Extracting Carbon Emission for Industrial Area by Using Landsat 8: Case study of Klang, Malaysia

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ABSTRACT: Industrial area attributed to 235.6% carbon emissions increase from 1990 to 2005. In 2009 Malaysia announced a voluntary commitment to reduce 40% of its greenhouse gases (GHG) emissions by 2020. The study aims to extract the carbon emission by industrial area using Landsat 8 processed through Land Surface Temperature (LST) data in quantifying carbon. The data required are obtained from the Sniffer4D drone, Landsat 8 LST and Department of Environment (DOE) data, which were analysed through comparative and statistical analysis. The findings showed that the high correlation of Site A, (= 0.7403) Site B, (= 0.607) and Site C, (= 0.0026) strength between data from the drone and satellite data. As a results, that band11 Thermal Infrared (TIRS) 2 in Landsat 8 can be used for extracting carbon value estimation and band 10 Thermal Infrared (TIRS) 1 for the measurement of the air temperature. These findings can assist in terms of calculating carbon emission using LST and determine the high concentration industrial carbon emission hence it can help in decision making in further industry area development.

1. INTRODUCTION

Industry activities play a major role in contributing in Malaysia economic growth. GHG emission can cause climate change to the country. In Malaysia, construction standards are controlled by the Uniform Building By-Laws 1984 and the Construction Industry Standards, both of which currently impose no energy efficiency requirements. Malaysia need to have policies and action towards low carbon emission towards developing industrial area. This research is expected to contribute in analyzing of carbon emission using open source data such as Landsat data at Klang Indsutrial Area, Selangor. It is hope that the developed data can be used by authorities to update and analyze information related to low carbon and GHG emissions.

2. THEORITICAL REVIEW

Greenhouse gas (GHG) is any gas that has the property of absorbing infrared radiation (net heat energy) emitted from Earth's surface and reradiating it. 21% of GHG emission comes from industrial activities. Industry primarily includes fossil fuels burned on-site at power plants. The Malaysian building sector and construction industry is yet to streamline and upgrade its conventional approach to innovative building systems and energy efficiency. The highest percentage of gaseous emission from industry are CO2 as of 2014, CO2 emissions from the manufacturing and construction sectors were 12.97 percent of total fuel combustion in Malaysia. GIS acts as both a database and an urban planning toolbox. Spatial and textual data can be stored and linked using the georelational model in a database based GIS. GIS can accomplish many functions that differentiate GIS from other information systems. More than 75% of human activities are related to the geographical location. Geospatial information is the operational objectives of GIS. It is the substantive substance of true which is communicated by GIS through disconnected model. The geographic spatial information is information of nature, society and human economic scene. GIS acts as a powerful tool to identify the most strategic location to develop a certain commercial or industrial building. Satellite data from USGS play an important role in determining the carbon emission in industrial area of Klang. Any development in Malaysia has to refer to the Malaysian statutory development plan hierarchy.

3. METHODOLOGY

3.1 Data Collection

Data collection is defined as a process of collecting and extracting specific information about a phenomenon or behaviour. This data gathering aims to ensure that the researcher obtains useful information to add to the study's findings and results. There are two types of data sources which are primary and secondary data used in this analysis. The satellite data collected from the USGS website will be analysed using ArcGIS software. Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) were valued to NDVI and LST. Landsat 8 images were used which are the thermal bands used to assess the LST values. validation was carried out using LST data results compared with the data from Department of Environment (DOE).

The drone flies at a height of 150 m with 75 percent front overlap and 65 percent side overlap. The drones had to complete the journey by 9 minutes and 50 seconds. The total captured image was 125 pieces. Take-off area was identified before operation was launched. The selected take-offs area was open and secure for drone operations.

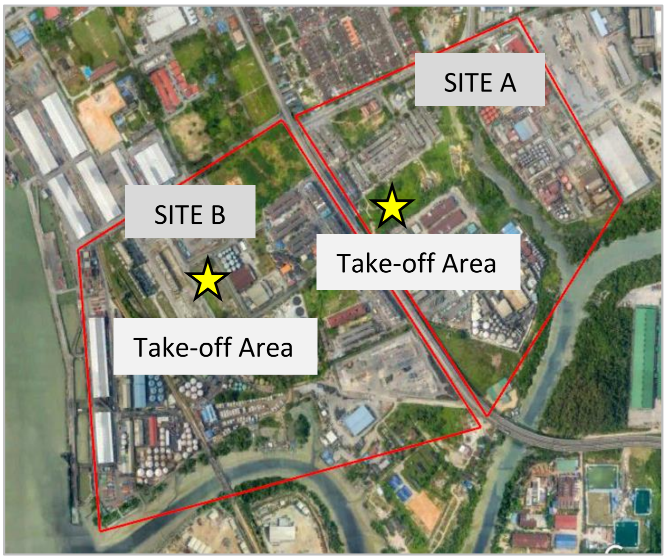


Figure 3.1 shows the Location of Take-off Area for Site A, B and C

In general, secondary data can be acquired from books and journal specifically in Urban and Regional Planning related to gaseous emission which can affect the GHG emission of certain area. In this research, the researcher can get the data of CO2 emission directly from the department of government or other agencies within the study area. The two types of data are involved in getting data from Landsat 8 satellite and data from Department of Environmental. These two data will abstract the value of carbon emission.

Landsat 8 comes with two separate image sets from the nine-banded Activity Land Imager (OLI) sensor (band 1 to 9) and two banded Thermal Infrared Sensor (TIR) (band 10 and 11) The satellite data can be downloaded in USGS website based on the case study area. After Landsat 8 data have been downloaded, the folder of data contains eleven layers of selected case study area data. Many recent studies have suggested that the 10 and 11 Thermal Infrared Sensor (TIR) bands were used to estimate brightness temperature. Landsat Level-1 products are supplied as digital numbers which can be converted into absolute radiance or reflection units. Studies also use DN or temperature (degrees Kelvin) for the thermal bands. Along similar lines with the pre-processing stages, based on (Rajeshwari and Mani, 2014) to estimate LST of an area, it uses brightness temperature of two bands of TIR, mean and land surface emissivity difference. The algorithm has to do with are:

i. *Extracting Brightness Temperature*

$$TB = \frac{K2}{Ln\left(\left(\frac{K1}{L\lambda}\right) + 1\right)}$$

Where,
K1 and K2 -Thermal conversion constant and it varies for both TIR bands (Table 1.1)
Lλ -Top of Atmospheric spectral radiance.

ii. *Top of Atmospheric Spectral Radiance*

$$L\lambda = M_L * Q_{cal} + A_L$$

Where,
Lλ - Top of Atmospheric Radiance in watts/ (m2*srad*μm)
ML - Band specific multiplicative rescaling factor (radiance_mult_band_10/11)
Qcal - band 10/ 11 image.
AL - Band specific additive rescaling factor (radiance_add_band_10/11)

iii. *Top of Atmospheric Spectral Radiance*

$$LSE = \varepsilon_s (1\text{-}FVC) + \varepsilon_v * FVC$$

Where,
εs and εv - soil and vegetative emissivity values of the corresponding bands.
εs (band 10 - 0.971, band 11-0.977) and εv (band 10 - 0.987, band 11-0.989)

FVC - Fractional Vegetation Cover was estimated for a pixel. FVC for an image was calculated by

$$FVC = \frac{NDVI - NDVIs}{NDVIv\text{-}NDVIs}$$

Where,
NDVIs – NDVI reclassified for soil
NDVIv – NDVI reclassified for vegetation

iv. NDVI Threshold

The NDVI image was reclassified into soil and vegetation to get NDVIs and NDVIv; the classified data were used to determine FVC. After generating LSE for both TIR bands, the mean and the difference LSE have been found as,

$$\varepsilon = (\varepsilon 10 - \varepsilon 11)/2$$
$$\Delta\varepsilon = \varepsilon 10 - \varepsilon 11$$

Where,
ε – Mean LSE
Δε – LSE difference ε10 and ε11 - LSE of band 10 and 11.

Finally, after these pre-processing stages the value of LST can be conducted in main processing stage.

3.2 Main Processing

To estimate LST of an area, it uses brightness temperature of two bands of TIR, mean and land surface emissivity difference. The algorithm has to do with

$$LST = TB10 + C1\,(TB10-TB11) + C2\,(TB10-TB11)2 + C0 + (C3+C4W)\,(1-\varepsilon) + (C5+C6W)\,\Delta\varepsilon$$

Where,

LST	- Land Surface Temperature (K)
C0 to C6	- Split-Window Coefficient values (Table 1.2)
TB10 and TB11	- Brightness temperature of band 10 and band 11 (K)
E	- Mean LSE of TIR bands
W	- Atmospheric water vapor content
Δ ε	- Difference in LSE

All data is analysed using Landsat 8 analysis and Sniffer4D Mapper. The correct method used to prepare the study paper determines the quality of the results. Some proposed techniques and methods are useful for a systematic data analysis process.

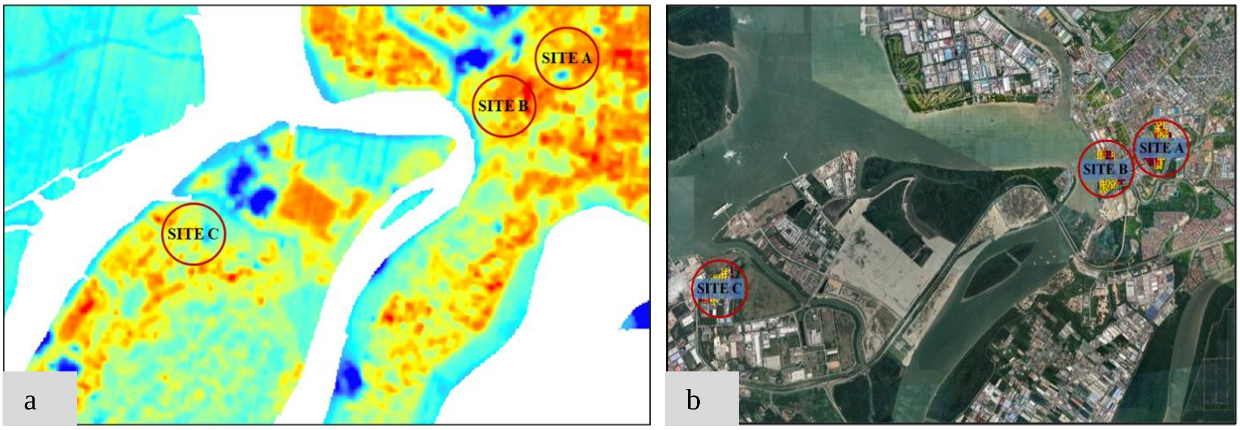
4. RESULT

4.1 Comparison of CO2 and CO Value from Sniffer 4d Mapper and Doe

There is big gap between the value of gaseous from Sniffer4D drone and DOE because this is caused by the total area taken from these two data. The data from drone are mostly focused on 3 sites. CO2 value emission is higher than CO either from drone data or DOE data. It is most probable; carbon monoxide emissions are most likely to cause high concentrations of carbon dioxide.

4.2 Correlation Analysis Between LST of Band 10, 11 and CO2

Each sites will be analysed by 3 points of ranging from low to high concentration to varies. The figures below show the exact location of data Site A, B and C for both side of data which are from LST and drone.



Figur4.1: a) Appointed Location for Correlation Analysis from LST, b) Appointed Location for Correlation Analysis from Drone

Based on these three sites, a table and graph has been presented to show detailed correlation value of CO2 from drone and LST of band 10 and 11. The scatterplot has been shown to illustrate the relationship between the value. Between these sites we can see that Site A of band ten LST show the smallest range value rather than Site B and C.

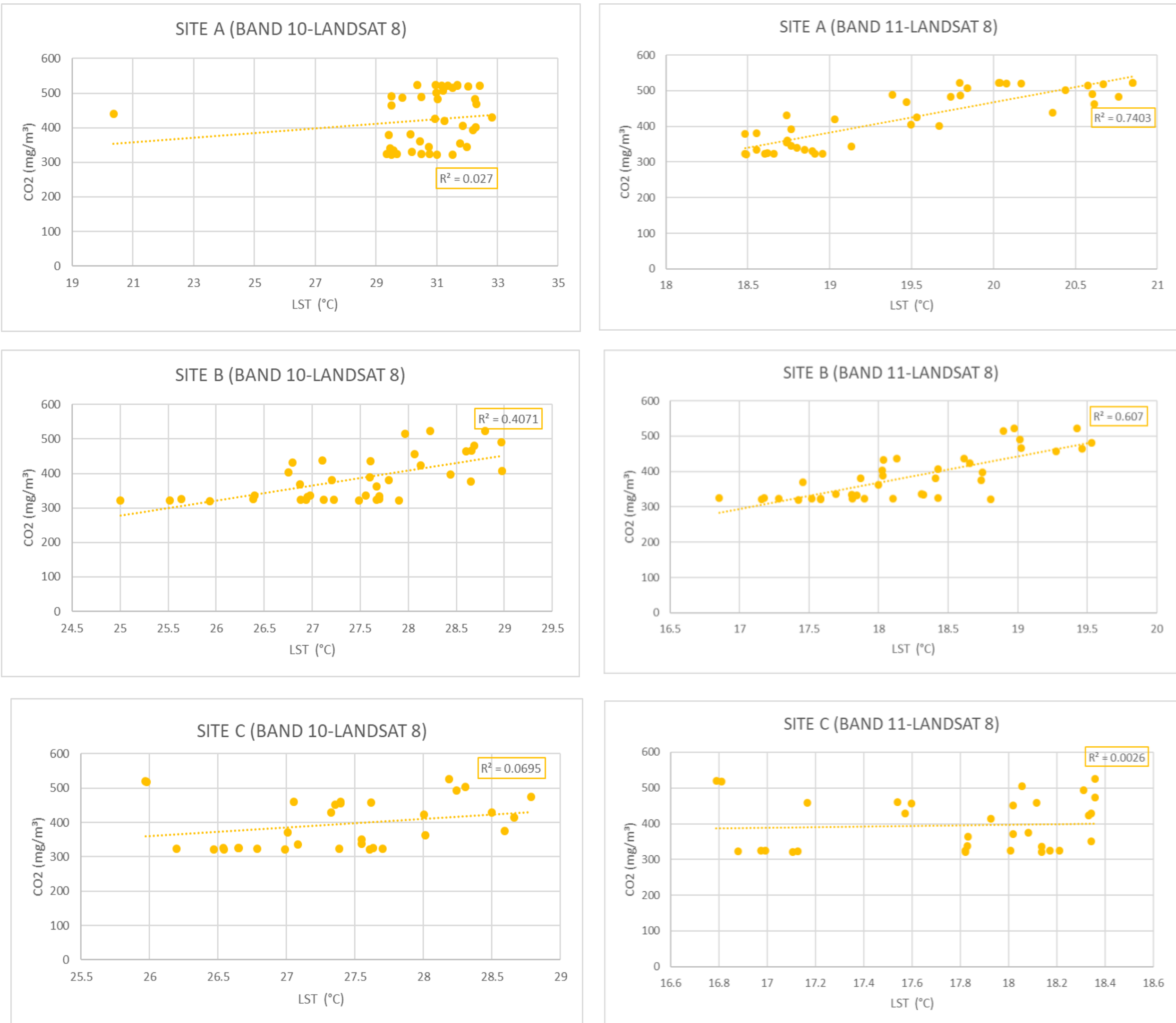


Figure 4.2: Comparision of R2 between band 10 and 11 of Site A, B and

Based on these three sites, the R2 of band 11 shows positive relationship. These 3 sites have small and large range of r value. Site C has lower correlation because of nonlinear relationship between the LST and CO2.

4.3 Carbon Hazardous Level

Carbon dioxide itself, at high levels, can cause headache, dizziness, nausea and other symptoms. It can cause asphyxiation as it replaces oxygen in the blood exposure to concentrations of about 40,000%. Motor vehicle exhaust and certain manufacturing operations, such as producing steel, are the primary sources of excess carbon monoxide. The safe level of CO must be maintained in order to achieve a sustainable development and avoid any environmental in near future.

5. RECOMMENDATION AND FUTURE OUTLOOKS

The study has found that LST of band 11 can be applied in quantifying CO2 levels. The data can be used in predicting the rate of CO2 concentration level in the future. Klang Municipal Council must take consideration in carbon emission in future development. Local authorities also play an important role as green economy regulators, asset owners and potential customers, the study says. The recommendation in zoning of industrial area based on gaseous emission is important because. based on findings medium and high concentration level are closely located to each other, it says. It says local and regional areas of industry will be an important analytical unit to ensure that the emission of gasesous takes place at the lowest concentration to avoid dangerous climate change in good time.

6. CONCLUSION

Overall, these research on using satellite data to quantify carbon is important in supporting the SDG number 11 which is "inclusive, safe and resilient communities". But this ambition is multifaceted and covers incongruous policy priorities and industries. One critical area of tension is evident between the goals of compact city (CC) growth (resource and land use, etc.) and urban green space (UGS) goals (important in, for example, living ability, biodiversity, and climate regulation) as GHG emission also related to climate change. However, the availability of reliable and accurate geospatial data plays an important role in developing web GIS solutions, given the increasingly the number of heterogeneous data sources that are usually developed at different times, based on different platforms, having different licenses, or created to match specific industries or departments, varying from country to country.

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