EVALUATING THE INFLUENCE OF THE RESISTANCE PARAMETER KB^{-1} ON SATELLITE-DERIVED EVAPOTRANSPIRATION ESTIMATES

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ABSTRACT

The estimation of evapotranspiration (ET) is important for efficient water resources management. Traditional ground-based techniques are limited by their coverage of spatial areas and therefore satellite-based methods are considered suitable alternatives. However, these possess limitations as well. Inadequate consideration for the influence of soil moisture on ET has been identified as a potential issue which would be relevant in water-stressed arid or semi-arid regions. The modification of the kB^{-1} parameter, which accounts for the difference between radiometric and atmospheric temperature, has been discussed as a possible means to improve upon this limitation. The objectives of this study were to first determine if overestimation of ET in a water-stressed environment does occur. Then to determine how sensitive estimates were to modifications of kB^{-1}. The Surface Energy Balance System (SEBS) model was chosen to test this and was run for an approximately two-month period in 2015. Estimates obtained were validated against *in-situ* data from an Eddy Covariance flux tower. The initial results showed that a significant overestimation of ET was occurring, possibly due to the soil moisture limitation in SEBS. The reduction of kB^{-1} values by varying degrees successfully reduced this overestimation. However, error days were identified on which kB^{-1} reduction did not yield this desired effect. This issue was found to be attributed to errors in the calculation of the evaporative fraction in the model. The exceedance of a threshold value resulted in the ET increasing with kB^{-1} reduction rather than decreasing. This evaporative fraction induced error could possibly be due to kB^{-1} being reduced too low to moderate the radiometric-atmospheric temperature gradient. Other underlying issues relating to sensible heat flux calculation and environmental factors may influence this as well. Ultimately it was found that kB^{-1} reduction will generally reduce ET overestimation under water-stressed conditions. However, the effect of potential error as a result of other influential parameters should be considered. The findings of the study would be relevant to future work concerned with the use of energy balance models in research and water resources management applications.

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LIST OF ABBREVIATIONS

ABL	Atmospheric Boundary Layer
AOT	Atmospheric Optical Thickness
ASL	Atmospheric Surface Layer
BLS	Boundary Layer Scintillometer
CIMEC	Calibration using Inverse Modelling at Extreme Conditions
ET	Evapotranspiration
EF	Evaporative Fraction
HPV	Heat Pulse Velocity
IRGA	Infrared Gas Analyser
MAP	Mean Annual Precipitation
METRIC	Mapping ET at high Resolution with Internalised Calibration
MODIS	Moderate Resolution Spectroradiometer
MOST	Monin-Obukhov Similarity Theory
MPDI	Modified Perpendicular Drought Index
NDVI	Normalised Difference Vegetation Index
LAI	Leaf Area Index
LAS	Large Aperture Scintillometer
LIDAR	Light Detection and Ranging System
LST	Land Surface Temperature
SCOPE	Soil Canopy Observation of Photochemistry and Energy fluxes
SEBAL	Surface Energy Balance Algorithm for Land
SEBS	Surface Energy Balance System
SEO	Satellite Earth Observation

SLS	Surface Layer Scintillometer
SSEB	Simplified Surface Energy Balance
S-SEBI	Simplified Surface Energy Balance Index
SMAC	Soil Moisture Atmospheric Correction
SVAT	Soil-Vegetation-Atmosphere Transfer
TSEB	Two-Source Energy Balance

1. INTRODUCTION

Evapotranspiration (ET) is a combined process which includes water being removed from plant and soil surfaces through evaporation and plant water losses through transpiration (Senay *et al.*, 2016). ET represents interactions between soil, vegetation, the atmosphere, and influences numerous ecosystem processes (Liu *et al.*, 2013). Hence it forms a central element of the surface energy balance and water budget. Accurate quantification of ET rates is therefore vital for planning and design of hydrological, agricultural and socio-economic systems. This is especially true for arid and semi-arid regions, such as South Africa, which has relatively high ET rates that return a significant portion of MAP to the atmosphere (Jarmain *et al.*, 2009a).

Water availability issues are aggravated by the spatial and temporal variability of rainfall (Gokool *et al.*, 2016). Hence accurate ET estimates are necessary to facilitate improved allocation of water resources. There are various techniques which have been traditionally used to estimate ET at field or local scales. These *in-situ* methods have been validated and tested in multiple environments and conditions, improved upon and become well-established through employment in hydrological studies and modelling (Drexler *et al.*, 2004). However, the spatial and temporal variability of ET creates the need to acquire accurate measurements at larger geographic scales and across multiple environmental settings (Elhag *et al.*, 2011). This reduces the applicability of *in-situ* methods due to issues such as feasibility, labour and time (Elhag *et al.*, 2011).

1.1 Rationale

Satellite-based Earth Observation (SEO) techniques have been shown to provide suitable alternatives to conventional ET estimation methods (Drexler *et al.*, 2004; Gibson *et al.*, 2013; Webster *et al.*, 2017). These allow for data capture over large areas and improved understanding of the hydrological cycle through various applications, including the estimation of ET (Wang and Dickinson, 2012). Several models exist which can use satellite-derived data to provide hydrological information. Techniques based on the parameterization of the shortened energy balance are among the most frequently applied operationally and for research purposes. These can be integrated into hydrological models for planning, design and informed decision making (Consoli and Vanella, 2014). However, several issues remain which cause discrepancies in satellite-based ET estimates. Trade-offs between satellite revisit time and spatial resolution remain an issue (Gokool *et al.*, 2017). There is also added difficulty in working with cloud cover in imagery (Peng *et al.*, 2013). Further general limitations include *inter alia*; difficulty when estimating over heterogeneous surfaces, mismatch of scale between satellite image pixel size and study area, failure to adequately account for underlying environmental conditions (Jarmain *et al*., 2009a; Gibson *et al*., 2013).

One of the major limitations with models grounded on the energy balance approach is linked to the estimation of ET under water-stressed conditions. This has been attributed to the failure to adequately account for soil moisture. kB^{-1} is an aerodynamic parameter used to account for the excess resistance to heat transfer (Gibson *et al.*, 2011). It corrects for the difference between radiometric and atmospheric temperature and is influenced by multiple variables relating to structural parameters and environmental conditions (Zhuang *et al.*, 2016). Several energy balance models include the parameter in their formulation. The modification of this parameter has been identified, through numerous studies, as a means of addressing the limitations associated with ET estimation in water-stressed conditions (Timmermans *et al*., 2013; Paul *et al*., 2014; Zhuang *et al*., 2016). Despite the modification of kB^{-1} being identified as a solution to inaccurate ET estimation, there remains a need to establish how sensitive ET is to changes in values of the parameter.

1.2 Research Aims and Objectives

The overall aim of the study is to obtain an improved understanding of how the kB^{-1} parameter can influence the accuracy of terrestrial flux and ET estimates. For this purpose, the following objectives were identified:

- Review current techniques which utilize satellite earth observation data to estimate total evaporation.
- Evaluate the accuracy of satellite-derived ET estimates during conditions of water stress.
- Evaluate the sensitivity of the satellite-based ET approach to modifications in the kB^{-1} parameter.

1.3 Research Questions

- Can a relationship be established between the kB^{-1} parameter and ET estimates produced by an energy balance model?
- Does the overestimation of ET under water-stressed conditions occur and will modifying kB^{-1} reduce the inaccuracy?

2. LITERATURE REVIEW

The majority of techniques for estimating ET are based on fundamental principles which describe energy distribution through surface-atmosphere interactions. The energy balance approach underlies most *in-situ* techniques and is generally described by the shortened energy balance equation (Allen *et al.*, 2011). This represents the relationship, with all fluxes in W m^{-2}, between soil heat flux, (G), sensible heat flux (H), latent heat flux (λE) and net radiation (R_n) as:

$$R_n = G + H + \lambda E \quad (2.1)$$

A secondary underlying principle is the Monin-Obukhov Similarity Theory (MOST). This theory is widely accepted and used for determining vertical profiles of mean flow within the surface layer by relating turbulence to energy and assuming similarity between fluxes (Savage *et al.*, 2004). The underlying principles are seen in both conventional approaches and energy balance models. A brief narrative of these approaches is provided in the following sub-sections.

2.1 Conventional Approaches of ET Estimation

The Bowen Ratio technique involves the measurement of gradients of air temperature and vapour pressure in the near-surface layer where evaporation is occurring (Allen *et al.*, 2011). There are two different types of Bowen ratio systems (Jarmain *et al.*, 2009b). The single-sensor method uses a hygrometer and two air temperature sensors, with air being pumped alternatively between levels. The oscillating system uses two sensors, one per measurement level to determine air temperature and water vapour pressure (Jarmain *et al.*, 2009b). The approach does not require aerodynamic data and offers automated measurements with non-destructive, direct sampling (Allen *et al.*, 2011). However, it requires sufficient fetch clear of obstructions and the parameterisation encounters error in conditions where H approximates zero (Jarmain *et al.*, 2009b).

Lysimetry has been extensively used to provide measurements for the calibration and validation of other ET estimation approaches (Allen *et al.*, 2011). This technique determines ET by measuring variations in the mass of the soil which rests on top of the lysimeter system, consisting of an underground scale and computer (Allen *et al.*, 2011). Measurements are translated into ET losses after considering other water inputs and outputs in the controlled environment. The method has a relatively small fetch requirement and can be mechanically calibrated for automated measurements. However, it is a point measurement and does represent the spatial variability of ET over a study area (Gibson *et al.*, 2013).

Scintillometry involves the measurement of fluctuations of an emitted light beam or wave between a transmitter and receiver, between one and five kilometres apart (Kleissl *et al.*, 2008). These measurements are converted to path-weighted H values according to MOST (Allen *et al.*, 2011). The various scintillometer types including the BLS, SLS and LAS vary according to path length sensitivity (Savage *et al.*, 2004). The foremost advantage of the scintillometry approach is that it provides spatially representative ET estimates over larger areas (Liu *et al.*, 2013). However, it is influenced by surface cover and wind changes, measures the magnitude of H only and assumes weak scattering which may not hold for strong turbulence conditions (Allen *et al.*, 2011).

The Light Detection and Ranging System (LIDAR) technique involves laser-based transmission of electromagnetic radiation in infrared, visible or ultraviolet wavelength ranges (Drexler *et al.*, 2004). Photomultiplier tubes or other sensors are used to receive backscattered radiation. The analysis of the wavelengths and scattering between the emitter and receiver allows for the estimation of temperature, wind and atmospheric constituent concentrations (Drexler *et al.*, 2004). Water vapour mixing ratio gradients are system outputs. Linear regression with MOST functions of surface fluxes is used to determine ET (Drexler *et al.*, 2004). The provision of a spatially-representative estimate of water vapour flux instead of a point measurement is a key advantage of LIDAR. However, the instrumentation required for this system is relatively expensive (Drexler *et al.*, 2004).

The Heat Pulse Velocity (HPV) technique is one of two commonly used sapflow techniques, with the other being the stem state heat energy balance approach (Savage *et al.*, 2004). Thermocouples and heater probes are fitted into the tree trunk. The increase in temperature measured above the points of heat introduction is used to indicate sapflow, which is then converted into transpiration measurements. A major limitation is that transpiration estimates are obtained for a single tree and is difficult to upscale over an area (Savage *et al.*, 2004). Furthermore, additional soil moisture estimates are needed to obtain ET. According to Savage *et al*. (2004), the HPV technique for sapflow measurement in woody plants is internationally recognised. Furthermore, it has been extensively applied under South African conditions.

The Surface Renewal approach is used to estimate H. Measurements are combined with values of G and R_n to estimate ET from the energy balance equation (Gokool *et al.*, 2016). The basis of the theory is heat transfer of air parcels, whereby parcels enriched by a scalar parameter, such as air temperature, near the surface are exchanged for air parcels from above (Drexler *et al.*, 2004). The method requires high frequency air temperature measurements, vegetation, measurement height and air temperature gradient data (Gokool *et al.*, 2016). Furthermore, a weighting factor, obtained by validation with another technique, such as Eddy Covariance must be applied. A further disadvantage of this approach is that it provides point-based estimates of ET (Zeri *et al.*, 2013). However, the method is fairly inexpensive, portable, has minimal instrumentation requirements, can be installed in dense canopies and allows for long term use in remote sites (Zeri *et al.*, 2013).

The Eddy Covariance technique is amongst the most frequently applied *in-situ* m*ethods* for estimating ET (Allen *et al.*, 2011). The statistical correlation between vertical fluxes of sensible heat or water vapour and the movement of air within turbulent eddies is determined, with the covariance being directly proportional to H (Jarmain *et al.*, 2009b). In other cases, evaporation can be estimated by using λE and the shortened energy balance equation. Eddy Covariance systems have a number of advantages including portability, non-invasive sampling, co-measurement of variables and system automation (Allen *et al.*, 2011). However, high frequency, data-intensive measurements are required and energy balance closure issues may arise from heat storage in vegetation canopies, horizontal advection and instrument failure (Allen *et al.*, 2011).

2.2 Satellite-Based ET Estimation Techniques

Conventional techniques have been extensively applied for ET estimation. However, these methods are limited in their ability to provide estimates at large geographic scales. Satellite-based ET estimation methods are able to cover larger areas. Hence, they are viewed as suitable alternatives to conventional techniques. They have been used to provide estimates over scales ranging from regional to global (Webster *et al.*, 2017). There are various types of satellite-based ET models which are frequently applied. However, only a few examples will be reviewed as part of the discussion in the following section.

The Surface Energy Balance Algorithm for Land (SEBAL) model is an extensively used, single-source model based on ET estimation utilising surface energy balance theory and can be applied at a variety of spatial and temporal scales (Paul *et al.*, 2014). The model only requires field information on shortwave atmospheric transmittance, height of the vegetation and the image acquisition time aside from calibration requirements for different geographical regions

(Wang and Dickinson, 2012). SEBAL calculates a single temperature gradient for the study area between two points of hydrological contrast, the dry and wet pixels of an image (Paul *et al.*, 2014). The wet pixel location is ideally a full canopy vegetation surface with no limiting soil water. The conditions for the contrasting pixels are user-dependent. According to Gibson *et al*. (2013), extensive application of the model has occurred in South Africa for numerous water resources management scenarios.

The Mapping ET at high Resolution with Internalised Calibration (METRIC) model was initially developed for field scale applications using Landsat imagery (Liaqat and Choi, 2015). It is derived from SEBAL by incorporating reference ET in order to reduce errors from aerodynamic resistance and account for regional advection of heat (Liaqat and Choi, 2015). A linear relationship between near-surface temperature gradient and surface temperature forms the basis of the model. This is achieved by applying the CIMEC process, which determines extreme or near-extreme conditions in an image to use as endpoints for ET estimation. These are generally taken as the dry and wet ends of the ET spectrum (Allen *et al.*, 2013).

The Two-Source Energy Balance (TSEB) model uses two different budgets, taking *H* as the sum of the contributions from soil and vegetative surfaces (Consoli and Vanella, 2014). Vegetation is assumed to transpire at a potential rate under unstressed conditions and soil evaporation rates, relative to unstressed conditions, can indicate vegetation stress and canopy transpiration (Chirouze *et al.*, 2014). Numerous variations associated with ET estimation pathways exist. The choice of application depends on the user's needs (Song *et al.*, 2016).

The Simplified Surface Energy Balance (SSEB) approach uses reference ET and LST data, derived from the Penman-Monteith approach applied to a reference crop with full vegetation cover and no water stress (Senay *et al.*, 2011). The formulation calculates ET utilising LST data obtained from satellite imagery. Pixels are identified by NDVI according to ET rates, assuming that dry, hot pixels experience the lowest ET rates while wet, cold pixels experience the highest or maximum rates (Senay *et al.*, 2011).

The Surface Energy Balance System (SEBS) is used for the estimation of atmospheric turbulent fluxes from SEO data (Su, 2002). It is a physically-based model, derived from the shortened energy balance equation, which estimates *H via* a single-source pathway (Gokmen *et al.*, 2012). The parameterisation includes an extended model for establishing the roughness height for heat transfer and estimation of the evaporative fraction, which is based on dry and wet limiting cases and remains constant during the day (Timmermans *et al.*, 2013). SEBS does not consider the effect of soil moisture and biophysical conditions during surface flux estimation, which may result in inaccurate estimates under water-stressed conditions (Gokool *et al.*, 2017).

A summary of the key structural components, strengths and limitations as associated with the aforementioned models is provided in *Table 2.1*. The SEBS model was identified to have the traits which were most suitable to the scope of the study. The model is versatile in usage, open-source and simple to implement. Furthermore, the model contains the parameter under investigation. Hence the study will utilise SEBS to investigate the influence of kB^{-1} on ET.

Table 2.1 Comparison of reviewed satellite-based approaches

Approach	Structure	Advantages	Disadvantages
SEBAL	Single-source model, calculates a single temperature gradient between points of hydrological contrast.	• Flexible application. • Reliable results.	• Commercial product.
METRIC	Variant of SEBAL, incorporates reference ET.	• Accounts for soil type and LST.	• Commercial product. • Requires high quality input data.
TSEB	Separates energy contributions from soil and vegetation and assumes transpiration at a potential rate.	• More defined energy balance for flux estimation.	• Requires validation against ground measurements.
SSEB	Uses reference ET and LST Employs Penman-Monteith and NDVI approaches.	• Accurate, rapid and cost-effective ET estimates over large areas.	• Assumptions are made for the extremes of pixel ET rates.
SEBS	Physically-based, single-source technique derived from the shortened energy balance equation.	• Open-source software. • Estimates various fluxes and parameters.	• Developed for energy-limiting conditions. • Displays inaccuracy in water-stressed environments.

2.3 SEBS Model Formulation

The main components of the SEBS model formulation are shown below; the complete formulation can be seen in Su (2002). The SEBS model is derived from the shortened energy balance equation (2.1). The equations to calculate R_n and G are given by:

$$R_n = (1 - \alpha)\, R_{swd} + \varepsilon\, R_{lwd} - \varepsilon \sigma T_0^4 \quad (2.2)$$

$$G = R_n\, [\Gamma_c + (1 - f_c)(\Gamma_s - \Gamma_c)] \quad (2.3)$$

Where α is the albedo, ε is the surface emissivity, R_{swd} is the downward solar radiation, R_{lwd} is the downward longwave radiation, σ is the Stefan-Bolzmann constant and T_0 is the surface temperature. Γ_c is the ratio of soil heat flux to net radiation for a full vegetation canopy and Γ_s is for bare soils. They are assumed values of 0.05 and 0.315 respectively. f_c is the fractional canopy coverage.

The principles of MOST are used to derive H and λE, with a distinction being made between the atmospheric boundary layer (ABL) and ASL. The bulk transfer parameter kB^{-1} and the roughness height for momentum transfer, z_{om}, is used to derive the scalar roughness height for heat transfer, z_{oh}. A quadratic weighting, kB_s^{-1} uses f_c to accommodate for conditions in between full vegetation and bare soil as shown below:

$$kB^{-1} = \frac{kC_d}{4C_t \frac{u_*}{u(h)}\left(1 - e^{\frac{-n_{ec}}{2}}\right)} {f_c}^2 + 2f_c f_s \frac{k \frac{u_*}{u(h)} \frac{z_{oh}}{h}}{C_t^*} + kB_s^{-1} f_s^2 \quad (2.4)$$

$$kB_s^{-1} = 2.46(R_{e*})^{\frac{1}{4}} - \ln[7.4] \quad (2.5)$$

$$z_{oh} = z_{om}/\exp(kB^{-1}) \quad (2.6)$$

Where B^{-1} is the inverse Stanton number, a dimensionless heat transfer coefficient, C_d is the drag coefficient of the foliage elements (assumed as 0.2), $u(h)$ is the horizontal wind speed at the canopy top, f_s is the soil fraction (a complement of f_c). C_t is the heat transfer coefficient of the leaf ($0.005N \leq C_t \leq 0.075N$ For most environments, N is the number of sides of a leaf to participate in heat exchange). The parameter n_{ec} is the within canopy wind speed profile extinction coefficient, C_t^* is the heat transfer coefficient of the soil and R_{e*} is the roughness Reynolds number. The parameterisations for these and other sub-parameters can be seen in Su (2002).

The SEBS model contains formulation for determining the evaporative fraction, Λ, at limiting cases. Under the dry limit, evaporation becomes zero due to the soil moisture limitation, while H is at a maximum rate, H_{dry}. Under the dry limit, evaporation occurs at a potential rate, λE_{wet}, while H is at a minimum, H_{wet}. These are used for determining the relative evaporative fraction, Λ_r. Bulk internal and external resistances are then used to derive λE:

$$\Lambda_r = 1 - \frac{H - H_{wet}}{H_{dry} - H_{wet}} \tag{2.7}$$

$$\lambda E = \frac{\Delta r_e\ (R_n - G\ ) + \rho C_p\ (e_{sat} - e)}{r_e(\gamma + \Delta) + \gamma\ r_i} \tag{2.8}$$

Where Δ is the rate of change of saturation vapour pressure with temperature, r_i is the bulk internal resistance, r_e is the aerodynamic resistance, r_{ew} is the external resistance at the wet limit, e and e_{sat} are the actual and saturation vapour pressures, respectively. ρ is the air density, C_p is the specific heat capacity at constant pressure and γ is the psychrometric constant.

The actual evaporative fraction, Λ is ultimately calculated as:

$$\Lambda = \frac{\Lambda_r\ \lambda E_{wet}}{R_n - G} \tag{2.9}$$

The daily ET value (mm d^{-1}) is then calculated as:

$$ET = 8.64\ \times 10^7 \times \frac{\Lambda . \overline{R_n}}{\lambda . \rho_w} \tag{2.10}$$

Where λ is the latent heat of vaporisation (J kg^{-1}), ρ_w is the density of water (kg m^{-3}), and $8.64\ \times 10^7$ is the constant for conversion of instantaneous ET to a daily value (Gibson *et al.*, 2013).

2.4 Modification of SEBS

The majority of energy balance models inadequately account for the influence of soil moisture on ET. Such models incorporate the effects of soil evaporation, soil moisture storage, transpiration and other processes into a single LST variable (Gokmen *et al.*, 2012). SEBS is designed for energy-limiting cases, which limits its ability to represent ET in water-limiting environments (Timmermans *et al.*, 2013).

The original SEBS formulation by Su (2002) was modified by Gokmen *et al*. (2012), to more effectively consider the influence of soil moisture on ET and improve estimation in water-stressed conditions. The SEBS-SM approach decreases kB^{-1} as water stress increases, according to stomatal conductance in a canopy. This in turn decreases aerodynamic resistance, which increases H and results in lower ET estimates (Gokmen *et al.*, 2012). The SEBS formulation is modified by the addition of a scaling factor (*SF*), presented by a sigmoid function:

$$SF = \left[a + \frac{1}{(1+\exp(b-c*SM_{rel}))}\right] \quad (2.11)$$

$$SM_{rel} = \frac{SM-SM_{min}}{SM_{max}-SM_{min}} \quad (2.12)$$

$$kB^{-1} = SF * kB^{-1}{}_{SEBS} \quad (2.13)$$

Where $a, b \, and \, c$ are coefficients of the stigmoid function. These are determined through performing an optimisation by error reduction between observed and simulated H values. SM_{rel} is the relative soil moisture value, used to determine water stress level. SM is the actual soil moisture (m^3 m^{-3}). SM_{min} and SM_{max} are the minimum and maximum soil moisture respectively (m^3 m^{-3}). Once the kB^{-1} parameter has been adjusted as shown in (2.13), the model must be re-run.

2.5 Case Studies

Gokmen *et al*. (2012) integrated soil moisture information into the SEBS model by Su (2002) to account for water stress and improve ET mapping in water-limited conditions. The excess resistance parameter, kB^{-1} was altered by the addition of a scaling factor which considered relative soil moisture (Gokmen *et al.*, 2012). Outputs of H from the updated version of the model, SEBS-SM, were then compared to the original as well as measurements obtained from the Bowen Ratio technique. The study was performed in the Konya Basin in Turkey (Gokmen *et al.*, 2012).

A study by Chirouze *et al*. (2014) involved assessing the performance of various models under conditions of water stress and where water was not a limiting factor. The study occurred over an irrigated agricultural area in the semi-arid region of New Mexico (Chirouze *et al.*, 2014). Here the performance of S-SEBI, SEBS and TSEB models were compared to *in-situ* data and against outputs from a soil-vegetation-atmosphere transfer (SVAT) model (Chirouze *et al.*, 2014).

Pardo *et al*. (2014) conducted a study to evaluate three variations of the SEBS model: the original formulation, SEBS-SM by Gokmen *et al*. (2012) and SEBS-NDVI which was modified with NDVI and surface temperature. The models were applied to a rotating agricultural cropland to evaluate SEBS for energy balance components and the evaporative fraction (Pardo *et al.*, 2014). The estimates of the evaporative fraction from the three SEBS variations were compared to those from Eddy covariance flux towers (Pardo *et al.*, 2014).

Paul *et al*. (2014) highlighted the use of kB^{-1} parameterization in SEBAL. The parameter accounts for the discrepancy between radiometric and aerodynamic temperature. These are used in determining the temperature gradient for estimating ET. The study involved SEBAL being applied to both dryland and irrigated conditions. Four variations of the model were used, two which utilized different fixed roughness heights; one which used a fixed kB^{-1} set at 2.3 and one which utilized a spatially-varying kB^{-1} (Paul *et al.*, 2014).

Zhuang *et al*. (2016) highlighted that the kB^{-1} parameter is difficult to obtain values for as it is influenced by both structural parameters characteristics and environmental conditions. This follows work by Gokmen *et al*. (2012), which discussed the influence of soil moisture on kB^{-1} and Paul *et al*. (2014), which showed ET estimation in SEBAL to be sensitive to the parameter. Therefore Zhuang *et al*. (2016) proposed an approach for estimating H without using kB^{-1}. Modification of the single-source bulk transfer equation from which kB^{-1} was derived occurred using canopy, environmental and radiometric surface temperature parameters. The study occurred over crop and grasslands in a river basin in northwest China. Results from methods based on kB^{-1} were compared to LAS and the new approach (Zhuang *et al.*, 2016).

A study conducted in a desert-oasis environment in North-western China by Yi *et al.* (2018) involved modifying the kB^{-1} parameter through integrating the modified perpendicular drought index (MPDI) into SEBS. The MPDI makes use of the Chinese HJ-1 satellite which has a fairly high spatial and temporal resolution for land surface variable measurement. This imagery was fed into SEBS with soil moisture estimates from the MPDI (Yi *et al.*, 2018). The soil moisture from MPDI was integrated into SEBS through a scaling factor, similar to work by Gokmen *et al.* (2012).

The studies which have been discussed highlight some of the limitations of satellite-based models which are linked to the kB^{-1} parameter. A summary of these can be seen in *Table 2.2*. Techniques have been developed to improve the performance of models in estimating ET through modifying kB^{-1}. However, the sensitivity of ET to the parameter remains to be fully established.

Table 2.2 Summary of case studies

Study	Objective	Findings
Gokmen *et al*. (2012)	To investigate if integrating soil moisture influence in SEBS through kB^{-1} yields improved ET estimates.	• Improved estimates of low ET values in drylands. • Maps displayed good contrasts between irrigated and dry areas in semi-arid regions. • Modification yields improved estimates of energy and water fluxes over water-stress areas.
Chirouze *et al*. (2014)	Evaluation of ET estimated from various models against *in-situ* measurements.	• TSEB and SWAT estimated water stress the most accurately. • SEBS overestimated ET, especially under conditions of strong soil moisture contrast.
Pardo *et al*. (2014)	Evaluate H and Λ outputs from variations of SEBS with observed data.	• Original formulation displays poor correlation. • SEBS-SM significantly improves H estimates but not Λ. • SEBS-NDVI improves both. However, improvement to H are more influential on ET estimates.
Paul *et al*. (2014)	Evaluation of the influence of kB^{-1} and roughness height in SEBAL.	• Constant kB^{-1} underestimates H. • Spatially-varying kB^{-1} yields more accurate estimates under water-limiting conditions.

		• ET estimates are more influenced by kB^{-1} values than roughness heights.
Zhuang *et al*. (2016)	Identifying an approach for estimating *H* without using kB^{-1}.	• kB^{-1} based estimates were more variable compared to LAS data than the new approach.
Yi *et al*. (2018)	Modifying kB^{-1} in SEBS by integrating soil moisture from the MPDI	• Improved *H* estimation for sparse and dense vegetation • Reduced ET overestimation for water-limiting conditions

2.6 Synthesis of Literature

ET is an important process in the global hydrological cycle. Accurate estimation is vital the management of water resources, especially in semi-arid areas such as South Africa where high ET rates coupled with variable rainfall reduce assurance of water supply. This process has characteristically high spatial and temporal variability and remains difficult to measure over heterogeneous surfaces.

While traditional *in-situ* techniques may provide accurate measurements at point or field scales, they are unable to adequately represent the heterogeneous nature of ET rates over large areas. Satellite-based techniques are seen as suitable alternatives to conventional approaches as they provide estimates at regional scales and potentially better capture ET variability. Despite these advantages, these techniques possess limitations. These include *inter alia*; trade-offs between spatial and temporal resolution of imagery used, mismatch of scale between study area and imagery pixel sizes, difficulty in estimating over heterogeneous surfaces or under cloud cover and inadequate representation of underlying environmental conditions.

These limitations could be attributed to model conceptualisation. A particular limitation, the inaccurate estimation of ET has been identified to be relevant to applications in water-stressed environments. Inadequately accounting for soil moisture has been cited as a possible reason for this discrepancy. Furthermore, several studies have attempted improvements through the modification of the kB^{-1} excess resistance to heat transfer parameter, which is found in most energy balance models. Therefore, it would be necessary to first establish if the parameter does influence ET estimation. It could be possible that there is an issue within the kB^{-1} parameterisation, which may impact model outputs. This would also need to be determined.

The SEBS model has been shown to inaccurately estimate ET under conditions of water stress, when compared to other energy balance models. This has been attributed to the model failing to adequately consider the influence of soil moisture. Numerous studies have attempted to improve estimates by modifying kB^{-1} through the application of various techniques. The integration of soil moisture influence in SEBS through kB^{-1} appears to be an appropriate technique to improving ET estimation in water-limited, semi-arid regions.

Despite being extensively discussed in literature, kB^{-1} remains a complex parameter, owing to being influenced by various soil-plant-atmosphere characteristics. Hence it can be inferred that an improved understanding of the relationship between kB^{-1} and ET is needed. This would likely be beneficial to any technique which employs the parameter. SEBS-SM is the modified version of SEBS which integrates soil moisture into the calculation of kB^{-1} values. Hence a similar route can be followed to test the sensitivity of ET to kB^{-1}. This would involve a comparison of estimates between SEBS, SEBS-SM and a reliable *in-situ* data set. Such a test would provide insight into the actual sensitivity of the model to kB^{-1} in conditions where soil moisture would have a strong influence. This would in turn provide a platform for future research into modifying kB^{-1} so that models which utilise it in flux calculations will yield more accurate estimates.

3. METHODOLOGY

The study made use of the SEBS model contained in the Integrated Land and Water Information System (ILWIS) software package (52°North, 2015). This required meteorological data on atmospheric properties as well as *in-situ* measurements of energy balance components.

3.1 Study Site Description

The study area falls within the Groot Letaba River Catchment in north-eastern South Africa. This is a semi-arid region and predominantly savannah environment, which experiences seasonal rainfall with the majority occurring in summer months (Gokool *et al.*, 2017). The river system has been known to experience water shortages, affecting water resources management activities (Gokool *et al*., 2017). These conditions make it suitable to the scope of the study, which seeks to examine ET estimation under water-stressed conditions. The study site is around the Malopeni Flux Tower (-23.833^0 S; 31.215^0 E). This is an Eddy Covariance system, which provided micrometeorological measurements and the validation data for the study.

3.2 Data Collection

The time frame of the study followed the period when the most continuous record of latent heat and ET data was available in the validation dataset. Missing records, required for modelling, were infilled using data from the nearest available flux tower (-23.658^0 S; 31.047^0 E). The period under study ran from the 12th of June to the 12th of August 2015. For the study period, Atmospheric measurements of Ozone, Water vapour and Atmospheric Optical Thickness (AOT), were obtained from the National Aeronautics and Space Administration (NASA) earth observations website (NASA, 2018b). Atmospheric parameters were obtained for the location closest to the study site (-23.875^0 S; 31.625^0 E). The parameter values, shown in *Table 3.1*, were assumed to remain constant throughout their respective months.

Table 3.1 Atmospheric parameters used in modelling

Parameter	June	July	August
AOT (550 nm)	0.091	0.051	0.157
Water Vapour (cm)	1	1	1
Ozone (atm. cm)	0.248	0.249	0.273

The imagery used was obtained from the NASA Level-1 and Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Centre (DAAC). The MODIS Terra data products with Level 1-B Calibrated Radiances (MODO21KM) and Geolocation (MODO3) imagery were used for each day in the study period. These products have a 16-day repeat cycle and provide 250 m, 500m, and 1000 m spatial resolutions for different bands. (NASA, 2018a).

3.3 Data Processing and Analysis

The imagery obtained underwent stages of pre-processing prior to being run through the SEBS model. These involved file formatting, Brightness Temperature Computation, Soil Moisture Atmospheric Correction (SMAC) and calculation of land surface variables. The methodology for pre-processing was taken from a SEBS model guide and other studies (Gibson *et al*., 2011; Su and Wang, 2013; Gokool *et al*., 2016).

The model was run using input maps generated during pre-processing as well as meteorological data inputs synchronous with the time of satellite overpass for image capture. A reference height of 2 m, planetary boundary layer (PBL) elevation of 1000m and 10 daily sunlight hours were assumed, as per SEBS default settings (Su and Wang, 2013). The model was run for each day in the study period for a total of 62 days, approximately a two-month period.

A primary objective of the study was to test the sensitivity of estimated ET values to the kB^{-1} parameter. Following completion of the base runs, the kB^{-1} maps generated were successively decreased by intervals of 10, 25, 50 and 75 percent. The decreased maps were then used in secondary model runs for the entire study period. The changes in ET estimation induced by altering the kB^{-1} parameter were then studied. In addition, the trends in kB^{-1} and evaporative fraction values were examined. Initially, the trends in data between the base ET values and validation data were to be analysed. Any differences induced by reducing kB^{-1} were then to be determined by examining the percentage differences between values from base runs, reduction runs and validation data. This involved graphical and statistical analysis.

4. RESULTS

4.1 Modelling of ET

The initial phase of modelling involved base runs for SEBS using input data and imagery. Thereafter, secondary runs in which kB^{-1} was successively reduced by percentage intervals were performed. The results from the percentage reduction runs in comparison to the base and validation ET values can be seen in *Figure 4.1*. It should be noted that on several days, the ET increased with kB^{-1} reduction, creating error days. These are included in the graphs and statistics shown in *Table 4.1*. However, the error days were removed for *Table 4.2* to determine their influence on overall results. kB shown in the graphs and tables represents kB^{-1}.

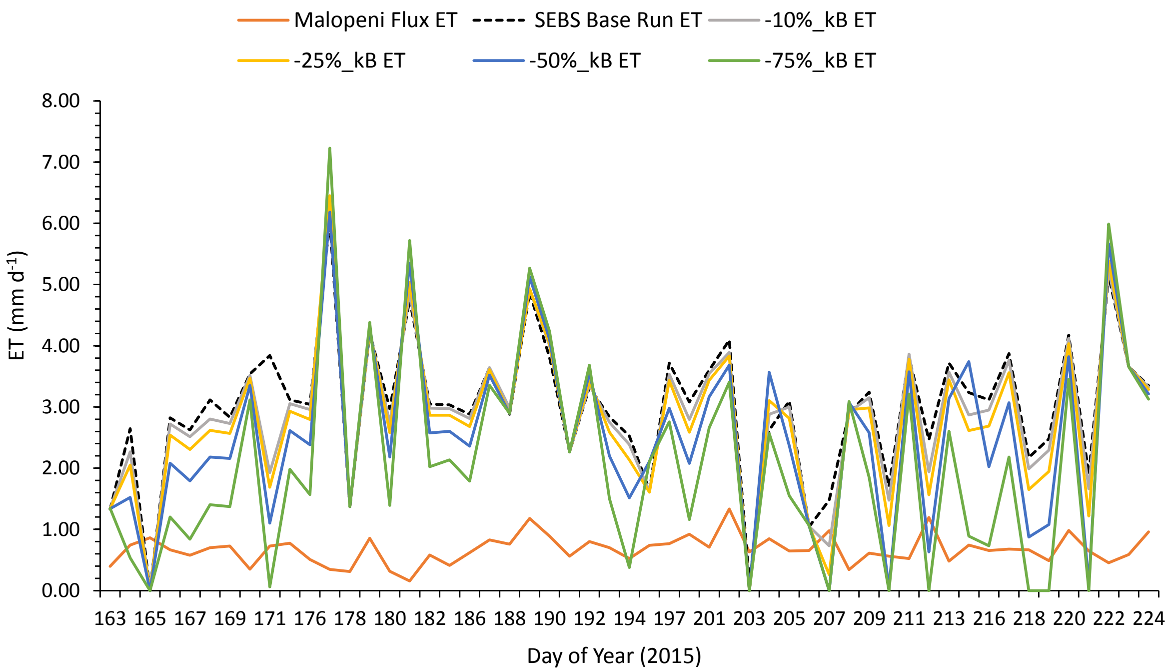

Figure 4.1 Trends in ET values throughout model runs

Table 4.1 Statistical analysis of ET modelling results

Statistic	Malopeni Flux ET (mm)	SEBS Base Run ET (mm)	-10% kB ET (mm)	-25% kB ET (mm)	-50% kB ET (mm)	-75% kB ET (mm)
Mean	0.673	2.996	2.870	2.759	2.527	2.096
Maximum	1.334	6.041	6.208	6.451	6.182	7.228
Minimum	0.157	0.000	0.000	0.000	0.000	0.000
Standard Deviation	0.231	1.128	1.194	1.272	1.435	1.680
Variance	0.053	1.273	1.425	1.618	2.059	2.824

Table 4.2 Statistical analysis of error-excluded modelling results

Statistic	Malopeni Flux ET (mm)	SEBS Base Run ET (mm)	-10% kB ET (mm)	-25% kB ET (mm)	-50% kB ET (mm)	-75% kB ET(mm)
Mean	0.694	2.842	2.644	2.470	2.120	1.502
Maximum	1.334	4.174	4.124	4.035	3.821	3.450
Minimum	0.316	0.000	0.000	0.000	0.000	0.000
Standard Deviation	0.206	0.928	0.963	1.004	1.127	1.143
Variance	0.043	0.860	0.927	1.007	1.270	1.307

It can be seen that the estimated ET values (*Figure 4.1)* are significantly higher than those in the validation data. Reducing the kB^{-1} parameter generally results in a lower ET than in the base run. There are however, certain days in which this does not occur. The days on which ET increases with kB^{-1} reduction are considered error days. There are more days in which kB^{-1} reduction does lower ET than not. The statistical analysis (*Table 4.1*) shows that the mean ET value decreased as kB^{-1} was successively lowered. The reduction appears to be non-linear. A similar trend is seen in the maximum values. However, the standard deviation and variances increase with kB^{-1} reduction. The reduction resulted in zero-values for the minimums. This was not excluded from the dataset as it was deemed to be an error free run. The minimum value was low for the validation data as well. There is significant reduction in mean ET when the error days are excluded (*Table 4.2*). This may be due to the error days containing significant ET overestimations. The standard deviations and variances increase with successive runs as well, however, they are lower when the errors are excluded.

4.2 Examination of Changes Induced By *kB*$^{-1}$ Reduction

The percentage differences between estimates of ET following *kB*$^{-1}$ reduction were compared to the ET values produced in the base run. This was performed to establish how much of a change reducing the parameter would induce on estimated ET. The trends in the percentage differences can be seen in *Figure 4.2*. Furthermore, the percentage differences between estimated ET values in each run and the ET from the validation data can be seen in *Figure 4.3*. This shows how altering *kB*$^{-1}$ may generate ET values closer to ground measurements.

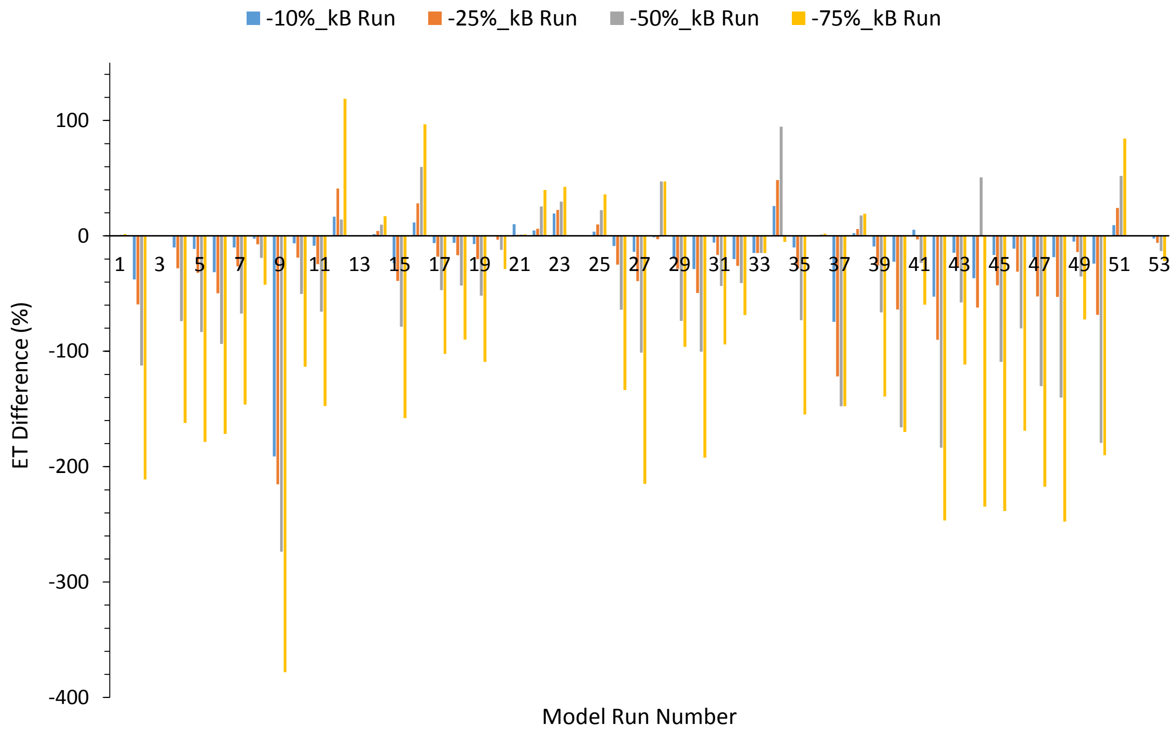

Figure 4.2 Percentage differences between kB-1 reduction runs and the base run

The percentage difference graph (*Figure 4.2*) shows that the majority of values in each run display a negative difference. This shows that most values decrease with *kB*$^{-1}$ reduction, in comparison to base run values. However, days which display positive differences correspond to error days. It can also be seen that the length of the percentage difference lines generally increase with *kB*$^{-1}$ reduction. This trend is shown on both positive and negative difference days. The increase is non-linear however; a clear change from base run values is visible.

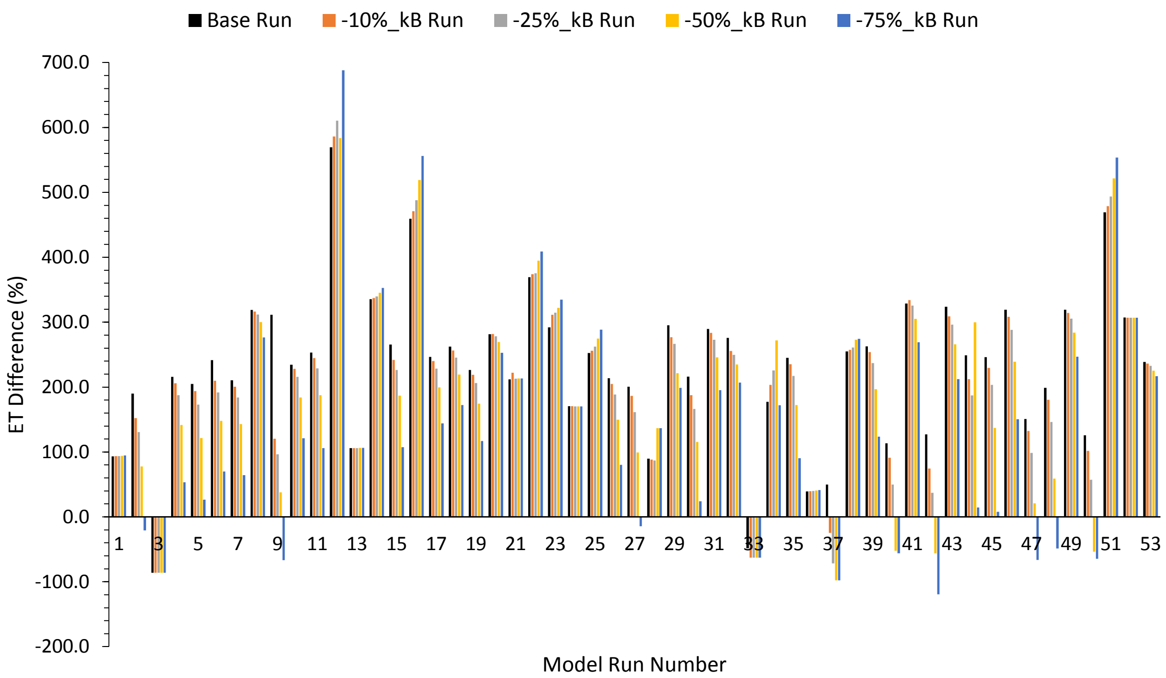

Figure 4.3 ET percentage differences between all model runs and the validation data

The percentage differences between estimated ET and the validation data (*Figure 4.3*) are much higher. This shows that in general, there is a significant overestimation of ET. The majority of values show positive differences. However, there are days in which negative differences are also displayed. The negative differences show that estimated ET was in fact lower. These may be attributed to modelling error. For days with positive differences, the majority of percentage differences appear to decrease as kB^{-1} decreases. The trend is non-linear and there are certain cases of exception. The overall result of the percentage difference tests shows that a decrease in kB^{-1} does not seem to yield a proportional decrease in ET.

4.3 Trends in Values of the kB^{-1} Parameter

In the initial phase of modelling, SEBS was allowed to generate values for kB^{-1} to use in ET estimation. In the secondary runs, the original values were reduced. The values varied from day to day and the distribution of kB^{-1} values over the study period can be seen in *Figure 4.4*.

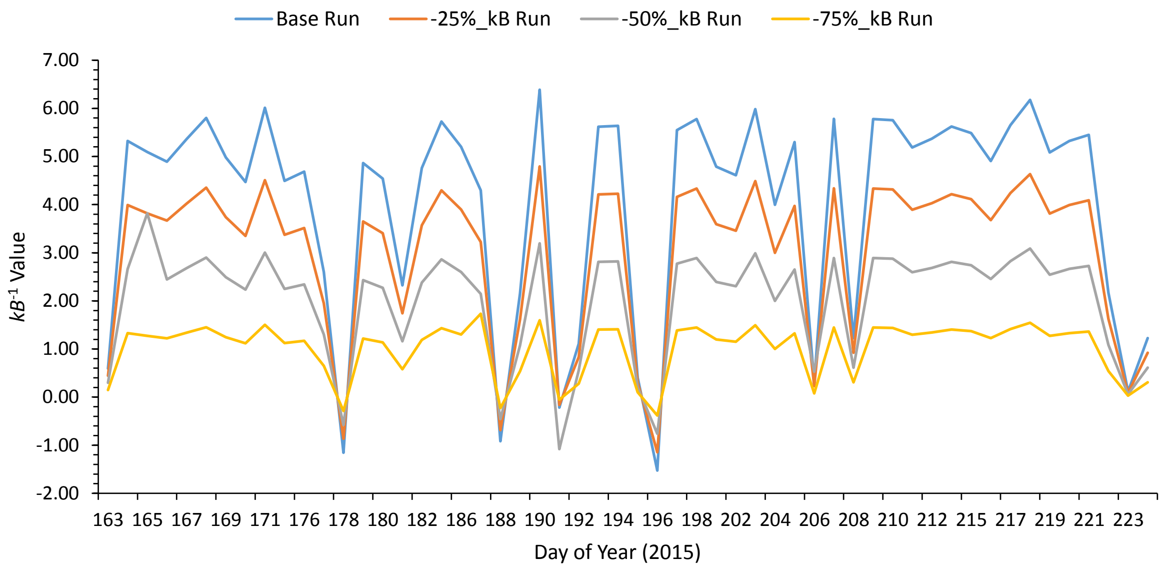

Figure 4.4 Trends in kB^{-1} values from base and reduction runs

The values of kB^{-1} vary over the study period, showing that various conditions may influence them. They are not fixed for the study location as environmental factors may change with time. Certain days display negative values which may be attributed to error. These may have contributed to the occurrence of ET error days.

4.4 Trends in the Evaporative Fraction Values

The evaporative fraction (EF) influences ET estimation. Therefore, an examination of values was reasoned as a possible means of explaining the ET error days. The EF is a SEBS output and the trends in calculated values alongside ET values from the base and 25 % reduction runs can be seen in *Figure 4.5*. A reference line showing the threshold for EF is also displayed.

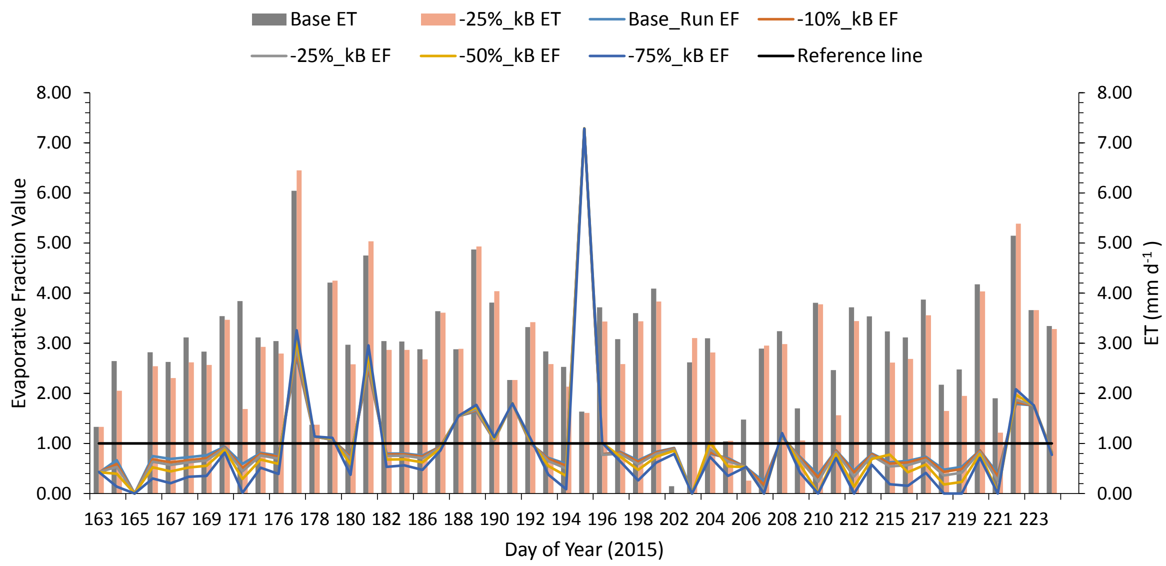

Figure 4.5 Trends in evaporative fraction values over the study period

The maximum possible value of the EF is represented by the reference line (*Figure 4.5*). There are certain days on which the EF is greater than this value. In general, values of ET on these days appear to increase rather than decrease. However, there is an exception to this as well where significantly high EF values did not yield an ET increase. Hence, in most cases when EF is already greater than 1 in the base run, a reduction in kB^{-1} induces a further increase, which in turn increases ET instead of decreasing it.

5. DISCUSSION

The base runs for the SEBS model resulted in ET estimates which were on average, significantly higher than ET values in the validation data. The estimated ET values were more than three times higher. This can potentially be attributed to SEBS inadequately accounting for the influence of soil moisture (Gokmen *et al*., 2012; Gibson *et al*., 2013; Yi *et al*., 2018). This limitation results in ET overestimation under water-limiting conditions, which is seen in the results of the base runs. Drought conditions induced by an El Nino period prevalent during the study time frame may have contributed to water-stress (Gokool *et al.*, 2017).

The general trends in the results showed that reducing kB^{-1} in the secondary runs successfully lowered the overestimated ET, bringing it closer to validation data values. The greatest change was induced when kB^{-1} was reduced by 75 %. There does not appear to be a linear relationship between kB^{-1} reduction and the change in ET obtained in comparison to the base run. It can be reasoned that since kB^{-1} is a highly sensitive parameter, the result obtained from altering values would vary. However, it appears that if the error in kB^{-1} value utilised is moderately low, the effect on model outputs will be relatively small. This is shown by the results of the 10 % and 25 % reduction runs, which did not yield ET values greatly different to those in the base run.

An assumption is being made that the validation data is correct. There is a possibility that since the Malopeni Eddy Covariance system did not have complete records on certain days, the daily ET values may not be accurate representations and could possibly be lower than what they should be. Hence the case of significant overestimation expressed by the SEBS estimated ET results could be less pronounced in reality.

It should be noted that there were certain days on which the estimated ET increased despite the kB^{-1} being decreased. Further examination of model outputs revealed a relationship between ET overestimation and values of the EF. It was found that when the EF exceeded the threshold value of 1 during the base runs, further reducing kB^{-1} generally resulted in an increase to the EF. This in turn caused ET to have a higher value than in the base run.

The function of kB^{-1} is correcting for the difference between radiometric and atmospheric temperature. Days which have a high difference, possible due to a high LST, would need a high kB^{-1} value to moderate it (Brenner *et al.*, 2017). However, since the value was reduced in this study, it could have been reduced to a lower value than was needed to moderate the radiometric-atmospheric temperature gradient. The higher the gradient, the higher the EF (Brenner *et al.*, 2017). Hence further decreasing kB^{-1} resulted in a higher gradient and a higher EF, which in turn resulted in ET increasing rather than decreasing.

Despite the EF threshold value being 1, there are known cases where it can exceed this value. One example is when model-estimated surface temperature is less than air temperature, which then results in a negative *H* value. This can occur in either stable or strong horizontal advection conditions (Lu *et al.*, 2013). In this instance, the *H* would be underestimated resulting in an overestimation of the relative evaporative fraction which in turn causes the EF to be overestimated (Lu *et al.*, 2013). The major reasons for *H* underestimation in SEBS and hence EF overestimation are lack of energy balance closure, underestimation of R_n - G, land types with higher ET in a MODIS pixel and incorrect calculation of aerodynamic parameters (Lu *et al.*, 2013). The model is highly complex and therefore any combination of several minor factors could have resulted in the EF values exceeding the threshold and resulting in error. The trends in the *H* values estimated could be studied further. However, due to time constraints and scope of the study, this was not possible.

The existence of such EF errors in the results suggests that either the kB^{-1} may have been reduced too low or some of the conditions for EF exceeding the threshold value had occurred. These possibilities would account for why ET increased on certain days despite kB^{-1} being decreased. However, EF is one of the last variables calculated in SEBS, there are numerous other variables which are calculated leading up to it, hence a straightforward relationship between EF overestimation and ET overestimation may not exist. Further examination of the major variables would be needed to determine the root cause of the error. However, the issue with kB^{-1} reduction and EF values discussed could be a major influencing factor in this case.

6. CONCLUSION

Satellite-based ET estimation is viewed as a suitable alternative to traditional *in-situ* techniques. However, energy balance models which utilise satellite data are not without limitations. Inaccurate ET estimation has been linked to inadequately accounting for soil moisture influence. ET reduces available water supply and therefore, accurate quantification is vital for water resources management in water-scarce environments. The purpose of this study was to evaluate the influence of kB^{-1} on satellite-based ET estimation in a water-stressed environment. Modification of kB^{-1} has been shown in several studies to improve upon the soil moisture limitation. However, there was a need to determine how sensitive ET estimates are to kB^{-1}.

The SEBS model was selected to test the influence of kB^{-1} on ET estimation. Initial results displayed an overestimation of ET in comparison to validation data from an Eddy Covariance system. This was followed by secondary runs in which reduced kB^{-1} values served as model inputs. In most cases, this resulted in lower ET estimates, which agreed with the literature reviewed. However, there were certain days on which ET increased as kB^{-1} was decreased. A key finding was that on such days, the EF had exceeded a threshold value and would generally continue to increase with successive model runs. This was determined to possibly be due to the kB^{-1} values being reduced too low to be able to moderate the radiometric-atmospheric temperature gradient, which allowed the EF to increase above the threshold value and cause ET to increase from base run values. Hence what was found is that the SEBS model will likely overestimate ET under water-limiting conditions, such as those in the study area and by lowering kB^{-1}, the overestimation will generally be reduced. However, there is a possibility that the parameter could be lowered further than necessary and induce an EF error.

The study was a relatively simple test on a complex model parameter. Although EF error was identified as a potential aggravator of ET overestimation, a more in-depth analysis over a longer time frame, considering other influential variables such as H, is needed. Future studies should consider the influence of the EF in greater detail and explore the possibility of modifying the parameterisation to limit exceedance of the threshold value. The key findings of this study may potentially contribute to a further understanding of the complexities of the kB^{-1} parameter in energy balance models. There is potential for application in future research where kB^{-1} is concerned and in the on-going improvement of satellite-based ET estimation techniques for water resources management in arid and semi-arid regions.

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