Applying Remote Sensing, Google Earth Engine, and Machine Learning to Predict the Carbon Sequestration Potential of Sundarbans Mangroves

ABSTRACT

Mangrove forests are pivotal in mitigating climate change impacts due to their exceptional carbon sequestration capabilities and their role as carbon sinks. Mangroves are designated blue zones, storing two to four times more carbon dioxide than global rates observed in mature tropical forests. This study utilizes both radar (Sentinel 1) and optical (Sentinel 2) remote sensing datasets. It compares various machine learning algorithms, such as Random Forest, SVM, and CART, to predict the mangrove distribution and allometric equations to estimate the aboveground biomass and the amount of carbon sequestration for the Sundarbans mangrove forest without requiring time-consuming field measurements. It was found that the Random Forest machine learning classifier yielded the highest accuracy of 0.984 with a Kappa metric of 0.962. Using this classifier, the aboveground biomass was calculated to be 125 Mg/ha and the amount of carbon sequestration was 257 Mg/ha per year. The aboveground biomass found was consistent with prior studies using traditional field work. The carbon sequestration values will aid in highlighting the importance of mangroves as blue-carbon storages and help in accurately monitoring and preserving these vital ecosystems efficiently on a global scale.

Keywords: Mangrove forests,Remote Sensing, , Google Earth Engine,climate change impacts

INTRODUCTION

Mangrove forests are essential to life on earth for their unique carbon sequestration abilities which aids in mitigating the negative effects of climate change. They are characterized as blue carbon zones and contain 2 to 4 times more carbon dioxide than tropical forests. This study uses machine learning and remote sensing on the Google Earth Engine platform to estimate the carbon sequestration of mangroves in the Sundarbans, a mangrove forest in India. The traditional method of classifying remote sensing images by scene is laborious and ineffective. Google Earth Engine (GEE) is a cloud-based framework for efficiently accessing and processing vast amounts of publicly accessible satellite imagery. Additionally, the GEE offers a collection of the most advanced pixel-based classifiers available, which can be applied to mangrove mapping (Kamal et al., 2019). This study eliminates the need for field work by using global mangrove datasets, machine learning classifiers, vegetation indices and allometric equations to predict the aboveground biomass as well as carbon sequestration of the mangrove forest. The carbon sequestration values will aid in highlighting the importance of mangroves as blue-carbon storages and help in accurately monitoring and preserving these vital ecosystems efficiently on a global scale.

Research in various regions has demonstrated the accuracy of machine learning models in predicting mangrove distribution. A study used Google Earth Engine to compare machine learning algorithms for mangrove mapping. This study was conducted in Indonesia (Kamal et al., 2019). Another study in India, estimated the carbon sequestration potential for agroforestry systems. The study used the CO2FIX model to estimate the carbon stocks (Ajit et al., 2016). Random forest as a machine learning classifier has also been widely used in this field. A phenology based study classified coastal mangroves using Sentinel-2 data in Hatiya (Mahmud et al., 2022).

The main objective of this study is to eliminate the need for traditional, time-consuming, and expensive field work by utilising remote sensing and satellite data to calculate mangrove carbon sequestration. This is achieved using machine learning techniques for mangroves in the Sundarbans region.

BACKGROUND

Mangroves

Mangroves are ecosystems found in coastal regions, in tropical and subtropical areas, primarily between the land and the sea. Recognized for their salt-tolerant trees and shrubs with intricate root systems, they are known for their remarkable ability to adapt to tough conditions, including high salinity, extreme tides, and anaerobic soils. These ecosystems play an important part in coastal protection, conservation, and carbon sequestration. Additionally, they serve as natural barriers against erosion and storms, nurseries for a myriad of marine species, and vital carbon sinks. Despite their importance, mangroves are under threat from deforestation, pollution, and climate change, making their conservation a global priority.

Carbon sequestration

Mangrove forests can store 4 times more carbon than normal forests can. Mangroves are powerful natural systems for capturing and storing carbon, a process known as carbon sequestration, which is vital in the fight against climate change. This carbon storage ability of mangroves not only helps reduce the amount of greenhouse gasses in the atmosphere but also aids in identifying the importance of preserving and restoring mangrove forests. As they face threats from deforestation, pollution, and climate change, protecting mangroves is essential for maintaining their critical role in carbon sequestration and in mitigating climate change. The mangrove biomass is a vital tool in calculating carbon sequestration. Biomass estimation can be done using three different methods, such as modeling, field measurements, and remote sensing.

Remote Sensing

Using remote sensing technology in mangrove ecosystems represents an innovative approach to environmental monitoring, offering crucial insights into these critical coastal habitats. Through the use of satellite imagery, both radar and optical, as well as aerial photos, remote sensing facilitates the comprehensive mapping, monitoring, and change detection of mangrove forests over expansive and often difficult-to-access areas. This technology emphasizes the need for effective conservation and management strategies.

Sentinel Data

The European Space Agency launched the Sentinel satellite series, which offers high-quality, free data for Earth observation. These satellites take pictures and gather information on the land, seas, and atmosphere of our globe. Sentinel-1, for instance, is an excellent tool for mapping sea ice and monitoring floods since it can see through clouds and darkness using radar. Sentinel-2's ability to take vivid pictures of the planet's surface makes it easier to monitor changes in the amount of flora and land used.

Machine Learning

Measuring mangrove biomass using machine learning represents an innovative approach that combines remote sensing data, such as satellite imagery, with machine learning algorithms to predict the mangrove vegetation in mangrove ecosystems. This method is critical for understanding carbon storage and mangrove distribution for the region. Machine learning operates on pixel-level data and offers an efficient method for estimating mangrove distribution over large areas and time periods. By automating the analysis of complex remote sensing data, machine learning enables highly detailed assessments that would not be possible through traditional field work.

Geographic Information System

A geographic information system (GIS) is a computer-based information tool used to address intricate planning, management, and research problems. It is capable of capturing, storing, manipulating, analysing, and displaying both geographical and non-spatial data. GIS is a powerful tool to perform spatial analysis to evaluate feasibility and optimise location (Shi et al. 2008).

Google Earth Engine

Google Earth Engine (Gorelick et al, 2017) is a cutting-edge calculating platform that enables scientists, researchers, and developers to analyze and visualize large datasets of satellite imagery and geospatial data over time. It provides access to a massive archive of historical and real-time Earth observation data, including satellite imagery, elevation data, and climate and weather datasets. This platform is designed to process and analyze the data at scale, especially remote sensing data. Traditional geographic information systems (GIS) do not allow the concatenation of datasets. This is where Google Earth Engine is a useful tool, especially for analysing large remote sensing datasets (Butler 2006).

MATERIALS AND METHODS

Sunderbans: Study Region

The largest mangrove ecosystem in the world and one of the most biologically productive natural settings is the Sundarbans Forest, which spans an area of about 10,000 square kilometers. The Sundarbans, located in West Bengal, is known to contain the single largest block of tidal halophytic mangrove forest globally. This forest contains a significant portion of the world's mangroves and contributes substantially to the carbon sequestration of mangroves. (Rodda and Thumaty, 2022). Mangroves account for only approximately 1% (13.5 Gt year-1) of carbon sequestration by the world's forests, but as coastal habitats, they account for 14% of carbon sequestration by the global ocean. (Alongi et al., 2014). This remarkable ecosystem spans across parts of Bangladesh (about 60%) and India (about 40%), providing critical habitat for many different species. Within its network of tidal waterways and islands, the Sundarbans support an estimated 334 species of trees, shrubs, and epiphytes, showcasing their rich biodiversity. The mangroves play a vital role in storing carbon. Despite the ecological value and protective services provided by the Sundarbans, the area is under considerable threat. Climate change, rising sea levels, and human activities all put a lot of stress on the environment and people. This situation underscores the urgent need for ongoing conservation and sustainable management efforts to ensure the survival of this natural treasure and its biodiversity for future generations. Mangrove deforestation is happening at a rate of 0.39% per year globally (Hamilton and Casey, 2016). Despite their importance, mangroves are under threat from deforestation, pollution, and climate change, making their conservation a global priority.

Data Sets

The input dataset was created by merging “Sentinel 1 radar and Sentinel 2 optical data for 2022 at 10 m resolution through Google Earth Engine” for the Sundarbans mangrove area. Combining both of these data types serves to deepen insights into mangrove ecosystem changes throughout different seasonal cycles (Ghorbanian et al., 2021).

The Sentinel 1 dataset has information from a Synthetic Aperture Radar (SAR) instrument with dual polarization that works at 5.405 GHz (C band). Level-1C ground range detected (GRD) images with 10 m spatial resolution for the year 2022 were utilized in this study. Two samples of this dataset are taken to represent the wet (March–September) and dry (October–April) seasons by applying a median reducer to the images for these periods. The prior median images were combined to create a composite image. There were

For this study, the Sentinel 2 Level 2 dataset (GEE Image Collection ID:

COPERNICUS/S2_SR_HARMONIZED), which has undergone atmospheric correction and is in the corrected geometric and radiometric form, is utilized as a baseline. The Sentinel 2 data is corrected with a “Bidirectional Reflectance Distribution Function” (BRDF) to get rid of BRDF effects that are too big to ignore in the visible, near-infrared, and short-wave infrared bands (Roy et al, 2017). This is followed by applying a cloud cover correction (filtering all image pixels with a cloud cover percentage higher than 20%, followed by applying a cloud masking function) to the preceding BRDF corrected data for the year 2022. Finally, the median value of this corrected data across the various bands is used for subsequent processing (Cardille et al., 2023).

There were 4000 elements and 87 columns in the dataset. The data points were in the form of pixels.

The Sentinel-2 multispectral bands chosen for Vegetation Index band computation are: Blue, Green, Red, RedEdge1 (705 nm central wavelength), and NIR based on Baloloy et al. (2018).

Approach

Figure 1 shows the methodology this study follows to predict carbon sequestration.
(2018)

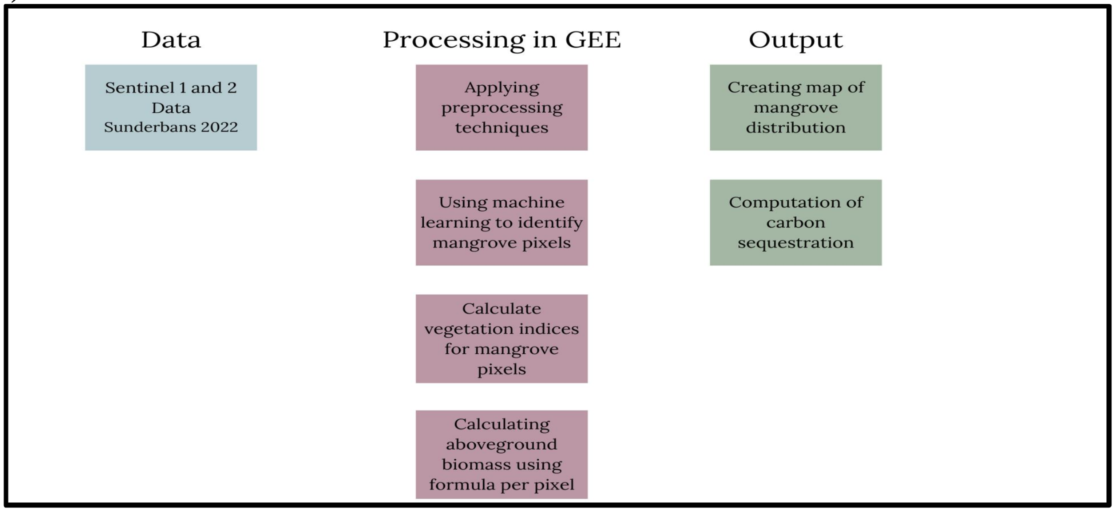


Figure 1: Methodology

Preprocessing

The preprocessing techniques include water making, land masking, and removing places with elevations greater than the mangrove threshold to create a mangrove buffer. This reduces the search area to classify mangroves and improves the accuracy of the machine learning algorithms (Ghorbanian et al., 2021). Figure 1 shows the sequence of preprocessing

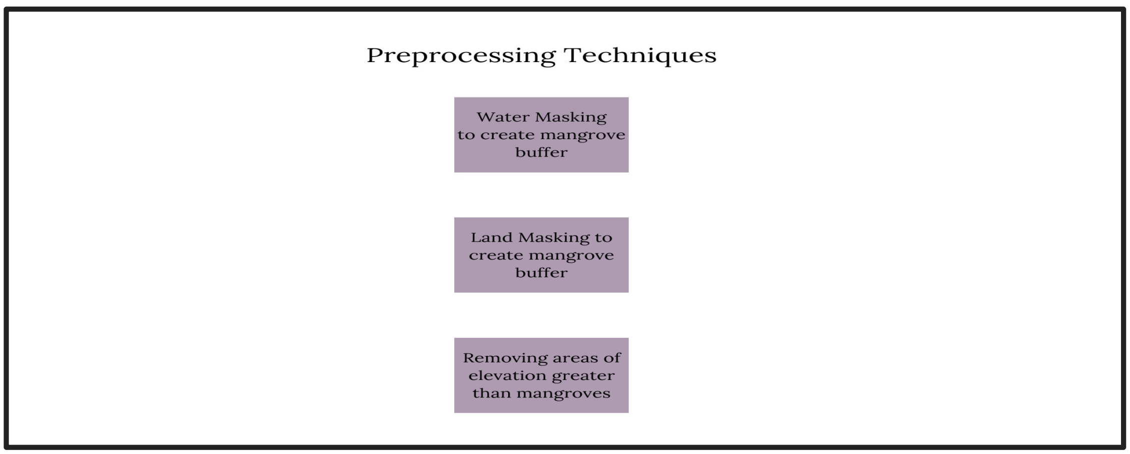


Figure 2: Preprocessing techniques

Prediction of Mangrove Coverage using Machine Learning

This study compares various supervised machine learning algorithms to predict mangrove coverage from remote sensing data using a pixel-based classification mechanism. Specifically, algorithms for a "Random Forest, Support Vector Machine (SVM), and Classification and Regression Trees" (CART) were utilized to predict the pixel area over which mangroves are present. The classifier with the maximum accuracy on the test data will be used to determine mangrove coverage and values used for subsequent processing. The problem statement requires classifying pixels into mangrove and non-mangrove areas; hence, these machine learning algorithms were chosen for their classification abilities as well as their high performance. These algorithms are also present on the Google Earth Engine platform without additional coding.

This is an algorithm for machine learning called Random Forest. It can be used for both classification and regression. It belongs to the group of learning categories where multiple models are combined to solve a problem, typically resulting in improved performance compared to a single model.

A Support Vector Machine (SVM) is a supervised method used mainly to classify, but it can also be used for regression.

A decision tree algorithm called "Classification and Regression Trees" (CART) can be applied to tasks involving both regression and classification predictive modeling. It is used for important machine learning methods, including bagging, random forest, and boosted decision trees.

These 3 algorithms were utilized to predict the mangrove coverage in the Sundarbans region, which aided in calculating the aboveground biomass.

Training and Testing of Machine Learning Models

Supervised training entails the use of training data to distinguish between mangroves and non-mangrove areas. One way of creating Labeled data is by utilizing experts to mark appropriate areas on the map that represent mangroves/non-mangroves. However, a less onerous approach is to use a pre-classified global mangrove landsat dataset as a reference to train the model. In this study, a Landsat mangrove dataset from 2000 (Giri et al., 2010) was used. This made training the model much easier and eliminated the need to manually create labels for the figures.

Vegetation Indices

The vegetation indices below were calculated for areas that were predicted to contain mangroves using the aforementioned machine learning models.

NDVI

The Normalized Difference Vegetation Index (NDVI) uses satellite data bands. This index assists in recognising vegetation such as mangroves, which is achieved in this study.

NDVI= (NIR+Red)/(NIR−Red)
Where:
NIR stands for "reflectance in the near-infrared" spectrum.
"Red" refers to reflection in the red portion of the spectrum.

This formula leverages the fact that good vegetation absorbs a lot of visible light (particularly in the red wavelength) for photosynthesis and reflects a larger part of the near-infrared light. Higher values indicate healthier and denser green vegetation. The NDVI values range from -1.0 to 1.0.

Simple Ratio

The Simple Ratio Vegetation Index (SRVI) is another vegetation index used to evaluate the density and health of vegetation using remote sensing data. Like NDVI, SRVI makes use of the variations in vegetation's reflectance characteristics in the red and near-infrared (NIR) regions of "electromagnetic spectrum". However, unlike NDVI, SRVI simply takes the ratio of these two measurements. The formula for SRVI is:

SRVI= NIR/Red
Where:
NIR is the reflectance in the near-infrared spectrum.
Red is the reflectance in the red portion of the spectrum.

Red edge Simple Ratio

The Red Edge Simple Ratio (SRre) is a vegetation index that focuses on the "red edge" spectral region, the narrow band in the electromagnetic spectrum. The red edge position is responsive to changes in chlorophyll concentration, making it a useful indicator for assessing biomass.

The Red Edge Simple Ratio is typically calculated as the ratio of reflection in the NIR, or near-infrared, band to reflection in a reds-edge band. While the exact wavelengths used can change depending on the sensor and the application, a general form of the RESR can be represented as
SRre= NIR/RedEdge
Where:
NIR is the reflectance in the near-infrared spectrum, usually around 800 nm to 850 nm
RedEdge is the reflectance in the red-edge region, often around 680 nm to 730 nm.

Estimation of Aboveground Biomass (AGB)

The aboveground biomass of a mangrove includes the total mass of living vegetation, including stems, branches, bark, and foliage, located above the soil surface within a mangrove ecosystem. The aboveground biomass (AGB) is calculated using allometric equations involving the vegetation indices for areas classified as mangroves using the best machine learning model. Figure 3 shows the allometric equation (Baloloy et al., 2018) used for this calculation.

Vegetation index	Formula	Reference
Normalized Difference Vegetation Index (NDVI)	*(NIR-R) / (NIR + R)*	Rouse et al, 1973
Simple ratio (SR)	*NIR/R*	Jordan

Satellite Data	Model and Basis Functions
Sentinel-2	*y* = *5.54388 - 0.384761 * BF2 - 1.25011 * BF3 - 1.37807 * BF4+ 9.34749 * BF6 - 0.0339066 * BF7 - 0.69426 * BF8+ 23.3997 * BF9 + 82.4958 * BF10* ***BF2*** = *max(0, 19 - SR);* ***BF3*** = *max(0, SRRE - 2.75);* ***BF4*** = *max(0, 2.75 - SRRE);* ***BF6*** = *max(0, 0.747658 - NDVI);* ***BF7*** = *max(0, SR - 10.5) * BF3;* ***BF8*** = *max(0, 10.5 - SR) * BF3;* ***BF9*** = *max(0, NDVI - 0.747658) * BF8;* ***BF10*** = *max(0, 0.747658 - NDVI) * BF8*

Figure 3 Formula for the calculation of AGB

Estimation of carbon sequestration

The Amount of Carbon Sequestered (ACS) by the mangroves is derived from the Above Ground Biomass (AGB) values using equations (Suardana et al, 2022). Only the AGB values for pixels that are classified as mangroves by the machine learning model are utilized for subsequent computation of the ACS. The calculation for carbon sequestration is as follows:

First belowground biomass is calculated using the aboveground biomass (Cairns et al., (1997).

$BGB = exp(-1.0587 + 0.8836 * Ln(AGB))$

Then carbon sequestration is calculated from the total accumulated biomass

$TAB = ABG + BGB$

TCS can be “calculated using the equation developed by “Westlake, (1963) shown below:

$TCS = TAB * \%\ COrganic$

TCS = the value of total carbon stock (Mg/ha), TAB = the value of total accumulated biomass (Mg/ha)

The carbon sequestration is found using the equation by the IPCC, (2001) below:

$ACS = 3.67 * TCS$

ACS = the “Amount of CO2 Sequestration (Mg/ha), TCS = the value of total carbon stock” (Mg/ha).

Results and Discussion

Each of the machine learning classifiers yielded a certain accuracy on the test/validation set. Those are shown in Table 1 below.

Table 1 depicts the accuracy of the machine learning algorithms Random Forest, Support Vector Machine and CART

Machine Learning Algorithm	Test Accuracy	Error

Random forest	0.984	0.016
SVM	0.982	0.018
CART	0.980	0.020

These figures are quite high in comparison to other studies in this field. A study from Kamal et al. (2019) resulted in 0.66 accuracy for SVM, 0.57 for Random Forest and 0.61 for CART.

Figure 4 shows the accuracy of each machine learning algorithm and a visual representation of the classification of mangroves.

SVM

Random Forest

CART

Orange: actual
Green: predicted

Orange: actual
Green: predicted

Orange: actual
Green: predicted

Figure 4: Mangrove biomass distribution map

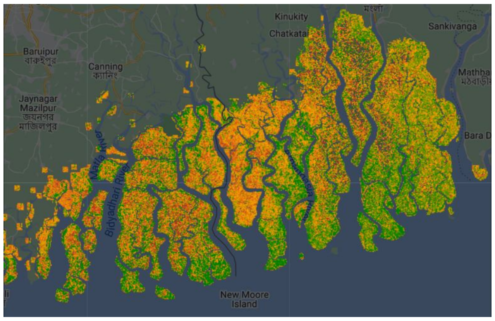
Figure 4 depicts the mangrove biomass distribution predicted by the machine learning algorithms. As shown in Table 1, all three classifiers displayed high accuracy; the random forest classifier was chosen for the calculation of the aboveground biomass as it was the most accurate. The Kappa score for the RF classifier was 0.9640, which was also acceptable. The high Kappa metric indicates a near-perfect machine learning model performance for predicting mangrove distribution, depicting the significance of the value (Mchugh 2012).

Table 2 depicts the values for the calculations stated in the methodology.

Aboveground Biomass	125 Mg/ha
Belowground Biomass	25 Mg/ha
Total Accumulated Biomass	149 Mg/ha
Total Carbon Stock	70 Mg/ha per year
Mean Carbon Sequestration	257 Mg/ha per year

The aboveground biomass value was consistent with a study (MdSaidur Rahman *et al*, 2021), where the values were in the range of 111.36 Mg/ha and 299.48 Mg/ha.

Figure 5 below depicts the distribution of the AGB in the Sunderbans and Figure 6 depicts the actual carbon sequestration distribution for the Sunderbans



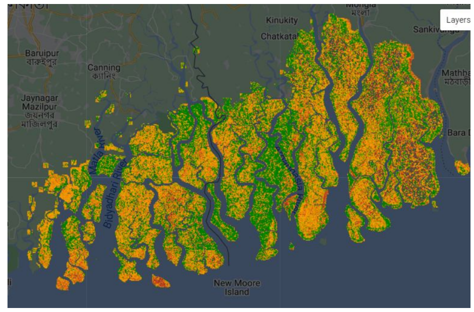


Figure 5: AGB Distribution
Brown: <60 Mg/ha
Yellow: 60–130 Mg/ha
Green: 130+ Mg/ha

Figure 6: Amount of carbon Sequestration
Brown: <130 Mg/ha
Yellow: 130-230 Mg/ha
Green: 230+ Mg/ha

Figures 5 and 6 show the aboveground biomass and carbon sequestration distribution based on the machine learning model predictions for the distribution of biomass.

CONCLUSION

The carbon sequestration value will aid in highlighting the importance of mangroves as blue-carbon storages and the conservation of these ecosystems. Acknowledging the significance of these coastal ecosystems as carbon reservoirs can catalyze conservation efforts and enhance their protection.

The current study uses remote sensing data and machine learning on Google's Earth Engine cloud platform to automatically predict mangrove distribution and allometric equations for the determined mangrove area, allowing the carbon sequestration potential of mangrove forests to be calculated without the need for fieldwork. Considering that the forecasted figures align with those from previous field research, this automated approach proves to be an effective method for globally tracking carbon sequestration levels in mangrove forests. The implementation of this technique can enhance mangrove conservation efforts, contributing to the stabilization of atmospheric greenhouse gas concentrations, thereby mitigating the greenhouse effect and helping to maintain the earth's average temperature.

The aboveground biomass values found were in line with prior studies using traditional field work, thereby validating the results of this study.

Future Work

Use allometric equations based on mangrove type

The species type can be identified, leading to more accurate predictions for aboveground biomass. Using regression analysis to estimate mangrove biomass based on mangrove type involves developing a model that accounts for the unique characteristics of different mangrove species or types. Mangroves vary significantly in their structure, growth patterns, and ecological functions, which in turn affects their biomass.

Monitor mangroves over time

This study can be extended to different years to find how carbon sequestration has differed through time in the Sunderbans.

Automate the machine learning model and allometric equations for easy reuse

Using Google Earth Engine, the methodology for the study can be reused and applied to different datasets for the calculation of mangrove carbon sequestration for any region around the world. A reusable Google Earth Engine App, with an API can be built for this purpose.

Disclaimer (Artificial intelligence)

The author hereby declares that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) or text-to-image generators have been used during the writing or editing of manuscripts.

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