Journal of Applied Ecology

Journal of Applied Ecology 2016, **53,** 1299–1304 doi: 10.1111/1365-2664.12777

EDITORIAL: MODEL-ASSISTED MONITORING OF BIODIVERSITY

Fostering integration between biodiversity monitoring and modelling

João P. Honrado[1,2]*, Henrique M. Pereira[1,3,4] and Antoine Guisan[5,6]

[1]*InBIO - Rede de Investigação em Biodiversidade e Biologia Evolutiva/CIBIO - Centro de Investigação em Biodiversidade e Recursos Genéticos, Universidade do Porto, Campus Agrário de Vairão, 4485-601 Vairão, Portugal;* [2]*Faculdade de Ciências, Universidade do Porto, Rua do Campo Alegre, Edifício FC4, 4169-007 Porto, Portugal;* [3]*German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Deutscher Platz 5e, 04103 Leipzig, Germany;* [4]*Institute of Biology, Martin Luther University Halle-Wittenberg, Am Kirchtor 1, 06108 Halle (Saale), Germany;* [5]*Department of Ecology & Evolution, University of Lausanne, 1015 Lausanne, Switzerland; and* [6]*Institute of Earth Surface Dynamics, University of Lausanne, 1015 Lausanne, Switzerland*

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).

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

*Correspondence author. E-mail: jhonrado@fc.up.pt

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.

References

Akçakaya, H.R., Pereira, H.M., Canziani, G., Mbow, C., Mori, A., Palomo, M.G., Soberon, J., Thuiller, W. & Yachi, S. (2016) Chapter 8: Improving the rigor and usefulness of scenarios and models through ongoing evaluation and refinement. *IPBES Deliverable 3(c): Policy Support Tools and Methodologies for Scenario Analysis and Modelling of Biodiversity and Ecosystem Services* (eds S. Ferrier & K.N. Ninan). IPBES, Bonn.

Amorim, F., Carvalho, S.B., Honrado, J. & Rebelo, H. (2014) Designing optimized multi-species monitoring networks to detect range shifts driven by climate change: a case study with bats in the North of Portugal. *PLoS One*, **9**, e87291.

Araújo, M.B. & New, M. (2007) Ensemble forecasting of species distributions. *Trends in Ecology and Evolution*, **22**, 42–47.

Araújo, M.B., Pearson, R.G., Thuiller, W. & Erhard, M. (2005a) Validation of species-climate impact models under climate change. *Global Change Biology*, **11**, 1504–1513.

Araújo, M.B., Whittaker, R.J., Ladle, R.J. & Erhard, M. (2005b) Reducing uncertainty in projections of extinction risk from climate change. *Global Ecology and Biogeography*, **14**, 529–538.

Barry, S. & Elith, J. (2006) Error and uncertainty in habitat models. *Journal of Applied Ecology*, **43**, 413–423.

Bastos, R., Pinhanços, A., Santos, M., Fernandes, R.F., Vicente, J.R., Morinha, F. *et al.* (2016) Evaluating the regional cumulative impact of wind farms on birds: how can spatially explicit dynamic modelling improve impact assessments and monitoring? *Journal of Applied Ecology*, **53**, 1330–1341.

Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W. & Courchamp, F. (2012) Impacts of climate change on the future of biodiversity. *Ecology Letters*, **15**, 365–377.

Boakes, E.H., McGowan, P.J.K., Fuller, R.A., Chang-qing, D., Clark, N.E., O'Connor, K. & Mace, G.M. (2010) Distorted views of biodiversity: spatial and temporal bias in species occurrence data. *PLoS Biology*, **8**, e1000385.

Brotons, L., Herrando, S. & Pla, M. (2007) Updating bird species distribution at large spatial scales: applications of habitat modelling to data from long-term monitoring programs. *Diversity and Distributions*, **13**, 276–288.

Buisson, L., Thuiller, W., Casajus, N., Lek, S. & Grenouillet, G. (2010) Uncertainty in ensemble forecasting of species distribution. *Global Change Biology*, **16**, 1145–1157.

Carlson, M. & Schmiegelow, F. (2002) Cost-effective sampling design applied to large-scale monitoring of boreal birds. *Conservation Ecology*, **6**, 11.

Carvalho, S.B., Brito, J.C., Pressey, R.L., Crespo, E. & Possingham, H.P. (2010) Simulating the effects of using different types of species distribution data in reserve selection. *Biological Conservation*, **143**, 426–438.

Carvalho, S.B., Brito, J.C., Crespo, E.G., Watts, M.E. & Possingham, H.P. (2011) Conservation planning under climate change: toward accounting for uncertainty in predicted species distributions to increase confidence in conservation investments in space and time. *Biological Conservation*, **144**, 2020–2030.

Carvalho, S.B., Gonçalves, J., Guisan, A. & Honrado, J.P. (2016) Systematic site selection for multispecies monitoring networks. *Journal of Applied Ecology*, **53**, 1305–1316.

Collen, B., Pettorelli, N., Baillie, J.E. & Durant, S.M. (eds) (2013) *Biodiversity Monitoring and Conservation: Bridging the Gap between Global Commitment and Local Action*. John Wiley & Sons, West Sussex, UK.

Couvet, D., Devictor, V., Jiguet, F. & Julliard, R. (2011) Scientific contributions of extensive biodiversity monitoring. *Comptes Rendus Biologies*, **334**, 370–377.

Dornelas, M., Gotelli, N.J., McGill, B., Shimadzu, H., Moyes, F., Sievers, C. & Magurran, A.E. (2014) Assemblage time series reveal biodiversity change but not systematic loss. *Science*, **344**, 296–299.

Edwards, T.C., Cutler, D.R., Zimmermann, N.E., Geiser, L. & Moisen, G.G. (2006) Effects of sample survey design on the accuracy of classification tree models in species distribution models. *Ecological Modelling*, **199**, 132–141.

Elith, J. & Leathwick, J. (2009) The contribution of species distribution modelling to conservation prioritization. *Spatial Conservation Prioritization: Quantitative Methods and Computational Tools* (eds A. Moilanen, K. Wilson & H. Possingham), pp. 70–93. Oxford University Press, Oxford.

Epanchin-Niell, R.S., Brockerhoff, E.G., Kean, J.M. & Turner, J. (2014) Designing cost-efficient surveillance for early detection and control of multiple biological invaders. *Ecological Applications*, **24**, 1258–1274.

Ferrier, S. (2011) Extracting more value from biodiversity change observations through integrated modeling. *BioScience*, **61**, 96–97.

Ferrier, S. & Guisan, A. (2006) Spatial modelling of biodiversity at the community level. *Journal of Applied Ecology*, **43**, 393–404.

Ferrier, S. & Watson, G. (1997) *An Evaluation of the Effectiveness of Environmental Surrogates and Modelling Techniques. Predicting the Distribution of Biological Diversity*. Environment Australia, Canberra.

Ficetola, G.F., Maiorano, L., Falcucci, A., Dendoncker, N., Boitani, L., Padoa-Schioppa, E., Miaud, C. & Thuiller, W. (2010) Knowing the past to predict the future: land-use change and the distribution of invasive bullfrogs. *Global Change Biology*, **16**, 528–537.

Geijzendorffer, I.R., Regan, E.C., Pereira, H.M., Brotons, L., Brummitt, N., Gavish, Y. *et al.* (2016) Bridging the gap between biodiversity data and policy reporting needs: an essential biodiversity variables perspective. *Journal of Applied Ecology*. doi: 10.1111/1365-2664.12417.

GEO BON (2015) *Global Biodiversity Change Indicators: Model-Based Integration of Remote-Sensing & In Situ Observations That Enables Dynamic Updates and Transparency at Low Cost*. GEO BON Secretariat, Leipzig, Germany.

Gonçalves, J., Honrado, J.P., Vicente, J.R. & Civantos, E. (2016) A model-based framework for assessing the vulnerability of low dispersal vertebrates to landscape fragmentation under environmental change. *Ecological Complexity*, doi: 10.1016/j.ecocom.2016.05.003.

Graham, C.H., Ferrier, S., Huettman, F., Moritz, C. & Peterson, A.T. (2004) New developments in museum-based informatics and applications in biodiversity analysis. *Trends in Ecology & Evolution*, **19**, 497–503.

Green, R.E., Balmford, A., Crane, P.R., Mace, G.M., Reynolds, J.D. & Turner, K. (2005) A framework for improved monitoring of biodiversity: responses to the world summit on sustainable development. *Conservation Biology*, **19**, 56–65.

Guillera-Arroita, G., Lahoz-Monfort, J.J., Elith, J., Gordon, A., Kujala, H., Lentini, P.E., McCarthy, M.A., Tingley, R. & Wintle, B.A. (2015) Is my species distribution model fit for purpose? Matching data and models to applications. *Global Ecology and Biogeography*, **24**, 276–292.

Guisan, A. & Theurillat, J.-P. (2005) Appropriate monitoring networks are required for testing model-based scenarios of climate change impact on mountain plant distribution. *Global Change and Mountain Regions, Advances in Global Change Research*, Vol. **23** (eds U. Huber, H.K.M. Bugman & M.A. Reasoner), pp. 467–476. Springer, Zurich, Switzerland.

Guisan, A. & Zimmermann, N.E. (2000) Predictive habitat distribution models in ecology. *Ecological Modelling*, **135**, 147–186.

Guisan, A., Broennimann, O., Engler, R., Vust, M., Yoccoz, N.G., Lehmann, A. & Zimmermann, N.E. (2006) Using niche-based models to improve the sampling of rare species. *Conservation Biology*, **20**, 501–511.

Guisan, A., Tingley, R., Baumgartner, J.B., Naujokaitis-Lewis, I., Sutcliffe, P.R., Tulloch, A.I.T. *et al.* (2013) Predicting species distributions for conservation decisions. *Ecology Letters*, **16**, 1424–1435.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A. *et al.* (2013) High-resolution global maps of 21st-century forest cover change. *Science*, **342**, 850–853.

Hanspach, J., Schweiger, O., Kuhn, I., Plattner, M., Pearman, P.B., Zimmermann, N.E. & Settele, J. (2014) Host plant availability potentially limits butterfly distributions under cold environmental conditions. *Ecography*, **37**, 301–308.

Haughland, D.L., Hero, J.M., Schieck, J., Castley, J.G., Boutin, S., Sólymos, P., Lawson, B.E., Holloway, G. & Magnusson, W.E. (2010) Planning forwards: biodiversity research and monitoring systems for better management. *Trends in Ecology and Evolution*, **25**, 199–200.

He, K.S., Bradley, B.A., Cord, A.F., Rocchini, D., Tuanmu, M.-N., Schmidtlein, S., Turner, W., Wegmann, M. & Pettorelli, N. (2015) Will remote sensing shape the next generation of species distribution models? *Remote Sensing in Ecology and Conservation*, **1**, 4–18.

Hely, C., Bremond, L., Alleaume, S., Smith, B., Sykes, M.T. & Guiot, J. (2006) Sensitivity of African biomes to changes in the precipitation regime. *Global Ecology and Biogeography*, **15**, 258–270.

Hirzel, A. & Guisan, A. (2002) Which is the optimal sampling strategy for habitat suitability modelling? *Ecological Modelling*, **157**, 331–341.

Jetz, W., McPherson, J.M. & Guralnick, R.P. (2012) Integrating biodiversity distribution knowledge: toward a global map of life. *Trends in Ecology & Evolution*, **27**, 151–159.

Jetz, W., Wilcove, D.S. & Dobson, A.P. (2007) Projected impacts of climate and land-use change on the global diversity of birds. *PLoS Biology*, **5**, e157.

Keil, P., Belmaker, J., Wilson, A.M., Unitt, P. & Jetz, W. (2013) Downscaling of species distribution models: a hierarchical approach. *Methods in Ecology and Evolution*, **4**, 82–94.

Kerr, J.T. & Dobrowski, S.Z. (2013) Predicting the impacts of global change on species, communities and ecosystems: it takes time. *Global Ecology and Biogeography*, **22**, 261–263.

Kery, M., Gardner, B. & Monnerat, C. (2010) Predicting species distributions from checklist data using site-occupancy models. *Journal of Biogeography*, **37**, 1851–1862.

Kery, M. & Schmid, H. (2004) Monitoring programs need to take into account imperfect species detectability. *Basic and Applied Ecology*, **5**, 65–73.

Kuemmerlen, M., Stoll, S., Sundermann, A. & Haase, P. (2016) Long-term monitoring data meet freshwater species distribution models: lessons from an LTER-site. *Ecological Indicators*, **65**, 122–132.

Le Lay, G., Engler, R., Franc, E. & Guisan, A. (2010) Prospective sampling based on model ensembles improves the detection of rare species. *Ecography*, **33**, 1015–1027.

Levrel, H., Fontaine, B., Henry, P.Y., Jiguet, F., Julliard, R., Kerbiriou, C. & Couvet, D. (2010) Balancing state and volunteer investment in biodiversity monitoring for the implementation of CBD indicators: a French example. *Ecological Economics*, **69**, 1580–1586.

Lindenmayer, D.B. & Likens, G.E. (2009) Adaptive monitoring: a new paradigm for long-term research and monitoring. *Trends in Ecology & Evolution*, **24**, 482–486.

Lindenmayer, D.B., Gibbons, P., Bourke, M., Burgman, M., Dickman, C.R., Ferrier, S. *et al.* (2012) Improving biodiversity monitoring. *Austral Ecology*, **37**, 285–294.

Manceur, A.M. & Kuhn, I. (2014) Inferring model-based probability of occurrence from preferentially sampled data with uncertain absences using expert knowledge. *Methods in Ecology and Evolution*, **5**, 739–750.

Martin, J., Kitchens, W.M. & Hines, J.E. (2007) Importance of well-designed monitoring programs for the conservation of endangered species: case study of the snail kite. *Conservation Biology*, **21**, 472–481.

McCarthy, M.A. & Possingham, H.P. (2007) Active adaptive management for conservation. *Conservation Biology*, **21**, 956–963.

McGill, B.J. (2003) A test of the unified neutral theory of biodiversity. *Nature*, **422**, 881–885.

Metzger, M.J., Brus, D.J., Bunce, R.G.H., Carey, P.D., Gonçalves, J., Honrado, J.P., Jongman, R.H.G., Trabucco, A. & Zomer, R. (2013) Environmental stratifications as the basis for national, European and global ecological monitoring. *Ecological Indicators*, **33**, 26–35.

Meyer, C., Kreft, H., Guralnick, R. & Jetz, W. (2015) Global priorities for an effective information basis of biodiversity distributions. *Nature Communications*, **6**, 8221.

Miller-Rushing, A., Primack, R. & Bonney, R. (2012) The history of public participation in ecological research. *Frontiers in Ecology and the Environment*, **10**, 285–290.

Moilanen, A., Runge, M.C., Elith, J., Tyre, A., Carmel, Y., Fegraus, E., Wintle, B.A., Burgman, M. & Ben-Haim, Y. (2006) Planning for robust reserve networks using uncertainty analysis. *Ecological Modelling*, **199**, 115–124.

Mouquet, N., Lagadeuc, Y., Devictor, V., Doyen, L., Duputié, A., Eveillard, D. *et al.* (2015) Predictive ecology in a changing world. *Journal of Applied Ecology*, **52**, 1293–1310.

Naujokaitis-Lewis, I.R., Curtis, J.M.R., Tischendorf, L., Badzinski, D., Lindsay, K. & Fortin, M.-J. (2013) Uncertainties in coupled species distribution–metapopulation dynamics models for risk assessments under climate change. *Diversity and Distributions*, **19**, 541–554.

Nichols, J.D. & Williams, B.K. (2006) Monitoring for conservation. *Trends in Ecology & Evolution*, **21**, 668–673.

Nobis, M.P., Jaeger, J.A.G. & Zimmermann, N.E. (2009) Neophyte species richness at the landscape scale under urban sprawl and climate warming. *Diversity and Distributions*, **15**, 928–939.

Pearman, P.B., Guisan, A. & Zimmermann, N.E. (2011) Impacts of climate change on Swiss biodiversity: an indicator taxa approach. *Biological Conservation*, **144**, 866–875.

Pearman, P.B. & Weber, D. (2007) Common species determine richness patterns in biodiversity indicator taxa. *Biological Conservation*, **138**, 109–119.

Pearman, P.B., Zimmermann, N.E., Guisan, A., Psomas, A. & Schmatz, D. (2014) Impacts on the biodiversty of widely distributed birds and vascular plants: species richness and turnover. *CH2014-Impacts (2014), Toward Quantitative Scenarios of Climate Change Impacts in Switzerland* (eds C.C. Raible & K.M. Strassman), pp. 69–78. OCCR, FOEN, MeteoSwiss, C2SM, Agroscope, ProClim, Bern, Switzerland.

Pearson, R.G., Thuiller, W., Araújo, M.B., Martinez-Meyer, E., Brotons, L., Mcclean, C. *et al.* (2006) Model-based uncertainty in species range prediction. *Journal of Biogeography*, **33**, 1704–1711.

Pereira, H.M. & Cooper, H.D. (2006) Towards the global monitoring of biodiversity change. *Trends in Ecology & Evolution*, **21**, 123–129.

Pereira, H.M., Navarro, L.M. & Martins, I.S. (2012) Global biodiversity change: the bad, the good, and the unknown. *Annual Review of Environment and Resources*, **37**, 25–50.

Pereira, H.M., Leadley, P.W., Proença, V., Alkemade, R., Scharlemann, J.P.W., Fernandez-Manjarres, J.F. *et al.* (2010a) Scenarios for global biodiversity in the 21st century. *Science*, **330**, 1496–1502.

Pereira, H.M., Belnap, J., Brummitt, N., Collen, B., Ding, H., Gonzalez-Espinosa, M. *et al.* (2010b) Global biodiversity monitoring. *Frontiers in Ecology and the Environment*, **8**, 459–460.

Pereira, H.M., Ferrier, S., Walters, M., Geller, G.N., Jongman, R.H.G., Scholes, R.J. *et al.* (2013) Essential biodiversity variables. *Science*, **339**, 277–278.

Peterson, A.T. (2001) Predicting species' geographic distributions based on ecological niche modeling. *Condor*, **103**, 599–605.

Petitpierre, B., Kueffer, C., Broennimann, O., Randin, C., Daehler, C. & Guisan, A. (2012) Climatic niche shifts are rare among terrestrial plant invaders. *Science*, **335**, 1344–1348.

Petitpierre, B., McDougall, K., Seipel, T., Broennimann, O., Guisan, A. & Kueffer, C. (2016) Will climate change increase the risk of plant invasions into mountains? *Ecological Applications*, **26**, 530–544.

Pettorelli, N., Laurance, W.F., O'Brien, T.G., Wegmann, M., Nagendra, H. & Turner, W. (2014) Satellite remote sensing for applied ecologists: opportunities and challenges. *Journal of Applied Ecology*, **51**, 839–848.

Pettorelli, N., Wegmann, M., Skidmore, A., Mücher, S., Dawson, T.P., Fernandez, M. *et al.* (2016) Framing the concept of satellite remote sensing essential biodiversity variables: challenges and future directions. *Remote Sensing in Ecology and Conservation*. doi: 10.1002/rse2.15.

Phillips, S.J., Dudik, M., Elith, J., Graham, C.H., Lehmann, A., Leathwick, J. & Ferrier, S. (2009) Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. *Ecological Applications*, **19**, 181–197.

Proença, V., Martin, L.J., Pereira, H.M., Fernandez, M., McRae, L., Belnap, J. *et al.* (2016) Global biodiversity monitoring: from data sources to essential biodiversity variables. *Biological Conservation*. doi: 10.1016/j.biocon.2016.07.014.

Rota, C.T., Fletcher, R.J., Evans, J.M. & Hutto, R.L. (2011) Does accounting for imperfect detection improve species distribution models? *Ecography*, **34**, 659–670.

Schipper, A.M., Belmaker, J., de Miranda, M.D., Navarro, L.M., Böhning-Gaese, K., Costello, M.J. *et al.* (2016) Contrasting changes in the abundance and diversity of North American bird assemblages from 1971 to 2010. *Global Change Biology*. doi: 10.1111/gcb.13292.

Scholes, R.J., Walters, M., Turak, E., Saarenmaa, H., Heip, C.H.R., Tuama, É.Ó. *et al.* (2012) Building a global observing system for biodiversity. *Current Opinion in Environmental Sustainability*, **4**, 139–146.

Skidmore, A.K., Pettorelli, N., Coops, N.C., Geller, G.N., Hansen, M., Lucas, R. *et al.* (2015) Agree on biodiversity metrics to track from space. *Nature*, **523**, 403–405.

van Strien, A.J., van Swaay, C.A.M. & Termaat, T. (2013) Opportunistic citizen science data of animal species produce reliable estimates of distribution trends if analysed with occupancy models. *Journal of Applied Ecology*, **50**, 1450–1458.

Tuanmu, M.N., Vina, A., Roloff, G.J., Liu, W., Ouyang, Z.Y., Zhang, H.M. & Liu, J.G. (2011) Temporal transferability of wildlife habitat models: implications for habitat monitoring. *Journal of Biogeography*, **38**, 1510–1523.

Vaz, A.S., Marcos, B., Goncalves, J., Monteiro, A., Alves, P., Civantos, E. *et al.* (2015) Can we predict habitat quality from space? A multi-indicator assessment based on an automated knowledge-driven system. *International Journal of Applied Earth Observation and Geoinformation*, **37**, 106–113.

Vicente, J., Randin, C.F., Goncalves, J., Metzger, M.J., Lomba, A., Honrado, J. & Guisan, A. (2011) Where will conflicts between alien and rare species occur after climate and land-use change? A test with a novel combined modelling approach. *Biological Invasions*, **13**, 1209–1227.

Vicente, J., Alagador, D., Guerra, C., Alonso, J.M., Kueffer, C., Vaz, A.S. *et al.* (2016) Cost-effective monitoring of biological invasions under global change: a model-based framework. *Journal of Applied Ecology*, **53**, 1317–1329.

Visconti, P., Pressey, R.L., Giorgini, D., Maiorano, L., Bakkenes, M., Boitani, L. *et al.* (2011) Future hotspots of terrestrial mammal loss. *Philosophical Transactions of the Royal Society B: Biological Sciences*, **366**, 2693–2702.

Weber, D., Hintermann, U. & Zangger, A. (2004) Scale and trends in species richness: considerations for monitoring biological diversity for political purposes. *Global Ecology and Biogeography*, **13**, 97–104.

Zielinski, W.J. & Stauffer, H.B. (1996) Monitoring Martes populations in California: survey design and power analysis. *Ecological Applications*, **6**, 1254–1267.