International Journal of Applied Earth Observation and Geoinformation 57 (2017) 86–92

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Potential of satellite-derived ecosystem functional attributes to anticipate species range shifts

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ARTICLE INFO

Article history:
Received 22 July 2016
Accepted 14 December 2016
Available online 29 December 2016

Keywords:
Climate change
Enhanced vegetation index
Essential biodiversity variables
Iberian Peninsula
Interannual variability
Multi-species monitoring
Species distribution models
Threatened plants

ABSTRACT

In a world facing rapid environmental changes, anticipating their impacts on biodiversity is of utmost relevance. Remotely-sensed Ecosystem Functional Attributes (EFAs) are promising predictors for Species Distribution Models (SDMs) by offering an early and integrative response of vegetation performance to environmental drivers. Species of high conservation concern would benefit the most from a better ability to anticipate changes in habitat suitability. Here we illustrate how yearly projections from SDMs based on EFAs could reveal short-term changes in potential habitat suitability, anticipating mid-term shifts predicted by climate-change-scenario models. We fitted two sets of SDMs for 41 plant species of conservation concern in the Iberian Peninsula: one calibrated with climate variables for baseline conditions and projected under two climate-change-scenarios (future conditions); and the other calibrated with EFAs for 2001 and projected annually from 2001 to 2013. Range shifts predicted by climate-based models for future conditions were compared to the 2001–2013 trends from EFAs-based models. Projections of EFAs-based models estimated changes (mostly contractions) in habitat suitability that anticipated, for the majority (up to 64%) of species, the mid-term shifts projected by traditional climate-change-scenario forecasting, and showed greater agreement with the business-as-usual scenario than with the sustainable-development one. This study shows how satellite-derived EFAs can be used as meaningful essential biodiversity variables in SDMs to provide early-warnings of range shifts and predictions of short-term fluctuations in suitable conditions for multiple species.

1. Introduction

In a world facing rapid environmental changes, anticipating impacts of climate and habitat change on biodiversity, particularly on threatened species, is of utmost relevance for monitoring and conservation (Guisan, 2014). Hence, effectively predicting the spatiotemporal patterns of change to anticipate the vulnerability of species and ecosystems have become a quest for scientists and managers, and thereby a hot topic in ecological research (Dawson et al., 2011). Currently, the increasing availability of remote sensing data offers a great potential for biodiversity assessment and monitoring (Nagendra et al., 2013; Pettorelli et al., 2016). In particular, the inclusion of satellite-derived descriptors of ecosystem functioning in Species Distribution Models (SDMs) is gaining interest (Cabello et al., 2012; Nagendra et al., 2013; He et al., 2015; Rocchini et al., 2015).

Remote sensing can provide meaningful information on species distributions through the direct detection of large species, the mapping of land-cover classes linked to species habitats, and the provision of biophysical descriptors of ecosystem functioning (Parviainen et al., 2013; He et al., 2015; Requena-Mullor et al., 2014). The latter are known as Ecosystem Functional Attributes

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http://dx.doi.org/10.1016/j.jag.2016.12.009
1569-8432/

(EFAs) and describe the exchanges of matter and energy between the biota and the physical environment including, among others, indicators of productivity, seasonality, and phenology of carbon gains (Alcaraz-Segura et al., 2006, 2009). The use of satellite-derived EFAs as predictor variables in SDMs has several advantages. First, EFAs offer an integrative response to environmental drivers and changes (Nagendra et al., 2013; Vaz et al., 2015), so species responses can be linked to pressures on ecosystem functioning and status (Pettorelli et al., 2005). Second, EFAs can be monitored through remote sensing (Alcaraz-Segura et al., 2006) and derived globally under common protocols at relatively high temporal and spatial resolutions (e.g. Tuanmu and Jetz 2015). Third, EFAs show a quicker response to environmental changes than structural or compositional attributes (e.g. land-cover, species richness; Mouillot et al., 2013), potentially allowing, when used as inputs in SDMs, to anticipate and provide early-warnings of future potential changes in species distributions. Fourth, with remotely sensed EFAs, both spatial and temporal (seasonal and interannual) variability can be easily included into SDMs (e.g. Tuanmu and Jetz, 2015), which has been shown to improve SDMs performance, compared to average conditions (Zimmermann et al., 2009; Fernández et al., 2012; Cord et al., 2014).

Based on the niche concept, both fundamental and realized (Araújo and Peterson, 2012), SDMs are often used to project habitat suitability and range change of species under different future scenarios of environmental conditions (Oliver et al., 2012). Climate-only-driven SDMs have been shown to provide better estimates for widely distributed species (Stockwell and Peterson, 2002), whereas for narrowly distributed species (usually rare and threatened) multiple predictors often become necessary (Lomba et al., 2010). Biodiversity monitoring and conservation can benefit from SDMs techniques (e.g. Amorim et al., 2014; Carvalho et al., 2016), but this requires models that can adequately predict potential future distributions or habitat suitability, particularly for rare and threatened species (Lomba et al., 2010; Sousa-Silva et al., 2014). Frequently, law protects these species of conservation interest and countries are subject to reporting obligations on their conservation status, trends and threats. An example of this is the Habitats Directive, a European legal framework aiming to promote the maintenance of species and habitats at a favorable conservation status (Bilz et al., 2011; Sousa-Silva et al., 2014). These assessments often include evaluations of forecasted species range shifts considering contrasting climate change scenarios. In addition, monitoring and early-warning systems often assess historical trends in the distribution of species and habitats, which may help to anticipate range changes and extinction risks (Virkkala et al., 2014).

The monitoring, management, and conservation of species of high conservation concern would benefit the most from a better capacity to anticipate the ecological effects of environmental variability. Since satellite observations can be used to derive EFAs annually (Müller et al., 2014), rates of change in habitat suitability derived from EFAs could be used as trends in the inferred distributions of species. Regions experiencing extreme interannual changes in EFAs can be considered more prone to showing fluctuations in habitat suitability, and therefore in population size, extent of occurrence, or area of occupancy (International Union for Conservation of Nature –IUCN– criteria B and C; IUCN 2012). Furthermore, in the European context, applying interannual changes of EFAs to estimate fluctuations in habitat suitability can be used to report on the conservation status of species of interest, which is required every six years under the Habitats Directive (European Commission, 1992). A comprehensive assessment of the potential effects of interannual changes of EFAs on multiple species can also be used to set priorities in multi-species monitoring schemes (Amorim et al., 2014; Carvalho et al., 2016).

Here we test the potential added value of using satellite-derived EFAs as input in SDMs to anticipate range shifts for a diverse set of plant species of conservation concern, covering different IUCN categories, range sizes, life-forms and habitats in the Iberian Peninsula. We illustrate how the annual frequency of EFAs reveals short-term changes in suitable conditions that could be used to anticipate mid-term shifts predicted by traditional climate-change-scenario models, and hence to improve biodiversity monitoring and management. SDMs fitted with EFAs were projected annually using remote-sensing observations, and SDMs fitted with climate variables were projected to two future contrasting scenarios of climate change: business as usual and sustainable-development. Since CO_2 emissions remained in the upper bound of emissions scenarios (Friedlingstein et al., 2014), we expected that changes in suitable habitat using remote-sensing observations should be closer to mid-term projected changes following a business as usual climate change scenario than a sustainable-development one. We discuss our results in the context of improving the conservation of biodiversity under environmental changes and the monitoring of ecosystem function essential biodiversity variables that are meaningful at the species level (Pettorelli et al., 2016).

2. Materials and methods

2.1. Study area and test species

The study area was the Iberian Peninsula, a very heterogeneous region in terms of biogeography, climate, orography, geology, and soil types. Such heterogeneity, its role as a Quaternary refuge, and the crossroad situation between Europe and Africa, the Mediterranean Sea and the Atlantic Ocean, have favored a unique environmental mosaic where many species with different ecological requirements coexist (Molina-Venegas et al., 2013), making this area a hotspot within the Mediterranean Basin biodiversity hotspot (Essl et al., 2013).

Our study targeted 41 plant species that are assessed due to legal obligations from the European Union Habitats Directive (Annexes II and IV), listed under the IUCN European Red List of Vascular Plants (Bilz et al., 2011) and Spanish Red List (Bañares et al., 2011). Datasets on species occurrences were available from ICNF (Portuguese Institute for the Conservation of Nature and Forests) and from the *Inventario Español de Especies Terrestres* (Spanish Ministry for the Environment), complemented with confirmed records from the ANTHOS (www.anthos.es) and FLORA-ON (www.flora-on.pt) online databases. The spatial resolution of the final dataset was the UTM 10′ × 10 km cell grid (6212 cells in the Peninsula), in agreement with the resolution required by Article 17th of the Habitats Directive for reporting (http://bd.eionet.europa.eu/activities/Reporting). As rule of thumb, a minimum of 5 occurrence records per predictor variable was considered for selecting species suitable for fitting SDMs (see section 2.2 Predictor variables; Araújo and Peterson, 2012). Accordingly, 41 plant species were selected under different IUCN (2012) categories (Table S1 in Supporting Information). The IUCN status was obtained from the European (Bilz et al., 2011) and national Red Lists (Bañares et al., 2011). For species with transboundary distribution across Portugal and Spain, expert-knowledge supported the assignment of an Iberian IUCN category by applying the relevant IUCN criteria (current status and recent trends) to the most-updated occurrence data across the Peninsula.

2.2. Predictor variables and future scenarios

Three climatic variables were selected due to their well-known role as drivers of species distributions at broader scales (e.g. Whittaker et al., 2007): annual precipitation (Prec), maximum temperature of the hottest month (Tmax), and minimum temperature of the coldest month (Tmin). Climatic data defined as 'baseline conditions' were available from the IBERIA CHANGE project, and were computed from monthly data available from Portuguese and Spanish meteorological stations for temperature and precipitation for the period between 1960 and 1990, and interpolated for the whole Iberian Peninsula to a regular grid of $10' \times 10$ (Araújo et al., 2011a). Climate change scenarios ('future scenarios' for simplification) were available from the ALARM project, downscaled for the Iberian Peninsula from the AOGCM climate models (Fronzek et al., 2012), and considered to reflect average climatic conditions for the period 2021–2050. The year 2020, at the beginning of the 'future scenarios' period, is coincident with both the Aichi Biodiversity Targets and the end of the current (mandatory) reporting cycle for protected species under the Habitats Directive. Two 'future scenarios' that reflect contrasting storylines (Fronzek et al., 2012) were considered: BAMBU (Business-As-Might-Be-Usual; corresponding to A2 SRES) and SEDG (Sustainable-European-Development-Goal; corresponding to B1 SRES). BAMBU extrapolates a sustained greenhouse gases emissions under the currently known and foreseeable socio-economic and policy trajectories in EU decision-making, whereas SEDG assumes a strong shift towards more environmentally, socially and economically sustainable development. With CO_2 emissions following the upper bound of climate change scenarios during the last decades (Friedlingstein et al., 2014), changes in habitat suitability based on remote sensing observations (see below) should exhibit greater agreement with mid-term projections based on BAMBU than on SEDG. All climatic information (both baseline and future conditions) was resampled from the initial resolution to the UTM10×10 km grid.

For SDMs that considered the effect of interannual changes of ecosystem functioning on species distributions, EFAs were derived from satellite images of the Enhanced Vegetation Index (EVI) obtained by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. The MOD13C2 product consists of monthly global images at a spatial resolution of $0.05^\circ \times 0.05^\circ$. Thirteen years were used (2001–2013), covering two thirds of the period between the baseline and the beginning of the climate projections (2001–2020). Three independent metrics of the EVI seasonal dynamics were calculated for each year, capturing most of the variability in time-series of vegetation indices in the Iberian Peninsula (Alcaraz-Segura et al., 2006, 2009): EVI annual mean (EVI_Mean); EVI seasonal coefficient of variation (EVI_sCV); and the date of the maximum EVI value (DMAX). EVI_Mean is a linear estimator of annual primary production, one of the most integrative descriptors of ecosystem functioning (Virginia and Wall, 2001); EVI_sCV is a descriptor of the differences in carbon gains between seasons; and DMAX is a phenological indicator of the growing season (Pettorelli et al., 2005). These EFAs were fed into SDMs at coarse resolution for the sake of comparability with climate-based SDMs, and because EFAs constitute an integrative proxy for multiple environmental drivers that might operate at this scale as well (Alcaraz-Segura et al., 2009).

2.3. Modeling framework

To compare predictions of species responses to environmental change, two sets of SDMs were fitted: one set based on climate predictors, and another set based on satellite-derived EFAs. Climatic models were calibrated for the baseline and projected to future conditions. EFAs models were calibrated for 2001, and the resulting model was projected yearly from 2001 to 2013.

Models were fitted using the biomod2 package (Thuiller et al., 2009) in R 3.1.0 software (R Development-Core-Team 2014), which allows calibrating 10 state-of-the-art modelling techniques in an ensemble forecast framework (e.g. Thuiller et al., 2009). All 10 available techniques were implemented for each set of models using default parameters. Due to the lack of absence data, 1000 pseudo-absences were randomly selected (following the recommendations of Barbet-Massin et al., 2012). The predictive performance of the models was assessed by dividing the species datasets into two subsets: 80% of the records (i.e. presences and pseudo-absences) were used for model calibration, and 20% for model evaluation (e.g. Araújo et al., 2011b). To control for uncertainty due to random selection of pseudo-absences and of calibration/evaluation datasets, five different sets of pseudo-absences were used for each species and the whole process was repeated 10 times. Model accuracy was measured as the Area Under the Curve (AUC), ranging between 0 and 1, since it is threshold independent and considers both the false-positive and the true-positive error rates (Elith et al., 2006).

For each species and set of SDMs, the resulting models were combined in an ensemble-forecasting framework following Araújo and New (2007). The ensemble was built in biomod2 based on all techniques (provided that AUC > 0.7) and giving higher importance (weight) to models with better performance. Thus, AUC was the metric implemented for excluding models with lower scores, for the binary transformations of model predictions, and for building the ensemble predictions. Significant differences in model performance between sets of models, and in habitat suitability changes across IUCN categories, were tested using the Mann–Whitney test, and expressed as median ± interquartile range.

2.4. Comparison of changes in habitat suitability

To compare trends from EFAs-based SDMs and projections from climate-based SDMs, we proceeded as follows. First, changes in habitat suitability were calculated from the climate-based SDMs between the baseline and future conditions, and from the EFAs-based models on a yearly basis between 2001 and 2013. Changes in the extent of suitable habitat indicate shifts between baseline and future habitat suitability for the species, and reflect the balance between gains (i.e. percentage of new sites considering the species' baseline distribution) and losses (i.e. percentage of baseline occupied sites to be lost). Second, we evaluated whether EFAs-based models along the 2001–2013 period could anticipate mid-term changes in the extent of suitable habitat expected from climate change scenarios and whether such agreement was greater for the BAMBU than for the SEDG scenario. For this, the agreement of contractions and expansions between both approaches was calculated. The resulting agreement matrix also constitutes an assessment, based on two independent sources of information, of the future trends that the 41 Iberian plant species of conservation concern might be facing. Interannual fluctuations in habitat suitability were also assessed as the 3-year standard deviation.

3. Results

3.1. Model performance

Overall, climate- and EFAs-based models exhibited very good performance regarding both AUCs and sensitivity: EFAs-based models showed high AUC values (0.96 ± 0.061), though performance was slightly higher for climate-based models (0.98 ± 0.035; $p < 0.05$; n = 41). Similarly, sensitivity was significantly higher for climate-based models (97.62 ± 4.054) but also high for EFAs-based models (91.67 ± 10.22; $p < 0.05$; n = 41).

3.2. Short-term fluctuations in habitat suitability from EFAs-based models (2001–2013)

According to EFAs-based models, most species presented persistent contractions in habitat suitability along the 2001–2013 period

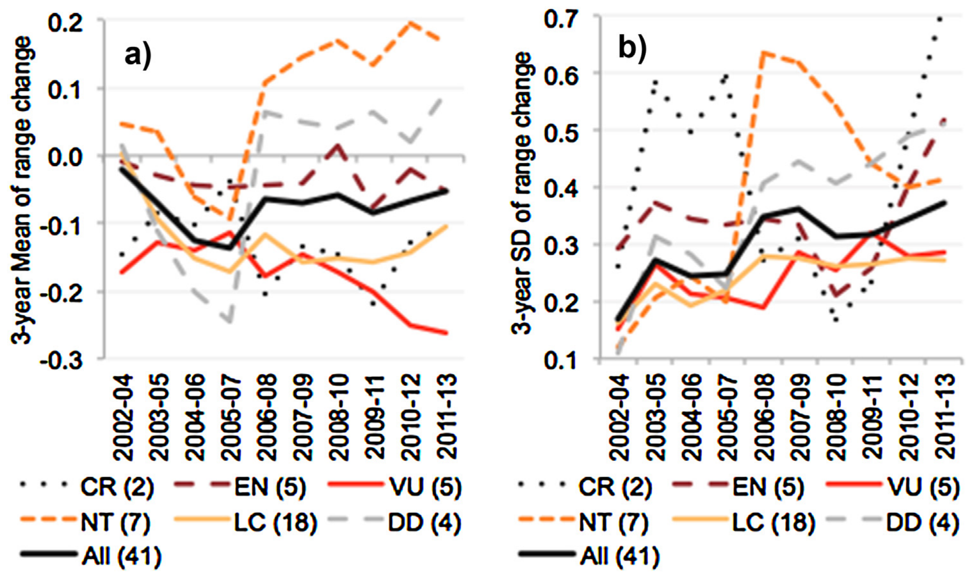

Fig. 1. Persistent range contractions (a) and increase of interannual fluctuations (b) in range change along the 2001–2013 period estimated by models fit with satellite-derived Ecosystem Functional Attributes for 41 plant species of conservation concern. A 3-year moving window was used to calculate mean and standard deviation (SD) on the annual range changes with respect to 2001. Lines represent the mean across the species in each IUCN (2012) category and black solid line represents the mean across all species. Brackets contain the number of species. CR: Critical risk, EN: Endangered, VU: Vulnerable, NT: Near threatened, LC: Least concern, DD: Data deficient.

(Fig. 1a; see also Fig. S1). Vulnerable (VU) species showed significant interannual trends towards contractions (slope = −0.01; $R^2 = 0.61$; $p < 0.05$; n = 10), whereas Near Threatened (NT) and Data Deficient (DD) species showed contractions up to 2005 but then displayed a persistent expansion (Fig. 1a).

Overall, interannual fluctuations in habitat suitability (black line in Fig. 1b), increased along the 2001–2013 period (average slope = 0.02; $R^2 = 0.69$; $p < 0.01$; n = 10). In particular, the 3-year standard deviation of habitat suitability change significantly increased ($p < 0.05$; n = 10) for DD (slope = 0.04, $R^2 = 0.80$), LC (slope = 0.01; $R^2 = 0.67$), and VU species (slope = 0.01; $R^2 = 0.52$; Fig. 1b).

3.3. Agreement between predictions from climate- and EFAs-based models

Range contractions were consistently predicted under the two climate change scenarios for 46% of the species, while expansions were consistently predicted for 24% of the species. The total agreement between scenarios was 70%.

The projection of EFAs-based models from 2001 to 2013 estimated interannual changes in habitat suitability (Figs. 1a and S1) that anticipated the mid-term shifts projected under future conditions (2021–2050) for the majority of species by traditional climate-change-scenario forecasting (Fig. 2a). Range changes forecast by the business as usual (BAMBU) climate change scenario agreed with short-term changes in habitat suitability from EFAs-based models for 64% of the species, with 49% showing contractions and 15% expansions (Fig. 2a). The agreement with the sustainable development scenario (SEDG) was lower: 54% of the species (44% contractions and 10% expansions). This higher agreement with the business as usual (BAMBU) scenario was observed across IUCN categories (Fig. 2b). The DD category showed the highest uncertainty in habitat suitability changes, with 3 out of 4 showing disagreement across sets of models.

4. Discussion

4.1. Performance of models based on satellite-derived EFAs

Remote-sensing variables showed slightly less predictive power than climate variables, as previously found (Zimmermann et al., 2007; Buermann et al., 2008); however, EFAs-based models were similarly accurate (median and average AUC > 0.9). This high accuracy and the advantage of the interannual variations in EFAs strongly support their use for monitoring habitat suitability and assist conservation and monitoring actions (Elith et al., 2006). Moreover, satellite descriptors of ecosystem functioning provide an integrative response not only to changes in climate, but also to other environmental drivers, from land use and management to soil properties (Alcaraz-Segura et al., 2006; Vaz et al., 2015). In this study, we only used descriptors of primary production, seasonality and phenology of carbon gains, yet other satellite-derived descriptors of ecosystem functioning can be included, e.g. surface temperature, albedo, evapotranspiration, or soil moisture (Cabello et al., 2012).

The combination of remote sensing and climate variables has been shown to improve model performance compared to only-climate variables (Zimmermann et al., 2007, 2009; Buermann et al., 2008; Saatchi et al., 2008). In fact, satellite-derived EFAs can inform about areas with suitable climate but with locally unsuitable habitat that are impossible to detect with climate variables only (Vaz et al., 2015), thus providing more refined predictions of species potential distribution (Vicente et al., 2011). However, the combined use of EFAs and climate variables in SDMs to monitor suitable habitat is limited by the unavailability of updated climate interpolated-surfaces at temporal resolutions that are most relevant for species monitoring and management (typically seasonal to annual). In addition, remote sensing EFAs could be preferred over climate interpolated-surfaces in regions with sparse meteorological station data (Deblauwe et al., 2016). Similarly, the availability of finer spatial resolution EFAs (e.g., MODIS at ∼250 m and LANDSAT at ∼30 m) provides an additional advantage for detailed assessments of threatened species or habitat quality within a protected area (Vaz et al., 2015). Thus, a framework for

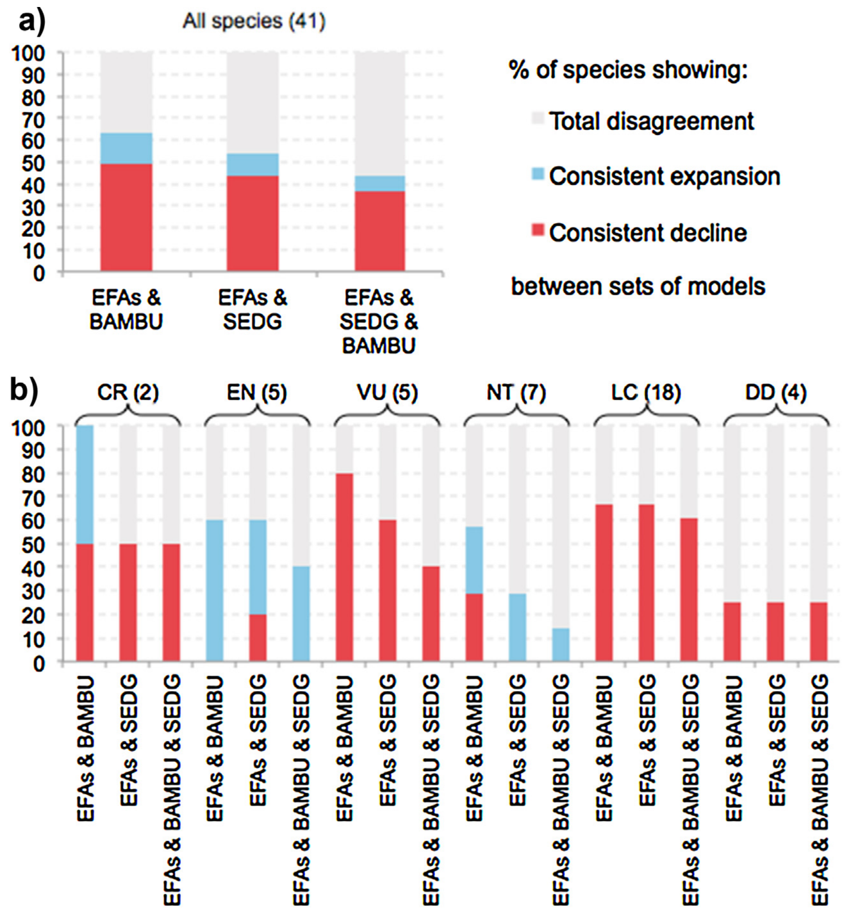

Fig. 2. Agreement between the average short-term range changes for the 2001–2013 period forecast by models fit with satellite-derived Ecosystem Functional Attributes (EFAs) and the expected mid-term range changes between 2001 and 2021–2050 forecast by models fit only with climate variables under two climate change scenarios: BAMBU (Business-As-Might-Be-Usual) and SEDG (Sustainable European Development Goal). Consistency (greater for BAMBU than for SEDG) is expressed as the percentage of (a) all 41 plant species of conservation concern that exhibited similar range changes across the different models, and (b) differentiated by IUCN category. CR: Critical risk, EN: Endangered, VU: Vulnerable, NT: Near threatened, LC: Least concern, DD: Data deficient.

designing monitoring schemes for focal species and for species-level essential biodiversity variables (Pettorelli et al., 2016) based on high-resolution remotely-sensed descriptors of ecosystem functioning would allow to overcome current constraints from climate interpolated-surfaces.

4.2. Annual EFAs for early-warning of biodiversity change

EFAs-based models were found to excel at modelling protected species distributions and, most importantly, annual evaluations of changes in habitat suitability offered early-warning of mid-term changes predicted from traditional climate-change-scenario forecasting, especially under a business as usual scenario (Fig. 2). Our results are encouraging and further support the use of annual descriptors of ecosystem functioning (i.e., EFAs) for implementing species monitoring programs (Cabello et al., 2012), given their advantage to provide a faster response than structural or compositional features to environmental changes (Mouillot et al., 2013). The large agreement of forecasts between EFAs- and climate-based models reflects that they capture similar environmental dynamics, but with EFAs incorporating information further than climate. As expected from the actual trends in CO_2 emissions and climate conditions in the upper bound of emissions scenarios (Friedlingstein et al., 2014), agreement was greater for the business as usual (BAMBU) scenario than for the alternative sustainable development (SEDG) one.

However, for 11 out of 41 species (27%), the predicted changes were consistently opposite between EFAs- and climate-models under both climate scenarios. This lack of total agreement should be expected since the period evaluated with EFAs (2001–2013) was still way ahead the 'future scenario' (2021–2050). This disagreement can also be related to differences in model accuracy (<10% in our case) or in species ecology. For instance, in the case of *Scrophularia grandiflora* DC., a narrow endemic megaforb from central Portugal, climate- and EFAs-based models were equally accurate (0.996 and 0.999 AUC respectively), but both climate scenarios forecast expansion under future conditions, whereas EFAs models estimated contraction of suitable habitat during the 2001–2013 period. This species finds suitable habitat on disturbed land such as woodland and cropland fringes or road edges (Ortega-Olivencia, 2009). Though climate change may be expected to expand its bioclimatic potential distribution, a local decrease of suitable habitats, e.g. following land-use intensification, conversion and/or abandonment, could produce an opposite result. In this sense, EFAs models are more likely to capture these changes associated with land-use dynamics, which is a key predictor of biodiversity patterns in the Iberian Peninsula (Martins et al., 2014).

Finally, models based on annually derived EFAs showed an increase in interannual variability of habitat suitability for most species (mainly VU, LC, and DD species) along the 2001–2013 period. This information is particularly useful to set priorities, since climate change is expected to increase climate variability and extremes (Thornton et al., 2014) and threatened species are especially sensitive to interannual fluctuations, given their small population sizes, narrow distribution ranges and small number (and often high isolation) of populations (Lomba et al., 2010). When interannual variability is very high, species may not be able to survive during adverse years, or to compensate in good years the losses during adverse ones. Hence, interannual variability, in addition to means, clearly affects range limits and its dynamics (Zimmermann et al., 2009).

In any case, monitoring programs should consider that both EFAs- and climate-based models are affected by known limitations and uncertainties of SDMs to anticipate species shifts (e.g. Araújo and Peterson, 2012): e.g., truncated niches, no-analogue future conditions, and missing important predictors or biotic interactions. In addition, further research is needed to evolve from the cumulative effect of interannual directional changes in suitable conditions towards mid-term species range shifts, further enhancing their usefulness for adaptive, model-assisted biodiversity monitoring (Carvalho et al., 2016).

Overall, our results show how SDMs driven by satellite-derived EFAs can support and improve multi-species monitoring and the assessment of species-level meaningful essential biodiversity variables related to ecosystem function (Pettorelli et al., 2016). The advantage of having EFAs at annual time frames allowed us to estimate short-term changes in habitat suitability that showed better agreement with a business as usual climate change scenario than with a sustainable development one. These findings sustain general guidelines on how SDMs driven by EFAs can be used to improve monitoring schemes towards anticipation of range shifts for multiple protected species. Special attention should be put on threatened species for which declines are predicted by both EFAs-based and climate-based SDMs.

Acknowledgements

Lomba to SYNTHESYS Project (ES-TAF-2669) under the FP7 "Capacities" Program at MNCN-CSIC, and to FCT grant SFRH/BPD/80747/2011. Alcaraz-Segura to the Spanish MINECO (grant JC2015-00316 and projects CGL2014-61610-EXP and CGL2010-22314), and to ERDF and Andalusian Government (projects GLOCHARID, RNM-7033, and P09-RNM-5048). Sousa-Silva to Belgian Research Action through Interdisciplinary Networks (PhD grant at KU-Leuven in the FORBIO Climate project). Nieto-Lugilde to University of Granada (Perfeccionamiento-de-doctores Fellowship) and to RNM-7033. Vicente to FCT (grant SFRH/BPD/84044/2012). Honrado to POCTEP (project 0479_BIODIV_GNP_1_E) and to ERDF/COMPETE and FCT (project PTDC/AGR-AAM/104819/2008). This research was also developed as part of project ECOPOTENTIAL, which received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No. 641762.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jag.2016.12.009.

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