Very high resolution Earth observation features for monitoring plant and animal community structure across multiple spatial scales in protected areas

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A R T I C L E   I N F O

Article history:
Available online xxx

Keywords:
VHR EO features
Biodiversity surrogates
Functional groups
Habitat quality
Monitoring

A B S T R A C T

Monitoring the status and future trends in biodiversity can be prohibitively expensive using ground-based surveys. Consequently, significant effort is being invested in the use of satellite remote sensing to represent aspects of the proximate mechanisms (e.g., resource availability) that can be related to biodiversity surrogates (BS) such as species community descriptors. We explored the potential of very high resolution (VHR) satellite Earth observation (EO) features as proxies for habitat structural attributes that influence spatial variation in habitat quality and biodiversity change. In a semi-natural grassland mosaic of conservation concern in southern Italy, we employed a hierarchical nested sampling strategy to collect field and VHR-EO data across three spatial extent levels (landscape, patch and plot). Species incidence and abundance data were collected at the plot level for plant, insect and bird functional groups. Spectral and textural VHR-EO image features were derived from a Worldview-2 image. Three window sizes (grains) were tested for analysis and computation of textural features, guided by the perception limits of different organisms. The modelled relationships between VHR-EO features and BS responses differed across scales, suggesting that landscape, patch and plot levels are respectively most appropriate when dealing with birds, plants and insects. This research demonstrates the potential of VHR-EO for biodiversity mapping and habitat modelling, and highlights the importance of identifying the appropriate scale of analysis for specific taxonomic groups of interest. Further, textural features are important in the modelling of functional group-specific indices which represent BS in high conservation value habitat types, and provide a more direct link to species interaction networks and ecosystem functioning, than provided by traditional taxonomic diversity indices.

Introduction

Over the past 50 years, the Earth’s ecosystems have been altered rapidly by human pressures (Millennium Ecosystem Assessment, 2005). In addition to reducing available habitat through land-use change, humans significantly impact biodiversity through the effects of their activities on habitat quality. In particular, the degradation of habitat quality characteristics related to resource availability (e.g., nutrients, refugia), phytomass, vegetation structure and microclimate, can result in alterations in the distribution of biodiversity surrogates, BS (i.e. species community descriptors) (Nagendra et al., 2013b). However, effective measurement and monitoring of changes in habitat quality can be challenging, because ‘quality’ is an inherently taxon-specific attribute (Lindenmayer et al., 2002), influencing species distributions at specific combinations of scale components (extent and grain, sensu Kotliar and Wiens, 1990). This is why conservation managers frequently require information on changes in habitat quality, and on their impact on multiple aggregate components of biodiversity, at differing spatial scales. Yet, it can be prohibitively expensive
to obtain fine-grained habitat quality data at large spatial extents through field surveys alone.

Remote sensing enables the estimation of environmental heterogeneity at differing grains across differing spatial extents, which can then be related to variation in species diversity and distribution (Palmer et al., 2002; Nagendra et al., this issue). Of particular note has been the potential utilization of very high resolution (VHR) Earth observation (EO) imagery features to discriminate some aspects of habitat characteristics (Nagendra et al., 2013a).

Biodiversity surrogates (e.g., species presence, abundance, probability of site occupancy, aggregate measures such as species richness, diversity, or carrying capacity) can be predicted with reasonable accuracy using habitat modelling (Wimble et al., 2005; Marcot, 2006) based on remotely-sensed measures of environmental attributes (e.g., primary productivity, vegetation structure) representing habitat quality. Habitat modelling (e.g., Townsend et al., 2009; Rocchini et al., 2010; Feingersh et al., 2007) and environmental niche modelling (e.g., Peterson, 2003; Haney, 2008), are also increasingly being used to obtain information on habitat suitability with regard to both threatened and invasive species in terrestrial and marine habitats.

A range of approaches have been utilized to obtain inferences on habitat quality from remote sensing (Townsend et al., 2009; Rocchini et al., 2010; Feingersh et al., 2007; Costanza et al., 2011; Schmidtlein et al., 2012). These broadly include the use of VHR to high-resolution (HR) satellite images, and the use of spectral and spatial information extracted from the images. It is likely that BS relevant to different taxa and functional groups will exhibit different relationships with varying spectral and textural diversity measurements at different spatial scales, but the selection of methods for up-scaling and down-scaling has not been fully resolved (He et al., 2002; Wessman and Bateson, 2006).

In this paper, we explore the potential of VHR EO features to predict habitat attributes valuable for biodiversity assessment and habitat quality change detection in threatened grassland ecosystem of Southern Italy (Labadessa, 2014). We adopt a habitat modelling approach using VHR-EO features as proxies for attributes of habitat quality at multiple spatial scales, relating these to BS derived from an intensive field survey of plant, invertebrate and vertebrate taxa.

This study was developed and tested within the European Union’s Seventh Framework Programme (EU-FP7) project Biodiversity Multi-SOurce Monitoring System: From Space To Species (BIO_SOS), that aimed to develop tools and models for consistent multi-annual monitoring of protected areas and their surroundings by the integrated use of RS and in-field data.

Methods

Study area

The study area is located in Southern Italy within the Natura 2000 “Murgia Alta” site (SCI/SPA IT9120007, according to EU Habitats Directive 92/43 and Bird Directive 1479/2009), spanning over 125,880 ha and partly designated as a National Park in 2004 (Fig. 1). Murgia Alta, a calcareous upland where semi-natural dry grasslands cover almost 24% of the total area of the site, represents one of the most important areas for the conservation of this kind of ecosystem in Europe (Mairota et al., 2013). Such grasslands are among the most species-rich plant communities in Europe (Wilson et al., 2012) and they host a remarkable set of endemic and protected plants (included within the Habitats Directive habitat categories, codes 62A0 and 6220*), together with threatened birds and insects listed in European and national red lists (van Swaay et al., 2010). The site has developed through a mix of anthropogenic and natural processes over long periods of time, and is maintained by human activities such as livestock grazing (Turbé et al., 2010). Therefore, any shift (e.g., agricultural intensification, land abandonment) from this long-term anthropogenic disturbance regime represents a pressure (sensu Nagendra et al., this issue) and induces impacts on habitat availability and habitat quality (e.g., grassland fragmentation, woody encroachment) and hence on biodiversity (Sutter and Brigham, 1998; Brotons et al., 2005).

Data collection

Sampling design

A hierarchical nested sampling strategy was adopted at three spatial extent levels—landscape, patch, and plot —according to the protocols of the BIO_SOS project (Mairota et al., 2013) and following Wu and David (2002) (Fig. 2). Twenty 1 km × 1 km local landscapes (landscapes hereafter) were selected according to the fragmentation gradient (from not- to highly-fragmented, also in relation to matrix quality), of the focal habitat (Mairota et al., 2013) within a 10 km × 10 km regional landscape. Within logistical and financial constraints, 30 local ecosystems-1 (patches, hereafter, of the focal habitat), one or two per landscape, were selected, ranging in size from 0.38 to 56.28 ha, to which corresponded 30 (5 m × 80 m) randomly identified local ecosystems-2 (plots hereafter) for detailed field surveys of biodiversity.

Field data

Species occurrence and abundance were recorded along the length of each of the 30 plots for four taxonomic groups: herbaceous plants, passerine birds, orthopterans (Tettigonioidea, Acridoidea) and lepidopterans (Rhopalocera). Plants directly indicate environmental conditions and changes, birds are often linked to plant community and land cover change (Brotons et al., 2005), orthopterans represent the majority of insect biomass in the herbaceous layer (Gangwere et al., 1997) and are strongly influenced by variation in vegetation structure (Ryszkowski et al., 1993), and lepidopterans strongly respond to changes in plant diversity (Weibull et al., 2000).

Cover values of all herbaceous plant species were recorded within plots. Adults of lepidopterans and orthopterans were identified and released (Pollard, 1979). Breeding passerine birds were counted in the early morning at a central point within each plot (Bibby et al., 1992). Surveys for all taxa were repeated every two weeks from the end of March to September 2012 (12 sampling
sessions), except for birds where data were collected during the local breeding season (late May–early July).

For each taxon, functional groups were defined using a combination of theoretical information and expert knowledge, considering species traits indicating variation in the quality of the focal habitat (Supplementary Material Table S1). Aggregated measures of species assemblages (i.e., species richness, total abundance and Shannon’s diversity index) were estimated for the taxon as a whole, as well as for each functional group.

Earth observation features and data

Our selected Earth observation features (Supplementary Material Table S2) included both first and second order statistical (texture) measures (i.e., Grey Level Co-occurrence Matrix, GLCM, metrics; Haralick et al., 1973; Miyamoto and Merryman, 2008), derived from the Normalized Difference Vegetation Index (NDVI). NDVI represents vegetation productivity and can be related to plant and butterfly species richness and diversity (e.g., Costanza et al., 2011; Hall et al., 2011; Levanoni et al., 2011). NDVI-GLCMs can be related to bird species richness and habitat preferences (St-Louis et al., 2009; Tuttle et al., 2006).

VHR-EO features were computed at the native image geometric resolution (2 m × 2 m pixel) from a DigitalGlobe™ World-View-2 image, April 2011, for an image subset of 10 km × 10 km (regional landscape) acquired at a time close to the period of maximum biomass and species richness in the study area. The standard deviation of each VHR-EO feature was computed within the zones defined by selected landscapes, patches and plots using the zonal-statistics tool in ArcGIS® Desktop 9.

NDVI standard deviation was used as a first order measure in preference to the mean, as NDVI is non-linear in its behaviour (Aman et al., 1992). Three second order GLCM metrics (Supplementary Material Table S2) were chosen based on their ecological relevance (despite collinearity due to their mathematical formulation), because they describe distinct aspects of the image pattern related to different aspects of heterogeneity of habitat characteristics (e.g., vegetation cover density, structure) relevant to animal perception. For instance, while standard deviation provides information on the relative degree of habitat heterogeneity, Inverse Difference Moment (IDM) or Homogeneity (Clausi, 2002), describes the local homogeneity of a pattern thus allowing for homogeneous areas to be characterized by ‘smoothness’ (Tuttle et al., 2006). Contrast (CON) describes the presence of variation in a pattern, and also takes into account the spatial orientation and direction of pixels. The Information Measure of Correlation (IMC) provides information on the similarity among the grey-levels of a pattern.

The intrinsic VHR-EO image resolution (2 m × 2 m) was assumed to be appropriate to represent the organisms’ lower limit of perception of the landscape (i.e., the grain, sensu Kotliar and Wiens, 1990) for both birds and insects, as the alternative use of pan-sharpened (e.g., 0.5 m × 0.5 m, 1 m × 1 m) NDVI data might have generated bias in the computation of textural metrics (Jiang et al., 2005). However, the computation of second order GLCM statistics affects the spatial scale (particularly the grain) through values of parameters such as window size, quantization, shift and direction of the computing algorithm. Therefore, in the definition of these parameters we carefully considered differences in the scale and mode of perception of the environment between different organisms (mainly based on spatial resolution abilities for birds, and on response to physical and chemical cues at the microhabitat level for insects; Dafni et al., 1997). For birds, existing studies (St-Louis et al., 2009; Tuttle et al., 2006) suggest that windows of similar sizes yield similar results for VHR-EO features. Thus, referring to hierarchic theory which recommends the consideration of levels of scale below and above the scale of interest (Kotliar and Wiens, 1990), we selected a set of scales defined by 3 × 3, 15 × 15 and 31 × 31 pixel windows, with the smallest window size representing the lower limit allowed by the data and probably reflecting the mode of perception of many insects while the largest window size probably reflects the limits of perception and home range of different passerine species. The intermediate scale reflects the upper limit of patch size, and thus the potential influence of patch context on the sample plot. The quantization parameter for NDVI (32 levels with uniform distribution) was selected to be consistent with the window size (Clausi, 2002), one pixel shift was selected with reference to Tuttle et al. (2006), and it was assumed that all textural information was contained in the spectral value spatial-dependency matrices for canonical angles (0°, 45°, 90°, 135°).

Habitat modelling

A model-based integrated approach was proposed to evaluate the relationship between the variability of VHR-EO features extracted at each extent level (predictors) and the biodiversity surrogates (response variables).

In order to discard redundant GLCM predictors computed at the different scales, as detected by a correlation matrix, principal components analysis (PCA) was used. The variables that contained the most information were identified with reference to the cumulative variance explained (defined as >80%) by a limited number of components and to the eigenvector, representing the influence of the corresponding variable in determining each component. These variables were used as predictors in a stepwise regression, adopting log transformations of the response variables when necessary. Model selection in the stepwise regression was based on the Akaike Information Criterion (AIC) index (Sawa, 1978), whereas the goodness of fit of the final models was based on an analysis of the residuals. This procedure was applied separately for each of the
Results

The results of the PCAs performed as an a priori selection among the GLCM predictors are shown in Supplementary Material (Table S3). For the three extent levels, landscape, patch and plot, the first three, four or five principal components were considered, respectively. For these principal components, there was only a smaller (but level-specific) set of GLCM metrics that were strongly associated with overall variation in VHR-EO features. At the landscape level, CON31 × 31, CON15 × 15, IDM3 × 3 and IMC3 × 3 were the main drivers of variation, while at the patch level the key drivers were CONPatch31 × 31, CONPatch3 × 3, IDMPatch3 × 3, IMCPatch15 × 15 and IMCPatch3 × 3, and at the plot level the key drivers were IMCPlot31 × 31, IDMPlot15 × 15, CONPlot3 × 3 and IDMPlot3 × 3.

The effectiveness of the selected VHR-EO features in predicting the selected BSS varied between taxa for all the three extent levels considered (Supplementary Material Tables S4–S6).

The ability of the selected VHR-EO features to predict spatial patterns of variation in BS (in terms of percentage of significant relationships over the total), for all taxa, was found to be higher for functional group diversity, rather than for overall taxonomic diversity (BS_overall) (Fig. 3).

The predictive ability of VHR-EO features for each taxon also varied across extent levels (Fig. 4). For example, bird diversity was better predicted at the landscape level, while plant and insect diversity were better predicted at the patch and plot levels, respectively. In the case of insects, in particular, landscape level variation in habitat features appeared not to be an appropriate level for modelling functional group diversity (Fig. 4).

The predictive ability of the NDVI and of the GLCM metrics also varied for different BS between and within taxa (Fig. 5). The NDVI and GLCM metrics corresponding to the finest grain (GLCM3 × 3) were more relevant for plants. For both birds and orthopterans the relative importance of the same GLCM3 × 3 metrics for the NDVI increased when only BS_functional groups were considered. In the case of lepidopterans, NDVI showed a very low importance when BS_overall was considered. GLCMs computed at the three window sizes showed the same relative importance when lepidopteron BS_functional groups were considered.

Finally, the same BS (e.g., N_Herbaceous plants, FestucoBrometea) could be predicted by a different individual EO feature or different combination of features, across different scales.

Discussion and conclusions

Selected VHR-EO features calculated at specific scales were determined to be useful for predicting empirical patterns of variation in a number of biodiversity surrogates, particularly those relevant to functional group responses to variation in habitat quality. For some taxa, NDVI (more specifically NDVI variability) is important for predicting taxonomic diversity of species assemblages (BS_overall), while for other taxa spatial prediction of both taxonomic diversity and functional group diversity (BS_functional...
groups) can be more effectively achieved using a combination of VHR-EO features including second order GLCM metrics. This is of particular relevance considering that the role of functional groups as biodiversity surrogates is gaining momentum, as these are capable of supplying synoptic information on community structure and on species-habitat relations as well as on ecological processes (Hooper and Vitousek, 1997; Nyström, 2006; Griman and Suding, 2010; Helsen et al., 2012). For the study area, the results suggest that also the most appropriate extents for monitoring the impact of landscape change on biodiversity depends on the taxa under investigation (Holland et al., 2004). Birds might be more effectively studied at spatial extents intermediate between the landscape level (~100 ha in extent) and patch level (~0.38–56.28 ha extent). For plants, the patch level is likely to be the relevant level of investigation concerning community assembly and structure, whilst insects are more linked to plot scale variation in habitat quality (~400 m² in extent), as might be expected from scale-dependence in taxon response to spatial structuring of the environment (Barton et al., 2013).

However we expect that other VHR-EO features measured at even finer spatial grains, such as those allowed by high-resolution satellite-borne synthetic aperture radars (SAR) or from VHR satellite-airborne hyperspectral data might be more appropriate in the future to predict aggregated measures of species assemblages (as suggested by Reynolds and Riley, 2002 for insects). Airborne SAR data have proven effective in discerning structural differences relevant to bird habitat quality (Imhoff et al., 1997), as well as in estimating micrometeorite parameters (e.g. soil moisture) important in critical phases of insect life cycles (e.g., reproduction) (Crooks and Archer, 2002). Hyperspectral imagery can provide additional information on within-vegetation variability (e.g., crop yield, phytomass), as compared to multispectral data (Yang et al., 2013). Moreover, airborne hyperspectral data can be used to differentiate among functional vegetation components (Lewis, 2000; Schmidtlein et al., 2012). In addition, these measures could be particularly effective in combination with other technologies used to assess temporal changes in insect community composition resulting from individual species movement and migration (e.g., Riley and Drake, 2002).

While we have confirmed the potential for VHR-EO features to be used for measuring and monitoring habitat quality and biodiversity, there are important scaling issues that must be taken into consideration. In particular, the assumptions underpinning selection of the extent and grain of the analysis must be given serious consideration for any target taxonomic group, and specified clearly. The computational costs involved in the choice of different computational scales for textural VHR-EO features can also be substantial (in our analysis computational time increased exponentially with increasing window size).

Given these considerations, we believe there are three main reasons why the approach proposed here could be considered within frameworks such as the European and international Long Term Ecosystem Research networks, and the global system of harmonized observations envisaged by the Biodiversity Observation Network of the Group on Earth Observations (GEO BON). First, the monitoring of community compositional change through habitat quality proxies represents one component of the Essential Biodiversity Variables, EBVs (Pereira et al., 2013) proposed within the framework of GEO BON. Second, a complete wall-to-wall and periodically repeated characterization of habitat quality based on VHR-EO features for each relevant site is not currently feasible due to data cost and availability. Third, a more targeted indirect assessment of habitat quality using VHR-EO (such as used here) complies with EBVs requirements for scalability, temporal sensitivity, feasibility and relevance to the Convention on Biological Diversity (Pereira et al., 2013).

Taken together, a targeted VHR-EO habitat modelling approach would provide timely and cost-effective delivery of data on biodiversity change at large (regional or continental) scales based on extrapolation from validated sample locations.

Acknowledgements

This work was supported by the European Community’s Seventh Framework Programme, within the FP7/SPA.2010.1.1-04: “Stimulating the development of GMES services in specific area”, under grant agreement 263435 for the project ‘Biodiversity Multi-Source Monitoring System: From Space To Species’ (BIO_SOS), www.biosos.eu. We wish to thank two anonymous Reviewers for their valuable suggestions.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jag.2014.09.015.

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Please cite this article in press as: Mairaota, P., et al., Very high resolution Earth observation features for monitoring plant and animal community structure across multiple spatial scales in protected areas. Int. J. Appl. Earth Obsr. Geoinf. (2014), http://dx.doi.org/10.1016/j.jag.2014.09.015


