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Argentina Water Resources

Evaluating Evapotranspiration in Humid Subtropical and Semi-Arid Climates with
NASA Earth Observations to Understand Water Balance in Paraná and the Patagonia
Steppe of Argentina

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1. Abstract

Evapotranspiration (ET) is a key indicator of hydrological balance across different ecosystems. Water availability is a vital ecosystem service for biota and communities. The transpiration and evaporation of water from vegetation and soil can be estimated through *in situ* ET measurements. However, *in situ* ET data sampling represents an expensive and challenging task, especially in geographically remote areas. Models used in this study utilized data from sensors aboard multiple NASA satellites including, Landsat 8, Aqua, and Terra. Two models, Operational Simplified Surface Energy Balance (SSEBop) and Moderate Resolution Imaging Spectroradiometer (MODIS) Global ET Project (MOD16) were validated by the Fall 2018 NASA DEVELOP Idaho Water Resources II team. The Global Land Data Assimilation Noah evapotranspiration (GLDAS-2-Noah) was validated in Reynolds Creek Experimental Watershed (RCEW) by our Argentina Water Resources team. SSEBop, MOD16, and GLDAS-2-Noah were applied in two study areas: Paraná, province Entre Ríos, Argentina, a humid subtropical (Pampean) bioregion, and the Patagonia Steppe in Argentina, a semi-arid region, climatically similar to the validation site at RCEW. Validation and implementation of the models applied in this study will allow our partners at Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET) and land managers in Argentina to use the model that best suits their needs while also making empirically based decisions regarding water resources.

Keywords

evapotranspiration, remote sensing, Landsat , climate, energy balance model, water balance

2. Introduction

2.1 Background Information

The primary focus of hydrologic studies has been on the supply side of water and not the demand side that includes Evapotranspiration (ET; Fisher et al., 2017). ET is the transport of water from different land surfaces to the atmosphere (United States Geological Survey, 2016). The water is converted to water vapor through the processes of evaporation, the physical process, and transpiration, the biological process (Stancalie, 2012). Within the hydrological cycle, ET is an important flux responsible for an estimated 60% of all terrestrial precipitation returned to the atmosphere (Zeng, 2012). ET measurements often give an indication of water balance and are an essential component of the hydrological cycle (Gavilán, Pastore, Quignard, Marasco, & Aceñolaza, *in review*). Obtaining empirical data from remote locations such as the semi-arid landscape of the Patagonia Steppe, which comprises 15% of Argentina, approximately 119 million acres (Fernandez & Busso, 1999), provides a challenge to land managers. Land managers rely on remotely sensed data sets during their decision making process due to the expenses and time associated with *in situ* data collection in remote locations. To improve the ability of land managers to make empirically based management decisions, high spatial and temporal resolution datasets are needed to understand the hydrologic cycle and annual water availability across remote and expansive landscapes.

In fall 2018, the Idaho Water Resources II team investigated remotely sensed ET models derived from remotely sensed NASA Earth observation data for the semi-arid sagebrush steppe of Idaho. The team used *in situ* data from eddy covariance towers at Reynolds Creek Experimental Watershed (RCEW) in southwest Idaho, to validate four ET models: Google Earth Engine Evapotranspiration Flux (EEFLUX), Operational Simplified Surface Energy Balance (SSEBop), Moderate Resolution Imaging Spectroradiometer (MODIS) Global Evapotranspiration Project (MOD16), and the North American Land Data Assimilation Systems 2 Noah (NLDAS-2-Noah). A simple regression analysis between the ET models and *in situ* data showed the highest correlations between NLDAS-2-Noah (R^2 of 0.70-0.87) and EEFLUX (R^2 of 0.32-0.83). The lowest correlations were found with SSEBop (R^2 of 0.21-0.85) and MOD16 (R^2 of 0.04-0.61). The work completed by the Idaho Water Resources II team demonstrated the potential application of various ET models in semi-arid landscapes.

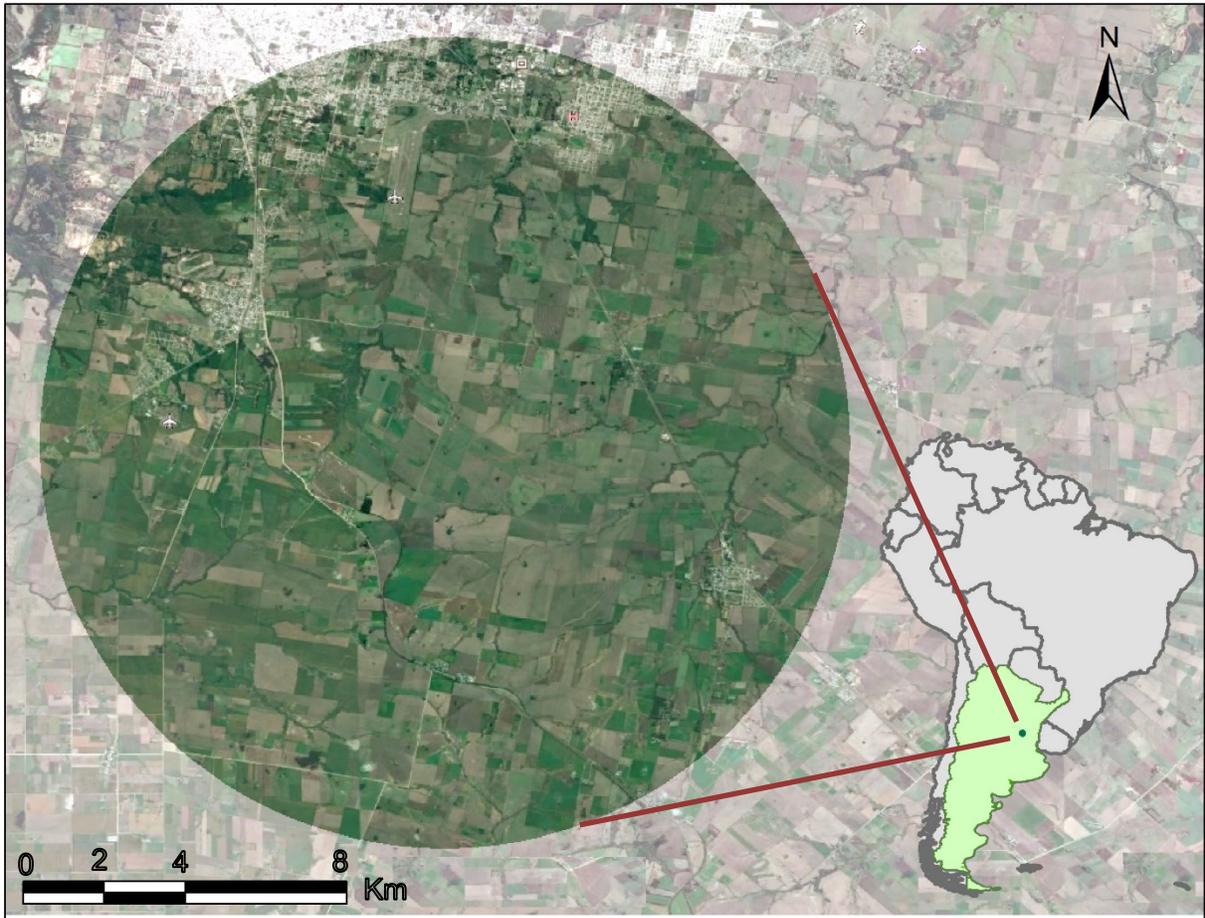


Figure 1. The first study area encompasses a 10-km radius circle in the Paraná region, Entre Ríos province, Argentina, South America. The green zone corresponds to the country of Argentina. The green dot indicates the Paraná location. (Image Source: Google Earth Pro, Digital Globe 2019. Coordinate System: GCS WGS 1984, Datum WGS 1984, Units: Degree).

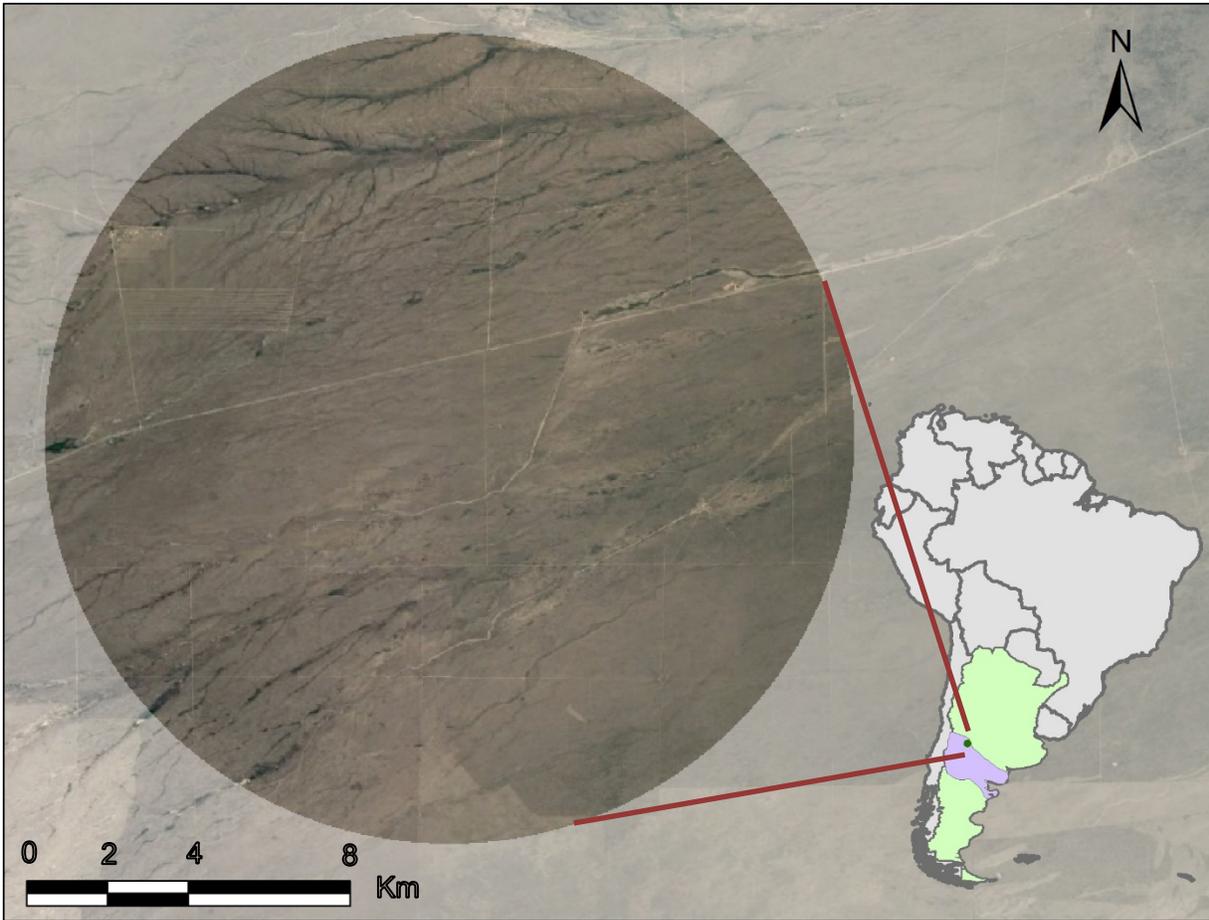


Figure 2. The second study area encompasses a 10-km radius circle in the Patagonia Steppe region, Argentina, South America. The green zone corresponds to the country of Argentina. The purple area represents the entire semi-arid steppe region. The green dot indicates the Patagonia Steppe location. (Image Source: Google Earth Pro, Digital Globe 2019. Coordinate System: GCS WGS 1984, Datum WGS 1984, Units: Degree).

Our Paraná, Argentina study area (Figure 1) is within an extensive agricultural region, primarily consisting of corn and soy. With global temperatures predicted to increase (Diffenbaugh & Giorgi, 2012) and shifts in precipitation regimes expected to occur (Trenberth, 2011) in a response to climate change, understanding ET, a vital constituent in the water cycle, is important when implementing water management strategies in agricultural regions. It is predicted that climate change will negatively affect water availability for vegetation by reducing precipitation and subsequent infiltration of water and by increasing temperature and atmospheric CO₂ fertilization that will increase reference evapotranspiration and vegetation growing capabilities (Pereira, 2011; Saadi et al., 2015). Research presented in this study can help land managers monitor shifts in hydrologic regimes and ET by implementing various validated ET models used in this study in the humid subtropical agricultural bioregion of Paraná, Argentina.

Both our Patagonia Steppe, Argentina study area (Figure 2) and our validation site, RCEW, are semi-arid regions. A land cover description for RCEW is presented in detail in Lauer, Jurkowski, Macek & Zurek (2018). Higher elevations in RCEW consist of various sage brush species and lower elevations consist of shrub species. Vegetation of the Patagonia Steppe is characterized by a semi-arid Monte rangeland, which constitutes a majority of arid rangeland in the country. The climate is dry and warm and becomes cooler towards the south. Monte vegetation consist of steppe scrub dominated by microphyllous xerophytic shrubs

1 to 3 m in height. Some plant species are short-lived summer or winter species whose abundance are strictly dependent on seasonal rainfall. (Fernandez & Busso, 1999).

The Patagonia Steppe study area was determined by analyzing the Köppen-Geiger climate classification map of Argentina (Beck et al., 2018), a climate classification map from an Argentinean science education resource (García, 2019), and using climatological analysis of precipitation data over RCEW and the semi-arid Patagonia Steppe region.

Climate classification maps were visually analyzed to investigate exactly what regions were semi-arid and what regions were considered steppe environments in Argentina. After identifying an optimum region to select a location we used precipitation to narrow our selection further. We used CMAP monthly standard mean precipitation rate data from NOAA/OAR/ESRL PSD, Boulder, CO, USA, to investigate precipitation over our validation site and Patagonia Steppe study area. CMAP precipitation values are estimated based on satellite data and gauge data at a spatial resolution of 2.5 x 2.5degree (NOAA, 2019). This then allowed us to pick a location in the Patagonia Steppe with a similar average monthly precipitation rate to our RCEW validation site for the peak month of each locations respective water year high point.

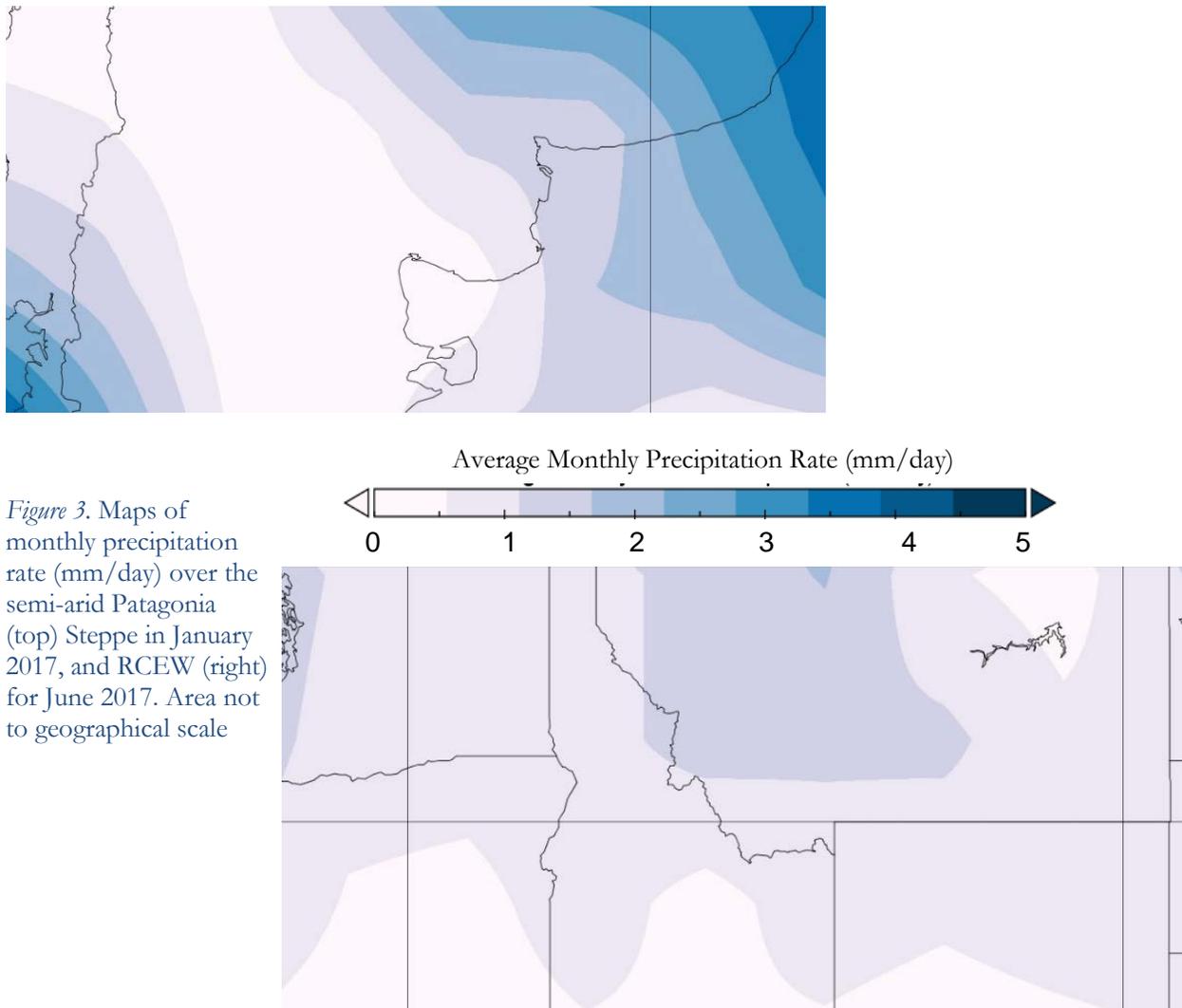


Figure 3. Maps of monthly precipitation rate (mm/day) over the semi-arid Patagonia (top) Steppe in January 2017, and RCEW (right) for June 2017. Area not to geographical scale

2.2 Project Partners & Objectives

CONICET is tasked with the promotion of science and technology within Argentina. Currently, models exist to measure ET for homogeneous agricultural lands, but many are generally untested for use in natural spatially heterogeneous land cover. In addition, some models tend to overestimate ET flux values, especially across heterogeneous natural systems, for example, Penman and Bartholic-Namken-Wiegand models in semi-arid environments (DehghaniSanij, Yamamoto, & Rasiyah., 2004; Hatfield, Reginato, & Idso et al., 1984), or Penman-Monteith in arid regions (Zhang, Kang, & Zhang, 2008). Dr. Pablo G. Aceñolaza and Sebastián Anibal Gavilán, current researchers for CONICET, were interested in using methods developed for the Snake River Plane, a semi-arid sagebrush steppe environment of western Idaho, to better understand water availability and transport in Argentina's Patagonia Steppe. Specifically, Dr. Aceñolaza is aiming to compare the ET models validated by the Idaho Water Resources II team (Lauer, Jurkowski, Macek, & Zurek, 2018), and one validated in this study, with his existing regional model. The collaboration between the NASA DEVELOP Idaho, Pocatello Node and CONICET provided a critical next step in the validation of these ET products and will allow CONICET to determine which models correlate best for use in areas that have limited *in situ* measurements. Providing researchers and land and resource managers with a calibrated methodology for effectively modeling ET rates and soil moisture utilizing NASA Earth observations will allow for the development of more targeted and effective water conservation strategies.

3. Methodology

3.1 Data Acquisition

The team analyzed data from three ET models: two from the Idaho Water Resources II project, and one new model. The study period of this project was from 2015 to 2017. Spatial and temporal resolutions varied between the ET models. Resolutions ranged from 500 m (MOD16) to ~28 km (GLDAS-2-Noah), shown in Figure 3. Temporal resolutions ranged from 3 hours (GLDAS-2-Noah) to 10 days (SSEBop). Operational Simplified Surface Energy Balance (SSEBop) ET estimates were collected from the United States Geological Survey via the Google Earth Engine (GEE) App, Climate Engine. SSEBop has a temporal resolution of 10 days, data reported in 10-day cumulative values, and a spatial resolution of 1 km. This product is derived from Aqua and Terra Moderate Resolution Imaging Spectroradiometer (MODIS) data (MYD16A2: MODIS/Aqua Net Evapotranspiration 8-Day L4 Global 500 m SIN Grid V006; Mu, Zhao, & Running, 2017). MOD16 ET was collected from GEE (MOD16A2: MODIS/Terra Net Evapotranspiration 8-Day L4 Global 500 m SIN Grid V006; Mu, Zhao, & Running, 2017). MOD16 data is a derived product with temporal resolution of eight days and a spatial resolution of 500 m. ET values are reported in eight-day cumulative ET. GLDAS-2-Noah Actual ET data were collected from NASA Giovanni (Global Land Surface Model L4 three Hourly 0.25 x 0.25 degree V002; Wang, Cui, Wang, & Chen, 2016). An Ancillary dataset was used to identify a Patagonia Steppe location. Standard monthly mean precipitation rate from the National Oceanic and Atmospheric Administration's (NOAA) Oceanic and Atmospheric Research(OAR)/Earth System Research Laboratory(ESRL)/Physical Sciences Division(PSD) CPC Merged Analysis of Precipitation (CMAP)(spatial resolution of 2.5 x 2.5 degree with units of mm/day)(NOAA, 2019).

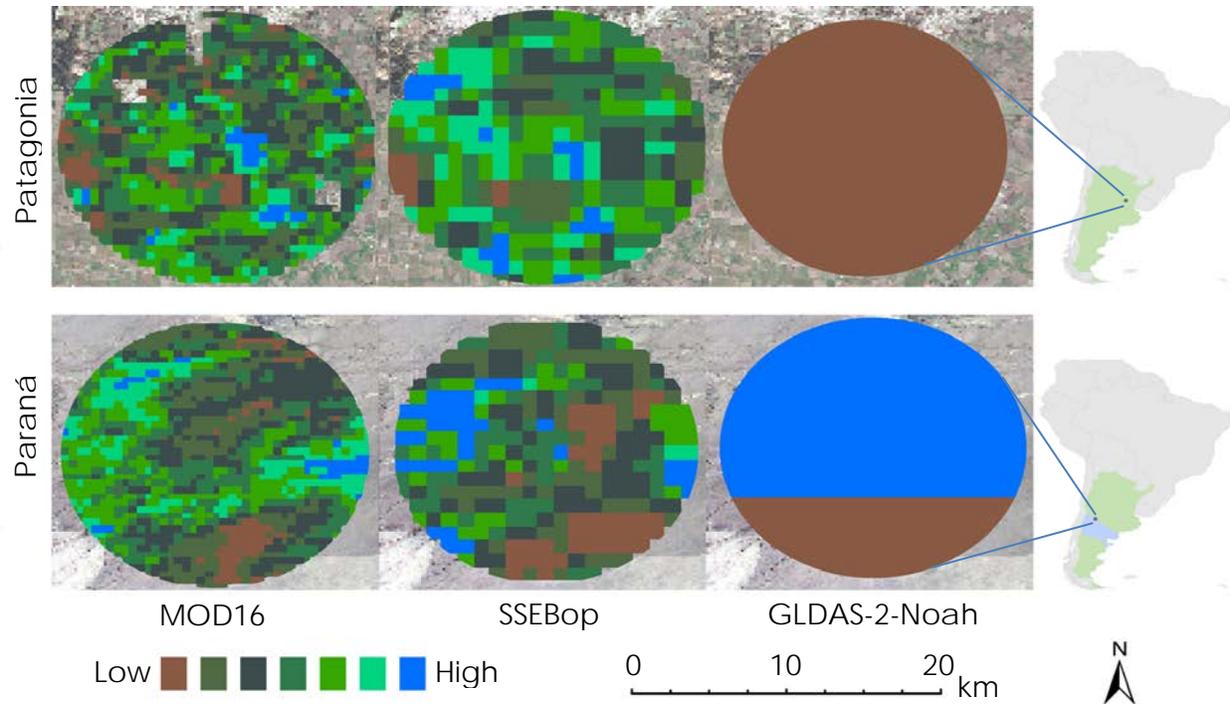


Figure 4. Comparison of spatial resolution of the three ET models in both study locations. Resolutions from left to right, MOD16 500 m, SSEBop 1 km, GLDAS-2-Noah ~28 km. The ET scale bar is relative and reported ET value ranges differ between study area. Numerical ET values are shown in the time series data.

Validation datasets for the RCEW were acquired from the Idaho Water Resources II team and included *in situ* meteorological and ET (eddy covariance flux towers) data for the period of 2015 to 2017.

3.2 Data Processing

The team used Esri ArcMap 10.6.1, ArcGIS Pro, and MS Office Excel, for spatial analysis of vectorial and raster data, as well as complementary processing of satellite-derived data, *in situ* data, and model outputs. ArcMap and ArcGIS Pro were also utilized to spatially process model output data layers including delimitation (clipping) and georeferencing (orthorectification) of study areas. Panoply 4.10.4 was used to visualize precipitation data to determine the Patagonia Steppe extent.

In order to have a standard time metric for the posterior systematic comparison, we calculated cumulative monthly ET values for all three models. We applied corresponding mathematical operations for the different temporal features: 8-day (MODIS), 10-day (SSEBop), and 3-hour (GLDAS-2-Noah). Using the R platform we aggregated the data into monthly basis and exported into csv files. These monthly values were sorted into corresponding water years for humid subtropical and semi-arid climates (corresponding to Paraná and Patagonia regions), then we generated annual time series to analyze seasonal and monthly patterns of ET. Because study sites were in a different hemisphere than the validation site, time series were reported in water year. The water year for Argentina is July-June and the water year for RCEW is from October-September. A detailed analysis and discussion about the validation done by the Idaho Water Resources II team can be found in Lauer et al. (2018). These time series were used for the final statistical analysis.

3.3 Data Analysis

Since each ET model has varying temporal resolutions (Table A1), we calculated the monthly average ET (mean). Statistical correlation analysis was performed using a linear regression and ANOVA (ANalysis Of VAriance). The coefficient of determination (r^2) and standard deviation (σ) were extracted from the regression analyses and the ANOVA table and compared to determine the most accurate models. We evaluated the

accuracy of GLDAS-2-Noah using *in situ* data from RCEW through three categories: weak ($r^2 \leq 0.3$), moderate ($0.3 < r^2 \leq 0.7$), and strong ($r^2 > 0.7$).

Next, Kruskal-Wallis test and a Student's t post hoc test were applied to the time series data to understand the relationship between the three models and their ability to predict ET in relation to each other. The Kruskal-Wallis test assumes a null hypothesis that all model medians are equal. The result provides a p value. The p value is considered significant if that number is below 0.05. To determine the difference between the models a Student's t post hoc test was done. The post hoc test tells us the p value between each pair of models (see section 4.1.4).

4. Results & Discussions

4.1 GLDAS-2-Noah

The North American Land Data Assimilation System (NLDAS) ET output had strong correlations with *in situ* eddy covariance data (r^2 of 0.7-0.87; Lauer et al. 2018). However, this dataset is not available in our Argentina study regions. Instead, GLDAS-2-Noah ET data were validated in RCEW with the same methodologies used by the Idaho Water Resources II team and then applied to our study areas in Argentina. GLDAS-2-Noah has the lowest spatial resolution of the models in the study at ~ 28 km, but it has the highest temporal resolution at 3 hours. Monthly summed ET regression coefficients for the study period ranged from 0.26 to 0.84 (0.43-0.84 for the 2017 water year; Figure 3). The time series analysis display a similar trend between the two study areas where ET is low in the beginning of the water year, increases during the growing season, and decreases after January until the start of the new water year. Peak ET values were reached at different months during both study years at both study areas. Paraná ET reached its maximum monthly sum in December and November in 2016 and 2017 respectively. Patagonia Steppe ET reached its maximum ET values in January and October in 2016 and 2017 respectively. As expected, ET values in Paraná were higher than the Patagonia Steppe, at times doubling total monthly cumulative ET (November; Figure 4). Similar to the NLDAS dataset, the GLDAS-2-Noah ET product assimilates meteorological datasets from across the earth. Therefore, high regression coefficients may be a product of these datasets and may not produce accurate results in regions that lack meteorological stations. Lower correlations may be the result of the lower spatial resolution of the data. A single pixel of the GLDAS-2-Noah ET output covered the entire RCEW validation site. Averaging ET over an area covered by GLDAS-2-Noah may artificially increase or decrease resulting ET outputs depending on the dominant land cover in each respective pixel.

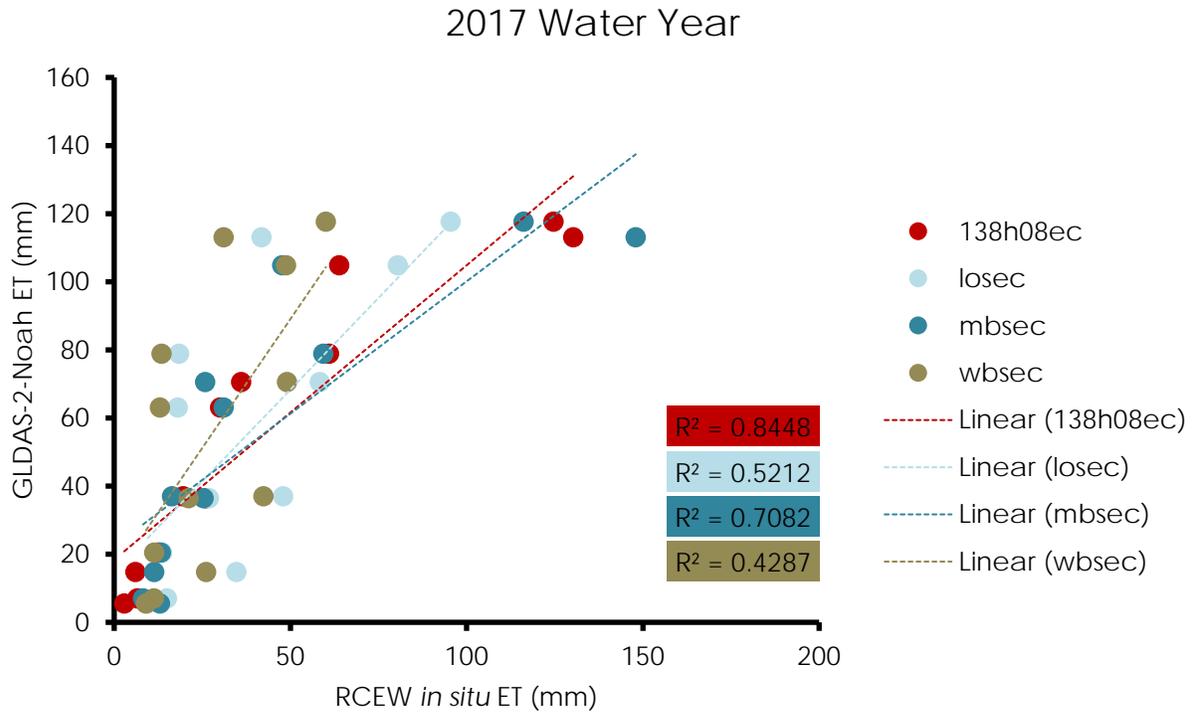


Figure 5. GLDAS-2-Noah modeled ET vs. RCEW ET regression analysis for the 2017 water year

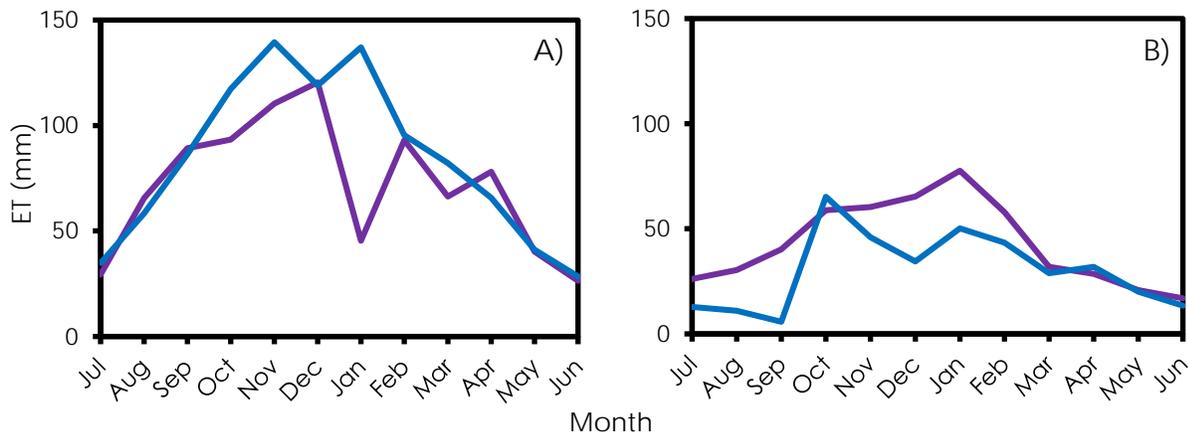


Figure 6. A) GLDAS-2-Noah time series for the water years 2016 (purple) and 2017 (blue) in Paraná. B) GLDAS-2-Noah time series for the water years 2016 (purple) and 2017 (blue) in the Patagonia Steppe.

4.2 SSEBop

Time series show an increase of ET to the peak of the growing season (January) in Paraná and a decrease in ET following the growing season (Figure 5a). Patagonia Steppe 2016 ET increased greatly after September until November. ET decreased following November but has a secondary spike in January. A substantial decrease in ET is seen following January until a third spike in April. 2017 ET data from the Patagonia Steppe

increase rapidly in September and decreases for the remainder of the year with small ET spikes in February, April, and June (Figure 5b).

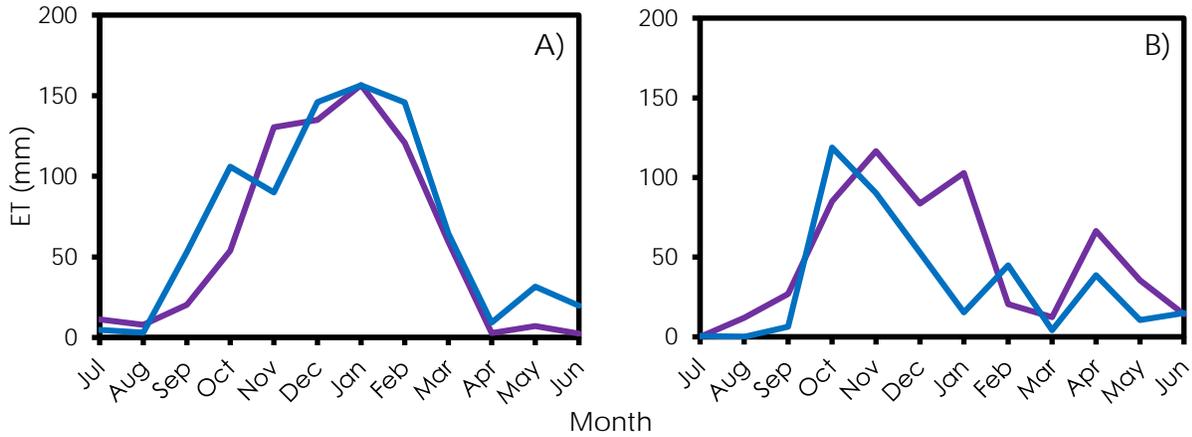


Figure 7. A) SSEBop time series for the water years 2016 (purple) and 2017 (blue) in Paraná. B) SSEBop time series for the water years 2016 (purple) and 2017 (blue) in the Patagonia Steppe.

4.3 MOD16

ET values in Paraná display a trend with an increase in ET and peaks during the growing season followed by a decrease in ET. ET does not drop below 55 mm during either year of our study period. ET in the Patagonia Steppe shows no definite trend in monthly values. A distinct increase in ET occurs in February and a distinct decrease in ET occurs in March in 2016 and 2017 respectively. Patagonia ET values do not drop below 40 mm during either year of our study (Figure 6).

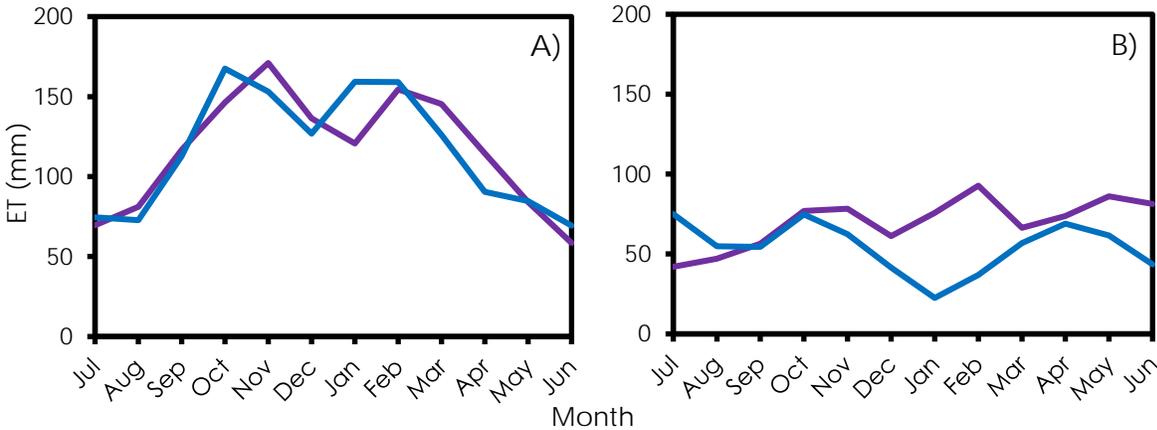


Figure 8. A) MOD16 time series for the water years 2016 (purple) and 2017 (blue) in Paraná. B) MOD16 time series for the water years 2016 (purple) and 2017 (blue) in the Patagonia Steppe.

4.4 Kruskal-Wallis Analysis of ET Models

A Kruskal-Wallis test was run to determine whether the medians of the models were similar in each study area. The data met all assumptions of the Kruskal-Wallis test except the assumption of homogenous variance.

To test the relationship of the two models we ran a Student's t test which individually compared the models to one another for Paraná and the Patagonia Steppe. Figures 8 and 9 show how MOD16 is different from SSEBop and GLDAS-2-Noah at both Paraná and Patagonia respectively. Table 1 shows that the Kruskal-Wallis test in Paraná for two water years resulted in a p value of 0.009, which gives 99% certainty that the models are statistically different and the same test in the Patagonia Steppe had a p value of 0.0011, a 99% significant level, again showing that the models are statistically different. For both study areas the null hypothesis was rejected, which states the medians of all groups are the same. The results for the Student's t test for Paraná (Table 1) showed that MOD16 when compared to SSEBop for two water years had a p value of 0.0001 while MOD16 when compared to GLDAS-2-Noah had a p value of 0.0035, a 99% significant level. Thus we can say MOD16 is significantly different from SSEBop and GLDAS-2-Noah. SSEBop and GLDAS-2-Noah in Paraná had a p value of 0.2927, which is not statistically different. The Student's t test results are similar in Patagonia with MOD16 once again being significantly different having p values of 0.0078 and 0.0018 from SSEBop and GLDAS-2-Noah giving once again a 99% significant level.

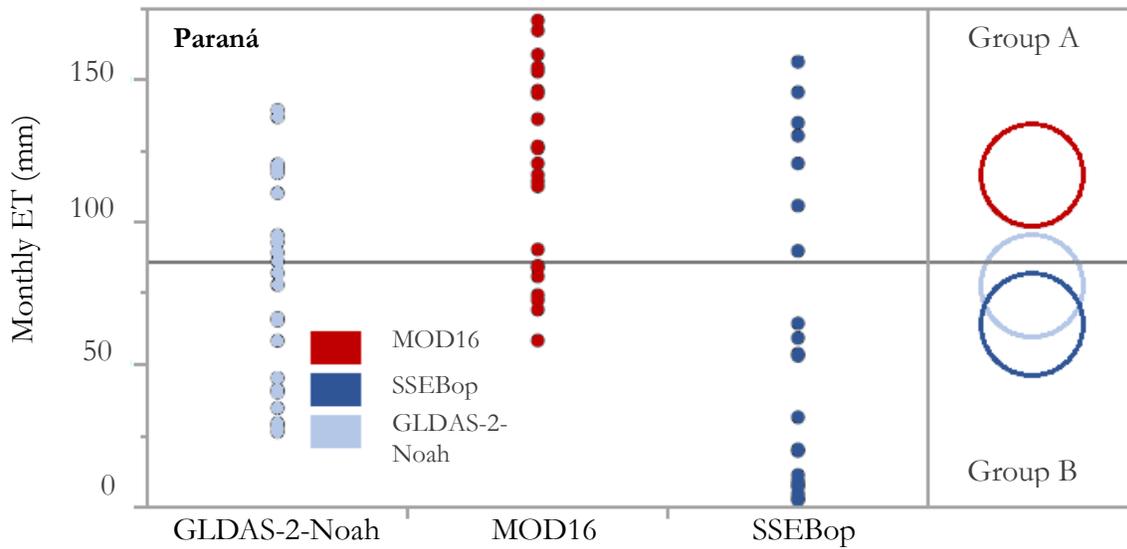


Figure 9. Kruskal-Wallis and Student's t tests for the Paraná study area.

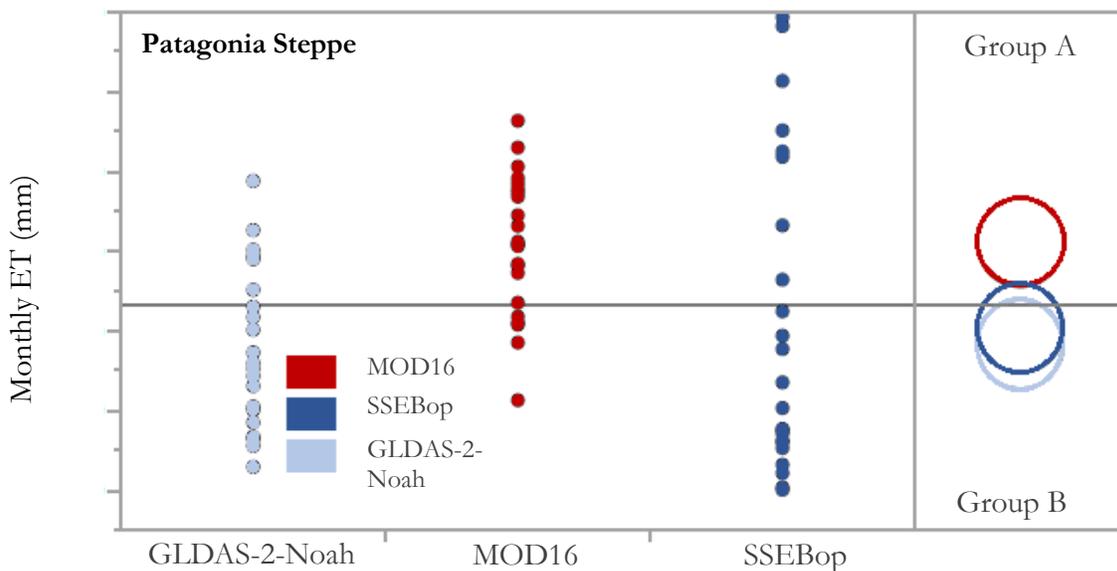


Figure 10. Kruskal-Wallis and Student's t tests for the Patagonia Steppe study area.

Paraná					Patagonia Steppe				
Water Years	Kruskal-Wallis	Student's t			Water Years	Kruskal-Wallis	Student's t		
	All Models	MOD16 vs. SSEBop	MOD16 vs. GLDAS-2-Noah	GLDAS-2-Noah vs. SSEBop		All Models	MOD16 vs. SSEBop	MOD16 vs. GLDAS-2-Noah	GLDAS-2-Noah vs. SSEBop
Two Water Years	0.0009**	0.0001*	0.0035*	0.2927	Two Water Years	0.0011**	0.0079**	0.0018**	0.6163
2016	0.0144*	0.0032*	0.0181*	0.4939	2016	0.0418*	0.0615	0.0229*	0.6553
2017	0.0523	0.0169*	0.0920	0.4400	2017	0.0139*	0.0540	0.0301*	0.7906
* Significant Level at 95%									
** Significant Level at 99%									

Table 1. Results from the Kruskal-Wallis and Student's t test for Parana on the left and the Patagonia Steppe on the right.

4.5 Future work

The ET models used in this study have been previously validated in RCEW. However, our study areas and validation site for this project are in different hemispheres. Validating various ET models using *in situ* equipment (eddy covariance tower) from a semi-arid region in the southern hemisphere may help land managers explore the applicability of ET models in geographically different but biophysically similar regions. There is also a continued interest in using the Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) to determine ET across different environments.

Currently, time series from the modified SEBAL model developed by our partners at CONICET, are not available. Developing a method to automate the process of image downloading and raster processing would allow our partners to apply their model across larger spatial extents and temporal timescales.

Because climate change is expected to influence global temperatures and precipitation regimes (Diffenbaugh & Giorgi, 2012; Pereira, 2017; Saadi et al., 2014; Trenberth, 2011), Analyzing long-term time series can help land managers understand shifts in hydrologic regimes as a response to shifting climates. Long-term data analysis in both Argentina and RCEW can make clear the differences in water availability in response to changing climate.

5. Conclusions

In our investigation of ET models we came to four main conclusions. The first being, MOD16 is significantly different from other models across both study areas. This could indicate that MOD16 uses a different equation or different variables when measuring ET. Secondly, GLDAS-2-Noah and SSEBop have no statistically significant difference for either study area. The third conclusion is that GLDAS-2-Noah and SSEBop have the potential to be applied to a semi-arid region like the Patagonia Steppe. Lastly, we would purpose the development of a hybrid model for GLDAS-2-Noah and SSEBop.

MOD16 was found to be statistically significant different from both GLDAS-2-Noah and SSEBop in the Paraná and the Patagonia Steppe with a 99% significant level according to the Student's t post hoc test for two water years (2016, 2017). This could indicate that MOD16 either uses different variables than the other models, or it could be a factor of MOD16 base equation, the Penman-Monteith equation. There is also inherent error with MOD16 as it tends to overestimate ET values, which is to be expected because the Penman-Monteith equation over estimates ET values in heterogeneous environments (DehghaniSanij et al., 2004).

GLDAS-2-Noah and SSEBop showed no statistically significant difference of ET values for either study area. Due to their statistical similarity GLDAS-2-Noah and SSEBop have the potential to be applied in a semi-arid study region like the Patagonia Steppe. Furthermore, a model could be developed that utilizes the important aspects of the two. GLDAS-2-Noah and SSEBop performed well over the semi-arid study region for this project. We would purpose developing a model that combines the temporal resolution of GLDAS-2-Noah and the spatial resolution of SSEBop. This model would be optimum for regional or global investigations of ET, and could be an effective way to measure ET more accurately. This hybrid model would likely be applicable in semi-arid study regions based on the individual models' performances in the Patagonia Steppe and in RCEW. We must keep in mind there could be error due a large difference in spatial resolution, 1km and 28km respectively. But this model would be a good combination of an energy balance model and estimated and observed ET measurements.

Throughout this project we have investigated the applicability of three different models in our study areas. With our analysis we discovered that GLDAS-2-Noah and SSEBop are statistically similar, and therefore have the highest confidence for use in a semi-arid region. GLDAS-2-Noah has better temporal resolution, but poor spatial resolution compared to that of SSEBop. SSEBop could allow for a more detailed spatial investigation for utilization by land managers. Both models can be applied in these kinds of locations to aid in decision making processes surrounding water availability. Use of either model would be beneficial in the advancement of studying ET across the global.

In general, monthly ET values during the study period in Paraná are more consistent compared to monthly ET values in the Patagonia Steppe. This might be the result of Agricultural irrigation providing a standard annual water use regime. Varying ET values during the study period in the Patagonia Steppe may be more closely related to water availability and variability of precipitation. In this region, there are a few vegetation species that are summer or winter ephemerals which are strictly dependent on seasonal rainfalls. For example, the peak in ET seen in February 2017 in the SSEBop time series might be the result of a summer ephemeral bloom.

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7. Glossary

CONICET – National Scientific and Technical Research Council

Evapotranspiration – The transport of water from different land surfaces and vegetation to the atmosphere

ET – Evapotranspiration

GEE – Google Earth Engine

GLDAS-2-Noah – Global Land Data Assimilation System-2-Noah

Microphyllous xerophytic – A plant found in relatively dry habitats with one single, unbranched leaf vein

MODIS – MODERate resolution Imaging Spectroradiometer

MOD16 – MODERate resolution Imaging Spectroradiometer Global Evapotranspiration Project

Reference evapotranspiration – Evapotranspiration from a standardized vegetated surface

SSEBop – Operational Simplified Surface Energy Balance

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9. Appendices

Primary Datasets

ET Model	Model Type	Date	Source	Satellite
Operational Simplified Surface Energy Balance (SSEBop)	Surface Energy Balance	2015 to 2017	https://cida.usgs.gov/gdp/	PRISM, TERRA MODIS, SRTM
Global Land Data Assimilation System (GLDAS-2) Noah	Land Surface Model	2015 to 2017	https://giovanni.gsfc.nasa.gov/giovanni/	AQUA AMSR-E, TRMM TMI, DMSP, NOAA-18, GOES
Penman-Montieth MOD 16	Penman-Montieth	2015-2017	https://lpdaac.usgs.gov/node/1191	TERRA MODIS

Ancillary Datasets

Dataset	Date	Use	Acquired From	Level	DOI
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FLUXNET	2015-2017	Co ² , Water Vapor, Energy Measurements	https://daac.ornl.gov/cgi-bin/dataset_lister.pl?p=9	NA	10.3334/ORNLLDAAC/1530
RCEW Soil Moisture	2015-2018	Soil Moisture	USDA-ARS	NA	NA
RCEW Precipitation	2017	Precipitation	USDA-ARS	NA	NA
Reynolds Creek - Soils, Vegetation, and Geology	1960-1970	Vegetation	Critical Zone Observatory - Reynolds Creek Experimental Watershed	NA	http://criticalzone.org/reynolds/data/dataset/3722/#policy
Reynolds Creek - Instrumentation, Regions, and Boundaries	2014	Boundaries and Instrument Locations	Critical Zone Observatory - Reynolds Creek Experimental Watershed	NA	http://criticalzone.org/reynolds/data/dataset/3934/#citation
Joint Research Centre Global Surface Water Mapping Layers, v1.0	2015-2017	Surface Water for Model Validation of ET Models	Google Earth Engine	NA	https://global-surface-water.appspot.com/download
USGS NED n44w117 1/3 arc-second 2013 1 x 1 degree	2013	Elevation	US Geological Survey	NA	https://catalog.data.gov/dataset/national-elevation-dataset-ned-1-3-arc-second-downloadable-data-collection-national-geospatial

ET model resolutions

ET Model	Spatial Resolution	Temporal Resolution
Moderate Resolution Imaging Spectroradiometer (MODIS) Global Evapotranspiration Project (MOD16)	500 m	8 day
Operational Simplified Surface Energy Balance (SSEBop)	1 km	10 day
Global Land Data Assimilation Noah evapotranspiration (GLDAS-2-Noah)	~28 km	3 hour