Spatial Variation in Mattic Epipedon Development and Environmental Factors in Alpine Meadows of the Central Qilian Mountains (Postprint)

Authors: Jin Chengwei, Zhao Yuguo, Li Xusheng, Zhi Junjun, Zhang Ganlin

Date: 2017-11-01T00:00:00+00:00

Abstract

The mattic epipedon underlying alpine meadow vegetation can provide ecological benefits such as soil and water conservation and water retention, and constitutes the core of ecological function in alpine meadow vegetation. Understanding the spatial variation in mattic epipedon development degree and its environmental influencing factors facilitates a deeper comprehension of the role of alpine meadows in plateau ecosystems. This study focuses on the alpine meadow distribution area in the middle Qilian Mountains as the research region, classifying mattic epipedons into weakly developed, moderately developed, and strongly developed categories based on root volume combined with mattic layer thickness and soil bulk density. Environmental characteristics including terrain, vegetation, and climate were analyzed for mattic epipedons of different development degrees, and their distribution was spatially mapped using a support vector machine model. The results indicate that in the middle Qilian Mountains, mattic epipedons with higher development degrees tend to be distributed in locations with favorable moisture conditions, including low altitudes, gentle slopes, lower slope positions, and north-facing slopes, and are dominated by Kobresia plants. Mattic epipedons with moderate or higher development degrees exhibit relatively good surface vegetation and moisture conditions. Mattic epipedons with higher development degrees have higher mean annual temperatures, while precipitation differences among mattic epipedons of various development degrees are not significant. The spatial distribution results demonstrate high overall consistency with the existing distribution of alpine meadow vegetation types, yet with more detailed spatial resolution, and have achieved spatial subdivision of mattic epipedons with different development degrees.

ChinaRxiv

Full Text

Spatial Distribution and Environmental Factors Affecting Matic Epipedon at Different Developmental Levels in Alpine Meadows in the Middle Qilian Mountains

JIN Chengwei[1], ZHAO Yuguo[2], LI Xusheng[1], ZHI Junjun[2], ZHANG Ganlin[2]

[1]School of Geographic and Oceanographic Sciences, Nanjing University, Nanjing 210023, China
[2]State Key Laboratory of Soil and Sustainable Agriculture, Institute of Soil Science, Chinese Academy of Sciences, Nanjing 210008, China

Abstract

The matic epipedon underlying alpine meadow vegetation provides critical ecological benefits such as water retention and soil conservation, forming the core of alpine meadow ecological functions. Investigating the spatial distribution of matic epipedon at different developmental levels and its relationship with environmental factors is essential for elucidating the role of alpine meadows in plateau ecosystems. This study focused on alpine meadow distribution areas in the middle Qilian Mountains, classifying matic epipedon into three developmental levels—weakly developed, moderately developed, and strongly developed—primarily based on root volume, supplemented by matic layer thickness and soil bulk density. We analyzed topographic, climatic, and other environmental characteristics across different developmental levels and employed a Support Vector Machine (SVM) model to map their spatial distribution. Results showed that strongly developed matic epipedon tended to occur in locations with superior moisture conditions: lower elevations, gentle slopes, lower slope positions, and north-facing aspects, where vegetation was dominated by *Kobresia* species. Both vegetation cover and moisture conditions were better at higher development levels. Strongly developed matic epipedon exhibited higher mean annual temperatures, though precipitation differences among developmental levels were not significant. The spatial distribution of different developmental levels was highly consistent with existing alpine meadow vegetation type distributions, but at finer spatial resolution, successfully distinguishing internal variations within alpine meadow vegetation types. This refined spatial classification of matic epipedon developmental levels provides data support and theoretical basis for further research on matic epipedon distribution across the Tibetan Plateau and its ecological functions.

Keywords: alpine meadow; matic epipedon; middle Qilian Mountains; spatial mapping

---

1. Introduction

The matic epipedon is a turf-like surface layer underlying alpine meadow vegetation, characterized by high organic carbon content and interwoven networks of living and dead roots [1-3]. This layer effectively intercepts precipitation and provides crucial ecological services including soil and water conservation [4-6], representing the core functional component of alpine meadow ecosystems. In China, matic epipedon is primarily distributed in the eastern and northern Tibetan Plateau. Given its vital role in plateau ecosystems, numerous studies have investigated its development mechanisms [7] and environmental impacts [8-10]. However, most research has conflated matic epipedon with alpine meadow vegetation types [11-13], and existing vegetation classification systems primarily distinguish surface coverage without addressing differences in subsurface matic epipedon characteristics. Variations in vegetation and local hydrothermal conditions lead to different developmental degrees of matic epipedon, resulting in significant differences in physical properties such as root volume and thickness. Current research lacks classification criteria for different developmental levels, and their spatial distribution patterns remain unclear. Distinguishing among different developmental levels will enhance our understanding of matic epipedon development mechanisms and improve the accuracy of regional ecological quality assessment and evolution modeling.

In the Chinese Soil Taxonomy, matic epipedon is defined as a diagnostic horizon [1] for identifying Turic Cambosols, establishing quantitative knowledge models linking matic epipedon with environmental factors. Digital soil mapping approaches [14-16] can be adapted to predict the spatial distribution of matic epipedon at different developmental levels. Given the complex, nonlinear relationships between soil and environmental factors, machine learning models such as Random Forest [17-18] and Artificial Neural Networks [19-20] are commonly employed. Support Vector Machine (SVM) demonstrates superior performance in classification and function fitting [21-22] and has been successfully applied in soil organic carbon mapping [23-24] and soil spectroscopy [24]. This study focuses on matic epipedon in the middle Qilian Mountains, classifying developmental levels based on physical characteristics to clarify differences in topographic, vegetation, and climatic factors among levels. Using SVM, we predicted the spatial distribution of different developmental levels, providing data support and theoretical basis for understanding matic epipedon' s role in plateau ecosystems.

---

2. Study Area

The study area is located in the middle Qilian Mountains on the northeastern edge of the Tibetan Plateau, geographically positioned at 98°34 22 -101°9 24 E, 37°43 13 -39°5 19 N, with elevations ranging from 1700 m to 5100 m. The region experiences a continental alpine mountain climate, cold and arid in the northwest, mild and humid in the southeast. Mean annual precipitation increases from northwest to southeast, averaging 327 mm and concentrated in the central-eastern part [25]. Vegetation is dominated by alpine meadows.

[Figure 1: see original paper] Location of study area and spatial distribution of main environmental factors

---

3. Sample Collection and Analysis

To ensure sampling points represented diverse elevation, vegetation, and climate characteristics, we employed a purposive sampling method based on typical sites [26]. Environmental factors including topography and biology were clustered to generate an environmental factor combination map expressed as membership degrees, where higher values indicated greater regional environmental typicality. Areas with membership >0.5 were considered typical environmental factor combination zones. Considering accessibility and sampling feasibility, final sampling points were located at the centers of these zones. In August 2014, 88 typical profiles were collected, including 69 matic epipedon profiles meeting Chinese Soil Taxonomy definitions and 19 non-matic profiles.

At each profile, we surveyed surface vegetation conditions and collected surface soil samples and ring samples. All samples were air-dried indoors for laboratory analysis. Matic epipedon thickness was measured, and root volume was assessed based on expert knowledge. Soil bulk density was determined using the ring knife method. For two samples where ring sampling was impossible, data were missing. Given the strong correlation between soil organic matter and bulk density [27], we established an exponential regression model: bd = 1.45e^(-0.01×soc) ($R^2 = 0.82$, $p < 0.01$), where bd is bulk density (g/cm^3) and soc is organic carbon content (g/kg). Soil organic carbon was measured using the potassium dichromate-sulfuric acid digestion method.

---

4. Developmental Level Classification

The Chinese Soil Taxonomy defines matic epipedon using three physical indicators: matic layer thickness (>5 cm), root volume (>20%), and bulk density (0.5-1.1 g/cm^3). This study primarily used root volume, supplemented by thickness and bulk density, to classify matic epipedon into three developmental levels: weakly developed, moderately developed, and strongly developed.

Main basis for classifying developmental levels of matic epipedon

[Figure 2: see original paper] Typical profiles and landscapes of matic epipedon at different developmental levels (a1&a2: weakly developed; b1&b2: moderately developed; c1&c2: strongly developed)

---

5. Environmental Factor Analysis

Differences in vegetation and climate created variations in matic epipedon development across the middle Qilian Mountains. Selected environmental factors included: elevation, slope, aspect, NDVI, mean annual temperature (MAT), and mean annual precipitation (MAP). Topographic data were derived from ASTER GDEM (30 m resolution). NDVI data used MOD13Q1 products (250 m resolution) from 2000–2014. Climate data were interpolated from 756 national meteorological stations. All environmental factors were resampled to 250 m resolution. Statistical analysis employed box plots and circular diagrams using ArcGIS 10.1 for topographic processing, ENVI 5.1 for remote sensing, SPSS 19.0 for statistical analysis, and Origin 9.1 for plotting.

---

6. Spatial Distribution Prediction

Environmental factors including topography, vegetation, and climate are closely linked to matic epipedon development. SVM can discriminate sample types with different environmental characteristics, establishing ecological models to predict spatial distribution of different developmental levels.

6.1 Model Principles SVM' s fundamental principle is identifying an optimal hyperplane that separates two classifiable sample groups. The distance between samples and the hyperplane indicates classification accuracy. When the geometric margin for all samples is maximized, the hyperplane is optimal [21-22]. For linearly inseparable cases, appropriate kernel functions map sample points into high-dimensional Hilbert space, enabling linear solutions to nonlinear classification problems. Samples on the margin boundaries are support vectors.

[Figure 3: see original paper] Diagram of optimal hyperplane (L: optimal hyperplane; S: support vector; G: geometric interval)

6.2 Model Construction and Prediction The SVM workflow was: (1) Build a classification model based on regional environmental factors to discriminate matic vs. non-matic samples, generating a probability distribution map; (2) Define areas with >50% probability as matic distribution zones; (3) Using 69 matic samples with the same environmental variables, build classification models for each developmental level; (4) Predict developmental levels within matic distribution zones. Environmental variables included topography (elevation, slope, aspect), vegetation (NDVI), and climate (MAT, MAP). The model used R 3.2.5 with the e1071 package, employing radial basis kernel function, with cost parameter C and gamma optimized.

6.3 Evaluating Environmental Factor Importance Given the lack of independent validation samples, we used cross-validation to assess model generalization [28-29], including leave-one-out and 10-fold cross-validation. SVM cannot directly evaluate factor importance, but comparing model accuracies with full versus partial factor sets reveals relative importance [30]. For the developmental level classification model, we compared: (1) all factors, (2) single factor removal, and (3) single factor only, using average 10-fold cross-validation accuracy to evaluate importance.

---

7. Results

7.1 Environmental Factor Analysis **Topography:** Elevation, slope, and aspect distributions differed significantly among developmental levels. Matic epipedon occurred at 3000–4000 m, with elevation decreasing as development increased: strongly developed at 3000–3300 m, moderately at 3200–3600 m, and weakly at >3500 m. Slope also decreased with development: weakly developed on >25° slopes, moderately on moderate slopes, strongly on <15° slopes. Slope position lowered with development: weakly developed on upper slopes, moderately on middle slopes, strongly on lower slopes. Matic epipedon predominantly occurred on north-facing slopes, with stronger development associated with more northerly aspects.

[Figure 4: see original paper] Topographical features distribution of matic epipedon at different developmental levels (a: elevation; b: slope; c: slope position; d: aspect)

Vegetation: NDVI and plant type distributions varied by developmental level. Higher development corresponded to higher vegetation cover, with mean NDVI values of 0.72, 0.85, and 0.85 for weakly, moderately, and strongly developed matic epipedon, respectively (weakly vs. others: $p < 0.05$). All levels were dominated by *Kobresia*, but weakly developed matic epipedon included cold-tolerant, drought-resistant species like *Potentilla* and *Achnatherum*, with some *Stellera chamaejasme* (toxic species). Moderately and strongly developed matic epipedon associated with hydrophilic plants like *Polygonum*.

[Figure 5: see original paper] NDVI and plant types of matic epipedon at different developmental levels

Climate: Mean annual temperature increased with development level: -3.0°C, -1.3°C, and -1.1°C for weakly, moderately, and strongly developed matic epipedon, respectively. Precipitation differences were not significant, with means of 354 mm, 357 mm, and 314 mm, respectively. Weakly and moderately developed matic epipedon showed wider precipitation ranges (301–429 mm and 297–454 mm), while strongly developed matic epipedon was concentrated at 320 mm.

[Figure 6: see original paper] Mean annual temperature and precipitation of matic epipedon at different developmental levels

Factor Analysis: Correlation analysis revealed elevation correlated most significantly with MAT (r = -0.93, $p < 0.01$) and positively with MAP (r = 0.48, $p < 0.01$). NDVI correlated negatively with elevation (r = -0.61, $p < 0.01$) and positively with MAT (r = 0.54, $p < 0.01$). Slope and aspect showed no significant correlations with other factors. Factor analysis extracted two principal components: PC1 (elevation, MAT, MAP) representing macro-environmental factors (61.7% variance), and PC2 (slope, aspect) representing local topography (23.0% variance).

Pearson correlations between environmental factors
Rotated factor loadings matrix

7.2 Spatial Distribution of Matic Epipedon **Probability Map:** SVM predicted matic epipedon distribution across 63.9% of the study area, showing a northwest-southeast orientation with two main regions: northwestern slopes and foothills, and southeastern plateau surfaces. High-probability areas (>50%) aligned closely with Landsat TM imagery showing dense vegetation and alpine meadow distribution zones. Model accuracy reached 83.3% overall, 81.5% for leave-one-out cross-validation, and 78.5% average for 10-fold cross-validation.

[Figure 7: see original paper] Occurring probability of matic epipedon and Landsat TM image (RGB: band 5/4/3 combination)

Developmental Level Distribution: Spatial distribution of different developmental levels showed weakly developed matic epipedon occupying the largest area (49.2%), followed by moderately (32.1%) and strongly (18.7%) developed. Development increased from northwest to southeast. Weakly developed matic epipedon dominated the northwest; moderately developed occurred in north-central foothills and southeast; strongly developed formed a northwest-southeast band along central valley foothills. Model accuracy reached 87.1% overall, 80.6% for leave-one-out, and 79.0% average for 10-fold cross-validation. Of 88 sampling points, 79 were accurately predicted.

[Figure 8: see original paper] Spatial distribution of matic epipedon at different developmental levels

7.3 Environmental Factor Importance Factor importance evaluation showed elevation and NDVI as most critical, with model accuracy dropping significantly when either was removed. MAT and MAP showed lower importance, likely due to information overlap with elevation.

[Figure 9: see original paper] Mean accuracy of 10-fold cross-validation run 10 times (All variables; Without variable; Only variable)

---

8. Discussion

In the arid Qilian Mountains, moisture is the most critical factor for plant growth. Lower elevations, gentler slopes, and lower slope positions facilitate water retention, promoting root growth and matic epipedon development. Elevation' s significant negative correlation with MAT and positive correlation with MAP creates contrasting conditions: elevations >3000 m are cold-humid (favorable), while <3000 m are warm-dry (unfavorable). Higher temperatures enhance microbial activity and root decomposition, but superior moisture conditions at lower elevations with high NDVI appear more critical. The factor analysis and model results confirm elevation and NDVI as key drivers, while MAT and MAP contribute less independently due to collinearity.

The spatial pattern shows matic epipedon is absent at >4000 m and <3000 m, with distribution closely tied to alpine meadow vegetation, highlighting the importance of elevation and vegetation. Strongly developed matic epipedon occurs not only in the warm, moist southeast but also along central valley foothills where higher elevation reduces evapotranspiration and improves moisture retention. This underscores moisture availability as the key factor controlling developmental level spatial variation.

---

9. Conclusion

Lower elevations, gentle slopes, lower slope positions, and north-facing aspects with superior moisture conditions and high vegetation cover are key factors influencing matic epipedon development. The SVM model effectively predicted spatial distribution of different developmental levels: weakly developed in the drier northwest, moderately developed in relatively moist northern foothills and southeast, and strongly developed in a band along central valley foothills. The classification method based primarily on root volume, supplemented by thickness and bulk density, successfully distinguished internal heterogeneity within alpine meadow vegetation types, providing valuable insights into alpine meadow ecosystem functions on the Tibetan Plateau.

Acknowledgments

We thank Dr. Yang Fei and Dr. Yang Renmin for fieldwork assistance. Landsat TM imagery was provided by the Heihe Plan Data Center.

References

[1] Chinese Soil Taxonomy Research Group, Institute of Soil Science, Chinese Academy of Sciences. Chinese Soil Taxonomy Retrieval. Hefei: University of Science and Technology of China Press, 2001.
[2] Kaiser K, Miehe G, Barthelmes A, et al. Turf-bearing topsoils on the central Tibetan Plateau, China: pedology, botany, geochronology. Catena, 2008, 73(3): 300-311.
[3] Yang RM, Zhang GL, Yang F, et al. Precise estimation of soil organic carbon

stocks in the northeast Tibetan Plateau. Scientific Reports, 2016, 6: 21842.
[4] [Chinese reference on human impacts on carbon processes]
[5] Yang F, Zhang GL, Yang JL, et al. Organic matter controls of soil water retention in an alpine grassland and its significance for hydrological processes. Journal of Hydrology, 2014, 519: 3086-3093.
[6] [Chinese reference on water retention functions]
[7] [Chinese reference on permafrost and root distribution]
[8] [Chinese reference on grazing impacts]
[9] [Chinese reference on degradation mechanisms]
[10] [Chinese reference on erosion processes]
[11] Chang XF, Bao XY, Wang SP, et al. Exploring effective sampling design for monitoring soil organic carbon in degraded Tibetan grasslands. Journal of Environmental Management, 2016, 173: 121-126.
[12] Wang GX, Wang YB, Li YS, Cheng HY. Influences of alpine ecosystem responses to climatic change on soil properties on the Qinghai-Tibet Plateau, China. Catena, 2007, 70(3): 506-514.
[13] Zeng C, Zhang F, Wang QJ, et al. Impact of alpine meadow degradation on soil hydraulic properties over the Qinghai-Tibetan plateau. Journal of Hydrology, 2013, 478(2): 148-156.
[14] McBratney AB, Mendonça Santos ML, Minasny B. On digital soil mapping. Geoderma, 2003, 117(1/2): 3-52.
[15] Hengl T, Heuvelink GBM, Stein A. A generic framework for spatial prediction of soil variables based on regression-kriging. Geoderma, 2004, 120(1/2): 75-93.
[16] [Chinese reference on fuzzy logic soil mapping]
[17] Grimm R, Behrens T, Märker M, Elsenbeer H. Soil organic carbon concentrations and stocks on Barro Colorado Island—Digital soil mapping using Random Forests analysis. Geoderma, 2008, 146(1/2): 102-113.
[18] Wiesmeier M, Barthold F, Blank B, Kögel-Knabner I. Digital mapping of soil organic matter stocks using Random Forest modeling in a semi-arid steppe ecosystem. Plant and Soil, 2011, 340(1/2): 7-24.
[19] Agyare WA, Park SJ, Vlek PLG. Artificial neural network estimation of saturated hydraulic conductivity. Vadose Zone Journal, 2007, 6(2): 423-431.
[20] Zhao ZY, Yang Q, Benoy G, et al. Using artificial neural network models to produce soil organic carbon content distribution maps across landscapes. Canadian Journal of Soil Science, 2010, 90(1): 75-87.
[21] Meyer D, Leisch F, Hornik K. The support vector machine under test. Neurocomputing, 2003, 55(1/2): 169-186.
[22] Ballabio C. Spatial prediction of soil properties in temperate mountain regions using support vector regression. Geoderma, 2009, 151(3/4): 338-350.
[23] Somarathna PDSN, Malone BP, Minasny B. Mapping soil organic carbon content over New South Wales, Australia using local regression kriging. Geoderma Regional, 2016, 7(1): 38-48.
[24] Aldana-Jague E, Heckrath G, Macdonald A, van Wesemael B, Van Oost K. UAV-based soil carbon mapping using VIS-NIR (480-1000 nm) multi-spectral imaging: Potential and limitations. Geoderma, 2016, 275: 55-66.

[25] [Chinese reference on soil carbon distribution]
[26] Zhu AX, Yang L, Li BL, et al. Purposive sampling for digital soil mapping for areas with limited data. In: Digital Soil Mapping With Limited Data. Netherlands: Springer, 2008: 233-245.
[27] Xu L, He NP, Yu GR. Methods of evaluating soil bulk density: Impact on estimating large scale soil organic carbon storage. Catena, 2016, 144: 94-101.
[28] [Chinese reference on digital soil mapping progress]
[29] Brus DJ, Kempen B, Heuvelink GBM. Sampling for validation of digital soil maps. European Journal of Soil Science, 2011, 62(3): 394-407.
[30] Rodrigues M, de la Riva J. An insight into machine-learning algorithms to model human-caused wildfire occurrence. Environmental Modelling and Software, 2014, 57: 192-201.
[31] Miehe G, Miehe S, Kaiser K, Liu JQ, Zhao XQ. Status and Dynamics of the *Kobresia pygmaea* Ecosystem on the Tibetan Plateau. Ambio, 2008, 37(4): 272-279.
[32] [Chinese reference on soil moisture factors]

Note: Figure translations are in progress. See original paper for figures.