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Remote sensing technology-based estimation of atmospheric CO_2 concentration to support efforts to reduce greenhouse gas emissions

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Abstract:

Due to the strong development of agricultural and industrial activities in this day and age, the widespread use of fossil fuels has caused the concentration of greenhouse gases in the atmosphere to significantly increase. With a high concentration of greenhouse gases comes an increase in the temperature of the Earth, which contributes to the acceleration of climate change. This paper presents a remote sensing technique capable of determining atmospheric CO_2 concentrations from spectral radiation values obtained by satellite images, thereby simulating the distribution of CO_2 concentrations over the entire city of Ho Chi Minh. This study uses two data sources: Greenhouse Gases Observing Satellite (GOSAT) and Moderate Resolution Imaging Spectroradiometer (MODIS) images. Calculation results show that throughout the city the average CO_2 concentration in the first 6 months of 2019 has a minimum value of 360 ppm and maximum value of 410 ppm; these values change monthly and depend on the type of surface land cover. The highest concentration of CO_2 is found over areas of water, bare land, and urban land. On the contrary, over green areas and forests, the CO_2 concentration values are about 360-370 ppm. These results are a suitable reference available to support strategic planners focused on CO_2 emission management, and suggest that expanding urban vegetation to increase the absorption capacity of carbon will contribute to the reduction of the greenhouse effect.

Keywords: **CO_2, GOSAT, greenhouse effect, MODIS.**

Classification number: **5.2**

Introduction

In the 21^{st} century, climate change is one of the most concerning issues to citizens all over the world. One of the many faces of this problem is global warming due to the greenhouse effect. Greenhouse gases, which are the main cause of the greenhouse effect, are able to absorb long-wavelength radiation of sunlight reflected from the Earth surface. Greenhouse gases include variety of gases, but CO_2 is the most important one. Therefore, the measurement of atomic CO_2 concentrations in the atmosphere is essential. Moreover, atomic CO_2 concentration is a required input for climate models, ecology models, and carbon cycle models. Climate change has become an international issue and global warming is one of many signs of this issue. Vietnam is one of the countries most impacted by this environmental problem. Despite accounting for only 1% of the atmosphere, greenhouse gases play a significant role as a cover of the Earth. This cover is responsible for preventing the escape of the heat from sunlight so that it stays inside the atmosphere longer and warms the planet. Without this blanket, the Earth's temperature would decrease by 30^0C. However, this blanket is becoming thicker because of human activities, such as burning of fossil fuels, changes in land use, and deforestation, all of which lead to the increase of global temperatures (Phan and Luu, 2006) [1].

Until now, there are three common research methods for estimating CO_2 according to the Intergovernmental Panel on Climate Change (IPCC). These methods include ground surveys, modelling, and remote sensing. It is crucial to expand the use of space technology in the study of atmospheric greenhouse gases because of its accuracy, efficiency, and low cost in observing and monitoring these gases, especially while ground-based measurements remain temporally and spatially limited. With the above advantages, the successful launch of Japan's GOSAT satellite increases the possibility of using remote sensing for the estimation of

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atmospheric CO_2 concentration.

In 2012, Guo, et al. [2] published research estimating the global CO_2 concentration based on MODIS images from NASA's TERRA satellite and GOSAT data. In 2014, J. Tao, et al. [3] calculated the CO_2 concentration for urban areas of Wu Han city by combining satellite images (Landsat 8) with on-site data (traffic density and CO_2 concentration) and used a Bayesian Network to analyse the correlational relationship between them. Then, the correlation was described by a regression model of CO_2 concentration, land cover, and traffic density. In 2015, M. Guo, et al. [4] applied a method from their previous 2012 research for a larger scale area, East Asia, with an improvement in validation. In this research, results from a regression model was compared to the measurements from three ground stations in the area. The comparisons demonstrated the largest difference was approximately +10.03 ppm and the overall fluctuation was 4.5 ppm. In 2018, J. Han, et al. [5] developed a model for estimating CO_2 concentrations of the Yellow River delta using the nightlight-based method. This model not only utilised remote sensing data (Landsat images) but also integrated statistical data such as fuel consumption and traffic surveys.

This paper presents the application of remote sensing to establish the spatial distribution of atmospheric CO_2 concentrations in Ho Chi Minh city, in order to support environment managers in the monitoring and reduction of impacts of the greenhouse effect.

Fig. 1. Study area.

The study area is Ho Chi Minh city, which has a decreasing altitude from North-West to South-East and the coast area, which has a mangrove forest site. The urban area of the city, one of the most ancient towns in Vietnam, is located in the centre and expands gradually and widely (Fig. 1).

Data and methods

Data

GOSAT data: contains values of XCO_2, which is the total column number of moles of CO_2 per mole dry air, is processed and stored as an HDF5 file. GOSAT data is classified into four levels: 1, 2, 3 and 4. Each level contains information from two different sensors and channels. The data used in this study was level 2 data, named as L2_FTS_SWIR, which contains the CO_2 information.

The GOSAT satellite completes a global coverage scan in 100 min. This satellite is equipped with a high accuracy instrument, which can observe 56,000 points on the Earth and is capable of tracking down a carbon source, as well as the path of greenhouse gases in the atmosphere. The total column of CO_2 described is the amount of CO_2 atoms in a unit of surface area.

MODIS data: in this study comes from a MODIS product, which is directly related to the processes of respiration and photosynthesis in plants. According to the study by [2], nine input parameters from MODIS products were selected to represent three main groups: 1) a variable representing the surface energy balance: LST (land surface temperature); 2) a group of four variables representing the physiological processes of plants: NDVI, EVI, LAI, FPAR; 3) a group of four variables representing the exchange of carbon between vegetation and the atmosphere: NPP, GPP, GN, NG. These acronyms are defined as NDVI: normalized differential index; EVI: enhanced vegetation index; LAI: the leaf area index; FPAR: fraction of photosynthetically active radiation; NPP: net primary production; GPP: the gross primary production; GN = GPP - NPP; and NG = NPP/GPP.

Data is collected daily and contains both the GOSAT data and MODIS data products. The temporal resolution of the MODIS products in this study is 8 days.

Method

The statistical methods used in this study, which are correlational analysis and linear regression modelling, establish the relationship between the XCO_2 parameter and the nine physical-ecological parameters that have a significant influence on the carbon cycle.

The nine parameters extracted from MODIS products, together with the GOSAT data, form a multi-variable regression equation, which is then used to estimate the atmospheric CO_2 concentration. The regression model is constructed from 24 sets of the 9 variables of MODIS products (independent variables), which include LST, NDVI, EVI, LAI, FPAR, GPP, NPP, NG, GN and CO_2 data of GOSAT (the dependent variable) during the years 2009-2015. The regression method is a stepwise regression, which gradually inputs from single to multi-variable in each step. During the stepwise regression process, statistical indicators are recorded to verify their correlational relationship with suitable tests.

The spatial and temporal resolution of the GOSAT CO_2 data is 2.5^0x2.5^0 and 6 h, respectively. MODIS products have the spatial resolution of 1 km and 0.5 km. Before being used for analysis, the data set must be converted to a resolution of 2.5^0x2.5^0. After completion of the regression model, atmospheric CO_2 concentration distribution modelling for any specific day will be built on MODIS products of that day. The data set is constructed by selecting days that have both GOSAT and MODIS data.

Results and discussion

Correlational analysis and linear regression model of CO_2 and nine parameters

The relationship between the independent and dependent variables commonly takes the form of a linear equation. For a lot of cases, in reality, the relationship can be non-linear, however, in order to simplify calculations, it is acceptable to approximate non-linear relationships as linear if there are no significant differences between the two. In some cases, when the relationship has been not yet identified, it can also be assumed as linear [6]. For this reason, to establish the relationship between dependent and independent variables in this study, the authors have used linear regression.

A scatter plot is used to demonstrate the pattern of the data sets (Fig. 2). The figure shows a correlational relationship. While XCO_2 and LST increase gradually with time, NDVI and EVI, which represent parameters related to vegetation, have the opposite pattern. This result can be explained due to the mutual effect of vegetation area decrease and temperature increase, which then leads to the reduction of photosynthesis followed by the rise of CO_2 concentration.

From the dataset of GOSAT and MODIS, a stepwise regression process allows a step-by-step observation of the relationship between each of the 9 dependent variables from MODIS and the independent variable XCO_2 from GOSAT. These observations provide comprehensive knowledge for future selection of input variables for the regression model. From these observations, the LST parameter is excluded, and the rest of the 8 parameters (EVI, NDVI, LAI, FPAR, GPP, NPP, GN, NG) have correlational relationship with XCO_2, as seen by the "sig" indicator, which denotes correlations lower than 1 or 5% (Table 1).

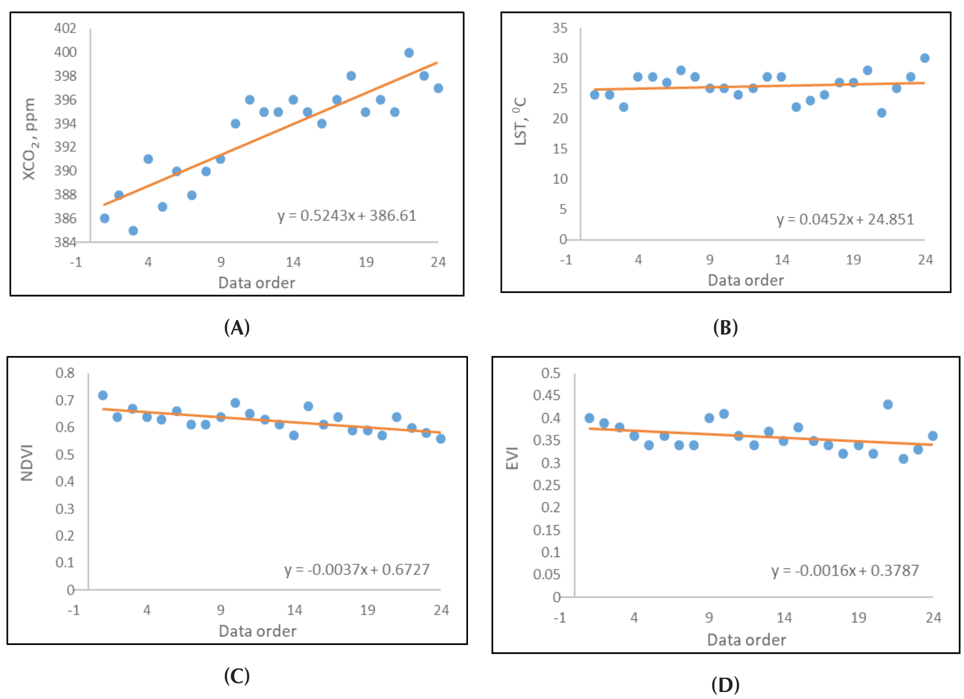

Fig. 2. Input data for models: (A) XCO_2, (B) LST, (C) NDVI, (D) EVI.

Table 1. Correlation Analysis.

	LST	EVI	NDVI	LAI	FPAR	GPP	NPP	GN	NG
XCO_2 - Sig	0.472	0.028 *	0.002 **	0.002 **	0.006 **	0.003 **	0.001 **	0.018 *	0.001 **

Note: **: 0.01 level; *: 0.05 level.

Despite the considerable correlation indicator of those variables, it does not mean that all of them will appear in the regression model. To accurately and completely verify these relationships, a stepwise regression is conducted. In the stepwise process, XCO_2 is the independent variable, and the 8 variables (EVI, NDVI, LAI, FPAR, GPP, NPP, GN, NG), which have been previously identified as having a correlation with XCO_2, are the dependent variables. Stepwise regression is helpful for eliminating variables that are unrelated and can potentially degenerate the regression equation. The result of this process is the below six equations which include single or multiple variables:

Independent variables: NPP (R=0.618, VIF_{mean}=1) (1)

Independent variables: NPP, EVI (R=0.855, VIF_{mean}=1.2) (2)

Independent variables: NPP, EVI, FPAR (R=0.886, VIF_{mean}=4.5) (3)

Independent variables: NPP, EVI, FPAR, NG (R=0.922, VIF_{mean}=3.9) (4)

Independent variables: NPP, FPAR, NG, LAI (R=0.945, VIF_{mean}=16.4) (5)

Independent variables: NPP, EVI, FPAR, NG, LAI (R=0.947, VIF_{mean}=18.7) (6)

Among these equations, the ones selected have the highest correlation index (R). Then, the VIF index is observed to consider the multicollinearity [6]. Multicollinearity is when there is a correlation between predictors (i.e. independent variables) with in a model. Its presence can adversely affect regression results. VIF stands for variance inflation factor. A rule of thumb for interpreting the VIF is as follows: if the VIF is 1, then they are not correlated; a VIF of 1-5 denotes moderate correlation; and a VIG>5 means they are highly correlated [7]. The results show that among the six equations, only equation (1) has a low correlation index (R=0.618), the others have a moderate correlation, and R varies from 0.85 to 0.95. Equations (3), (4), (5), and (6) have a high VIF index. This means that there is multicollinearity in these equations, which indicates that the dependent variables not only regress with the independent but also with each other. This phenomenon significantly influences the R index, making the R index artificially high. Thus, equation (3), (4), (5), and (6) must be eliminated, which leaves the remaining equations (1) and (2). Between the two equations, equation (2) has a higher R index of R=0.855, compared to R=0.618 for equation (1). Consequently, equation (2) is selected as the final model for the estimation of the atmospheric CO_2 concentration of the study area. The form of equation (2) is given below:

$$XCO_2 = 400.275 - 0.042 * NPP - 52.72 * EVI \tag{7}$$

Establishing the map of atmospheric CO_2 concentration distribution

Equation (7) is used to model the distribution of the atmospheric CO_2 concentration for the study area. The NPP and EVI parameters for the study area are derived from the MODIS products with a resolution of 0.5 km. This paper models the CO_2 concentration during the period of the first six months of 2019, on the days that MODIS data available. Fig. 3 presents the model.

The model demonstrates that the 390-400 ppm region is mostly located in an urban area, which has sparse and unevenly distributed vegetation. The 380-390 ppm region appears in the suburbs of Binh Chanh, Nha Be, District 9, Hoc Mon, and Cu Chi, which is mostly covered by agriculture. The evergreen mangrove forests caused the CO_2 concentration of the Can Gio district to fluctuate from 360 to 370 ppm, but remained lower than the other areas.

During the peak of the dry season, February - April and the first half of May, the red area denoting 390-400 ppm CO_2 is found around the downtown area, which accounts for 20-25% of the city area. At the beginning of June, the rainy season begins and thus the vegetation grows and thrives. Consequently, there is an increase of photosynthesis and the CO_2 concentration reduces, which is seen by the shrinking red region.

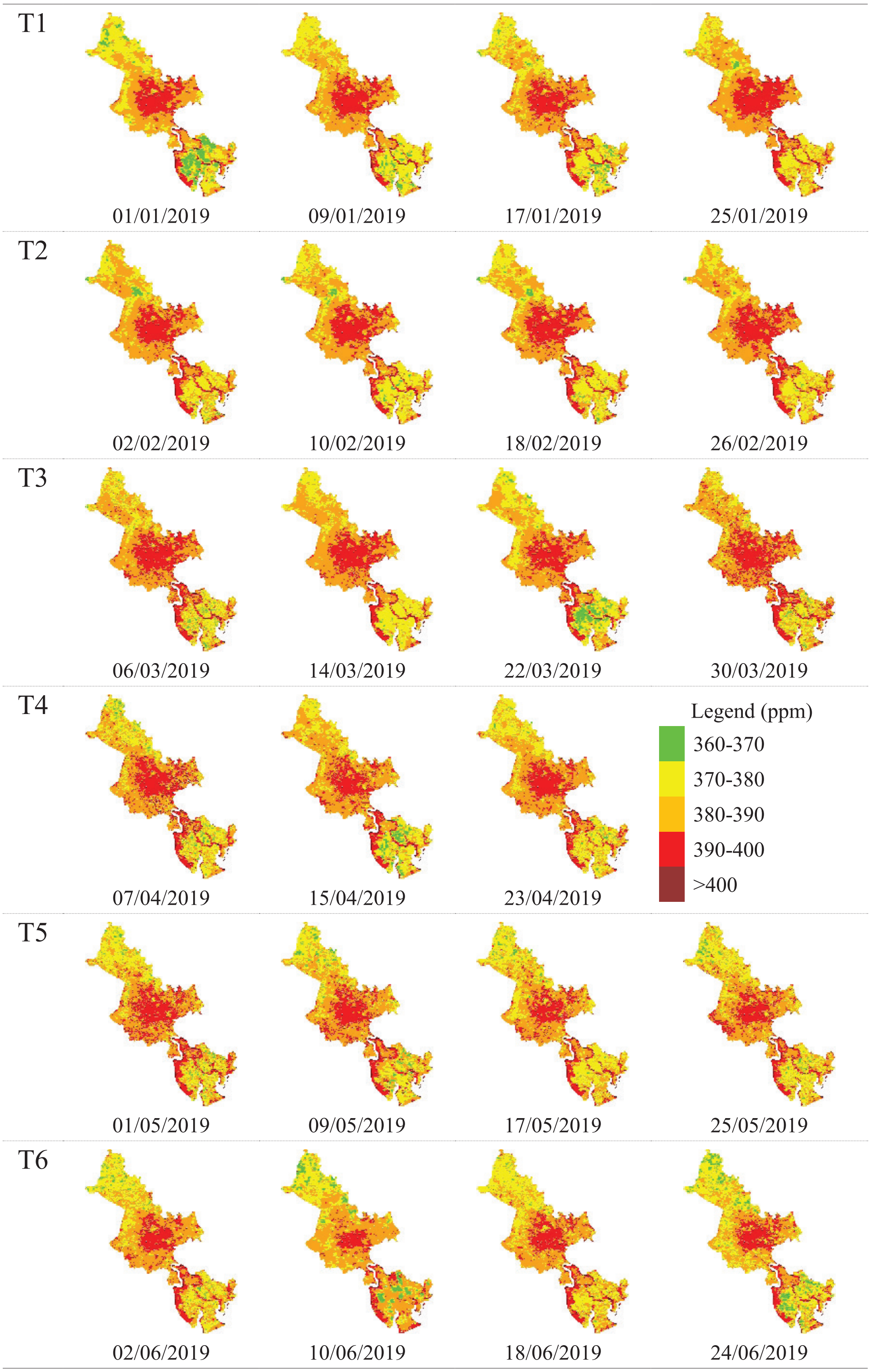

Fig. 3. Spatial distribution of atmospheric CO_2 concentration in first half of 2019.

Figure 4 shows the extrema of the CO_2 concentrations found in the study area during first half of 2019. The minimum line has high fluctuations and a downward trend starting from the beginning of dry season to the beginning of wet season. The lowest CO_2 concentration of Ho Chi Minh city is 365 ppm. Meanwhile, the maximum line has a more stable pattern around 405.66 ppm, which increases 0.1 ppm every 8 days (along with the MODIS data). Among of them, April has the highest CO_2 concentration of approximately 410 ppm. In Ho Chi Minh city, April is characterized as the hottest month of the year, when the majority of agriculture is uninhibited, causing heightened emissions of CO_2 from the land to the atmosphere.

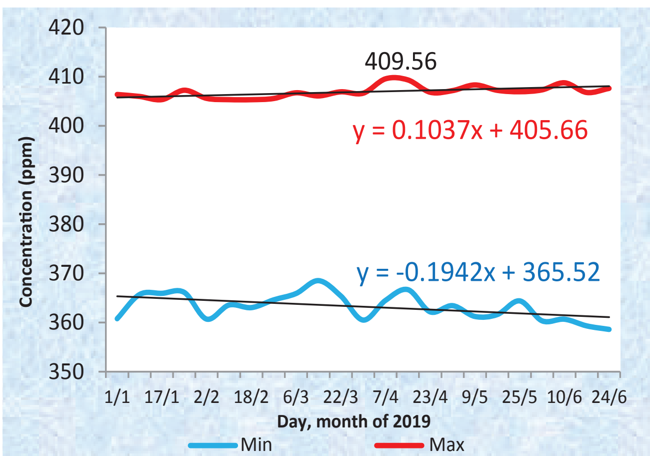

Fig. 4. Extrema of CO_2 concentration in the first 6 months of 2019.

Figure 5 and Table 2 represent the average concentration of CO_2. It can be seen that in the first half of 2019, the average CO_2 concentration of the city is 384 ppm and has an unstable pattern. Meanwhile, the monthly minimum average decreases from January (beginning of dry season) to June (beginning of rain season), ranging from 360 to 365 ppm. The maximum average CO_2 concentration shows the opposite pattern, with values between 405 and 408 ppm.

Figure 6 and Table 3 indicate the proportion of the study area at different concentration ranges. The range of 370-400 ppm CO_2 comprises 20 to 60% of the study area. Specifically, the 380-390 ppm range covers the majority of the study area, which accounts for nearly half of the city, 42 to 59%. The others two ranges, 360-370 ppm and >400 ppm, cover the smallest areas, which vary from 0.2 to 7% of the total study area.

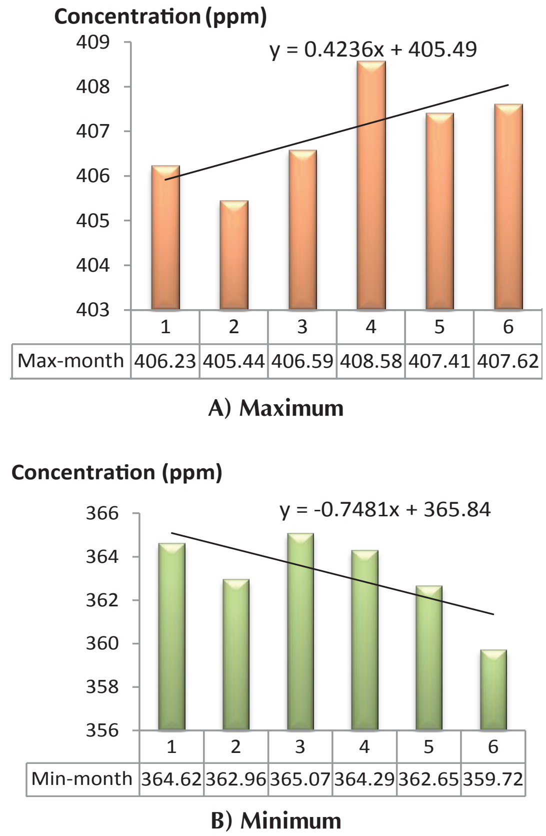

Fig 5. Extreme values of CO_2 concentrations averaged monthly for the first 6 months of 2019.

Table 2. Statistics of extreme data in the first half of 2019.

Month	Min-month	Max-month	Mean-month
1	364.62	406.23	383.77
2	362.96	405.44	384.70
3	365.07	406.59	384.84
4	364.44	408.58	384.33
5	362.65	407.41	383.97
6	359.72	407.62	383.16
Average	363.24	406.98	384.13

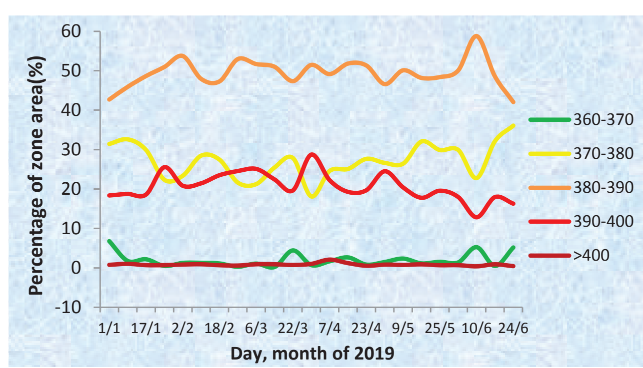

Fig 6. Percentage of total study area for CO_2 concentration ranges in Ho Chi Minh city during the first 6 months of 2019.

Table 3. Percentage of total study area for CO_2 concentration ranges during the first 6 months of 2019.

CO_2 concentration area (ppm)	Min (%)	Max (%)
360-370	0.21	6.76
370-380	18.11	36.08
380-390	42.05	58.79
390-400	12.83	28.72
>400	0.38	2.08

Validation

This paper successfully constructs a multi-variable regression model for the estimation of atmospheric CO_2 concentration of Ho Chi Minh city, based on two data sources: CO_2 from GOSAT and MODIS products. The GOSAT satellite is the first world satellite programmed to observe two greenhouse gases, CO_2 and CH_4. It is from the collaboration efforts of Japan Ministry of Environment, Japan National Institute of Environment Studies, and Japan Aerospace Exploration Agency. It has remained on duty since 2009. From that moment until now, GOSAT continually provides CO_2 data, which is widely used by researchers from every corner of the world. This data has been validated as global coverage data, has high accuracy and precision, and an error range of only 1 ppm to 4 ppm [4].

The MODIS products are used as a bridge in this study, where a physical-ecological equation is developed to interpret the atmospheric CO_2 concentration in a higher resolution than what is currently available. The input variables represent surface-energy balance, and the relationship between the physical-ecological characteristics of vegetation and the exchange of carbon between land and atmosphere. MODIS products appear frequently in academic research and is a credible resource. This approach wipes out the disadvantages of absent ground-based measurement stations, thus, provide a method for observing and quantifying the CO_2 concentration. The limit of this paper is the lack of in-situ measurement validation, which is also the general problem of the Vietnamese monitoring system. This limit inspires the authors to improve future studies.

Conclusions

The method of combining remote sensing with statistical models to calculate the atmospheric CO_2 concentration is suitable for the conditions of Vietnam since there is a lack of ground measurements of CO_2. Currently, environmental management only focus on carbon monoxide CO. This paper successfully models the distribution of CO_2 concentration of Ho Chi Minh city during a period spanning the first 6 months of 2019. This result shows that the monthly average CO_2 concentration varies from 360 ppm to nearly 409 ppm. Unfortunately, this range is within the warning range given by international scientists that stated the global CO_2 has crossed 350 ppm and is continually increasing over 400 ppm. The resulting CO_2 concentration depends accordingly on the type of land cover, where lower concentrations exist in areas that have dense vegetation and higher concentrations are found in areas with sparse vegetation. Therefore, in effort to reduce atmospheric CO_2 concentration and the impacts of climate change, especially in urban areas, increased vegetation areas play a central role.

The authors declare that there is no conflict of interest regarding the publication of this article.

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