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Original Article

Application of Google Earth Engine to Estimate the Water Capacity of Saigon–Dongnai Basin in the Period of 2005–2023 Using MODIS and CHIRPS Satellite Data

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Abstract: This study used the Google Earth Engine (GEE) platform to calculate the water capacity of the Saigon-Dongnai basin using remote sensing-derived products related to evapotranspiration (ET) and precipitation (P). The GEE was used to retrieve two important inputs: MODIS evapotranspiration spanning the drainage basin and CHIRPS satellite precipitation. We found that there was a net decrease in the water capacity from January to April every year as a result of greater evaporation and less precipitation. Due to the increase of precipitation from May to October following the decrease of solar radiation, and the drop in temperature, the rainy season imposed the highest values of the change in water capacity. Rainfall and evapotranspiration show a positive association, as does the relationship between water capacity and inputting water.

Keywords: Water capacity, evapotranspiration, Google Earth Engine, CHIRPS, MODIS.

1. Introduction

In river basins, water is essential for industrial processes, power generation, food security, and human survival. Water is essential to both terrestrial and aquatic ecosystems in order to deliver important ecosystem services for present and future generations. Managing the complex water flow paths to and from these various water-use industries necessitates a quantitative grasp of hydrological processes. To support water-use management more effectively through retention, withdrawals, and changes in water use, quantitative insights, background data are required.

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The water capacity is the relationship between its input and outflow of water [1]. The capacity between input water by precipitation (P) and outgoing water from evapotranspiration (ET) denoting the sum of evaporation from the land surface plus transpiration from plants, groundwater recharge and soil storage (ΔS) [2], and streamflow (Q) is referred to as the watersheds overall water capacity [3]. In its simplest form, the water capacity can be defined as Eq. (1). Due to urbanization, socioeconomic development, and population growth, there is some cases of a greater demand for water than there is supply among municipal, industrial, and agricultural interests.

$$P = Q + ET + \Delta S \quad (1)$$

Many studies have demonstrated how susceptible the water resources of river basins are to climate change. For examples, during the years 1965–2012 and 1981–2010, respectively, López-Moreno et al., [4] and Hunziker et al., [5] reported temperature increases in the Altiplano of about 0.20 °C decade^{-1}. The effects of long-term temperature increases on the water resources in the northern Altiplano were calculated by Hoffmann and Requena, who concluded that there would be a significant decrease in the amount of water in lakes, rivers, glaciers, and wetlands, particularly during the dry season. Nigatu et al., (2013) [6] examined the components of water capacity, such as surface water intake, over-lake rainfall, and variance in evaporation patterns, and how these factors affected Tana Lake's water capacity in Ethiopia. This analysis was based on three distinct climate change scenarios for future time horizons: the 2020s (2010–2039), the 2050s (2040–2069), and the 2080s (2070–2099). The over-lake evaporation was measured using Hardgrave's approach; the over-lake rainfall was calculated using the inverse distance weighing (IDW) method; and the surface inflows were simulated using the HBV model.

Cloud computing services have been used recently by the Google Earth Engine Platform (GEE) to enable online analysis of satellite data [7]. The Application Programming Interface (API) is used to handle geospatial datasets and enables the development of programs to access datasets containing publicly accessible remotely sensed imagery and other data. Its capacity to quickly evaluate global, regional, and local data makes it a valuable tool for data visualization as a remote sensing platform [8]. Numerous environmental science and earth science-related sectors have applied GEE [7]. Applications of GEE include land studies [9, 10]; agriculture, forestry [11], urbanization [12], wetlands monitoring [13], and disaster analysis [14, 15]. Additionally, GEE has aided in the creation of fresh techniques for mapping and tracking land use/cover, carbon emissions, and other environmental indicators, providing critical insights for sustainable development planning and policy-making.

In this study, we applied GEE to assess the water capacity of Saigon-Dongnai basin in the period of 2005-2023 using Modis evapotranspiration and precipitation Chirps. We're using a simplified study approach to make things more accessible. To calculate water capacity, evapotranspiration outflow will be subtracted from precipitation inflow. We aim to quantify water capacity over time and space by utilizing satellite-based observations of evapotranspiration and precipitation to confirm whether or not there is a difference in water storage capacity over time and space.

2. Data and Methods

2.1. Study Area

Sai Gon - Dong Nai river basin and its surroundings cover an area of approximately 49643.53 km^2 including 11 provinces: Dac Nong, Lam Dong, Binh Phuoc, Binh Duong, Dong Nai, Tay Ninh, Ho Chi Minh City, Long An, Ninh Thuan, Binh Thuan, and Ba Ria Vung Tau (Figure 1) [16]. The impacts of climate change are highly vulnerable to the downstream area of the river basin, including the subbasins of

Go Dau Ha, Ben Luc, Nha Be, Dong Nai, Sai Gon, Ha Dau Tieng and Tay Ninh. Recent river tides have severely impacted the socioeconomic growth of numerous communities downstream of the basin, most in Ho Chi Minh City.

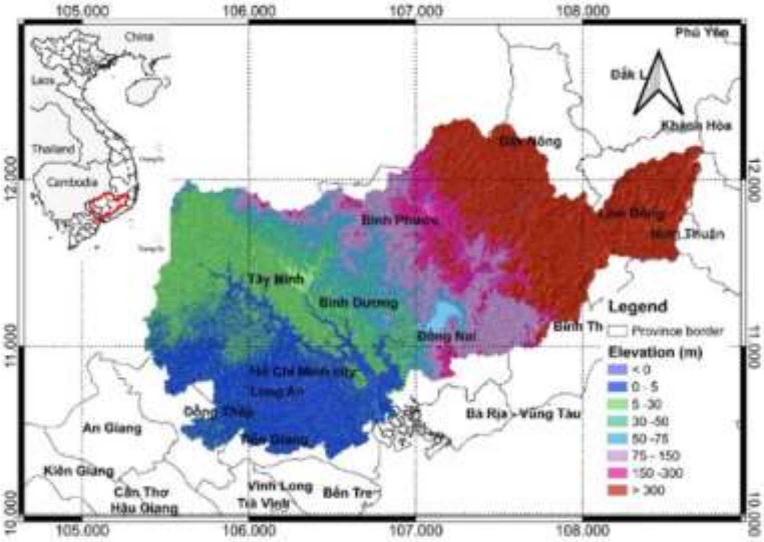


Figure 1. Boundaries of Saigon-Dongnai basin is shared resources among provinces.

2.2. Data

The Saigon-Dongnai basin shapefile data was extracted from Hydrosheds [17].

The Terra Moderate Resolution Imaging Spectroradiometer (MODIS) MOD16A2GF Version 6.1 from NASA; a year-end gap-filled 8-day composite dataset generated at 500m pixel resolution, is the source of the evapotranspiration product (2005–2023) in this study. The MOD16 algorithm is grounded in the logic of the Penman-Monteith equation, which takes as inputs eight-day remotely sensed vegetation property dynamics from MODIS and daily meteorological reanalysis data.

The precipitation used in this study was taken from the quasi-global rainfall dataset, The Climate Hazards Group InfraRed Precipitation with Station (CHIRPS from Climate Hazards Center) data, which spans more than 35 years. Precipitation data at a spatial resolution of 0.5° (~ 5 km) is provided by CHIRPS. The dataset uses satellite data along with information from weather observation stations to estimate precipitation. In hydrology research, CHIRPS data can be quite helpful since it offers a lengthy and reliable time series with precipitation estimates at a relatively high spatial resolution. The data is accessible at intervals ranging from daily to annual.

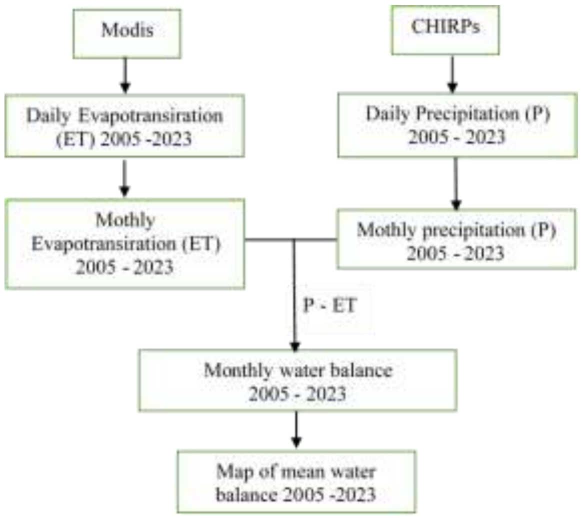


Figure 2. Study approach process.

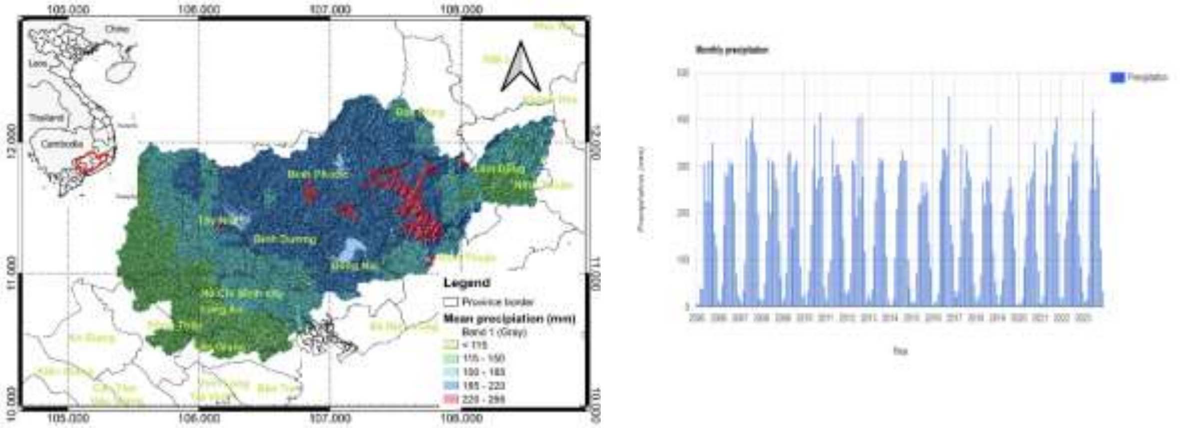
We calculated the portion of Q and ΔS on a pixel level and aggregated that information to the Saigon – Dongnai basin: $P - ET = Q + \Delta S$ where

P is monthly precipitation (mm), ET is monthly evapotranspiration (mm), Q is streamflow (m/s), and ∆S is groundwater recharge and soil storage. Figure 2 described the study approach process. All calculations and graphics were performed in GEE.

3. Results and Discussion

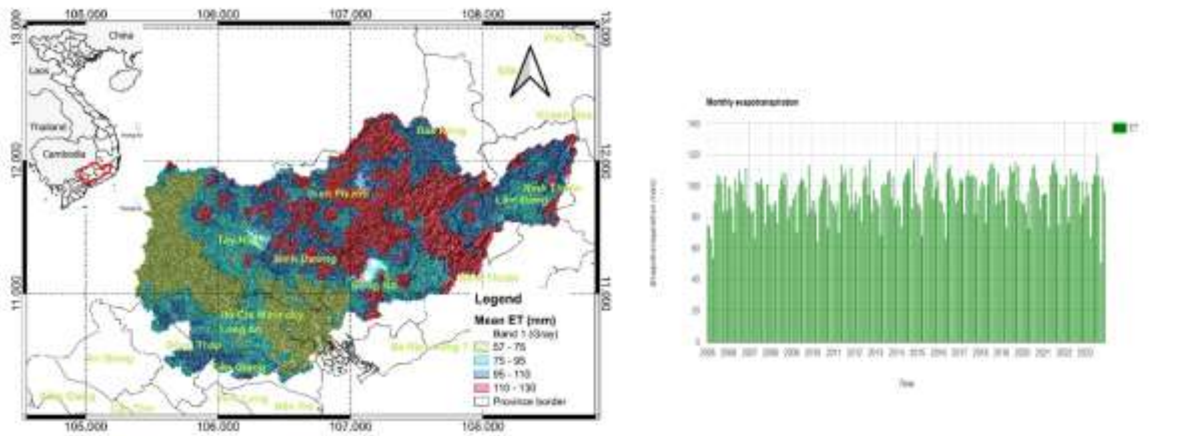
3.1. Monthly Precipitation in Period of 2005 – 2023

Mean monthly precipitation ranged from 114.4 mm to 253.6 mm in the period of 2005 – 2023 that concentrated in Dong Nai, Binh Duong, Binh Phuoc, and Lam Dong provinces (Figure.3a). Figure 3b showed the distribution of the monthly total of precipitation. The Saigon-Dongnai basin experiences unequal yearly and monthly rainfall; 85% of the total annual rainfall occurs during the rainy season, which runs from May to October each year [18]. In the period of study, the precipitation was highest in October 2016, July 2023, and October 2010 with approximately 450 mm, 420 mm, and 415 mm respectively. The annual total quantity of precipitation was high in 2007, 2012, 2021, and 2022, reaching 2400 mm.



a. b.

Figure 3. Mean precipitation in the Saigon-Dongnai basin (a) and the monthly average precipitation (b) in the period of 2005 – 2023.



a. b.

Figure 4. Mean evapotranspiration in the Saigon-Dongnai basin (a) and the monthly average evapotranspiration (b) in the period of 2005 – 2023.

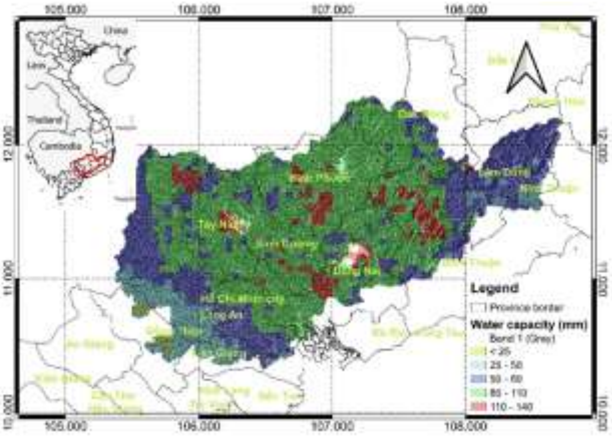
3.2. Monthly Evapotranspiration in Period of 2005 – 2023

The annual average evapotranspiration rate is around 1,191.06 mm, with a maximum evapotranspiration of above 100 mm in June to September. The evapotranspiration process has its highest value in June to September due to a rise in soil temperature and a decrease in relative humidity, which leads to increased evaporation. Most of the studied years were marked by a rise in the evaporation, the maximum value was 1,216 mm in 2018 (Figure 4b). The annual total quantity of evapotranspiration was high in 2017, 2018, 2019, and 2021 that reached approximately 1,200 mm/year. The increase tendency of annual evapotranspiration was observed (Figure 4b) in the period of 2005 – 2023. Mean monthly evapotranspiration ranged from 57.75 mm to 128.15 mm that concentrated in Binh Duong, Binh Phuoc, and Lam Dong provinces (Figure. 4a).

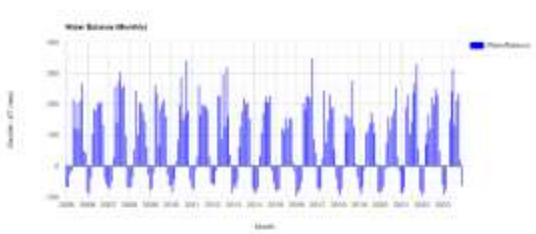
3.3. Monthly Water Capacity in Period of 2005 – 2023

The mean monthly water capacity (Q+AS) in the Saigon – Dongnai basin in the period of 2005 – 2023 concentrated from 80 to 110 mm in Tay Ninh, Binh Duong, Binh Phuoc, Dong Nai province and Ho Chi Minh city (Figure 4a). A negative tendency in water capacity was observed in months of January, February, and March whereas an opposite trend can be seen in the rest of months in the period of study (Figure 4b).

Water loss and incoming water in the river must be controlled in order to control the process of water capacity, which is crucial for managingwater resources. Equation 1 is used to limit these water losses in order to reach water capacity and determine the amount of storage change with respect to the river (Q). In order to manage the water surplus and the benefits of water for agriculture, the economy, and society, reservoirs must be established to the preservation of all water needs for the years. This will guarantee that all future water needs will be met. There was an equivalent amount of water deficit during the sunny season due to excessive evaporation in the majority of the years, which decreased water capacity and caused a water deficit. It is vital to address the issues that lead to water deficit in most years, such as reducing the rate of evaporation, temperatures, wind speed, and relative humidity, in order to reduce this phenomenon, achieve the water capacity, and manage and control the water.



a.



b.

Figure 5. Mean water capacity in the Saigon – Dongnai basin (a) and the monthly average water capacity (b).

4. Conclusion

The findings observed that, for each year considered, there was a negative tendency in the water capacity from January to April as a result of greater evaporation and less precipitation. Due to an increase in precipitation from May to October, a decrease in solar radiation, and a drop in temperature, the rainy season observed the highest values of the alter in water capacity. Precipitation and evapotranspiration have a positive correlation, as does the relationship between water capacity and income water. We mapped the amount of water in space and time with the use of Earth Engine's satellite data products that have capacity to quickly evaluate global, regional, and local data. It allows us to divide water into its consumptive uses and assess the impact of these divisions on a wide range of significant functions within a water basin. However, the study has limitations in that it has not verified satellite rain and evapotranspiration data with gaussed monitored data. Therefore, in the next studies we will take steps to evaluate this satellite data.

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