

Impact of mountain wind farms on different vegetation types: A case study in Yunnan Province

Chenhao Zhang^{a,b}, Xiaobing Li^{a,b,c,*}, Xin Lyu^{a,b,**}, Dongliang Dang^{a,b,d}, Siyu Liu^{a,b}, Ning Su^{a,b}

^a School of Natural Resources, Faculty of Geographical Science, Beijing Normal University, Beijing, 100875, China

^b State Key Laboratory of Earth Surface Processes and Disaster Risk Reduction, Beijing Normal University, Beijing, 100875, China

^c School of Geography and Tourism, Shaanxi Normal University, Shaanxi, 710062, China

^d School of Environment, Beijing Normal University, Beijing, 100875, China

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ABSTRACT

While wind power is regarded as a natural green energy source, the construction and operation of wind farms will inevitably have an impact on the local and even broader ecological environment. Therefore, exploring the ecological impacts caused by the construction and operation of wind farms to achieve a balance between energy transition and environmental protection is highly important. There is a paucity of research examining the impact of mountain wind farms on regional vegetation. This study examined the impact of mountain wind farms on different vegetation types, including forest, farmland, and grassland, in Yunnan Province, China, from 2008 to 2022. This study aimed to identify the potential causes of spatial heterogeneity in the impact of mountain wind farms on regional vegetation. The findings indicated that the influence of mountain wind farms on diverse vegetation types was predominantly evident within a 0.5 km radius. The wind farms exhibited notable uniformity in their inhibitory impact on the fractional vegetation cover (FVC) and the normalized difference vegetation index (NDVI) across the different vegetation types, whereas the effects on the leaf area index (LAI) exhibited greater variability. The spatial heterogeneity in the impact of mountain wind farms on the FVC, NDVI, and LAI was associated with a range of factors. The study also revealed that the negative impact of mountain wind farms on forests is due mainly to their direct destruction during wind farm construction, so the area occupied by forests should be strictly controlled during wind farm construction, with stronger management of damaged vegetation restoration.

1. Introduction

In recent years, global warming has resulted in a significant increase in the occurrence of extreme weather and climate events, which potentially pose considerable threats to food security, public health, economic growth, social stability and other areas and present serious challenges to the survival and development of humankind (Liu et al., 2023; Ji et al., 2024; Wei et al., 2024). In response to this global challenge, China is implementing significant measures to increase the utilization of renewable energy sources (Liu et al., 2015; Zhao et al., 2022). As a clean and renewable energy source, wind power has become an important energy pillar for China to achieve its “dual-carbon” goal. By

the end of 2022, China's installed wind power capacity reached approximately 370 million kilowatts, accounting for 14.5 % of the country's cumulative installed power generation capacity (National Energy Administration, 2023).

While wind power is a natural green energy source that does not emit pollutants or greenhouse gases, the construction and operation of wind farms can nevertheless have a significant impact on the local ecological environment (Baidya Roy and Traiteur, 2010). To date, scholars around the globe have conducted numerous theoretical and empirical research on the impacts of wind farm construction and operation on regional climate, vegetation, and soil. Firstly, the construction and operation of wind farms have a direct impact on vegetation and soil. During the

* Corresponding author. School of Natural Resources, Faculty of Geographical Science, Beijing Normal University, Beijing, 100875, China.

** Corresponding author. School of Natural Resources, Faculty of Geographical Science, Beijing Normal University, Beijing, 100875, China.

E-mail addresses: 202221051152@mail.bnu.edu.cn (C. Zhang), xbli@bnu.edu.cn (X. Li), lyuxin@bnu.edu.cn (X. Lyu), 201931051060@mail.bnu.edu.cn (D. Dang), 202231051076@mail.bnu.edu.cn (S. Liu), 202331051060@mail.bnu.edu.cn (N. Su).

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construction of wind farms, vegetation on the turbine platforms and roads within the wind farm needs to be cleared, resulting in a significant reduction in vegetation coverage. Some wind farms also harden the road surface, thereby altering the land cover in the wind farm area and increasing the proportion of construction land (Pekkan O I et al., 2021). Heavy vehicles used for construction or operation and maintenance of wind farms also crush the vegetation and soil, a process that not only directly damages the soil structure, but also changes the composition of the local plant communities to a certain extent, significantly reducing their biodiversity and productivity (Li et al., 2016). Secondly, the operation of wind farms changes the local microclimate, which indirectly affects the growth and development of vegetation and the physicochemical properties of the soil (Tang et al., 2017; Wang et al., 2023). In a study of the impact of wind farms on grassland ecosystems, Tang et al. (2017) reported a significant inhibitory effect on vegetation growth in the dam area of northern China. This was evidenced by reductions in the leaf area index (LAI), enhanced vegetation index (EVI), and normalized difference vegetation index (NDVI) of 14.5 %, 14.8 %, and 8.9 %, respectively, over the course of the study period. A study conducted by Wu et al. (2019) demonstrated that the construction of wind farms in Xilingol League, Inner Mongolia, resulted in a notable reduction in the summer NDVI within the designated study area. However, it has also been noted that the construction of wind farms affects the vegetation in different areas through different mechanisms, with the interior of the wind farms being unfavorable to the growth of vegetation and the upwind and downwind areas being favorable (Li et al., 2016).

China's wind energy resources are widely distributed and are concentrated mainly in the northwestern, northeastern and northern regions of the country, where most of the country's first wind farms were developed and constructed (He and Kammen, 2014). However, the development of onshore wind power, which is concentrated in the "Three North" region, is unable to meet the demand for power supply in the peak load areas of central and southeastern China (Han et al., 2023; Tian et al., 2023). To solve the problem of regional mismatch between the development of wind energy resources and electricity demand, China has introduced a policy for the development and consumption of wind energy in the near vicinity of the east-central and southeastern regions. These regions are rich in low-wind-speed resources, accounting for approximately 68 % of China's wind energy resource area. According to the National Energy Administration, from January–September 2021, 16.43 million kilowatts of new grid-connected wind power were installed nationwide, approximately 60 % of which were distributed in the east-central and southern regions (National Energy Administration, 2023). In the context of the "southward movement of wind power" in China in recent years, how to balance the relationship between the development of low-wind resources and protection of the ecological environment in the central and southeastern parts of the country has become an important issue.

Although scholars globally have performed many theoretical and empirical studies on the topic of "ecological impacts and intrinsic mechanisms of wind farm construction and operation", to the best of our knowledge, few studies have focused on the ecological impacts and intrinsic mechanisms of wind farms in mountainous areas, and there is an urgent need to carry out relevant studies to enrich the research results in this field. Existing studies are usually based on field surveys and sampling or remote sensing to investigate the impacts of mountain wind farms on vegetation or soil. Pătru-Stupariu et al. (2019), through field survey sampling, revealed that wind farms in the southern Carpathians of Romania did not significantly affect the plant community structure. Yao et al. (2014) similarly concluded that a mountain wind farm in Guizhou Province had no impact on the effective surviving population size of wild plants or on ecosystem structure and function. In terms of remote sensing analysis, Ma et al. (2023), in a study in Chuxiong City, Yunnan Province, revealed that the construction of mountain wind farms led to a significant decrease in vegetation growth in the region, whereas Zhang et al. (2022) in Yunnan Province similarly revealed that

the NDVI and FVC of mountain wind farms were reduced by 7.04 % and 10.02 %, respectively. There were also many studies indicating that the construction of mountain wind farms led to increased regional soil erosion, with significant reductions in soil moisture, organic carbon, and total nitrogen content (Zhang et al., 2022; Ma et al., 2023; Xu et al., 2023). Although these studies have evaluated the impact of a few mountain wind farms on vegetation or soil and drawn consistent conclusions, systematic exploration is still needed at a larger scale to further reveal the impact and mechanisms of mountain wind farms on the ecological environment.

Yunnan Province, as a green energy province in the southern region of China, is an important area for the future development of low-wind-speed resources. This study focuses on the following two questions: (1) What are the scope and degree of impact of mountain wind farms on regional forests, farmlands, and grasslands? (2) What is the underlying mechanism behind the spatially heterogeneous distribution of impacts of mountain wind farms on regional forests, farmlands, and grasslands? The results of this study will provide theoretical foundations and suggestions for scientific development toward balancing the relationship between green energy low-carbon transition and ecological environmental protection in mountainous areas.

2. Materials and methods

The framework of this research was shown in Fig. 1. Based on an independently decoded dataset of wind farm distribution in Yunnan Province from 2008 to 2022, the impacts of wind farms on the FVC, NDVI and LAI of regional forests, farmlands, and grasslands were analyzed. Among them, NDVI reflects the spectral reflectance characteristics and biomass status of vegetation, mainly reflecting the "greenness" of vegetation and being sensitive to chlorophyll content and vegetation health status; FVC measures the proportion of the surface covered by green vegetation, directly characterizing the spatial distribution and coverage of vegetation; LAI directly reflects the canopy structure and photosynthetic potential, and is an important parameter for vegetation productivity and carbon cycling. The three jointly depict the state of vegetation in different dimensions (spectral characteristics, spatial coverage, structural features), which can reduce the bias of a single index. Eight indicators were selected from three perspectives, namely, wind farm attributes, natural climatic conditions and topographic features, and the possible reasons for the spatial heterogeneity in the impact of mountain wind farms on regional vegetation were explored via Pearson correlation analysis and multiple linear regression analysis.

2.1. Study area

Yunnan Province is located in southwestern China, with geographic coordinates between 21° 8' - 29° 15' N latitude and 97° 31' - 106° 11' E longitude (Fig. 2a) (Xie et al., 2023), and has a total area of 394,100 square kilometers. Yunnan Province is a low-latitude inland area whose terrain is high in the northwest and low in the southeast, gradually decreasing from north to south. Yunnan Province has a mountainous plateau topography, with the mountainous area accounting for 88.64 % of the total area of the province, of which the area of the 1000–3500 m mid-altitude region accounts for 87.21 % of the land area of the province (Ma et al., 2024). The regional climate is essentially a subtropical and tropical monsoon climate, but northwestern Yunnan has a highland mountain climate. According to the National Energy Administration (NEA), the total reserves of wind power resources in Yunnan Province are approximately 123 million kilowatts (kW), and the total installed capacity of wind power projects that can be supported for implementation is approximately 20 million kW. According to the China Electric Power Statistical Yearbook, the process of wind power generation in Yunnan Province started in 2008, and its installed wind power capacity grew rapidly between 2013 and 2016 and has been developing

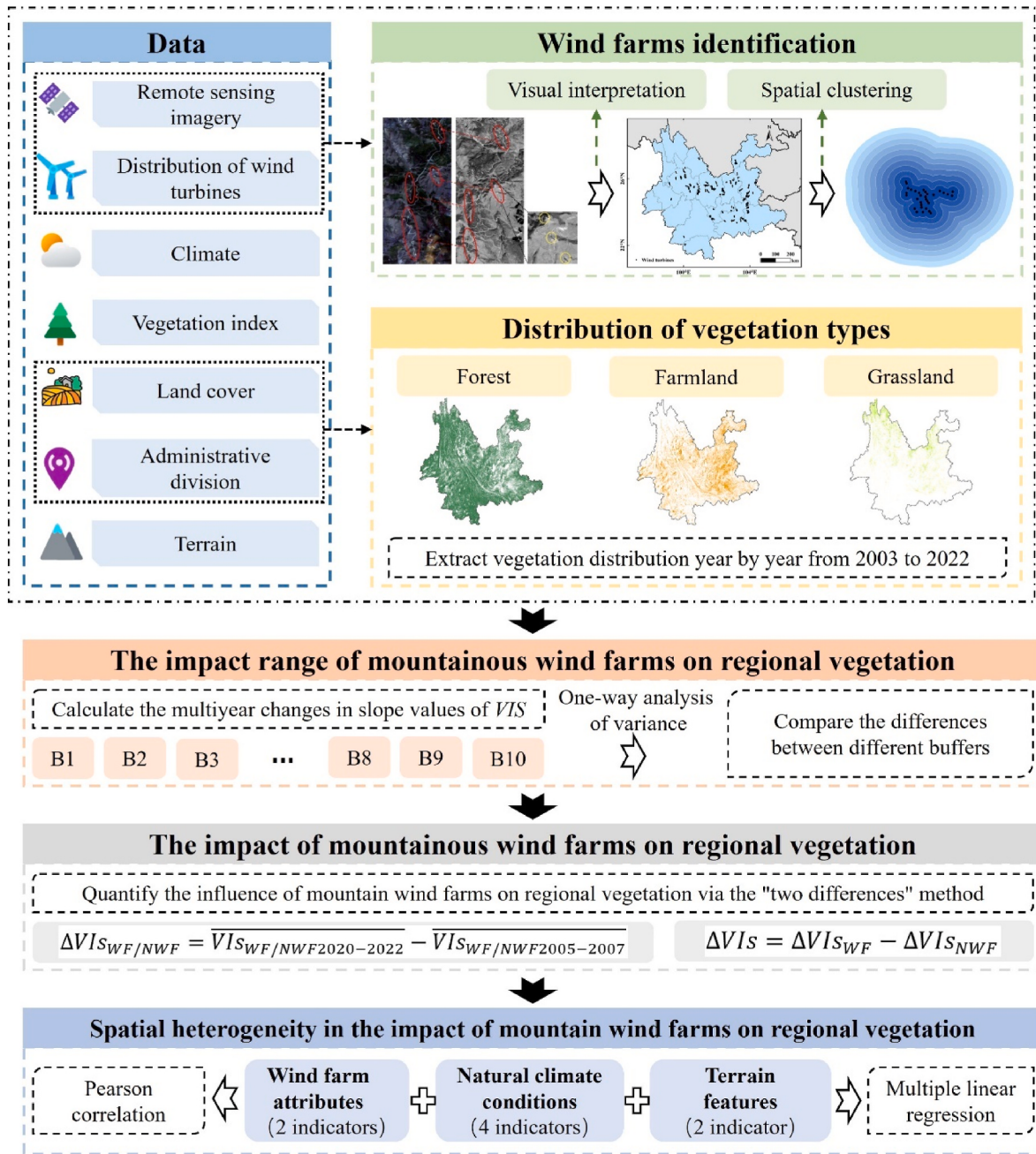


Fig. 1. Research framework.

steadily since then (Fig. 2b).

2.2. Data sources

The data used in this study include remote sensing image data, wind turbine distribution data, statistical data, land cover data, vegetation index data, climate data, terrain data, and administrative division data (Li et al., 2019; He et al., 2020; Gao et al., 2022; Nan et al., 2022; Gao et al., 2023; Yang and Huang, 2023) (Table 1). For the obtained remote sensing images, preprocessing such as projection conversion, geometric correction, image fusion, and image enhancement were required.

2.3. Wind turbine identification and wind farm clustering

First, by visually interpreting the remote sensing images from the Sentinel-2 satellite, the distribution of wind turbines in Yunnan Province

as of the end of 2022 could be preliminarily obtained. Then, by combining remote sensing images from the Gaofen-2 satellite and Jilin-1 satellite, as well as the AI Earth Chinese wind turbine distribution dataset (AIE_WindTurbine), the accuracy of the wind turbine distribution was verified. On this basis, spatial clustering was performed on the wind turbines, with those located less than 5 km away being considered to belong to the same wind farm. Finally, this study identified a total of 4879 wind turbines and spatially clustered them into 78 wind farms (Fig. 3a). According to the mountain map classification system established by Nan et al. (2016) (Tbl. 2), a total of 4854 wind turbines were located in mountainous areas of Yunnan Province, with proportions of 41.8 %, 32.7 %, 14.5 %, 6.3 %, 4.5 %, and 0.2 % located in “mid altitude and moderate undulation” (CG), “mid altitude and small undulation” (BG), “medium to high altitude and moderate undulation” (CH), “medium to high altitude and large undulation” (DH), “high altitude and large undulation” (DI), and “medium to high altitude and small

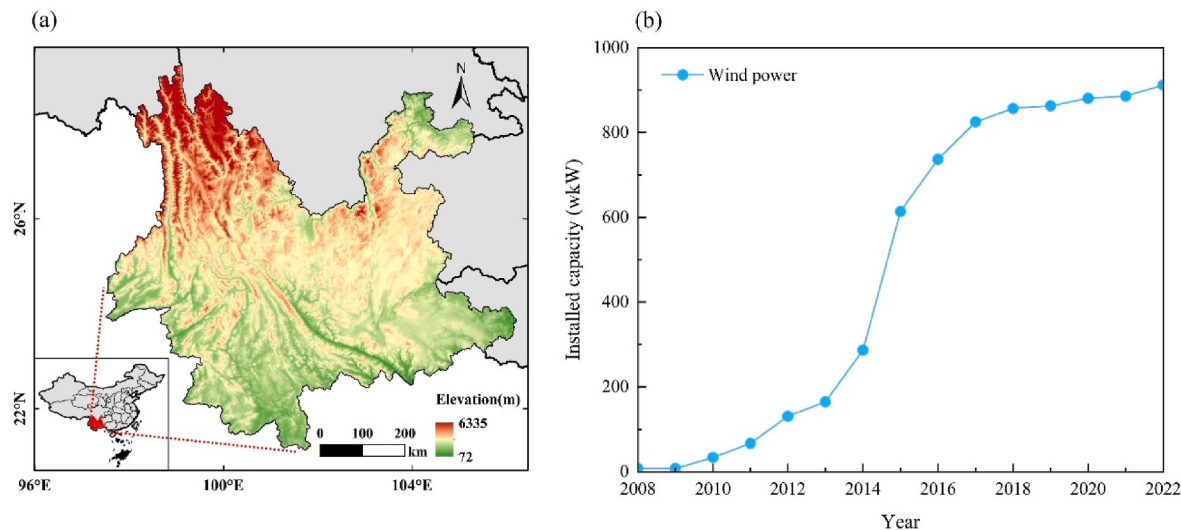


Fig. 2. Overview of the study area (a) Location and elevation of the study area, (b) Installed wind power capacity in Yunnan Province from 2008 to 2022.

Table 1
Data sources.

Type	Name	Characteristic	Spatial resolution	Temporal resolution	Sources
Remote sensing images	Sentinel-2	Raster data	10 m	2022	Google Earth Engine
	Gaofen-2		1 m		
Distribution of wind turbines	JiLin-1	Vector data	0.75 m	\	China Centre for Resources Satellite Data and Application (https://data.cresda.cn/#/home)
	AIE_WindTurbine		\		
	Wind farms databases		\		
Wind power installed capacity		Statistical data	\	2022 annually	AI Earth (https://engine-aiearth.aliyun.com) The Wind Power (https://www.thewindpower.net/) China Electric Power Statistical Yearbook
Land cover	China's 30 m annual land cover dataset and its dynamic changes (1985–2022)	Raster data	30 m	annually	National Cryosphere Desert Data Center (https://cstr.cn/CSTR:11738.11.NCDC.ZENODO.DB3943.2023)
Vegetation index	FVC	Raster data	250 m	monthly	National Tibetan Plateau/Third Pole Environment Data Center (https://www.tpdac.ac.cn/home)
	NDVI		500 m	monthly	
	LAI		500 m	monthly	
Climate	Solar radiation	Raster data	5 km	annually	Geographic Data Sharing Infrastructure, global resources data cloud
	Air temperature		1 km	annually	
	Precipitation		1 km	annually	
	Near-ground wind speed		1 km	annually	
Terrain	DEM	Raster data	90 m	\	National Earth System Science Data Center (https://www.geodata.cn/oldindex.html)
	Slope	Raster data	30 m	2022	
	Altitude and undulation	Vector data	\	2015	
Administrative division		Vector data	\	2022	A Big Earth Data Platform for Three Poles Resource and Environmental Science Data Platform (https://www.resdc.cn/Introduction.aspx) Open Topography (https://portal.opentopography.org/datasetMetadata?) National Tibetan Plateau/Third Pole Environment Data Center (https://cstr.cn/18406.11.Terre.tpdac.272523) National Geomatics Center of China (https://www.ngcc.cn/)

undulation” (BH), respectively (Fig. 3b).

The existing open-source wind farm databases identified a total of 2684 wind turbines in Yunnan Province as of the end of 2022. Compared with this dataset, the accuracy of the wind turbine distribution interpreted independently in this study was significantly improved.

2.4. The impact range of mountainous wind farms on regional vegetation

In this study, 10 buffer zones, each with a width of 0.5 km, were set up sequentially outward and centered on wind turbines belonging to the same wind farm after clustering (Fig. 4). Based on the 30 mannual land cover dataset, we extracted the distribution of forest, farmland, and grassland within the wind farm area annually, and calculated the multiyear changes in slope values of FVC, NDVI, and LAI for each vegetation types within each buffer zone of the wind farm. Finally, a one-way analysis of variance was conducted to compare the differences

in the slope values of the same vegetation type and vegetation index over the years among 78 wind farms in Yunnan Province with different buffer zones. If the significance level was less than 0.05, it was considered that for all mountain wind farms in Yunnan Province, the construction and operation of the wind farms had a significant impact on the vegetation within that distance.

2.5. The impact of mountainous wind farms on regional vegetation

In this study, the buffer zone influenced by the wind farm was referred to as the wind farm area (WF), while the buffer zone unaffected by the wind farm was termed the non-wind farm area (NWF). For the WF, the vegetation in this region had been directly and indirectly impacted by wind turbines, as well as influenced by climate change over the years. Conversely, the NWF had only been affected by climate change over the years. To eliminate the impact of climate change on the

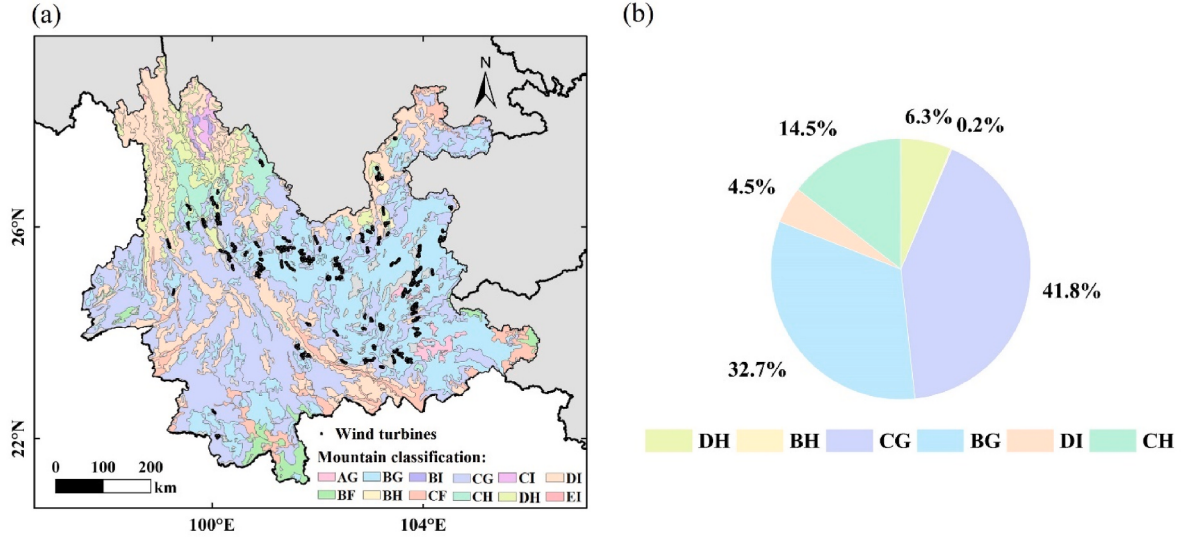


Fig. 3. (a) Classification of mountains in Yunnan Province and distribution of wind turbines in 2022, (b) The proportion of wind turbines belonging to various mountain classifications in Yunnan Province in 2022.

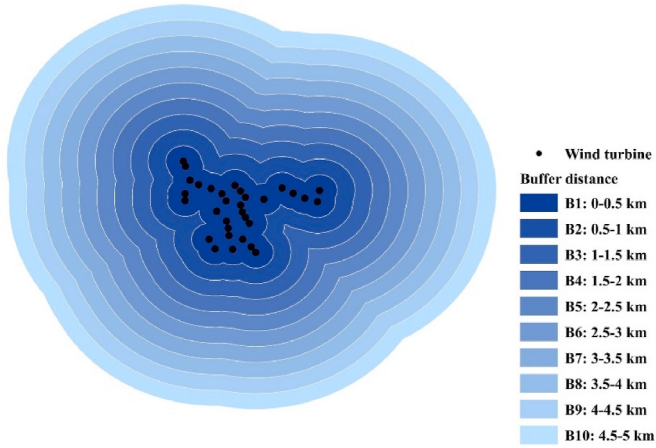


Fig. 4. Schematic diagram of buffer partitioning.

vegetation in the WF, we quantified the direct and indirect effects of mountain wind farms on regional vegetation using the “two differences” method (Zhou et al., 2012). The specific formulas were as follows:

$$\Delta Vis_{WF/NWF} = \overline{Vis_{WF/NWF2020-2022}} - \overline{Vis_{WF/NWF2005-2007}} \quad (1)$$

$$\Delta Vis = \Delta Vis_{WF} - \Delta Vis_{NWF} \quad (2)$$

where VIs are vegetation indices, which in this study included FVC, NDVI and LAI. $\overline{Vis_{WF/NWF2020-2022}}$ and $\overline{Vis_{WF/NWF2005-2007}}$ refer to the average values of the VIs of the WF or the NWF from 2020 to 2022 and 2005–2007, respectively. According to the results of the difference test, the impacts of wind farms on different vegetation types were mainly concentrated in the surrounding 0.5 km. Therefore, in this study, the area within 0.5 km from the wind turbine (B1) was considered the WF, and the area from 0.5 to 5 km (B2-B10) was considered the NWF.

Notably, since the first wind farm in Yunnan Province was built in 2008, the period from 2005 to 2007 was considered the preconstruction period. ΔVis_{WF} refers to the change in the vegetation index in the WF; ΔVis_{NWF} refers to the change in the vegetation index in the NWF. The ΔVis obtained by subtracting two variables refer to the changes in the vegetation index caused by wind farms after excluding the influence of climate factors on vegetation (see Table 2).

2.6. Spatial heterogeneity in the impact of mountain wind farms on regional vegetation

As shown in Table 3, we selected 8 indicators from three perspectives, namely, wind farm attributes, natural climate conditions, and terrain features, to explore the possible reasons for the spatial heterogeneity in the impact of mountain wind farms on regional vegetation (Qin et al., 2022; Liu et al., 2023; Su et al., 2024). The wind farm attributes included the number of wind turbines and the wind farm shape index; the natural climate conditions included solar radiation, precipitation, near-ground wind speed (10 m), and air temperature; and the terrain features referred to digital elevation models and slope.

For the wind farm shape index, which considers the wind farm as a landscape, the minimum boundary geometry tool of ArcGIS 10.4 was first used to obtain the range of the wind farm, and then Fragstats 4.2 was used to calculate its landscape shape index. For each climate indicator, based on the previously extracted range of forests, farmlands, and grasslands within 0.5 km around the wind farms, calculated the multi-year average values of climate indicators within each range.

This study explored the following two aspects: first, Pearson correlation analysis of ΔVis and other indicators was performed via SPSS, and second, multiple linear regression analysis was performed via SPSS using ΔVis as the dependent variables and each indicator as the independent variable. The calculation formulas for pearson correlation analysis and multiple linear regression analysis were as follows:

(1) Pearson correlation

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X - EX)(Y - EY)]}{\sigma_X \sigma_Y} \quad (3)$$

In the formula, X and Y represented ΔVis and other indicators respectively; $COV(X, Y)$ was the covariance of X and Y ; σ_X was the standard deviation of X ; σ_Y was the standard deviation of Y .

(2) Multiple linear regression

To eliminate the impact caused by differences in the magnitude or dimension of each indicator factor, normalization was first performed:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (4)$$

In the formula, X' was the normalized value of X ; X was the indicator

Table 2
Mountain map classification system and representative symbol.

	Low altitude (<1000m)	Mid altitude (1000~2000m)	Medium to high altitude (2000~4000m)	High altitude (4000~5000m)	Extremely high altitude (>5000m)
Minimal undulation (<200m)	AF	AG	AH	AI	\
Small undulation (200~500m)	BF	BG	BH	BI	BJ
Moderate undulation (500~1000m)	CF	CG	CH	CI	CJ
Large undulation (1000~2500m)	\	DG	DH	DI	DJ
Extremely large undulation (>2500m)	\	\	EH	EI	EJ

Table 3
Various indicators used to analyze the spatial heterogeneity of the impact of mountain wind farms on regional vegetation.

Indicator category	Indicator name			
Wind farm attributes	Number of wind turbines		Wind farm shape index	
Natural climate conditions	Solar radiation	Precipitation	Near-ground wind speed (10 m)	Air temperature
Terrain features	Digital elevation models		Slope	

value; X_{max} and X_{min} were the maximum and minimum values of the indicator, respectively.

Linear regression analysis was conducted with ΔVIs as the dependent variable and each indicator as the independent variable. The fitting equation was as follows:

$$\Delta VIs = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n \quad (5)$$

In the formula, β_0 was the intercept; $x_1, x_2, \dots, x_n$ were the various indicators; $\beta_1, \beta_2, \dots, \beta_n$ were the regression coefficients of the corresponding indicators.

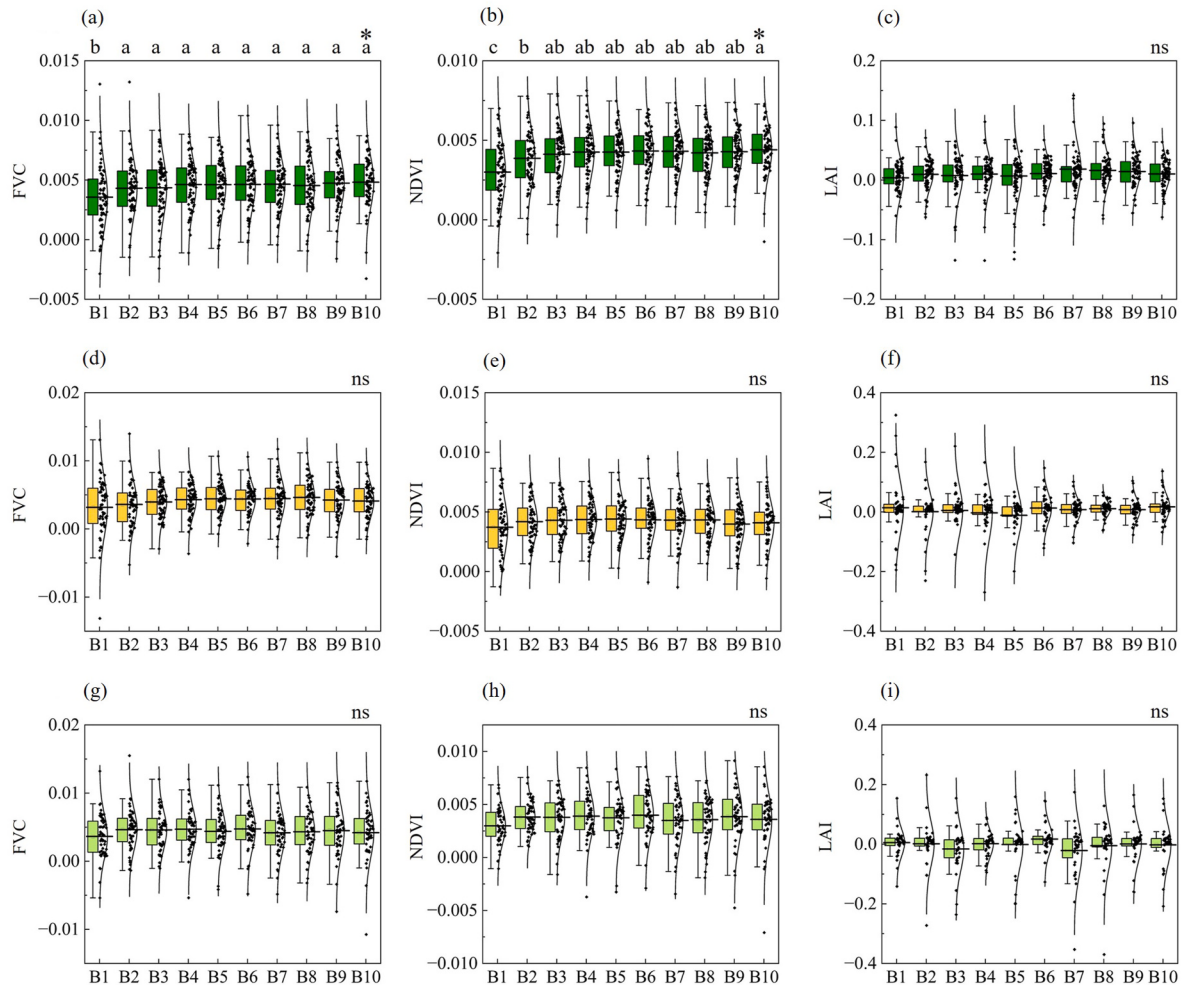


Fig. 5. The range of impact of mountainous wind farms in Yunnan Province on regional vegetation. (a)–(c), (d)–(f), and (g)–(i) present the growth rates of the FVC, NDVI, and LAI during the growing season (April–October) in forest, farmland, and grassland, respectively, in different buffer zones around the wind farm from 2008 to 2022. The black horizontal lines in the boxes represent the average value (* indicates $p < 0.05$; ns indicates no significance).

3. Results

3.1. Range of impact of wind farms on regional vegetation

Overall, compared with vegetation in the 0.5–5 km range (B2–B10), significant or nonsignificant reductions in the growth rates of FVC and NDVI and nonsignificant increases or decreases in the growth rate of LAI occurred in forests, farmlands, and grasslands within the 0.5 km range (B1) (Fig. 5).

For forests (Fig. 5a–c), the wind farms significantly reduced the growth rates of the FVC and NDVI within B1 compared to those within B2–B10, whereas the growth rate of the LAI did not significantly decrease. The average growth rates of the FVC, NDVI, and LAI within B2–B10 were 0.0046, 0.0042, and 0.0114, whereas the average growth rates within B1 were 0.0036, 0.0030, and 0.0036, representing decreases of 21.7 %, 28.6 %, and 68.4 %, respectively.

For farmlands (Fig. 5d–f), the wind farms did not significantly reduce the growth rates of the FVC and NDVI within B1 compared to those within B2–B10, whereas the growth rate of the LAI did not significantly increase. The average growth rates of the FVC, NDVI, and LAI within B2–B10 were 0.0042, 0.0043, and 0.0052, whereas the average growth rates within B1 were 0.0032, 0.0037, and 0.0141. The FVC and NDVI decreased by 23.8 % and 14.0 % respectively, while the LAI increased by 171.2 %.

For grasslands (Fig. 5g–i), the wind farms did not significantly reduce the growth rates of the FVC and NDVI within B1 compared to those within B2–B10, whereas the growth rate of the LAI did not significantly increase. The average growth rates of the FVC, NDVI, and LAI within B2–B10 were 0.0045, 0.0037, and -0.0027 , whereas the average growth rates within B1 were 0.0036, 0.0030, and 0.0053. The FVC and NDVI decreased by 20.0 % and 18.9 % respectively, while LAI increased by 296.3 %.

These results indicated that mountainous wind farms in Yunnan Province had a significant impact on vegetation within a 0.5 km radius and had consistent inhibitory effects on the FVC and NDVI of different vegetation types, whereas their impacts on the LAI varied.

3.2. Extent of the impact of wind farms on regional vegetation

The impact and spatial distribution of mountainous wind farms in Yunnan Province on forest, farmland, and grassland are shown in Fig. 6. Overall, wind farms significantly or insignificantly reduced the FVC and NDVI in all vegetation types but did not significantly reduce the LAI in forests or significantly increase the LAI in farmlands and grasslands.

In forests (Fig. 6a–c), the average FVC decreased by 0.010 ($p < 0.05$) during the growing season, the average NDVI decreased by 0.013 ($p < 0.05$), and the average LAI decreased by 0.124 ($p > 0.05$). More than half of the wind farms experienced decreases in the FVC, NDVI, and LAI, with decreases of 71.6 %, 79.7 %, and 58.1 %, respectively.

In farmlands (Fig. 6d–f), the average FVC decreased by 0.006 ($p > 0.05$) during the growing season, the average NDVI decreased by 0.002 ($p > 0.05$), and the average LAI increased by 0.004 ($p > 0.05$). The proportions of wind farms with reduced or increased values were 52.3 %, 56.9 %, and 50.9 %, respectively.

In grasslands (Fig. 6g–i), the average FVC decreased by 0.018 ($p < 0.05$) during the growing season, the average NDVI decreased by 0.014 ($p < 0.05$), and the average LAI increased by 0.159 ($p > 0.05$). More than half of the wind farms experienced decreases in the FVC and NDVI, with decreases of 64.6 % and 66.2 %, respectively.

These results indicate that the impact of wind farms on the FVC and NDVI was consistently inhibitory throughout all the vegetation types, whereas the impact on the LAI varied.

In addition, we validated the results by combining remote sensing images (Fig. 7a–b), which clearly identified the bare land caused by wind farm construction. Through the line chart of the changes in VIS values of different vegetation types around a wind farm built in Yunnan

at the end of 2012 (Fig. 7c–e), it could be seen that the construction of the wind farm led to a significant decrease in VIS values of forest, farmland, and grassland in 2012, and showed a decreasing trend from 2010 to 2016.

3.3. Spatial heterogeneity in the impact of wind farms on regional vegetation

To explore the possible reasons for the spatial heterogeneity in the impact of mountain wind farms on regional vegetation, we first analyzed the correlation between the Δ FVC, Δ NDVI, and Δ LAI of forests, farmlands, and grasslands within a range of 0.5 km around the wind farm, as well as eight other indicators. The results are shown in Fig. 8.

In forests (Fig. 8a), the Δ FVC was significantly negatively correlated with precipitation, with a correlation coefficient of -0.25 , while the Δ NDVI was significantly positively correlated with wind speed, with a correlation coefficient of 0.25. There was no significant correlation between the Δ LAI and any indicator. In farmlands (Fig. 8b), there was no significant correlation between the Δ FVC and any indicators, while the Δ NDVI was significantly positively correlated with the number of wind turbines and negatively correlated with precipitation, with correlation coefficients of 0.31 and -0.33 , respectively. The Δ LAI was significantly positively correlated with solar radiation, with a correlation coefficient of 0.33. In grasslands (Fig. 8c), the Δ FVC was significantly positively correlated with the number of wind turbines and near-surface wind speed, with correlation coefficients of 0.31 and 0.33, respectively. The Δ NDVI was significantly positively correlated only with the number of wind turbines, with a correlation coefficient of 0.3. There was no significant correlation between the Δ LAI and any indicator. In addition, the Δ FVC, Δ NDVI, and Δ LAI of the three vegetation types were not significantly correlated with the DEM, slope, air temperature, or shape index.

These results indicate that four indicators, including the number of wind turbines, solar radiation, precipitation, and near-surface wind speed, may explain the spatial heterogeneity in the impact of mountain wind farms on regional vegetation. However, these factors were not consistent with the correlations between the Δ FVC, Δ NDVI, and Δ LAI of the different vegetation types.

Based on these results, we further conducted multiple linear regression analyses of the Δ FVC, Δ NDVI and Δ LAI with eight other indicators for the different vegetation types, and the results are shown in Table 4.

In forests, the eight selected indicators did not explain the Δ FVC, Δ NDVI, or Δ LAI. In farmlands, these indicators did not explain the Δ FVC or Δ NDVI but together explained 25.2 % of the variance in the Δ LAI. Among the indicators, solar radiation could positively predict the Δ LAI, whereas the DEM and precipitation could negatively predict the Δ LAI. In grasslands, the eight selected indicators explained 13.0 % of the variance in the Δ FVC and 12.5 % of the variance in the Δ NDVI. The near-surface wind speed positively predicted the Δ FVC and Δ NDVI, whereas none of the indicators explained the Δ LAI. The results show that for farmlands within 0.5 km around the wind farms, stronger solar radiation promote higher LAI, while higher precipitation and elevation lead to lower LAI; for grasslands within 0.5 km around the wind farms, higher near-surface wind speed promote higher FVC and NDVI.

4. Discussion

4.1. Comparison with existing related research

This study quantified the impact range and degree of mountainous wind farms in Yunnan Province on different vegetation types based on the trend and magnitude of vegetation index changes over time. Multiple linear regression was used to explore the possible reasons for the spatial heterogeneity in this impact. In existing similar studies, although the impact range and degree of mountainous wind farms on regional vegetation have been quantified, the types of vegetation have not been

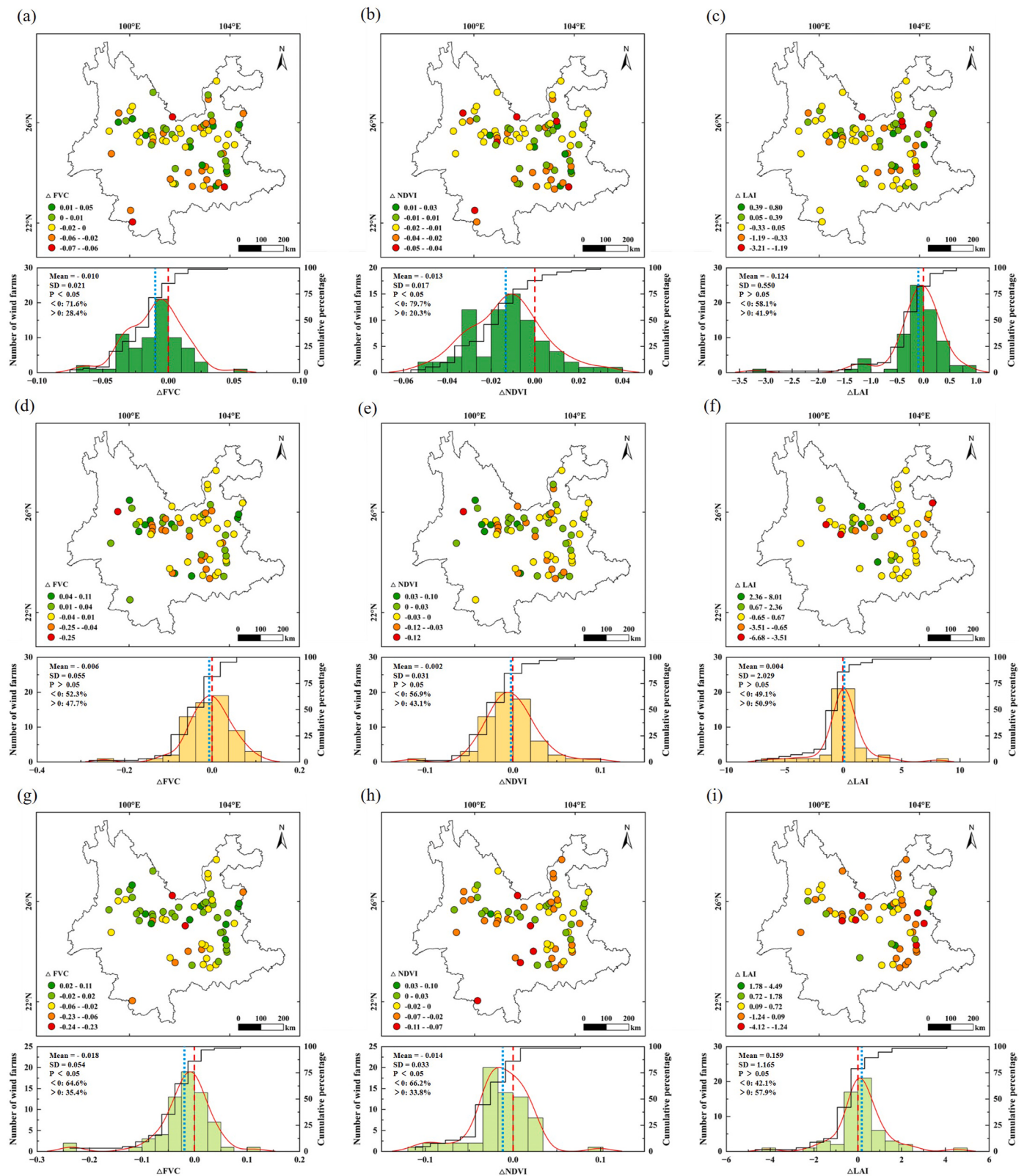


Fig. 6. The impact and spatial distribution of mountainous wind farms on regional vegetation in Yunnan Province. (a)–(c), (d)–(f), and (g)–(i) present the changes in the FVC, NDVI, and LAI during the growing season in forest, farmland, and grassland, respectively, within a 0.5 km radius of the wind farm from 2008 to 2022. The red dashed lines in the histograms represent the 0 value, the blue dashed lines represent the average change, the black dashed lines represent the cumulative percentage, and the red curves represent the kernel smoothing curve. The p value was calculated via a single sample t -test.

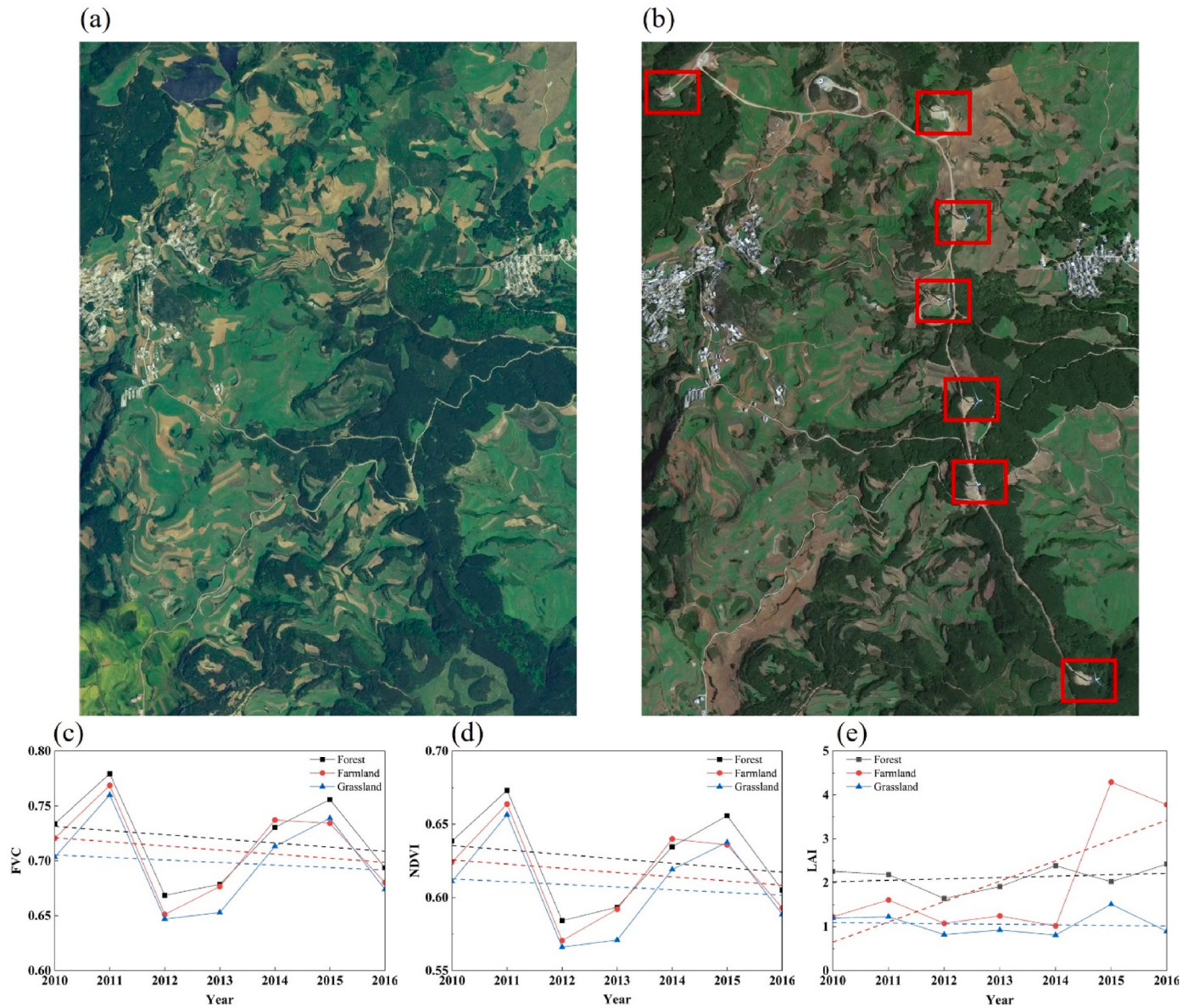


Fig. 7. (a) And (b) were remote sensing images of a wind farm in Yunnan before and after its construction, (c)–(e) respectively showed the changes in FVC, NDVI, and LAI of different vegetation types in a wind farm built in Yunnan at the end of 2012 from 2010 to 2016.

distinguished, and the sample size has been small, making further exploration of spatial heterogeneity difficult (Zhang et al., 2022; Ma et al., 2023). In this study, we not only compared the similarities and differences in the range and degree of impact of mountain wind farms on different vegetation types but also explored the heterogeneity in the spatial distribution and possible driving factors of this impact and preliminarily discussed its underlying mechanisms. In addition, most studies have explored the impact of wind farms on regional vegetation by comparing the differences in vegetation index values across different buffer zones. To eliminate the influence of altitude on vegetation, this study determined the impact range of wind farms by comparing the differences in the slope values of VIs in different buffer zones over time and then explored the impact of wind farms on regional vegetation. These research conclusions could provide ideas, methods, and directions for further exploration of the impact and underlying mechanisms of mountain wind farms on regional vegetation in the future.

4.2. Analysis of the impact and mechanism of mountain wind farms on regional vegetation

4.2.1. Differences and similarities in the impact ranges of wind farms on different vegetation types

As shown in Fig. 5, the impact range of mountainous wind farms on forest, farmland, and grassland within the region did not exceed 0.5 km, which was consistent with the conclusions of existing research (Zhang et al., 2022; Ma et al., 2023). The range of impact of mountainous wind farms on regional vegetation is clearly much smaller than that of wind farms in flat terrain areas (Harris et al., 2014; Chang et al., 2016; Tang et al., 2017). In addition, with the overall improvement in regional vegetation quality, mountainous wind farms significantly reduced the growth rates of the FVC and NDVI in surrounding forests but caused nonsignificant decreases in the growth rates of the FVC and NDVI in farmlands and grasslands. This may be due to the direct and strong destructive effects on forest with high succession levels during the construction of wind farms, such as deforestation. Compared with forest, grassland has a faster recovery rate after damage, whereas farmland is

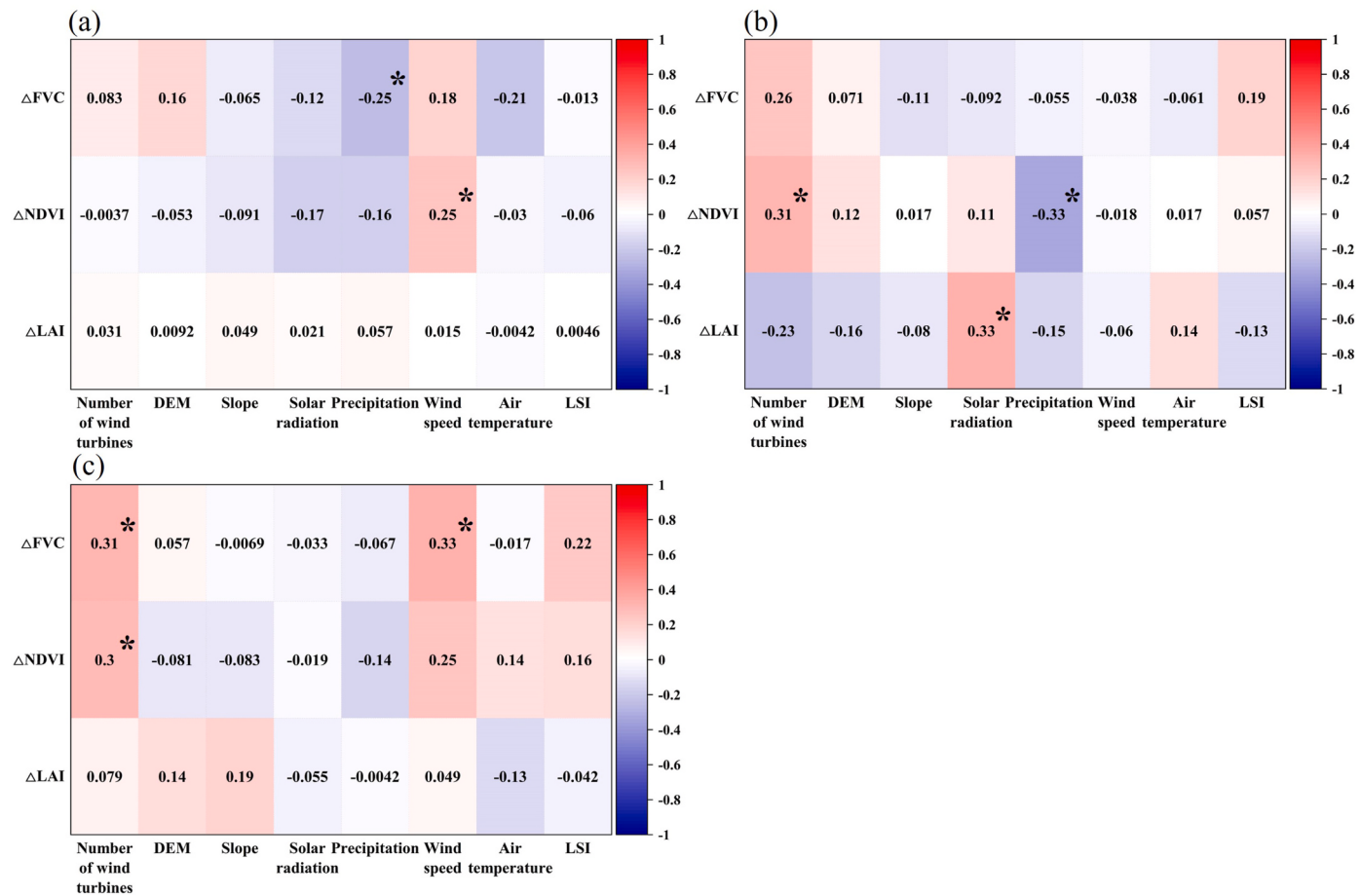


Fig. 8. (a), (b), and (c) Correlation coefficients between the Δ VI of forests, farmlands, and grasslands, respectively, within 0.5 km around the mountainous wind farm in Yunnan Province and various indicators (* indicates $p < 0.05$).

Table 4

Results of multiple linear regression analysis.

Vegetation type	Vegetation index	R ²	p	Number of wind turbines	DEM	Slope	Solar radiation	Precipitation	Near-surface wind speed	Air temperature	LSI
Forest	Δ FVC	0.029	0.275	0.093	-0.093	-0.074	-0.165	-0.252	0.042	-0.220	-0.099
	Δ NDVI	0.032	0.258	0.157	-0.418	-0.027	-0.130	-0.187	0.153	-0.305	-0.241
	Δ LAI	-0.102	0.996	0.149	-0.062	0.092	0.059	0.142	0.082	-0.056	-0.093
Farmland	Δ FVC	-0.050	0.756	0.380	-0.369	-0.129	0.051	0.071	-0.096	-0.301	-0.221
	Δ NDVI	-0.020	0.571	0.461	-0.245	-0.074	0.063	-0.086	-0.049	-0.164	-0.307
	Δ LAI	0.252	0.004	-0.278	-0.893*	-0.268	0.604**	-0.346*	-0.155	-0.702	0.197
Grassland	Δ FVC	0.130	0.042	0.065	0.488	0.000	-0.176	-0.079	0.263*	0.255	0.244
	Δ NDVI	0.125	0.047	0.094	0.317	-0.016	-0.216	-0.200	0.264*	0.211	0.168
	Δ LAI	-0.052	0.730	0.315	0.013	0.241	-0.131	0.080	0.085	-0.017	-0.312

Note: * indicates $p < 0.05$, and ** indicates $p < 0.01$. The values in the table were standardized coefficients obtained from multiple linear regression analysis.

affected mainly by human planting activities, so the inhibitory effect of wind farms on both is relatively small. The influence range of mountain wind farms on regional vegetation is clearly much smaller than that of wind farms in flat terrain areas (Harris et al., 2014; Chang et al., 2016; Tang et al., 2017). In addition, under the overall improvement in regional vegetation quality, mountain wind farms caused a significant decrease in the growth rates of the FVC and NDVI in neighboring woodlands and a nonsignificant decrease in the growth rates of the FVC and NDVI in the farmland and grassland. This may be due to direct and strong destructive effects (e.g., deforestation) on forests with relatively high successional levels when wind farms are constructed. Compared with forests, grasslands had a faster recovery rate after damage, whereas farmlands are affected mainly by human cultivation activities; thus, both types of vegetation were relatively less inhibited by wind farms.

The research results also indicated that, compared with non-wind farm areas, the growth rate of the LAI in forests around mountainous wind farms did not significantly decrease, while the growth rates of the LAI in farmlands and grasslands did not significantly increase, and the magnitude of decrease or increase was relatively large. On the one hand, this may be directly caused by the construction and operation of mountain wind farms; on the other hand, it may be due to the high diversity of plant species in Yunnan Province, resulting in significant differences in the growth rates of the LAI in different regions (Qian et al., 2020). Therefore, further in-depth research is still necessary in the future to clarify the underlying mechanisms of this impact.

4.2.2. Differences and similarities in the impacts of wind farms on different vegetation types

As shown in Fig. 6, the mountainous wind farm significantly reduced the FVC and NDVI of forest and grassland within a 0.5 km radius and did not significantly reduce the FVC and NDVI of farmland. These findings indicate that mountain wind farms mainly have inhibitory effects on regional vegetation growth, which is consistent with existing research conclusions (Zhang et al., 2022; Ma et al., 2023). In addition, the FVC and NDVI of forests around wind farms decreased by 71.6 % and 79.7 %, respectively, but for grasslands, these percentages were only 64.6 % and 66.2 %, respectively. This indicated that the negative effects of mountain wind farms on forests were significantly stronger than those on grasslands. For the LAI, mountain wind farms did not significantly reduce the LAI of forests but did not significantly increase the LAI of farmlands or grasslands. This indicated that mountain wind farms may have a certain inhibitory effect on the LAI of forests while having a certain promoting effect on the LAI of farmlands and grasslands, but this inhibitory or promoting effect was limited. The research results also indicated that mountain wind farms had a relatively small impact on farmland, with average decreases of 0.006 and 0.002 in the FVC and NDVI, respectively and an average increase in the LAI of 0.004. This may be because farmland is mainly maintained and managed by humans, making it less susceptible to the impact of wind farms.

4.3. Possible reasons for the spatial heterogeneity in wind farms impact

For the forest within 0.5 km of the mountain wind farm, the results of the Pearson correlation analysis revealed that the ΔFVC was significantly negatively correlated with precipitation, the $\Delta NDVI$ was significantly positively correlated with wind speed, and the ΔLAI was not significantly correlated with any of the indicators. However, the results of the multiple linear regression revealed that the eight selected indicators had no explanatory power for their ΔFVC , $\Delta NDVI$ or ΔLAI . This may be due to the high level of forest succession, which itself has good stability and resilience; therefore, the indicators do not have a significant relationship with the spatial heterogeneity in the distribution of the ΔVIs . This finding also suggests that the ΔVIs in forests are more likely to be affected by direct damage during wind farm construction.

The results of the Pearson correlation analysis revealed that there was no significant correlation between the ΔFVC and any indicators for farmland within a 0.5 km radius of mountainous wind farms. The $\Delta NDVI$ was significantly positively correlated with the number of wind turbines and negatively correlated with precipitation, whereas the ΔLAI was significantly positively correlated with solar radiation. The results of multiple linear regression indicated that the selected 8 indicators did not have explanatory power for their ΔFVC and $\Delta NDVI$ but together explained 25.2 % of the variation in ΔLAI . Among them, solar radiation could positively predict the ΔLAI , whereas the DEM and precipitation could negatively predict the ΔLAI . This indicated that the heterogeneity in the spatial distribution of ΔVIs in farmland was influenced not only by human cultivation activities but also by climatic conditions (e.g., solar radiation and precipitation).

In grasslands within a 0.5 km radius of mountainous wind farms, the Pearson correlation analysis results revealed that the ΔFVC was significantly positively correlated with the number of wind turbines and near-surface wind speed, the $\Delta NDVI$ was significantly positively correlated with the number of wind turbines, and the ΔLAI was not significantly correlated with any indicators. The results of multiple linear regression indicated that near-surface wind speed could positively predict the ΔFVC and $\Delta NDVI$, but the selected 8 indicators did not have explanatory power for the ΔLAI . This indicated that, to some extent, the increase in near-surface wind speed could promote the growth of grassland plants. This may be because the rainy season (May–October) in Yunnan is concentrated during the plant growth season (April–October). When the rainfall exceeds the adaptive threshold of grassland plants, the intensity of photosynthesis weakens or even stagnates (Chen and Zhang, 2023;

Yang et al., 2008; He et al., 2022). In addition, relatively high air humidity can weaken the transpiration of grassland plants, which is not conducive to their growth and development. Strong near-surface wind speeds can increase surface evaporation and bring dry air from the upper boundary layer of the atmosphere to the near surface by increasing turbulence, thereby reducing air humidity and indirectly promoting the growth of grassland plants (Roy et al., 2004). In the future, further experiments with sample plots should be combined to explore the underlying principles and mechanisms.

4.4. Policy suggestions

According to the results of this study, the development and construction of wind farms in mountainous areas were destructive mainly to forestland. On the one hand, the infrastructure of wind farms directly occupied forestland; on the other hand, wind farms significantly inhibited the growth rate of vegetation in neighboring forestland, and the quality of vegetation was significantly reduced. Owing to the time-consuming and costly nature of forest restoration, the construction of mountain wind farms should strictly control the area of occupied forestland and minimize damage to native vegetation, especially to vegetation communities with relatively high levels of succession. In addition, although mountain wind farms did not significantly reduce the vegetation growth rate of the surrounding grassland, they still significantly reduced the quality of the vegetation. Therefore, grassland restoration and management should be further intensified after wind farm construction. Moreover, local grass species that are suitable for environmental changes after wind farm construction should be selected for vegetation restoration to minimize the negative impact of wind farms on the local environment.

4.5. Limitations and future directions

First, the extent of the impact of mountain wind farms on regional vegetation may be overestimated because of the limited resolution of the remote sensing data used. Specifically, Ma et al. (2023) used the flexible spatiotemporal data fusion (FSDAF) model to obtain NDVI data with high spatial resolution (30 m), and their results revealed that the range of impact of wind turbine foundations on regional vegetation was 0–90 m. Therefore, in the future, it is necessary to assess the impact range and characteristics of mountain wind farms on different vegetation types in a refined manner on the basis of remote sensing data with high spatial and temporal resolutions. Second, for the wind farms constructed from 2021 to 2022, this study also used the average VIs from 2020 to 2022 to represent the regional vegetation conditions after the wind farms were constructed, which may have led to an overestimation of the vegetation conditions and thus underestimation of the impact of the wind farms on vegetation to some extent. However, this underestimation of impacts could be ignored because the construction of wind farms in Yunnan Province was mainly concentrated from 2013 to 2016. Furthermore, due to the current lack of research on the impact mechanism of mountain wind farms on microclimate, this study only conducted a preliminary exploration and analysis of the impact mechanism of wind farms on regional vegetation. In the future, further exploration should be conducted on the impact mechanism of wind farms on microclimate, and based on this, the intrinsic relationship between wind farms, microclimate, vegetation, and soil should be explored.

5. Conclusion

This study investigated the impact of mountain wind farms on different vegetation types in a region at the provincial scale based on the trend and magnitude of changes in the VIs over time and preliminarily explored the possible reasons for the heterogeneity in their spatial distribution using multiple linear regression. The results of the study revealed that the impact of mountain wind farms on different vegetation

types in the region does not exceed 0.5 km and mainly inhibits the growth of regional vegetation. This study not only shows the impact of mountain wind farms on regional vegetation in Yunnan Province in an intuitive and comprehensive way but also provides policy recommendations for the future development of wind resources in Yunnan Province. This study not only provides scientific reference for similar studies in the same region but also provides practical guidance for promoting synergistic development between wind energy resource development and ecological environmental protection in highland mountainous regions.

CRedit authorship contribution statement

Chenhao Zhang: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Xiaobing Li:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Xin Lyu:** Writing – review & editing, Data curation. **Dongliang Dang:** Writing – review & editing, Methodology. **Siyu Liu:** Project administration. **Ning Su:** Project administration.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used the Chat GPT service only to improve language readability and clarity with caution and precision. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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