



RESEARCH ARTICLE

Evaluation of Simplified Surface Energy Balance Index (S-SEBI) Method for Estimating Actual Evapotranspiration in Kangsabati Reservoir Command Using Landsat 8 Imagery

Utkarsh Kumar¹  · Bhabagrahi Sahoo² · Chandranath Chatterjee³ · Narendra Singh Raghuwanshi³

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Abstract

Evapotranspiration (ET) is an important hydrological variable for better irrigation management, water budgeting, and runoff estimation which should be estimated as precisely as possible both in space and time. However, most of the available crop coefficient-based ET computation methods provide point-scale estimates which need upscaling to apply at the catchment or command area scale. This study evaluates the applicability of the simplified surface energy balance index (S-SEBI) method to compute the spatially distributed daily ET in the Kangsabati reservoir command in eastern India considering the crop coefficient-based coupled Hargreaves–Samani (ET_{c_HG}) method as the benchmark. The study is based on two major crops of paddy and potato in the Rabi season of 2015 at 100 surveyed ground truth locations in the selected command area having different crop growth stages and using the site-specific Landsat 8 images on three cloud-free dates. The S-SEBI method shows improved ET estimates during the crop development stage characterized by higher canopy cover than that during the initial crop development stage with lesser canopy cover that traps less radiation. Results revealed that S-SEBI-based ET estimates correlated well with ET_{c_HG} with *r* and RMSE value of 0.06 and 1.13 mm/day (initial stage), 0.71 and 0.52 mm/day (development stage) and 0.77 and 0.52 (maturity stage) for paddy. The *r* and RMSE value for potato is found to be better during the development stage (0.43, 0.69 mm/day) than the initial stage (0.17, 0.64 mm/day) in a similar trend with paddy. Therefore, the crop coefficient-based method could be advantageous at point-scale with adequate data availability conditions, whereas the S-SEBI method could be used in data-scarce areas to estimate the spatially distributed ET values.

Keywords Crop coefficient · Canopy · Evapotranspiration · Energy balance · Irrigation · Landsat 8

✉ Utkarsh Kumar
utkarsh.kumar@icar.gov.in

Bhabagrahi Sahoo
bsahoo2003@yahoo.com

Chandranath Chatterjee
cchatterjee@agfe.iitkgp.ernet.in

Narendra Singh Raghuwanshi
nsr@agfe.iitkgp.ernet.in

¹ Crop Production Division, ICAR-Vivekananda Parvatiya Krishi Anusandhan Sansthan, Almora, Uttarakhand 263601, India

² School of Water Resources, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal 721 302, India

³ Agricultural and Food Engineering Department, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal 721 302, India

Introduction

Evapotranspiration (ET) plays an important role in regional and global climates. ET computation is of prime importance in the evaluation of groundwater recharge, forecasting crop yield, land use planning, irrigation scheduling, streamflow estimation, regional water resource management, drought analyses, enhancing crop water productivity and climate change variability (Thornthwaite 1948; Blaney and Criddle 1950; Zwart and Bastiaanssen 2007; Raziqi and Pereira 2013; Guler 2014; Pandey et al. 2016; Djaman et al. 2018; Srivastava et al. 2017, 2018; Elbeltagi et al. 2020). Agriculture is the largest user of freshwater resources worldwide, and due to an increase in population, industrialization and urbanization, nowadays there is a growing concern enhancing the water use efficiency,

simultaneously maintaining high crop yields (Allen et al. 1998; Kumari and Srivastava 2019). About 65% of rainfall received is lost in the form of ET to the atmosphere in India (Bandyopadhyay and Mallick 2003). For enhancing the water use efficiency, efficient irrigation scheduling is needed which indirectly requires an accurate estimate of actual ET.

ET can be estimated by multiplying reference evapotranspiration (ET_0) with crop coefficient, K_c (Allen et al. 1998). The value of ET_0 can be estimated by the FAO-56 Penman–Monteith, Hargreaves, Priestley–Taylor, FAO-24 radiation and other methods (e.g., Sahoo et al. 2012; Srivastava et al. 2020b). The conventional actual ET estimation methods, such as the weighing lysimeters, eddy covariance towers, energy balance Bowen ratio (EBBR), pan evaporation method, sap flow, and scintillometer require intensive field measurements which are used at local and field scales. Although these approaches are the most accurate, they are tedious, time-consuming and expensive too. However, in data-scarce condition, ET_0 can be estimated by using spatial interpolation technique in the regions where limited data are available and, subsequently, are extended to the regional scale (Dile et al. 2020; Srivastava et al. 2020a; Wambura and Dietrich 2020).

In this context, remote sensing (RS)-based energy balance model and availability of multi-temporal high-resolution satellite datasets play a promising role in near-real-time irrigation water management. The salient feature of energy balance models is that it uses less data (only RS). With limited data, the S-SEBI technique could be used to estimate the actual ET using satellite data having a thermal band (Roerink et al. 2000). There are limited studies: Singh et al. (2020) used mapping evapotranspiration with internalized calibration (METRIC); Bala et al. (2016) and Patel et al. (2006) used surface energy balance algorithm for land (SEBAL); Danodia et al. (2019) used S-SEBI, Paul et al. (2020) used modified surface energy balance algorithm for land (M-SEBAL) and two-source energy balance (TSEB) and Shwetha and Kumar (2020) used two-source energy balance (TSEB) models for estimating actual ET. However, in Indian context, the evaluation of S-SEBI method is done by very few researchers (Danodia et al. 2019) because of non-availability of field survey data, information regarding crop characteristics (crop type, date of sowing, latitude and longitude, crop height) at different crop growth stages for calculating crop coefficient to estimated actual ET in the study area. Many a times, crop coefficient data for different crops are also not available to convert the reference ET into actual ET (ET_c) value for estimating water requirement of crops at critical stages of crop growth (Adamala and Srivastava

2018). The S-SEBI method of ET estimation is a physically based approach which can be popular in Indian context if the non-available radiation data can be estimated by using the remote sensing methodology as carried out in this study. The existing crop coefficient-based method of ET_c estimation provides ET at a point-scale. However, the use of S-SEBI method can provide the ET_c estimates at the field to regional scale, which is advantageous for basin-scale irrigation management. Moreover, limited studies have been carried out worldwide to test the efficacy of the S-SEBI method under data-scarce regions in relation to the data-hungry crop coefficient-based method, considered as the benchmark in this study. This study uses exhaustive survey data regarding crop characteristics at different growth stages for several locations in the study area to calculate crop coefficient and subsequently multiplied by ET_0 for evaluation of S-SEBI-based ET estimate at different locations (Shwetha and Kumar 2020).

Keeping the aforementioned challenges in mind, the specific objectives of the present study are (1) to estimate the daily ET using the S-SEBI and crop coefficient-coupled ET_0 methods, and (2) to evaluate the S-SEBI-based ET estimates for two major crops (viz. paddy and potato) in the Kangsabati reservoir command (KRC), West Bengal, considering the crop coefficient method as the benchmark using the field survey data.

Study Area and Data Used

Project Site

The KRC (5796 km²) is located in the West Bengal state of Eastern India. It extends from 86°E–87°30'E longitudes and the 22°20'N–23°30'N latitudes (Fig. 1). The Kangsabati reservoir is situated at 22°56'N and 86°47'E. The terrain elevation of the KRC ranges from 2 to 223 m above mean sea level (MSL). The climatology of the KRC is tropical-monsoon with mean annual precipitation of 1400 mm, while 80% of the normal rainfall occurs in 5 months of June to October. The prime source of ET loss is from the cultivable crops cultivated in the command area. Paddy is the major crop grown, along with diversified crop areas of paddy, potato, and wheat. The paddy fields located in KRC are predominantly irrigated or low land paddy fields. The KRC is traditionally considered drought-prone with varying rainfall, intense summer temperature and high ET rates. The main soil type (about 70%) of the study area is lateritic which is unsuitable for growing high water-consuming crops like paddy, as the porous nature of the soil is very much susceptible to percolation.

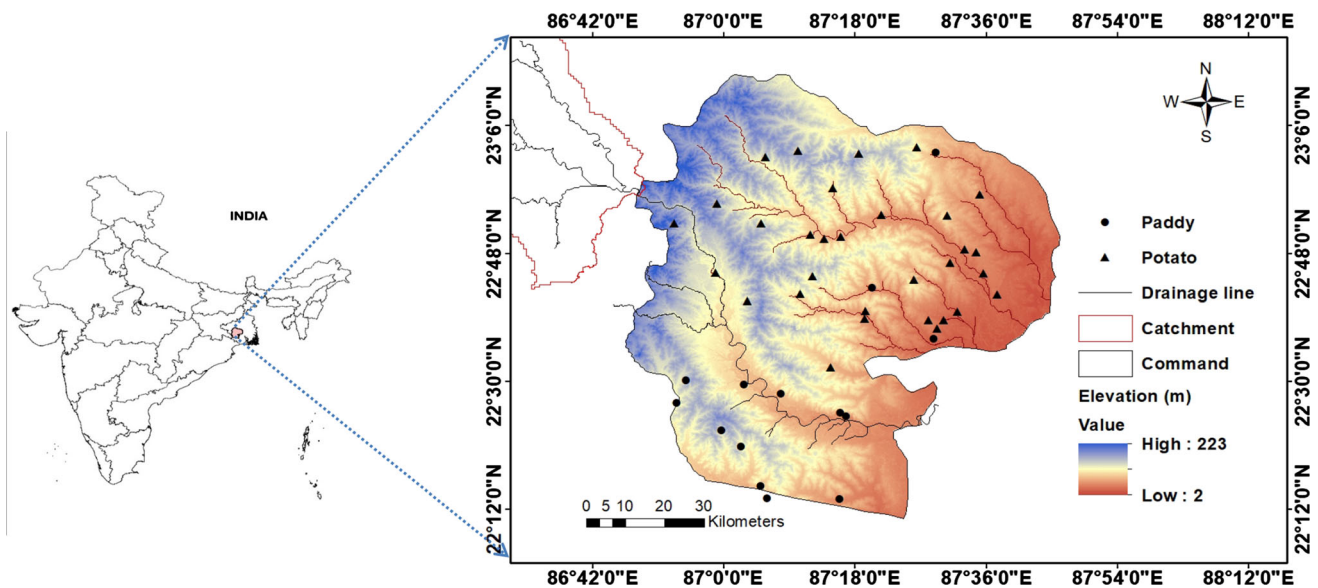


Fig. 1 Elevation map of the study area showing paddy and potato crops points

Data Sources

The digital elevation model (DEM) data used in this for calculating transmissivity as input for S-SEBI is Shuttle Radar Topography Mission (SRTM). It was acquired from the SRTM website (<https://srtm.csi.cgiar.org/>). The spatial resolution of one pixel is 30 m. For testing the S-SEBI-based method, operational land imager (OLI) and thermal infrared sensor (TIRS) imageries of Landsat 8 with 30 m spatial and 16-day temporal resolutions were downloaded for three different dates of January 10, 2015, February 27, 2015 and March 15, 2015 (cloud-free). These GeoTIFF datasets were collected corresponding to the path No. 139 and row No. 44. Landsat 8 has a fine resolution as compared to moderate resolution imaging spectroradiometer (MODIS) data making it suitable for accurate estimation of actual ET with different land-use types (Lian and Huang 2015). There were favorable clear sky weather conditions in these selected dates for applying the optical remote sensing. The vegetation index and albedo were calculated using optical bands of Landsat 8 while the thermal band was used for estimating land surface temperature (LST). A field survey was carried out at 100 locations (ground truth data points) in the KRC during the crop season of Rabi 2015 to collect the information on the type of crop, plant height, canopy coverage and date of sown or transplanting for estimating the K_c at different growth stages of the crop by using the FAO-56 manual. The selected sites with major crops (paddy and potato) are shown in Fig. 1. For estimating the reference ET, the observed $1^\circ \times 1^\circ$ gridded India Meteorological Department (IMD) products (maximum and minimum temperature) were used in the Hargreaves–Samani method. Similarly, the agro-climatology

data of relative humidity and wind speed at 2 m height for the selected three dates were collected from the NASA Power site (<https://power.larc.nasa.gov/>).

Methodology

Model Description

S-SBI is a remote sensing-energy balance (RSEB) model, which was developed by Roerink et al. (2000) to estimate surface energy fluxes from remote sensing satellite data. It has two major benefits over other RSEB model: (a) no additional meteorological data are required for calculation of energy flux, (b) it requires the presence of hot and cold pixels in the study area image. It is used to estimate ET_c from remote sensing image by calculating evaporative fraction using albedo and LST from hot and cold edge temperature of the corresponding image. Several researchers (Jin et al. 2005; Gomez et al. 2005; Sobrino et al. 2005; Garcia et al. 2007; Santos et al. 2010; Mattar et al. 2014) have already tested and validated worldwide with the in situ flux data.

S-SEBI Method of ET Estimation

In the S-SEBI approach, the ET_c can be calculated using the latent heat flux (λE , W/m^2) and latent heat of vaporization, in which the latent heat flux is calculated by solving Eq. (3). At daily time scale, the soil heat flux (G , W/m^2) can be often ignored for which the net available energy ($R_n - G$) reduces to net radiation (R_n , W/m^2). The

daily actual ET_c (mm/day) can be estimated by the S-SEBI method as

$$ET_c = \frac{86400 * 10^3}{\lambda * \rho_w} \Lambda R_n \tag{1}$$

where λ = latent heat of vaporization (J/kg), Λ = evaporative fraction, and ρ_w = the density of water (kg/m³).

The fundamental equation of ET estimation based on surface energy balance approach is given by Bastiaanssen et al. (1998)

$$R_n = G + H + \lambda E \tag{2}$$

Equation (2) can be rewritten as

$$\lambda E = R_n - G - H \tag{3}$$

To check the reliability of the associated fluxes using the energy balance closure, Λ at any time during a day can be computed using Eqs. (4) and (3) can be written in following form

$$H + \lambda E = \Lambda(R_n - G) \tag{4}$$

Estimation of Surface Energy Flux Using Landsat 8

Net Radiation

The net radiation (R_n) can be computed as (Liang 2000)

$$R_n = (1 - \alpha)RS \downarrow + RL \downarrow - RL \uparrow - (1 - \epsilon_0)RL \downarrow \tag{5}$$

The net short-wave radiation (R_{si}) is determined using Eq. (6)

$$R_{si} = G_{sec} \times \cos \theta \times \tau_{sw} \tag{6}$$

where α = surface albedo, G_{sec} = solar constant (W/m²), θ = (90° - θ_{SE}) is the angle of solar incidence, θ_{SE} is the sunset hour angle, and τ_{sw} is transmissivity of atmosphere.

For any clear sky day, τ_{sw} can be determined as (Allen et al. 1998):

$$\tau_{sw} = 0.75 + 2 \times 10^{-5}(h) \tag{7}$$

where h is the surface height (m).

The normalized difference vegetation index (NDVI) is ratio of difference between near-infrared (ρ_{NIR}) and red (ρ_R) reflectance divided by their sum (Rouse et al. 1973; Sellers 1985) as

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \tag{8}$$

where ρ_R = reflectance of the red band and ρ_{NIR} = reflectance of the near-infrared band.

The land surface emissivity (ϵ_λ) is calculated based on NDVI threshold method as (Sobrino et al. 2008)

$$\epsilon_\lambda \begin{cases} a_\lambda + b_\lambda \rho_R & NDVI < NDVI_s \\ \epsilon_{V\lambda} p_V + \epsilon_{S\lambda}(1 - p_V) + C_\lambda & NDVI \leq NDVI < NDVI_V \\ \epsilon_{V\lambda} p_V + C_\lambda & NDVI > NDVI_V \end{cases} \tag{9}$$

where $\epsilon_{V\lambda}$ and $\epsilon_{S\lambda}$ are emissivity of vegetation and soil, respectively; a_λ and b_λ are the parameters retrieved from metadata of particular Landsat 8 image; C_λ represents surface roughness ($C_\lambda = 0$ for a plane surface); p_V is the partial vegetation computed using Eq. (10) (Sobrino et al. 2008)

$$P_v = \left(\frac{NDVI - NDVI_s}{NDVI_V - NDVI_s} \right)^2 \tag{10}$$

where $NDVI_V$ and $NDVI_s$ are the threshold NDVI for healthy vegetation and a dry soil pixel, respectively, evaluated from the NDVI histogram. If NDVI is greater than $NDVI_V$, a numerical value (0.985) is used for emissivity (Sobrino et al. 2008).

There are many algorithms devised to calculate the LST from thermal infrared (TIR) band of Landsat 8. We have adopted the methodology (Sobrino et al. 2004) for computing surface radiometric temperature (T_s).

The $RL \downarrow$ is the downward long wave radiation reflected from atmosphere calculated as

$$RL \downarrow = \epsilon_a \times \sigma \times T_a^4 \tag{11}$$

where T_a = near surface air temperature (K); and ϵ_a = atmospheric emissivity calculated as

$$\epsilon_a = 0.85 \times (-\ln(\tau_{sw}))^{0.09} \tag{12}$$

The $RL \uparrow$ is computed by using Eq. (13):

$$RL \uparrow = \epsilon_0 \times \sigma \times T_s^4 \tag{13}$$

Soil Heat Flux (G)

It is calculated using the semi-empirical relationship among net radiation, surface albedo, surface temperature and NDVI as (Bastiaanssen 2000)

$$\frac{G}{R_n} = \frac{T_s}{\alpha} (0.0038\alpha + 0.0074\alpha^2)(1 - 0.98NDVI^4) \tag{14}$$

The daily soil heat flux can be taken to be zero as the land gives out the heat that it absorbs during the day.

Evaporative Fraction (Λ)

A parameterization method was used to solve the surface energy balance of the S-SEBI algorithm. S-SEBI method incorporates the evaporative fraction theory accounting for the diurnal variability of the evaporative fraction. The value of Λ is estimated using two-dimensional scatter of

LST and albedo using Landsat 8 image for each date as (Roerink et al. 2000)

$$\Lambda = \frac{T_H - T_s}{T_H - T_{\lambda E}} \tag{15}$$

where T_H is the maximum LST ($= T_{smax}$) on hot edge temperature, controlled by the radiation as a linear function of the surface albedo (K), $T_s =$ LST (K), and $T_{\lambda E}$ is the minimum LST ($= T_{smin}$) on cold edge, controlled by evaporation as a function of surface albedo (K).

Estimation of Actual ET Using the Hargreaves–Samani Method

ET_o can be estimated by the Hargreaves method using the decision support system DSS_ET (Bandyopadhyay et al. 2012). Due to the limited meteorological data availability, the daily ET_o for the selected date is calculated using the Hargreaves–Samani method as:

$$ET_{o(HG)} = 0.408 \times R_a \times C_H \times (T_{avg.} + 17.8) \times \sqrt{(T_{max} - T_{min})} \tag{16}$$

where $ET_{o(HG)} =$ Hargreaves–Samani-based ET_o (mm/day), $T_{avg.} =$ average air temperature, $T_{max} =$ maximum air temperature, $T_{min} =$ minimum air temperature and $R_a =$ extraterrestrial radiation calculated as:

$$R_a = \frac{24 \times 60}{\pi} G_{sc} d_r [\omega_s \sin(\varphi) \sin(\delta) + \cos(\varphi) \cos(\delta) \sin(\omega_s)] \tag{17}$$

where $R_a =$ extra-terrestrial radiation ($MJ\ m^{-2}\ day^{-1}$), $G_{sc} =$ solar constant ($= 0.0820\ MJ\ m^{-2}\ min^{-1}$), $d_r =$ inverse relative distance between Earth and Sun, ω_s is the sunset hour angle (rad), φ is the latitude (rad), and δ is the solar declination (rad). C_H is regional Hargreaves empirical constant set to 0.0023 for arid and semiarid regions.

The crop actual evapotranspiration can be estimated as

$$ET_{c(HG)} = K_{c(modified)} \times ET_{o(HG)} \tag{18}$$

The different crop characteristics were used to determine the Kc at different crop growth stages (Doorenbos and Pruitt 1977). There are a wide variety of agricultural crops in the study area which in the previous studies have been classified using coarse resolution satellite imageries such as LANDSAT ETM+. The coarse resolution leads to erroneous estimation of ET due to inaccurate vegetation distinction. Therefore, in the present study, LISS IV satellite imageries having an output spatial resolution of $5\ m \times 5\ m$ were used which is best suited for vegetation distinction in comparison with LANDSAT or LISS III which have comparatively coarser spatial resolution. These crop information of crop type, date of sowing and harvesting, and growth-stage

were collected by field survey from National Remote Sensing Center (NRSC), India, for the Rabi season of 2014–2015 (Nov. 2014–Mar. 2015) at 100 field-based crop survey observations in KRC. These detailed verification of the agricultural land use crops are verified from the previous studies and produced good results for estimation of ET (Srivastava et al. 2020b; Zhang and Schilling 2006). The global crop-specific Kc values as recommended in the FAO-56 manual (Allen et al. 1998) were modified to obtain the local crop coefficient values as

$$K_{c(modified)} = K_{c(table)} + [0.04(u_2 - 2) - 0.004(RH_{min} - 45)] \left(\frac{h}{3}\right)^{0.3} \tag{19}$$

where $K_{c(table)}$ is the tabulated values for K_c in Table 12 of FAO-56 (Allen et al. 1998), RH_{min} is the average value of minimum relative humidity for given stage (%) for $20\% \leq RH_{min} \leq 80\%$, h is surveyed average crop height for given stage (m) for $0.1\ m < h < 10\ m$, and u_2 is the wind speed at 2 m height collected from the NASA Power site. The modified crop coefficients for the paddy and potato are given in Table 1.

The Inverse Distance Weighting (IDW) interpolation technique can be employed to obtain the spatial variation of ET_o in the command area, in which distance weightings are used to estimate the unknown spatial ET_o that are adjacent to the known site as

$$\hat{R}_p = \sum_{i=1}^N w_i R_i \tag{20}$$

$$w_i = \frac{d_i^{-2}}{\sum_{i=1}^N d_i^{-2}} \tag{21}$$

where R_p is the unknown ET_o (mm/day); R_i is the estimated ET_o of any known i th location (mm/day); N is the no. of known locations; w_i is the weighting of each ET station; and d_i is the distance from each data available location to the unknown site.

Accuracy Assessment

For testing the efficacy of the S-SEBI method with respect to the crop coefficient coupled Hargreaves–Samani method, four performance indicators, viz. root-mean-squared error (RMSE), correlation coefficient (r), mean squares error (MSE) and index of agreement (d), were used in this study. For this, 100 surveyed sites in the study area with the potato and paddy crops were selected for comparative evaluation. The RMSE, r , d and MSE are estimated as

Table 1 Crop coefficient (K_c) and modified crop coefficient (Mod_Kc) values for paddy and potato crops in the selected study area

| Growth stage | Paddy | | | | Potato | | | |
|--------------|--------|-------------------|------------|------------|--------|-------------------|------------|------------|
| | FAO Kc | 10/01/2015 Mod_Kc | 27/02/2015 | 15/03/2015 | FAO Kc | 10/01/2015 Mod_Kc | 27/02/2015 | 15/03/2015 |
| Initial | 1.00 | 1.00 | 1.00 | 1.00 | 0.15 | 0.15 | 0.15 | 0.15 |
| Development | 1.15 | 1.18 | 1.13 | 1.12 | 1.10 | 1.12 | 1.08 | 1.07 |
| Maturity | 0.70 | 0.80 | 0.72 | 0.71 | 0.60 | 0.68 | 0.63 | 0.62 |

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n [E_i(l) - \hat{E}_i(l)]^2} \quad (22)$$

$$r = \frac{\sum_{i=1}^n (E_i(l) - \bar{E}_i) (\hat{E}_i(l) - \bar{\hat{E}}_i)}{\sqrt{\sum_{i=1}^n (E_i(l) - \bar{E}_i)^2 \sum_{i=1}^n (\hat{E}_i(l) - \bar{\hat{E}}_i)^2}} \quad (23)$$

$$d = 1 - \left(\frac{\sum_{i=1}^n (E_i(l) - \hat{E}_i(l))^2}{((\sum_{i=1}^n |\hat{E}_i(l) - E_{i\text{mean}}(l)| + \sum_{i=1}^n |E_i(l) - E_{i\text{mean}}(l)|)^2)} \right) \quad (24)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (E_i(l) - \hat{E}_i(l))^2 \quad (25)$$

where $\hat{E}_i(l)$ is the estimated ET using S-SEBI at the i th crop location, $E_i(l)$ is the estimated ET using the crop coefficient-coupled Hargreaves–Samani method at the i th crop location, and N is total number of selected locations for paddy and potato for respective comparison.

Results

Crop Inventory Map of the Study Area

In this study, land use/land cover (LULC) classification map of the Kangsabati command area was taken from a food security project report by Roy (2016). Satellite data used for LULC classification is Linear imaging and Self Scanning Sensor IV (LISS IV), having path/row combination of 107/56. The spatial resolution of the satellite imagery is 5.8 m. It provides the detailed features of the land surface, which are necessary for the mesoscale characterization of different LULC in the Kangsabati command area. Different crops were identified using the LISS IV image of 2014–2015 and survey data of Rabi season. Supervised land use classification was done using a maximum likelihood classifier algorithm. The satellite image was classified into nine classes, and the class names are assigned with the help survey data, taken as the ground

truth data. Major crops grown in this area are paddy, potato and wheat. The land use had an overall classification accuracy of 92.50% and kappa coefficient (K) of 0.90. The percent area of the different crops under agricultural land comprises of 44% (paddy), 31% (potato), 19% (mustard) and 5% (wheat) in the study area. Land use class of paddy, potato and wheat were clipped and converted into a vector file. LULC map of mustard, paddy and potato of the Kangsabati command area is shown in Fig. 2.

Relation Between Surface Albedo and Surface Temperature

The hot edge (T_H) and cold edge (T_c) were calculated from the space plot (surface reflectance versus LST) as suggested by Roerink et al. (2000) for the selected three survey dates. The spatial map of NDVI, LST and albedo for three dates is shown in Fig. 3. The expressions for estimating T_H and T_c as linear function of surface albedo for the study region are shown in Fig. 4 for January 10, 2015. In the similar way, expression for T_H and T_c is derived for February 27, 2015 and March 15, 2015 which is summarized in Table 2. T_H and T_c are functions of specific site and time.

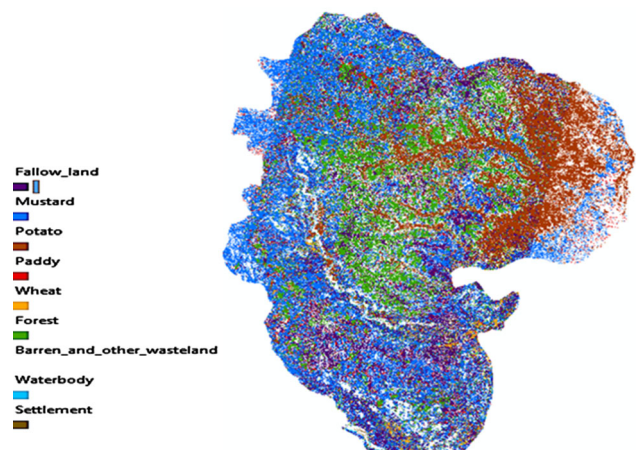


Fig. 2 Crop inventory map of study area with different landuse/land-cover classification

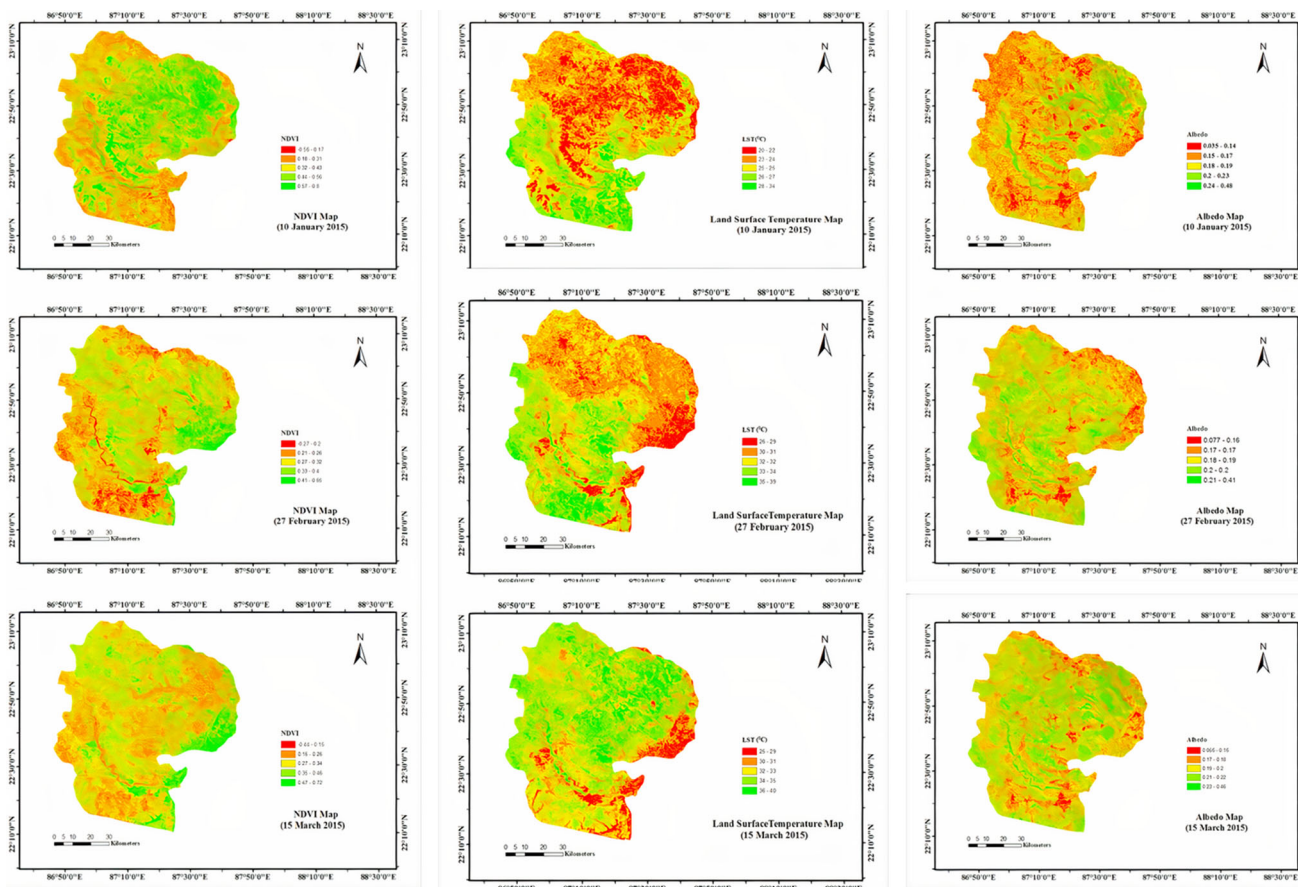


Fig. 3 Spatial variation of NDVI, LST and Albedo for three different periods January 10, 2015, February 27, 2015 and March 15, 2015 over the study area

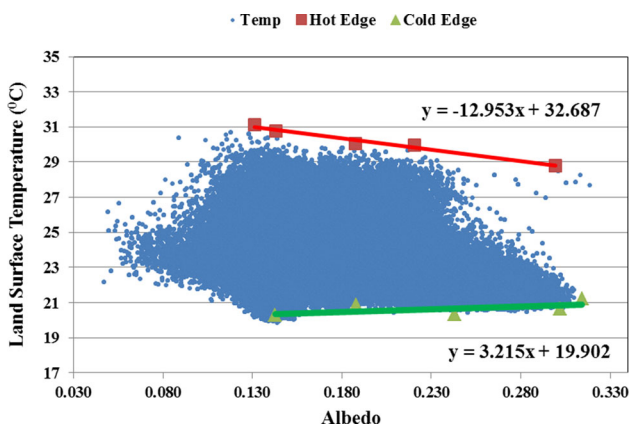


Fig. 4 Relationship between albedo and land surface temperature for January 10, 2015,

The spatial maps of daily actual ET show increased trend from January to March, probably because of the change in the growth stage of Rabi crops as shown in Fig. 5. The minimum ET value was found in January because the crop is in the initial growth stage. These observations prove that the S-SEBI model can capture spatial and temporal trends of different crops within the study area.

The estimated point-scale ET_0 estimates were interpolated in the KRC using IDW spatial interpolation technique. From the reference ET map of each sampling date, ET values were extracted for all the survey points for potato and paddy crops in the command area. Subsequently, crop ET is calculated by multiplying ET_0 obtained by meteorological data and modified crop coefficients

Table 2 Equation of hot edge and cold edge for KRC

| Sampling date | Hot edge | Cold edge |
|---------------|--------------------------------------|--|
| 10/01/2015 | $T_H = -12.95 \times \alpha + 32.68$ | $T_{LE} = 3.21 \times \alpha + 19.90$ |
| 27/02/2015 | $T_H = -23.27 \times \alpha + 41.72$ | $T_{LE} = 11.27 \times \alpha + 23.93$ |
| 15/03/2015 | $T_H = -8.90 \times \alpha + 40.56$ | $T_{LE} = 17.45 \times \alpha + 23.46$ |

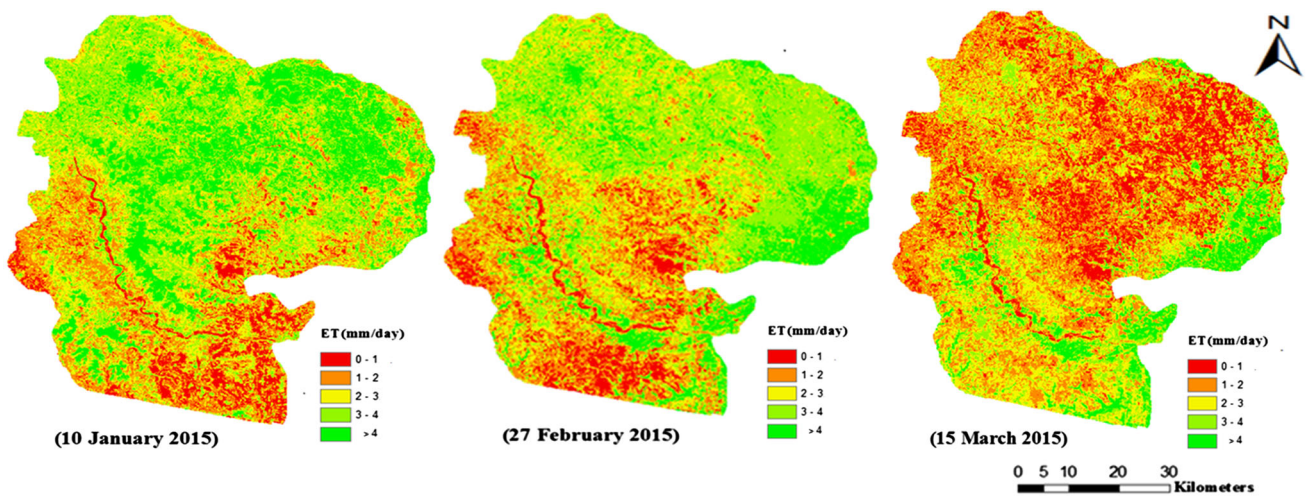


Fig. 5 Typical actual ET map for three dates as estimated by the S-SEBI method

using the FAO-56 guidelines. The ET values for the major crops (paddy and potato) for the selected three typical sampling dates are given in Fig. 6.

Performance of S-SEBI Method in Comparison with Hargreaves–Samani Method

Figure 7 illustrates the comparative scatter plots between the ETc_{HG} and ETc_{S-SEBI} for different crop growth stages of the paddy crop. ETc_{S-SEBI} model correlated well with the ETc_{HG} with r and RMSE value of 0.06 and 1.13 mm/day (initial stage), 0.71 and 0.52 mm/day (development stage) and 0.77 and 0.52 (maturity stage) for paddy. During the field survey in March 2015, there was no potato crop in the command area because of harvesting; hence, a comparison for the potato crop is done for initial and development stage, which is shown in Fig. 8. Actual ET estimated using S-SEBI (ETc_{S-SEBI}) yielded good

agreement with the crop coefficient coupled Hargreaves–Samani ETc estimate (ETc_{HG}). The r and RMSE value for potato is found to be better during the development stage (0.43, 0.69 mm/day) than initial stage (0.17, 0.64 mm/day) in a similar trend with paddy. Table 3 shows statistical parameters for the different growth stages of paddy and potato in the study area. Index of agreement was found 0.69 and 0.63 during the crop development stage for paddy and potato, respectively. In this study, the crop coefficient-coupled Hargreaves method has been improved with the inclusion of modified crop coefficient using the exhaustive survey data. The summary of statistical parameter for S-SEBI comparative performance is given in Table 3.

The poor correlation in the ETc_{S-SEBI} estimates during initial stage may be attributed to the less canopy cover of paddy and wet condition on 10/01/2015 than that of the crop development and maturity stages with good

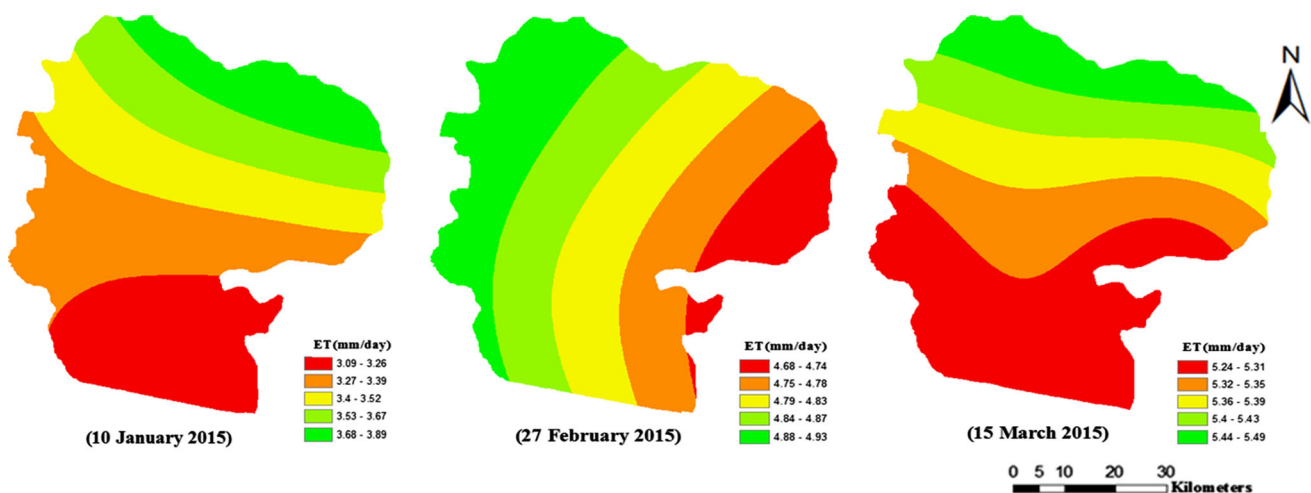


Fig. 6 Typical actual ET map for three dates as estimated by the Hargreaves–Samani method

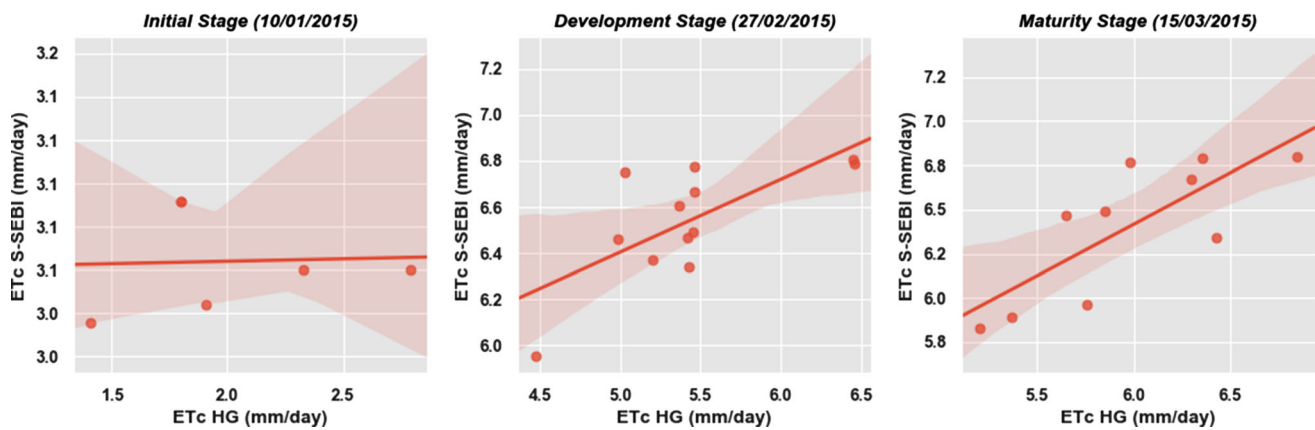


Fig. 7 Comparative scatter plots between the ETc_HG and ETc_S-SEBI for paddy

Fig. 8 Comparative scatter plots between the ETc_HG and ETc_S-SEBI for potato

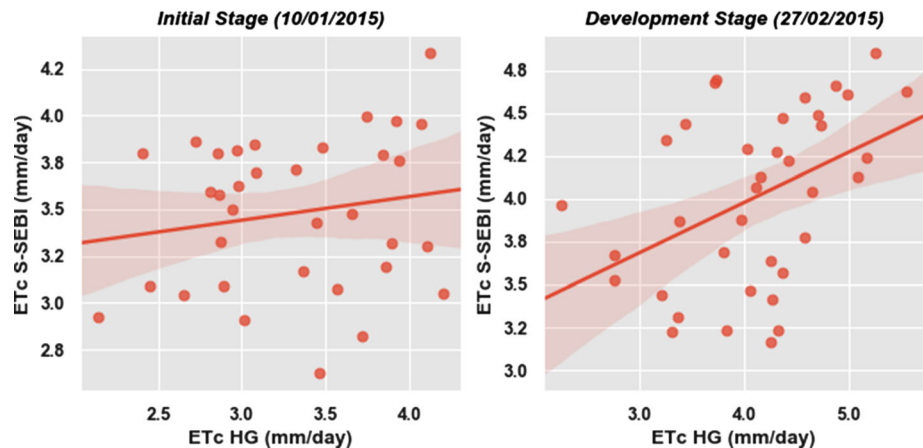


Table 3 Summary of comparative performance of ETc_S-SEBI

| Crops | Date | Pearson's <i>r</i> | <i>p</i> value | MSE | RMSE | <i>d</i> |
|--------|------------|--------------------|----------------|------|------|----------|
| Paddy | 10/01/2015 | 0.06 | 0.89 | 1.29 | 1.13 | 0.37 |
| | 27/02/2015 | 0.71 | 0.009 | 0.27 | 0.52 | 0.69 |
| | 15/03/2015 | 0.77 | 0.007 | 0.27 | 0.52 | 0.69 |
| Potato | 10/01/2015 | 0.17 | 0.326 | 0.41 | 0.64 | 0.51 |
| | 27/02/2015 | 0.43 | 0.007 | 0.47 | 0.69 | 0.63 |

canopy cover with lesser wet area exposed to atmosphere. During the lower canopy cover, the trapped radiation is also less that reduces the performance of the S-SEBI method in estimating the actual ET. This comparison could be satisfactorily given that the crop coefficient approach does not incorporate for water stress, as ETc_HG represents accurate estimation of ET only under no water stress condition. It was found that good agreement is observed between the crop development and maturity stages than in initial crop growth stage. The poor agreement during the initial crop growth stage might be associated with lesser

canopy cover of the crop capturing less solar radiation, consequently generating lesser sensible and latent heat fluxes than during the crop development and maturity stages.

Discussion

This study demonstrates the comparative evaluation of the S-SEBI model, which used only satellite data to estimate actual ET in data-scarce conditions (Zhang et al. 2016). To check the capability of S-SEBI model in data-scarce condition, various researchers (Srivastava et al. 2018; Shwetha and Kumar 2020) have used regionally calibrated Hargreaves method multiplied by crop coefficient for comparing ET estimates of Variable Infiltration Capacity (VIC-3L) land surface model and two-source energy surface balance (TSEB) model. To succeed in dealing with the existing limits of meteorological variables of the FAO-PM model, various efforts aiming to estimate ET_o with finite observations have been performed and stated using Hargreaves method as the best (Srivastava et al. 2018; Vanderlinden

et al. 2004; Zanetti et al. 2019). We have extended the methodology of Srivastava et al. (2018) for a comparison of ET_c-S-SEBI in the present study. In general, S-SEBI performed well as crop growth progress for both paddy and potato (Wagle et al. 2017). However, the S-SEBI model slightly underestimated actual ET as compared with the crop coefficient-coupled Hargreaves method, which was in line with the previous result Shwetha and Kumar (2020) and Srivastava et al. 2018 in the same study area. The S-SEBI model provides instantaneous actual ET value and to be converted on a daily scale, whereas in the case of the crop coefficient method such conversion is not required. The present study could even capture temporal as well as the spatial trend in the study area. Nevertheless, it will be more advantageous for ET stakeholders, if ET_c-S-SEBI is validated with the observed values for other different land cover classes and climatic conditions. It is clearly shown in this study that the ET_c-S-SEBI can be utilized to calculate the water requirement of the crop in a command area with only satellite data.

Conclusions

In this study, the S-SEBI method has been used to estimate the spatially distributed actual ET in the KRC. Due to the non-availability of experimental ET data, the S-SEBI-based ET estimates were only validated with the point-based ET estimates by the Hargreaves–Samani method. The result showed that the S-SEBI is a practical tool for estimating ET at command scale using the remote sensing-based reflectance data under data-scarce conditions and diversified cropping system. The comparison between the daily ET estimates by the Hargreaves–Samani and S-SEBI methods shows good agreement on the sampling dates February 27, 2015, March 15, 2015, than on January 10, 2015. The results reveal that, with more canopy cover during the crop growth stage, the S-SEBI method performs better as compared to lesser canopy cover. These results suggest that the integration of S-SEBI method with the measured flux and weather datasets can be very beneficial for precision agricultural practices (e.g., precision irrigation), particularly under data-scarce conditions. The method proposed herein can be implemented for efficient irrigation water management for large command areas for better crop production as well as high water use efficiency. However, future research is needed to improve the ET estimates by the S-SEBI method at finer resolution with a diversified cropping system. Moreover, this study provides an alternative way of estimating spatially distributed ET in a data-scarce region.

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