Quantifying the effects of the ‘Internet plus Ecology’ framework on carbon sink in the digital age: a representative study of Ant Forest in China

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Abstract

Ecological afforestation is a positive measure to increase the absorption of carbon dioxide and curb global warming. Ant Forest, a successful example of an ‘Internet + voluntary tree planting’ gamified app with more than 500 million users, has contributed to substantial progress on ecological afforestation in China. It represents a new model of transforming the environmental awareness and low-carbon actions of users (e.g. walking, sharing bikes, and reducing plastics and papers) into actual environmental benefits via planting trees. The implications of Ant Forest can provide useful references for linking ecosystem restoration with the internet worldwide. However, the spatial distribution and quantitative effects on the carbon sink of Ant Forest on a finer scale are not fully understood. In this study, 588 Ant Forest blocks with a total area of 136,314 ha were identified based on area of interest data using the web crawler approach. The forest blocks involved 20 cities in 7 provinces and included 11 varieties of trees. More than 90% of these forest blocks were located in Inner Mongolia, Qinghai, and Gansu Provinces, and mostly shrubs were planted. Based on the Carnegie Ames Stanford approach model, the net primary productivity (NPP) of Ant Forest was estimated. The simulated total annual NPP of all Ant Forest areas was $1.06 \times 10^{11}$ gC, and an obvious increasing trend in NPP from 2016 to 2020 was observed, indicating effective carbon sequestration. We found that Hippophae rhamnoides and Caragana korshinskii had carbon sink advantages over other shrubs due to their higher NPP values per unit area. By strengthening individuals’ low-carbon awareness for reducing carbon emissions and increasing forest NPP to enhance the carbon sink, Ant Forest uses a representative and inspirational ‘Internet plus Ecology’ framework that has much significance for achieving carbon neutrality in China and tackling global climate change.

1. Introduction

Faced with the serious threats raised by global warming, many countries and international organizations are exploring positive actions to reduce carbon emissions and increase carbon sinks to address climate change (World bank 2020, IPCC 2021, IRENA 2022). On September 2020, China announced that it would aim to control carbon dioxide (CO$_2$) emissions, reach a peak before 2030, and achieve carbon neutrality by 2060. However, this goal represents a tremendous challenge. China is the world’s largest developing country and the priorities of climate action and economic development are usually inextricable and their effects on each other are complicated (Meidan 2020). Internationally, there is interest in understanding how China will reach carbon neutrality and establish an effective low-carbon development path. Planting...
trees, as one of the natural climate solutions in combating climate change (Cabon et al. 2022), has been proven to be effective for increasing carbon sequestration in land ecosystems (Green and Keenan 2022). According to recent satellite data (2000–2017), China alone accounts for 25% of the global net increase in leaf area, and the largest contribution to greening China is from forests (42%) (Chen et al. 2019). These forests have played an important role in increasing carbon storage and have great potential for carbon sequestration (Liao et al. 2016).

Ant Forest is a gamified app in the Alipay mobile payment platform in the domain of ‘Internet plus Ecology’ and was initiated by China’s largest Fintech company, Alibaba. Planting trees (i.e. ecological afforestation) is the ultimate purpose of Ant Forest and is achieved by encouraging its users to reduce their carbon footprints (section S1 in the supplementary material). Benefiting from the gamification design (e.g. stealing energy points from friends), as well as the incentive mechanism (e.g. virtual certification issued by the China Green Foundation), Ant Forest has become well known and has achieved much success since it was launched in 2016 (Xiong and Meng 2018, Yang et al. 2018, Mi et al. 2021). On April 22, 2019, Alipay announced that 500 million users of Ant Forest had contributed to the planting of 100 million trees in China (Zhang et al. 2021). Some researchers have analyzed the trigger reasons for users’ participation in Ant Forest through questionnaires using structural equation models (Chen et al. 2020a), partial least squares path models (Zhang et al. 2020), and two-dimensional Kano models (Wang and Yao 2020). They found that high satisfaction was shown in all the surveyed users, and individual environmental awareness was the most important motivation. By integrating mobile applications, big data and financial technology, Ant Forest can effectively improve individuals’ intention to protect the ecological environment. This provides a new opportunity and successful model for inspiring greater public participation in global action against climate change (Xiong and Meng 2018, Yang et al. 2018, Chen et al. 2020a, Mi et al. 2021, Zhang et al. 2021). However, previous studies have mainly focused on user participation from the perspective of economics, and the spatiotemporal variations in Ant Forest and its associated contribution to carbon neutrality, especially to carbon sinks, have rarely been studied. To fill this gap, it is important to explore where the Ant Forest is located and how much carbon could be fixed by these artificial forests using a quantitative approach from the perspective of physical geography.

Net primary productivity (NPP) is an essential factor reflecting vegetation activity and a key component of the terrestrial carbon cycle (Field et al. 1998, Luysaert et al. 2007, Feng et al. 2019). As one of the important variables of carbon sources and sinks in ecosystems, NPP can reflect the exchange of CO₂ between vegetation and the atmosphere, as well as the carbon footprint (Garbulsky and Paruelo 2004, Running et al. 2004, Chen et al. 2020b). The Carne-gie Ames Stanford approach (CASA) model, a powerful tool for large-scale NPP estimation based on plant physiology and carbon sequestration processes (Potter et al. 1993, Field et al. 1995), is commonly used in many regions globally. In China, the CASA model has been widely applied for NPP estimation (Piao et al. 2001, Yuan et al. 2006, Zhu et al. 2007, Feng et al. 2019, Guo et al. 2020, Xu et al. 2020, Chen et al. 2020b), demonstrating its capability for quantifying the NPP of Chinese terrestrial vegetation in different regions.

In this context, integrating web crawler, remote sensing (RS), and geographic information system (GIS) approaches, the purpose of this study is to quantify the effects of Ant Forest on the carbon sink via: (a) identifying the amount, location, area, spatial distribution, and tree species of the existing Ant Forest; (b) simulating the NPP of these forests and analyzing the spatial variations in NPP dynamics during 2016–2020; and (c) discussing the comprehensive contribution of this ‘Internet plus Ecology’ pattern and its potential use to combat global climate change by linking online green users (OGUs) with ecological afforestation activities in today’s digital age.

2. Materials and methods

2.1. Area of interest (AOI) collection of Ant Forest
Crawling the AOI in digital maps based on computer programming has become a practicable and popular method for GIS analysis (Zhou 2022, Yan et al. 2002). We crawled the AOI data of the Ant Forest based on the AutoNavi map (figure 1), obtained multiple geographic information (including names, locations, and tree species). The detailed processes are provided in the supplementary material (section S2).

2.2. NPP simulation based on the CASA model
The calculation of vegetation NPP in the CASA model (Potter et al. 1993, figure 1) is mainly determined by two variables: absorbed photosynthetically active radiation (APAR) and light use efficiency (ε) absorbed by vegetation:

\[ NPP_{(x,t)} = APAR_{(x,t)} \times \varepsilon_{(x,t)} \]  \hspace{1cm} (1)

where \( NPP_{(x,t)} \) is the total fixed NPP of pixel x in month t, and \( APAR_{(x,t)} \) and \( \varepsilon_{(x,t)} \) are equivalent.

2.2.1. Calculation of APAR
APAR depends on the total solar radiation and the absorption ratio of vegetation to photosynthetically active radiation, which can be calculated by equation (2).

\[ APAR_{(x,t)} = SOL_{(x,t)} \times FPAR_{(x,t)} \times 0.5 \]  \hspace{1cm} (2)

where \( SOL_{(x,t)} \) is the total solar radiation (MJ m⁻²) of pixel x in month t, and \( FPAR_{(x,t)} \) is the fraction of
photosynthetically active radiation absorbed by the canopy. The constant 0.5 represents the proportion of solar effective radiation (wavelength 0.4 – 0.7 μm) that can be used by vegetation.

Fraction of photosynthetically active radiation (FPAR) is related to vegetation type and vegetation coverage. The normalized differential vegetation index (NDVI) obtained from RS data can reflect the vegetation coverage in general (Potter et al. 1993). Based on NDVI dynamics obtained using RS data (see section 2.3), we calculated the simple ratio (SR) of NDVI by equation (3),

$$SR_{(x,t)} = \frac{1 + NDVI_{(x,t)}}{1 - NDVI_{(x,t)}}$$  \hspace{1cm} (3)

Then, we calculated FPAR_{(x,t)} based on SR by equation (4).

$$FPAR_{(x,t)} = \frac{SR_{(x,t)} - SR_{min}}{SR_{max} - SR_{min}} \times (FPAR_{max} - FPAR_{min}) + FPAR_{min}$$  \hspace{1cm} (4)

where SR_{max} and SR_{min} represent the maximum and minimum ratios of SR, respectively, and FPAR_{max} and FPAR_{min} refer to the maximum value (0.95) and minimum value (0.001) of FPAR, respectively.

2.2.2. Calculation of light energy conversion rate ε

The light energy conversion rate refers to the efficiency of vegetation to convert absorbed photosynthetically active radiation into organic carbon.

$$\varepsilon_{(x,t)} = \varepsilon_{max} \times T_{c1(x,t)} \times T_{c2(x,t)} \times W_{c(x,t)}$$  \hspace{1cm} (5)

where \(\varepsilon_{max}\) is the maximum value of \(\varepsilon\), and different vegetation has different values (see table S1 in the supplementary material). \(T_{c1(x,t)}\) and \(T_{c2(x,t)}\) represent the stress effects of low temperature, high temperature and water, respectively.

$$T_{c1(x,t)} = 0.8 + 0.02 \times T_{opt(x,t)} - 0.0005 \times \left[T_{opt(x,t)}\right]^2$$  \hspace{1cm} (6)

$$T_{c2(x,t)} = \frac{1.184}{1 + e^{3.2 \times (T_{opt(x,t)} - 10 - T_{(x,t)})}} \times \frac{1}{1 + e^{8 \times (T_{opt(x,t)} - 10 - T_{(x,t)})}}$$  \hspace{1cm} (7)

where \(T_{opt(x,t)}\) refers to the monthly average temperature in a certain year when NDVI is the largest in the region. When the value is less than or equal to \(-10^\circ C\), \(T_{c1(x,t)}\) takes 0. The plant growth reaches the fastest speed when NDVI reaches its maximum, and the temperature at this point is important for measuring plant growth.

$$W_{c(x,t)} = 0.5 + 0.5 \times \frac{E_{(x,t)}}{P_{(x,t)}}$$  \hspace{1cm} (8)

where \(E_{(x,t)}\) and \(P_{(x,t)}\) represent the actual and potential regional evapotranspiration, respectively, which are calculated from precipitation and sunshine hours (Zhu 2005).

2.3. Data sources of NPP calculation

We calculated the 2016–2020 vegetation NPP in each Ant Forest area obtained in section 2.1. Based on the CASA model, the vegetation NPP with a 250 m grid as the pixel and monthly as the time interval was simulated. The detailed data sources are provided in the supplementary material (section S3).
3. Results

3.1. Spatial pattern of Ant Forest

Through AOI searching, 588 pieces of forests named Ant Forest with a total area of 136 314 ha were collected, and they were distributed in seven provinces in China (figure 2). Specifically, the number of forest pieces per province (presented in descending order) in the Inner Mongolia, Gansu, Qinghai, Hebei, Sichuan, Shanxi, and Yunnan Provinces were 350, 132, 44, 40, 12, 7, and 3, respectively. With respect to the area of Ant Forest in each province, the ranked order changed to Inner Mongolia, Gansu, Qinghai, Shanxi, Sichuan, Hebei, and Yunnan Provinces, with area proportions of 47.36%, 36.95%, 8.00%, 6.60%, 0.54%, 0.53%, and 0.01%, respectively.

Notably, Inner Mongolia was the greatest contributor in terms of both piece number and forest area, with approximately half of Ant Forest located in that province (figure 3). Moreover, we found that the provinces of Gansu and Qinghai were ranked 2nd and 3rd in terms of both piece number and forest area (figure 3). It should be noted that most areas of these three provinces (except for the four leagues in eastern Inner Mongolia) were found in the arid and semiarid region of Northwest China, which faces serious land degradation and a fragile ecological environment. In total, approximately 81.7% of the Ant Forest area was located in western Inner Mongolia, Gansu and Qinghai (figure 3), which highlighted the vital contributions of this ecological afforestation project to ecological restoration and environmental protection in Northwest China. From the perspective of different tree species of Ant Forest, mostly drought-resistant shrubs (e.g. *Haloxylon ammodendron, Caragana korshinskii*) were planted in these three provinces with arid and semiarid climates (figure 3).

Hebei and Shanxi Provinces, located in North China and adjacent to Beijing, exhibited opposite characteristics in terms of piece number and total area of Ant Forest. Hebei ranked 4th among the seven provinces in piece number of Ant Forest, but this province ranked 6th in total area, indicating that the spatial distribution of Ant Forests in Hebei exhibited a fragmental structure. In contrast, Shanxi Province ranked 6th among the seven provinces in piece number of Ant Forest, while it ranked 4th in total area, indicating that many large-area forests were located in this province. Comparing the different species of Ant Forest (figure 3), it is notable that all individuals planted in Hebei were arbor trees, whereas all individuals planted in Shanxi were shrubs.

In Southwest China, Sichuan and Yunnan were two provinces distributed with little Ant Forest. In Sichuan Province, only Xiaojin County of Aba Prefecture was involved and had 12 forest blocks of *Hippophae rhamnoides*, with a total area of 740 ha (figure 3). In Yunnan Province, only Yunlong County of Dali Prefecture was involved and had three forest blocks of *Pinus armandii* and *Picea asperata*, with a total area of approximately 19 ha (figure 3). Planting trees in Southwest China should have positive effects on vegetation restoration and carbon storage in karst regions with vulnerable ecological environments (Liu et al. 2015).

3.2. Spatial pattern of NPP in Ant Forest areas

In general, a higher carbon sequestration was found in the forest areas of Northwest China according to the total NPP (figure 4). The annual average NPP in western Inner Mongolia, Gansu, and Qinghai provinces was $2.5 \times 10^{10}$ gC, $2.3 \times 10^{10}$ gC, and $1.4 \times 10^{10}$ gC, respectively. The corresponding proportions of the total amount were 23.56%, 22.01%, and 13.42%, respectively. For the two provinces in North China, the annual average NPP in Shanxi was $1.7 \times 10^{10}$ gC, which almost decoupled the corresponding result of $1.9 \times 10^{9}$ gC in Hebei. The NPP of Ant Forest in these two provinces accounted for approximately 18.15% of the total NPP. Similarly, for the two provinces in Southwest China, there was also a difference in order of magnitude between Sichuan ($4.2 \times 10^9$ gC) and Yunnan ($1.3 \times 10^9$ gC), which had a 4.04% total Ant Forest NPP amount. In addition, the annual average NPP in eastern Mongolia was $2.0 \times 10^{10}$ gC, accounting for 18.82% of the total amount. The NPP per unit area is listed in table S2 in the Supplementary material. The prefecture-level city with the highest carbon sequestration was Qingsheng in Gansu Province, with an annual average NPP of $1.8 \times 10^{10}$ gC, followed by Xinzhou in Shanxi Province ($1.6 \times 10^{10}$ gC) and Haidong in Qinghai Province ($1.4 \times 10^{10}$ gC). Notably, these three cities ranked 3rd, 7th and 4th in terms of forest area nationwide (figure 3), indicating that they were not the cities with the largest Ant Forest area. This finding revealed that the spatial pattern of Ant Forest NPP was not exactly the same as the forest distribution, and meteorological variables such as temperature and precipitation might affect the NPP to some extent. Moreover, the vegetation species variation was another important factor that influenced the estimated NPP value.

Therefore, the carbon sequestration effects of different vegetation species in the Ant Forest were further analyzed below (figure 5). In terms of the NPP amounts of different tree species, *Hippophae rhamnoides* ($5.1 \times 10^9$ gC yr$^{-1}$) had the greatest value, followed by *Caragana korshinskii* ($4.3 \times 10^9$ gC yr$^{-1}$). We found that the *Hippophae rhamnoides* forest contributed 48.38% of the total NPP with only 24.02% of the total Ant Forest area, and the *Caragana korshinskii* forest contributed 40.15% of the total NPP with only 26.16% of the total Ant Forest area. This indicated that the carbon sequestration effects of both *Hippophae rhamnoides* and *Caragana korshinskii* were prominent (figure 5). The NPP of
Figure 2. The Ant Forest in China and its four representative areas with different species of vegetation.
Figure 3. The distributions of Ant Forest varied among provinces and cities, as did the different vegetation species. Note that the figure on the left is the area of Ant Forest on the spatial scale of prefecture-level cities, and the background color refers to different provinces. The figure on the right shows the tree species planted in different provinces (or regions), and the width of the band indicates the planting area. A province (or region) in the left and right figures has the same color. We divide the 11 species into shrubs and trees at the bottom, and give the morphological characteristics of each arbor species (the pictures come from the Alipay app interface).
Figure 4. Spatial pattern of annual average NPP during 2016–2020 of the Ant Forest area in seven provinces.

Figure 5. Statistical characteristics of Ant Forest NPP with different vegetation species in each city and province. The NPP value is presented as the length of the ring from multiple dimensions (a), the innermost circle refers to the distribution of NPP in the 4 regions (see the legend), the sub-inner circle refers to the distribution of NPP in the 8 provinces (or regions), and the third circle represents the distribution of NPP in 20 cities. The outermost ring refers to the NPP distribution of 11 tree species. The NPP values of shrubs (b) and arbors (c) per unit area over a five-year period planted in Ant Forest are consistent with the color of the outermost circle of subgraph (a).
Figure 6. Interannual variations of NPP in the Ant Forest in 8 provinces (or regions) from 2016 to 2020. The orange bar refers to a decrease in value compared to the previous year, and the green bar refers to an increase in value compared to the previous year.

Hippophae rhamnoides and Caragana korshinskii was 157 gC m\(^{-2}\) yr\(^{-1}\) and 120 gC m\(^{-2}\) yr\(^{-1}\), respectively; although both shrubs, theirs was close to or even greater than the NPP per unit area of Pinus sylvestris, a kind of arbor tree. We also found that Haloxylon ammodendron was the vegetation species with the highest proportion of planting area (31.15%), but its total carbon sequestration ranked only 5th among 11 vegetation species due to its low NPP value of 5.5 gC m\(^{-2}\) yr\(^{-1}\). It is possible that wind prevention and sand fixation were the main afforestation goals of this type of shrub, which usually has a well-developed root system but lower leaf area. Among all species, Picea asperata had the highest carbon sequestration capacity (with an NPP value of 780 gC m\(^{-2}\) yr\(^{-1}\)), which was approximately more than 142 times the value of Haloxylon ammodendron and approximately more than 3.7 times the average level of all 11 vegetation species. However, due to having the smallest proportion of planted area (0.014%), the two arbor forests of Picea asperata and Pinus armandii had the lowest total NPP.

3.3. Interannual variation of NPP in Ant Forest areas

In all seven provinces, the total NPP of Ant Forest showed an increasing trend during the period from 2016 to 2020 (figure 6), indicating that this ‘Internet + voluntary tree planting’ project contributed to carbon sequestration and sinks in China. However, influenced by the interannual variation in meteorological factors, the NPP did not exhibit a monotonic increasing change. Except for a common increase found in all seven provinces from 2019 to 2020, the interannual changes in forest NPP between different regions varied; a detailed description is provided in the supplementary material (section S4). Using linear regression, the variation rates of forest NPP in different regions were assessed (figure 6). A rapidly-increasing trend was found in Northwest China, with a range of 1.00 \times 10^9 - 4.94 \times 10^9 gC yr\(^{-1}\). The other four provinces, listed in descending order, were Shanxi, Sichuan, Hebei, and Yunnan, with variation rates of 1.41 \times 10^9 gC yr\(^{-1}\), 6.46 \times 10^8 gC yr\(^{-1}\), 2.53 \times 10^7 gC yr\(^{-1}\), and 1.58 \times 10^7 gC yr\(^{-1}\), respectively.
respectively. In addition, in eastern Inner Mongolia, which is located in Northeast China, a linear increasing rate of forest NPP of $6.49 \times 10^8$ gC yr$^{-1}$ was found, which was slightly lower than the variation speed in western Inner Mongolia.

With calculations based on different vegetation species, we found that the variation rate of shrub NPP was slightly higher than that of arbor NPP (figure 7). These differences (supplementary materials section S5) might be related to the spatial variations in precipitation, temperature, terrain, and elevation throughout different regions in China.

### 4. Discussion

#### 4.1. Comprehensive analysis of Ant Forest’s contribution to carbon neutrality

Since the launch of Ant Forest in 2016, it has attracted nearly 500 million OGUs and is, to date, the world’s largest online public environmental platform (Chen et al 2020a). Aside from the forest carbon sink, the contribution to carbon neutrality of Ant Forest also includes carbon emission reduction through carbon-light behavioral changes of OGUs motivated to collect green-energy points.

A total of 304 valid questionnaires from OGUs aged between 18 and 60 years old in 35 provinces of China were analyzed. The results showed that 35.8% of the surveyed OGUs selected environmental awareness as the most important motivation (figure 8(a)), implying that OGUs had a strong wish to improve the environment as a public good through real tree planting. This finding was consistent with Chen et al (2020a), which indicated that both environmental awareness and social motivation had significant positive promotional effects on Ant Forest OGUs’ online immersion and that environmental awareness was higher than social motivation. Moreover, 20.0% and 16.0% of the surveyed OGUs selected the game interaction and the immersive experience of tracking the planted trees as the major attraction, respectively (figure 8(a)). Wang and Yao (2020) also demonstrated that the gamification design elements of Ant Forest had a positive influence on OGUs’ satisfaction.

To further analyze the low-carbon behaviors for collecting green points of Ant Forest users, the surveyed samples were divided into two groups: college students (aged between 18 and 21 years old) and other people. We found that green commuting, reducing use of paper and plastics, and reducing...
Figure 8. The participation statistics (a), carbon footprint (b), and low-carbon actions to collect green energy (c) of the 304 surveyed Ant Forest users. The length of each ring in subgraph (b) refers to the number of online green users (OGUs) that choose this low-carbon action. Each human icon in the college students group and other people group of subgraph (b) denotes eight persons and three persons, respectively, based on the surveyed results.
trips were the three major categories of OGUs' low-carbon behaviors (figure 8(c)). In terms of the specific low-carbon action in the green commuting category, walking, subway, and public transport were the most commonly used pathways to collect the green points among all surveyed users (figure 8(c)). For college student OGUs, sharing bikes was another main action for reducing carbon emissions related to green commuting (figure 8(c)).

Of the 304 surveyed samples, the average accumulating carbon footprint in personal carbon accounts was 99 658 g (figure 8(b)). Calculating based on the average accumulating carbon footprint of 99 658 gC/person, the estimated carbon emission reduction of the 500 million Ant Forest users was approximately $4.98 \times 10^{13}$ gC in total. The results of these analyses emphasized the significant impact of Ant Forest on incentivizing individuals' low-carbon behaviors, which is vital for achieving carbon neutrality in China.

4.2. The innovation of Ant Forest for carbon neutrality

As a burgeoning 'Internet plus Ecology' platform, the Ant Forest has been proven to be an effective strategy to increase public engagement in climate change and enhance the contribution of individuals to carbon neutrality through the rapid advancement of digital technology. On the one hand, it aims to encourage users to adopt a low-carbon lifestyle, which would reduce carbon emissions from the perspective of carbon sources. On the other hand, it promotes ecological afforestation by planting trees, which could increase carbon sequestration from the perspective of carbon sinks. Therefore, the Ant Forest should have innovativeness and can be a model for Chinese carbon neutrality as well as combating climate change on a global scale. Ant Forest won the Champion of the Earth Award (the United Nations’ highest environmental honor) and the United Nations Lighthouse Award (the highest honor in the world for Combating Climate Change) in 2019, reflecting the high level of recognition from the international community achieved by this Chinese 'Internet + voluntary tree planting' digital green solution.

The Ant Forest, associated with its 'digital technology + gamification design + public participation' framework, is a significant product for enhancing the efforts of individuals to tackle climate change. It is a globally representative case with ecological, environmental and economic benefits. We found that by August 2021, the total area of identified Ant Forest was 136 314 ha, which was equal to the area of 1.9 Singapore; the accumulating NPP of the Ant Forest from 2016 to 2020 was $5.31 \times 10^{11}$ gC, which was approximately 1.03 times the carbon emissions of Singapore in 2019. Moreover, it should be noted that the Ant Forest also played an important role in Chinese poverty alleviation through ecological protection. For instance, Hippophae rhamnoides is a type of economic tree that is usually used to produce drinks due to its abundant vitamin C and medicinal value. In the future, if we could collect more data, further work assessing the comprehensive benefit of economic forests and ecological forests separately should be performed.

4.3. Limitation and future outlook

This paper is an innovative quantitative study aiming to identify and estimate the distribution of Ant Forest and its effect on carbon sinks based on the independent data source from RS rather than the macroscopic panel data published by Alibaba; it fills the gap of geographically discussing this world's first 'Internet plus ecology' project. Some uncertainties might exist in the NPP estimation taking 2016–2020 as the analysis period by using the boundary of Ant Forest crawling from the AutoNavi platform in 2021. However, it could be reasonably explained by the assumption that the area with planted trees was almost completely converted from barren land, which usually had no vegetation cover (section 5.1 in the supplementary material). Our results showed that there was an increasing trend of NPP variations in the Ant Forest area during 2016–2020, which provided a solid scientific foundation for the effectiveness of this ecological afforestation and its carbon sequestration. If more data can be collected, the parameters relevant to meteorological data used in the CASA model, and the consideration regarding forest age and the growth changes of different vegetation species, may be improved in the future. However, this limitation did not affect the most novel aim of this study: to quantitatively estimate the spatial pattern of Ant Forest and its carbon sequestration effect.

More than 90% of the Ant Forest were located in the arid and semi-arid areas, which might exacerbate more severe water shortages after planting trees. Another improvement would be to simulate on the effects on the water cycle along with the carbon cycle to estimate this ecological afforestation more comprehensively.

5. Conclusions

Through the application of web crawlers, 588 forest blocks with a total area of 136 314 ha of Ant Forest were obtained, and were found to be distributed in 20 municipal blocks of 7 provinces in China, involving 11 different vegetation species. More than 90% of the Ant Forest was located in Inner Mongolia, Qinghai, and Gansu provinces, which were mostly concentrated in the arid and semiarid areas of northwest China. In addition, a few forest areas were planted in...
Hebei and Shanxi Provinces of North China (~7.1%), and Sichuan and Yunnan Provinces of Southwest China (~0.5%), respectively.

The NPP of vegetation in the above 588 forest blocks exhibited an increasing trend since the construction of the Ant Forest project in 2016, with an annual average amount of $1.06 \times 10^{14}$ gC yr$^{-1}$, which indicated an obvious effect on the increasing carbon sink. The interannual changes and linear increasing rate of NPP were quite variable in different regions and were comprehensively influenced by vegetation species as well as climate conditions. The total area of *Hippophae rhamnoides* and *Caragana korshinskii* was approximately 50% of all Ant Forest, but the sum NPP of these two species was nearly 90% of the total, indicating that these two shrubs have relatively higher carbon sequestration capacity.

As an integrating ‘Internet plus Ecology’ platform in the ‘digital technology + gamification design + public participation’ framework, Ant Forest did have positive effects on China's carbon neutrality by increasing carbon sinks and reducing carbon emissions. The successful application of this ecological afforestation project, as the world’s first and largest online public environmental platform, might suggest an effective strategy for increasing the participation of individuals in addressing climate change globally.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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CRediT authorship contribution statement

Nan Wang: Methodology, Visualization, Data Curation, Investigation, Writing—Original Draft. Wenjuan Hou: Conceptualization, Methodology, Formal analysis, Writing—Review & Editing, Supervision, Project administration. Xueliang Zhang: Conceptualization, Formal analysis, Validation, Visualization, Writing—Original Draft, Writing—Review & Editing, Supervision. Zihui Wang: Methodology, Data Curation, Visualization. Linsheng Yang: Conceptualization, Writing—Review & Editing, Project administration.

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