Schwieder, Florian Pötzscher, José R. R. Pinto, Ana M. C. Tedeschi, Fernando Pedroni, Maryland Sanchez, Christian Rogass, Sebastian van der Linden, Mercedes M. Bustamante, and Patrick Hoster.
Results:

- Woody plant community maps

\[ R^2 = 0.710 \quad R^2 = 0.392 \]
Results:

- Spectral band contribution

<table>
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<th>Relative contribution</th>
<th>Spectral band</th>
<th>Relative contribution</th>
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<td>569.27 (G)</td>
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<td>874.53 (NIR)</td>
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</table>
Conclusions & Discussion

- Our method allowed for mapping species community turnover using spaceborne imaging spectroscopy

- Relevant considerations/challenges for the generalization of SGDM include:
  - The method is not suitable for data extrapolation (i.e. models need to include the full data space)
  - Input spectral data needs to be harmonized
  - It is sensitive to
    - Detection/correction of atmospheric effects
    - Topographic/shading effects
    - Phenological changes
  - Sensitivity to temporal or physiological changes needs to be tested
Thank you for your attention

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Where to from here? – strategies for accessing or generating data to further test and develop ideas

- Combine existing spaceborne hyperspectral data (e.g. Hyperion archive) and coincident existing vegetation plot data (e.g. sPlot database)

- Simulate spaceborne hyperspectral data by aggregating existing airborne data (e.g. AVIRIS) across areas with existing vegetation plot data

- Commission spaceborne data (e.g. DESIS) across areas with existing vegetation plot data

- Collect new vegetation plot data across areas with good spaceborne and/or airborne hyperspectral data coverage
Over 93,000 of the 1.12 million vegetation plots in the sPlot database fall within Hyperion scenes.
Where to from here? – strategies for accessing or generating data to further test and develop ideas

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➢ Collect new vegetation plot data across areas with good spaceborne and/or airborne hyperspectral data coverage
Where to from here? – numerous challenges in refining and extending the analytical approach – for example ...

➢ Accommodating shorter-term temporal dynamics (seasonality, drought, fire etc)

➢ Disentangling natural and anthropogenic drivers of variation in community composition

➢ Coupling spaceborne imaging spectroscopy with other cutting-edge observation technologies – e.g. eDNA / metabarcoding / metagenomics
Connecting Earth observation to high-throughput biodiversity data

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Evaluating a multigene environmental DNA approach for biodiversity assessment

Alexei J. Drummond¹,², Richard D. Newcomb¹,³,⁴, Thomas R. Buckley¹,³,⁵, Dong Xie¹,², Andrew Dopheide¹,³,⁴, Benjamin CM Potter¹,³, Joseph Heled¹,², Howard A. Ross¹,³, Leah Tooman¹,⁴, Stefanie Grosser¹,⁴, Duckchul Park¹, Nicholas J. Demetra², Mark L. Stevens⁶,⁷, James C. Russell¹,³, Sandra H. Anderson², Anna Carter¹,¹⁰ and Nicola Nelson¹,¹⁰

Fig. 3 The number of OTUs at the 97% clustering threshold assigned to phyla. Unclassified OTUs and OTUs containing low-complexity sequences are not included. OTUs from phyla that are represented by less than 0.1% of the OTUs are grouped into the ‘Others’ category.
Sensing biodiversity

Sophisticated networks are required to make the best use of biodiversity data from satellites and in situ sensors.

Global-regional coverage

Regional-local coverage

Citizen scientist with cell phone

Drone

Camera trap

Collecting environmental DNA

Satellite

Aircraft

UAV

Wildlife officer with receiving antenna

Transmitting collar

Sound recorder
Thank you

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