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Citation: Zheng, Niting, Li, Sheng, Wang, Yunpeng, Huang, Yuwen, Bartoccid, Pietro, Fantozzid, Francesco, Huang, Junling, Xing, Lu, Yang, Haiping, Chen, Hanping, Yang, Qing and Li, Jianlan (2021) Research on low-carbon campus based on ecological footprint evaluation and machine learning: A case study in China. Journal of Cleaner Production, 323. p. 129181. ISSN 0959-6526

Published by: Elsevier

URL: https://doi.org/10.1016/j.jclepro.2021.129181 <https://doi.org/10.1016/j.jclepro.2021.129181>

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Research on low-carbon campus based on ecological footprint

evaluation and machine learning: A case study in China

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ABSTRACT

Universities, the important locations for scientific research and education, have the responsibility to lead ecological civilization and low carbon transition. Ecological footprint evaluation (EFE) is usually used to measure sustainability of campuses. Although it can provide guidance and reference for overall campus planning, it lacks effective significance for individual behavior, especially when the reduction of carbon emissions is the aim. On the other hand a possible solution can be represented by machine learning. It can identify the key factors that will influence individual's overall carbon emissions caused by students' daily behavior, it can be used to find effective ways to reduce individual carbon emissions. This paper applied EFE and machine learning to comprehensively evaluate campus sustainability and students' carbon emissions. Huazhong University of Science and Technology (HUST), a "University in the Forest", was used as a study case in China. Even if HUST is endowned with a forest coverage of 72%, here we showed that its Ecological Footprint Index was -8.9, indicating strong unsustainability. This is mainly due to the high energy and food consumption, caused by the large population living in the campus and the lacking of energy saving measures. The per capita ecological footprint was relatively high, compared with other universities in the world, which meant more efforts needed to be done on ecological sustainability. Low carbon emission is a key feature for a sustainable campus. Based on the questionnaire survey delivered to 486 students who live in the campus, their daily active data were collected in terms of students' personal clothing, food, housing, consumption and transportation. And their associated carbon emissions were calculated based on emission intensities of Chinese population. Based on 486 detailed datasets, machine learning was then used to identify the key daily behavior to influence students' total carbon emission. Results showed that making behavior changes in air conditioning, food and electric bicycle were the most effective ways to reduce carbon emissions. Finally, while effective suggestions were proposed based on qualitative and quantitative evaluations, it is concluded that it is imperative for universities in China to formulate effective low-carbon policies, to achieve sustainable development and to confront global climate change.

Keywords: Low carbon campus, Ecological footprint evaluation, Machine learning, China

Abbreviations

EFE - ecological footprint evaluation EFI - ecological footprint index HUST - Huazhong University of Science and Technology TJPU - Tianjin Polytechnical University BNU - Beijing Normal University JUST - Jordan University of Science and Technology GAUC - Global Alliance of Universities on Climate LCA - life cycle assessment LCC - life cycle cost RF - random forest

1. Introduction

Nowadays, sustainable development has become one of the most important issues in the development of the human society (Kang et al., 2020; Yang et al., 2021). Colleges and universities bear responsibilities and obligations in the country's implementation of sustainable development strategies. In 1990, university presidents from 22 countries in the world signed the Talloires Declaration, marking the beginning of sustainable campus construction. Subsequently, many foreign universities took actions to promote sustainable Campus construction (Table 1), such as the Green University Promotion Committee of the George Washington University in the United States, the Green Campus Initiative of Harvard University and the University of Waterloo in Canada, and the Environmental Agenda of the University of Edinburgh in the United Kingdom(Wang et al., 2010). In 1998, Tsinghua University took the lead in China to promote the construction of a sustainable campus, and announced a new idea and method for university education. Since then, domestic scholars have also started to study the establishment of sustainable universities. Among them, Harbin Institute of Technology put forward the overall plan of building a center (environmental and social research center) and doing well in three aspects (theoretical research, publicity and education, and direct action). Beijing Normal University (BNU) has promoted the construction of green university with the content of promoting green education, building green campus, advocating green actions, and shaping green personality. And Guangzhou University implemented the "Green Education Plan" in setting up green education courses, carrying out green scientific research, strengthening the construction of green websites and promoting the cultivation of advanced green education professionals(Tian, 2009). Both of them have achieved good results because of their characteristic measures. However, due to the different understanding and starting times of sustainable development in colleges, there are obvious differences in construction progress and evaluation standards. In 2008, the seminar on building a sustainable campus organized by the Ministry of Education was held in Tongji University(Chen, 2010). The conference issued a declaration on the construction of sustainable campuses, which emphasized the importance and urgency of accelerating the construction of resource-conserving and environment-friendly sustainable campuses. Table 1

Country	University	Year	Important measures	Results
		1000		Learn about the environment to
The United States	Tuft University	1990	Tufts CLEAN Plan	reduce the impact of the internal
				workings of the university
The United States	George Washington	1994	Green University	become the first green university in
The United States	University	1994	Promotion Committee	the United States
The United States	Harvard University	1991	Green Campus Initiative	Self-propelled reduction of
The Onited States	That vard Onlyeisity	1991	Green Campus Initiative	greenhouse gas emissions

Main initiatives in the framework of sustainable camp	ouses construction.
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Canada	University of Waterloo	1990	Green Campus Initiative	Establish the best environmental policies and implement sustainable development concepts in higher education
Britain	University of Edinburgh	1997	Environmental Agenda	Establish environment-related courses to raise awareness of environmental protection
Australia	AustralianCampusesTowardSustainability(ACTS)	1997	Address issues related to campus sustainability	Establish the path of sustainable development education
China	Tsinghua University	1998	Create green university demonstration project	Aim to build a "green university" by 2006

Universities, the important locations for talent training and technological innovations, should play an exemplary role in responding to climate change. Lowcarbon campus construction is an inseparable and important part of sustainable campus construction, which will be the best development model for future campuses. Universities in the world actively carry out the practice of low-carbon campus construction. In order to achieve the main emission reduction targets, the University of Tokyo cooperated with society and scientific research institutions to finally realize the construction of a low-carbon city. The University of California, Berkeley focused on improving efficiency and developing renewable energy sources to reduce CO₂ emissions. China has also clearly proposed to build a low-carbon emissions campus. Tsinghua University took advantage of scientific research and carried out technological transformation. Then in 2019, the university led the establishment of the Global Alliance of Universities on Climate (GAUC), aiming to share the low-carbon practices of global universities. Now, energy conservation and emission reduction have become a spirit of Tsinghua University. Peking University carried out a series of reforms around energy conservation, strengthened campus publicity and reduced resource consumption. However, the current theoretical research on low-carbon campuses is still immature, and there is no widely used low-carbon campus indicator system.

In recent years, the construction of sustainable campuses has attracted great attention from the society and the universities themselves. And many efforts have been undertaken in global universities. Main research strategies mainly include the following important methods: ecological footprint model(Jiang, 2018; Yao et al., 2011), comprehensive sustainability evaluation indicators(Chen et al., 2019; White, 2014) carbon footprint model(Li et al., 2020), full time equivalent and life cycle assessment(Raeanne et al., 2020; Sangwan et al., 2018; Xue et al., 2019). Yao *et al.* used the ecological footprint model to calculate the ecological footprint of transportation, energy and daily life of teachers and students with Peking University as an example(Yao et al., 2011). Na *et al.* propose a comprehensive low-carbon-oriented evaluation method to build an evaluation index system for low-carbon campuses and both original data and experts' experience were integrated to quantify the index (Na and Zhao, 2020). Li *et al.* used the carbon footprint model to study the carbon emissions of low-carbon campuses (Li et al., 2020). Abu *et al.* describe the efforts undertaken to

convert the large university campus of Jordan University of Science and Technology (JUST) into a green, resource-efficient and low-carbon campus by calculating the full time equivalent(Qdais et al., 2019). In Xue et al.'s work, a life cycle assessment-life cycle cost (LCA-LCC) integrated model is used to analyze the teaching buildings at a university in Northern China and the results show that the environmental impacts and economic costs are larger in the operation phase of the life cycle, mainly because of the use of electric energy(Xue et al., 2019). The previous studies have shown that the ecological footprint method has been widely used to evaluate the sustainability of the campus, due to the fact that it presents a single indicator and can be easily implemented. The results of the carbon footprint in schools can intuitively show the distribution of different emission sources. But the current studies are mostly fragmented, by focusing on a single target, instead of focusing on comprehensive studies and they are unable to distinguish the importance of student behavioral changes. Then, machine learning tools are discussed, which can use algorithms to analyze the internal relationships of high dimensional data and find out the degree of impact of the individual behavior on campus carbon emissions. Therefore, the ecological footprint evaluation (EFE) and machine learning tools are integrated into this paper, to quantitatively calculate the overall sustainability of the campus and find the key factors of personal carbon emission, to guide the development of new strategies on personal emission reduction.

The whole paper is organized as follows: first, the basic information of HUST is presented, and data sources are described in detail. Second, the research methods are proposed, in which the carbon footprint of students, and the ecological footprint evaluation (EFE) and machine learning are introduced, to evaluate a low carbon emissions campus. Third, the results of the ecological footprint index (EFI) are calculated and discussed. Then the characteristics of the carbon footprint of the students are analyzed, and the values of personal carbon emissions of students are obtained through machine learning. According to the analysis results, targeted guidelines on campus low-carbon emissions are provided. Finally, the research conclusions are drawn.

2. Methods and data

Huazhong University of Science and Technology (HUST) was established in 1952, located in Wuhan, the capital city of Hubei Province. There are 61,879 full-time students and around 13,000 faculty members. HUST's picturesque environment covers an area of over 472 hectares, and the campus has 72% greenery coverage, which has earned it the honorary title "University in the Forest".

As a particular social environment, the carbon emissions structure on campus has its unique characteristics. Based on the actual situation of the campus, the composition of students' carbon emissions has been obtained through questionnaire survey while group consumptions, including garbage, electricity, water and transportation, are obtained by the school logistics management office.

2.1 Carbon footprint of students

Considering there is no standardized and widely used tool for collecting individual carbon footprint at present, the study adopts the method of a questionnaire survey to investigate students' carbon emissions. Questionnaires which were designed to investigate students' data on clothing, food, housing, consumption and transportation, were mainly completed online through public classes, and some questionnaires were distributed offline to ensure the diversity of samples. Finally, 486 questionnaire samples have been collected from 24 departments, covering different grades such as undergraduate, master and doctor, and different dormitory areas such as Zisong (A), Xiqu (B), Yunyuan (C) and Qinyuan (D), which can objectively and comprehensively reflect the carbon emission status of all kinds of students on campus. The specific sample characteristics are shown in Table 2.

Table 2

		Grade			Ger	ıder	D	ormito	ory Area*	Sur	vey Da	te
	Bachelor	210	43.21%	М	285	58.85%	Α	166	34.16%	Working	260	74.49%
Specific	Master	180	37.04%	F	201	41.15%	В	156	32.10%	day	362	/4.49%
Items	Doctor	96	19.75%				С	136	27.98%	Waalsond	100	25 510/
							D	28	5.76%	Weekend	122	25.51%
Total		486	100%		486	100%		486	100%	day	486	100%

Statistics of sample characteristics of questionnaire survey.

*A, B, C, and D in the "Dormitory Area" respectively represent the 4 dormitory groups located on the east and west sides of the campus, namely A-Zisong, B-West District, C-Yunyuan, and D-Qingyuan.

(1) Calculation method used for the evaluation of the carbon footprint in the campus

The carbon footprint of students mainly involves five aspects of "clothing, food, housing, transportation and consumption". In this paper, carbon emissions are expressed in CO₂ equivalent emissions. Among them, "clothing carbon emission" includes the energy consumption of washing and drying clothes; "food carbon emission" includes that of food, meat, vegetables, fruits, drinks and other consumption; "housing carbon emission" mainly considers the energy consumption of students in the dormitory, including the energy consumption of computer, hair dryer, air conditioning and other appliances. "Consumption carbon emission" includes the energy consumption of document printing and electric vehicle charging, while "transportation carbon emission" means the carbon emission generated by students when using different means of transportation in the campus for spatial displacement.

The carbon emission factors are shown in Table 3.

Table 3

Carbon emission factors on campus.

	items	Unit	Carbon emission factors
Clothing	Washing machine Dryer	kgCO2eq/(kW·h)	0.78 ^a
Food	Meat	kgCO2eq/300g	1(Audsley et al., 2010)

	Rice	kgCO ₂ eq/kg	0.8 ^b
	Vegetables	kgCO ₂ eq/kg	1.45 ^c
	Fruit	kgCO ₂ eq/kg	1.5 ^c
	Milk	kgCO2eq/kg	1.9 ^c
	Air conditioner	kgCO2eq/(kW·h)	
Housing	Hair drier	kgCO2eq/(kW·h)	0.78^{a}
	Computer	kgCO2eq/(kW·h)	
	Printing	kgCO2eq/100pages	1.5 ^d
Consumption	Electric vehicle charging	$kgCO_2eq/(kW\cdot h)$	0.78^{a}
	Walking	kgCO2eq/km	0
Transportation	Bicycle	kgCO2eq/km	0
Transportation	Electric vehicle	kgCO2eq/km	0.00942 ^e
	School Bus	kgCO2eq/km	0.0495 ^b

Notes: ^a Ref. (Ministry of Natural Resources of the PRC, 2010).^b Ref. (China Carbon Trading Network).^c Ref. (Carbon Footprint Calculator).^d Ref. (Technical Requirements for Environmental Labeling Products Printer, Fax Machine and Multifunction devices).^e Ref. (Energy Saving Guidelines for Electric Vehicles in China).

The carbon footprint is calculated as follows:

$$CF = \sum_{I=1}^{n} Q_I \times EF_I$$

(1)

CF is the carbon footprint (expressed in CO_2eq), Q_1 is the quantity or intensity of activity, EF_1 is the carbon emission factor (expressed in CO_2eq / unit).

(2) Calculation method used for the evaluations of the carbon emissions due to transportation

As the carbon emissions of transportation are quite low, this part focuses on the spatial distribution of carbon emission intensity. In this part, we skillfully set questions and diagrams (such as Figure 1) to obtain the detailed travel trajectories of all major activities of the respondents in a day.

By setting a series of detailed topics in the questionnaire, such as the starting point, end point, specific path, midway node, time and other information of each activity, the data of the main activity track of the respondents in their daily life are obtained. For example, we use letters to represent all possible route choices between two activities, and numbers to represent the place where the main activities take place. We asked the respondents to select the trajectories in Figure 1 according to their actual situations. Then, we assigned a value to each track by combining the traffic mode of each track of the carbon emission factor in Table 3. Then the assigned data is imported into ArcGIS for visualization. Finally, the trajectories of all samples were summarized and linear density analysis is conducted, which represents the emission intensity of student travel in spatial distribution.

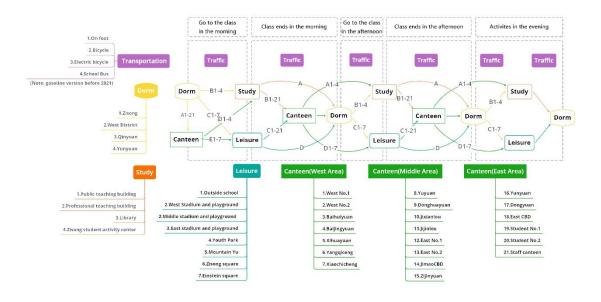


Fig. 1 Diagram of the travel trajectory inside the campus in the questionnaire survey

2.2 Overview and calculation method for Ecological Footprint Evaluation (EFE)

The research of the method to better evaluate low-carbon campus performance is one of the hot spots in the field of sustainable development tailored to universities' needs. The EFE usually considers the land area of biologically productive land as the quantitative index to evaluate the sustainability of campuses, which has the advantage to be a single indicator and to have strong comparability. The main factors to be considered in the EFE calculation method are the following:

(1) Ecological productive area

The ecological footprint of a region is the area of the bio productive land that is needed to produce all the resources consumed by the people in this region and to absorb all the wastes produced by these people, including six types of land (fossil energy reserves, arable land, forest, pasture, built area and sea). Each type of land has its own ecological functions. The calculation formula of the ecological productive area is as follows:

$$A_i = \sum_{i=1}^n \frac{c_i}{P_i} \tag{2}$$

 A_i is the ecologically productive area (hm²), C_i is the resource consumption of process i (kg or t), P_i is the global average annual production of process i (kg/hm² or t/hm²), and i is the type of consumables.

(2) Ecological footprint

Since the ecological productive capacity of these 6 land types is different, it must be converted using an equivalence factor to summarize the ecological footprint and ecological carrying capacity. The formula of the equivalence factor is as follows:

$$R_i = \frac{D_i}{D} (i=1,2,3...6) \tag{3}$$

R_i is the equivalence factor, D_i is the average ecological productive capacity of an area

(kg/hm² or m^3/hm^2), and D is the average ecological productive capacity of the ecological system in the world (kg/hm² or m^3/hm^2).

The equivalence factors used in this article are shown in the table 4. Table 4 Equivalence factors based on the world(Wackernagel et al., 1999).

luiv	divalence factors based on the world (waekernager et al., 1999).						
	Land type	Fossil energy	Arable land	Forest	Pasture	Built area	Sea
	Equivalence factor	1.1	2.8	1.1	0.5	2.8	0.2

The ecological footprint calculation formula is as follows:

 $EF = \sum_{i=1}^{6} A_i * R_i$

(3) Ecological carrying capacity

Ecological carrying capacity refers to the area of biologically productive land that can be provided to humans in a region. Taking into account different climates, locations and development level of the regions, there is a huge difference in the ecological productivity per unit area. Therefore, the different types of areas need to be standardized, and the yield factor is used to solve this problem. The formula used in the calculation is as follows:

$$Y_j = \frac{q_j}{q} \tag{5}$$

 q_j is the productive capacity of a certain ecological productive area in the region (kg/ hm²), q is the average national productive capacity (kg/ hm²)

The yield factors of Hubei Province in 2019 are shown in Table 5 below. The average national productive capacity is 0.677t/hm²(Ling and Jin, 2011), the consumption data come from the Hubei Provincial Statistical Yearbook.(HBBS, 2020) Because built area comes from arable land, the yield factor is equal to the arable land; and energy mainly refers to the greenhouse gas absorbed by forest land, therefore, the yield factor of energy land is equal to the one of forest land.

Table 5

Yield factor of Hubei Province in 2019.

Land type	Fossil energy	Arable land	Forest	Pasture	Built area	Sea
Area (10000 hm ²)		523.54	40.52	4.45		183.96
Output (10000 tons)		2724.98	421.65			469.54
Average productive capacity (t/ hm ²)	10.41	5.20	10.41		5.20	2.55
Yield factor	15.37	7.69	15.37	0.19(Li, 2010)	7.69	3.77

The ecological carrying capacity is expressed as follows:

$$EC = \sum_{j=1}^{6} A_j * R_j * Y_j$$

(6)

(4)

 $\begin{array}{l} EC \text{ is the ecological carrying capacity (global hectares), } A_j \text{ is the actual area of the} \\ j \text{ land type, } R_j \text{ is the equivalence factor and } Y_j \text{ is the yield factor.} \\ Table 6 \end{array}$

Land use function structure of HUST.

Land use function structure	Area (hm ²)	Proportion
Residential land	73.06	15.48%
Design land for education and research	141.18	29.91%
Green land	133.62	28.31%
Land for the dormitory	43.42	9.20%
Land for logistics integrated service facilities	51.46	10.90%
Road land	29.26	6.20%
Sum	472	100.00%

According to the functional structure of land use in HUST, the main functions of land use are residential land, land for scientific research and education, and land for supporting public facilities. Among the public facilities, medical care, culture and sports occupy a high proportion. Therefore, the total Built area is 338.38 hm².

From the perspective of layout form, the scale of each land use function is moderate, interspersed with each other, showing an obvious mixed land form. Considering the actual situation of the school, the Forest area is calculated with the coverage rate of 72%.

(4) Ecological footprint index (EFI)

If the ecological footprint exceeds the ecological carrying capacity that the region can provide, an ecological deficit will appear, on the contrary, ecological increase will appear. The regional ecological deficit or ecological surplus reflects the utilization of natural resources of the region. The formula is as follows: ED/ER = EC - EF (7)

ED expresses an ecological deficit when EC≤EF, while ER expresses an

ecological remainder when EC>EF.

The ecological footprint index refers to the ratio of the difference between ecological carrying capacity and ecological footprint to the ecological carrying capacity, which can be used to judge the degree of regional sustainability. The calculation formula is as follows:

$$EFI = \frac{EC - EF}{EC}$$
(8)

2.3 Machine learning: Random forest (RF)

Compared to other machine learning methods(Chen et al., 2011; Maltecca et al., 2019), RF (Breiman, 2001) can predict results well, even on small datasets, due to its ensemble properties. This is undoubtedly the most appropriate method for our limited research dataset (Table 7).

Table 7

The comparison of machine learning model

Models	Random forest	Artificial neural network
Dataset	Little required data	Big data
Complexity	Lowcost and few parameters	Large hyper-parameters
Speed	Fast build and fast run	Slow build and fast run

Performance	Strong robustness	Easy to overfit	
Ability of feature processing	High dimensional and	High dimensional	
	measured importance	ringii dimensional	

The typical RF combines multiple decision trees into one model to improve the performance; it has been widely applied in many scientific and engineering fields, such as statistics, materials and biology (Butler et al., 2018; Carrete et al., 2014; Lei et al., 2018). The main steps of RF are shown in Fig. 2 and can be expressed as:

(1) Data preprocessing

In the present study, data representation is conducted to preprocess carbon emissions data from questionnaire survey, with the purpose of converting data into language that can be understandable for computers. Subsequently, the dataset is divided into training set TA and testing set TE, according to a certain ratio.

(2) Implementation of the model

Based on a processed dataset TA, the bootstrap resampling method (Yi et al., 2016) is used to randomly generate K sets of data. Then, K decision trees will be grown. For example, for calculating the results shown in Fig. 8b, each dataset includes eight features (computer, air conditioner, washing machine, dryer, food, transportation, electric bicycle, printed document) and the label (carbon emission). In each node of a decision tree, the node will split the dataset into two parts, according to the value of a chosen feature. After considering all features, the final node will be the label (CO2 emission) of the considered data. The prediction of the model is evaluated by K decision trees.

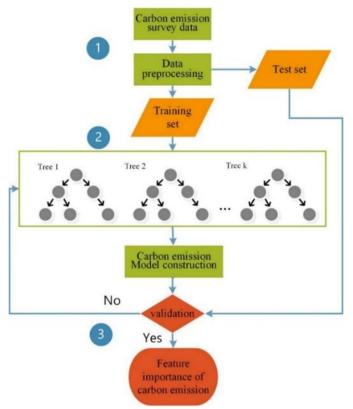


Fig. 2 Scheme on the application of the random forest model in the study of the importance of the different considered factors.

(3) Model validation

The test dataset TE, which is not used for training during the model construction, is used for evaluating the accuracy of the model. If the accuracy of TA is much higher than the accuracy of TE (e.g. 0.9 for TA and 0.5 for TE), the model is considered as overfitting. If the accuracy of TE and TA are too low (e.g. 0.5 for TA and 0.5 for TE), the model is considered as underfitting. Both overfitting and underfitting are unacceptable, this implies that the model has to be retrained. If the accuracy of TA and TE are high enough and the accuracy of TE is similar as that of TA, the model is trained well and the output of the final model is reliable.

After model construction, feature importance can be calculated by the random forest's intrinsic attribute (Ma et al., 2018).

3. Results and discussion

3.1 Results of the ecological footprint model

This paper studies the sustainability of the university campus, based on the ecological footprint theory. According to the characteristics of the university, the evaluation method of this paper adopts the component method (Wang, 2017), which mainly considers the five aspects (energy, water, garbage, food, and transportation). Because the school's traffic control is strict, and students mainly walk and bike to school, the ecological footprint of transportation is very small, which can be reasonably ignored. Other data is obtained through field surveys and questionnaire interviews. The data on electricity, water, and garbage disposal of 2019 come from the school's logistics management office. Food consumption (grain and meat) comes from the results of questionnaires, and the average value is used to estimate the amounts consumed by teachers and students in the school. The above data sources related to the ecological footprint are listed in the table 8.

Table	8
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Туре		Consumption	Data source
Electric power	Consumption(kW·h)	159773837	The school's logistics management office
	Unit CO2 emissions (t/GW·h)	964	(Liu et al., 2017)
Water	Consumption(t)	8511923	The school's logistics management office
	Unit power consumption (kW·h/t)	2.5	(Liu et al., 2017)

The data sources related to the ecological footprint of HUST in 2019.

Garbage		Emissions(t)	16060	The school's logistics management office
		Total CO2 of a unit of garbage(t)	0.6077	(Liu et al., 2017)
Food -	Casia	Per capita consumption (kg)	94.3525	Average value of questionnaire survey
	Grain	Total number of people	74879	The school's logistics management office
	Meat	Per capita consumption (kg)	28.6525	Average value of questionnaire survey
		Total number of people	74879	The school's logistics management office

Therefore, the energy ecological footprint, water ecological footprint, garbage ecological footprint and food ecological footprint of HUST in 2019 are obtained, as shown in the tables 9.

Table 9

Ecological footprint of HUST in 2019.

Туре		Consumption	Average productivity (t/hm2)	Equivalence factor	EF (hm2)	Land type
Electric	e power	159773837/kW·h	5.2	2.8	82934.91	Built area
Wa	ater	8511923/t	5.2	1.1	4339.44	Fossil energy
Garl	bage	16060/t	5.2	1.1	2064.54	Fossil energy
De e J	Grain	7065020.8475/kg	2.744	2.8	7209.20	Arable land
Food	Meat	2145470.5475/kg	0.033	0.5	32507.13	Pasture

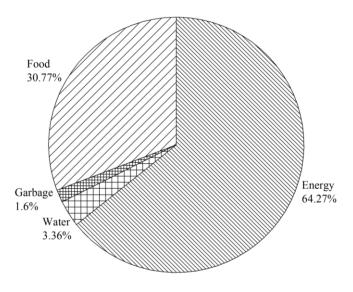


Fig.3 Ecological footprint composition of HUST in 2019.

It can be seen from Fig.3 that energy and food constitute the largest proportion of the ecological footprint of HUST, accounting for 64.27% and 30.77% respectively, garbage accounts for 1.60%, and water accounts for 3.36%. The above data shows that the construction of a low-carbon campus needs to focus on reducing energy consumption. Colleges should give full play to their advantages in scientific research and strengthen the development and application of energy-saving and emission-reduction technologies, specifically focusing on saving electricity, materials, and reducing consumption. In other words, the construction of a sustainable campus is closely related to the further improvement of low carbon systems, including at the technical and management levels.

Table 10

Some relevant indicators of the ecological footprint of HUST in 2019.

					Global	The ratio to
Ecological	Ecological carrying capacity(hm ²)	EFI	Total number of people	Per capita ecological footprint(hm ² /per)	average	the global
footprint(hm ²)					ecological	average
					footprint	ecological
					(hm ² /per)	footprint
129055.23	13030.18	-8.9	74879	1.72	2.70	63.83%

According to the results in Table 9, the sum ecological footprint of HUST is 129055.23 hm², and the actual ecological carrying capacity is calculated to be 13030.18 hm². On the whole, the total ecological footprint is very large, which is related to the scale of the school, the area occupied, and the number of teachers and students. Some other relevant indicators about the ecological footprint of HUST in 2019 are shown in Table 10. The per capita ecological footprint is 1.72 hm² /per, accounting for 63.83% of the global average ecological footprint(Liu et al., 2017). While the actual ecological carrying capacity is only 0.17 hm²/per, so the per capita ecological deficit has reached 1.55 hm²/per, indicating that the school's demand for green surfaces far exceeds the ecological carrying capacity. Also, the EFI is -8.9, which shows that is in a strong unsustainable state according to the standard of Table 11. Universities, as frontiers in developing a sustainable society, are essential for China's carbon neutrality path. So, the HUST is expected to alleviate the current situation, such as learning from the successful experience of domestic and foreign universities (Guerrieri et al., 2019), among which low-carbon models, energy-saving infrastructure, green planning and new technologies, have been realized to improve the sustainable development of campuses.

Table 11

Ecological footprint index rating standard.

Items	level						
	I	II		IV	V		
EFI	0.5-1	0-0.5	0	-1-0	<-1		
Characterization state	Strong sustainable	Weak sustainable	Critical point	Unsustainable	Strong unsustainable		

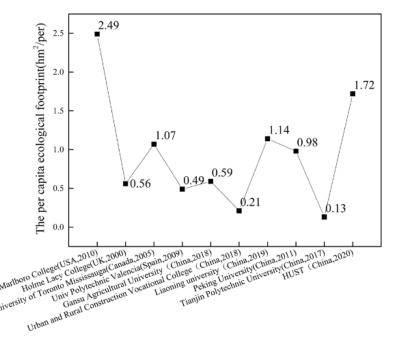


Fig.4 The per capita ecological footprint of HUST compared with other universities worldwide.

The per capita ecological footprint is compared with other universities (Jiang, 2018; Mao and Tian, 2019; Yao et al., 2011; Zhou, 2012) in Fig.4, it shows that the results of HUST are relatively high but still normal, even though HUST is often referred to as the "University in the Forest". Obviously, Tianjin Polytechnical University (TJPU) is a very successful case, which has a per capita ecological footprint of only 0.13 hm², mainly due to its innovative efforts in energy use and scientific management. At the hardware level, LED semiconductor lighting system, rainwater utilization, ground source heat pump and geothermal gradient utilization system, solar utilization system, and wastewater reuse are widely used. While at the software level, TJPU attaches great importance to low fossil carbon culture and low fossil carbon management. Hence, China's universities can do a lot to achieve the goal of building sustainable campuses. At the same time, the summary and study of successful experiences will help to formulate and improve our own evaluation criteria and specify guidelines.

3.2 The characteristics of the carbon footprint on campus

Through the statistical analysis of the questionnaire results, the students' average consumption in the five aspects of "clothing, food, housing, consumption and transportation" can be calculated. Carbon emission factors have already been known in table 3, then carbon emissions distribution is shown in Fig. 5. It should be noted that the results are based on the quantitative analysis of sample data, and the results are reasonable by referring to other universities. From the analysis results, it is indicated that students' carbon emission activities mainly occur in the three aspects of "food", "housing" and "consumption". The daily electrical appliances used in dormitories, "housing carbon emissions" account for the largest proportion, about 38.64% of the total. Among the five kinds of electrical appliances commonly used by students, the carbon emissions of air conditioning are the highest, accounting for about 65.13%, followed by computers, accounting for about 22.31%. The results show that transforming existing high-carbon behaviors is a key aspect to the success of a lowcarbon campus. First of all, teachers and students should be guided to cultivate a lowcarbon lifestyle-saving water and electricity, avoiding wasting food, and taking public transportations(Li et al., 2020).

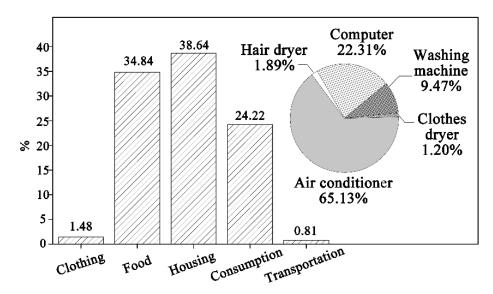


Fig. 5 Carbon emission proportion of "clothing, food, housing, consumption and transportation" among College Students.

The carbon footprint of transportation is very small, but behavior trajectory data can be used to analyze student aggregation and activities(Wang et al., 2018). The route information in the questionnaire survey is processed into the track data format, which is imported into ArcGIS for spatial visualization. The color of the route indicates the carbon emission intensity: the warmer the color of the route, the higher the carbon emission intensity, as shown in Fig. 6. It can be seen that the most concentrated red area is correspondent to four dormitory areas: A, B, C, D and two public teaching building areas E, F (which can be saw in the legend), followed by the campus main roads connecting these areas. The most concentrated blue area is the staff apartment area in the north of the campus, followed by the garden green area in the middle and south of

the campus. On the whole, the areas with the highest carbon emission intensity of students' transportation show an obvious aggregation state in space, which is highly relevant to students' life and learning.

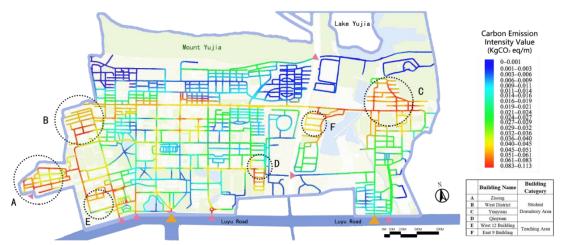


Fig. 6 Spatial distribution of students' carbon emission intensity in HUST's Campus Based on the transportation modes

Then, combined with the characteristics of the respondents in Table 2, we analyzed the questionnaire data and found that the carbon footprint of the respondents of different genders is slightly different as a whole. In terms of hair dryer, clothes dryer and washing machine, the carbon footprint of female respondents is significantly more significant than that of male respondents. On the contrary, in terms of computers, the carbon footprint of male respondents was more significant. Similar differences are also reflected in different grades. For example, master's and doctoral students spend more time on computer use than lower grade undergraduates, and produce more carbon footprint. However, there are no significant differences in air conditioners, washing machines and dryers. In addition, the carbon footprints of respondents in different dormitory areas have little difference in the above items. The above results are basically consistent with students' habits in school.

3.3 Results of machine learning algorithms

In order to avoid overfitting and further quantify the effect of dataset, the initial dataset was separated into three combinations of train/test set, which are 70%/30%, 80%/20% and 90%/10%, respectively. The results are summarized in Fig.7. As can be seen, with the decrease of test set, there is no obvious difference between different models. The results indicate that the dataset is sufficient to obtain convergence results.

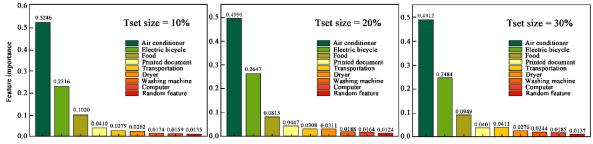


Fig.7 Results of convergence test

As a starting point, RF is used for building a carbon emission model and measuring their importance. In order to avoid overfitting and enhance the reliability of results, the initial dataset is divided into train/test set according to the proportion of 80%/20% during the training process. Subsequently, the 10-fold cross validation of training set is performed for finding the most appropriate algorithm hyperparameters. The final result of the RF model is shown in Fig.8.

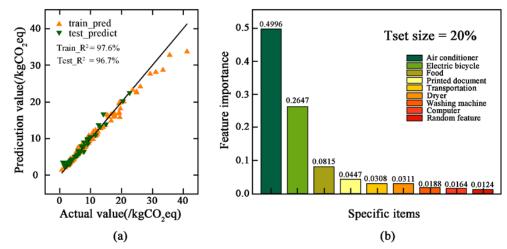


Fig.8 (a) Carbon emission prediction model constructed by random forest. (b) Result of feature importance.

As shown in Fig. 8(a), the RF model could get a higher R2 closer to 1, which means a good prediction between the simulation of carbon emissions and true values. Based on the high accuracy of the prediction model, the results of Fig.8(b) are highly significant. The results indicate that air conditioning is the most important cause of carbon emissions, among all chosen features, which is largely higher than expected. Mainly because the survey work was completed in winter when air conditioners are frequently used and the power of the air conditioning is really high. Besides that, the calculation results show that the importance of transportation is largely lower. It turns out that school is a particular social environment where the carbon emissions structure has its own unique characteristics. And it is reasonable to ignore the transportation on ecological footprint model.

As for other features in Fig.8 (b), it can be seen that electric bicycle are another important feature, followed by food. The importance value is 26.47%, 8.15% respectively. And the remaining factors are relatively small. So, according to the feature results, making changes in air conditioning use, electric bicycle use, and food consumption, would have the most significant impact on emissions reductions.

As can be concluded from above, although machine learning has conducted some meaningful results, it should be emphasized that due to the limitation in the availability of adequate data, the current analysis is more qualitative than quantitative. It is worth acknowledging that a big dataset of school carbon emissions will help to push the field forward.

3.4 Investigation about students' low carbon awareness in HUST

The questionnaire survey also conducts an investigation about students' low carbon awareness in HUST. It's found that the vast majority of students (70.78%) think that the construction of a low-carbon campus will affect the normal life of students and teachers to a certain extent (Fig. 9-a), indicating the realization of low-carbon life is difficult in the cognition of students. At the same time, 53.91% of the students focus on the low-carbon life, while 45.27% mainly emphasize the convenience of life. It shows students' actual low-carbon actions are insufficient with the absence of clear guidance (Fig.9-b). In addition, among the five important issues related to the construction of low carbon campuses, the number of people who know what the "Paris Agreement" is the most, accounting for 73.25%. On the whole, the school still has a lot to do in the publicity and education of environmental protection. It can be a good idea to set up related courses like the University of Edinburgh (Fig. 9-c). From the results, we can also infer that there are two main obstacles for college students to realize the low-carbon lifestyle: one is that they emphasize the convenient and comfortable life more than the ecological costs and externalities; the other is that they lack effective guidance and feel confused about how to start the low-carbon lifestyle (Fig. 9-d). So HUST is expected to take practical actions in the guidance of energy conservation and emission reduction. Teachers' and students' sense of ownership is essential in building a low-carbon campus and healthy campus culture.

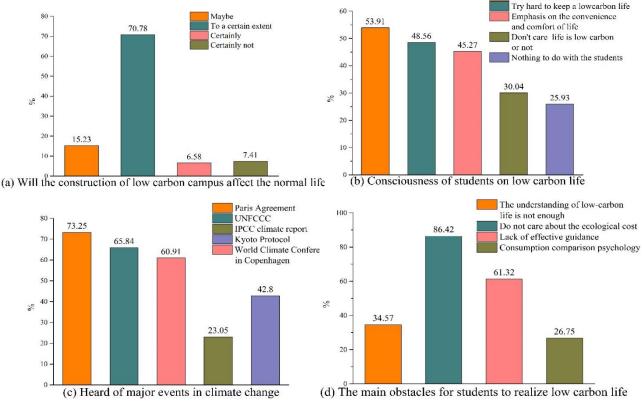


Fig. 9 Investigation about students' low carbon awareness in HUST.

Focus on this issue

4. Conclusions

The low-carbon emissions campus implementation, which focuses on energy conservation and emissions reduction, is gaining more and more attention in China and abroad. As an important place for scientific research and education, the university should incorporate sustainability into campus development. This paper focuses on lowcarbon campuses, evaluating the aspects of the school sustainability practices and students' behavior, whose results are relatively comprehensive and intuitive. The ecological footprint evaluation (EFE) can quantify the impact of campus production and operation on the ecological environment. Based on the campus characteristics, the ecological footprint of energy, garbage, water and food is calculated to analyze the sustainability of the campus. The ecological footprint index (EFI) is -8.9, reflecting the current situation is in a position of moderate unsustainability. The status quo is performing much lower than expected. To alleviate the situation, the university should clearly put forward the plan of "creating a green campus", and gradually develop a green campus path, integrating technology, management and education, and actively creating a healthy campus culture. Then, the characteristics of the carbon footprint on campus were analyzed based on the questionnaire results, including five aspects of "clothing, food, housing, consumption and transportation". The results show that students' carbon emission activities mainly occur in three aspects of "food", "housing" and "consumption", indicating students should be guided to avoid food wasting and cultivate a low-carbon lifestyle. Also, a typical machine learning algorithm, random forest, is used to calculate the most important features of students' carbon emissions. Feature importance which is regarded as the internal driving force of carbon emissions, is used to identify the internal key factors. The results indicate that the feature importance of students' carbon emission has obvious uniqueness, changes in air conditioning use, electric bicycle use, and food would have the most significant impact on carbon emissions reductions. And the investigation about students' low carbon awareness in HUST reflects that the school's propaganda and guidance work is not enough. Students should strengthen their understanding and belief in the importance of low-carbon campus development and be encouraged to carry out a low-carbon life, in terms of clothing, food, housing, transportation and consumption. Specifically, they should pay special attention to energy saving, which accounts for the vast majority of a person's carbon footprint. Meanwhile, the comprehensive evaluation method presented in this paper can be extended to other low-carbon campuses, EFE is used for overall sustainability evaluation and machine learning is beneficial for guiding students' behavior. Contemporary universities are focusing on the overall sustainable development of society, environment, ecology and politics. All students, teachers and staff should make efforts together for the sustainable development of the country and universities.

Acknowledgments

This work was supported by National Natural Science Foundation of China (No. 52076099), the Foundation of State Key Laboratory of Coal Combustion (No. FSKLCCA1902), the Double first-class research funding of China-EU Institute for Clean and Renewable Energy (No. 3011120016), and the Graduates' Innovation Fund, Huazhong University of Science and Technology (No. 2020yjsCXCY067). We also would like to thank members of the Harvard-China Project on Energy, Economy and Environment for useful comments and suggestions, and the Harvard Global Institute for an award to the Harvard-China Project on Energy, Economy and Environment.

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