Modeling the Dynamics of Carbon Dioxide Over an Educational Institute

Srikumar Sastry, Arnav Saha and Ranendu Ghosh

Abstract Carbon dioxide is a major contributor to climate change. It absorbs the outgoing longwave radiation, thereby increasing the temperature in the atmosphere. This study examines the variables which contribute to the flux of CO_2 over the 50-acre sprawling green campus of DA-IICT at Gandhinagar, Gujarat. The previous approach to this problem was to employ differential equations to model the CO_2 emissions. We believe that a compartment-based model that incorporates fossil fuels, electricity, human emissions, and a Light Use Efficiency (LUE) model would provide a better approximation. The LUE based model computes the total carbon that is sequestered by plants. It uses the Primary Productivity Capacity (ε) of plants and APAR (Absorbed Photosynthetically Active Radiation) to calculate the Gross Primary Productivity (GPP). Further, the Net Primary Productivity (NPP) is derived from the GPP. Three dedicated separate models using monthly MODIS NDVI, MODIS FPAR, and MODIS NPP time-series datasets were used to model this. To integrate the above, a Decision Tree-based algorithm was applied to compute the best fit curve and approximate it to the Keeling curve which is a graph of the accumulation of CO_2 in the Earth's atmosphere recorded at the Mauna Loa Observatory, Hawaii for all the three cases. The resultant curves indicated an MSE (Mean Square Error) close to zero and an upward trend was noticed for the future validation dataset.

Keywords CO_2 · LUE · FPAR · NDVI · GPP · Modeling

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1 Introduction

Carbon dioxide is one of the major greenhouse gases. It occurs naturally as a trace gas. It is released mainly through human activities and natural processes. Carbon is one of the main components of CO_2. 99.96% of carbon is found in the Lithosphere and 0.00206% is found in soil and plants. It is interesting to note that 80% of a plant/tree volume is composed of moisture and the remaining 20% is just dry mass (biomass). Biomass has approximately 9% of carbon. Pertaining to DA-IICT campus, major carbon sources include burning of PNG, electricity consumption, and human respiration. Major carbon sinks include plants and soil.

A compartmental model approach [1] has been adhered to in which each sub-compartment has been allotted a factor that releases or absorbs CO_2 on campus. We incorporate the burning of PNG, electricity consumption, human respiration, and vegetation (plants and trees) into this model. Each of these have been explored in detail in the following sections. Methodology and various techniques applied in all of these four compartments have been discussed and a final composite of these have also been discussed in the sections ahead. Results obtained from this study are fitted with the actual CO_2 concentrations that are observed at the NOAA Laboratory, Mauna Loa [2].

2 Compartmental Model

We make use of a simple compartmental model [1] to study the dynamics of carbon dioxide in the institute campus.

$$\Delta CO_2 = \alpha \times \text{fossilfuel} + \beta \times \text{respiration} + \gamma \times \text{electricity} + \varepsilon \times \text{GPP} \times 0.5 \quad (1)$$

where α, β, γ, ε are model parameters.

- ΔCO_2 represents the flux of CO_2 on campus.
- fossilfuel represents the contribution to carbon dioxide from fossil fuel burning on campus.
- respiration represents the contribution to carbon dioxide from human respiration on campus.
- electricity represents the contribution from the electricity usage on campus.
- GPP represents the Gross Primary Productivity of the plants.

Note: All assumptions for the model and data sources are mentioned below.

3 Carbon Cycle

3.1 Carbon Dioxide Data

The carbon cycle is the key component of Earth Science. To quantify the trend in carbon cycle we use the data measured by NOAA observatory [2]. It has been recording the CO_2 concentrations from 1958 to date. The observatory is located in Hawaii which is a deciduous region and proves an ideal candidate for validation as Gandhinagar is also a deciduous region. Due to its location, Mauna Loa proves to be the least affected location from human activities [1]. But one thing to be noted is Mauna Loa could be the source of additional carbon dioxide from frequent volcanic eruptions. The yearly cycle can be observed with the slopes representing the seasons. A single year in the graph if isolated shows peaks for the winter months, November to January. A peak represents the low absorption of CO_2 by the vegetation during the nongrowing season. So, the overall concentration of CO_2 in the atmosphere increases. The graph also correctly shows a dip for CO_2 in the post-monsoon season, August to September, which is the onset of the growing season where the vegetation absorbs comparatively more CO_2. So, the overall concentration of CO_2 in the atmosphere decreases. There is an overall upward trend as we advance in the time scale which clearly shows that CO_2 levels are increasing yearly (Fig. 1).

3.2 Fossil Fuel Burning Data

There are mainly two sources of biomass burning within the campus—Piped Natural Gas (PNG) used in the canteen and burning of petrol in vehicles. Both of these data were collected in-situation through purchase bills and statistics, respectively.

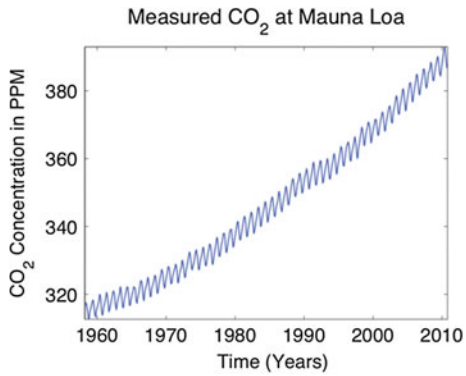

Fig. 1 Graph shows monthly CO_2 concentration in ppm from 1950 to 2010 at Mauna Loa, Hawaii

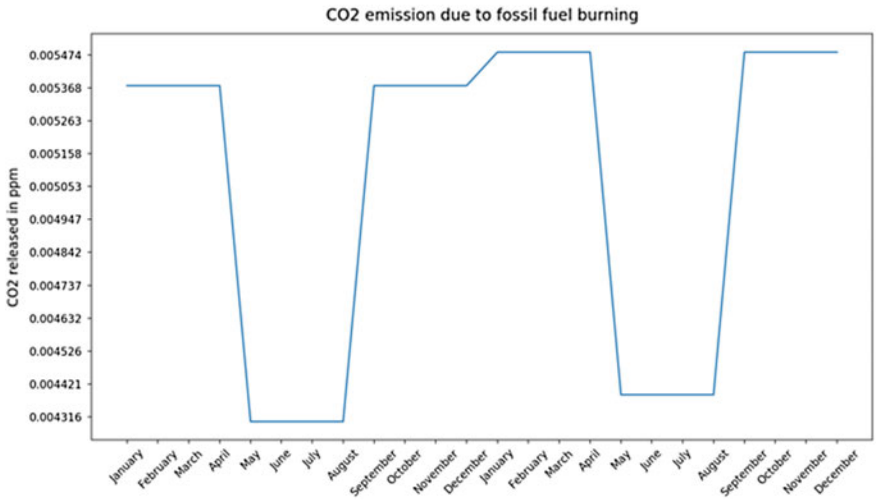

Fig. 2 Graph shows monthly CO_2 (ppm) emission due to fossil fuel burning. We can see a 2% increase in CO_2 emission between the year

We measure PNG in SCM (Standard Cubic Meter) unit and the relation between SCM and KG is: 1 kg = 1.423 SCM. PNG has a major component of Methane (CH_4) and 1 kg of CH_4 produces 2.75 kg CO_2. In total, 1608.54 kg of PNG gas was used in a normal academic month (Note: kg can be converted to ppm by dividing it by 1 million). Analyzing previous data, we assumed a 20% decrease in the PNG used in the nonacademic months (May to July). Also, we assumed a 2% yearly increase in the overall PNG use to incorporate the growing number of students on the campus.

Further, petrol consists of approximately 87% carbon, which is roughly 652 g (Note: 1 kg petrol weights approximately 750 g). Additionally, this carbon converts into CO_2 with the help of 1740 g of oxygen. So the total amount of CO_2 that is generated from 1 L of petrol is (652 + 1740 = 2392 g) or 2.392 kg. There are around 99 vehicles on the campus and each uses around 0.64 L of petrol per month. So, a total of $99 \times 0.64 = 63.36$ L of petrol. This gives a total of 151.557 kg of CO_2. Again, a 20% decrease was assumed for nonacademic months and 2% overall yearly increase (Fig. 2).

3.3 *Electricity Consumption*

DA-IICT uses electricity from the Torrent power plant located in Gandhinagar. It generates electricity from coal which eventually produces CO_2. Torrent uses bituminous coal which produces 0.3538 kg of CO_2 per unit of electricity. Total units of electricity consumed in a month are around 2,11,805. So, the total CO_2 produced due

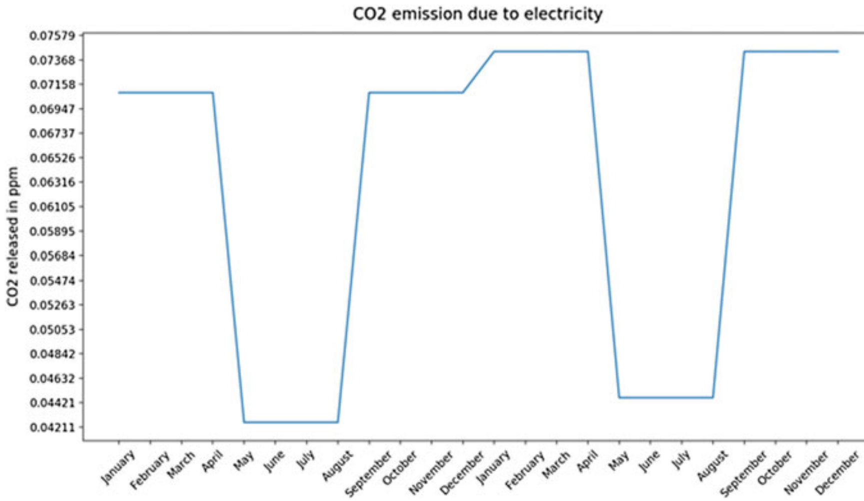

Fig. 3 Graph shows monthly CO_2 (ppm) emission due to electricity consumption

to electricity is around 84936.609 kg. From the previous statistics, A 40% decrease in nonacademic months and a 5% yearly increase was assumed (Fig. 3).

3.4 Human Respiration

An average adult produces 1.043 kg of CO_2 per day. There are approximately 1,400 people at DA-IICT. This gives a total of 43,806 kg of CO_2 monthly. The growing number of seats in the institute was noted and the number of students staying in the campus in nonacademic months was carefully examined, and thus a 40% decrease in nonacademic months and 10% yearly increase was assumed (Fig. 4).

3.5 Satellite Data

There are various biophysical variables which are associated with modeling environmental parameters such as type of vegetation, transpiration, carbon content, etc. Some of the important variables which are of our interest are the Normalized Difference Vegetation Index (NDVI), GPP, NPP, etc. We use NDVI and FPAR to quantify NPP and present three separate models. In simple terms, NDVI measures the amount of greenness of a vegetation canopy. For that, it uses the reflectance of the Near-Infrared (NIR) and Red bands (R) of the sun's incoming electromagnetic radiation. Vegetation reflects the incoming radiation as a function of wavelength. More in green wavelength due to chlorophyll followed by less reflected energy in the red wavelength and in NIR

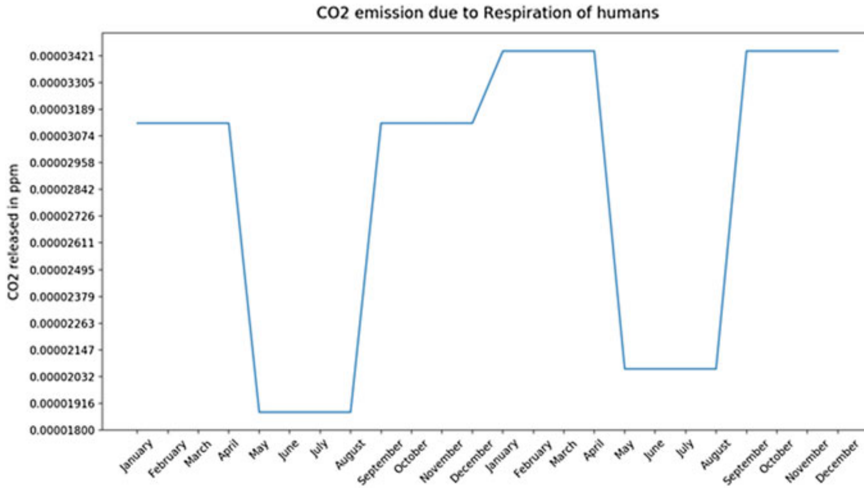

Fig. 4 Graph shows monthly CO_2 (ppm) emission due to respiration of humans

it is very highly reflected energy due to intercellular activity. So, more the difference between those reflected values, more is the NDVI, more is the chlorophyll content and healthier is the vegetation [3].

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - R}{\mathrm{NIR} + R} \tag{2}$$

The Moderate Resolution Imaging Spectroradiometer (MODIS) datasets are recorded by NASA's Terra platform on board two sun-synchronous satellites. It contains NDVI dataset at a spatial resolution of 250 m with 16-days composite [4]. It contains FPAR dataset at a spatial resolution of 500 m with 4-days composite [4]. Finally, it contains the NPP dataset at a spatial resolution of 500 m with 8-days composite [5]. PAR is calculated from solar radiation, in the short wave region which is obtained from IDAHO Terra Climate data (http://www.climatologylab.org/terraclimate.html). This dataset has a spatial resolution of 4 km and monthly temporal resolution. DA-IICT is at geolocation Latitude—23.184179° and Longitude—72.633213°. Monthly datasets for each of these were collected ranging from 2001 to 2018 (DA-IICT was established in 2001). The average value of the pixels falling inside DA-IICT campus will give a single value for these variables. Some of the values in the above datasets were null. These values were imputed to the mean of the rest of the data.

4 Light Use Efficiency (LUE) Based Model

On the land, the major exchange of carbon with the atmosphere results from photosynthesis and respiration [6]. Carbon sequestered into plants, also known as vegetation carbon comes from the Primary Productivity of plants using CO_2, sunlight, and moisture. The rate at which plants convert radiant energy into organic substances and other by-products is known as its Primary Productivity or Gross Primary Productivity (GPP). A fraction of this food reserve is used by the plants to participate in respiration, during this it releases back some of the CO_2 back into the atmosphere. Thus, the effective carbon sequestered by the plants is actually the respiration subtracted from the GPP. This end product is known as NPP. There are a lot of ways to measure the GPP of plants including allometric, Flux Tower method, Extrapolation, Light Use Efficiency-based model (LUE), and Process-based models.

To measure the primary productivity in the institute campus, we use the Light Use Efficiency model based on Monteith's Light Use Efficiency concept [7]. It indicates that the annual productivity of plants is directly linked to the Absorbed PAR (Photosynthetically absorbed radiation) (400–700 nm) and LUE. LUE (ε) is the efficiency with which plants convert the Absorbed PAR into dry matter.

$$\text{GPP} = \text{APAR} \times \varepsilon \tag{3}$$

APAR is expressed as the product of the PAR and the fraction of Absorbed Photosynthetically Active Radiation (FPAR).

$$\text{APAR} = \text{FPAR} \times \text{PAR} \tag{4}$$

PAR refers to that spectral range of solar radiation that can be fruitfully used by plants to participate in photosynthesis. The range is between 400 and 700 nm in the short infrared region. Similarly, FPAR is defined as the fraction of PAR that is actually absorbed by a vegetation canopy.

$$\text{GPP} = (\text{FPAR} \times \text{PAR}) \times \varepsilon \tag{5}$$

FPAR shows a linear relationship with NDVI [8]. By critical examination of this equation, we calculate the FPAR on campus.

$$\text{FPAR} = 1.164 \times \text{NDVI} - 0.143 \tag{6}$$

The SI unit of PAR is μmole m^2/s and the SI unit of Solar radiation (SR) is W/m^2. 1 $W/m^2 \approx 4.6$ μmole m^2/s [9]. But this approximation accounts solar radiation only for wavelengths from 400 to 700 nm. This region only represents about 45% of the entire spectrum. As a result:

$$\text{PAR} = 0.4762 \times \text{SR} \tag{7}$$

Combining all of the above equations

$$\text{GPP} = \text{PAR} \times \text{FPAR} \times \text{LUE} \tag{8}$$

If we factor out the energy given out during plant respiration over the same period, the Net Primary Productivity (NPP) is achieved.

$$\begin{gathered}\text{NPP} = \text{GPP} - \text{RE} \\ \text{RE} : \text{Respiration done by plants.}\end{gathered} \tag{9}$$

However, calculating the amount of energy released during respiration is very tough and mundane. Most remote sensing applications are driven by this equation:

$$\text{NPP} = 0.5 \times \text{GPP} \tag{10}$$

5 Decision Tree-Based Regression

The Decision tree is a supervised machine learning algorithm used for both classification and regression. The compartmental model uses a decision tree-based regressor to predict the CO_2 emission in the next month. The regressor uses a binary tree structure which is constructed on the basis of a loss function which is taken to be Mean Squared Error (MSE) in the model. Before training the model, the entire dataset is considered to be at the root. The dataset is then divided into two parts depending on the standard deviation and mean and this becomes the child of the root. This process continues until the max depth is reached which is taken to be 5 in this model. After the tree is constructed, the data is rearranged according to the MSE and the value at the leaves of the tree are used to predict the next value.

6 Results and Validation

The compartmental model was used for modeling all the obtained data. Data from 2001 to 2013 was used for training and the rest of the data served the purpose of validation and testing. All the three models (NDVI, FPAR, NPP) have been separately fitted using decision tree regression. The first model uses NDVI to predict NPP and is shown in Fig. 5. The second model uses FPAR data to predict NPP and is shown in Fig. 6. The final model uses NPP data directly and is shown in Fig. 7.

It can be quite clearly seen that the model using NPP gives the least validation error while the model using NDVI gives the largest validation error. This indicates NPP is quite a good quantifier to understand the dynamics of carbon Dioxide (Table 1).

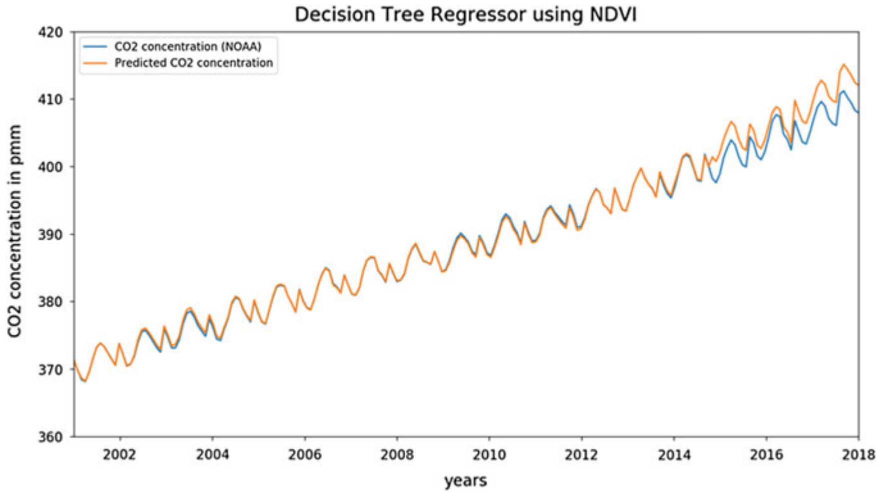

Fig. 5 Graph shows true CO_2 concentration against the concentration predicted by this model. The model uses NDVI for computing LUE. The training Mean Squared Error (MSE) was 2.918e−08 ppm. The validation MSE was 0.0003

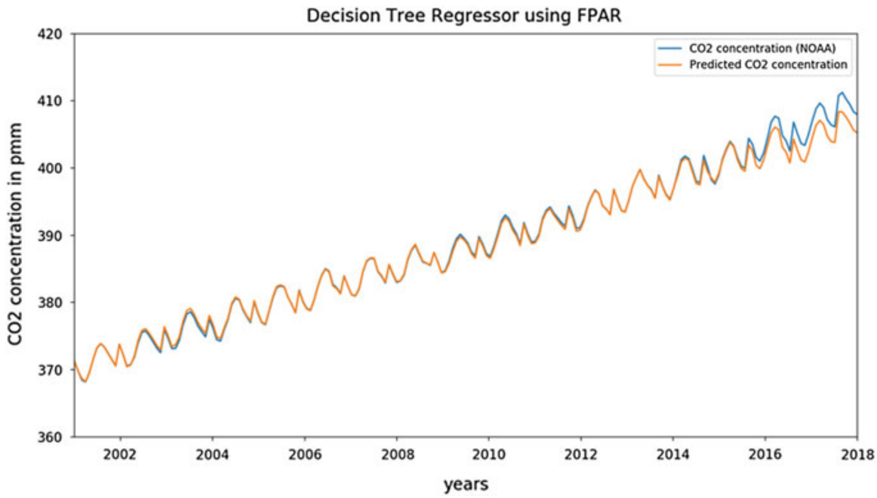

Fig. 6 Graph shows true CO_2 concentration against the concentration predicted by this model. The model uses FPAR for computing the LUE. The training Mean Squared Error (MSE) was 2.918e−08 ppm. The validation MSE was 0.000297

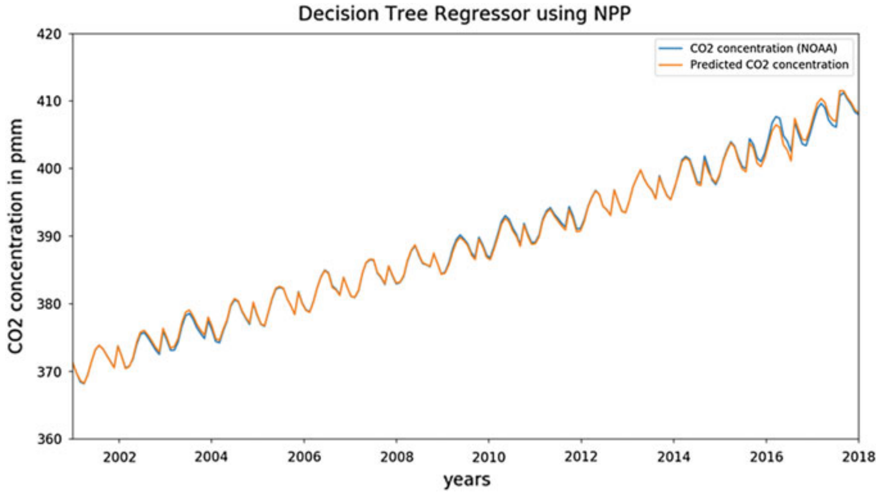

Fig. 7 Graph shows true CO_2 concentration against the concentration predicted by this model. The model uses FPAR for computing LUE. The training Mean Squared Error (MSE) was 2.918e−08 ppm. The validation MSE was 3.98e−05

Table 1 Table summarizing model using (NDVI, FPAR, and NPP) values

Model using	Training error (ppm)	Validation error (ppm)	Predicted CO_2 for January 2019 (ppm)
NDVI	3.937e−08	0.0003	411.140
FPAR	2.774e−08	0.000297	413.615
NPP	2.417e−08	0.0000398	413.87

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