RESEARCH ARTICLE

Effects of ecological restoration measures on the distribution of *Dicranopteris dichotoma* at the microscale in the red soil hilly region of China

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Abstract

Little is known about the evaluation of ecological restoration measures using species distribution models (SDMs) at the microscale. This study investigated the effect of arbor–bush–herb mixed plantation (ABHMP) on the potential distribution of *D. dichotoma* using SDMs in the typical microtopographies of the red soil hilly region of China. We examined *D. dichotoma* growth, microtopography, and environment-related factors at the microscale. The percentages of microtopographies and *D. dichotoma* physiology factors increased in the order from the valley to the ridge in the *D. dichotoma* patches. The valley had milder temperatures, higher humidity, and more fertile soil than the ridge in the gullies. Microclimate factors were the most critical environmental factors affecting the distribution of *D. dichotoma*, followed by soil factors, whereas the microtopography factors had only a marginal effect. The predicted potential distribution of *D. dichotoma* under the ABHMP scenario was nearly 3-fold higher than the current distribution, and the suitable area was located mostly in the level trenches and the valley. ABHMP had a strong effect on the potential distribution of *D. dichotoma*, and SDMs proved to be a valuable tool for assessing ecological restoration measures at the microscale.

Introduction

Plant restoration is frequently used as the primary indicator in ecological restoration programs [1]. For example, 20% vegetation cover appears to be the threshold between natural recovery and artificial restoration, when vegetation cover drops below 20%, artificial restoration is needed in China’s Fujian province [2]. Successful management of ecological restoration projects depends largely on our ability to identify the environmental factors that affect the spread of plants and to predict their potential distribution [3]. Species distribution models (SDMs), also known as ‘bioclimatic envelope models’, rely on the niche concept [4]. SDMs statistically relate the distribution of a given species to environment-related factors which typically include...
available resources, limiting factors and disturbances, improving the understanding of the
environmental factors affecting the species, and prediction of the potential distribution of the
species [5]. A wide range of algorithms have been applied in SDMs including the Generalized
Linear Model, Maximum Entropy, Artificial Neural Network, Support Vector Machine, Classi-
fication and Regression trees, Random Forest, and Generalized Boosted Regression [6]. The
combined use of geographic information systems (GIS) and SDMs has proven to be an effec-
tive methodology for analyzing global patterns and ecological requirements of species [7].
SDMs have potential for multiple applications in land science, ecological restoration, and ecol-
y [5, 8]. They are often used in regional to continental scales, and frequently rely on rela-
tively coarse-precision data sets [9]. However, detailed knowledge of the environmental factors
affecting plants and their potential distribution is fundamental for conservation planning and
forecasting [10]. Thus, the use of SDMs at a relatively small scale offers improved perspectives
for local conservation and management activities [11].

Many regions are flat from a large-scale perspective. At a relatively small scale, however, the
microtopography is often heterogeneous [12]. Microtopography, broadly defined as topo-
graphic variability at the scale of individual plants, describes surface variation within an eleva-
tion range from roughly several centimeters to several meters [13]. Microtopography can
influence factors such as plant distribution [14], seedling establishment [15], soil nutrient
pools and fluxes [16], and temperature and humidity [17]. Therefore, microtopography and
geomorphological processes can influence microhabitat diversity [18, 19], and the manipula-
tion of microtopography to promote plant community and ecosystem development has impli-
cations for ecological restoration measures [13]. However, to our knowledge, relatively few
studies have identified environmental factors affecting plants and predicted the potential dis-
tribution of plants using SDMs to evaluate ecological restoration measures at the microscale.

The red soil hilly region of China lies between 32˚N and 18˚N, spanning an area of 1.13
million km$^2$. The term “red soil” refers to well-drained red loams containing argillic, oxic, or
plinthitic horizons and high content of Fe and Al [20]. Demographic and economic growth
has put considerable pressure on the environment and resources, and many ecosystems have
been overexploited and damaged in the red soil hilly region of China. A number of ecological
restoration measures have been adopted to reduce these pressures [21], and $D. dichotoma$
dominated surface plant communities some years later regardless of the ecological restoration
measures applied [22]. $D. dichotoma$, a perennial fern of the family Gleicheniaceae, is one of
the most widely distributed ferns throughout the tropical and temperate regions. $D. dichotoma$
can resist, tolerate, or thrive in very poor soils, making it a pioneer species for ecological resto-
ration in the red soil hilly region of China [22].

To our knowledge, this is the first study to identify the main environmental factors affecting
the distribution of $D. dichotoma$ and predict its potential distribution under an ecological res-
oration scenario so as to evaluate ecological restoration measures at the microscale, using
SDMs. The principal objectives were to (1) obtain information about the distribution and
physiological factors of $D. dichotoma$ and environmental factors in microtopographies; (2)
identify the main environmental factors affecting the distribution of $D. dichotoma$; and (3) pre-
pdict the potential distribution of $D. dichotoma$ under the ABHMP scenario at the microscale
and assess the effectiveness of ABHMP.

Materials and methods

Study area

In China, the most serious soil and water loss with the longest history occurs in the red soil
hilly region in Changting County, Fujian Province [20]. Based on the information provided by
the Soil and Water Conservation Bureau in Changting County, ABHMP represents the chief ecological restoration measure applied in the high-to-violent soil and water loss regions in Changting County, and involves planting trees, bushy plants, and herbs such as Schima superba, Liquidambar formosana, Lespedeza bicolor, and Paspalum wettsteinii in level trenches (400 cm × 50 cm × 40 cm, 600 hm⁻²), with Ca, Mg, and P compound fertilizer applications.

The experimental plot in Laiyoukeng, with four stands with ABHMP in Changting County, was selected as the study area (116°23′30″ to 116°30′30″E, 25°38′15″ to 25°42′55″N). The climate of the area is subtropical and monsoon-influenced with warm and humid characteristics [20], and the soil is classified as an Alumic Ferralsol (World Reference Base for Soil Resources). The area of Laiyoukeng is 402.72 m², the elevation ranges from 345 m to 365 m AMSL, the plant community is dominated by D. dichotoma with scattered shrubs, and the ecosystem is severely degraded (Fig 1). The four stands with ABHMP, that is, Duimountian, Longjing, Youfang, and Bashilihe were established in 2011, 2006, 2000, and 1983, respectively.

No specific permissions were required for the experimental plot in Laiyoukeng or the four stands, which are considered wasteland, and our field studies did not involve endangered or protected species.

Methods

Measurement of microtopography and D. dichotoma patches. The locations (longitude, latitude and altitude) were measured using a Trimble 5800 GPS (mean position accuracy = ± 0.1 m) in Laiyoukeng in August, 2012 (S1 File). The number of points measured was 3,358. A point layer was created by importing a measured point, and a triangulated irregular network (TIN) layer was created from the point layer in ArcGIS 10. The TIN layer was then converted to a GRID layer to produce a high-resolution digital elevation model (DEM) with a cell size of 0.1 m × 0.1 m. The Topographic Position Index (TPI), plus the slope of the cell, can be used to classify the cell into a microtopography. The TPI is the difference between a cell elevation value and the average elevation of the neighborhood around that cell. Positive values mean the cell is higher than its surroundings while negative values mean it is lower. If it is significantly higher than the surrounding neighborhood, then it is likely to be at, or near, the top of a hill or ridge. Otherwise, significantly low values suggest the cell is at, or near, the bottom of a valley. TPI values near zero may mean either a flat area or a middle slope area, and thus the cell slope can be used to distinguish the two. A method to define threshold TPI values is to use standard deviations from the elevation, which takes into account the variability of elevation values within that neighborhood. Based on both the fieldwork and our own assessment of microtopography accuracy, we used a circular neighborhood with a 1 m radius, meaning that the TPI value for each cell reflected the difference between the elevation of that cell and the average elevation of all cells within 1 m of that cell [23]. We used both TPI and the slope to form a microtopography layer that included valley, lower slope, flat slope, middle slope, upper slope, and ridge [23] (Table 1, Fig 2). The borders of the D. dichotoma patches were measured using the same method, then converted to shapefile to produce a D. dichotoma patch layer in the ArcGIS 10 (S1 File). The D. dichotoma patch layer and the microtopography layer were overlain to calculate the areas and percentages of the different microtopographies in the D. dichotoma patches (Fig 2). To determine the stabilization of D. dichotoma patches, we measured the borders of the patches using a Trimble 5800 GPS once a year in August from 2012 to 2016.

Location of sampling points. Three gullies with, and three gullies without, D. dichotoma were chosen for sampling, and three types of microtopographies (ridge, slope, and valley) were set in Laiyoukeng. The slope included the lower slope, flat slope, middle slope, and upper slope, which were narrow and limited for sampling. Thus, 54 sampling points (nine on the
ridges, nine on the slopes, and nine on the valleys in the gullies with or without *D. dichotoma* were determined to distinguish the *D. dichotoma* physiological, soil, and microclimate factors (Fig 2).

**Environment factors.** Three microtopography factor layers were derived from the DEM layer: altitude, slope, and aspect layers (S1 Table).

A metal ring (diameter 35 cm) was placed at each sampling point for *D. dichotoma* physiological and soil factors in August 2012. According to our previous study [24], we selected the
mean plant height (PH), aboveground biomass per unit area (ABPUA), underground biomass per unit area (UBPUA), and total biomass per unit area (TBPUA) as the D. dichotoma physiological factors. We measured the mean PH within each ring. Given that D. dichotoma is an herbaceous plant, our analysis considered only measurements relative to the rooting zone (upper = 20 cm of the soil profile). We harvested aboveground and underground plant biomass separately by digging each ring to a depth of 20 cm, and then drying and weighing the plant material to determine ABPUA, UBPUA, and TBPUA (S1 Table).

Soil was sampled and pooled into a composite sample from the base of D. dichotoma to a depth of 20 cm within each ring. A set of eight soil factors, including organic matter, total N, available N, total P, available P, total K, available K, and pH were selected and measured. We determined organic matter by the method of oxidation with potassium dichromate in a heated oil bath; total N by means of alkali distillation; total P by means of atomic absorption spectrophotometry; total K by digestion with hydrofluoric acid and perchloric acid; available N, available P, and available K by the alkaline KMnO₄ method, Bray’s P I method, and NH₄OAc method, respectively; and we measured pH with a pH meter at a soil/water ratio of 1:2.5. All the soil analyses were carried out according to standard guidelines [25] (S1 Table).

D. dichotoma germinates in spring, grows in the summer and autumn, and withers in winter [26]. Based on expert knowledge from the Soil and Water Conservation Bureau of Changting County, we distinguished the following three periods: spring (March–May), summer and autumn (June–November), and winter (December–February of the following year). As plants and soil had been removed and destroyed in the sampling points for the D. dichotoma physiological and soil factors in August 2012, each sampling point for the microclimate factors was located approximately 0.1 m from the sampling point for the physiological factors. Two kinds of sampling points were located in the same microtopography to minimize differences. We measured the underground (5 cm) temperature (UT) and moisture (UM) using a soil hygrothermograph (RR-7210, mean temperature accuracy = ±0.2˚C, mean humidity accuracy = ±3%) at the sampling points for the microclimate factors in the spring (4/22-4/29), summer and autumn (6/29-7/6), and winter (1/25-2/1) of 2015, using a 10-min time interval (S1 Table).

We sampled and analyzed the soil and microclimate factors using the same methods in the level trenches in Duimountian.

**Species distribution models.** The D. dichotoma patch layers were converted to the point layers using ArcGIS10 and 13,639 points for presence and 44,707 points for absence of D. dichotoma were generated.

Three types of environmental factors were collected. (1) Microtopography factor layers: altitude, slope, and aspect. Slope layer and aspect layer were generated based on DEM using the Slope and Aspect functions in ArcGIS10. The aspect layer was recategorized and valued as sunny

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| Microtopography | Classification criteria |
|-----------------|-------------------------|
| Ridge           | TPI > 0.4 SD            |
| Upper slope     | TPI > 0.15 SD and < = 0.4 SD |
| Middle slope    | TPI > -0.05 SD and = 0.15 SD Slope > 7 degrees |
| Flat slope      | TPI > -0.05 SD and < = 0.15 SD Slope < = 7 degrees |
| Lower slope     | TPI > -0.3 SD and < = -0.05 SD |
| Valley          | TPI < = -0.3 SD         |

Note: SD, standard deviation from elevation.

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Fig 2. Microtopographies and sampling points in Laiyoukeng.

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slope (135–225˚)-4, half-sunny slope (45–135˚)-3, half-shady slope (225–315˚)-2, and shady slope (0–45˚, 315–360˚)-1; (2) soil factor layers: raster layers for 8 soil factors were created by the Geostatistical Analyst method in ArcGIS10 using 54 sampling points; (3) microclimate factor layers: the mean, maximum, and minimum UT and UM values were calculated for spring, summer and autumn, and winter to generate 18 microclimate factors whose raster layers were created by the Geostatistical Analyst method in ArcGIS10 using 54 microclimate sampling points. Ordinary Kriging interpolation treatments were applied to eight soil factors and 18 microclimate factors by the Geostatistical Analyst method in ArcGIS10. The mean prediction errors and root-mean-square standardized prediction errors were used to validate the accuracy of raster layers generated by the ordinary Kriging interpolation, and the result was satisfactory. The raster layers are not shown due to limited space (S2 File).

We designed the ABHMP scenario and generated the level trench layer in Laiyoukeng (Fig 3 and S1 File). Based on expert knowledge from the Soil and Water Conservation Bureau of Changting County, the eight soil factors and 18 microclimate factors of the level trenches were valued according to the average values of the corresponding factors from the level trenches in Duimountian. We overlaid the level trench layers and the raster layers for three microtopography factors, 8 soil factors, and 18 microclimate factors to generate the new raster layers in Laiyoukeng. Accordingly, we obtained the new environmental factor layers under the ABHMP scenario to predict the potential distribution of *D. dichotoma*. All models were run using the ModEco Platform. ModEco is a software package for species distribution modeling which provides a user-friendly platform enabling users to model species distribution data with relative ease, and includes relatively comprehensive tools for data visualization, feature selection, and accuracy assessment [27]. The four presence and absence models for species used were as follows: Generalized Linear Model, Maximum Entropy, Artificial Neural Network, and Support Vector Machine. We first calibrated the four models with current environmental factor layers and then ran the four models using the new environmental factor layers to generate the probability layers of *D. dichotoma* under the ABHMP scenario. Some researchers have advocated the use of combinations of multiple models. However, it has been concluded that when a single best model can be identified, incorporation of other models will bias the final model away from the best model’s predictions [28]. Therefore, we did not use combinations of models.

Model results were evaluated using the area under the curve (AUC), which is a nonparametric threshold-independent measure of accuracy commonly used to evaluate SDMs [29]. An approximate guide for classifying the accuracy of models using AUC is: excellent AUC > 0.9, good 0.9 > AUC > 0.8, fair 0.8 > AUC > 0.7, poor 0.7 > AUC > 0.6 and fail 0.6 > AUC > 0.5 [30]. We selected the models with AUC > 0.9 that have a strong predictive performance among the four models. The ABHMP scenario in Laiyoukeng was the same as the ABHMP used in the four stands (Duimountian, Longjing, Youfang, and Bashilihe), which to some extent represented the spread of *D. dichotoma* in the future. Thus, we compared the potential distribution of *D. dichotoma* under the ABHMP scenario in Laiyoukeng with that of Duimountian, Longjing, Youfang, and Bashilihe by visual examination to select the best model and its probability layer according to the similarity of the distribution of *D. dichotoma* in microtopographies. We reclassified the selected probability layer into the classification layer that included three types: ‘Suitable area’, ‘Sub-suitable area’, and ‘Unsuitable area’ for *D. dichotoma*.

We evaluated the importance of the factor values for the distribution of *D. dichotoma* using the selected best model and the current environmental factor layers.

**Plant quadrat.** Three representative standard plots (20 m × 20 m) were established, and four subplots (1 m × 1 m) were placed along a diagonal line in each plot in Duimountian,
Fig 3. ABHMP scenario in Laiyoukeng.

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Longjing, Youfang, and Bashilihe. We visually estimated the vegetation cover (VC) of *D. dichotoma* in each subplot and the averages were obtained from the VC of *D. dichotoma* in Duimountian, Longjing, Youfang, and Bashilihe.

**Statistical analyses.** Normality and homogeneity were verified using Kolmogorov-Smirnov’s test and Levene’s test, respectively, prior to analysis. When necessary, data were natural log-transformed to meet the assumption of normality and homogeneity [31]. A one-way analysis of variance (ANOVA) with least square difference (LSD) was used to compare differences among *D. dichotoma* physiological factors, soil factors, and microclimate factors. Significance levels were set at $P = 0.05$. All statistical analyses were performed using SPSS software.

**Results**

**The distribution and physiological factors of *D. dichotoma* and environmental factors in microtopographies**

The *D. dichotoma* patches were very stable from 2012 to 2016, covering an area of 138.82 m$^2$, equivalent to 30.09% of the total area of Laiyoukeng. The percentages of microtopographies decreased in the order from the valley through the slope (the upper slope, the middle slope, and the lower slope) to the ridge in the *D. dichotoma* patches ($P < 0.05$). We did not analyze the flat slope due to its negligible percentage (Table 2).

The four *D. dichotoma* physiological factors (PH, ABPUA, UBPUA, and TBPUA) decreased in the order from the valley through the slope to the ridge in Laiyoukeng ($P < 0.05$) (Table 3).

Among 26 soil and microclimate factors, 15 showed significant differences among the three microtopographies (ridge, slope, and valley) in the gullies with or without *D. dichotoma* ($P < 0.05$), and the valley was more humid and milder compared to the ridge in Laiyoukeng. The valley was more fertile in the gullies with *D. dichotoma*, while soil factors were not significantly different among the three microtopographies (ridge, slope, and valley) in the gullies without *D. dichotoma* (except for total N) in Laiyoukeng (Table 4).

**Main environmental factors affecting the distribution of *D. dichotoma***

Five environmental factors largely contributed to the distribution of *D. dichotoma*: average UT in the summer and autumn, average UM in the spring, minimum UT in the spring, maximum UT in the summer and autumn, and minimum UM in the spring.

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**Table 2. Areas and percentages of microtopographies in the *D. dichotoma* patches in Laiyoukeng.**

| Areas and percentages | Valley | Lower slope | Flat slope | Middle slope | Upper slope | Ridge |
|-----------------------|--------|-------------|------------|--------------|-------------|-------|
| Area m$^2$             | 40.04  | 33.44       | 0.77       | 27.97        | 24.74       | 11.86 |
| Percentage %           | 29.64 ± 3.84a | 23.45 ± 1.02ab | 0.61 ± 0.46c | 20.08 ± 2.57b | 17.09 ± 1.19bc | 9.14 ± 1.09c |

Different letters in the Percentage column indicate significant differences at $P < 0.05$.

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**Table 3. Means (±SE) of *D. dichotoma* physiological factors among microtopographies in Laiyoukeng.**

| Physiological factors | Microtopography |
|-----------------------|-----------------|
|                       | Valley | Slope | Ridge |
| PH cm                 | 43.38 ± 3.84a  | 25.44 ± 2.26b | 11.64 ± 1.12c |
| ABPUA g·m$^{-2}$      | 1054.63 ± 155.62a | 434.35 ± 61.55b | 110.28 ± 18.50c |
| UBPUA g·m$^{-2}$      | 355.24 ± 125.84 | 250.38 ± 63.38 | 88.80 ± 9.19 |
| TBPUA g·m$^{-2}$      | 1409.86 ± 260.67a | 684.72 ± 51.80b | 199.08 ± 20.58c |

Different letters in the same column indicate significant differences at $P < 0.05$.

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Table 4. Means (±SE) of soil factors and microclimate factors among microtopographies in Laiyoukeng.

| Factors | Gullies with D. dichotoma | Gullies without D. dichotoma |
|---------|----------------------------|----------------------------|
|         | Valley | Slope | Ridge | Valley | Slope | Ridge |
| Maximum UT in spring °C | 32.05 ± 1.15a | 32.05 ± 1.15a | 32.05 ± 1.15a | 31.30 ± 0.85b | 31.46 ± 0.57a | 32.73 ± 0.62a |
| Minimum UT in spring °C | 16.08 ± 0.10abc | 15.88 ± 0.15bc | 16.12 ± 0.08ab | 15.77 ± 0.10bc | 15.58 ± 0.09c | 40.64 ± 0.15a |
| Average UT in spring °C | 21.35 ± 0.11b | 21.97 ± 0.08a | 20.90 ± 0.09b | 21.33 ± 0.08b | 22.13 ± 0.10a | 23.17 ± 0.07 |
| Maximum UT in summer and autumn °C | 34.22 ± 1.29ab | 40.26 ± 0.81a | 36.97 ± 0.95ab | 38.96 ± 0.39a | 40.64 ± 0.15a | 29.25 ± 0.02a |
| Minimum UT in summer and autumn °C | 23.13 ± 0.18 | 23.02 ± 0.13 | 23.07 ± 0.09 | 23.11 ± 0.18 | 23.17 ± 0.07 | |
| Average UT in summer and autumn °C | 27.38 ± 0.09c | 28.87 ± 0.07a | 27.57 ± 0.05c | 28.31 ± 0.05b | 29.25 ± 0.02a | |
| Maximum UT in winter °C | 26.51 ± 0.77 | 27.61 ± 1.29 | 23.41 ± 1.78 | 24.34 ± 1.29 | 25.33 ± 0.89 | |
| Minimum UT in winter °C | 8.59 ± 0.19 | 8.59 ± 0.19 | 7.68 ± 0.53 | 7.93 ± 0.40 | 8.57 ± 0.15 | |
| Average UT in winter °C | 13.26 ± 0.07a | 13.22 ± 0.06d | 13.54 ± 0.09bc | 13.78 ± 0.05b | |
| Maximum UM in spring % | 16.08 ± 0.34a | 19.93 ± 1.92b | 22.91 ± 0.84ab | 28.89 ± 3.68a | 18.49 ± 1.54b | |
| Minimum UM in spring % | 12.18 ± 1.28 | 8.30 ± 0.70 | 11.73 ± 0.70 | 8.08 ± 0.38 | 8.14 ± 1.34 | |
| Average UM in spring % | 15.67 ± 1.66a | 14.95 ± 0.76ab | 10.89 ± 0.76bc | 13.98 ± 0.61ab | 10.40 ± 0.26c | 10.35 ± 1.06c |
| Maximum UM in summer and autumn % | 23.77 ± 1.49ab | 19.93 ± 1.92b | 22.91 ± 0.84ab | 28.89 ± 3.68a | 18.49 ± 1.54b | |
| Minimum UM in summer and autumn % | 13.79 ± 0.68ab | 8.62 ± 0.58c | 12.56 ± 0.90abc | 10.33 ± 1.65bc | 4.56 ± 0.61d | |
| Average UM in summer and autumn % | 19.86 ± 0.68a | 16.94 ± 0.48a | 15.96 ± 0.74ab | 13.61 ± 1.24bc | 8.37 ± 0.42d | |
| Maximum UM in winter % | 8.95 ± 1.12 | 13.23 ± 1.94 | 15.83 ± 0.91 | 13.39 ± 1.17 | 12.97 ± 1.43 | |
| Minimum UM in winter % | 7.64 ± 0.94 | 10.28 ± 2.08 | 13.24 ± 0.97 | 10.83 ± 0.95 | 11.10 ± 1.62 | |
| Average UM in winter % | 9.10 ± 1.08 | 11.50 ± 1.99 | 14.50 ± 0.98 | 11.97 ± 1.11 | 12.04 ± 1.47 | |
| Organic matter g kg⁻¹ | 5.71 ± 0.78b | 1.89 ± 0.15c | 1.42 ± 0.11c | 1.55 ± 0.09c | 1.91 ± 0.14c | |
| Total N g kg⁻¹ | 0.58 ± 0.06a | 0.21 ± 0.02c | 0.27 ± 0.01c | 0.30 ± 0.01b | 0.31 ± 0.02b | |
| Available N mg kg⁻¹ | 55.47 ± 6.25a | 24.21 ± 1.73c | 29.11 ± 2.11bc | 30.76 ± 1.89bc | 30.60 ± 1.30bc | |
| Total P g kg⁻¹ | 0.09 ± 0.00 | 0.13 ± 0.04 | 0.08 ± 0.01 | 0.08 ± 0.01 | 0.09 ± 0.00 | |
| Available P mg kg⁻¹ | 0.07 ± 0.01 | 0.04 ± 0.01 | 0.06 ± 0.01 | 0.07 ± 0.01 | 0.05 ± 0.01 | |
| Total K g kg⁻¹ | 2.15 ± 0.20 | 2.15 ± 0.13 | 1.92 ± 0.32 | 1.63 ± 0.27 | 1.85 ± 0.23 | |
| Available K mg kg⁻¹ | 18.11 ± 2.23a | 5.28 ± 1.46c | 4.18 ± 1.11c | 5.65 ± 1.44bc | 3.07 ± 0.00c | |
| pH | 4.61 ± 0.03a | 4.61 ± 0.03a | 4.61 ± 0.03a | 4.61 ± 0.03a | 4.62 ± 0.02a | |

Different letters in the same column indicate significant differences at P<0.05.

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UT in the spring, and average UT in the spring, followed by total N and total P; microtopography factors, on the other hand, had only marginal effects on the 29 factors in Laiyoukeng (Fig 4).

Average UT in summer and autumn, average UM in spring, minimum UT in spring, maximum UT in spring, average UT in spring, and total N showed significant differences among the three microtopographies (ridge, slope, and valley) in the gullies with or without D. dichotoma in Laiyoukeng (P < 0.05). Average UT in summer and autumn, maximum UT in spring, and average UT in spring tended to increase in the order from the valley through the slope to the ridge, while minimum UT in spring and average UM in spring showed the opposite trends. Total N also showed decreasing trends in the gullies with or without D. dichotoma. Total P was not significantly different among the three microtopographies (ridge, slope, and valley) in the gullies with or without D. dichotoma (Table 4).

The potential distribution of D. dichotoma

The best selected model was the Generalized Linear Model with AUC 0.906. The predicted potential distribution of D. dichotoma using the Generalized Linear Model was 402.72 m²
(68.99%), and the unsuitable area was 181.02 m\(^2\) (31.01%) for *D. dichotoma* under the ABHMP scenario in Laiyoukeng. Out of a total of 402.72 m\(^2\), 152.36 m\(^2\) (26.10%) was identified as the suitable area and 250.36 m\(^2\) (42.89%) as the sub-suitable area for *D. dichotoma*. The suitable area was located mostly in the level trenches and valleys (Fig 5).

VC was 79.83%, 88.08%, 84.67%, and 67.33% in Duimountian, Longjing, Youfang, and Bashiliehe, respectively.

**Discussion**

**Microtopography had strong effects on the distribution and growth of *D. dichotoma***

In our study, we found that the percentages of microtopographies decreased in the order from the valley through the slope to the ridge in the *D. dichotoma* patches, most of the *D. dichotoma* physiological factors decreased in the order from the valley through the slope to the ridge, and the valley provided gentler temperatures and higher humidity than the ridge. This indicates that microtopography has strong effects on the distribution and growth of *D. dichotoma*, and the valley is more suitable for *D. dichotoma*. With regard to soil and water, the valley is a run-on area, in the slope run-on equals runoff, and the ridge is a runoff area [32]. Soil and water loss in a runoff area results in poorer water, less soil nutrient content, and lower soil depth and stability, with subsequent negative effects on plants such as seed death [33]. A run-on area, where runoff soil and water converge, tends to have better plant growth and development [34]. For example, the soil seed bank and ground vegetation decreased in the order of bottom slope > lower side slope > middle side slope > upper side slope > crest slope in fixed sand of the Mu Us sandy land, China [35]; and in the hilly Loess Plateau region of China, the biomass of the grassland community and annual fine root production were in the order of lower > middle > upper > top in the shady slope [36]. Thus, the valley usually becomes the microrefugium, a small area with local favorable environmental features in which small populations can survive outside their main distribution area, protected from unfavorable regional environmental conditions. For example, relict glacial bodies and active geomorphological processes along alpine valleys favor microrefugial niches where alpine species are able to survive in Alpine regions during interglacial phases [18].
Fig 5. Potential distribution of *D. dichotoma* under the ABHMP scenario in Laiyoukeng.

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Main environmental factors affecting the distribution of *D. dichotoma*

The microclimate factors were the most critical environmental factors affecting the distribution of *D. dichotoma*, followed by the soil factors, while the microtopography factors only had marginal effects. Temperature-related factors in summer and autumn, and spring, and moisture-related factors in spring, were the most important microclimate factors. In previous reports, temperature and moisture have been identified as major factors influencing *D. dichotoma* in terms of growth, survival, metabolic rate, reproduction, and dispersal [37]. If a soil is hot and dry, the root and rhizome of *D. dichotoma* cannot survive, especially when the soil temperature is over 45˚C [38]. It has been reported that *D. dichotoma* starts to sprout and its roots, rhizomes, and leaves start to grow in spring [39]. Therefore, temperature and moisture levels in spring are important drivers shaping the distribution of *D. dichotoma*.

One of our previous studies showed that total P was low due to severe soil and water loss in the red soil hilly region of China [24]. In another of our studies, the coverage, total biomass, and height of *D. dichotoma* were positively correlated with total N [22]. This suggests that the distribution of *D. dichotoma* may be constrained by total N and total P. However, in the present study, total P was not significantly different among the three microtopographies in the gullies with *D. dichotoma* and gullies without *D. dichotoma*, with the opposite trend being observed for total N in the gullies with or without *D. dichotoma*. This result was unexpected and difficult to explain, and the effects of soil on *D. dichotoma* and the effects of soil on *D. dichotoma* need to be investigated further.

Interestingly, the microtopography factors had only marginal effects on the distribution of *D. dichotoma*, which seemed contrary to the distribution and growth of *D. dichotoma* among microtopographies. We used both the TPI and the slope to form 6 microtopographies including valley, lower slope, flat slope, middle slope, upper slope, and ridge. The microtopography in this study is an integration of microtopography factors including topographic positions, altitude, and slope which can act either indirectly, by modulating microclimatic and soil properties, or directly, through slope and associated gravitational processes [40]. Altitude, slope, and aspect are likely the same in different microtopographies; for example, slope and aspect are very similar in valleys and ridges with different altitudes while altitude, slope, and aspect may be different within the same microtopography; for example, aspects are opposite in two upper slopes. Consequently, microtopography is a comprehensive variable and altitude, slope, and aspect cannot completely replace microtopography. It has been argued that topographical factors are not important for plant distribution [41]; for instance, although altitude was not specifically selected, climate was shown to be a better and more detailed predictor of red panda conservation than altitude *per se* [42]. Further research is needed to find out more appropriate microtopography factors to represent microtopography and better understand how microtopography affects other environmental factors and plant distribution.

Effects of ABHMP on the potential distribution of *D. dichotoma* and implications for ecological restoration

The predicted potential distribution of *D. dichotoma* under the ABHMP scenario was nearly three times higher than the current distribution, and the suitable area was located mostly in the level trenches and valleys in Laiyoukeng. The VC in Laiyoukeng was in the range of Duimountian, Longjiing, Youfang, and Bashilihe, which indicated that the prediction was accurate to some extent. The results showed strong effects of ABHMP on the potential distribution of *D. dichotoma*, and SDMs proved to be a valuable tool to identify the main environmental factors, predict potential species distribution, and assess ecological restoration measures at the microscale. Our method can provide a geographic template that can potentially be applied to a
diverse set of areas and species. The main requirement for using the template is the availability of good quality datasets, but acquiring datasets is difficult. Recently, remote sensing has achieved the high spatial resolution and physical accuracy needed to model species distribution [43]. For example, hyperspectral sensors mounted on satellites or airplanes can now gather data enabling the calculation of temperature or moisture variables at a high resolution, in addition to raw bands or vegetation indices [40]. Determining the presence and absence of species in the good quality datasets mentioned above generally requires a considerable amount of fieldwork, which then decides what kind of SDMs should be used. SDMs can be roughly divided into two groups, depending on the origin of the species: presence–absence and presence-only SDMs [44]. Presence–absence SDMs use information about locations where the species is found and not found, whereas presence-only SDMs usually search for correlations between environmental parameters and observation records [45]. Because datasets with recorded absences of species are scarce, background or pseudo-absence locations are widely used [44], leading to sampling bias [46]. Presence–absence SDMs may result in higher accuracy when reliable presence–absence information is available [45]. In this work, we indicated locations where *D. dichotoma* was absent with high precision using continuous observation from 2012 to 2016. In addition, the distribution pattern of species and environment factors is an important aspect of the good quality datasets, which has major influence on interpolation methods. The 54 sampling points used to create the soil factor layers and microclimate factor layers are aggregated in space, which would lead to errors to some extent in some areas without points in our study. Thus, the effects of the distribution pattern of species and environment factors on SDMs are in need of further study.

**Conclusions**

Microtopography had strong effects on the distribution and growth of *D. dichotoma*, and the valley was the most suitable for *D. dichotoma*. Microclimate factors were the most critical environmental factors for the distribution of *D. dichotoma*, followed by soil factors, whereas microtopography factors had only limited effects. Microtopography is a comprehensive variable and altitude, slope, and aspect cannot completely replace microtopography. The predicted potential distribution of *D. dichotoma* under the ABHMP scenario, using SDMs, was accurate. ABHMP had strong effects on the potential distribution of *D. dichotoma*, and SDMs proved to be a valuable tool for identifying the main environmental factors, predicting potential species distribution, and assessing ecological restoration measures at the microscale.

**Supporting information**

S1 File. Layers.  
(ZIP)

S2 File. Soil and microclimate factor.  
(DOCX)

S1 Table. Physiological factors, soil factors and microclimate factors.  
(XLS)

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References

1. Kazakov NV. Assessment of soil disturbance upon oil and gas prospecting in western Kamchatka. Eurasian Soil Science. 2010; 43(2):216–25. https://doi.org/10.1134/S1064226310020122

2. Ma H, Wang YQ, Yue H, Zhong BL. The threshold between natural recovery and the need for artificial restoration in degraded lands in Fujian Province, China. Environmental Monitoring & Assessment. 2013; 185(10):8639–48.

3. Teixeira TSM, Weber MM, Dias D, Lorin ML, Esbérard CEL, Novaes RLM, et al. Combining environmental suitability and habitat connectivity to map rare or Data Deficient species in the Tropics. Journal for Nature Conservation. 2014; 22(4):384–90. https://doi.org/10.1016/j.jnc.2014.04.001

4. Heubes J, Schmidt M, Stuch B, Marquez JRG, Wittig R, Ziska G, et al. The projected impact of climate and land use change on plant diversity: An example from West Africa. Journal of Arid Environments. 2013; 96(3):48–54.

5. Martins J, Richardson DM, Henriques R, Marchante E, Marchante H, Alves P, et al. A multi-scale modelling framework to guide management of plant invasions in a transboundary context. Forest Ecosystems. 2016; 3(1):17. https://doi.org/10.1186/s40663-016-0073-8

6. Bouska KL, Whitledge GW, Coad BW, Mahini AS, Schneegger R, Unfer G, et al. Predicting presence and absence of trout (Salmo trutta) in Iran. Limnologia. 2014; 46:1–8. https://doi.org/10.1016/j.limno.2013.12.001 PMID: 24707064

7. Chefaoui RM, Assis J, Duarte CM, Serrão EA. Large-Scale Prediction of Seagrass Distribution Integrating Landscape Metrics and Environmental Factors: The Case of Cymodocea nodosa (Mediterranean–Atlantic). Estuaries & Coasts. 2016; 39(1):123–37.

8. Mostafavi H, Pletterbauer F, Coad BW, Mahini AS, Schneegger R, Unfer G, et al. Predicting presence and absence of trout (Salmo trutta) in Iran. Limnologia. 2014; 46:1–8. https://doi.org/10.1016/j.limno.2013.12.001 PMID: 24707064

9. Crego RD, Didier KA, Nielsen CK. Modeling meadow distribution for conservation action in arid and semi-arid Patagonia, Argentina. Journal of Arid Environments. 2014; 102; 68–75. https://doi.org/10.1016/j.jaridenv.2013.11.008

10. Mikolajczak A, Marechal D, Sanz T, Isenmann M, Thierion V, Luque S. Modelling spatial distributions of alpine vegetation: A graph theory approach to delineate ecologically-consistent species assemblages. Ecological Informatics. 2015; 30:196–202. https://doi.org/10.1016/j.ecoinf.2015.09.005

11. Maes D, Jacobs I, Segers N, Vanreusel W, Van Daele T, Laurijssens G, et al. A resource-based conservation approach for an endangered ecotone species: the Ilex Hairstreak (Satyrium ilicis) in Flanders (north Belgium). Journal of Insect Conservation. 2014; 18(5):939–50. https://doi.org/10.1007/s10841-014-9702-0

12. Shida Y, Nakamura F. Microenvironmental conditions for Japanese alder seedling establishment in a hummocky fen. Plant Ecology. 2011; 212(11):1819–29. https://doi.org/10.1007/s11258-011-9951-x

13. Moser K, Ahn C, Noe G. Characterization of microtopography and its influence on vegetation patterns in created wetlands. Wetlands. 2007; 27(4):1081–97. https://doi.org/10.1672/0277-5212(2007)27[1081:COMAILJ2.0.CO;2]

14. Kooch Y, Hosseini SM, Mohammadi J, Hojjati SM. Effects of uprooting tree on herbaceous species diversity, woody species regeneration status and soil physical characteristics in a temperate mixed forest of Iran. Journal of Forestry Research 2012; 23(1):81–9. https://doi.org/10.1007/s11676-012-0236-6

15. Burke IC, Lauenroth WK, Vinton MA, Hook PB, Kelly RH, Epstein HE, et al. Plant-soil interactions in temperate grasslands. Biogeochimia. 1998; 42:121–43. https://doi.org/10.1080/978-94-017-2691-7_7

16. Tokuchi N, Takeda H, Yoshida K, Iwatsubo G. Topographical variations in a plant–soil system along a slope on Mt Ryuoh, Japan. Ecological Research. 1999; 14(4):361–9. https://doi.org/10.1046/j.1440-1703.1999.00309.x
17. Barbosa JM, Asner GP. Prioritizing landscapes for restoration based on spatial patterns of ecosystem controls and plant–plant interactions. Journal of Applied Ecology. 2017;54(5).

18. Gentili R, Baroni C, Caccianiga M, Armiraglio S, Ghiani A, Citterio S. Potential warm-stage microrefugia for alpine plants: Feedback between geomorphological and biological processes. Ecological Complexity. 2015; 21:87–99.

19. Rull V, Iacute. Microrefugia—Rull—2008—Journal of Biogeography—Wiley Online Library. Journal of Biogeography. 2009.

20. Zou AP, Chen ZB, Chen LH. Spatio-temporal variation of eroded landscape in typical small watershed in the hilly region of red soil: A case study of Zhuxihe small watershed in Changing County, Fujian Province. Science of Soil and Water Conservation. 2009; 7(2):93–9. https://doi.org/10.3969/j.issn.1672-3007.2009.02.016

21. Li CB, Qi JG, Feng ZD, Yin RS, Guo BY, Zhang F. Process-based soil erosion simulation on a regional scale: the effect of ecological restoration in the Chinese loess plateau. Dordrecht: Springer Netherlands; 2009. 113–30 p.

22. Li XF, Chen ZB, Chen ZQ, Zheng LD, Zhang XY, Li RL. Response of disranopteris dichotoma growth to environmental factors in Eroded Red-soil Region of Southern China. Bulletin of Soil and Water Conservation. 2013; 33(3):33–7.

23. Weiss A, editor Topographic position and landforms analysis. ESRI User Conference; 2001; San Diego, CA.

24. Chen ZQ, Chen ZB, Yan XY, Bai LY. Stoichiometric mechanisms of Dicranopteris dichotoma growth and resistance to nutrient limitation in the Zhuxi watershed in the red soil hilly region of China. Plant and Soil. 2016; 398(1):367–79. https://doi.org/10.1007/s11104-015-2670-7

25. Liu GS. Soil physical and chemical analysis and description of soil profiles. Beijing: Standards Press of China; 1996. 5–40 p.

26. Chen J. Dynamic pattern of the biomass of Dicranopteris dichotoma communities in different environments. Chinese Journal of Ecology. 1991; 10(4):18–22.

27. Guo Q, Liu Y. ModEco: an integrated software package for ecological niche modeling. Ecography. 2010; 33(4):637–42.

28. Virkkala R, Marmion M, Heikkinen RK, Thuiller W, Luoto M. Predicting range shifts of northern bird species: Influence of modelling technique and topography. Acta Oecologica. 2010; 36(3):269–81. https://doi.org/10.1016/j.actao.2010.01.006

29. Bertelsmeier C, Luque GM, Courchamp F. The impact of climate change changes over time. Biological Conservation. 2013; 167(1):107–15.

30. Crego RD, Didier KA, Nielsen CK. Modeling meadow distribution for conservation action in arid and semi-arid Patagonia, Argentina. Journal of Arid Environments. 2014; 102(2):68–75.

31. Han X, Sistla SA, Zhang YH, Li XT, Han XG. Hierarchical responses of plant stoichiometry to nitrogen deposition and mowing in a temperate steppe. Plant and Soil. 2014; 382(1–2):175–87. https://doi.org/10.1007/s11104-014-2154-1

32. Yao J, Peters DPC, Havstad KM, Gibbens RP, Herrick JE. Multi-scale factors and long-term responses of Chihuahuan Desert grasses to drought. Landscape Ecology. 2006; 21(8):1217–31. https://doi.org/10.1007/s10980-006-0025-8

33. Yoshida N, Ohsawa M. Seedling success of Tsuga sieboldi along a microtopographic gradient in a mixed cool-temperate forest in Japan. Plant Ecology. 1999; 140(1):89–98. https://doi.org/10.1023/A:1009740016420

34. Martinez-Turanzas GA, Coffin DP, Burke IC. Development of microtopography in a semi-arid grassland: effects of disturbance size and soil texture. Plant and Soil. 1997; 191(2):163–71. https://doi.org/10.1023/A:1004286605052

35. Han HY, Chen YY, Li WX. The distribution and relationships of ground vegetation, soil seed bank and soil water content of fixed sand under different micro-landform conditions. Praticultural Science. 2014; 31(10):1825–32. https://doi.org/10.11829/j.issn.1001-0629.2014-0164

36. Ru HL, Zhang HD, Jiao F, Yue CY, Guo ML. Impact of micro-landform on grassland plant community structure and function in the hilly Loess Plateau region, China. Chinese Journal of Applied Ecology. 2016; 27(1):25–32. https://doi.org/10.13287/j.1001-9332.201601.039 PMID: 27228589

37. Gallardo B, Aldridge DC. Evaluating the combined threat of climate change and biological invasions on endangered species. Biological Conservation. 2013; 160:225–33. https://doi.org/10.1016/j.biocon.2013.02.001

38. Deng H, Lin QW, Teng HQ, Zhao YJ, Deng YD. Analysis on the growth regularity of Dicranopteris dichotoma in areas of intensive soil erosion. Journal of Fujian College of Forestry. 2004; 24(3):262–4. https://doi.org/10.13324/j.cnki.jfjf.2004.03.017
39. Lin XX. Growth and development and artificial propagation technique of *Dicranopteris dichotoma*. Fujian Soil And Water Conservation. 2004; 16(2):60–2. https://doi.org/10.3969/j.issn.1002-2651.2004.02.017

40. Pradervand JN, Dubuis A, Pellissier L, Guisan A, Randin C. Very high resolution environmental predictors in species distribution models: Moving beyond topography? Progress in Physical Geography. 2014; 38(1):79–96.

41. Chen YH. Habitat suitability modeling of amphibian species in southern and central China: environmental correlates and potential richness mapping. Science China Life Sciences. 2013; 56(5):476–84. https://doi.org/10.1007/s11427-013-4475-3 PMID: 23633079

42. Kandel K, Huettmann F, Suwal MK, Regni GR, Nijman V, Nekaris KAI, et al. Rapid multi-nation distribution assessment of a charismatic conservation species using open access ensemble model GIS predictions: Red panda (*Ailurus fulgens*) in the Hindu-Kush Himalaya region. Biological Conservation. 2015; 181:150–61. https://doi.org/10.1016/j.biocon.2014.10.007

43. Questad EJ, Kellner JR, Kinney K, Cordell S, Asner GP, Thaxton J, et al. Mapping habitat suitability for at-risk plant species and its implications for restoration and reintroduction. Ecological Applications. 2014; 24(2):385–95. PMID: 24689149

44. Domisch S, Kuemmerlen M, Jähnig SC, Haase P. Choice of study area and predictors affect habitat suitability projections, but not the performance of species distribution models of stream biota. Ecological Modelling. 2013; 257:1–10. https://doi.org/10.1016/j.ecolmodel.2013.02.019

45. Coro G, Magliozzi C, Berge EV, Bailly N, Ellenbroek A, Pagano P. Estimating absence locations of marine species from data of scientific surveys in OBIS. Ecological Modelling. 2016; 323(1):61–76. https://doi.org/10.1016/j.ecolmodel.2015.12.008

46. Jarnevich CS, Stohlgren TJ, Kumar S, Morisette JT, Holcombe TR. Caveats for correlative species distribution modeling. Ecological Informatics. 2015; 29:6–15. https://doi.org/10.1016/j.ecoinf.2015.06.007