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EDITORIAL: MODEL-ASSISTED MONITORING OF BIODIVERSITY

Fostering integration between biodiversity monitoring and modelling

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Modelling and monitoring: adaptive biodiversity management in the 21st century

With increasing threats on biodiversity, informed conservation decisions need to be based on currently observed and future predicted trends of biodiversity (Pereira, Navarro & Martins 2012; Guisan *et al.* 2013). In this regard, two essential components supporting informed biodiversity conservation decisions are good monitoring data to assess recent and ongoing trends (Collen *et al.* 2013; Pereira *et al.* 2013) and robust models to anticipate possible future trends (Pereira *et al.* 2010a; Akçakaya *et al.* 2016). Models benefit from robust monitoring data sets, that is repeated observations of biodiversity, as they need data to be fitted or validated, but models can also help assess data representativeness (e.g. by highlighting any bias), support proper data collection (e.g. covering the relevant gradients) or be used to make more effective use of biodiversity observations (Guisan *et al.* 2006, 2013; Ferrier 2011).

On the data side, species occurrence data bases with global coverage – like the Global Biodiversity Information Facility (GBIF; Scholes *et al.* 2012) – provide increasingly large amounts of data, but these are often geographically and taxonomically biased, revealing highly uneven sampling efforts across regions and countries (Boakes *et al.* 2010; Meyer *et al.* 2015; Proença *et al.* 2016). The Group on Earth Observations Biodiversity Observation Network (GEO BON) has proposed the development of national monitoring programmes for a variety of habitats and taxa, thus potentially representing a more unbiased data source to support biodiversity management (Pereira *et al.* 2010b; Scholes *et al.* 2012). This is a challenging endeavour, as biodiversity monitoring is expected to provide relevant data not only for large-scale policy but also to meet regional and local management needs, while ensuring that resources are allocated efficiently (Green *et al.* 2005; Haughland *et al.* 2010).

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Biodiversity monitoring has already proven essential to improve management and evaluate success of policies (Pereira & Cooper 2006; Collen *et al.* 2013), but it also represents a valuable support to basic research (Couvet *et al.* 2011), as exemplified by the multiple research studies using data from the North American Breeding Bird Survey (e.g. Miller-Rushing, Primack & Bonney 2012; Schipper *et al.* 2016) or from other monitoring programmes (e.g. Weber, Hintermann & Zangger 2004; Pearman & Weber 2007; Hanspach *et al.* 2014). However, monitoring schemes also have limitations. For instance, they can be underpinned by unclear objectives and may consequently fail to identify clear trends or to properly evaluate the success of conservation actions (e.g. Nichols & Williams 2006; Lindenmayer *et al.* 2012). Also, they are often limited in extent (spatial and/or temporal) due to lack of human and financial resources (Levrel *et al.* 2010). Nevertheless, despite these limitations, even monitoring schemes targeting individual species at small scales or particular habitats still deliver data that may often prove valuable for modelling (e.g. Bastos *et al.* 2016).

On the modelling side, predictive biodiversity modelling has developed as a core field of ecological research during the last two decades (see Ferrier & Watson 1997; Guisan & Zimmermann 2000; Peterson 2001; Mouquet *et al.* 2015). While consolidating as a powerful research tool, predictive models of species distributions have also been helpful in providing insights on the drivers of biodiversity across scales and in delivering spatially explicit forecasts of biodiversity responses to environmental pressures (Guisan *et al.* 2013), such as climate change (e.g. Bellard *et al.* 2012), land-use change (e.g. Ficetola *et al.* 2010), invasion by non-native species (e.g. Petitpierre *et al.* 2012) and interactions between these drivers (e.g. Vicente *et al.* 2011; Gonçalves *et al.* 2016). Predictions can be made at different levels of biological complexity, from species and communities to habitat or ecosystem types (Ferrier & Guisan 2006; Hely *et al.* 2006; Kerr & Dobrowski 2013). However, so far there has been limited use of predictive models in support of biodiversity monitoring. Even if there are examples in the literature illustrating their potential added value (e.g. Guisan & Theurillat 2005; Tuanmu *et al.* 2011; Amorim *et al.* 2014), a more systematic application of models would benefit the planning of monitoring as well as the integration of observations into valuable data products. This would then enable the improvement of model predictions and the reporting of biodiversity changes near real-time (GEO BON 2015).

The four papers in this Special Feature represent a starting point to fill existing gaps and pave some ways towards fostering integration between biodiversity monitoring and modelling (Bastos *et al.*, Carvalho *et al.*, Geijzendorffer *et al.*, Vicente *et al.*). In this editorial, we provide a general review of recent advances and identify some future research directions. We emphasize the species-level dimensions of biodiversity in our analysis, and particularly species distributions and populations (Pereira *et al.* 2013). We start by identifying how models can be used to improve the design of monitoring programmes and networks. We then assess how monitoring data can be used to improve models and validate their predictions. We discuss how models can be used to integrate biodiversity observations from different sources and other environmental data to produce estimates of biodiversity measures in space and time. Finally, we discuss how modelling and monitoring could be further integrated to improve biodiversity conservation and management across scales.

Models as tools to improve biodiversity monitoring

The number of biodiversity monitoring programmes is increasing in order to respond to demands from decision-makers and society for information on biodiversity changes (Pereira *et al.* 2010b). But there are already many biodiversity monitoring programmes in place, which have collected valuable data over many years or decades. Models can be used both to design new monitoring programmes or to assess and improve existing ones. Below we describe two broad categories of modelling applications which could improve biodiversity monitoring, particularly when used together.

DESIGNING EFFICIENT SAMPLING SCHEMES

Models have been used before with optimization objectives, to improve the coverage of protected areas in a conservation planning context (e.g. Elith & Leathwick 2009; Carvalho *et al.* 2010, 2011). Designing cost-efficient monitoring networks is a distinct but related challenge, involving optimal allocation of monitoring sites across space (e.g. Amorim *et al.* 2014; Vicente *et al.* 2016). It aims at maximizing the cost-efficiency of monitoring networks, for example to detect population trends in multiple species, by allocating monitoring sites to the most informative areas while minimizing the total number of sites (Amorim *et al.* 2014; Carvalho *et al.* 2016). Models can also be valuable to improve existing programmes, by contributing to identify gaps, remove bias, and fine-tune the spatial and temporal coverage as the first data are collected and analysed (Martin, Kitchens & Hines 2007). Optimization based on power analysis and cost models (e.g. Zielinski & Stauffer 1996; Carlson & Schmiegelow 2002) can define priorities for local densification of observation networks whenever additional resources can be mobilized (Le Lay *et al.* 2010). Models can additionally contribute to optimize the testing of hypotheses from monitoring data, by supporting stratified sampling strategies along gradients of expected biodiversity drivers (e.g. Guisan & Theurillat 2005; Amorim *et al.* 2014) or considering the goals of related management programmes (e.g. Vicente *et al.* 2016). Sensitivity or uncertainty analyses can be used to define expected variation at each site, allowing to differentiate real trends from background variation (e.g. Zielinski & Stauffer 1996) while accounting for uncertainty in projections (e.g. Naujokaitis-Lewis *et al.* 2013).

IDENTIFYING AREAS OF SPECIES OR HABITAT OCCURRENCE AND RAPID CHANGE

Potential benefits of a model-based monitoring design may also arise from increasing the detectability of target species or habitat types (e.g. Guisan *et al.* 2006; Metzger *et al.* 2013). Predictive modelling can especially assist in identifying areas where the monitored feature is more likely to change, for example where a given species is expected to gain or lose climatic suitability (Carvalho *et al.* 2011) or a given habitat may lose quality (Vaz *et al.* 2015). Models can also locate areas particularly threatened by invasion of alien species (Vicente *et al.* 2011, 2016; Epanchin-Niell *et al.* 2014) or by combined effects of climate and land-use changes (e.g. Jetz, Wilcove & Dobson 2007; Gonçalves *et al.* 2016). Such information can then be incorporated in spatial prioritization algorithms, setting targets to achieve a minimal number of monitoring sites per species or habitat type across areas with different predicted trends (e.g. Carvalho *et al.* 2016; Vicente *et al.* 2016). Model predictions can also allow the design of efficient monitoring schemes aimed to assess the effect of landscape barriers on species' responses to changes in their environment (e.g. Gonçalves *et al.* 2016).

Predictive modelling is known to be prone to uncertainty (e.g. Barry & Elith 2006), but methodological advances such as ensemble forecasting and sensitivity analyses (e.g. Pearson *et al.* 2006; Araújo & New 2007; Buisson *et al.* 2010; Carvalho *et al.* 2010, 2011) have increased our capacity to quantify that uncertainty and thereby inform conservation and management decisions. Guisan *et al.* (2013) discuss how uncertainty in model predictions can influence decisions in four conservation-related domains, which in the case of monitoring could translate into overestimating or underestimating costs of running monitoring efforts. For instance, in the case of monitoring biological invasions, underpredicting the extent of suitable habitat for an invasive species may lead to failure to monitor new critical areas of introduction or spread, whereas overpredictions may waste monitoring resources. Similar issues arise when using models to support reserve selection or translocations, both of which need monitoring efforts to assess their actual efficiency. As the different types of uncertainty can be incorporated in spatial conservation prioritization processes (Moilanen *et al.* 2006), the same could – and should – be done when designing spatial monitoring schemes (using, e.g., the uncertainty typology in Barry & Elith 2006). This would allow setting confidence intervals around the monitored features and help interpret the robustness of observed biodiversity trends.

Monitoring data can improve biodiversity models

Well-designed monitoring networks (possibly supported by models) not only provide the necessary information to track biodiversity trends and thereby meet governmental and international targets, but they also provide potentially valuable data to validate model predictions and to fit better models for species, habitats or biodiversity measures. We have seen that a key problem in using existing archived global biodiversity data bases, such as GBIF (Scholes *et al.* 2012), to fit biodiversity models is that such data can be (and often are) heavily biased (Meyer *et al.* 2015) and often collected opportunistically (van Strien, van Swaay & Termaat 2013). This bias can be difficult to reduce by using statistical methods only (as, e.g., Phillips *et al.* 2009; Manceur & Kuhn 2014; Guillera-Arroita *et al.* 2015), and it is much more efficient to use data that have been collected with a proper sampling strategy (Hirzel & Guisan 2002; Edwards *et al.* 2006).

Using monitoring data could also contribute to build better models and predict future trends, since the aim of monitoring network design is precisely to avoid bias in the estimation of biodiversity patterns, measures and trends (e.g. Brotons, Herrando & Pla 2007; Nobis, Jaeger & Zimmermann 2009; Pearman, Guisan & Zimmermann 2011; Pearman *et al.* 2014). Data from long-term monitoring programmes can be especially valuable to fit robust models, which can pinpoint problems or gaps in the design of the monitoring schemes and thereby improve them (e.g. Kuemmerlen *et al.* 2016). Extensive monitoring schemes, where repeated observations of populations of species, such as birds, butterflies or amphibians, are carried out, often for full community assemblages, have proved particularly useful (McGill 2003; Dornelas *et al.* 2014; Proença *et al.* 2016). Monitoring schemes targeted at evaluating specific questions or impacts can also provide valuable data for fitting models and delivering predictions of future impacts (e.g. Bastos *et al.* 2016).

One of the challenges in the development of Species Distribution Models is that often the data sets used for calibration and validation are not independent, and in reality are a subpartition of the same data set, for example an atlas of species distribution for a given period of time (Araújo *et al.* 2005a,b). Using data from two repeated surveys of the Breeding Birds of Britain, Araújo *et al.* (2005a) tested the performance of Species Distribution Models in projecting range shifts for 116 species. The models were calibrated with the 1970 species distribution data, and projections based on climate change for 1990 were compared with the species survey data. They found that the predictive capacity of the models was lower when the independent validation was used, but that some models still had good performance.

Of course, data even from the best monitoring programmes are not error-free, and species detectability, in particular, remains a recurrent problem (Kery & Schmid 2004), but biodiversity distribution models can also incorporate imperfect detectability when estimated so as to obtain improved predictions (Kery, Gardner & Monnerat 2010; Rota *et al.* 2011; Guillera-Arroita *et al.* 2015). In any case, estimating imperfect detection and bias in data should be much easier on data sets from well-designed monitoring networks, because the required measures to make these estimations and posterior corrections exist or can be applied a posteriori, such as repeated measurements (e.g. capture–recapture; Kery & Schmid 2004), whereas they are mostly unavailable for data from global occurrences data bases (Graham *et al.* 2004; Meyer *et al.* 2015).

Models to harmonize and integrate multi-source observations

In an effort to harmonize and integrate biodiversity monitoring globally, GEO BON has been developing a framework of Essential Biodiversity Variables (EBVs), as the key variables that need to be monitored to understand and model the consequences of biodiversity change (Pereira *et al.* 2013; Skidmore *et al.* 2015; Geijzendorffer *et al.* 2016). They include variables ranging from genetic composition to ecosystem function, including species-level variables such as species distributions, population abundances and taxonomic diversity (Pereira *et al.* 2013; Geijzendorffer *et al.* 2016). The goal is that estimates of these variables become available for any point in space and time with a reasonable degree of taxonomic and ecological coverage. These EBVs can be used to develop and validate models of responses of biodiversity to drivers of change, but the EBVs themselves can also be generated by models, especially by integrating observations from in situ and remote sensing (GEO BON 2015).

There are multiple ways in which models can be used to integrate in situ and remote sensing observations of biodiversity. Many environmental variables that can be tracked by remote sensing, or for which global data sets exist, are highly correlated with species distributions (He *et al.* 2015; Pettorelli *et al.* 2016). Therefore, based on the statistical relationship between species point occurrences and environmental variables, it is possible to project the area of potential occurrence of a species using predictive models of species distributions (Guisan *et al.* 2013) or to use these for changing the scale of the data (e.g. downscaling atlas data; Keil *et al.* 2013). Furthermore, coarse species distributions based on point occurrences may be refined with land-cover data by using habitat suitability models and other ancillary data (Visconti *et al.* 2011; Jetz, McPherson & Guralnick 2012; GEO BON 2015). Therefore, as annually updated high-resolution global forest-cover data sets are now available (Hansen *et al.* 2013), it is now possible to estimate changes in forest species distributions yearly (GEO BON 2015). Models can also be used to estimate population abundances (e.g. Pettorelli *et al.* 2014) or ecosystem attributes (e.g. Vaz *et al.* 2015) from the integration of remote sensing variables and field biodiversity data.

Towards seamless integration of data and models for biodiversity management

There is thus an opportunity to improve biodiversity monitoring by taking advantage of previous experience of using models to optimize resource allocation (Elith & Leathwick 2009; Guisan *et al.* 2013), and in turn to improve models with robust biodiversity data. Models can contribute to design better novel schemes and to improve several features of existing monitoring programmes, promoting cost-efficiency by allocating efforts where they can be most informative. The potential contributions of models to monitoring, and of monitoring to models, are manifold and largely underexplored.

We see three levels where a more systematic application of models in biodiversity monitoring could prove useful and should be further developed in future research agendas: (i) the design and set-up of new programmes, or the assessment and improvement of existing ones, for example to make them efficient to track biological trends from global change drivers; (ii) the regional to global coordination and integration of monitoring programmes under overarching initiatives (such as GEO BON); and (iii) the expansion of the application of monitoring data in effective conservation management.

The first level represents two distinct stages in the life cycle of monitoring programmes under an adaptive framework, in which programmes can be adapted to novel circumstances while still maintaining their fundamental attributes (Lindenmayer & Likens 2009). Models can improve existing programmes by contributing to identify gaps, correct any bias, and fine-tune the spatial and temporal coverage. They can also assist adaptation of programmes to novel scenarios or forecasts for the focal drivers of biodiversity change (e.g. Bellard *et al.* 2012; Vicente *et al.* 2016). In the second level, in order to advance the coordination of global monitoring efforts, models can foster integration of multisource observation data, pinpoint biases and data gaps, support robust estimates of EBVs and predict future trends (GEO BON 2015). Finally, the third level relates to fostering the use of monitoring data in research programmes or applied management (e.g. Guisan *et al.* 2013). A striking paradox of ecological monitoring is that it is usually meant to improve management, but it is seldom effectively applied to support or improve management, often due to the lack of explicit questions or hypotheses (Lindenmayer & Likens 2009). For instance, models could be used more systematically to anticipate future impacts on biodiversity (e.g. Bastos *et al.* 2016) or to increase the efficiency of prospective surveying in the case of confining biological invasions (Petitpierre *et al.* 2016). Models can also play a central role in communicating monitoring results to stakeholders, thereby promoting their effective application for management (Guisan *et al.* 2013).

Given all of this, systematic application of predictive models could contribute to optimize coverage of observation networks, to improve detectability of rare species and habitats, and to enable earlier detection of the effects of focal pressures on biodiversity, bringing biodiversity monitoring closer to policy and management needs while ensuring adaptability in the face of rapid environmental change. Monitoring changes in areas more exposed to the impacts of core biodiversity drivers will improve the knowledge about the ecological effects of those drivers and the ability to adapt conservation actions in space and time (McCarthy & Possingham 2007; Guisan *et al.* 2013). Still, a substantial development at the three levels described above will require investment in targeted research, which should be prioritized in the development agendas of international organizations related to biodiversity monitoring and conservation. Testing model-based solutions for designing new programmes or assessing and improving existing ones would provide unique opportunities for expanding model-assisted monitoring and integration of satellite and in situ observations.

Data accessibility

Data have not been archived because this article does not contain data.

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