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RESEARCH ARTICLE

Identifying factors that affect environmental air quality using geographical detectors in the NKEFAs of China

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Abstract The establishment of the National Key Ecological Function Areas (NKEFAs) is an important measure for national ecological security, but the current ecological and environmental evaluation of NKEFAs lacks research on the air quality in the NKEFAs. This study presented the current status of the air quality in the NKEFAs and its driving factors using the geographic detector q-statistic method. The air quality in the NKEFAs was overall better than individual cities and urban agglomeration in eastern coast provinces of China, accounting for 9.21% of the days with air quality at Level III or above. The primary air pollutant was PM_{10}, followed by $PM_{2.5}$, with lower concentrations of the remaining pollutants. Pollution was more severe in the sand fixation areas, where air pollution was worst in spring and best in autumn, contrasting with other NKEFAs and individual cities and urban agglomerations. The main influencing factors of air quality index (AQI) in the NKEFAs were land use type, wind speed, and relative humidity also weighted more heavily than factors such as industrial pollution and anthropogenic emissions, and most of these influence factors have two types of interactive effects: binary and nonlinear enhancements. These results indicated that air pollution in the NKEFAs was not related with the emission by intensive economic development. Thus, the policies taking the NKEFAs as restricted development zones were effective, but the air pollution caused by PM_{10} also showed the ecological status in the NKEFAs, especially at sand fixation areas was not quite optimistic, and more strict environmental protection measures should be taken to improve the ecological status in these NKEFAs.

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1 Introduction

In 2010, the State Council of People's Republic of China issued the "The Main Functional Area Plan" policy, which established the norms and guidelines for China's future land and space development. The National Key Ecological Function Areas (NKEFAs) were set up officially and taken as restricted development areas (Zheng et al., 2005; GF 46-2010), to assure national ecological security and promote the coordinated development of economic, society, ecology and environment (Li et al., 2013; Zhao et al., 2014; Huang et al., 2015; Yu et al., 2015; Jiang et al., 2016; Wu et al., 2016; Xu et al., 2019a and 2019b). To clarify the assessing the effectiveness of ecological and environmental protection measures, the Ministry of Ecology and Environment has organized and implemented the assessment of ecological environment quality for all counties in the NKEFAs (Zou et al., 2014; Huang et al., 2015; Wu et al., 2016).

However, the ecological and environmental quality assessment in the NKEFAs mainly focused on ecological environment quality change and its relationship with ecological compensation (Li et al., 2013; Li et al., 2014; Xu et al., 2019b; Zhao et al., 2019; Liu et al., 2020), while a few studies have also paid attention to the change in water quality (Liu, 2013; Yu et al., 2017; Wang et al., 2019). Air pollution has become one of the most serious risk factors for death in China today (Zhou et al., 2019b) and is receiving more concern (Zhang and Crooks, 2012; Ren et al., 2004; Deng et al., 2014; Jiang et al., 2018). Air quality is also a sensitive indicator of ecological and environmental quality. The current research on air quality mainly included the spatial and temporal distribution characteristics and driving factors of air quality from individual cities to urban agglomerations (Liu et al., 2010; Kassomenos et al., 2012; Luo et al., 2016; Wang et al., 2015; Liu et al., 2016; Zhang et al., 2016; Luo et al., 2017; Zhan et al., 2018). Few studies on air quality were conducted in the NKEFAs (Dai and Zhou, 2017; Zhang and Gong, 2018; Zhang and Lin, 2020). It should be pointed that the pollutants affecting air quality in the NKEFAs are different from those of current studies. The pollutants include not only the suspended particulates smaller than 2.5 μm in aerodynamic diameter ($PM_{2.5}$) and other pollutants emitted by economic activities, but also the suspended particulates smaller than 10 μm in aerodynamic diameter (PM_{10}) caused by ecological damage (Zhou et al., 2017). It is of great significance to study the air quality status and its driving forces in the NKEFAs so that the benchmark suggesting air quality changes can be provided. The results can support not only the assessment of the effectiveness of ecological and environmental protection measures but also the optimization of ecological and environmental construction measures and transfer payment policies in the NKEFAs.

The most commonly used methods to analyze the driving forces of air quality are based on correlation (Li et al., 2013; Xiao et al., 2015; Xu et al., 2019a; Zhao et al., 2019), using time series or spatial gradient data (Huang et al., 2015; Jiang et al., 2018). However, these traditional methods are not effective in detecting the strength of the driving factors and the magnitude of their interactions (Liu, 2013; Wang et al., 2015; Dong et al., 2020). Detecting spatial differentiation has always been one of special advantages of the geographic detector method, it was originally proposed by Wang et al. (2010) as a tool to detect and assess disease analysis. Compared with traditional statistical analysis, it can effectively test the relationship between geographical phenomena and their potential drivers, as well as the relationship between each influencing factor (Wang et al., 2014; Wang et al., 2016; Wang and Xu, 2017). By analyzing the spatial distribution and driving factors of air quality, it should be possible to provide an accurate picture of the current status of air quality in the NKEFAs, and understand what factors have the greatest impact on the air quality of the NKEFAs. Thus, this paper tried to quantify driving forces of air quality in the counties receiving financial subsidies from a central government using the geographic detector *q*-statistic method and assumed that the AQI will be exceeded to some degree even though in the NKEFAs, and both emissions and ecological status, as well as their interaction, will have a profound influence on the AQI of NKEFAs.

2 Materials and methods

2.1 Study area

The initial delineation of the NKEFAs in 2010 included 25 areas, covering a total of 3.86 million km^2 (40.2% of the country's land area). The NKEFAs were divided into four types: water conservation, soil and water conservation, sand fixation, and biodiversity conservation (State Council of the People's Republic of China., 2011). To compensate for the loss of economic development in the NKEFAs, the central government provided financial subsidies through national transfer payment for county-level governments located in the NKEFAs since 2008. Financial subsidies are mainly used for livelihood compensation and supported 452 counties in 2008. By 2018, a total of 818 counties have received financial subsidies, with a total area of 5.63 million km^2, accounting for more than half of the country's land area (Fig. 1). By the end of 2018 the central government has provided a cumulative sum of nearly 520 billion RMB of transfer payment funds. Figure 1 shows the locations of all monitoring stations involved and the distribution of NKEFAs in this study.

2.2 Dataset

2.2.1 Air quality data

The air quality data used in this research obtained from the 818 counties in the NKEFAs in 2018. The data were observed by county-level environmental monitoring agencies and reported to the China Environmental Monitoring Station. The monitored pollutants included sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), PM_{10} and $PM_{2.5}$. The monitoring data of the six pollutants were 24-hour average values, except O_3 which was an 8-hour average.

First, we checked the quality of all monitoring data, eliminated outliers, and removed vacant items. Then, we calculated the individual air quality index (IAQI) of each pollutant and AQI according to the technical requirements of China's Ambient Air Quality Standards (GB3095-2012) and Technical Regulation on Ambient Air Quality Index (on trial) (HJ 633-2012). Finally, we calculated the daily, quarterly, and annual AQI average value, which was used for the spatial and seasonal statistical analysis of air quality in the NKEFAs and the detection of the driving factors affecting ambient air quality.

2.2.2 Geographical proxies

All the geographical proxy data are obtained from the Resource and Environmental Science Data Center (available at Resource and Environmental Science Data Center website) and the National Earth System Science Data Center (available at National Earth System Science Data Center website). All data sources are summarized in Table 1. The precipitation was from the China Meteorological Background Dataset (Fig. 2(a)). Wind speed, relative humidity was collected from the National Earth System Science Data Center (Figs. 2(b) and 2(c)). The elevation was from the Shuttle Radar Topography Mission (SRTM 90m) Digital Elevation Database (Fig. 2(d)). Vegetation types were derived from the Vegetation Map of the People's Republic of China 1:1000000 (Fig. 2(e)). The normalized difference vegetation index (NDVI) was derived from the Spatial distribution dataset of annual vegetation index (NDVI) in China (Fig. 2(f)). The land use type came from the China Land use Remote Sensing Monitoring Database (Fig. 2(g)). To compare the differences of above indicators between different counties, we use the ArcGIS zoning statistical tools to discretize the above data into county-level. Population density and per capita GDP was derived from the Chinese Population Spatial Distribution Kilometer Grid Dataset and the Chinese GDP Spatial Distribution Kilometer Grid Dataset (Figs. 2(h) and 2(i)).

Distribution of the 818 counties in the NKEFAs and air quality monitoring stations.

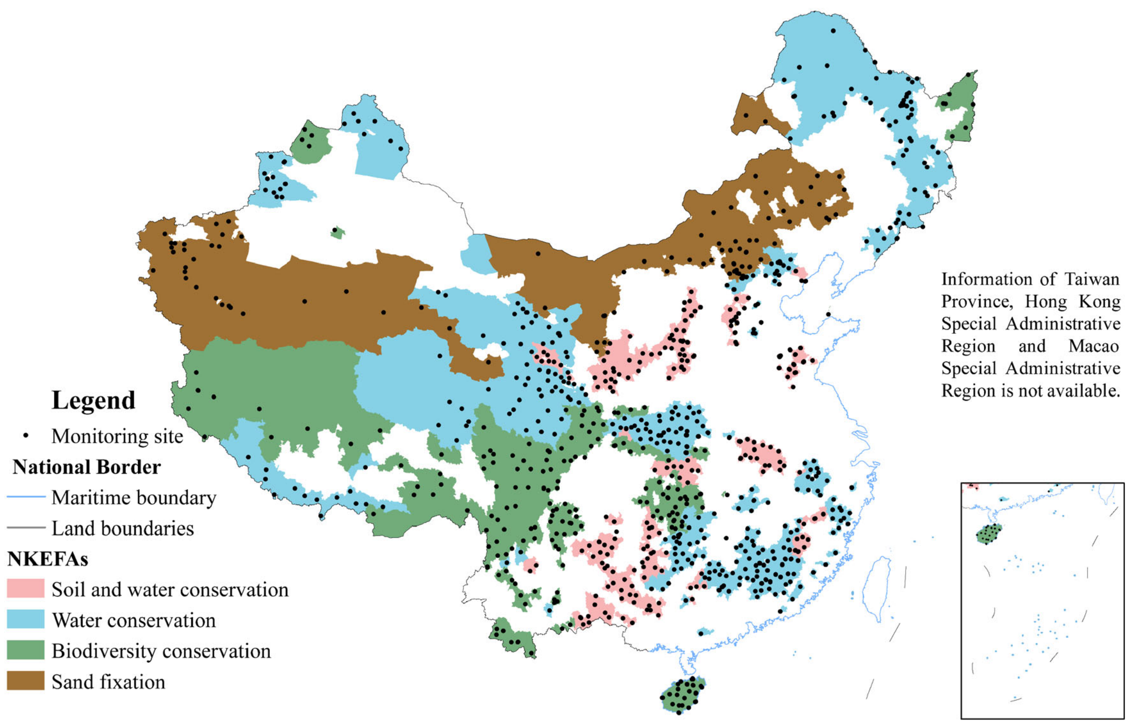
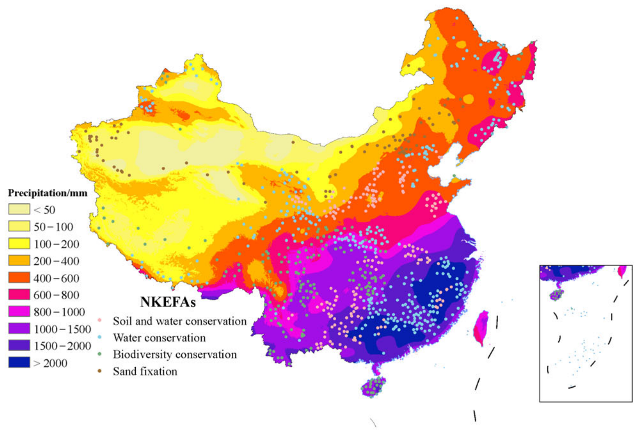


Fig. 1 Distribution of the 818 counties in the NKEFAs and air quality monitoring stations.

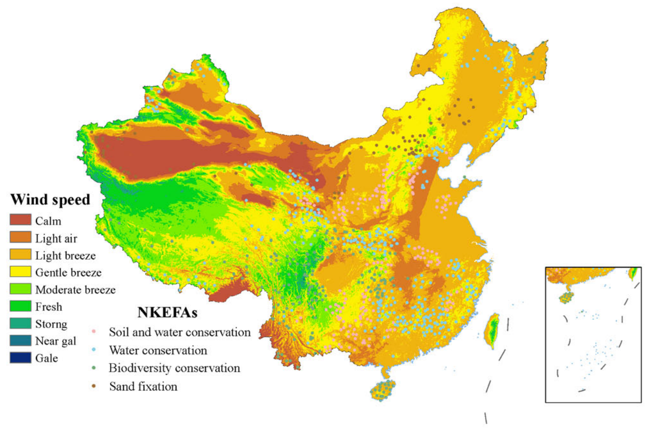
Table 1 Data used in this study

Indicators	Data source	Time	Spatial resolution	References
Precipitation	available at Resource and Environmental Science Data Center website	2018	500 m × 500 m	Xu and Zhang (2017)
Wind speed	available at National Earth System Science Data Center website	2015	1 km × 1 km	Sun (2020)
Relative humidity	available at National Earth System Science Data Center website	2015	1 km × 1 km	Sun (2020)
Elevation	available at Resource and Environmental Science Data Center website	2000	90 m × 90 m	Jarvis et al. (2008)
Vegetation	available at Resource and Environmental Science Data Center website	2001	1 km × 1 km	The Editorial Committee of Vegetation Map of China (2001)
NDVI	available at Resource and Environmental Science Data Center website	2018	1 km × 1 km	Xu (2018a)
Land use type	available at Resource and Environmental Science Data Center website	2018	1 km × 1 km	Xu et al. (2018)
Population density	available at Resource and Environmental Science Data Center website	2018	1 km × 1 km	Xu (2018b)
Per capita GDP	available at Resource and Environmental Science Data Center website	2018	1 km × 1 km	Xu (2018c)



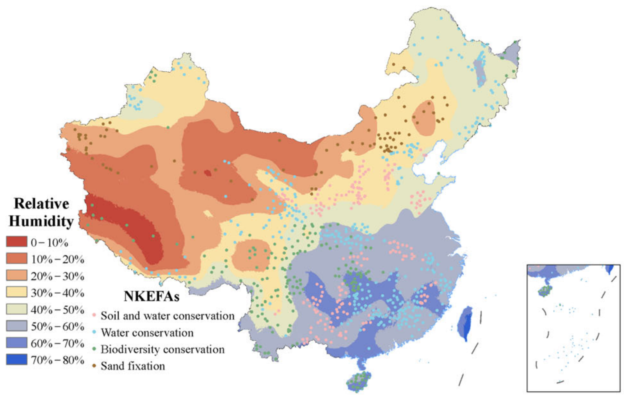
Precipitation/mm
< 50
50 – 100
100 – 200
200 – 400
400 – 600
600 – 800
800 – 1000
1000 – 1500
1500 – 2000
> 2000
NKEFAs
Soil and water conservation
Water conservation
Biodiversity conservation
Sand fixation

(a)



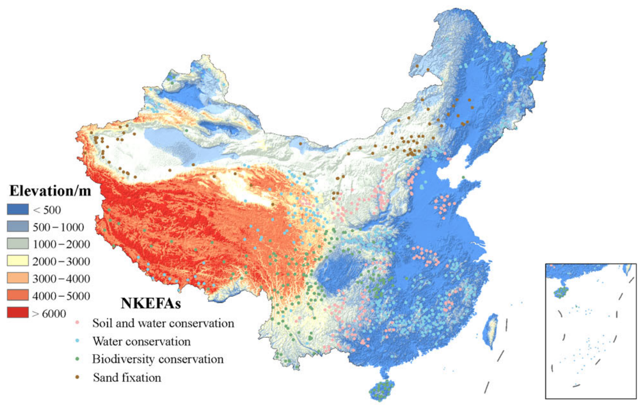
Wind speed
Calm
Light air
Light breeze
Gentle breeze
Moderate breeze
Fresh
Storng
Near gal
Gale
NKEFAs
Soil and water conservation
Water conservation
Biodiversity conservation
Sand fixation

(b)



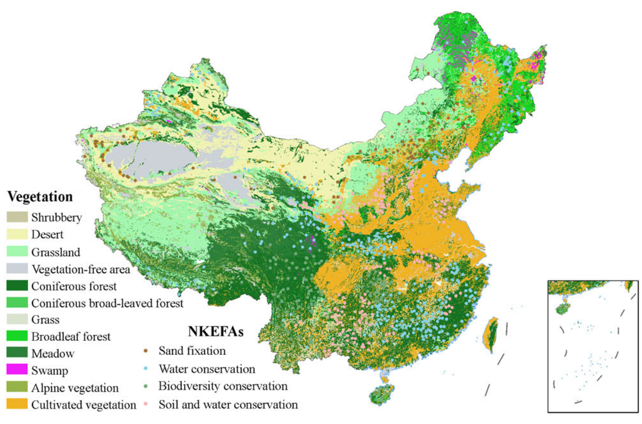
Relative Humidity
0% – 10%
10% – 20%
20% – 30%
30% – 40%
40% – 50%
50% – 60%
60% – 70%
70% – 80%
NKEFAs
Soil and water conservation
Water conservation
Biodiversity conservation
Sand fixation

(c)



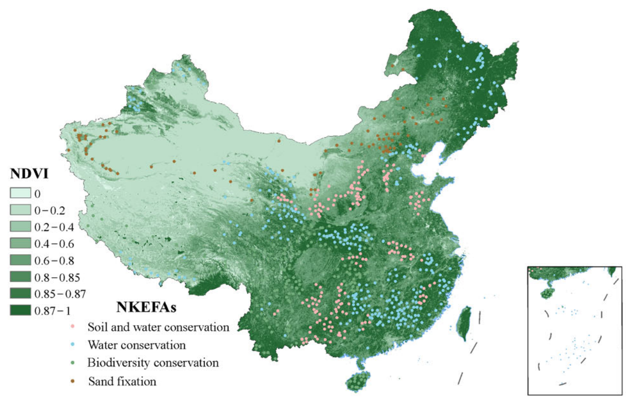
Elevation/m
< 500
500 – 1000
1000 – 2000
2000 – 3000
3000 – 4000
4000 – 5000
> 6000
NKEFAs
Soil and water conservation
Water conservation
Biodiversity conservation
Sand fixation

(d)



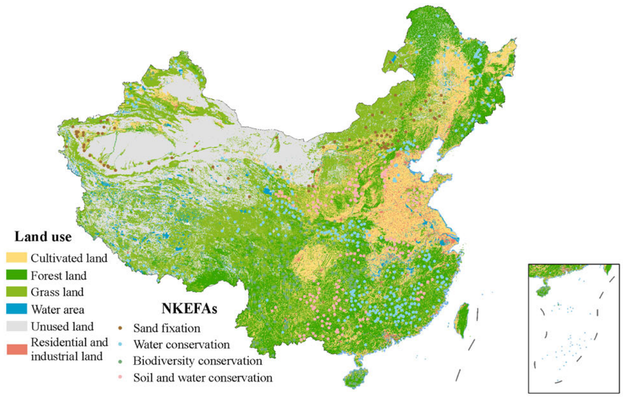
Vegetation
Shrubbery
Desert
Grassland
Vegetation-free area
Coniferous forest
Coniferous broad-leaved forest
Grass
Broadleaf forest
Meadow
Swamp
Alpine vegetation
Cultivated vegetation
NKEFAs
Sand fixation
Water conservation
Biodiversity conservation
Soil and water conservation

(e)

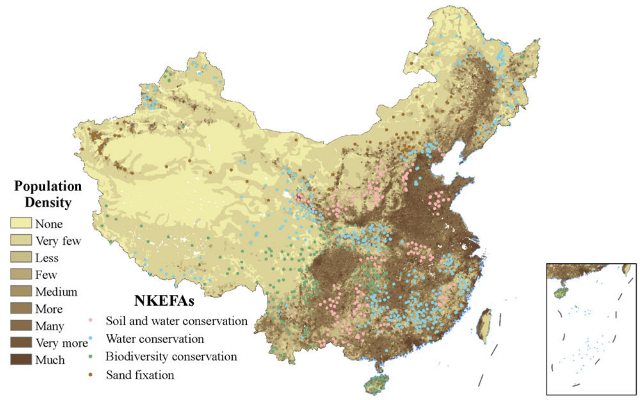


NDVI
0
0 – 0.2
0.2 – 0.4
0.4 – 0.6
0.6 – 0.8
0.8 – 0.85
0.85 – 0.87
0.87 – 1
NKEFAs
Soil and water conservation
Water conservation
Biodiversity conservation
Sand fixation

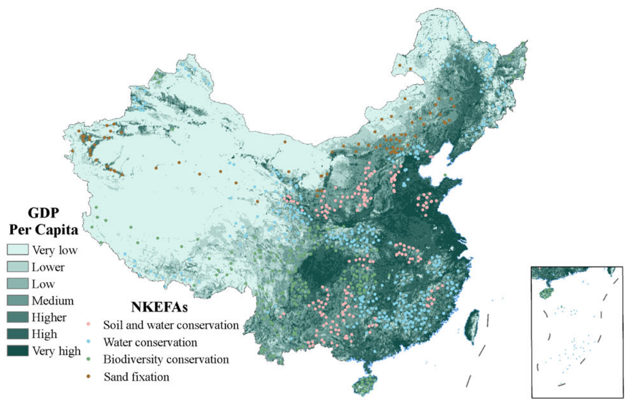
(f)



(g)



(h)



(i)

Fig. 2 The spatial distribution of geographical proxies. (a) Precipitation, (b) Wind speed, (c) Relative humidity, (d) Elevation, (e) Vegetation, (f) NDVI, (g) Land use type, (h) Population density, (i) GDP per capita.

2.3 Method and model

2.3.1 Air quality index

Nowadays, most countries have environmental quality standards set up by their governments. With the continuous updating in recent decades, the name of specific indexes, pollutant items, and classification methods have changed greatly (Wang et al., 2013). China`s ambient air quality monitoring of pollutants includes six basic elements (SO_2, NO_2, CO, O_3. PM_{10} and $PM_{2.5}$) and other items (total suspended particles (TSP), nitrogen oxides (NO_x), lead (Pb), benzo[a]pyrene (BaP)) (GB 3095-2012). In this study, the AQI was determined by the concentrations of six basic items based on the Technical Regulation on Ambient Air Quality Index (on trial) (HJ 633-2012). The individual air quality index value of each pollutant is calculated according to its pollutant concentration limit value. The IAQI was calculated as follows:

$$\mathrm{IAQI_P} = \frac{\mathrm{IAQI_{Hi}} - \mathrm{IAQI_{Lo}}}{BP_{\mathrm{Hi}} - BP_{\mathrm{Lo}}}(C_{\mathrm{P}} - BP_{\mathrm{Lo}}) - \mathrm{IAQI_{Lo}}, \quad (1)$$

where $\mathrm{IAQI_P}$ is the individual AQI of pollutant P; C_{P} is the concentration value of pollutant P; BP_{Hi} is the high value of the pollutant concentration limit to C_{P} in Table 2; BP_{Lo} is the low value of the pollutant concentration limit to C_{P} in Table 2; $\mathrm{IAQI_{Hi}}$ is the IAQI corresponding to BP_{Hi} in Table 2, and $\mathrm{IAQI_{Lo}}$ is the IAQI corresponding to BP_{Lo} in Table 2.

To calculate the overall AQI, Eq. (2) was used:

$$\mathrm{AQI} = \max(IAQI_1,\ IAQI_2,\ IAQI_3,\ldots,\ IAQI_6). \quad (2)$$

AQI levels are divided into six levels based on the Technical Regulation on Ambient Air Quality Index, the specific grades are shown in Table 3, with higher AQI levels indicating more serious air pollution.

2.3.2 Determinants and proxies of ambient air quality

Many studies have shown that AQI is influenced by a large number of natural and human factors (Agarwal and Melkania, 2018; Zhan et al., 2018; Zhang and Gong, 2018; Huang et al., 2020; Dong et al., 2020). In terms of

Table 2 Individual air quality index and corresponding pollutant concentration limit values (HJ 633-2012)

IAQI	Indicators (except for the unit of CO as mg/m³, the rest is μg/m³)					
	$PM_{10}\leqslant$	$SO_2\leqslant$	$NO_2\leqslant$	$CO\leqslant$	$O_3\leqslant$	$PM_{2.5}\leqslant$
0	0	0	0	0	0	0
50	50	50	40	2	100	35
100	150	150	80	4	160	75
150	250	475	180	14	215	115
200	350	800	280	24	265	150
300	420	1600	565	36	800	250
400	500	2100	750	48	-	350
500	600	2620	940	60	-	500

Table 3 Air Quality Index grade limit values (HJ 633-2012)

AQI Value	AQI Level	AQI category
0 – 50	Ⅰ	Excellent
51 – 100	Ⅱ	Good
101 – 150	Ⅲ	Lightly Polluted
151 – 200	Ⅳ	Moderately Polluted
201 – 300	Ⅴ	Heavily Polluted
> 300	Ⅵ	Severely Polluted

natural factors, climatic factors tend to influence pollutant concentrations clearly (Kimbrough et al., 2012; Dai and Zhou, 2017) and so we chose wind speed, relative humidity, rainfall, and temperature to represent these factors. Vegetation type and NDVI represent the ability of vegetation to convert some of the harmful gases and particulate matter into organic compounds. The main sources of pollutants, such as particulate matter, are from energy consumption, industrial emissions, and urbanization, which allow air pollutants to enter directly into the air (Wang et al., 2015; Yang et al., 2016; Lou et al., 2016; Zhou et al., 2017). Therefore, we selected NKEFAs type, land use type, population density per capita, and GDP per capita as anthropogenic influences. The proxy variable associations of the potential factors that could affect ambient air quality are shown in Fig. 3 and the indicators of environmental air quality impact factors are shown in Table 4.

2.3.3 Geographic detector

The geographic detector q-statistic model, which can be used to measure spatial differentiation, detect explanatory factors, and analyze the interaction between variables, has been applied in many fields of natural and social sciences to detect the causes and mechanisms of spatial patterns in geographical elements (Wang and Xu, 2017; Wang et al.,

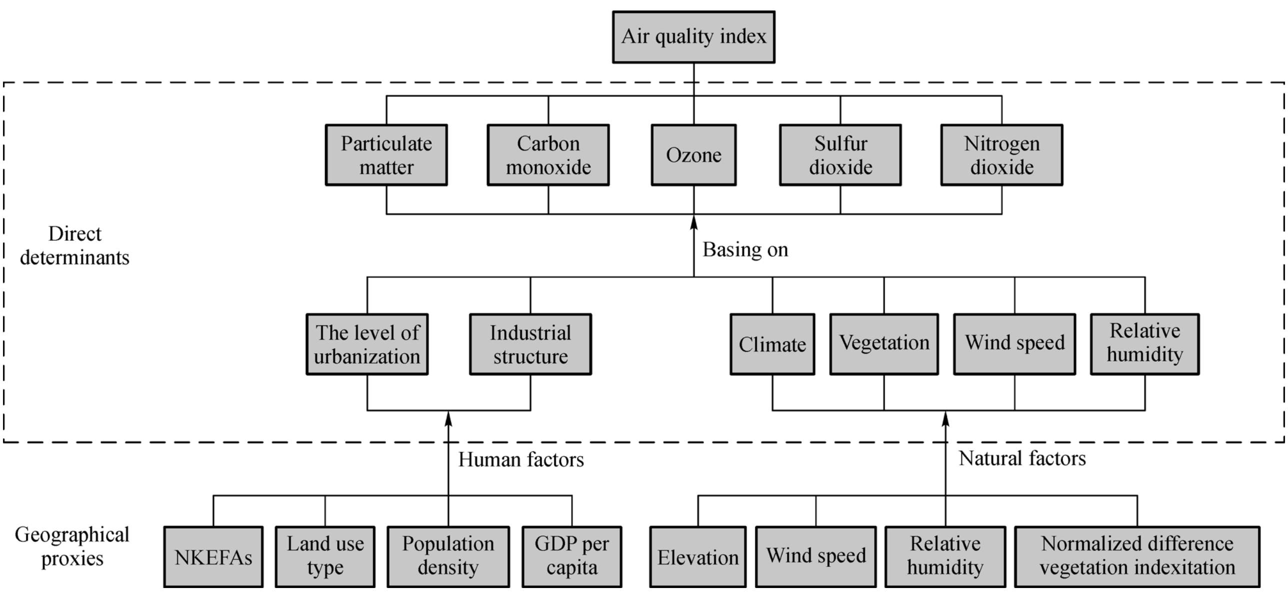


Fig. 3 Determinants of air quality and their proxies.

Table 4 Indicators of factors affecting ambient air quality

The target layer	The dimension	Indicators (X)	Unit
AQI	Natural Factors	Total annual rainfall	mm
		Average annual wind speed	m/s
		Average annual relative humidity	%
		Elevation	m
		Vegetation type	-
		NDVI	-
	Human Factors	Land use	-
		Population density	1000 persons/km^2
		GDP per capita	1000 RMB/person
		Ecological Function Area type	-

2018). The study area is divided into several sub-regions and this model assumes that if the sum of the variances of the sub-regions is less than the total variance of the regions, there is spatial differentiation; if the spatial distribution of two variables tends to be consistent, there is a statistical correlation between them (Wang et al., 2016). In this study, it was used to compare the spatial consistency of the AQI with the geographical layers which potentially affect the air quality such as land use type, vegetation type, terrain, or temperature. The geographic detector q-statistic was used to detect whether impact factors such as wind speed had a significant effect on AQI and the magnitude of their influence. The q value is computed using the following formula (Wang et al., 2010):

$$q = 1 - \frac{\sum_{h-1}^{L} N_h \sigma_h^2}{N\sigma^2} \tag{3}$$

where N denotes that the AQI is composed of N units, divided into $h = 1, 2, \ldots,$ L layer, N_h is the unit number of layer h, σ^2 and σ_h^2 represent the total variance of the AQI and the variance of layer h. The range of q-statistic is limited to (0, 1). The larger the value of q, the smaller the $\acute{o}_h^2$, indicating that the spatial distribution of the AQI is more similar to the interpretation factor, and vice versa (Wang and Xu, 2017; Wang et al., 2018).

The interactive detector can be used to identify the interaction between different explanatory factors, which is used to evaluate whether two or more factors increase or decrease the interpreted ability of AQI when they work together. Table 5 provides the detailed interaction for pairs of explanatory factors (Wang, 2010 and 2016; Wang and Xu, 2017).

The value of $q(X1 \cap X2)$ represents the interaction of the AQI from two explanatory factors X1 and X2. According to the relationship between the values of $q(X1 \cap X2)$ with q (X1) and q (X2), the interaction can be divided into nonlinear weaken, weaken, binary enhance, independent and nonlinear enhance (Wang, 2010 and 2016; Wang and Xu, 2017). The computation was conducted using R language geodetector package (Song et al., 2020).

Table 5 Interaction between explanatory variables

Description	Interaction
q (X1∩X2) < Min (q (X1), q (X2))	Weaken, nonlinear
Min (q (X1), q (X2)) < q (X1∩X2) < Max (q (X1), q (X2))	Weaken, uni-
q (X1∩X2) > Max (q (X1), q (X2))	Enhance, bi-
q (X1∩X2) = q (X1) + q (X2)	Independent
q (X1∩X2) > q (X1) + q (X2)	Enhance, nonlinear

3 Results

3.1 Seasonal and spatial variation in the air quality index

Although the NKEFAs are in the functional areas focusing more on ecological protection, the AQI still exceeded the standard at Level III to some degree. Table 6 shows that the number of the days with air quality at Level III or above accounted for 9.21% and that of heavily polluted days still accounted for 1.28% in the the NKEFAs. PM_{10} and $PM_{2.5}$ were the pollutants that had the greatest impact on the AQI. The IAQI of PM_{10} was higher than other pollutants and the primary pollutant. The IAQI of $PM_{2.5}$ was relatively high too, just slightly lower than PM_{10}. The AQI median, quantile of 75% and 90% of PM_{10} were 46.2, 60.1, and 79.2. Those of $PM_{2.5}$ were 36.2, 52.9, and 76.9 respectively (Table 7).

AQI in the different NKEFAs showed obvious differences. The air quality in sand fixation areas was the worst, followed by soil and water conservation areas and water conservation areas, and biodiversity conservation areas were the best. The number of days of Level III or above in sand fixation areas reached about 23%, Level IV or above also exceeded 10%, and air pollution was quite serious.

The number of days of Level III or above in soil and water conservation areas accounted for 14.5%, water conservation areas for 6.5%, and biodiversity areas for less than 3%.

AQI indicated a seasonal difference in the NKEFAs. AQI was the highest in winter (69.1), followed by 64.4 and 50.7 in spring and autumn, and the lowest in summer (44.8), of which AQI in winter is 1.5 times that in summer. Generally, most functional areas showed a consistent seasonal variation of AQI but sand fixation areas showed certain uniqueness from other types of functional areas. Contrary to other types of the NKEFAs, AQI was highest in spring and even reached moderate levels of pollution, then followed by winter, summer, and autumn, but in the other three types of functional areas pollution was the worst in winter (Fig. 4).

Spatially, the distribution of AQI also presented obvious regional differences in the NKEFAs. Air quality was relatively poor in Northwest, North, and Central China, with AQI basically at Level II or above (Fig. 5). In the oasis around the Taklimakan Desert area in southern Xinjiang and Hilly and parts of Loess Plateau in North China, the air quality is mainly at Level III or above, while at other regions, it is mostly at Level II. The air quality in northeast China, southwest China, and south China was much better. In most regions, the AQI was at Level I, and only in limited areas AQI was at Level II.

3.2 The q-statistic of geographical factors

The magnitude of the AQI was mainly related with land use type, also with relative humidity, wind speed, and functional area type, which were clearly smaller than land use type. According to Table 8, the annual average value of q for land use was 0.42 and much higher than other factors, with the strongest explanation for AQI. The q values of relative humidity, wind speed, and functional area type were around 0.2, while other factors were less than 0.05.

The driving factor of PM_{10} was the same as that of AQI, but the driving factor of $PM_{2.5}$ indicated somewhat difference from that of AQI. The effect of land use type and wind speed on $PM_{2.5}$ was consistent with that of PM_{10}, but relative humidity and function zone type were no longer the main influencing factors. The explanatory strength of land use type for $PM_{2.5}$ can still be maintained at the standard line of 0.2 for the q-statistic chosen in this study, and the explanatory strength of wind speed can be

Table 6 Descriptive statistics of AQI in each NKEFAs

NKEFAs Type	Ⅰ	Ⅱ	Ⅲ	Ⅳ	Ⅴ	Ⅵ	25%	Median	75%
Water conservation	57.16	36.33	4.84	1.09	0.49	0.08	32	46	62
Soil and water conservation	42.03	43.42	10.14	2.57	1.59	0.25	38	56	80
Biodiversity conservation	73.79	23.37	2.20	0.44	0.14	0.06	27	36	52
Sand fixation	39.85	37.41	12.28	4.49	3.71	2.25	40	58	95
NKEFAs	55.25	35.54	6.30	1.63	0.85	0.43	32	47	66

Notes: I, II, III, IV, V, VI means days for different AQI levels, unit is % of the number of AQI level days; 25%, 75% means quartile, three-quarters for AQI value.

Table 7 IAQI statistics of different pollutants in each NKEFAs

NKEFAs Type	Statistics	PM_{10}	SO_2	NO_2	CO	O_3	$PM_{2.5}$	AQI	Level
Soil and water conservation	Median	52.7	11.0	21.6	20.0	41.2	44.3	52.7	Ⅱ
	75%	71.0	18.2	38.1	27.5	57.5	63.9	71.0	Ⅱ
	90%	89.9	29.5	53.4	36.7	78.9	89.6	89.9	Ⅱ
Water conservation	Median	45.4	10.0	18.0	20.0	42.3	36.0	45.4	Ⅰ
	75%	57.5	15.0	25.9	25.0	52.3	50.6	57.5	Ⅱ
	90%	72.2	21.7	35.6	33.5	65.9	70.8	72.2	Ⅱ
Biodiversity conservation	Median	34.9	8.0	13.4	17.5	37.2	26.0	34.9	Ⅰ
	75%	49.1	12.0	20.4	22.5	46.1	37.9	49.1	Ⅰ
	90%	59.7	17.9	27.4	28.1	55.9	55.6	59.7	Ⅱ
Sand fixation	Median	58.0	10.8	14.5	17.5	44.9	45.7	58.0	Ⅱ
	75%	86.3	16.4	23.8	25.0	63.3	70.0	86.3	Ⅱ
	90%	161.2	23.4	36.3	45.3	81.5	125.0	161.2	Ⅳ
NKEFAs	Median	46.2	9.8	17.1	19.7	40.9	36.2	46.2	Ⅰ
	75%	60.1	15.1	26.5	25.6	52.0	52.9	60.1	Ⅱ
	90%	79.2	23.0	39.2	33.8	69.6	76.9	79.2	Ⅱ

Notes: 75% 90% means three-quarters, 90% percentile for IAQI value.

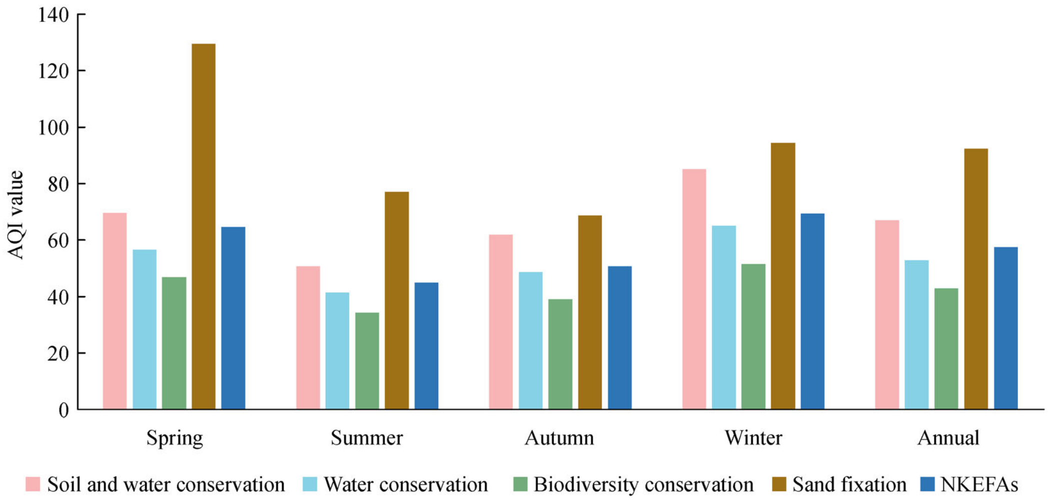


Fig. 4 Seasonal means of the air quality index

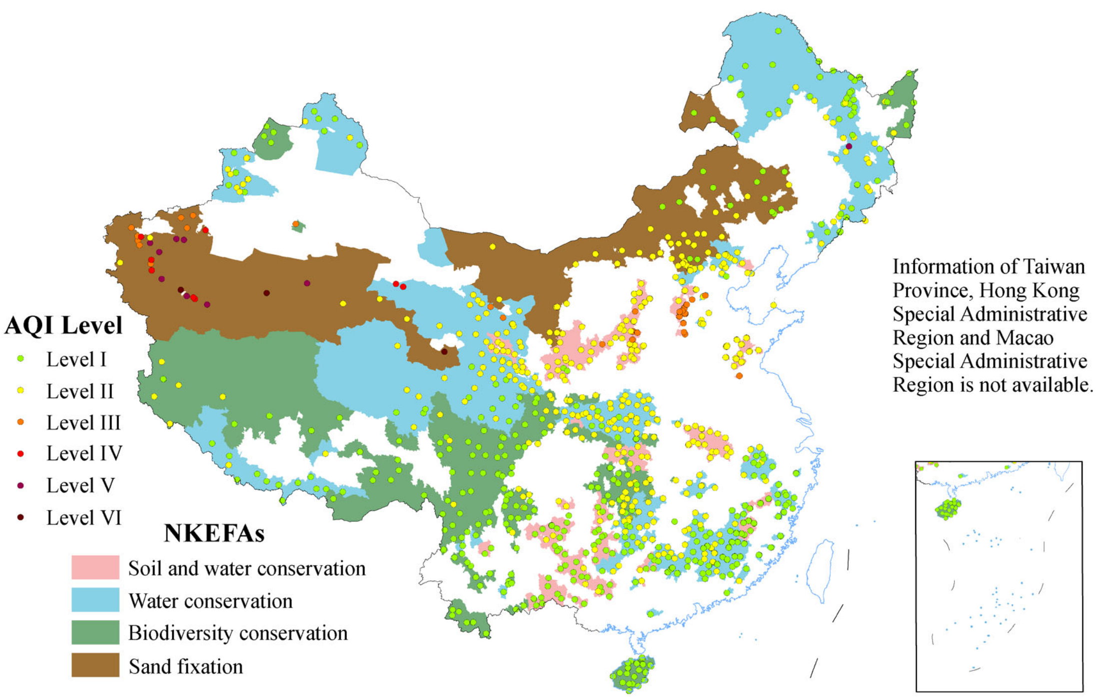


Fig. 5 The annual average level of county air quality in 2018 in this study

generally met. While the q-statistic values of other factors were far less than each other factors and cannot be counted as the main influencing factors.

The effects of wind speed and functional area types were generally more pronounced in the spring, while the effects of relative humidity became more pronounced in both spring and summer, and only land use types can maintain significant effects throughout the year. This variation in the strength of the influence of different explanatory factors with seasonal variation holds for all three indicators including AQI, PM_{10}, and $PM_{2.5}$.

3.3 Interactive q-statistic of geographical factors

The effect of different explanatory factors interacting with each other is stronger than the effect of a single factor.

Table 8 The q-statistic value of determinants on the three indicators in the NKEFAs.

Indicators	Season	A	B	C	D	E	F	G	H	I	J
AQI	spring	0.05	0.21	0.24	0.01	0.04	0.04	0.37	0.05	0.01	0.24
	summer	0.04	0.09	0.22	0.01	0.02	0.03	0.31	0.04	0.02	0.18
	autumn	0.04	0.19	0.18	0.01	0.02	0.04	0.31	0.04	0.01	0.19
	winter	0.04	0.15	0.05	0.02	0.03	0.04	0.22	0.03	0.01	0.14
	annual	0.05	0.21	0.23	0.01	0.04	0.05	0.42	0.04	0.01	0.22
PM_{10}	spring	0.05	0.23	0.23	0.01	0.04	0.03	0.37	0.04	0.01	0.22
	summer	0.03	0.11	0.23	0.01	0.02	0.02	0.33	0.04	0.01	0.16
	autumn	0.04	0.2	0.17	0.01	0.03	0.04	0.35	0.03	0.01	0.18
	winter	0.05	0.16	0.1	0.01	0.04	0.04	0.27	0.03	0.01	0.15
	annual	0.05	0.23	0.23	0.01	0.04	0.04	0.43	0.04	0.01	0.21
$PM_{2.5}$	spring	0.05	0.17	0.2	0	0.03	0.04	0.26	0.05	0.02	0.22
	summer	0.03	0.09	0.21	0.01	0.01	0.03	0.27	0.03	0.01	0.18
	autumn	0.03	0.22	0.09	0.02	0.02	0.03	0.22	0.03	0.01	0.17
	winter	0.04	0.16	0.03	0.02	0.02	0.04	0.16	0.04	0.01	0.12
	annual	0.04	0.25	0.11	0.01	0.03	0.04	0.3	0.03	0.01	0.17

Notes:A: Precipitation, B: Wind speed, C: Relative humidity, D: Elevation, E: Vegetation, F: NDVI, G: Land use type, H: Population density, I: GDP per capita, J: NKEFAs type. Bold font indicates that the q-statistic value is greater than 0.2 and has a strong driving force.

Most of the interaction effects of explanatory factors are a binary enhancement especially for the interaction between topography and land use type, NDVI and land use type. Their interactions all achieved nonlinear enhancement (Table 9), which means that whether there were significant differences in AQI between land use types depended on elevation and vegetation greenness.

4 Discussion

4.1 Improvement in this study

The main purpose of this study was to reveal the seasonal and spatial distribution and changes in air quality in the NKEFAs in China and to analyze the factors that affected the environmental air quality. The AQI still exceeded the standard at Level III to some degree, yet, it was much less polluted than the eastern coastal provinces (Zhan et al., 2018; Dong et al., 2020). The main pollutant in the NKEFAs was also different from that in the east, where the major pollutant is $PM_{2.5}$ (Wang et al., 2015; Chen et al., 2018; Zhou et al., 2019a), and the primary pollutant in the NKEFAs is PM_{10} followed by $PM_{2.5}$.

The NKEFAs were generally similar to the national urban ambient air quality characteristics, with the worst air pollution in winter and the best air quality in summer (Jiang et al., 2016; Zhan et al., 2018; Xu et al., 2019b). However, there were still some regions with different performances. For example, air pollution in the sand fixation areas was the worst in spring and reached the maximum of all statistical values as shown in Fig. 4 and Table 4. In terms of spatial distribution, there were clearly spatial differences in the air quality of the NKEFAs. The air pollution in NKEFAs was characterized by spatial clustering and poor air quality was mainly found in some ecological functional areas in Northwest and North China, while regional differences in air quality in major cities are relatively small and some air pollution hotspots are located in densely populated areas with high economic levels (Zhan et al., 2018).

Table 9 Interactive detector results of determinants to AQI PM_{10}, and $PM_{2.5}$ in the NKEFAs.

Indicators	B	C	D	F	G	J	B ∩ G	C ∩ G	D ∩ G	F ∩ G	G ∩ J
AQI	0.21	0.23	0.01	0.05	0.42	0.22	0.55	0.51	0.56	0.52	0.55
PM_{10}	0.23	0.23	0.01	0.04	0.43	0.21	0.55	0.51	0.56	0.53	0.55
$PM_{2.5}$	0.25	0.11	0.01	0.04	0.3	0.17	0.49	0.4	0.42	0.44	0.45

Notes: B: Wind speed, C: Relative humidity, D: Elevation, F: NDVI, G: Land use type, J: NKEFAs type, ∩: Interaction. Bold font indicates the presence of nonlinear enhancement of two explanatory factors.

The influence factors of AQI in the NKEFAs were different from those of the current major developed urban areas. The main influencing factors of AQI in the NKEFAs were land use type, wind speed, and relative humidity also weighted more heavily than factors such as industrial pollution and anthropogenic emissions. The major pollutant in the developed urban areas is $PM_{2.5}$, reflecting the more prominent influence of human factors on air quality (Wang et al., 2015; Yang et al., 2016; Zhou et al., 2019a; Huang et al., 2020).

4.2 Formation causes analysis of air quality

This study finds that the AQI still exceeded the standard at Level III to some degree with the major pollutant of PM_{10} in the NKEFAs and the overall pollution level in the sand fixation areas was clearly higher than in other areas. The AQI was mainly related with land use type, but also with humidity, functional area type, and wind speed. Excessive unused land area and small green areas resulted in poor ambient air quality in the sand fixation area. Land use/land cover change is the most direct signal characterizing the effects of human activities on the natural ecosystems of the earth's land surface and is a major process leading to loss of effective habitat for species and ecosystems (Wei et al., 2015; Sun et al., 2016). Studies have shown that changes in human activities reflected by land use patterns have a significant influence on air pollutant concentrations and there is a strong seasonal effect (Zhao et al., 2014; Xu et al., 2015; Sun et al., 2016; Zhou et al., 2017). Differences in land use type imply changes in the landscape pattern, which can indirectly reflect spatial differences in pollutant emission sources (Schaufler et al., 2010, Chen et al., 2012).

Table 10 showed the county-level land use type proportion of the different types of functional areas, as can be seen, the largest proportion in the NKEFAs overall was still forest land and grass land. The proportion of forest land and grass land in sand fixation area is the least, and the proportion of unused land reaches an amazing 29%, which directly leads to serious wind erosion and PM_{10} and $PM_{2.5}$ cannot be restricted accordingly in sand fixation area. Under the action of wind, the polluted weather is frequent and the ambient air quality is poor (Xu et al., 2015; Jiang et al., 2016). Some studies have shown that wind speed and relative humidity are negatively correlated with air pollution and have a certain effect on air pollutants (Chen, 2018; Liu, 2018), which is consistent with our results. In general, for the NKEFAs, factors such as land use type, relative humidity, ecological function area type, and wind speed had a greater impact on AQI than socioeconomic factors.

Sand fixation areas indicating high AQI were mainly located in the oasis around the Taklimakan Desert area in southern Xinjiang, where the land is heavily desiccated and dust storms are frequent (Fan, 2015; Jiang et al., 2016; Xu et al., 2019a, and 2019b), environmental quality is poorer. Frequent wind-sand activity especially in spring and winter causes the AQI values to be quite high. The ambient air quality in biodiversity conservation areas was maintained at high levels throughout the year. This is largely due to biodiversity conservation areas are largely intact ecosystems, mostly forested or wetland areas and sparsely populated, so air quality is generally good (Zhao et al., 2014), also benefit from China's efforts in biodiversity conservation (Ma et al., 2012). Besides, water and soil conservation areas with higher population density have distinct seasonal characteristics, with emissions increasing as heating demand expands in winter, thus resulting in significantly higher AQI value than other seasons. (Zhang et al., 2016; Jiang et al., 2018).

4.3 Suggestions for improvement of the status quo

The AQI in the NKEFAs is much less polluted than the eastern coastal provinces and the main pollutant is PM_{10}, which is different from those developed cities in the east. Thus, air pollution in the NKEFAs was not related to the emission by intensive economic development. This indicated that the policies taking in the NKEFAs as restricted development zones were effective. However, the air pollution caused by PM_{10} also showed the ecological status in the NKEFAs, especially at sand fixation areas was not quite optimistic. In the sand fixation areas, according to the annual routine ecological and environmental quality monitoring data of China's environmental monitoring, from 2011 to 2018, the area of forest land and grassland, which help improve the air quality of the environment,

Table 10 Proportion of land use types in each NKEFAs (Unit: %)

NKEFAs Type	Cultivated land	Forest land	Grass land	Water land	Residential and industrial land	Unused land
Soil and Water Conservation	28.16	41.81	26.44	1.13	2.02	0.45
Water Conservation	10.00	33.26	32.88	2.79	0.82	20.24
Biodiversity Conservation	7.42	28.17	37.79	4.45	0.33	21.85
Sand Fixation	5.44	2.79	35.01	2.05	0.57	54.15
NKEFAs	9.38	23.58	34.28	2.87	0.71	29.18

actually decreased by 1142.02 km^2, but cultivated land increased by 84133 km^2. This indicated that strict environmental protection measures should be taken to improve the status of these NKEFAs.

These findings will contribute to more effective targeting and implementation of measures to optimize air quality in the NKEFAs region in the future, especially focusing on sand fixation areas where springtime pollution is more severe, and will also provide positive feedback on the implementation of environmental protection policies. This study only explores the annual and spatial distributions of AQI and the factors affecting AQI, but there are still many shortcomings such as insufficient multi-temporal samples and insufficient ecosystem studies, and subsequent studies need to be continuously improved. After that, we will focus on the evaluation of ecosystem functions, establish a scientific and effective evaluation system for the core service functions of each type of functional area, and carry out a quantitative evaluation on this basis, to improve the NKEFAs index system, and provide more efficient improvement on ecological conditions to provide strong support.

5 Conclusions

The air quality in the NKEFAs was overall better than individual cities and urban agglomerations in eastern coast provinces, accounting for 9.21% of the days with air quality at Level III or above. The primary air pollutant was PM_{10}, followed by $PM_{2.5}$, with lower concentrations of the remaining pollutants. Pollution was more severe in the sand fixation areas, where air pollution is worst in spring and best in autumn, contrasting with the other NKEFAs and individual cities and urban agglomerations. The main influencing factors of AQI in the NKEFAs were land use type, wind speed, and relative humidity are also weighted more heavily than factors such as industrial pollution and anthropogenic emissions, and most of major influence factors have two types of interactive effects: binary and nonlinear enhancements. These results indicated that air pollution in the NKEFAs was not related with the emission by intensive economic development. Thus, the policies taking in the NKEFAs as restricted development zones were effective, but the air pollution caused by PM_{10} also showed the ecological quality status in the NKEFAs, especially at sand fixation areas was not quite optimistic, and more strict environmental protection measures should be taken to improve the ecological status in these NKEFAs.

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