

Remote sensing at the interface between ecology and climate sciences

Anthropogenic climate change is causing a severe impact on the survival of organisms (Brondizio et al., 2019; Shukla et al., 2019). Climate is one of the major drivers of species distributions, and the velocity at which the current climate is changing, owing to human activities, already induces a redistribution of life on Earth at an unprecedented speed, especially in the oceans where marine life is shifting towards the poles six times faster than the velocity at which terrestrial life is shifting poleward on land (Lenoir et al., 2020). Besides, biodiversity redistribution may enhance climate warming through positive feedback loops (e.g., the shrubification of the Arctic altering the surface albedo), thus indirectly affecting human well-being (Pecl et al., 2017). For this reason, both essential climate variables (ECVs) and essential biodiversity variables (EBVs) have been developed as proxies for the early detection of climate change and biodiversity redistribution (Bojinski et al., 2014; Pereira et al., 2013; Schmeller et al., 2018).

Worldwide, organizations have tried building research and policy networks to seriously face the problem, or, at least, to build robust projections that might allow the monitoring of future changes. One of the main examples is the Group on Earth Observation (GEO, <https://www.earthobservations.org/index.php>), namely a global partnership of governments and organizations to

develop a Global Earth Observation System of Systems (GEOSS, <https://www.earthobservations.org/geoss.php>).

A specific branch of GEO – GEO BON (<https://geobon.org>) – is devoted to the development of suitable EBVs as proxies for improving the effectiveness of biodiversity conservation over the entire planet. The 22 proposed EBVs are trying to cover several aspects of diversity, clumped into six classes: (i) genetic composition (e.g., co-ancestry, allelic diversity); (ii) species populations (e.g., species distribution, population abundance); (iii) species traits (e.g., phenology, morphology); (iv) community composition (e.g., taxonomic diversity, functional diversity, species interactions); (v) ecosystem function (e.g., net primary productivity, nutrient retention); and (vi) ecosystem structure (e.g., habitat structure, extent and fragmentation) (Pereira et al., 2013; see also <https://geobon.org/ebvs/what-are-ebvs/>). Variables useful for the research fields at the interface of ecology and climate sciences might include, among the others: (i) species occurrence detection and plant traits (e.g., leaf area and leaf nitrogen content) based on multispectral and hyperspectral data; (ii) plant canopy height and biomass based on light detection and ranging (LiDAR) data (see, e.g., the Global Ecosystem Dynamics Investigation mission [GEDI, <https://gedi.umd.edu/>]); and (iii) habitat fragmentation and land-cover change (LCC) data based on time series of Landsat images (Skidmore et al., 2015).

A common language between the remote sensing community, on the one hand, and the ecological and climate research communities, on the other, was definitively defined by the proposal of ecosystem-based EBVs that can be transposed from field observations to remotely-sensed perspectives. A key concept is the reinforcement of the link between ecological patterns to be observed and a direct relationship with potential ecological processes shaping them. For instance, spatial heterogeneity in biophysical conditions might represent a good proxy of ecological variation over space and can be related to several ecological processes, from habitat fragmentation to niche variability, to biodiversity (Hernandez-Stefanoni

Abbreviations: ADAPT, Advanced Data Analytics Platform; EBVs, essential biodiversity variables; ECMWF, European Center Medium Weather Forecast; ECVs, essential climate variables; ESA, European Space Agency; EUMETSAT, European Organization for the Exploitation of Meteorological Satellites; GEDI, Global Ecosystem Dynamics Investigation mission; GEO, Group on Earth Observation; GEO BON, Group on Earth Observation Biodiversity Observation Network; GEOSS, Global Earth Observation System of Systems; GOES, Geostationary Operational Environmental Satellite; LCC, land-cover change; LiDAR, light detection and ranging; LST, land surface temperature; NASA, National Aeronautics and Space Administration; MODIS, Moderate Resolution Imaging Spectroradiometer; OMI, Ozone Monitoring Instrument; SMCE, Science Managed Cloud Environment; WMO, World Meteorological Organization.

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et al., 2012). From this point of view, requirements explicitly expressed by the communities of ecologists and climate scientists towards the community of remote sensing specialists include the availability of different spatial grains as well as several meaningful wavelengths to further process remotely-sensed data and perform global-scale analyses (Randin et al., 2020; Schmeller et al., 2018).

In the era of big data, such accomplishments can be reached in a simple manner, overall when the community of ecologists and climate scientists is directly asked to provide technical advances about the development of current and future sensors (e.g., <https://sentinel.esa.int/web/sentinel/events>). A knowledge gap is still open about the possibility to monitor genetic composition (see the first EBVs' class described above) and variation over space by using remote sensing data products. Some studies have already demonstrated the feasibility of using remotely-sensed and geographic data for studying population genetic variability (see Vernesi et al., 2012). From this point of view, proxy indicators might represent an effective method to bridge the gap between remotely-sensed and field-based observations on genetic diversity. However, the relationship between genetic diversity and the ecological space appears to be too complex to be directly faced with remote sensing proxies, since it is dependent on too many factors like demographic history, population genetics, environmental management, gene flow, spatial barriers, and so forth (Bruford et al., 2017).

Climate projections are critical for ensuring a proper management of ecosystems in light of past and recent changes. Gathering field observations of meteorological data worldwide with a high temporal resolution (e.g., daily or hourly data) and at a fine spatial resolution (i.e., microclimate) might not be affordable from a logistical and cost-effective perspective. However, there are promising attempts such as the recent SoilTemp initiative (Lembrechts et al., 2020), to gather detailed micrometeorological data at a global scale. Hence, remote sensing might represent a powerful tool for providing important covariates to interpolate scattered field observations of micrometeorological data worldwide and thus spatialize micrometeorological and microclimatic conditions from satellite images as well as forecasting future scenarios on climate change at an unprecedented spatio-temporal resolution (Lembrechts & Lenoir, 2020; Maclean, 2020). As an example, satellite data, using NASA Ozone Monitoring Instrument (OMI), have been used to monitor air quality in the Galapagos Islands, providing for the first time baseline levels of air contaminants in one of the most important and vulnerable biodiversity hotspots on Earth (Cazorla & Herrera, 2020). Additionally, long time series on temperature as a proxy of climate change have been generated deriving land surface temperature (LST) layers with different levels of spatial resolution, from coarse at 5 km

(e.g., MODIS, <https://terra.nasa.gov/about/terra-instruments/modis>, Figure 1) and 4 km (GOES network, <https://www.nasa.gov/content/goes>) to fine at 10 m (Sentinel, <https://sentinel.esa.int/web/sentinel/missions>) or 30 m (Landsat, <https://landsat.gsfc.nasa.gov/>) through intermediate at 1 km (Envisat, <https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/envisat>). Similarly, these layers can be derived at different levels of temporal resolutions, from monthly to daily basis (see Tomlinson et al., 2011 for a review).

Examples showed the feasibility of predicting trends in climatic conditions by remote sensing from medium (e.g., Metz et al., 2014) to very fine (e.g., Lenoir et al., 2017; Zellweger et al., 2019) spatial resolutions. Such trends have been demonstrated to rule out a number of ecological processes such as follows: (i) species dispersal (Bellier et al., 2012); (ii) biological invasions (Gallien et al., 2010); and (iii) habitat loss (Bartel & Sexton, 2009). This is especially true considering that species facing habitat fragmentation are generally less resistant to additional and detrimental effects related to climate change (Travis, 2003). From this perspective, aerial photography dating back to the 50s can help classifying landscape (Rocchini & Ricotta, 2007) and linking multi-temporal land-use changes to current climate change estimated from satellite imagery (Gillespie et al., 2008). Furthermore, global remote sensing products are now able to track climate change trends from above, with a high repetition rate, up to four global images per day at a spatial resolution of a few kilometres (Wan, 2008), such as the moderate resolution imaging spectroradiometer (MODIS) land surface temperature/emissivity product. From a monitoring perspective, trend analysis can now be affordable using satellite data, since long time series are now available.

Satellite remote sensing has long been a core part of the World Meteorological Organization (WMO, <https://public.wmo.int/en>) to provide estimates of cloud cover and motion vectors, atmospheric and surface temperature as well as snow and ice cover starting from the 80s (Leese, 1987), under the flag of the World Weather Watch Programme (<https://www.wmo.int/>). Such data can now be combined to provide complete time series of intra- and inter-annual weather and climate changes to find potentially severe impacts on biodiversity. Furthermore, the Copernicus program (<https://www.copernicus.eu/>) – coordinated and managed by the European Commission and implemented with Member States, the European Space Agency (ESA), the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT), and the European Center Medium Weather Forecast (ECMWF) – is now providing worldwide scale estimates of different Earth variables related to both ecosystem

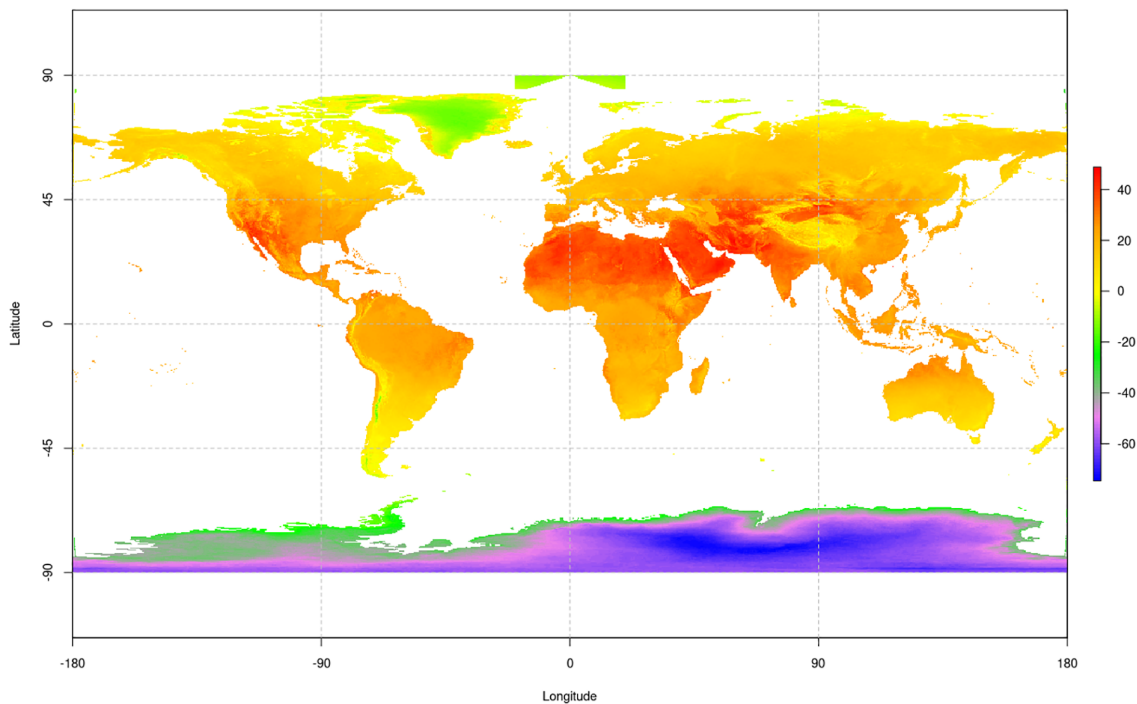


FIGURE 1 An example of land surface temperature (LST, in °C) map derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data (monthly average of daily averages for June 2016) at a spatial resolution of 5 km. MODIS monthly LST data from 2003 to 2016 are freely available at: <https://zenodo.org/record/1115666#.X4Q6z3UzbJk>, while the code to implement this plot is available at: <https://github.com/ducciorocchini>. Refer to Metz et al. (2017) for data throughput analysis description

properties (e.g., leaf area index, fraction of green vegetation cover, burnt areas) as well as energy (e.g., top of canopy reflectance, surface albedo) climatic-related layers (e.g., LST, cryosphere, snow cover), including different sensors like the Proba-V and the MODIS sensors. Furthermore, global estimates of climatic variables are now available under Copernicus at an hourly basis. As an example, global LST product on an hourly basis is now available from the geostationary constellation (<https://land.copernicus.eu/global/products/lst>).

Moreover, the Copernicus initiative promoted the launch of Sentinel satellites, with a very high revisit time, up to 5 days, a high spatial resolution (10 m, a reasonably high spatial resolution for free data) and the possibility to gather free sets until 2028 (Skidmore et al., 2015). This is dramatically useful for the ecology community since it allows to study local as well as global processes under a free analysis environment, ensuring that all researchers over the globe can perform their studies in a reproducible manner. This is especially important in those countries where research funds are low but the habitats to be preserved are extremely important for the whole planet (e.g., African and South-American tropical forests) and the related threats like deforestation or fire spread should be constantly monitored.

Besides, airborne remote sensing helps predict microclimatic conditions at a very detailed spatial grain based

on both hyperspectral remote sensing and LiDAR laser scanning (Zellweger et al., 2019). While hyperspectral images allow seeing ecosystems in spectral wavelengths in which there might be peaks related to microclimate change, LiDAR images can be used to track structural changes in vegetation cover strictly related to microclimate dynamics (Lenoir et al., 2017; Zellweger et al., 2020). For instance, airborne LiDAR and hyperspectral imagery have already been combined to derive gap and canopy properties and model forest microclimate dynamics of the Frame Wood New Forest in southern England (Latif & Blackburn, 2008). Such applications of airborne remote sensing technologies to model microclimate at very high spatial resolution have the potential to inform species distribution models about potential microrefugia for species to persist locally under anthropogenic climate change (Lembrechts et al., 2019; Lenoir et al., 2017).

LiDAR data have also been successfully used to track local spots of sudden changes in meteorological conditions like local turbulence (Hon & Chan, 2020; Wildmann et al., 2019), wind radial velocity (Frehlich et al., 1997), wake vortices characteristics (Holzapfel et al., 2003), and hub height ocean winds (Hasager et al., 2013). Modelling such meteorological spot-events is important since they can – as well as longer temporal dynamics like climate change – alter ecosystem functioning in a very short period

of time, leading to devastating changes threatening organism survival and challenging ecosystem resilience, until the potential loss of single species and entire habitats.

Remote sensing products provide cutting-edge technology to support the interdisciplinarity research between ecology and climate sciences. Besides, a number of free and open-source packages and software modules have been recently developed to relate remotely-sensed data from both disciplines. Several of these packages are freely available under the R statistical software (R Core Team, 2020), like, for example, the rasterdiv package to track diversity and climate changes from space (Marcantonio et al., 2020), the climate package to download in situ meteorological data (Czernecki et al., 2020), the ClimInd package to compute climate indices (Reig-Gracia et al., 2019), the hsdar and the lidR packages to manage and analyse hyperspectral and LiDAR data, respectively (Lehnert et al., 2020; Roussel et al., 2020), the RStoolbox to analyse remote sensing data (Leutner et al., 2019).

Numerical weather prediction is far from being free from uncertainty, considering both weather and climate modelling. The physics of forecasting are well grounded on robust equation sets (Abbe, 1901), and the steps to represent physical processes by ensemble models are known. On the other hand, mapping errors is crucial to get an estimate of the bias beside the estimated variables (Rocchini et al., 2013). Examples exist to implement such maps dating back to the 50s based on both error growing models (Thompson, 1957) and chaos theory (Lorenz, 2006). The basic idea is that any forecast is strictly related to boundary conditions (including, e.g., emission scenarios) and is sensitive to error propagation (Pijanowski et al., 2011) and non-stationarity in the spatial distribution of errors (Foody, 2004; Gillespie et al., 2008). Care must then be taken in meteorological and climatic modelling applied to the prediction of ecological processes, in order to avoid the propagation of errors in final models due to the initialization of the climatic forecasts.

The use of remote sensing in cross-disciplinary research between ecology and climate is still at its infancy and a very promising frontier research for cross-disciplinary research between ecology and climate sciences. In the past, it was considered as a cutting-edge technology for forecasts and modelling of ecological functions related to climatic drivers, like nutrient cycling and energy flow. However, over time, researchers realized there are still challenges to be faced before such tools can be considered a robust throughput standard. Such challenges might concern, for instance, technical issues, such as spatial grain (resolution, *sensu*; Dungan et al., 2002). A very high spatial resolution would add noise instead of information into the model, while a coarse spatial resolution will create smoothed surfaces, which are definitively useless for further ecological modelling (Nagendra & Rocchini, 2008).

Furthermore, high data volumes and computational needs should be faced once dealing with any meteorological or climatic observations, especially across wide spatial extents and at a high temporal resolution (Li et al., 2017). From this point of view, a number of initiatives are now worldwide devoted to promote cloud computing as a frontier for collaborative cyberinfrastructure development. Examples include the NASA projects ADAPT (<https://www.nccs.nasa.gov/systems/adapt>), Goddard Private Cloud (<https://www.nas.nasa.gov/SC18/demos/demo34.html>), and SMCE (<https://www.nccs.nasa.gov/systems/SMCE>) to virtualize, by high-performance throughput techniques, unprecedented big data gathering and analysis and leverage data-intensive calculus. Finally, the reduction of the uncertainty of physical parameterization is another important issue (Bauer et al., 2015) to build a robust empirical framework for further modelling of ecological changes, by guaranteeing that the complex geospatial models rely on (at least, potentially) unbiased data.

Given the above drawbacks and challenges, remote sensing is now providing useful data guaranteeing efficient monitoring of ecological processes to be linked with meteorological and climatic variables, to enable scientists and practitioners from climate and ecological sciences to work together. The forthcoming “Climate Science for Ecological Forecasting Symposium” will be the first interdisciplinary conference between climate and ecology, jointly hosted by the Royal Meteorological Society and British Ecological Society. Together, attendees will explore the needs and opportunities for greater interaction between the disciplines and establish the cross-disciplinary networks that are necessary to better predict and plan the future of our planet. More information is available at the Royal Meteorological Society's website: <https://www.rmets.org/event/climate-science-ecological-forecasting>

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Duccio Rocchini^{1,2}
Jonathan Lenoir³ 

¹BIOME Lab, Department of Biological, Geological and Environmental Sciences, Alma Mater Studiorum University of Bologna, Bologna, Italy

²Department of Spatial Sciences, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Praha - Suchbátka, Czech Republic

³UMR 7058 CNRS “Ecologie et dynamique des systèmes anthropisés” (EDYSAN), Université de Picardie Jules Verne, Amiens, France

Correspondence

Duccio Rocchini, BIOME Lab, Department of Biological, Geological and Environmental Sciences, Alma Mater Studiorum University of Bologna, via Irnerio 42, 40126, Bologna, Italy.
Email: duccio.rocchini@unibo.it

ORCID

Jonathan Lenoir  <https://orcid.org/0000-0003-0638-9582>

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