Team Number:	2021apmcm2109836
Problem Chosen:	C

2021 APMCM summary sheet

From 1962 to 2021, with the development of Saihanba Forest Farm, the local ecological environment of Saihanba and the climate problems of its surrounding cities such as Beijing have been significantly improved. This research firstly established an evaluation model including six aspects and 11 indicators to fully confirm the effects of Saihanba forest farm's restoration on the local ecosystem. After that, this research found that there was a negative linear correlation between the logarithm of strong winds days in Beijing and the forestland area in Saihanba. That means the Saihanba forest farm reduced the impact of sandstorms on Beijing by reducing the number of strong winds days per year, which significantly improved the image and ecology of Beijing. This research hopes to promote the successful experience of Saihanba forest farm to the whole country and the Asia-Pacific region through simulation experiments. In this stage, we firstly reduced the dimension of the variables containing five Sigmoid functions, then obtained the provinces that might be suitable for the establishment of Saihanba-type forest farm through clustering, and finally selected cities to establish Saihanba-type forest farm by comparing the days of strong wind and average wind speed. The forestland area of such Saihanba-type forest farm was determined by the severity of local sandstorms or strong winds, and the size of surrounding cities as Saihanba is to Beijing. The study also focused on the Carbon-neutral contribution of the proposed forest farms. This research used Cubic Spline Interpolation to estimate the annual Carbon dioxide absorbed by these proposed forest farms based on 60 years' data of Saihanba Forest Farm. Then the Carbon dioxide emissions of these cities were compared with the absorption to evaluate the promoting effect of the proposed forest farm on the local Carbon neutralization process.

Keywords: Saihanba   Proposed forest farm   Carbon neutralization

Expound Saihanba Forest Farm Improves the Ecological Environment of Local and Surrounding Cities and Simulate to create Saihanba-type Forest Farms in China and North Korea

Contents

I. Introduction About Saihanba

Saihanba is located in Chengde City, Hebei Province, with an average altitude of 1,500 meters and an area of about 20,000 hectares. Since the 1950s and 1960s, with the efforts of three generations, Saihanba has been transformed from a barren plateau with severely damaged forest vegetation into a national forest park with dense forests. This part will emphasize the improvement of environmental conditions in Saihanba during the 60 years.

Figure 1: Saihanba

1.1 Environmental Conditions of Saihanba Forest Farm at Its Establishment in 1962

Due to the policy publiced by Qing Dynasty in 1863 to encourage logging and farming in Saihanba, the forest vegetation was severely destroyed in the following nearly 100 years. In addition, owing to the Japanese invaders' predatory logging and mountain fire in Saihanba, Saihanba actually became a barren plateau in 1960s. There are some environmental condition data about Saihanba in 1962.

Table 1 Environmental Conditions About Saihanba in 1962

Environmental Indicator	Specific Figure in 1962
Water conservation ($10^8 \cdot m^3$)	0.09
Carbon sequestration ($10^4 \cdot t$)	2.74
Oxygen release ($10^4 \cdot t$)	1.90
Forest stock ($10^4 \cdot m^3$)	33.00
Forestland area ($10^4 \cdot mu$*)	19.00
Forest coverage rate	11.40%
Annual average precipitation (mm)	<410

*Mu is an area unit used in China. $1mu \approx 666.67m^2$

1.2 Environmental Conditions of Saihanba Forest Farm Have Been Improved Greatly

According to *Typical Cases of Ecological Restoration in China* publiced by Ministry of Natural Resources of China on October 14, 2021, compared with the initial stage of construction, the forest stock increased by 30.4 times, and the annual average precipitation incresed to 479 millimeters. There a graph showing the significant improvement on Water Conservation during these 60 years.

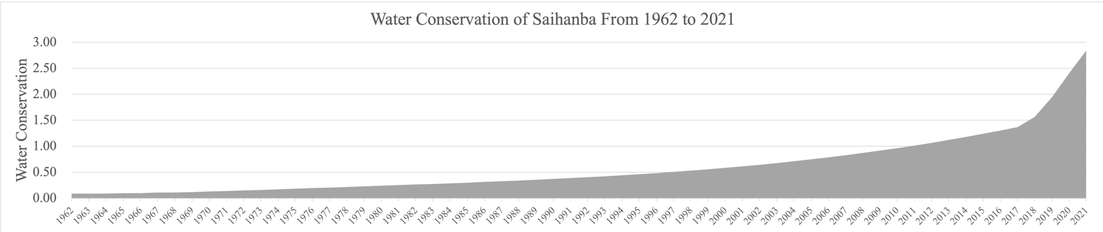


Figure 2: Water Conservation of Saihanba From 1962 to 2021

Saihanba's improment is overall. Many other essential aspects also impove hugely.

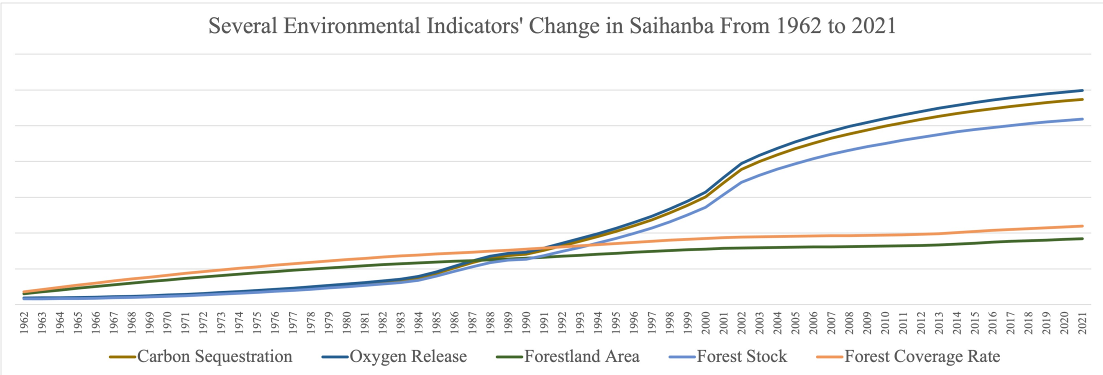


Figure 3: Cabon Sequestration, Oxygen Release, Forestland Area,
Forest Stock and Forest Coverage Rate of Saihanba From 1962 to 2021

II. Evaluation Saihanba's Impact on Local Ecological Environment

2.1 Performance of Ecological Environment Improvement in Nature Reserves

For saihanba and other land nature reserves, the main ecological environment improvement is mainly shown in the following 6 aspects.

- Water conservation
- Species protection
- Soil and water conservation

- Carbon sequestration and oxygen release
- Windbreak and sand-fixation
- Weather

We can establish an evaluation system by comparing the initial status with the final status of these six aspects.

2.2 An Effective Land Nature Reserve Evaluation System

According to *Evaluation Criteria for Ecological and Environmental Protection in Nature Reserves* pubilced by Chinese Academy of Environmental Sciences in November, 2020, ecological environment change index (EC) of a nature reserve can represent its ecological status assessment. EC is a comprehensive analysis of a nature reserve's changes from T1 to T2. T1 is its initial status while T2 is its end status. EC involves the six aspects in 2.1, the full mark is 100. We have such a equation:

$$EC = \sum_{i=1}^{6} w_i C_i \tag{1}$$

In equation (1), w_i refers to the weight of each aspects, C_i refers to the mark of each aspects. It is of more significance for land nature reserves like Saihanba to conserve water and improve the weather conditions. Due to this, we set w_i in the Table 2:

Table 2 Weight of Each Aspects in Evaluation System

Aspect	Indicator	Weight	Total
Water conservation	Water conservation	10	20
	Annual average precipitation	10	
Species protection	Species richness	15	15
Soil and water conservation	Degree of soil and water conservation	15	15
Carbon sequestration& oxygen release	Carbon sequestration	7.5	15
	Oxygen release	7.5	
Windbreak and sand-fixation	Foreatland area	5	15
	Forest stock	5	
	Forest coverage rate	5	
Weather	Average air quality index	10	20
	Rate of no strong wind	10	
Total	-	100	100

For every indicator in Table 2, suppose A_0 and A_t are the specific figure in the initial and end status. C_i is given by following scoring criteria.

$$\Delta A_i = \frac{A_t - A_0}{A_0}$$

Table 3 Scoring Criteria in Evaluation System (Excluding Average Air Quality Index)

ΔA_i	$\Delta A_i > 0$	$-0.1 \le \Delta A_i \le 0$	$\Delta A_i \ge -0.1$
C_i	1	$10(\Delta A_i + 0.1)$	0

Table 4 Scoring Criteria in Evaluation System (Average Air Quality Index)

ΔA_i	$\Delta A_i < 0$	$0 \le \Delta A_i \le 0.1$	$\Delta A_i \ge 0.1$
C_i	1	$1 - 10\Delta A_i$	0

After this step, EC can be calculated by equation (1). Divide the change of ecological environment into 3 classes according to the value of EC. If $EC \ge 95$, we say this land nature reserve is turning better. If $90 \le EC < 95$, it keeps. If $EC < 90$, however, the ecological environment conditions of this nature reserve are becoming terrible.

2.3 Evaluation to Saihanba by the Evaluation System

The specific data we can find directly is in this table:

Table 5 Comparision on Saihanba's environmental conditions between 1962 and 2021

Indicator	A_0	A_t	ΔA_i	C_i
Water conservation ($10^8 \cdot m^3$)	0.09	2.84	350.62	1
Carbon sequestration ($10^4 \cdot t$)	2.74	86.03	30.40	1
Oxygen release ($10^4 \cdot t$)	1.90	59.84	30.49	1
Forest stock ($10^4 \cdot m^3$)	33.00	1036.80	30.42	1
Forestland area ($10^4 \cdot mu$)	19.00	115.10	5.06	1
Forest coverage rate	11.40%	82%	6.19	1
Annual average precipitation (mm)	<410	470	>0.15	1
Rate of no strong winds	77.26%	85.48%	0.11	1
Average air quality index*	93.53	73.58	-0.21	1

*Because the current AQI standards had not publiced until 2012, we choose A_0 as the average AQI in 2014. Because Saihanba is a part of Chengde City, and AQIs equal most of the time within the same geographical range, we use the AQI of Chengde City to replace it.

There are two indicators remaining about which there is not enough data. However, with the increasing of forestland area in Saihanba, the degree of soil and water conservation must increase due to that a large number of trees' root growth can effectively prevent soil erosion. For species richness, according to Yuan et al. (2017), In Saihanba, there were 53 families, 197 genera and 365 species of vascular plants in 184 sample area, accounting for 65.4%, 63.1% and 59.1% of the total, respectively. (P. 496- P. 501) This is a great progress compared with the sparse forest and grass vegetation in the early days when Saihanba forest farm was established. In general, when the richness of plant species increases in a place, the richness of all species will also increases. This is partly because of the increasing flowing energy through the ecosystem and partly because a wider variety of plants can meet the needs of a wider range of animals and microbes.

Therefore, it is also precise to conclude that ΔA for degree of soil and water conservation and species richness are also positive. That means $C_i = 1$ for all the indicators. EC for Saihanba forest farm is 100. Saihanba forest farm definitely turns to have a better ecology during this 60 years.

III. Evaluation of Saihanba's Influence on Surrounding Cities (Take Beijing for Example)

3.1 The Significance of Evaluating Saihanba's Influence on Surrounding Cities

Saihanba is a land nature reserve. With the forestland area increasing in Saihanba, the local ecological environment conditions improve markedly. From another perspective, improvement of natural environment in Saihanba forest farm not only helps the native to live in a better forest, but enhances the residents' life quality in the surrounding cities as well.

In this part, we will take Beijing for example. It mainly has two reasons to choose Beijing rather than closer Chengde City. The first reason is that Beijing's population is around 6.42 times that of Chengde City. The influence on residents' life equality will be more significant in cities of larger population. The second reason is that many key metrics in Saihanba and Chengde City is the same because ecological variables of Saihanba which is a part of Chengde City have no indepence with those of Chengde City.

Beijing is located in a piedmont alluvial fan, which in many places has sand and gravel beneath a thin layer of surface soil, meaning the city is prone to dust during high winds or strong winds. Sandstorm is a severe disastrous dusty wind weather phenomenon in which strong winds blow a large amount of sand and dust from the ground into the air, making the air cloudy and visibility less than 1,000 meters. In the past few decades, Beijing has seen many sandstorms. After the establishment of Saihanba forest farm, the increase of forest area, by restraining strong winds, has played a role in the suppression of sandstorms.

3.2 Effects of Saihanba's Forestland on Beijing's Sandstorm Suppression

3.2.1 *The Number of Beijing's Strong Wind Days Is Correlated With Saihanba's Forestland Area*

Consider the positive impact of windy weather on sandstorms, we gathered the annual days when the maximum wind speed is greater than force 8 (the speed of wind is beyond $17.2m/s$), and denoted these strong winds days as **SWD**.

Through the data analysis of the strong wind days and the forest area in Saihanba, we found that there may be a linear relationship between logarithmic function of SWD and the forest area (from the scatter plot in *Figure 4*), and made a regression analysis of these two variables from 1973 to 2000. The results are as follows:

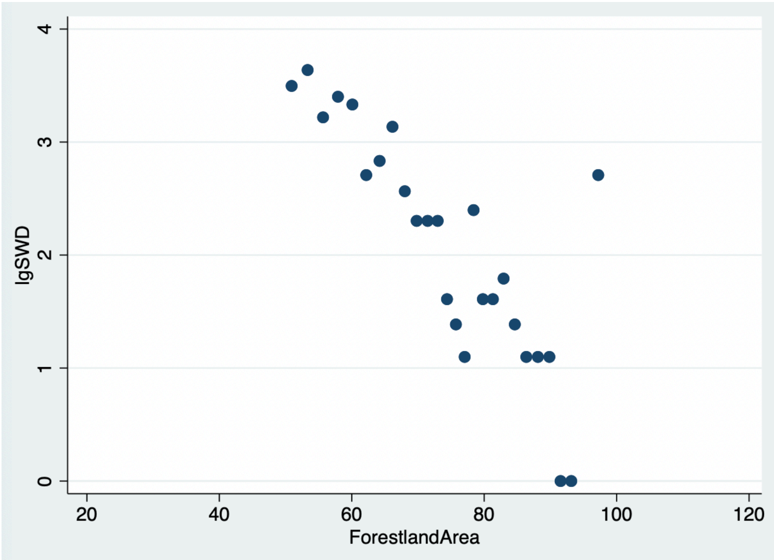


Figure 4: Scatter plot of logarithmic function of SWD and forestland area ($10^4 \cdot mu$) from 1973 to 2000

. reg lgSWD ForestlandArea

Source	SS	df	MS
Model	17.8097977	1	17.8097977
Residual	8.40356506	24	.350148544
Total	26.2133628	25	1.04853451

Number of obs	=	26
F(1, 24)	=	50.86
Prob > F	=	0.0000
R-squared	=	0.6794
Adj R-squared	=	0.6661
Root MSE	=	.59173

lgSWD	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ForestlandArea	-.0648854	.009098	-7.13	0.000	-.0836626	-.0461081
_cons	6.906332	.6863459	10.06	0.000	5.489784	8.32288

Figure 5: Regression analysis and test results of logarithmic function of SWD and forestland area ($10^4 \cdot mu$)

Acorrding to the data in *Figure 5*, we find such a regression equation between logarithmic function of SWD and forestland area:

$$\widehat{\lg \text{SWD}} = -0.065\text{ForestlandArea} + 6.906 \tag{2}$$

Because $\lg(1+x) \approx x$ by Taylor's expension as $x \to 0$, we have:

$$\lg(x+\Delta x) - \lg(x) = \lg(1+\frac{\Delta x}{x}) \approx \frac{\Delta x}{x}$$

Due to this, the regression result means that, within a certain range, one more square kilometer of forestland in Saihanba can reduce the number of Beijing's strong winds days by about 0.065%. According to t-statistic, this result is highly reliable.

3.2.2 *The Intensity of Sandstorms in Beijing Is Correlated With Saihanba's Forestland Area*

At the same time, considering that the forestland area in Saihanba may inhibit the intensity of sandstorm, we collected the annual wind intensity levels of sandstorm in Beijing since 1962 and calculated the annual average intensity, named **windscaleofBJ**. Through the regression analysis of intensity levels and the forestland area in Saihanba, we also found a linear relationship.

```
. reg windscaleofBJ ForestlandArea
```

Source	SS	df	MS
Model	34.6496121	1	34.6496121
Residual	43.6636312	35	1.24753232
Total	78.3132432	36	2.17536787

Number of obs	=	37
F(1, 35)	=	27.77
Prob > F	=	0.0000
R-squared	=	0.4424
Adj R-squared	=	0.4265
Root MSE	=	1.1169

windscaleofBJ	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ForestlandArea	-.0376908	.0071517	-5.27	0.000	-.0522096	-.023172
_cons	11.00754	.5390642	20.42	0.000	9.913182	12.1019

Figure 6: Regression analysis and test results of windscaleofBJ and forestland area (km^2)

Acorrding to the data in *Figure 6*, we find such a regression equation:

$$\text{windscaleofBJ} = -0.038\text{ForestlandArea} + 11.008 \tag{3}$$

That means one more square kilometer of forestland in Saihanba could help reduce the wind level of Beijing's sandstorms by 0.038. Accroding to the t-statistic hypothesis test results, this linear relationship is very statistical significant.

3.2.3 *Conclusion on Effects of Saihanba's Forestland to Beijing's Sandstorms*

The forestland in Saihanba not only reduces the possibility of sandstorm by reducing the frequency of gale weather, but also reduces the destructiveness of sandstorm by reducing the intensity of sandstorms. In general, it has a good restraining effect on the sandstorms in Beijing. In recent years, the annual average number and intensity of sandstorms in Beijing have been significantly reduced, which cannot be separated from Saihanba forest farm's great contribution.

IV. Applications of Saihanba's Successful Experience in Other Regions

The ecological environment of Beijing has been improved by the existence of Saihanba. This has implications for many other cities with similar problems with Beijing. This research aims to use the models in 3.2 to evaluate which cities needs a forest farm like Saihanba and how large and how far this forest farm is.

4.1 Saihanba-type Nature Reserves That China Needs to Build

4.1.1 *Processing of Relevant Data From Different Parts of China*

Hypotheses:

Through consulting relevant information, we come to the following hypotheses:

- The amount of fine dust in the air of the city (area) with high precipitation is low.
- Sandstorm is more likely to occur in areas with more desertification.
- The degree of land dryness will affect land desertification. Measures of dryness include temperature and humidity.
- Forest coverage rate affects the feasibility of forest farm projects. Areas with low forest cover are more likely to improve the sandstorm weather by building forest farms.

To sum up, our analysis mainly includes five indicators:

- Forest coverage Rate (%)
- Mean annual temperature (^{o}C)
- Mean annual precipitation (mm)
- Mean annual relative humidity (%)
- Proportion of desertified land to total land area (%)

Methods:

The Sigmoid function prototype $f(x) = \frac{1}{1+e^{-x}}$. We use the variation of this function:

$$f(x) = \frac{\text{max}}{1 + e^{-\text{slope}(x-\text{centralAxis})}}$$

In this variation, max refers to the upper limit of how much data can be transformed, denoted as m; slope refers to the rate at which data diverges to both ends, denoted as s; centralAxis refers to the central axis of this function, denoted as a.

By adjusting weight parameters through experiments, namely (m, s, a) above, we obtain:

Table 6

Indicator	Function	Note
Forest coverage Rate (%)	$f(x)=\frac{50}{1+e^{50-x}}$	
Mean annual temperature (^{o}C)	Not change	
Mean annual precipitation (mm)	$f(x)=\frac{70}{1+e^{5(600-x)}}$	Above 600 is humid area, below 600 is arid area
Mean annual relative humidity (%)	$f(x)=\frac{20}{1+e^{65-x}}$	65 is the mean
Proportion of desertified land to total land area (%)	$f(x)=\frac{30}{1+e^{3(1-x)}}$	Desertification degree is relatively high for land with x=1

Data Dimension Reduction:

Through principal component analysis (PCA), we reduce the data from five dimensions to two dimensions, and the retention degree of data features is more than 99%.

►PCA:

1. The column vector x is represented by five orthogonal basis vectors $v_1,\ v_2,\ v_3,\ v_4,\ v_5$.

$$x=\sum_{i=1}^{5} x_i v_i \qquad x_i=\frac{x^\top v_i}{v_i^\top v_i}$$

2. Approximate x with a 2-D new vector $(u_1,\ u_2)$.

$$\widehat{x}=\sum_{i=1}^{2}\gamma_i u_i$$

3. Minimize $||x-\widehat{x}||$.

►Specific process: There are M data points: $x_1,\ x_2,\dots,\ x_M$.

1. Find the mean.

$$\bar{x}=\frac{1}{M}\sum_{i=1}^{M} x_i$$

2. Find the covariance matrix Σ_x.

$$\Sigma_x=\frac{1}{M}AA^\top \qquad A=[\Phi_1,\dots,\Phi_M] \qquad \Phi_i=x_i-\bar{x}$$

$x_i\in\mathbb{R}^n$, $\forall i=1,\ 2,\dots,$ M, then Σ_x is a n×n matirx.

3. Calculate the eigenvectors and eigenvalues of Σ_x.

$$\Sigma_x u_i=\lambda_i u_i \qquad \lambda_1>\lambda_2>\cdots>\lambda_5$$

$$\gamma_i=\frac{(x-\bar{x})^\top u_i}{{u_i}^\top u_i} \qquad \widehat{x}-\bar{x}=\sum_{i=1}^{2}\gamma_i u_i$$

4. Calculate the percentage of information retained.

$$E_r=\frac{\lambda_1+\lambda_2}{\sum_{i=1}^{5}\lambda_i}\times 100\%$$

4.1.2 *Clustering and Modeling*

Model:

a. Divided the data into possible and impossible areas to build forest farm.

b. μ_C represents the arithmetic square mean of two subsets.

c. Optimize the least square error.

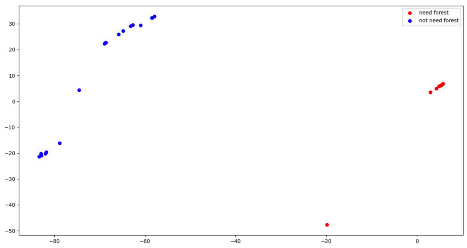
$$\mathrm{SSQ} = \sum_C \sum_d \sum_{x_i \in C} (x_{i,d} - \mu_{C,d})^2,\ d \text{ represents the dimension.}$$

Specific process:

By analyzing the contour coefficients ($S(i) = 0.744$) of the clustering results, we adjust the parameters of Sigmoid function in 4.1.1.

Selection Provinces:

The possible provinces can be obtained by selecting the provinces obtained by clustering. After the experiment, if the desertified land data of the province after processing ranked the top 13, it could be selected.



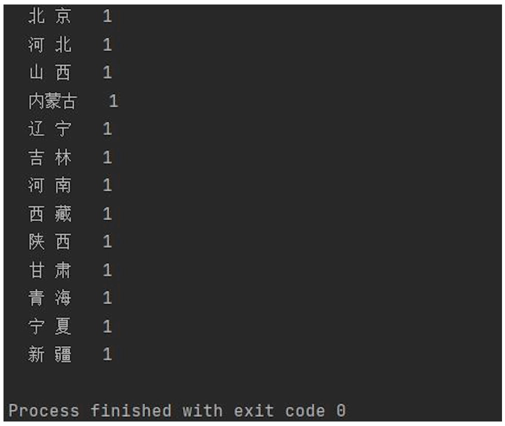


Figure 7, 8: Python code result showed the province to be chosen.

Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Henan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang were selected. Beijing was exclued because we had studied it before.

4.1.3 *Selection Among Chinese Cities*

Hypotheses:

a. According to the influence of sandstorm and the above discussion, the wind speed and strong wind days in the selected cities have a good correlation with the sandstorm prevention effect after the establishment of forest farms.

b. We generally selected several cities in the target provinces for discussion. We chose the capital city of the target province first, because capital cities tend to have the largest population. If the province covers a wide area, for the sake of the universality of data, we chose the cities that are far away from the provincial capital. According to this principle, Zhangjiakou, Taiyuan, Hohhot, Shenyang, Changchun, Zhengzhou, Lhasa, Xi'an, Lanzhou, Jiuquan, Xining, Golmud, Yinchuan, Urumqi and Karamay were chosen.

Specific Process:

a. We first calculated the sample mean and sample variance of the target city, and then modified the sample variance.

b. We studied Beijing's wind speed in recent 3 years by quantile-quantile plot (figures following), and found the days of wind speed at all levels are normally distributed to some extent.

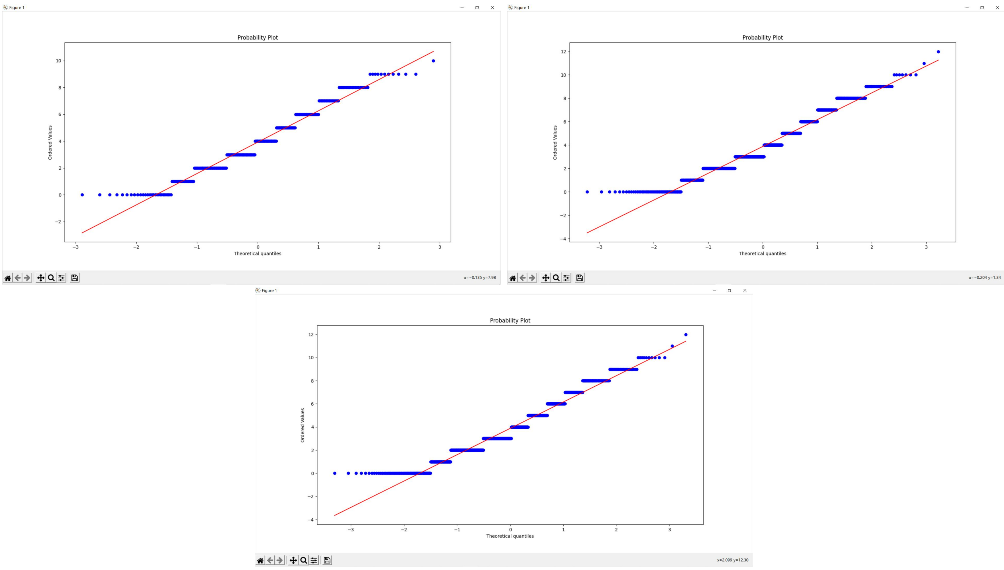


Figure 9-11: Quantile-quantile plot of Beijing's wind speed in recent three years

c. Through equation $P = 1 - \Phi(\frac{8-\mu}{se})$ (μ is mean, se is standard deviation, Φ is the standard normal distribution), we calculated the probability of wind speeds greater than force 8. Then we calculated the number of strong winds days based on the probability.

d. Select the top 3 cities with the weight of 50% of the mean maximum wind speed and 50% of the mean number of strong winds days. Karamay (85.30E, 45.57N), Shenyang (121.64E, 43.26N) and Hohhot (110.37E, 46.00N) were selected to build forest farms.

4.1.4 *Consideration of Site and Scale of Forest Farms*

Hypotheses:

a. The greater the area of sand or desert around a city, the greater the severity of the city's sandstorms.

b. The larger the urban area, the larger the area of forestland needed to be built.

c. The forestland area has an effect on the degree of sandstorm.

Model:

$$\mathbf{SWD} = e^{\beta_0 + \beta_1 S} \frac{CA \cdot SA}{PCA \cdot OSA} k \tag{4}$$

In equation (4), **SWD** is a measure of sandstorm severity. S is the forestland area. SA is the area of sand or desert. CA is the area of the city. PCA is Beijing's area. OSA is Otindag Desert's area. k, β_0 and β_1 are unknown constants. Among these constants, β_0 and β_1 are coefficients in the regression equation $\lg \widehat{SWD} = \beta_0 + \beta_1 S$.

Outcomes:

We used the data of Beijing to scale the forestland area required by other cities according to the formula.

Table 7 The Selected Cities' Required Forestland Area

City	Required Forestland Area
Karamay	$101.43\times10^4 \cdot mu$
Shenyang	$107.60\times10^4 \cdot mu$
Hohhot	$98.77\times10^4 \cdot mu$

As for the sites of these forest farms, a fact is that it is difficult to carry out effective protection of the city for too far away forest farms.

According to the distance between Beijing and Saihanba, we selected a site about 200 kilometers from the city on the line between the city and the surrounding sand or desert. If possible, locate along roads or water sources.

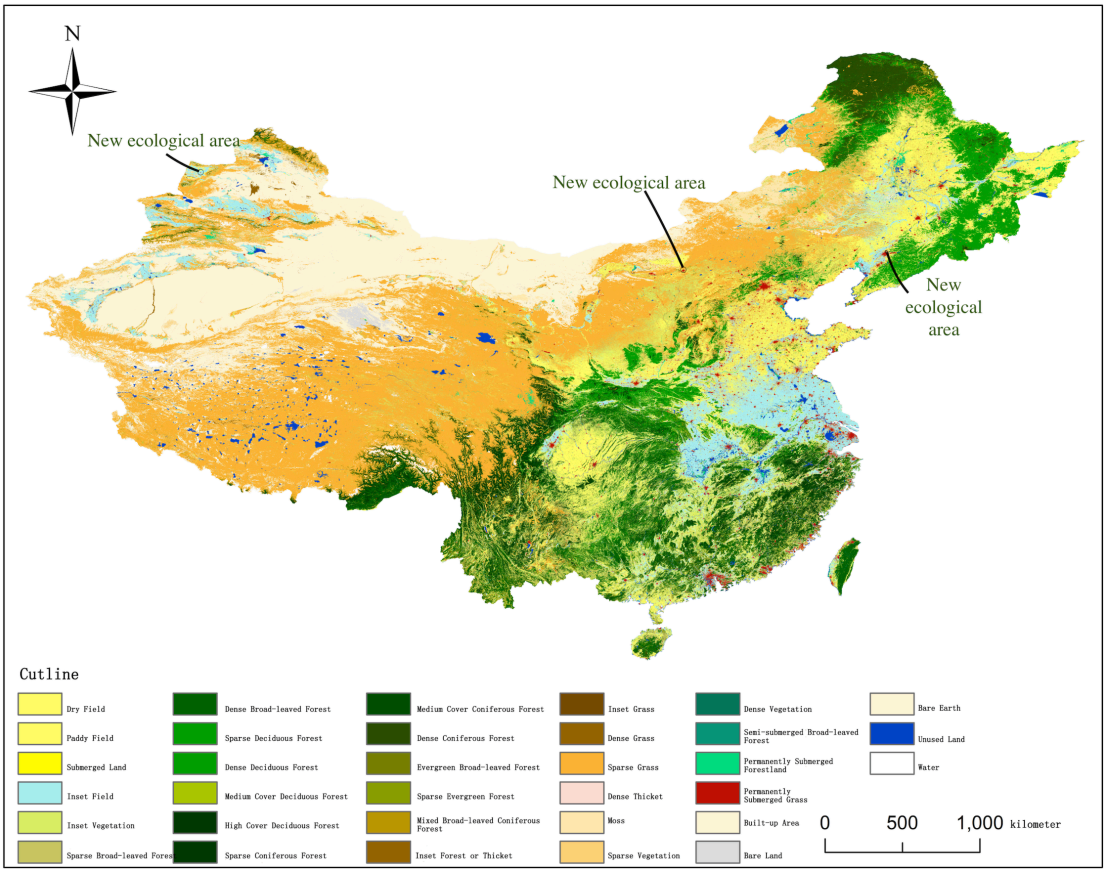


Figure 12: Location of forest farms

4.1.5 *Roles of New Forest Farms in Local Carbon Neutrality*

Using Cubic Spline Interpolation to the data of Saihanba Forest Farm from 1962 to 2021, we drew the following figure by code listed as *Listing 1* in Appendix. This precisely presented the relation between forestland area and Carbon sequestration due to the dense points.

After we got the Carbon sequestration (denoted as CS_i) of each forest farm, we calculated the amount of Carbon dioxide (denoted by $M^i_{CO_2}$) that each forest farm could absorbe annually by $M^i_{CO_2} = \frac{44}{12}CS_i$ (CO_2's molecular weight is $\frac{44}{12}$ times that of Carbon). Results were in Table 8:

Comparing with the Carbon dioxide emissions in these three cities in 2019 (in Table 9), the CO_2 absorbed by forest farms will play a significant role in promoting local carbon neutrality.

Table 8 CO_2 **Absorbed by Each Forest Farm**

City Where Each Forest Farm Locates	CO_2 Absorption ($10^4 \cdot t$)
Karamay	263.021
Shenyang	298.137
Hohhot	201.667

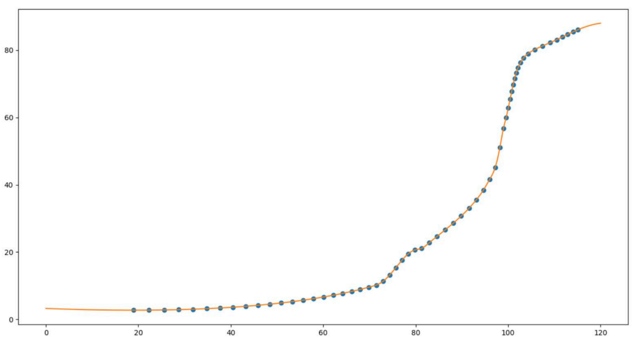


Figure 13: Relation between forestland area and Carbon sequestration per year

Table 9 CO_2 **Emitted by Three Selected Cites in 2019**

City	CO_2 Emissions ($10^4 \cdot t$)	Rate of Forest Farm's Absorption
Karamay	714.185	36.83%
Shenyang	3736.156	7.80%
Hohhot	2776.278	7.26%

4.2 Saihanba-type Nature Reserves That North Korea Needs to Build

4.2.1 *The Reason to Evaluate North Korea*

North Korea is an Asia-Pacific country with a temperate monsoon climate, which is very similar as Beijing and Saihanba. In this research, many basic data to build models are from Beijing and Saihanba. Therefore, choosing North Korea as the target country can lead to more precise consequences. Another reason is that North Korea's area is not so large, and it will be easier and preciser to find the location and calculate the scale of the foreast farm. One more reason is that desertification has been increasing in recent years and north Korea is also affected by sandstorms. The last reason is that North Korea's land is less developed and it is more realistic to build forest farms around its cities.

4.2.2 *Specific Process of Selecting the City*

Data Collection:

We looked at the top 10 cities in North Korea by population (also the 10 cities with more than 300,000 people in 2008), beacuse the forest farm plan will be of little use if the target city has very few residents. This 10 cities were Pyongyang, Hamhung, Cheongjin, Nampo, Wonsan, Sinuiju, Dancheon, Gaechon, Gaesong and Sariwon.

Clustering Results

According to some data on forest coverage rate, desertification rate and average relative humidity provided by North Korea's weather stations, we used the model introducted in 4.1.2 again and gained the following clustering figure. The contour coefficient of North Korea clustering is 0.845 after calculation.

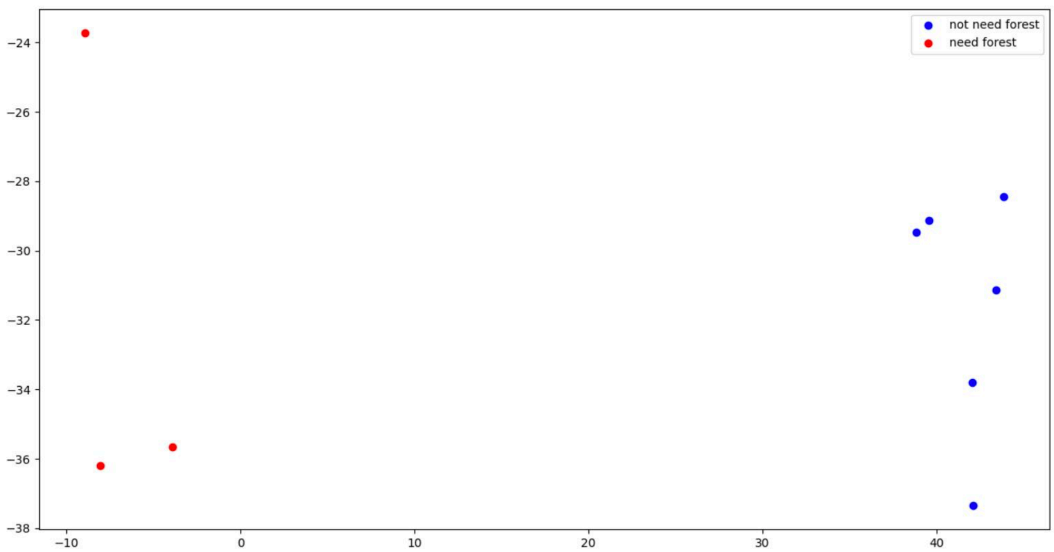


Figure 14: Clustering figure about North Korea's cities

In this figure, three red points are Pyongyang, Sariwon and Kaecheon.

Selecting Pyongyang to build a forest farm

Among these three cities, we used annual average wind speed to approximate the strong winds days (the same process as 4.1.3). We selected one city with the weight of 50%of the mean maximum wind speed and 50% of the mean number of strong winds days. Pyongyang (126E 39.3N) was chosen to build a new forest farm.

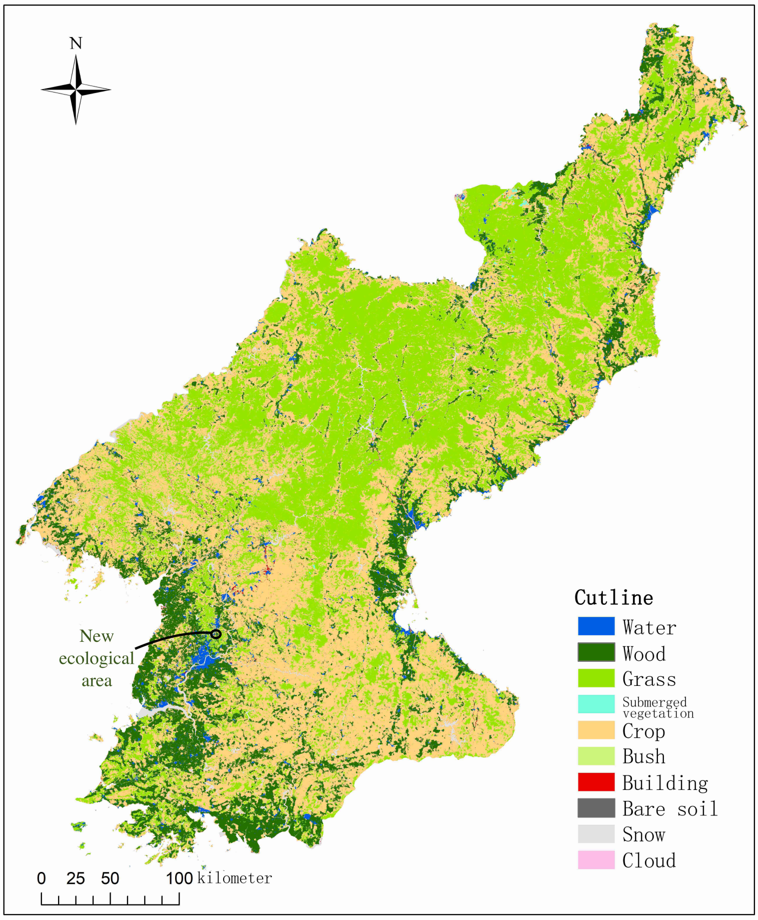


Figure 14: Location of the forest farm in North Korea

4.2.3 *Roles of the New Forest Farm in Carbon Neutrality*

According to Saihanba's data about forestland area and the degree of sand dust suppression, the forestland area of the new forest farm in Pyongyang is better to be larger than or equal to $26.46 \times 10^4 \cdot mu$ (176.4km^2). By using Saihanba's data betwwen forestland area and Carbon sequestration presented in Listing 2 in Appendix, its CO_2 absorption per year is $10.226 \times 10^4 \cdot t$.

In 2018, North Korea emitted 15.3 million tons of CO_2, and the new forest farm can absorb about 1.73% CO_2 of the total country, which must be an extremely beneficial project for North Korea's Carbon neutrality target.

4.3 Conclusions of Enlightenment of Saihanba

Saihanba Is not a lonely case. Such forest farms can be built in many parts of China and the world, and will greatly promote the improvement of local and surrounding cities' ecological environments and the realization of Carbon neutrality. Moreover, the forest farm itself can be converted into a continuous supply of timber, which is also beneficial to the development of local timber manufacturing industry.

V. References

[1] Yuan, Y., Sun, G., Yuan, M.& Zhang,Z.(2017). *Distributional Patterns of Plant Species Richness Along an Elevational Gradient in Saihanba*. *Journal of Anhui Agricultural University*, 44(03), 496-501. www.cnki.net/kcms/doi/10.13610/j.cnki.1672-352x.20170524.023.html

VI. Appendix

Listing 1: Relation between forestland area and Carbon sequestration per year

```
df = pd.read_excel('Saihanba pro.xlsx')
x_data = df['forestland area'].tolist()
y_data = df['Carbon sequestration 10^4 t'].tolist()
spl = splrep(x_data, y_data) # Cubic spline interpolation
x2 = np.linspace(0, 120, 2400) # generate test data
y2 = splev(x2, spl) # calculate test value
plt.plot(x_data, y_data, 'o', x2, y2) # draw function image
y_k = splev(101.43, spl) # calculate target
y_s = splev(107.6, spl)
y_h = splev(98.77, spl)
print('Karamay: '+str(y_k)+'\nShenyang: '+str(y_s)+'\nHohhot: '+str(y_h))
```

Listing 2: Relation between forestland area and Carbon sequestration per year in North Korea

```
df = pd.read_excel('Saihanba pro.xlsx')
x_data = df['forestland area'].tolist()
y_data = df['Carbon sequestration 10^4 t'].tolist()
spl = splrep(x_data, y_data) # Cubic spline interpolation
x2 = np.linspace(0, 120, 2400) # generate test data
y2 = splev(x2, spl) # calculate test value
plt.plot(x_data, y_data, 'o', x2, y2) # draw function image
y_p = splev(24.46, spl) # calculate target
```