

THE EVALUATION OF THE INFLUENCE OF LAND SURFACE TEMPERATURE IN ENERGY BALANCE ESTIMATED BY S-SEBI MODEL

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ABSTRACT:

Evapotranspiration (ET) is one of the least understood components of the hydrological cycle. Its application is varied, from agricultural, ecological and hydrological monitoring, to control of the evolution of climate change. The goal of this work was to analyze the influence that uncertainties in the estimate of Land Surface Temperature (LST) can cause on ET estimates by S-SEBI model in Pampa Biome area. The results indicate that the daily evapotranspiration is higher when the pixel LST is lower, which also shows the influence of land use on the variability of ET. They also demonstrated the importance of LST's accuracy in the selection of the driest and wettest pixels in applying S-SEBI model, because when there are uncertainties in estimates of LST, the errors in the estimates of the energy components multiply. The Pampa Biome native grass crops have lower Latent Heat Flux (LET) than other land uses, with higher values of LET during the spring-summer period when compared to autumn-winter.

1. INTRODUCTION

The physical, chemical and biological processes responsible for life on Earth depend practically on solar energy. Monitoring energy and soil-vegetation-atmosphere mass transfers is a key step in the management of water and agricultural resources. It is also useful for a better understanding and prediction of climate evolution (Oliosio et al., 1999).

Physically, the energy balance is obtained by determining the magnitude of radioactive and non-radiative fluxes. The radiation balance of the radiative fluxes represents the energy absorbed by the system. Its magnitude is shared by the energy used in the evaporation of water latent heat flux (LE), or evapotranspiration on vegetated surfaces, sensible heat flux (H) and soil heat flux (G).

Land surface temperature (LST) is one of the sources of input data for modelling land surface processes, such as actual and potential evapotranspiration (ET) or net radiation flux, that are a critical component of many agricultural and ecological studies (Courault et al., 2005; Cristóbal et al., 2018; Rubert et al., 2018; Sobrino et al., 2005).

In this way, ET is one of the least understood components of the hydrological cycle, it is estimated that 60% of the precipitated water returns to the atmosphere through evapotranspiration (Oki and Kanae, 2006). In the Pampa biome the estimate of Latent Heat Flux (LET) by eddy-covariance was assessed seasonally by Rubert et al., (2018) in two different study areas with the same native vegetation cover, but with different soil types. The authors concluded that 65% of the available energy was used for

evapotranspiration and, even with the differences in soil moisture, there was no apparent distinction in energy partition in the two study areas.

Conventional measurements of ET have limited application because they are not spatially representative and because of the dynamic's nature of heat transfer processes. Therefore, remote sensing analyses could be an alternative to solve these problems by different methods. The S-SEBI model estimates evapotranspiration from the relationship between LST and albedo, since it calculates the evaporative fraction by defining the temperatures in drier and wetter regions. Therefore, the estimation of LST is an important step for the proper functioning of this model.

The main objective of this work was to analyze the influence that the uncertainties in the estimate of LST can cause on ET estimates by S-SEBI model.

1.1 Study area

The Pampa biome is considered by the *Ministério do Meio Ambiente (MMA/Brazil)* as one of the most important temperate field areas on the planet. In South America, this biome extends over an area of approximately 750,000 km², shared by Brazil, Uruguay and Argentina. In Brazil, this biome is restricted to 63% of the State of Rio Grande do Sul (RS) and represents 2.07% of the national territory.

From the point of view of biodiversity and environmental services, the fields are a fodder source for cattle ranching, shelter

diversity of plant and animal species, and ensure the conservation of water resources (Overbeck et al., 2006). In addition, they control soil erosion and carbon sequestration that mitigate climate change.

The experimental site in Pampa biome is in the experimental area of the Federal University of Santa Maria (UFSM), covering 24 ha of natural vegetation (native grassland). There is a tower flux located in the study area, under the responsibility of the Micrometeorology Laboratory of UFSM, which provided some important variables used in this work (Figure 1).

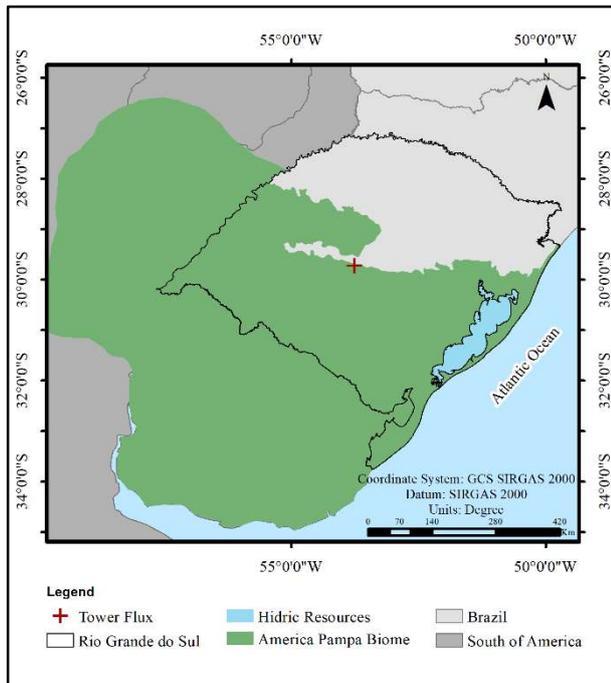


Figure 1. American Pampa Biome and Tower Flux location

This study area is part of the International Long Term Ecological Research (ILTER) network and is used for experiments of the Federal University of Santa Maria in several areas of knowledge, mainly focused on the morphology of native species for livestock production (Confortin et al., 2017; Oliveira et al., 2015).

2. METHODOLOGY

2.1 Materials

Five images from Landsat 8 were acquired, for the year 2018, and treated with geometric rectification and clipped using a study area border. Radiometric calibration and atmospheric correction procedures were conducted to ensure that the change detection analyzes truly detected changes at the Earth’s surface rather than at the sensor level, solar illumination differences, and potential differences in atmospheric conditions.

From the tower flux we have been acquired the global incident solar radiation (R_g) and the incident atmospheric radiation over the spectral domain (R_a), obtained with the satellite overpass (Table 1).

Acquisition Date	Season	DOY	Global Radiation (R_g)	Incident atmospheric
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					radiation (R_a)
16	Dec	Spring	349	916.7	508.54
26	Aug	Winter	237	670.05	399.63
07	Jun	Autumn	157	483.14	394.00
04	Apr	Autumn	93	414.85	437.9
15	Feb	Summer	45	838.31	474.02

Table 1. Satellite Landsat 8 OLI/TIRS data and meteorological information (R_g and R_a) from the tower flux by each day of year (DOY) used in this work

2.2 Methods

To estimate the balance energy by remote sensing models some pre-processing of image data are needed and some indices had to be calculated. Table 2 shows the algorithms used to calculate Normalized Difference Vegetation Index (NDVI), Albedo (α), Soil Heat Flux (G), Land Surface Temperature (LST) and Land Surface Emissivity (LSE).

Variable	Equation
NDVI	$(\rho_{NIR} - \rho_{RED}) / (\rho_{NIR} + \rho_{RED})$; ⁽¹⁾ (Rouse et al., 1973)
Albedo (α)	$0.365b_2 + 0.130b_4 + 0.373b_5 + 0.085b_6 + 0.072b_7 - 0.0018$; (Liang, 2000; Liang et al., 1998).
LSE and LST	$T_i - 0.268(T_i - T_j) + 1.378(T_i - T_j)^2 + 16.4 + (0.183 + 54.3w)(1 - \epsilon) + (-2.238 - 129.2w)\Delta\epsilon$; ⁽²⁾ (Jimenez-Munoz et al., 2014; Sobrino et al., 1996)
Soil Heat Flux (G)	$((T_s / \alpha) * (0.0038 * \alpha) + (0.0074 * \alpha^2) * (1 - 0.98 * NDVI^4)) * R_n$; (Bastiaanssen, 2000)

Table 2. Equations used to the pre-processing image data

Where:

⁽¹⁾ ρ_{NIR} and ρ_{RED} are calculated using Landsat 8 channel 5 (0.86) and channel 4 (0.65);

⁽²⁾ T_i and T_j are the at-sensor brightness temperatures at the SW bands i and j (in kelvins), ϵ is the mean emissivity, $\epsilon = 0.5(\epsilon_i + \epsilon_j)$, $\Delta\epsilon$ is the emissivity difference, $\Delta\epsilon = (\epsilon_i - \epsilon_j)$, w is the total atmospheric water vapor content (in g/cm⁻²), and c_0 to c_6 are the Split Window (SW) coefficients to be determined from simulated data.

We used S-SEBI model proposed by (Roerink et al., 2000) to obtain instantaneous latent heat flux (LET) for all acquired images. The surface energy balance is obtained by determining the magnitude of the radiative and non-radiative fluxes. It is written as follow, when considering instantaneous condition.

$$R_n = LET + G, \quad (1)$$

Where:

Rn ($W m^{-2}$) is the available net radiation flux,

G ($W m^{-2}$) is the soil heat flux (see Table 2),

LET ($W m^{-2}$) is the latent heat flux (both atmospheric convective fluxes: sensible heat flux and latent energy exchanges).

Once the surface energy balance equation is discriminated, the Rn is calculated as the rest term of all incoming and outgoing shortwave (sw) and longwave (lw) radiation, as describing below:

$$Rn = (1-\alpha) Rg + \varepsilon Ra - \varepsilon \sigma LST^4, \quad (2)$$

Where:

Rg ($W m^{-2}$) is the global incident solar radiation;

Ra ($W m^{-2}$) is the incident atmospheric radiation over the thermal spectral domain;

α is the surface albedo;

ε is the surface emissivity;

LST (Kelvin) is the land surface temperature;

σ is the Steffan–Boltzmann constant ($5.67 \times 10^{-8} W m^{-2} K^{-4}$).

The latent heat flux (LET) depends on the evaporative fraction (Λ) and is given as follow.

$$LET = \Lambda (Rn - G) \quad (3)$$

The evaporative fraction concept (Λ) was proposed by (Roerink et al., 2000), adapted and tested by (Sobrino et al., 2007, 2005), and it is described by the equation below.

$$\Lambda = \frac{T_H - LST}{T_H - T_{LE}} \quad (4)$$

Where:

T_H (K) is the temperature corresponding to dry conditions;

T_{LE} (K) is the temperature corresponding to wet condition.

This method can be only applied when the atmospheric conditions are constants over the image and the study site includes simultaneously wet and dry areas (Roerink et al., 2000; Sobrino et al., 2007, 2005). Besides of that, this method works better in a homogeneous vegetated area - with higher variance between dry and wet pixels.

2.2.1 Land Surface Temperature (LST):

In order to analyze the influence that possible uncertainties in the estimation of LST may have on the estimates of LET, a noise was applied to the LST images, with a Gaussian variation of -2 K and + 2 K. Many authors believe that LST retrieval precision varies around 1-2 K depending on the heterogeneity atmospheric conditions and the resolution of the sensor used in the process (Jimenez-Munoz et al., 2014; Skokovic et al., 2017; Sobrino and Skoković, 2016).

It is important to emphasize that, with this noise, the average LST of the images does not vary, but the minimum and maximum temperatures do, as we can see in Table 3.

DOY	Average	Max	Max*	Min	Min*
45	301.99	308.29	309.81	298.23	295.65
93	289.59	291.15	293.82	288.9	285.511
157	286.39	287.91	290.67	284.77	282.14
237	288.06	291.07	293.58	284.57	282.71
349	301.55	349.65	348.58	297.6	295.43

Table 3. Land Surface Temperature stats of the images, without noise and with noise (*)

3. RESULTS AND DISCUSSION

To analyze the influence of LST on ET estimation, these variables were plotted on a graph with the relationship to each pixel of the images. The Figure 2 shows the results for DOY 349 and 237 of 2018, where we can see that the daily evapotranspiration is higher when the pixel temperature is lower.

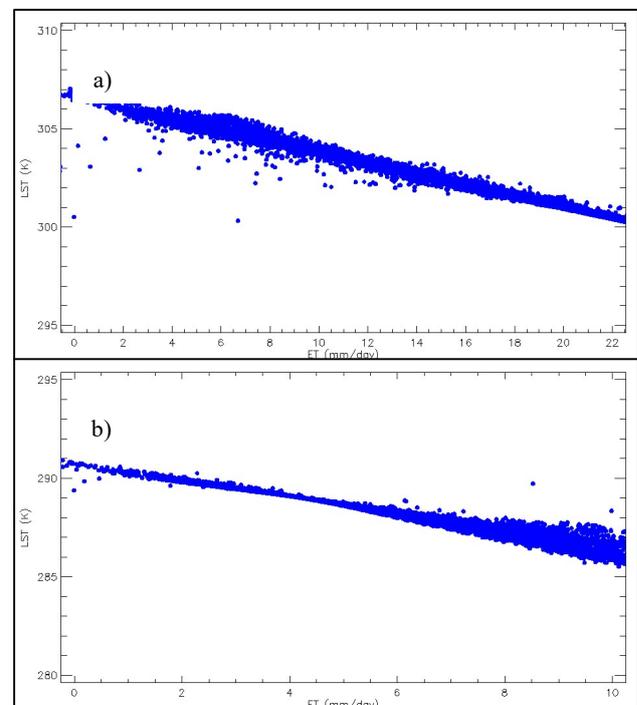


Figure 2. Land Surface Temperature versus Evapotranspiration (mm/day) for a) DOY 349 and b) DOY 237

Another important consideration is the LST and ET maximums, which in winter the LST varies between 285 K and 290 K (Figure 2b) and in summer can reach 310 K in the warmer months, in Figure 2a the LST, on this December day, reaches 305 K. In this way, evapotranspiration in summer is twice as high as in winter, which is already expected. Those analyses corroborate studies conducted by Rubert et al., (2018), where the authors demonstrate the high seasonal variability of evapotranspiration, with higher values during the spring-summer period when compared to autumn-winter.

This behaviour can be explained by differences in air and soil temperatures and by the heterogeneity of land cover. For example, in a Forest the daily ET is higher than a Native Grass but the LST is higher in the second one. In Figure 3 we can compare these differences for Native Grassland and Forest with the Mean image of LET for each day.

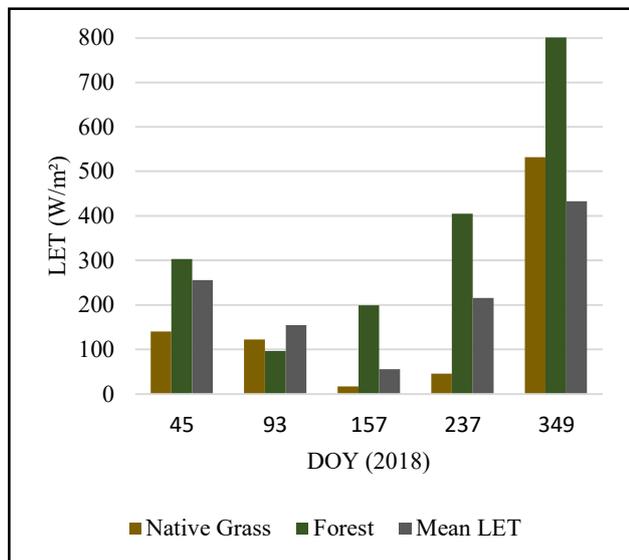


Figure 3. Latent Heat Flux (W/m²) for different land surface use

3.1 The influence of LST on LET estimates

In Figure 4 we can see the LET and LST for Pampa Biome at the tower flux site in the experimental area. The LET for all days are different with the noise in the land surface temperature (LST*), mostly during the winter, but the LST in this point does not vary. The most variance has occurred in DOY 157 with 164 W m⁻² of difference between real LST and noise LST, in a Native Grass land use. The less variance has occurred during the summer in DOY 45 and 349, with 4.5 W m⁻².

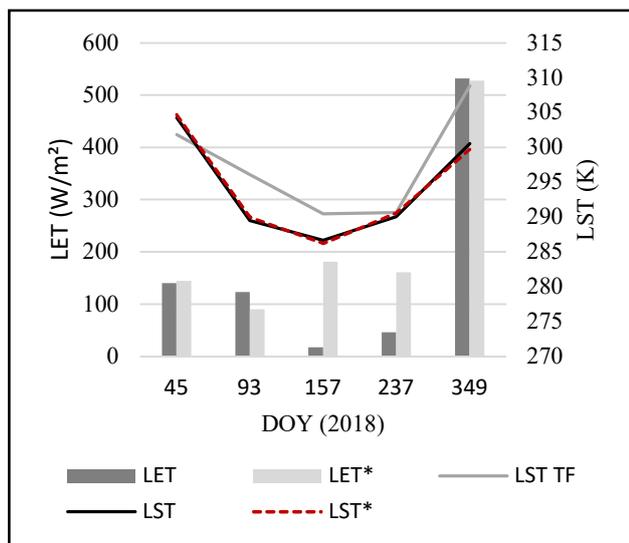


Figure 4. Land Surface Temperature (LST) and Latent Heat Flux (LET) to Native Grass at Tower Flux point, with (*) and without a noise applied to the images

These results demonstrate the importance of LST's accuracy in the selection of the driest and wettest pixels, this being the greatest challenge in applying this method to estimate ET.

When there are uncertainties in estimates of LST, the errors in the estimates of the energy components multiply for the entire study area, as shown in Figure 5, even though the average LST is the same in both estimates, the maximum and minimum values are responsible for the variation in the LET estimate. In the same figure we can see that LST vary much more during summer season, however during winter season de maximum and minimum LST are closer.

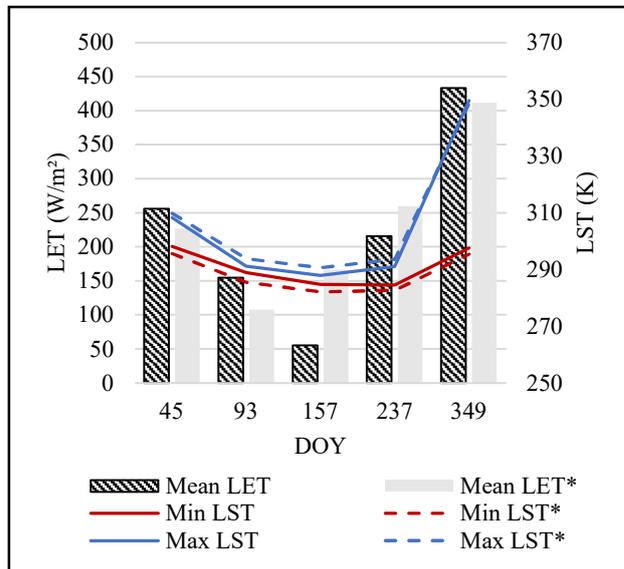


Figure 5. Mean, Minimum and Maximum Land Surface Temperature (LST, Kelvin) and Latent Heat Flux (LE, W/m²) of images

3.2 Application

The use of remote sensing to estimate evapotranspiration is the best way to spatialize this variable and optimize hydrological management processes. Figure 6 demonstrates the heterogeneity of ET in two seasons of the year: summer (a) and winter (b). In the same figure we can see the higher seasonal variability that was discussed by Rubert et al., (2018), but spatially in space.

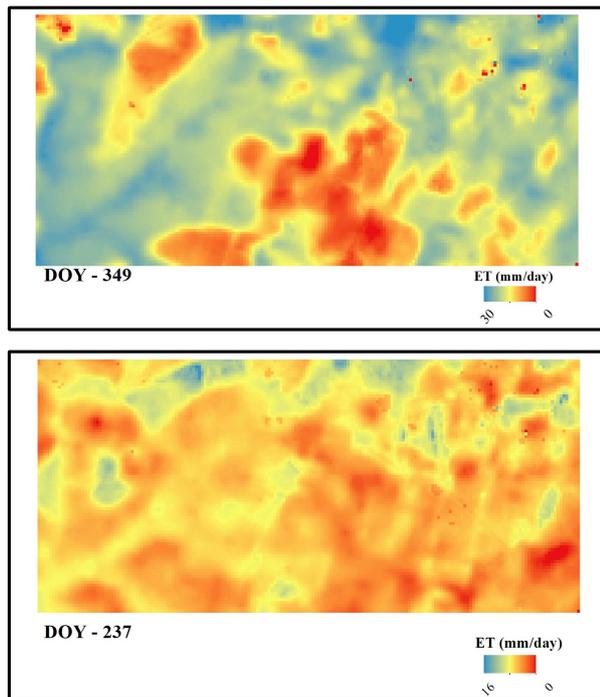


Figure 6. Daily evapotranspiration (mm/day) for Pampa Biome a) in summer (DOY 349) and b) in winter (DOY 237)

During the winter the vary between maximum and minimum evapotranspiration is lower than during the summer, this result can be explained by the fact that during summer season the maximum and minimum LST variation is greater than during the winter.

Schirmbeck et al., (2018) studied the Pampa Biome fluxes by SEBAL model using MODIS images, they conclude that the low spatial variability of temperature in the winter does not allow the correct determination of the extreme water conditions, and this may be occurring in the results of this work as well.

In Figure 7 is possible to see the variability of Daily ET in both images a) DOY 349 and b) 237. In the first one, most of the pixels (area) have around 20 mm/day of ET, but there are some pixels between 5 mm/day and 10 mm/day. This heterogeneity did not occur in the second one, where most of the area have between 5 mm/day and 7 mm/day of evapotranspiration.

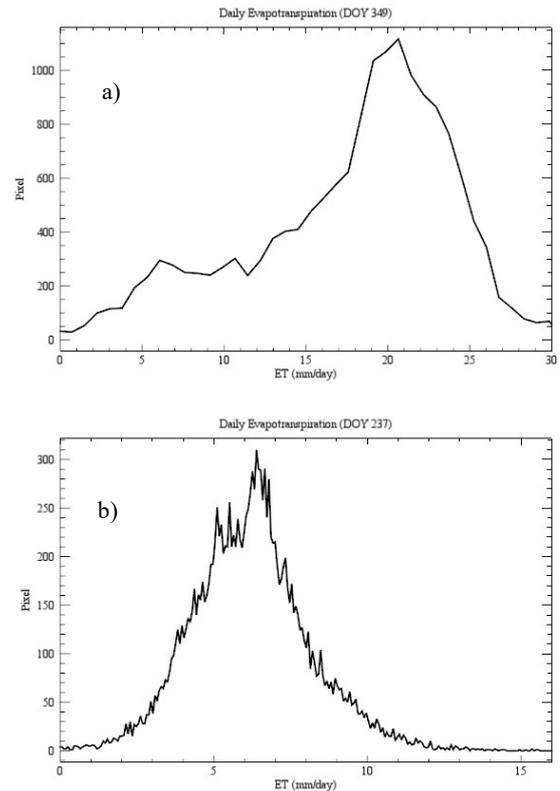


Figure 7. Daily evapotranspiration (mm/day) graphic distribution for Pampa Biome a) in summer season (DOY 349) and b) in winter season (DOY 237)

4. CONCLUSIONS

The S-SEBI model estimates evapotranspiration from the relationship between LST and albedo. In order to analyze the influence that the uncertainties in the estimation of LST may have on the estimates of latent heat flux (LET), a Gaussian noise was applied to the LST images.

The higher variance between LET has occurred in DOY 157 with 164 W m^{-2} of difference between real LST and noise LST, in a native grassland use. The results indicated that the maximum and minimum values of LST are responsible for the variation in the LET estimate. Also, the highest variation between LST values is produced in the summer season, which allow the selection of the driest and wettest pixels, mostly important step in applying S-SEBI model.

The Pampa Biome native grassland have lower LET than forest, with higher values of LET during the spring-summer period when compared to autumn-winter, in this way the daily evapotranspiration is higher when the pixel LST is lower.

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REFERENCES

Bastiaanssen, W.G.M., 2000. SEBAL-based sensible and latent

- heat fluxes in the irrigated Gediz Basin, Turkey. *J. Hydrol.* 229, 87–100. [https://doi.org/10.1016/S0022-1694\(99\)00202-4](https://doi.org/10.1016/S0022-1694(99)00202-4)
- Confortin, A.C.C., Quadros, F.L.F., Santos, A.B., Seibert, L., Severo, P.O., Ribeiro, B.S.R., 2017. Leaf tissue fluxes of Pampa biome native grasses submitted to two grazing intervals. *Grass Forage Sci.* 72, 654–662. <https://doi.org/10.1111/gfs.12261>
- Courault, D., Seguin, B., Olioso, A., 2005. Review on estimation of evapotranspiration from remote sensing data: From empirical to numerical modeling approaches. *Irrig. Drain. Syst.* 19, 223–249. <https://doi.org/10.1007/s10795-005-5186-0>
- Cristóbal, J., Jiménez-Muñoz, J.C., Prakash, A., Mattar, C., Skoković, D., Sobrino, J.A., 2018. An improved single-channel method to retrieve land surface temperature from the landsat-8 thermal band. *Remote Sens.* 10. <https://doi.org/10.3390/rs10030431>
- Jimenez-Munoz, J.C., Sobrino, J.A., Skokovic, D., Mattar, C., Cristobal, J., 2014. Land surface temperature retrieval methods from landsat-8 thermal infrared sensor data. *IEEE Geosci. Remote Sens. Lett.* 11, 1840–1843. <https://doi.org/10.1109/LGRS.2014.2312032>
- Liang, S., 2000. Narrowband to broadband conversions of land surface albedo I Algorithms. *Remote Sens. Environ.* 76, 213–238.
- Liang, S., Strahler, A.H., Walthall, C., 1998. Retrieval of land surface albedo from satellite observations: a simulation study. *J. Appl. Meteorol.* 38, 712–725.
- Oki, T., Kanae, S., 2006. Global Hydrological Cycles and World Water Resources. *Science* (80-.). 313, 1068–1072.
- Olioso, A., Chauki, H., Courault, D., Wigneron, J.-P., 1999. Estimation of Evapotranspiration and Photosynthesis by Assimilation of Remote Sensing Data into SVAT Models. *Remote Sens. Environ.* 68, 341–356. [https://doi.org/https://doi.org/10.1016/S0034-4257\(98\)00121-7](https://doi.org/https://doi.org/10.1016/S0034-4257(98)00121-7)
- Oliveira, L.B., Soares, E.M., Jochims, F., Tiecher, T., Marques, A.R., Kuinchtner, B.C., Rheinheimer, D.S., De Quadros, F.L.F., 2015. Long-Term Effects of Phosphorus on Dynamics of an Overseeded Natural Grassland in Brazil. *Rangel. Ecol. Manag.* 68, 445–452. <https://doi.org/10.1016/j.rama.2015.07.012>
- Overbeck, G.E., Müller, S.C., Pillar, V.D., Pfadenhauer, J., 2006. Floristic composition, environmental variation and species distribution patterns in burned grassland in southern Brazil. *Brazilian J. Biol.* 66, 1073–1090. <https://doi.org/10.1590/S1519-69842006000600015>
- Roerink, G.J., Su, Z., Menenti, M., 2000. S-SEBI: A simple remote sensing algorithm to estimate the surface energy balance. *Phys. Chem. Earth, Part B Hydrol. Ocean. Atmos.* 25, 147–157. [https://doi.org/10.1016/S1464-1909\(99\)00128-8](https://doi.org/10.1016/S1464-1909(99)00128-8)
- Rouse, J.W., Hass, R.H., Schell, J.A., Deering, D.W., 1973. Monitoring vegetation systems in the great plains with ERTS. *Third Earth Resour. Technol. Satell. Symp.* 1, 309–317. <https://doi.org/citeulike-article-id:12009708>
- Rubert, G.C., Roberti, D.R., Pereira, L.S., Quadros, F.L.F., Velho, H.F. de C., de Moraes, O.L.L., 2018. Evapotranspiration of the Brazilian Pampa biome: Seasonality and influential factors. *Water (Switzerland)* 10, 1–18. <https://doi.org/10.3390/w10121864>
- Schirmbeck, J., Fontana, D.C., Roberti, D.R., 2018. Evaluation of OSEB and SEBAL models for energy balance of a crop area in a humid subtropical climate. *Bragantia* 77, 609–621. <https://doi.org/10.1590/1678-4499.2017208>
- Skokovic, D., Sobrino, J.A., Jimenez-Munoz, J.C., 2017. Vicarious Calibration of the Landsat 7 Thermal Infrared Band and LST Algorithm Validation of the ETM+ Instrument Using Three Global Atmospheric Profiles. *IEEE Trans. Geosci. Remote Sens.* 55, 1804–1811. <https://doi.org/10.1109/TGRS.2016.2633810>
- Sobrino, J.A., Gómez, M., Jiménez-Muñoz, J.C., Olioso, A., 2007. Application of a simple algorithm to estimate daily evapotranspiration from NOAA-AVHRR images for the Iberian Peninsula. *Remote Sens. Environ.* 110, 139–148. <https://doi.org/10.1016/j.rse.2007.02.017>
- Sobrino, J.A., Gómez, M., Jiménez-Muñoz, J.C., Olioso, A., Chehbouni, G., 2005. A simple algorithm to estimate evapotranspiration from DAIS data: Application to the DAISEX campaigns. *J. Hydrol.* 315, 117–125. <https://doi.org/10.1016/j.jhydrol.2005.03.027>
- Sobrino, J.A., Li, Z.L., Stoll, M.P., Becker, F., 1996. Multi-channel and multi-angle algorithms for estimating sea and land surface temperature with ATSR data. *Int. J. Remote Sens.* 17, 2089–2114.
- Sobrino, J.A., Skoković, D., 2016. Permanent Stations for Calibration/Validation of Thermal Sensors over Spain. *Data* 1, 10. <https://doi.org/10.3390/data1020010>