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# Spatio-Temporal Analysis of Carbon Storage in Urban Areas After Wildfires: The Case of Marmaris Fire[1]

**Zennure Uçar**

Izmir Katip Celebi University, Faculty of Forest, Department of Forest Engineering, Izmir, Turkey

## Abstract

Cities and urban areas are the primary source of $CO_2$ worldwide by using around 70% of global energy and emitting more than 71% of $CO_2$. Urban vegetation, referring to all trees and shrubs, are important components of urban environments. They provide many ecosystem services to human beings both directly and indirectly. Especially, they play a key role in reducing carbon emissions in urban areas by storing and capturing the carbon. However, recently, an increase in the number and intensity of wildfires that occur within urban areas has been observed. It resulted in losing stored carbon, releasing GHG to the atmosphere. Hence, quantifying above-ground carbon stored by urban trees and its distribution is essential to better understanding urban vegetation's role in urban environments and to better urban vegetation management. This study aimed to examine how forest fire affects the amount and distribution of stored carbon in the urban environment for the case of the Marmaris fire in the Summer of 2021 in Türkiye. For the study, urban forest carbon storage maps were generated before and after the Marmaris forest fire using remote sensing-based methodology with freely available remote sensing (RS) data. The results indicated that using the existing methodology could be rapid and cost-effective in monitoring the carbon storage change after an anthropogenic and natural disaster. However, for precise and reliable estimation of total carbon storage and the change in total urban carbon storage, the methodology needs to be developed at a local scale using field sampling along with RS data.

**Keywords:** Urban forest, Forest fire, Carbon storage mapping, Spatio-temporal change.

## 1. Introduction

The world's population in urban areas has been rapidly growing. The UN (2018) reported that more than half of the world's population (around 55%) lives in cities. Due to population growth, the increased vehicle uses, and industrial activities, cities and urbanized areas have become a main source of global $CO_2$ emissions (Hutyra et al., 2011b). Also, population growth has had a notable direct or indirect impact on land cover change processes. The need for infrastructure for housing, transportation, education, and health care facilities mainly destroys trees, forests, and green areas within, adjacent to, or around the cities. Thus, it causes deterioration of the structure, pattern, and function of the urban ecosystem within and around urban areas (Nowak et al., 1996; McPherson et al., 2011; Berland, 2012; Sağlam and Elvan, 2017).

Urban vegetated areas, meaning all woody vegetation in urban areas, are vital for the urban ecosystem (Berland 2012; Konijnendijk et al., 2006; Nowak et al., 2010; Richardson and Moskal 2014). They offer many benefits for human beings, such as providing aesthetic values and recreational opportunities, reducing energy use by facilitating cooling effects, improving water and air quality and biodiversity, and increasing human health and well-being (Nowak et al., 1996; Konijnendijk and Randrup 2004; Nowak and Greenfield 2010; Safford et al., 2013; Pasher et al., 2014; Richardson and Moskal 2014). All these ecosystem services obtained from urban vegetated areas are related to the amount of healthy and functioning vegetation, used to measure and monitor tree health, remove pollutants, and estimate carbon storage and sequestration (Pasher et al., 2014). The removal of the vegetation in urban areas due to the expansion of cities or natural disasters (fire, flooding, etc.) significantly affects the amount of carbon emissions on both local and global scales (Hutyra et al., 2011a).

All these changes in urban and suburban development cause a significant threat to the ecosystem and its services. For example, the extension of settlement towards wildland vegetation results in an increase human-caused fire ignition. It is reported that more than 50% of forest fires worldwide are accidental or intentional human-caused fires, and this rate rises to over 90% in Mediterranean regions (FAO, 2007; Ganteaume et al., 2013). Türkiye is one of the Mediterranean

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*Corresponding Author: Tel: +90 5304751645 E-mail: zennure.ucar@ikcu.edu.tr
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countries that experience the most significant number of forest fires in the south and western parts of the country. This region also experienced the highest number of fires and the largest burning area between 2020-2022 (European Forest Fire Information System, 2022).

Although fire has always been a part of many ecosystems, such as the Mediterranean ecosystem, in the current context, climate change, desertification, and human activities such as shaping fuels and vegetation indirectly through land use and directly causing or controlling fire (Pyne et al., 1996; Krebs et al., 2010; Ricotta et al., 2018; Chen and Jin, 2022) make these ecosystems more vulnerable to wildfires. These fires also cause increasingly serious environmental, economic and social losses.

In particular, wildfires release significant amounts of greenhouse gases, mainly $CO_2$ (Harrison et al., 2010). They also cause a reduction in carbon sinks by burning Above Ground Biomass (AGB) or carbon-rich fuels (Kirschbaum, 2003). Unfortunately, those areas in the landscape lose their ability to capture and store carbon until mature trees grow back. Recovery time after fire disturbance is related to the severity and ecosystem types. The forest ecosystem requires a longer recovery time, which is varied between two decades to a century, compared to other ecosystems, such as grasslands and peatlands (Reichstein et al., 2013; Fu et al., 2017). The loss of vegetation due to fire in the urban environment, a major source of global $CO_2$ emission, not only increases released carbon and reduces air quality but will significantly impact the amount of captured and stored carbon in the future within cities. Therefore, assessing and mapping ecosystem services, especially stored carbon by forests in urban environments, following wildfire disturbance is essential to understand spatial and temporal changes in ecosystem services, contributing to natural resource management planning and policy-making processing in the conservation and sustainable use of natural resources in urban environments.

Remote sensing technology provides new approaches with various data sources to monitor and detect changes and conditions of natural resources at local, regional, and global scales (Navalgund et al., 2007; Kumar et al., 2015; Szpakowski and Jensen 2019). They have been used increasingly for monitoring natural disturbances, including but not limited to fire disturbances (fire detection, burned severity mapping, fuel mapping, and fires risk mapping) (Chuvieco and Congalton 1989; Saatchi et al., 2007; Escuin et al., 2008; Adab et al., 2013; Satir et al., 2016; Filizzola et al., 2017; Xu and Zhong 2017; Collins et al., 2018; Akay and Şahin 2019; Huesca et al., 2019; Adaktylou et al., 2020; Ozenen Kavlak et al., 2021; Kantarcioglu et al., 2023) and insect infestation (Bone et al. 2005; Goodwin et al., 2008; Oumar and Mutanga 2011; Dalponte et al, 2022). Also, RS technology is widely employed in monitoring and mapping land use land cover change (Green et al., 1994; Shalaby and Tateishi 2007; Rwanga and Ndambuki 2017), vegetation recovery (Sever et al., 2012; Aicardi et al., 2016; Bolton et al., 2015; Samiappan et al., 2019) and urban expansion (Dereli, 2018; Al-Bilbisi, 2019; Dhanaraj and Angadi, 2022; Liu et al., 2022).

Moreover, RS data have been used to assess and monitor Green House Gas (GHG) emissions, including released carbon, nitrogen, and pollutants after natural disturbances such as wildfire (Hashim et al., 2004; Mirzaei et al., 2018; Sannigrahi et al., 2020; Yin et al., 2020; Singh et al., 2021; Akyürek 2022) or the amount of sequestered carbon by land cover such as forest areas (Turner et al., 2004; Baccini et al., 2012; Wicaksono et al., 2011; Vicharnakorn et al., 2014; Hastuti et al., 2018; Keles et al., 2021; Vatandaslar and Abdikan 2022; Çinar et al., 2024) and urban environments (Myeong et al., 2006; Sanga-Ngoie et al., 2012; Dobbs et al., 2014; Hutyra et al., 2011; Dobbs et al., 2018; Tonyaloğlu 2020; Dewanto and Jatmiko, 2021; Değermenci, 2023). Especially carbon emission in an urban environment that consumes around 70% of global energy and emits more than 71% of $CO_2$ worldwide (Hutyra et al., 2011a) requires regular monitoring, and the continuously available remote sensing data makes it possible.

Additionally, the use of remote sensing satellite images for carbon storage assessment, mapping, and monitoring provides a time and cost-effective approach rather than using limited ground measurements. The methodology, developed by Myeong et al. (2006) using spatially explicit freely available remote sensing data, was employed to estimate stored carbon in urban ecosystems. It pointed out that RS data offers fast and reliable estimates of stored carbon in urban ecosystems. In addition, this method was applied by many researchers to explore the ecosystem services provided by urban forests in different urban environments. For example, Dobbs et al. (2018) used the method in the case of Bogota (Colombia) and Santiago (Chile). The researcher also conducted another study in 2014 by using the same methodology to examine global drivers and tradeoffs of three urban vegetation ecosystems (carbon storage, recreational potential and habitat development). All these studies concluded that remote sensing data-based methodology helps to understand past patterns and consequences of urbanization that will contribute to future urban land management and urban forest conservation plans.

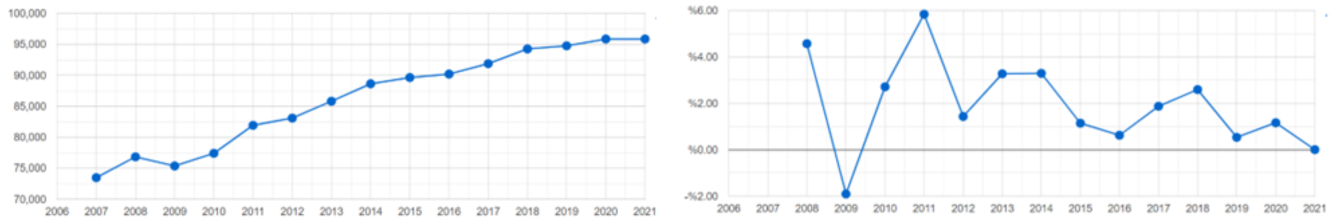
In this study, our main objective is to examine spatio-temporal changes in the amount of stored carbon in the urban environment for the case of the Marmaris fire that took place in the Summer of 2021 Türkiye. The spatio-temporal data provided by satellite images make it possible to determine total burned urban forested areas and estimate the amount of the stored carbon lost in those areas. Urban forest carbon storage maps were generated for before and after the Marmaris fire using remote sensing-based methodology, developed by Myeong et al. (2006), with freely available remote sensing (RS) data. The method has been used widely to estimate carbon emission within urban environments. However, the method has not been used to assess the amount of the stored carbon change due to fire within urban areas. It would help to understand whether remote sensing-based methodology can be useful for immediately assessing fire-caused ecosystem services loss, particularly the amount of stored carbon, in urban environments for sustainable cities.

## 2. Material and Methods

### 2.1. Study area

Marmaris is a township of Muğla province, located in southwest Türkiye, along the shoreline of the Turkish Riviera. Marmaris, one of the most popular destinations, is a port city and tourist resort on the Mediterranean coast. The total population of Marmaris is 95,849 and during summer, it reaches over 670,000 (TUIK, 2022). Figure 1 showed that there has been an increase trend in population in Marmaris since 2010. Although the growth rate was not changed in 2021, this rate jumped during Covid-19 (especially in 2020).

More than %50 of the Marmaris population is located in Armutalan, Siteler, Cildir, Hatipirimi, Kemeralti, Tepe and Camdibi districts. Thus, the administrative boundary of these 7 districts was used as study area (Figure 2). The total study area was 1,491.12 ha and the dominant tree species was *Pinus brutia* Ten., (Turkish pine) that ranges from Mediterranean to Aegon coasts of Türkiye and very sensitive to forest fires although they are fire adapted species (Boydak et al., 2006).




a b

Figure 1. Population of the Marmaris (a) and the growth rate (b) (TUIK, 2022).


Figure 2. The study area consists of the most populated seven districts of Marmaris township.

Tourism is one of the primary sources of income for Marmaris. Total number of tourists in 2021 was more than 3.2 million (Muğla İl Kültür ve Turizm Bakanlığı, 2022). Since the early 1960s, many touristic places, such as hotels, motels, and resorts, have been built to encourage tourism activities in the city with government support (Arslan, 2021). It led to the converting of green areas into developed areas and an uncontrolled increase in human activities in those areas.

### 2.2. Data

In this study, remote sensing-based methodology with freely available remote sensing (RS) data was employed to assess stored carbon change due to forest fire that caused Above Ground Biomass (AGB) loss. Hence, Landsat 8 Operational Land Imager (OLI) satellite images were used to assess stored carbon change due to forest fire. Two Landsat 8 OLI images were selected to represent pre and post Marmaris fire, occurred between July 29$^{th}$, 2021, and August 7$^{th}$, 2021. While selecting images, the cloud condition and smoke haze on the images was considered. Landsat 8 OLI images taken on May 26, 2021, and August 30, 2021, were used in this study as pre-fire and postfire images, respectively. Landsat 8 OLI images consist of nine spectral bands in the visible, near infrared, and shortwave infrared portions (VNIR, NIR, and SWIR) of the spectrum with a spatial resolution of 30 meters for Bands 1 through 7 and 9 that was employed in this study. The data were downloaded from the United States geological Survey (USGS) webpage (https://earthexplorer.usgs.gov/) for path: 179 and row:35. USGS has developed research quality and analysis ready products from the Landsat images. The data used in this study is level 2 science products, meaning already preprocessed and ready for analysis (i.e., radiometric and atmospheric corrections) (Chander et al., 2009).

In addition, the boundary of study area (administrative the boundary of seven districts) was obtained from Marmaris municipalities as a. *shp* file. Marmaris forest management plan was obtained from Marmaris Forest Management Enterprise. The plan provides the stand volume that is used to estimate above ground carbon from AGB in forested areas.

## 2.3. Methods

In the sections below, estimating stored carbon from RS-based method, including delineating the burned area and estimate carbon loss within that area, are described as showed in workflow of the study (Figure 3).

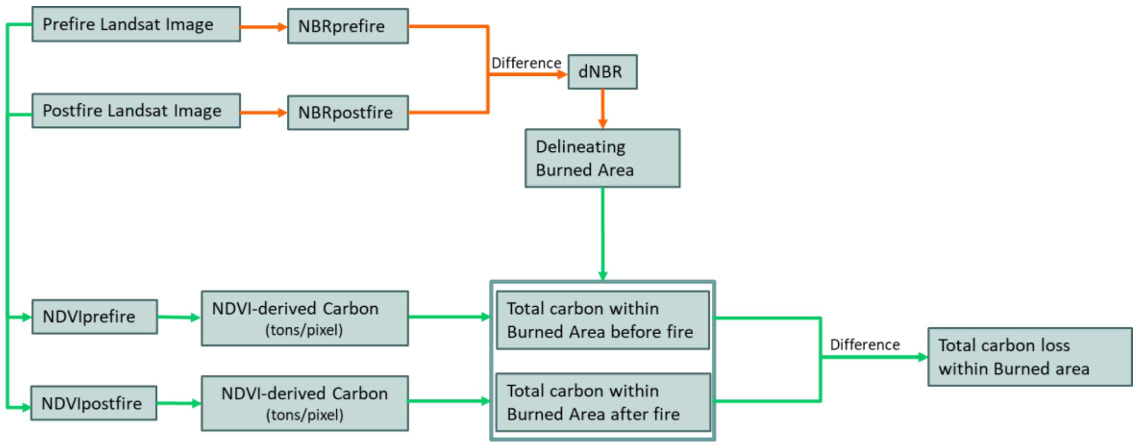



Figure 3. The workflow of the study.

### 2.3.1. Estimating stored carbon from RS-based method

In order to quantify the amount of stored carbon within the study area, we first need to quantify vegetation greenness. Normalized Difference Vegetation Index (NDVI) is a simple indicator that measures the amount and vitality of vegetation on land surface. NVDI is commonly used to determine biomass, photosynthetic capacity of vegetation, and vegetation health (Tucker 1979). Also, it has been widely used vegetation index in urban environments for distinguishing vegetation from non-vegetated areas such as water, bare soil and developed areas (Myeong et al., 2006; Chen et al., 2012; Dobbs et al., 2014; Hastuti et al., 2018; Ucar et al., 2018; Tonyaloğlu, 2020). NDVI is calculated for each pixel in satellite imagery from NIR band, where vegetation strongly reflects, and the red band, using following formula (Rouse et al., 1974):

$$NDVI = (NIR - RED) / (NIR + RED) \quad (1)$$

NDVI values range between -1 and +1, and higher NDVI values indicate a large amount of green vegetation (Chen et al., 2012). In this study, two Landsat 8 OLI images, before and after the Marmaris fire, were used to calculate NDVI. Then, these Landsat-derived NDVIs were used to calculate stored carbon in vegetation along with an existing model developed by Myeong et al. (2006). The model was designed explicitly for urban vegetation and has been validated with field data. That is why we selected the boundary of the heavily populated district as a study area rather than for the entire Marmaris sub-city boundary. Also, this spatially explicit model has been used earlier in different cities to calculate the stored carbon in urban forests (Myeong et al., 2006; Dobbs et al., 2014; 2018; Tonyaloğlu, 2020; Değermenci, 2023; Shanafelt et al., 2023) using following regression equation (Myeong et al., 2006):

$$Carbon = 0.10702e^{(NDVI*0.0194)} \quad (2)$$

where *Carbon* represents stored carbon (tonnes C / pixel) and *NDVI* is the Landsat-derived NDVI value.

With this model, two carbon maps were generated; one was before the Marmaris fire, and the other was after the Marmaris fire.

Also, generated NDVI map for before fire was used to classified forested area within study area. In order to distinguish urban vegetated areas from impervious surface, a threshold for NDVI values needs to be determined. In general, NDVI values is 0.2 or greater is suggested (McBride, 2011; Chen et al., 2012). However, when we applied this threshold, it did not clearly differentiate woody vegetated areas from impervious surface. Thus, 0.23 was selected as threshold value for classification of urban woody vegetation within the study area after visual assessment.

### 2.3.2. Delineating burned area

The total burned forested area within our study area were determined with Normalized Burn Ratio (NBR) index to assess the amount of stored carbon only in burned urban forested areas. NBR is a commonly used index to highlight burned areas in large fires and provide a measure of severity. The formula of NBR is quite similar to NDVI, but it combines NIR, where healthy vegetation has high reflectance in NIR band and low reflectance in SWIR band. In contrast, burned areas show low reflectance in NIR band and high reflectance in SWIR band. Thus, it is calculated by using ratio between NIR and SWIR bands (Key and Benson, 1999; Key et al., 2002; Escuin et al., 2008; Keeley 2009; Picotte and Robertson, 2010):

$$NBR = (NIR - SWIR) / (NIR + SWIR) \quad (3)$$

NBR with high values represents healthy vegetation while a low NBR value indicates bare ground or recently burned areas.

The difference between the pre and post fire NBR derived from satellite images has been used to calculate the differenced Normalized Burn Ratio (dNBR), which is a powerful tool for successfully mapping burned area and relative burn severity. The following formula is used to calculate dNBR:

$$dNBR = PrefireNBR - PostfireNBR \quad (4)$$

The value of dNBR varies depending on the case, but the higher value of dNBR indicates more severe damage while the lower dNBR indicates less severity. For this study, firstly, the prefire NBR and postfire NBR were generated using Landsat images and then they were used to calculate dNBR. Secondly, the total burned area within the study area boundary was delineated by classifying dNBR as burned and unburned areas using threshold values. A study by Rahman et al. (2018) suggested that a dNBR value of + 0.1 is an appropriate threshold for differentiating burned from unburned areas. In our study, the dNBR value ranged from – 0.7066 to + 0.6897 and after visual comparison, + 0.1261 was used to avoid false positives. Nevertheless, some salt and paper effects were observed in this classification (misclassified isolated pixel). Post-classification processes were applied in ArcGIS 10.8.x to accurately delineate the boundary of burned area. After that, the zonal statistic was applied to determine the Min, Max, and Mean value of Carbon (tons/pixels) in the delineated burned area using the carbon map, calculated from NDVI based remote sensing model. Last but not least, the amount of carbon in pixels estimated from before and after fire NDVI based remote sensing model were summed for entire burned forest area obtained from the dNBR to estimate stored carbon change within urban environment due to fire.

## 3. Results and Discussion

After reclassifying NDVI (only used before fire), estimate of total urban forested area within our study area was 783.99 ha, and it was 47% of entire study area. The effect of the fire on urban forest were clearly seen in the southwestern part of the study area. In Figure 4, before the fire, healthy functioning urban forest at the southwestern part of the study area, indicating higher NDVI values, were represented in green color on the map. However, after the fire, the lower NDVI value was observed within same areas, green color was obviously turned into red color. It means that urban forest at the southwestern part of the study area were lost ability to capture and sequestered carbon.

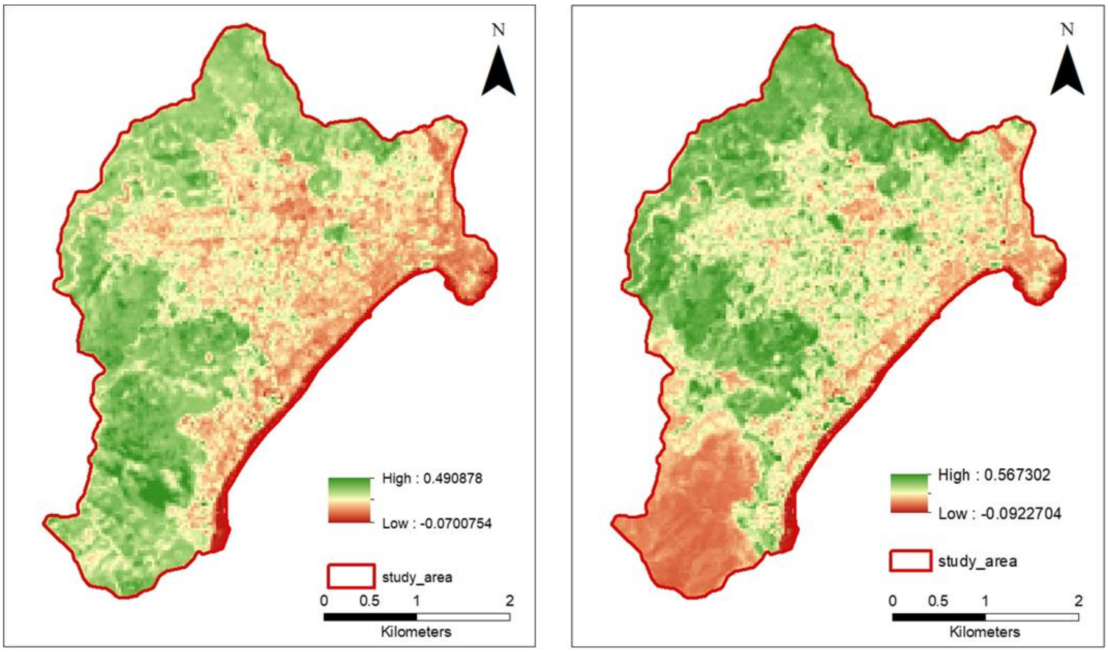



Figure 4. NDVI maps before (left) and after fire (right).

Total burned area delineated from dNBR map was 249.66 ha (Table 1 and Figure 5). Total burned area covered 20% of the entire study area and 32% of the urban forested area within the study area. Total stored carbon was estimated by summing the mean value of stored carbon (tons/pixel) within the burned urban forest area for both before and after fire. Then, stored carbon change of urban forest due to the fire was estimated as 2.23 tons in ha (Table 1). It was estimated that there was an 3.25% decrease in total stored corbon due to urban forest lost during fire. Our estimation for stored carbon map, derived from satellite image based NDVI, showed that the maximum value of the stored carbon (tons/pixel) within study area was quite similar when compared to before and after fire (Figure 6a and 6b). However, the minimum value of the stored carbon (tons/pixel) within the study area were reduced (Table 1). A similar trend was observed for the mean value of the stored carbon (tons/pixel).

Table 1. Estimated stored carbon change due to forest fire within urban forest in Marmaris.

| | **Burned Area** (as pixel) | **Burned Area** (ha) | **Min** (tons/pixels) | **Max** (tons/pixels) | **Mean** (tons/pixels) | **Total C*** (ha) |
|---|---|---|---|---|---|---|
| **Before Fire** | 2774 | 249.66 | 0.2808 | 0.2874 | 0.2852 | 71.20 |
| **After Fire** | 2774 | 249.66 | 0.2596 | 0.2852 | 0.2762 | 68.97 |

*Total C (ha): Total carbon storage was estimated by summing carbon storage values (Mean) for all pixels after converting pixel to ha (1 pixel = 0.09 ha) in the study area.

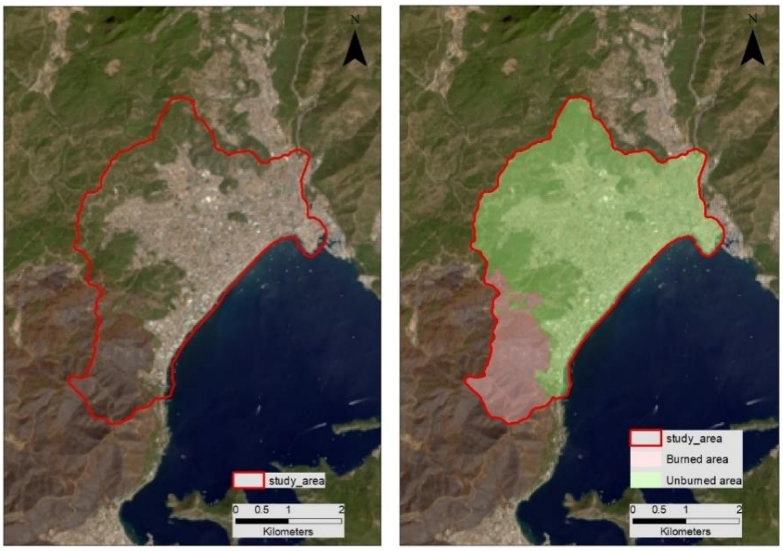



Figure 5. Burned area within study area (left - RGB), total burned area and unburned area delineated by classifying dNBR within study area.

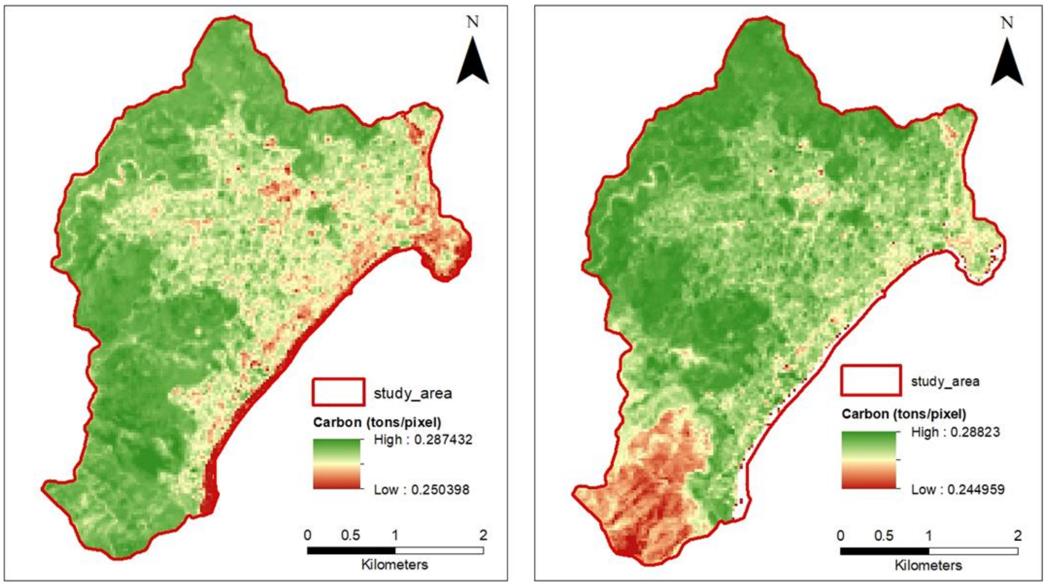



Figure 6. Total carbon amount estimated from NDVI derived model within study area before and fire. a) stored carbon (tons/pixel) map before fire, and b) stored carbon (tons/pixel) map after fire.

Terrestrial ecosystems are an important and dynamic component of the global carbon cycle. In particular, carbon emission in an urban environment consumes around 70% of global energy and emits more than 71% of $CO_2$ worldwide. Urban forests are the main component of the urban environment by providing many ecosystem services, especially sequestering and storing carbon. In addition to the interactions between human activities and land use land cover change, natural disturbances, such as fire, and its recovery dynamic are controlled carbon balance in urban environment. Hence, mapping and assessing ecosystem services in dynamic urban environments are key elements for sustainable cities (Dobbs et al., 2018). Many studies have been integrated and used RS technology in mapping and monitoring carbon stores, sinks, and sources in the forests (Krankina et al., 2004: Turner et al., 2004; Wicaksono et al., 2011; Baccini et al., 2012; Vicharnakorn et al., 2014; Hastuti et al., 2018; Keles et al., 2021; Vatandaslar and Abdikan 2022). They pointed out that integration of RS technology into the methods offers a promise for monitoring and mapping carbon at spatial and temporal scale. It is also time and cost effective.

In this study, we employed the RS-based methodology developed by Myeong et al. (2006) that related AGB and NDVI to estimate and map carbon stock loss in urban environment of Marmaris due to forest fire. Although trees are the main carbon sink even after fire maintaining the carbon, they lose ability to capture carbon due to losing their leaves. Thus, the study mainly focused on assessing the amount of stored carbon change using AGB change. The method has been used by many researchers to estimate dynamics of urban ecosystems services. For instance, Dobbs et al. (2014; 2018) applied this method to explore temporal dynamics of urban vegetation ecosystem services, Hutyra et al. (2011a; and 2011b), Tonyaloğlu (2020) and Değermenci (2023) used the method to address impact of urban expansion on terrestrial carbon stock. They stated that carbon models based on NDVI are affected by vegetation conditions and cover. Similar to previous studies, our results also showed that because of forest fire, woody vegetation lost green canopy cover or affected the health condition of vegetation where photosynthetic activity takes place. Thus, there was a 3.25% decrease in total stored carbon in the study area.

Urbanization causes carbon loss in above-ground biomass (Hutyra et al., 2011b) by disturbing trees. In addition, natural disasters such as fire release $CO_2$ into the atmosphere in a short period compared to urbanization, resulting in a fast decline in the net sink of carbon in urban areas (Climate Action Reserve, 2014). Thus, it is important to estimate the size of the affected area and total carbon loss accurately and quickly after a natural disaster. Remote sensing technology, which offers a variety of spatial and temporal continuous data, has been increasingly used to assess and monitor ecosystem services in forested areas and urban environments. For instance, a study by Picotte and Robertson (2010) pointed out that the use of dNBR methods derived from RS data is useful for monitoring burned areas due to fire and is also cost-effective. Similarly, a study by Key and Benson (1999) demonstrated an additional advantage of the dNBR method: the ease and reliability of delineating burn perimeters. Lately, the dNBR method derived from different satellite image sources has been widely used to estimate burned areas immediately after fires. Thus, the burned area perimeter before and after fires was delineated for this study using the dNBR method derived from Landsat images.

However, there are some limitations, such as data availability, quality, and quantity for estimating and monitoring ecosystem services in urban environments. This study showed that using satellite images (30 x 30 m pixels), which are freely available and accessible worldwide, makes it easy to examine changes in ecosystem services due to urbanization and natural disasters. In urban ecosystem services assessment studies, the data resolution, with 30 x 30 m pixels, can make it challenging to identify heterogeneous characteristics of urban environments, such as differing grass from forest areas or buildings and trees that can be located within the same cell. However, it was not an issue in this study because the fire occurred in a homogenous forested area adjacent to developed areas and did not scatter. In addition, it needs to be emphasized that the model was developed based on temperate urban forests and only considers three above-ground carbon estimated from AGB. Our study area is located in a temperate urban forest zone, but the lack of estimated carbon stack from ground inventory data to compare the accuracy of the model could be counted as another limitation. To improve the accuracy of estimation and mapping stored corban, it would be better to develop local models using inventory data with finer resolution RS data.

## 4. Conclusion

Today, urban areas and cities represent a small proportion of the world; however, they are responsible for about 70% of the world's energy consumption and more than 71% of the world's CO2 emissions. Also, there is a continuous change in urban ecosystems at local, regional, and global levels due to urbanization dynamics. Urban woody vegetation in urban environments provides many ecosystem services, particularly reducing carbon emissions in urban areas by storing carbon. In addition to urbanization, natural disasters, such as wildfires, have a huge impact on urban ecosystem services provided by urban woody vegetation. This study aimed to explore and address the spatio-temporal variation of ecosystem services in urban areas due to natural disasters using the RS-based method. The results of the study provide insight into the consequences of unexpected forest fires in urban environments by providing a rapid estimate of stored carbon loss. This explanatory study allows us to better understand the role of urban vegetation in urban ecosystem services using RS-based methodology. Thus, authorities, planners, and policymakers can take immediate action using the results from the RS-based method to reverse the changes in urban environments by planting new trees in urban areas or reforestation the burned areas. The results from this study showed that the method can be applied for fast and easy calculation of stored carbon loss due to fire. However, future studies need to integrate ground inventory data with finer-resolution images to develop a new method at the local scale.

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