Predictive mapping of plant diversity in an arid mountain environment (Gebel Elba, Egypt)

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Abstract

Aim: This study aimed to predict the alpha and beta plant diversity of an arid mountain based on environmental variables derived from remotely sensed and ground truth data.

Location: Gebel Elba, Egypt.

Methods: Based on 133 vegetation plots of 100 m², we calculated alpha (Shannon index) and beta [the first ordination axis of nonmetric multidimensional scaling (NMDS1)] plant diversity. Generalized additive models (GAMs) were used to map alpha and beta diversity based on various environmental variables derived from a digital elevation model, the SoilGrids dataset, and very high resolution PlanetScope satellite imagery. The predictive models for alpha and beta diversity were mapped within the northern slopes of Gebel Elba. An ANOVA post hoc test was used to compare Shannon index and NMDS1 values among plant communities.

Results: The selected models revealed the importance of altitude, landforms, solar insolation, catchment area, and modified soil-adjusted vegetation index for Shannon diversity and NMDS1. The GAMs explained 54.9% of Shannon diversity and 80.6% of NMDS1. The predicted diversity maps showed that the mountainous area was more diverse and substantially different from the open desert. The post-hoc test revealed a clear separation of mountain and desert vegetation.

Conclusions: Employing remotely sensed variables combined with ground truth data offers great opportunities for exploring spatial patterns of biodiversity. By mapping alpha and beta diversity, it was possible to determine the spatial distribution of plant diversity in Gebel Elba; the results highlighted the importance of the wadi systems and higher slopes of this mountain area. We expect our findings can be generalized to similar arid mountains in the region.

KEYWORDS
Acacia, alpha diversity, beta diversity, floristic gradient, Gebel Elba National Park, predictive mapping, protected area, remote sensing, satellite imagery, woodland
Mapping regional biodiversity is necessary for conservation planning and delimiting biodiversity hotspots in arid mountain areas (von Wehrden et al., 2009; Brinkmann et al., 2011; Muenchow et al., 2013); however, the inaccessibility of these areas and the lack of available information on environmental drivers of diversity are important challenges for conservation management. Remote sensing can potentially overcome these challenges as it can provide basic information required for modeling and predicting patterns of diversity (Ferrier, 2002; Hüttrich et al., 2011; Levanoni et al., 2011). For example, topography, edaphic parameters, climate variables, and productivity can be determined by remote sensing (Turner et al., 2003); such parameters can be used to model species diversity along environmental gradients and predict species distribution patterns (Ferrier, 2002; Hüttrich et al., 2011; Levanoni et al., 2011). Both the availability of remotely sensed data and new powerful statistical techniques are already supporting the production of predictive diversity maps (Levin et al., 2007; Muenchow et al., 2013; Vanselow & Samimi, 2014; Hein et al., 2019). However, such maps are often not prepared for arid ecosystems.

Predictive mapping of alpha (diversity within sampling units) and beta diversity (variation in species composition between habitats; Whittaker, 1972) can help identify areas of high local diversity caused by species turnover along environmental gradients (Botta-Dukát, 2018; Ochoa-Franco et al., 2019). Oldeland et al. (2010) demonstrated that using the Shannon index improves the ability to estimate alpha diversity with hyperspectral remotely sensed data: \( R^2 \) values were up to fivefold higher than those obtained when considering species richness only. The Shannon index is useful in this context because it is less affected than species richness by the presence of rare species (Rocchini et al., 2016). Estimation of beta diversity begins with the use of distance matrices, which are designed to quantitatively describe multivariate gradual transitions in the species composition of sampled sites. Measuring the distance between two sampling sites in multidimensional ordination space is an effective method for representing species turnover (Rocchini et al., 2018). When this measure is related to the environmental distance between the sampled sites, beta diversity at this scale can be estimated (Rocchini et al., 2018).

The spatial patterns of alpha and beta diversity reflect species representation in various habitats; such patterns depend on specific environmental parameters, which can strongly influence species persistence (Domisch et al., 2019). In general, patterns of species diversity are influenced by parameters including climatic variation, anthropogenic activities, dispersal limitation, and habitat heterogeneity (Sabatini et al., 2018; Gebrehiwot et al., 2019). Studies in arid mountains have also explored the influence of topography, vegetation indices, climate, and soil parameters on the distribution of plant species and communities; the rugged topography of mountains offers many niches, wherein specialized plant species can thrive in arid environments (Brinkmann et al., 2011; Vanselow & Samimi, 2014; Abutaha et al., 2020).

The arid mountain Gebel Elba is one of the most important conservation areas in Egypt (Abutaha et al., 2019). Mist oases provide a unique ecosystem on the mountain tops of Gebel Elba (Zahran & Willis, 2009); however, there is little information on the spatial distribution of plant diversity for this mountain. Previous studies have reported on patterns of plant diversity on Gebel Elba (Abutaha et al., 2019, 2020); they have shown how a combination of elevation and soil factors shapes the species diversity and distribution of plant communities in the wadi systems, but the high elevations of the mountain have received less attention. Cartographic representations of plant diversity on Gebel Elba are currently lacking; these could provide important information for conservation management.

In this study, we aimed to map alpha and beta plant diversity in the wadi systems and inaccessible higher slopes of Gebel Elba based on remotely sensed information. Based on our previous work, we hypothesized that the mountainous areas would be more diverse than the surrounding plains of the desert. Moreover, we expected the dissimilarity between sites to increase with elevation. We further hypothesized that topography, plant productivity, and soil parameters would be important for determining patterns of diversity along the altitudinal gradients on the northern slopes of Gebel Elba, from the open desert to the mist oases.

## 2 | METHODS

### 2.1 | Study area

The Gebel Elba range is a group of six granite mountains situated near the Red Sea in the extreme southeast corner of Egypt at 22° N and between 36° and 37° E (Al-Gohary, 2008). Gebel Elba is the most northern mountain of the range with the highest peak at 1,435 m above sea level (asl; Ball, 1912). From another more central peak (1,428 m asl), drainage lines radiate in all directions (Ball, 1912). Our study area was located on the northern slopes of Gebel Elba (Figure 1). Wadi Aidieb and Wadi Yahmib are the principal wadis that drain these slopes. The topography varies from open sandy plains to complex mountain drainage systems. The Gebel Elba region has a hyperarid climate wherein precipitation is <50 mm/year and mean annual temperature is approximately 26.1°C (Abutaha et al., 2020). The mid and high elevations of the mountain receive coastal mist, which creates "mist oases." This orographic precipitation supports woody vegetation that is more diverse than in any other region of Egypt (Zahran & Willis, 2009).

Floristically, Gebel Elba contains elements of the Afrotropical flora and is dominated by two woodland types: *Vachellia* and *Olea* woodlands. While *Vachellia* woodland is dominant from low to mid elevations, *Olea* woodland is restricted to higher elevations (Abutaha et al., 2020). Seven plant communities have been identified in the area, one (I) was described within the *Olea* woodland and six (II–VII) were within the *Vachellia* woodland (see table 1 in Abutaha et al., 2020). These identified communities show an
altitudinal zonation and occupy different habitats along the elevational gradient from the open plain to the higher mountain elevations.

2.2 | Field sampling and variable assessment

The Gebel Elba National Park is inaccessible as it is partly a military area. Permission is required to access the mountain area, which is usually restricted to a few days per field visit. Hence, only five field visits were made in January or March after the rainy season (i.e., from October to December) during 2013, 2015, and 2016. To assess plant diversity, 133 vegetation plots (10 m × 10 m) distributed along the elevational gradient of the northern slopes of Gebel Elba were studied. We sampled across the altitudinal gradient from 130 to 680 m; this area covered four wadis: Yahmib, Marafai, Acow, and Kansisrob. Ensuring that the intervals were fixed between sampling plots was difficult due to the rugged topography; therefore, plots were randomly positioned within altitudinal intervals of 100 or 50 m in the main wadi or smaller wadis, respectively. Vegetation plot coordinates (geodetic datum: WGS84) were recorded in the center using a GPS device (eTrex 30, Garmin International, Inc., Olathe, Kansas, USA). For each plot, a complete species list was assembled, and the percentage cover of perennial species was estimated. The taxonomical identification of plant species followed Täckholm (1974) and Boulos (1999, 2000, 2002, 2005, 2009). However, we updated the nomenclature according to Plants of the World Online (POWO, 2019).

We have previously shown that altitude and soil properties were important in determining the vegetation structure and diversity patterns on Gebel Elba (Abutaha et al., 2019, 2020). In addition, the availability of water has been related to the rugged topography and orographic precipitation on the higher northern slopes of Gebel Elba, which support dense vegetation (Zahran & Willis, 2009). Based on these studies, we tested 14 environmental parameters as predictors (see Appendix S1 for a description). We extracted the altitude, catchment slopes, catchment area, openness, solar insolation (the increase in shadow), and landforms (four classes: plains, streams, valleys, and slopes and ridges) from a digital elevation model (DEM: ASTER DEM 30 m, retrieved from https://lpdaac.usgs.gov/). Moreover, we used very high-resolution PlanetScope satellite data (3 m) from March 2019 to calculate a vegetation index representing living green plant biomass. The satellite data were provided as a level 3A PlanetScope Ortho Tile Product in units of spectral reflectance with four spectral bands covering infrared (780–860 nm), red (590–670 nm), green (500–590 nm) and blue (455–515 nm). The imagery was atmospherically preprocessed using the 6S algorithm (Vermote et al., 1997). Besides that, the images also were geometrically corrected, and the final product was delivered in UTM projection (Planet Team, 2017). Due to the hyperarid conditions of the study area, it was necessary to calculate a modified soil-adjusted vegetation index (MSAVI₂) according to Qi et al. (1994) from the four-band (RGB-NIR) PlanetScope satellite images. SAGA-GIS version 7.2.0 (Conrad et al., 2015) and QGIS
version 3.4.2 (QGIS Development Team, 2019) were used to prepare the raster data. For soil parameters, i.e., cation exchange capacity, pH, organic carbon, coarse fragments, silt, sand, and clay, we used soil layers (depth: 0–5 cm) from the SoilGrids dataset at a spatial resolution of 250 m (Hengl et al., 2017) and used a raster package (Hijmans, 2020) in R (R Development Core Team, 2020) to crop all 14 environmental raster layers to the extent of the study area. We then resampled all raster layers to the same resolution of the DEM, e.g., 30 m × 30 m. Finally, we extracted the values from these raster layers for each vegetation plot at its center coordinate.

We calculated alpha and beta diversity from the vegetation plot data. For alpha diversity, we chose the Shannon index (Magurran, 2004) over species richness because information on abundance was important for differentiating among communities. We compared our results to those from richness-based models; however, as the Shannon index produced better results, we reported the Shannon index results only (see Appendix S2 for richness-based models). To quantify beta diversity as an increase in dissimilarity between vegetation plots, we performed non-metric multidimensional scaling (NMDS) to represent the floristic gradient using a reduced number of dimensions that could easily be visualized (Lovelace et al., 2019). Using the Bray–Curtis dissimilarity distance, the best NMDS solution reached a stress value of 0.107. The NMDS ordination identified altitude as the most important predictor in explaining the turnover of species. Moreover, we found that the first axis of NMDS (denoted “NMDS1”) clearly captured the main floristic gradient. Thus, we used NMDS1 to model beta diversity. We rotated the NMDS axes (as this improves interpretation of the axes) so that NMDS1 contained the largest variance in ordination space (Schmidtlein et al., 2007; Lovelace et al., 2019). NMDS was performed using the vegan package (Oksanen et al., 2020).

2.3 | Data analysis

The relationship between vegetation and environment is often complex and difficult to capture with linear or unimodal models (Dobrowski et al., 2008; Song et al., 2013; Matus-Hernández et al., 2018). GAMs (Wood, 2006) are more flexible than generalized linear models; they can model both linear and non-linear relationships between response and predictor variables. Furthermore, we previously found that a GAM effectively described the non-linear and linear diversity patterns of the wadi systems of Gebel Elba (Abutaha et al., 2019). Given the continuous nature of the normally distributed Shannon values and the negative and positive continuous values centered at zero for the NMDS axis, we used GAMs with a Gaussian distribution to model alpha (Shannon index) and beta (NMDS1) diversity with the selected environmental parameters. The catchment area was log10-transformed to adjust the data to a normal distribution. Moreover, we tested correlations between the environmental predictor variables to avoid multicollinearity problems in GAM regression analysis (Performance Analytics package; Peterson & Carl, 2020). Consequently, we excluded all soil variables, catchment slopes, and openness due to high correlations ($r > 0.7$) with altitude or with each other (Appendix S3).

After removing the correlated predictors, only five parameters remained: altitude, landforms, solar insolation, catchment area, and MSAVI$_2$. These parameters were used to model alpha (Shannon index) and beta diversity (NMDS1). As smoothing terms, we used thin-plate regression splines with shrinkage-to-zero for the numeric variables (altitude, catchment area, solar insolation, and MSAVI$_2$) and a simple random effect for the factor variable (landforms). We fitted all GAMs using the mgcv package in R (Wood, 2011). The residuals of the GAMs were checked with diagnostic plots to identify deviations from an expected random pattern. Furthermore, the residuals for spatial autocorrelation were analyzed using a Moran’s I correlogram with the spdep package (Bivand et al., 2013); however, effects were not detected in this analysis. The Akaike information criterion was used to compare a set of candidate models containing all possible models without interaction. Model selection was performed with the MuMln package (Barton et al., 2020). The best models were subsequently used to produce diversity maps via their application to the raster data. To assess the usefulness of the models, we related observed and predicted values for the vegetation plots and used the $R^2$ value as an indicator of model quality (Piñeiro et al., 2008).

To verify the findings of our previous study (Abutaha et al., 2020), we used the scores along the first and second axes of NMDS to describe the floristic gradient on Gebel Elba in ordination space. ANOVA post hoc tests (Tukey’s honestly significant difference [HSD] test) were used to test for differences in Shannon index and NMDS1 values between the seven plant communities using the multcompView package (Graves et al., 2019). Preparation of diversity parameters and all statistical analyses for predictive modeling and mapping were conducted in R version 4.0.3.

3 | RESULTS

3.1 | Diversity–environment models

Of 32 candidate models, the best model selected for alpha diversity (Shannon index) required all five parameters, i.e., the vegetation index MSAVI$_2$ and four topographical parameters (altitude, solar insolation, landforms, and catchment area; Table 1); this model explained 54.9% of the variation. The accuracy of the alpha diversity model as obtained by comparing predicted and observed Shannon values reached a fit of $R^2 = 0.55$. Altitude showed a non-linear pattern, whereas catchment area and MSAVI$_2$ were linear, and the landforms parameter was a factor (Appendix S4). The most diverse landforms class was “streams” in the mountainous area; the least diverse class was “plains” (Figure 2a). The best model selected for beta diversity (NMDS1) was the full model, which again comprised all five parameters; this model explained 80.6% of the spatial variability (Table 1). Altitude showed a non-linear pattern, catchment area showed a complex pattern, and solar insolation and MSAVI$_2$ showed a linear pattern (Appendix S5). The accuracy of the beta diversity
model was rather high ($R^2 = 0.81$). However, it should be noted that for both models no independent evaluation was possible given the low number of vegetation plot data and the strong environmental heterogeneity.

### 3.2 | Diversity maps

The GAMs were extrapolated for the whole study area and predictive maps of alpha and beta diversity were produced as shown in Figure 2. Both maps could discriminate between open desert and mountainous areas. In the alpha diversity map, the change in diversity strongly depended on topography. The predicted Shannon diversity map corresponded to the pattern of alpha diversity observed in the field at Gebel Elba. The Shannon index strongly increased from low to mid elevations toward the mountain; it reached a plateau from the mid to high elevations in the mountainous wadi systems. Alpha diversity was higher in the main streams of the drainage systems (wadis) than on the slopes (Figure 2a). The beta diversity map showed increasing dissimilarity according to elevational gradient, with mountainous areas being very different from the plain in terms of species composition (Figure 2b). A Shannon value of 1 and NMDS1 of 0 marked the beginning of the mountain, representing a clear change in the floristic gradient of the study area. NMDS1 values $<0$ marked the deciduous Vachellia woodland at the foot of the mountain, whereas values $>1$ represented the evergreen Olea woodland at higher elevations. The area with NMDS1 values between 0 and 1 represented a transition between Vachellia and Olea woodlands, and it was occupied by a Ficus community; thus, we interpret this area as an ecotone.
3.3 | Diversity gradients

The Shannon diversity and NMDS1 values highlighted the differences in plant diversity between the Olea and Vachellia woodlands. These parameters were moderately correlated ($r = 0.53$); thus, they provide slightly different perspectives on diversity (or its components). Using Tukey’s post hoc test, we clarified the differences in Shannon index and NMDS1 between the seven identified communities (Table 2). The communities along the elevational gradient of Gebel Elba were classified into two groups according to alpha and beta diversity. The first group was more diverse and contained communities from the mid to high elevations, while the second group contained communities that occupied the lower part of the elevational gradient. Specifically, three communities were recorded from mid to high elevations: Euphorbia nubica, Solanum–Ficus, and Dracaena–Olea (which showed the highest Shannon index values; Table 2). The most common community in Gebel Elba, the Vachellia tortilis community, had the widest range of Shannon indices (Table 2). We observed small differences between the communities from low to mid elevations.

The dissimilarity of the floristic composition strongly changed with elevation. NMDS ordination (axes 1 and 2) showed that the vegetation communities changed from deciduous to evergreen (Appendix S6). The first axis of NMDS explained the change in floristic gradient, whereas the second axis explained the variation within the deciduous plant communities at the foot of the mountain. According to Tukey’s post hoc tests, there were significant differences among the NMDS1 values of the seven communities (Table 2). The highest mean NMDS1 value (1.19) was found in the Dracaena–Olea community, which occupied higher elevations, with the next highest value for the Solanum–Ficus community (0.70). The Vachellia tortilis and Balanites–Vachellia raddiana communities on the open desert plain showed the lowest mean values (~0.47 and ~0.55, respectively). Furthermore, communities found from the low to mid elevations (III–VII) differed from each other with a low level of significance (Table 2).

4 | DISCUSSION

4.1 | Diversity modeling

Remotely sensed data are a valuable source for modeling spatial biodiversity patterns in mountains with complex and diverse topography (Liu et al., 2018; Lazarina et al., 2019). In arid mountains, changes in topography and altitude constitute a proxy for the gradient of water availability, the most important factor in determining species composition and distribution (Muenchow et al., 2013; Dorji et al., 2014; Vanselow & Samimi, 2014). The elevational gradients of Gebel Elba mirror an inverse environmental stress gradient (Abutaha et al., 2019), as indicated by the upper and lower vegetation belts visibly dominated by evergreen and deciduous trees, respectively (Abutaha et al., 2020). To date, altitude has been described as the major factor explaining the change in species diversity and floristic composition in Gebel Elba (Abd El-Ghani & Abdel-Khalik, 2006; Abutaha et al., 2019, 2020). However, several studies have shown that more environmental variables resulted in more accurate models (Feilhauer & Schmidtlein, 2009; Vanselow & Samimi, 2014; Brun et al., 2020). The best models for alpha and beta diversity reported in this study included multiple remotely sensed environmental parameters. Our findings support previous studies (von Wehrden et al., 2009; Muenchow et al., 2013; Vanselow & Samimi, 2014) showing that the use of combined environmental variables in addition to altitude is more beneficial than using only altitude as a predictor of plant alpha and beta diversity. Thus, the predicted patterns of alpha and beta diversity on Gebel Elba reported in this study are likely to be robust since they are based on multiple remotely sensed environmental parameters and ground truth data.

**TABLE 2** Shannon index and NMDS1 (first ordination axis of nonmetric multidimensional scaling) for the identified communities in the study area (according to Abutaha et al., 2020). See also Appendix S6

| Community No. | Community name | Altitude range (m) | No. of species/plot | Shannon index (Mean ± SD) | NMDS1 (Mean ± SD) |
|---------------|----------------|-------------------|---------------------|--------------------------|------------------|
| I             | *Dracaena ombet–Olea europaea* subsp. cuspidata | 560–680 | 9 ± 4 | 1.97 ± 0.42$^a$ | 1.19 ± 0.34$^a$ |
| II            | *Solanum incanum–Ficus salicifolia* | 346–550 | 8 ± 4 | 1.71 ± 0.61$^{abc}$ | 0.70 ± 0.36$^b$ |
| III           | *Vachellia tortilis* subsp. tortilis | 131–383 | 5 ± 4 | 1.10 ± 0.95$^c$ | −0.47 ± 0.45$^{de}$ |
| IV            | *Euphorbia nubica* | 264–379 | 9 ± 4 | 1.79 ± 0.59$^{ab}$ | −0.16 ± 0.26$^{cd}$ |
| V             | *Aerva javanica–Abutilon pan nossus* | 237–275 | 7 ± 2 | 1.49 ± 0.59$^{ab}$ | −0.25 ± 0.25$^{cde}$ |
| VI            | *Euphorbia cuneata* | 241–320 | 9 ± 2 | 1.79 ± 0.27$^{ab}$ | −0.08 ± 0.29$^c$ |
| VII           | *Balanites aegyptiaca–Vachellia tortilis* subsp. raddiana | 196–361 | 5 ± 3 | 1.35 ± 0.59$^{bc}$ | −0.55 ± 0.42$^e$ |

Different lowercase letters denote statistical differences between groups (ANOVA post hoc test: Tukey’s HSD)
The predictive models presented here show that remotely sensed environmental data can explain the pattern of alpha and beta diversity on arid mountains. Models in which a vegetation index and topographical parameters were combined indicated that both variable groups were required for modeling, which is in agreement with other studies on arid mountains (Brinkmann et al., 2011; Vanselow & Samimi, 2014). In contrast to temperate mountains (Leathwick et al., 1998; García-Gutiérrez et al., 2018), favorable climatic conditions are found at higher elevations in arid mountains (Abutaha et al., 2019). In our study area, productivity and moisture availability increased with elevation, whereas temperature and solar insolation were notably lower at higher elevations. Patterns of diversity can also be related to the environmental heterogeneity hypothesis, and structural predictors (not used in this study) might likely enhance the Shannon diversity model (Hernández-Stefanoni et al., 2014; Sabatini et al., 2018). Indeed, the variation in diversity in the mountainous area seems to be connected to changes in topography, as is visible in the predicted diversity maps. Mountainous wadis cover a variety of microhabitats, such as wadi beds, side slopes, cliffs, and soil pockets (Abutaha et al., 2019). Such high diversity in habitats promotes the growth of dense vegetation. In contrast, the open desert consists of sandy plains with little variation in topography; thus, it contains lower diversity in habitats and supports the growth of scattered vegetation only (Zahran & Willis, 2009; Abutaha et al., 2020). In previous studies (de la Estrella et al., 2012; Tukainen et al., 2019), including environmental predictors that capture run-off water enhanced the predictive power of diversity modeling. In our study, moist landforms, such as streams in the mountainous area and U-shaped valleys at the foot of the mountain, had higher plant diversity than that in the open desert plain. Less abundant evergreen species such as Olea europaea subsp. cuspidata, Ficus salicifolia, and Searsia flexicaulis were found in water courses at higher elevations, whereas trees that were more drought-resistant, such as Vachellia tortilis and Balanites aegyptiaca, dominated the open desert at lower elevations (Abutaha et al., 2020). The environmental predictors used in our models reflected water availability, changes in topography, and microclimatic conditions along the environmental gradient of Gebel Elba.

4.2 Predictive mapping

The predictive mapping of alpha and beta diversity quantified the spatial changes in Shannon diversity (alpha diversity) and species composition (beta diversity) in our study area. This approach offers information on areas in which conservation efforts should be focused (de la Estrella et al., 2012). Topographic gradients regulate species diversity and distribution in mountainous ecosystems (Dörnböck et al., 2003; Brinkmann et al., 2011); although altitude is the major factor controlling the predictive mapping of alpha and beta diversity (von Wehrden et al., 2009; Muenchow et al., 2013), we cannot neglect the importance of landforms in determining species diversity patterns. Our predictive mapping of alpha diversity clearly showed that species diversity in the wadi systems was higher than on the slopes of the mountain. On the other hand, the predictive mapping of beta diversity reflected the floristic gradient and dissimilarity between the communities in the plains and at higher elevations. The turnover (roughly NMDS1 >0) between the two main woodland communities occurred at mid elevations. The change in topography from open desert to mountain habitat regulated species diversity and distribution at Gebel Elba. Thus, our predictive diversity maps show where conservation efforts should be focused, e.g., the wadi areas at higher elevations of Gebel Elba.

Mapping the alpha and beta diversity of Gebel Elba highlights the importance of topographic variables, especially altitude and landforms, when mapping diversity in arid mountains. Similar to the work of von Wehrden et al. (2009), the small scale of our study area was not a limitation as we identified a change in primary productivity (MSAVI2) along the examined gradient. Soil quality in mountainous areas is known to differ from that at the foot of the mountain (Abutaha et al., 2020); however, we found that soil parameters extracted from SoilGrids were highly correlated with elevation (r > 0.70; obviously because altitude was used to model the SoilGrids data). Therefore, we removed soil parameters from our predictive model to avoid issues with collinearity. Another possible limitation may be unmeasured microclimatic parameters along the elevational gradient. Gebel Elba is characterized by mist oases at higher elevations (Zahran & Willis, 2009); however, data on moisture content along the environmental gradient were not available. In addition, due to the mismatch between the coarse resolution of the climatic research unit (CRU) data (0.5° × 0.5°) and the fine-scale heterogeneity of our study area, we decided not to use climatic parameters in our predictive modeling. Nevertheless, altitude is often a proxy for soil and microclimatic variables (Muenchow et al., 2013). Future studies, in which improved fine-scale predictors are used along the environmental gradient, could improve the power of predictive diversity modeling for mountainous study systems.

5 Conclusion

In this study, we have created the first model-based plant diversity maps for the arid mountain Gebel Elba. Specifically, we mapped alpha and beta diversity on the northern slopes of Gebel Elba based on remotely sensed information combined with ground truth data. We found that topographical parameters and plant productivity (MSAVI2) played important roles in explaining the predictive models of alpha and beta diversity in the study area. Our predictive mapping showed that the change in topography at Gebel Elba from an open desert to a mountain ecosystem regulated species diversity and distribution. Furthermore, the floristic composition changed from deciduous woodland at low elevations to evergreen woodland at higher elevations, and the turnover between the two woodlands occurred at mid elevations. Future studies setting out to generate plant diversity maps for arid mountains adjacent to Gebel Elba could verify our approach. As remote-sensing products are globally available in
high quality, we recommend that more effort should be made on sampling high-quality vegetation data.

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AUTHOR CONTRIBUTIONS
JO conceived of the research idea; MA collected data and performed statistical analyses; MA wrote the first draft of the manuscript with a contribution from JO; all authors discussed the results and commented on the manuscript.

DATA AVAILABILITY STATEMENT
The data that support the findings of this study and the R script used to generate the analyses presented in this paper are available in Zenodo.org at http://doi.org/10.5281/zenodo.4662118.

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section.

**Appendix S1.** Environmental factors used to model alpha and beta diversity

**Appendix S2.** Results of Shannon index and richness-based models

**Appendix S3.** Correlation matrix of the environmental predictors used to select variables

**Appendix S4.** Partial effects of selected explanatory variables on the Shannon index

**Appendix S5.** Partial effects of selected explanatory variables on the first ordination axis of the non-metric multidimensional scaling (NMDS)

**Appendix S6.** Distribution of seven vegetation communities along the non-metric multidimensional scaling (NMDS) axes 1 and 2

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