Evapotranspiration Climatology of Indiana Using In Situ and Remotely Sensed Products

Dev Niyogi, Saijad Jamshidi, David Smith, and Olivia Kellner

Department of Agronomy, Purdue University, West Lafayette, Indiana
Department of Earth, Atmospheric and Planetary Sciences, Purdue University, West Lafayette, Indiana
Indiana Department of Natural Resources, Division of Water, Indianapolis, Indiana
Climate Impact Company, Plymouth, Massachusetts

ABSTRACT: An intercomparison of multiresolution evapotranspiration (ET) datasets with reference to ground-based measurements for the development of regional reference (ETref) and actual (ETa) evapotranspiration maps over Indiana is presented. A representative ETref equation for the state is identified by evaluating 10 years of in situ measurements (2009–19). A statewide ETref climatology is developed using the ETref equation and high-resolution surface meteorological data from the gridded surface meteorological dataset (gridMET). For ETa analyses, MODIS, Simplified Surface Energy Balance Operational dataset (SSEBop), Global Land Evaporation Amsterdam Model (GLEAM) (versions 3.3a and 3.3b), and NLDAS (Noah and VIC) datasets are evaluated using AmeriFlux data. Thirty years of rainfall data from Climate Hazards Group Infrared Precipitation with Station Data Rainfall (CHIRPS) are used with the ET datasets to develop effective precipitation fields. Results show that the standardized Penman–Monteith equation performs as the best ETref equation with median symmetric accuracy (MSA) of 0.37, Taylor’s skill score (TSC) of 0.89, and \( r^2 = 0.83 \). The analysis shows that the gridMET dataset overestimates wind speed and requires adjustment before a series of statewide ETref climatology maps are generated (1990–2020). For ETa, the MODIS and GLEAM (3.3b) datasets outperform the rest, with MSA = 0.5, TSC = 0.8, and \( r^2 = 0.8 \). The state ETa dataset is generated using all MODIS data from 2003 and blending the MODIS data with GLEAM (3.3b) to cover data unavailability. Using the top-performing datasets, annual ETref for Indiana is computed as 1110 mm, ETa as 708 mm, and precipitation as 1091 mm. A marginal increasing climatological trend is found for Indiana’s ETref (0.013 mm yr\(^{-1}\)) while ETa is found to be relatively stable. The state’s water availability, defined as rainfall minus ETa, has remained positive and stable at 0.99 mm day\(^{-1}\) (annual magnitude of +3820 mm).

KEYWORDS: Climatology; Evapotranspiration; Agriculture

1. Introduction

Approximately 55% of Indiana’s land is devoted to agricultural farms and 21% is devoted to forests (Matli 2018). With more than half of the state’s land devoted to agricultural operations and row cropping, a well-balanced regional water budget primarily sustained by precipitation is key to preserving a successful agriculture enterprise. Recognizing the importance of rainfall for the state, data from surface weather observing networks like the Global Historical Climatology Network (GHCN), and the citizen science Community Collaborative Rain, Hail and Snow Network (CoCoRaHS) program, have been implemented for precipitation monitoring. However, evapotranspiration (ET) data, an important component of the state’s water balance, are not as readily available as precipitation data. To accurately evaluate the regional water resources and seasonal hydrological cycle, information about ET data is necessary. This lack of ET data is not unique to Indiana and is indeed more broadly sought regionally and in different countries (e.g., Martínez and Thepadia 2010; Azorin-Molina et al. 2015; Hidalgo et al. 2005; Bandyopadhyay et al. 2009; Peng et al. 2017; Di Bella et al. 2000).

Evapotranspiration can be referred to as reference (ETref) and actual (ETa). ETref is the ability of the atmosphere to remove water from a hypothetical well-watered grass surface (or alfalfa), while ETa signifies the actual quantity of water removed from a surface (Allen et al. 1998). Many in situ experimental efforts have been made to measure ETa and ETref. Such experiments include utilizing pan evaporation (Grimes et al. 2002), atmometers (Straatmann et al. 2018), lysimeters (Gebler et al. 2015), plant chamber and sap flow meters (Zhang et al. 2014), water balance measurements (Jamshidi et al. 2020), Bowen ratio and energy balance measurements (Todd et al. 2000), and flux towers (Hirschi et al. 2017). Alternatives to in situ ET measurements are empirical, semiempirical, and analytical equations based on meteorological data and vegetation-specific variables (Allen et al. 1998; Hargreaves and Samani 1985; Wright 1982). Measuring ET is inherently complex and commonly constrained by spatiotemporal availability. ET estimates typically obtained through parameterizations are subject to calibrations and do not account for spatial variability of ET that results from topography, soil heterogeneity, and land-cover heterogeneity. The spatiotemporal variability of
ET, however, is required for many hydroclimatic assessments such as water resource management (Anderson et al. 2012), drought propagation (Chen et al. 2020; Gocic and Trajkovic 2014), regional water budget and water productivity (Sun et al. 2015), agronomic decision support systems (Navarro-Hellin et al. 2016), and climate change and climate fluctuation assessments (Yeh and Wu 2018).

To circumvent the spatiotemporal limitations of single point ET estimates, satellite products and land surface models (LSM) are used. Data from satellite optical and thermal infrared sensors coupled with surface energy balance algorithms are typically used for capturing seasonal vegetation dynamics and retrieving surface energy fluxes (Cavalcante et al. 2020; Jamshidi et al. 2019; Sharifnezhadazizi et al. 2019). Land surface models use a process-based approach and simulate energy, heat, and water exchange in the soil–vegetation–atmosphere continuum to derive ET (Clark et al. 2011; Niu et al. 2011). Examples of ET products developed from satellite and LSM products include the Moderate Resolution Imaging Spectroradiometer (MODIS) global evapotranspiration product (MOD16; Mu et al. 2011), the North American Land Data Assimilation System (NLDAS) (Chen et al. 1996; Liang et al. 1994), the Simplified Surface Energy Balance Operational (SSEBop) dataset (Senay et al. 2013), climatically interpolated products of the gridded surface meteorological dataset (gridMET; Abatzoglou 2013), and the satellite and model-combined ET products (Anderson et al. 2011) including the Global Land Evaporation Amsterdam Model (GLEAM; Gonzalez Miralles et al. 2011; Martens et al. 2017).

Depending on the initialization datasets and parameterization schemes used to develop the datasets, each product has different spatiotemporal resolution and uncertainty. An accuracy assessment by Long et al. (2014) for ET products based on MODIS, LSM, and a water budget approach in the south-central United States shows the lowest uncertainties in LSM ET (\(5 \text{ mm month}^{-1}\)), moderate uncertainties in MODIS (\(-12 \text{ mm month}^{-1}\)), and the highest uncertainties in the water budget approach (\(-25 \text{ mm month}^{-1}\)). In an intercomparison study of ET datasets across Australia by Khan et al. (2020), MOD16 performance was found to be relatively poor (coefficient of determination \(r^2 = 0.25\)–0.83), and with higher accuracy provided by GLEAM \((r^2 = 0.80–0.94)\) and Global LDAS \((r^2 = 0.73–0.90)\) datasets. Therefore, the preevaluation of an ET dataset as applicable to the geographical location of a study region is required.

There are limited studies focusing on ET climatology, trend, and variability using remotely sensed ET data, as studies have mostly focused on using the pan evaporation method (Lawrimore and Peterson 2000; Roderick and Farquhar 2002). Such pan evaporation climatologies have, however, reported paradoxical trends (Hobbins et al. 2004; Ohmura and Wild 2002; Szilagyi et al. 2001; Walter et al. 2004; Roderick and Farquhar 2002; Peterson et al. 1995).

This study seeks to develop ET climatology for use in regional water budget assessments, taking Indiana as the study domain. Using statistical analyses, the aim is to assess a robust remotely sensed dataset that represents spatiotemporal variability of ET for Indiana, United States. The study motivation stems from the ET data requirement posed for (i) assessing drought status; (ii) assessing drought impact assessments, particularly on regional cereal and specialty crop production; (iii) revised state water shortage planning under way; and (iv) developing hydroclimatological assessment for the agriculture-dominated states. Accordingly, four study objectives are outlined: (i) analyze decade-long ET\(_{\text{ref}}\) measurements from ET sensors installed across agriculturally sensitive regions of Indiana; (ii) evaluate different ET\(_{\text{ref}}\) equations against in situ measurements to assess representative ET\(_{\text{ref}}\) equation; (iii) evaluate remotely sensed ET\(_a\) and ET\(_{\text{ref}}\) data from gridMET, MODIS, SSEBop, NLDAS, and GLEAM to determine a representative ET dataset for the study region (Indiana); and (iv) generate maps of ET\(_{\text{ref}}\) (for the last 30 years) and ET\(_a\) (based on all the available data from 2003) for the region. As an ancillary objective, 30 years of Climate Hazards Group Infrared Precipitation with Station Data Rainfall (CHIRPS) data are used to generate rainfall maps for the region and estimate the regional water balance status. Because the study domain has different soil types, geophysical formations, climate classifications/zones, microclimates, and aquifer sensitivities, the method used and the results obtained are expected to be of relevance to the broader global regions especially over agriculture dominated landscapes.

2. Material and methods

a. Study region

Land use in Indiana, as throughout the midwestern United States, is agriculture dominated. The state’s topography, soil, and land cover result in a north–south climate zone gradient, which is clustered into nine climate divisions (Fig. 1) that also align with the USDA crop reporting districts (Guttmann and Quayle 1996). The state shows distinct seasonal variations, with air temperatures varying from \(70^\circ\text{F} (20^\circ\text{C})\) in the summer to \(25^\circ\text{–}35^\circ\text{F} (–4^\circ\text{–}1^\circ\text{C})\) in the winter (Oliver 2009). Indiana has an agriculture-intensive economy with over 12.7 million acres of agriculture and 60 000 farms (Matli 2018). Indiana ranks fifth nationally in the production of corn (815 million bushels in 2019) and soybeans (273 million bushels in 2019), which make up more than 60% of all agricultural products sold in Indiana (USDA 2019). Additionally, Indiana is home to microclimates that support specialty crop production highly dependent on evapotranspiration data for irrigation and crop management (Kistner et al. 2018). While agricultural production in the state is primarily rain fed, the northern portion of the state has seen an increase in irrigation for row crops and water supply for confined feeding operations. This shift in groundwater use is due to both high-yield aquifer systems and having soils of higher hydraulic conductivity (i.e., a higher rate of water transfer through the soil profile due to increased sand content).

b. Data

1) In situ data

In situ observations of daily measurements of wind speed, solar radiation, air temperature, humidity, precipitation, and ET\(_{\text{ref}}\) data are collected from the Purdue Mesonet, automated weather stations in operation at Purdue Agricultural Centers (PACs). These stations include Davis (DPAC), Northeast (NEPAC), Pinney (PPAC), Southeast (SEPAC), Southwest (SWPAC), and Northwest (NWAC) PACs. These stations cover a wide range of climatic conditions and are located within the state’s geographical boundaries. The data are collected at 30-minute intervals and are available through the Purdue University Mesonet website. The dataset covers a period from 2003 until the present, providing a comprehensive view of the spatiotemporal variability of ET in Indiana. The data are quality controlled and include measurements of air temperature, relative humidity, precipitable water, solar radiation, wind speed, and wind direction. The data are used to assess the performance of remotely sensed ET products and to validate in situ ET measurements. The data are also used to determine the representativeness of ET products for the study region (Indiana) and to generate maps of ET\(_{\text{ref}}\) (for the last 30 years) and ET\(_a\) (based on all the available data from 2003) for the region.
In situ measurements by comparing the corresponding spatial grids for which the in situ observations are available.

The MODIS ET/latent heat flux product (MOD16A2, version 6), with an 8-day composite and 500-m spatial resolution (https://earthdata.nasa.gov/), is used as an ET\(_a\) source. The MODIS dataset implements the MOD16 algorithm (Mu et al. 2011) in combination with the Penman–Monteith equation (Allen et al. 1998) with remotely sensed data products of land cover, fraction of photosynthetically active radiation (PAR), albedo, leaf area index (LAI), and surface meteorology data to generate ET\(_a\) data.

An additional ET\(_a\) source assessed in this study is a surface energy balance-based dataset known as SSEBop available from the U.S. Geological Survey (https://earlywarning.usgs.gov/) (Senay et al. 2013). The dataset uses MODIS thermal images, building from hot and cold pixel principles of the Surface Energy Balance Algorithm for Land (SEBAL; Bastaanssen et al. 1998) and Mapping Evapotranspiration with Internalized Calibration (METRIC; Allen et al. 2007) algorithms. The result provides predefined dynamic boundary conditions for operational applications (Senay et al. 2013). The dataset provides ET\(_a\) on a daily scale with 1000-m spatial resolution covering the contiguous United States.

A third ET\(_a\) source is evaluated over Indiana and is retrieved from the GLEAM dataset. The dataset (https://www.gleam.eu) utilizes the Priestley and Taylor equation (Priestley and Taylor 1972) and applies an evaporative stress factor (derived from soil moisture and vegetation optical depth) to estimate daily land evaporation data on a 0.25° grid (~25 km). ET\(_a\) data from the latest release of the GLEAM datasets (versions 3.3a and 3.3b) are used. The two versions of the dataset differ in terms

(SWPAC), Southern Indiana (SIPAC), and Throckmorton (TPAC), as well as the Agricultural Center for Research and Education (ACRE; Fig. 1). Automated collection of weather data from PAC sites are available at the Indiana State Climate Office (https://ag.purdue.edu/indiana-state-climate). During the growing season, ET\(_{ref}\) is monitored using atmometers. Measurements are initiated after the last frost (during May), and the sensors are dismantled postharvest before the first frost date (during September). A modified ceramic Bellani Plate atmometer (manufactured by ET Gage Company of Loveland, Colorado) is used. The ceramic plate is mounted on top of the distilled water reservoir (30-cm capacity) and is covered with a GoreTex green canvas. A more detailed description of the atmometer and its field application can be found from the Cropwatch project (https://cropwatch.unl.edu/using-atmometer-or-etgage).

Latent heat flux observations from two AmeriFlux tower sites (US-MMS and US-Bo1) are used to evaluate remotely sensed sources of ET\(_a\) data. The US-MMS tower station is located at Morgan Monroe State Forest (categorized as deciduous broadleaf forest; 39°19' N, 86°24'W) with data available from 1999 to the present. The US-Bo1 tower station is located at Bondville (categorized as croplands with annual rotation between corn and soybeans; 40°00' N, 88°17'W) with data availability from 1996 to 2009 (Fig. 1b). The AmeriFlux site data are used in many studies as the reference for evaluating model simulations (Lokupitiya et al. 2016; Purdy et al. 2016; B. Zhang et al. 2020). Nonetheless, it is also important to note that most eddy covariance sites have a general lack of energy balance closure as they do not account for all the energy sources and sinks (Barr et al. 2012; Foken 2008). An evaluation of 22 AmeriFlux sites found similar results in that there is an underestimation of sensible and latent heat fluxes (Wilson et al. 2002). While the fluxes at AmeriFlux sites may not represent ideal measurements, their accuracy is highly acceptable in that the sites due to account for a majority of heat flux variability.

2) REMOTELY SENSED DATA

To generate spatially distributed ET\(_a\) and ET\(_{ref}\) data at the regional scale, different remotely sensed datasets are evaluated. The assessment is done against PAC and AmeriFlux
of input variables, with the “a” version using reanalysis datasets (ERA5) as the primary inputs for radiation and air temperature, and the “b” version mainly using satellite datasets including Clouds and the Earth’s Radiant Energy System (CERES) and Atmospheric Infrared Sounder (AIRS).

Last, assimilated ETa data from NLDAS are considered. NLDAS (https://ldas.gsfc.nasa.gov/nldas) integrates ground-based observations and National Centers for Environmental Prediction–North American Regional Reanalysis (NCEP–NARR) reanalysis datasets using land surface models and data assimilation techniques to generate spatially and temporally consistent (with 0.125° grid and ~9000 m at hourly time steps) flux datasets. ETa data from two versions of NLDAS Phase 2 (Xia et al. 2012) are retrieved for analysis. One dataset is assimilated using the Noah LSM L4 V002 (NLDAS-Noah-LSM), and the other is derived using VIC LSM L4 V002 (NLDAS-VIC-LSM). Note that the ETa outputs of these datasets are different, because of the differences in the underlying model equations representing the exchange processes in the plant–soil–atmosphere system. The models differ in that the Noah-LSM considers land–atmosphere interaction processes at grid scale with relatively limited grid-to-grid lateral exchanges, while the VIC-LSM (Liang et al. 1994) is a macroscale hydrologic model. NLDAS model analyses are routinely used to assess the onset of drought conditions.

Assessing the climatic variation that influences Indiana’s water cycle requires a robust rainfall dataset with 30 plus years of observed data. Therefore, 30 years of rainfall data are retrieved from CHIRPS data (https://data.chc.ucsb.edu/products/CHIRPS-2.0/). The dataset provides quality-controlled rainfall estimates by combining the Tropical Rainfall Measuring Mission Multi-Satellite Precipitation Analysis, version 7 (TRMM; Huffman et al. 2015), and global Cold Cloud Duration (CCD; Funk et al. 2015).

Maps using ETref and ETa datasets and the observed rainfall estimates from CHIRPS are generated to present “rainfall minus evapotranspiration” or “P – ET” maps; P – ETref and P – ETa are generated, as P – ETref maps help to identify a flood or drought-susceptible landscape while P – ETa maps are helpful to assess the current hydrologic state of the surface and subsurface, allowing for water managers to better assess soil moisture, runoff, and groundwater stress. The summary of the data used in this study is presented in Table 1.

c. Analysis

1) ETref

Ground-based observational data from the Purdue Mesonet stations from 2009 to 2019 are collected, quality controlled, and preprocessed. The period is selected based on the duration for which ETref data are measured at the stations. Daily weather data are used in the Ref-ET tool (Allen 2009, University of Idaho) to generate standardized calculations of ETref using eight frequently applied ET equations (Table 2).

ETref estimates, as determined by the Ref-ET Tool, are compared with the Purdue Mesonet station ETref observations. The equations delivering the most accurate results are then identified based on statistical analysis. ETref equations and details about the formulations are presented in the Ref-ET manual (Allen 2009).

The standardized ASCE Penman–Monteith equation is provided below:

\[
ETref = \frac{0.408 \Delta (R_n - G) + \gamma \frac{900}{T + 273} U_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34 U_2)},
\]

where ETref is daily reference crop evapotranspiration (mm day⁻¹); \(R_n\) is net radiation at the crop surface (MJ m⁻² day⁻¹); \(G\) is the soil heat flux density at the soil surface (MJ m⁻² day⁻¹); \(T\) is the mean daily air temperature (°C); \(U_2\) is the mean daily wind speed at 2 m height (m s⁻¹); \(e_s\) and \(e_a\) are saturation and actual vapor pressure, respectively; \(\Delta\) is the slope of the vapor pressure–temperature curve (kPa °C⁻¹); and \(\gamma\) is the psychometric constant (kPa °C⁻¹).

To generate regional ETref maps, the accuracy of the spatially distributed gridMET meteorological data at the daily level is assessed over the study region by comparing the gridMET data with the ground-based PAC station data. Data calibrations are performed as required, and the data are used with the representative ETref equation to generate the regional maps.
Table 2. List of ETref methods used in the REF-ET tool and the resulting statistics in comparison with in situ observations at PACs.

<table>
<thead>
<tr>
<th>Method name</th>
<th>Developer</th>
<th>Abbreviation</th>
<th>MBE</th>
<th>RMSE</th>
<th>TSC</th>
<th>MSA</th>
<th>$r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standardized ASCE Penman–Monteith</td>
<td>Walter et al. (2000)</td>
<td>ASCE-PM</td>
<td>1.04</td>
<td>1.19</td>
<td>0.89</td>
<td>0.51</td>
<td>0.83</td>
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<tr>
<td>FAO 56 Penman–Monteith</td>
<td>Allen et al. (1998)</td>
<td>FAO56</td>
<td>1.65</td>
<td>1.85</td>
<td>0.78</td>
<td>0.57</td>
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<tr>
<td>Blaney–Criddle</td>
<td>Doorenbos and Pruitt (1975)</td>
<td>BC</td>
<td>1.08</td>
<td>1.23</td>
<td>0.89</td>
<td>0.51</td>
<td>0.83</td>
</tr>
<tr>
<td>Hargreaves</td>
<td>Hargreaves and Samani (1985)</td>
<td>Harg</td>
<td>1.57</td>
<td>1.72</td>
<td>0.86</td>
<td>0.56</td>
<td>0.75</td>
</tr>
<tr>
<td>Kimberly Pennman</td>
<td>Wright (1996)</td>
<td>Kpen</td>
<td>1.40</td>
<td>1.57</td>
<td>0.84</td>
<td>0.55</td>
<td>0.78</td>
</tr>
<tr>
<td>Makkink</td>
<td>Makkink (1957)</td>
<td>Makk</td>
<td>1.40</td>
<td>1.57</td>
<td>0.81</td>
<td>0.56</td>
<td>0.84</td>
</tr>
<tr>
<td>Priestley–Taylor</td>
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<td>PrsTylr</td>
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<td>0.62</td>
<td>0.69</td>
<td>0.80</td>
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<tr>
<td>Turc</td>
<td>Turc (1961)</td>
<td>Turc</td>
<td>1.13</td>
<td>1.28</td>
<td>0.88</td>
<td>0.52</td>
<td>0.85</td>
</tr>
</tbody>
</table>

2) ET$_a$

To generate the statewide ET$_a$ data, the accuracy of the retrieved datasets is first assessed by comparing against ET$_a$ data from the AmeriFlux tower observations. Comparisons are made for overlapping time frames of the datasets and flux tower observations (2003 to 2009 for the Bondville site and 2010 to 2019 for the Morgan State Forest site). Statistical analyses are performed to select the ET$_a$ dataset that delivers the most accurate results.

Based on the selected datasets, monthly average ET$_{ref}$, ET$_a$, and rainfall maps are generated and presented in this study. For the ET$_{ref}$ and rainfall, 30 years of data are analyzed and used to develop an ET$_{ref}$ climatology. Because the remotely sensed data used in this study are only available from 2003 to the present, the ET$_a$ climatology is developed based on the available data. The resulting monthly mean is analyzed over the state for each climate division to depict the hydrological trend across the state.

d. Statistics

The accuracy of the ET$_a$ and ET$_{ref}$ datasets is assessed using statistical measures with reference to the ground-based measurements. The statistical measures include Pearson correlation coefficient $I$, as well as regression model accuracy factors including coefficient of determination $r^2$, mean square error (MSE), and mean bias error (MBE) to assess the magnitude of bias. While these metrics provide relative accuracy, the drawbacks of each such as penalizing over/underestimations or poor representation of central tendency in skewed distribution using mean-based metrics are also known (Morley et al. 2018; Tofallis 2015). Therefore, two additional criteria, the median symmetric accuracy (MSA) and Taylor’s skill score (TSC), are used.

The MSA measure is based on the logarithmic ratio of the predicted value to the observed value, interpreted as a percentage error. It provides a robust measure that compensates the known issues in other accuracy metrics (Morley et al. 2018). The factor ranges over $[0, \infty)$, with “0” indicating the ideal accuracy from the predicted (model) values, and, as the percentage increases, the magnitude of accuracy decreases:

$$\text{MSA} = 100(\exp \exp\{M[\log_e(P/O)]\} - 1), \quad (2)$$

where $M$ is the median of the data, $P_i$ is the predicted value, and $O_i$ is the observed value.

For selecting the “best” model to determine ET$_{ref}$, the method proposed by Taylor (2001) developed for evaluating a model’s accuracy in amplitude and pattern in variability is considered. The TSC and its diagram are defined based on a dataset’s intercorrelation, RMSE difference, and the normalized variance ratio:

$$\text{TSC} = \frac{4(1 + R)}{(\sigma + 1/R)^2 (1 + R_0)}, \quad (3)$$

where $\sigma = \sigma_{m}/\sigma_{0}$ is the normalized standard deviation as the ratio of modeled and observed values, $R$ is the correlation coefficient, and $R_0$ is the maximum attainable correlation. When the variance of ET estimates from the experimented datasets approaches the variance of ET observations (i.e., $\sigma \rightarrow 1$ and $R \rightarrow R_0$), the skill approaches unity, showing the ideal pattern match between the two.

3. Results and discussion

a. Reference ET; method selection

The comparison of daily ET$_{ref}$ data calculated using the Ref-ET tool and the ET$_{ref}$ data obtained from ET sensors at weather stations is illustrated in Fig. 2. Statistical analysis (Table 2) indicates that the ASCE Penman–Monteith (PM; Walter et al. 2000) has the best performance for the study region (RMSE of 1.18 mm day$^{-1}$ and MSA of 50%). Methods like Makkink (Makkink 1957) and Turc (Turc 1961), perform better for the goodness of regression fit; however, they yielded higher errors in ET estimates and are not as well suited to the climate of the study region. While benefiting from fewer inputs and having optimal performance, methods like Hargreaves (Hargreaves and Samani 1985) require local calibration (Trajkovic 2007) and a larger time frame (e.g., 10 days and longer) to determine ET$_{ref}$ estimates (Cobaner et al. 2017). Penman–Monteith has been selected as the reference equation for modeling and assessments in several studies (Ficklin et al. 2015; Rojas and Sheffield 2013; Shiri et al. 2012) because it considers the energy budget and mass transfer by coupling the atmospheric and canopy conditions to drive ET.

Despite ASCE-PM outperformance relative to the other equations, its bias from in situ observations values is notable. The source of error, however, cannot be assigned to a specific
reason. Bias may stem from the ET$_{ref}$ error inherent in atmometer measurements, particularly under windy conditions (e.g., Gavilán and Castillo-Llanque 2009). Beyond this bias, the measurement accuracy is highlighted in a number of studies (Alam and Trooien 2001; Broner and Law 1991; Gleason 2013; Magliulo et al. 2003). Bias may also stem from inherent instrumentation calibration error in the equipment used to capture the meteorological data that are utilized in the Ref-ET tool. Those data are then used to calculate the ASCE-PM ET$_{ref}$ values. The error in the equation may also cause disparities. Nevertheless, the objective here is to perform a relative comparison between ET equations to select the
appropriate model that approximates agricultural field conditions in Indiana with respect to available measurements. The findings presented here conform with the recommendation of the ASCE Environmental and Water Resources Institute (EWRI) Task committee for using a standardized form of Penman–Monteith equation (Allen et al. 2005); accordingly, this equation is selected as the ET_{ref} equation for further assessment for Indiana.

**FIG. 4.** Comparison of (a),(b) adjusted gridMET wind speed (using bias correction) and (c),(d) recomputed ET_{ref} using gridMET data with in situ observations at PAC stations.

**FIG. 5.** Time series comparison between ET_{a} data from MODIS, NLDAS (Noah and VIC), GLEAM (versions 3.3a and 3.3b), and SSEBop with respect to AmeriFlux observation of ET_{a} at the (a) Bondville agricultural site for 2003–09 and (b) Morgan Forest site for 2010–19. Also shown are comparisons between monthly observed and model-estimated values of ET_{a} for the (c)–(h) Bondville and (i)–(n) Morgan Forest sites.
b. Reference ET at the regional scale

The gridMET dataset is used to generate ET\textsubscript{ref} maps for the region. In addition to primary surface meteorological data, gridMET provides gridded daily ET\textsubscript{ref} products using its high-resolution surface meteorological data with the ASCE Penman–Monteith equation.

An evaluation is performed to determine the accuracy of the gridMET ET\textsubscript{ref} product with respect to the ET\textsubscript{ref} calculated from the ASCE Penman–Monteith at Purdue Mesonet weather stations (Fig. 3, top row). The comparison shows overestimation in the gridMET ET\textsubscript{ref} data over with MAE and MSE of 3.95 and 1.41 mm day\textsuperscript{-1}. To identify the source of errors, the gridMET surface meteorological data is evaluated against the in situ observations available from the Purdue Mesonet weather stations. Good agreement is found between the gridMET maximum and minimum temperature and shortwave solar radiation data and the ground-based PAC data (Fig. 3). While the wind speed data are highly correlated with the observed values (\(r^2\) of 0.89), an underestimation (MSE of 2.69 and MAE of 1.40 mm day\textsuperscript{-1}) is captured considering the time series plot in Fig. 3. The uncertainties in gridMET wind speed data are also highlighted in the initial dataset evaluation (for the western United States) with positive and negative biases (Abatzoglou 2013). For this study, as the underestimations in gridMET wind speed data are relatively consistent through time, the dataset is simply adjusted with a linear data shift using the mean absolute error between the two datasets. The adjusted wind speed yields a lower error relative to the observations (MSE of 0.21 and MAE of 0.003 m s\textsuperscript{-1}) and consequently improves the recomputed ET\textsubscript{ref} using the gridMET data (Fig. 4). The error in calibrated gridMET ET\textsubscript{ref} data is reduced to 1.03 and 0.39 mm day\textsuperscript{-1} for MSE and MAE, respectively. The calibrated ET\textsubscript{ref} dataset is generated for a 30-yr period over the domain, and the monthly average maps and data are presented (section 3d) with spatiotemporal trends in seasonal precipitation.

c. ET\textsubscript{a} model selection

For selection of a model/dataset to generate ET\textsubscript{a} data for Indiana, an initial evaluation of selected datasets is done using AmeriFlux tower observations. The time series and cross correlation between all datasets (based on Pearson’s coefficient) correspond to the two flux towers locations and are provided in Figs. 5 and 6. For the Bondville site (from 2003

<table>
<thead>
<tr>
<th>Site</th>
<th>Dataset name</th>
<th>MBE</th>
<th>MSE</th>
<th>MAE</th>
<th>MSA</th>
<th>(r^2)</th>
<th>TSC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bondville</td>
<td>SSEBop</td>
<td>0.20</td>
<td>3.29</td>
<td>1.32</td>
<td>0.82</td>
<td>0.59</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>NLDAS-MOSAIC</td>
<td>0.37</td>
<td>2.85</td>
<td>1.25</td>
<td>0.60</td>
<td>0.57</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>NLDAS-VIC</td>
<td>-0.63</td>
<td>3.31</td>
<td>1.36</td>
<td>1.40</td>
<td>0.52</td>
<td>0.74</td>
</tr>
<tr>
<td></td>
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<td>1.08</td>
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<td>0.65</td>
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<tr>
<td></td>
<td>GLEAM-b</td>
<td>-0.37</td>
<td>2.07</td>
<td>1.07</td>
<td>0.68</td>
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<td>0.79</td>
</tr>
<tr>
<td></td>
<td>GLEAM-a</td>
<td>-0.63</td>
<td>2.39</td>
<td>1.16</td>
<td>0.83</td>
<td>0.66</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td>NLDAS-Noah</td>
<td>-0.47</td>
<td>2.29</td>
<td>1.11</td>
<td>0.81</td>
<td>0.66</td>
<td>0.81</td>
</tr>
<tr>
<td>Morgan Forest</td>
<td>SSEBop</td>
<td>0.98</td>
<td>3.37</td>
<td>1.35</td>
<td>0.66</td>
<td>0.75</td>
<td>0.87</td>
</tr>
<tr>
<td></td>
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<td>1.12</td>
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<td>0.73</td>
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<td>NLDAS-VIC</td>
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<td>MODIS</td>
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<tr>
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<td>GLEAM-b</td>
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<td>0.46</td>
<td>0.82</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>GLEAM-a</td>
<td>-0.29</td>
<td>1.76</td>
<td>0.95</td>
<td>0.55</td>
<td>0.78</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>NLDAS-Noah</td>
<td>-0.94</td>
<td>3.58</td>
<td>1.24</td>
<td>0.78</td>
<td>0.60</td>
<td>0.66</td>
</tr>
</tbody>
</table>
to 2008), the ET<sub>a</sub> data from the GLEAM-b (3.3b) dataset show the highest accuracy with the AmeriFlux tower observations (MSE = 2.07 mm day<sup>-1</sup>, MSA = 0.62, and r<sup>2</sup> = 0.68), followed by the MODIS ET<sub>a</sub> (MOD16) product (MSE = 2.28 mm day<sup>-1</sup>, MSA = 0.61, and r<sup>2</sup> = 0.65). For the Morgan State Forest site (from 2010 to 2019), the MODIS ET<sub>a</sub> has the highest accuracy (MSE = 1.36 mm day<sup>-1</sup>, MSA = 0.52, and r<sup>2</sup> = 0.82) followed by the ET<sub>a</sub> estimates from GLEAM-b (MSE = 1.45 mm day<sup>-1</sup>,

**Fig. 7.** Comparison of MODIS, SSEBop, NLDAS (Noah and VIC), and GLEAM (3.3a and 3.3b) datasets and the AmeriFlux ET measurements over Indiana using Taylor diagrams for the (left) Bondville site (2003–09) and (right) Morgan Forest site (2010–19). The gray lines connecting the x and y axes denote the standard deviation; the dotted line denotes standard deviation of the observations, and the radial lines denote the RMSE.

**Fig. 8.** Demonstrating different criteria for model selection based on scaled bias, accuracy, and spatiotemporal resolution (between 0 and 1) for MODIS, SSEBop, GLEAM (3.3a and 3.3b), and NLDAS (Noah and VIC) datasets. TSC = Taylor skill score, SpR = spatial resolution score, TmR = temporal resolution score, MSE = mean square error, RMSE = root MSE, MAE = mean absolute error, and MSA = median symmetric accuracy.
MSA = 0.53, and $r^2 = 0.82$). A summary of the statistics is provided in Table 3.

The ET$_a$ estimates from other datasets are reasonable with both positive and negative biases across the datasets. While using input from MODIS to generate a daily gap-filled ET$_a$ product, SSEBop parameterizations overestimate the ET$_a$ rate at both sites and do not provide as accurate estimates as the MOD16 algorithm, similar to the findings noted by Senay et al. (2013) and Velpuri et al. (2013). The performance of Noah LSM-driven or VIC LSM-driven NLDAS ET$_a$ estimates is site dependent. NLDAS ET$_a$ estimates using the Noah LSM show better performance over cropland (Bondville site) while the NLDAS ET$_a$ estimates using VIC LSM has better performance over the forest ecosystem (Morgan Monroe State Forest site). The disparities in the NLDAS ET$_a$ estimates between the two LSMs may stem from the spatial land surface heterogeneity of the grid. The method implemented in these LSMs to capture the land surface heterogeneity differs in that the Noah LSM considers one dominant vegetation type over a grid cell, while the VIC LSM tiles the grid into different vegetation types. Additionally, differences between the soil hydraulic parameterization schemes, aerodynamic transfer schemes, and radiative transfer schemes, especially as related to topography and hill shade, likely generate the differences in ET$_a$ estimate accuracy by site, as the Morgan Monroe State Forest site is located in the most uneven region of the state, and the Bondville site is located in a flat region of Illinois. The ET$_a$ data from GLEAM-b dataset show relatively better performance for both sites when compared to the GLEAM-a. Both datasets use the same physics for deriving ET$_a$; however, the uncertainties associated with the different inputs used for driving ET$_a$ in GLEAM-a and GLEAM-b highlight the
difference in $ET_a$ outputs. Radiation, air temperature, and soil moisture are the prime factors affecting the rate of evapotranspiration (Allen et al. 1998). The GLEAM-a and GLEAM-b products are generated using a similar source for soil moisture data [ESA Climate Change Initiative (ESA-CCI); Gruber et al. 2017]. However, for the radiation and air temperature forcing, GLEAM-b uses satellite products of CERES for radiation (Wielicki et al. 1996) and AIRS for air temperature (Aumann et al. 2003), while GLEAM-a is generated using reanalysis data of ERA5. Several studies have reported a higher accuracy from satellite observations compared to reanalysis products (e.g., Jia et al. 2013; X. Zhang et al. 2020). Therefore, implementing satellite observational data to derive ET products in GLEAM-b likely led to its higher accuracy compared to GLEAM-a. Note that the intent is not to discuss the rationale of the model’s performance but to select the appropriate model for developing the $ET_a$ dataset. With this in mind, a Taylor graph (Fig. 7) was used for intercomparison of the models’ correlation, RMSE, and standard deviation. In addition, the statistical criteria (i.e., Taylor score, bias, accuracy, and spatiotemporal resolution) are normalized, scaled (between 0 and 1), and mapped in one plot (Fig. 8). The accuracy metrics included Taylor score, spatial and temporal resolution, and $r^2$ (colored as green in Fig. 8) with the highest accuracy ranked as 1 and the lowest ranked as 0. Spatial and temporal resolutions are scaled considering “1 km” and “1 day” as the ideal option (scored as 1), and the datasets are ranked accordingly. The bias metrics included MSE, RMSE, MAE, and MSA (colored as red in Fig. 8), with the highest error ranked as 1 and the lowest ranked as 0. MODIS and GLEAM-b dataset show the lowest bias (i.e., highest accuracy).
accuracy) with the former providing a better spatial resolution, and the latter providing a higher temporal resolution. Considering the objective of the study, the spatial resolution has a higher priority for developing the $ET_a$ dataset. Therefore, the MODIS ET dataset is applied as the main product for the development of $ET_a$ maps. Nevertheless, analysis of the MODIS data shows the data suffer from ~32% of data unavailability (in 8-day composite) over Indiana during a typical growing season due to cloudiness. Considering the relatively high accuracy of the GLEAM-b dataset and its availability, it is used to gap-fill unavailable MODIS data. This combined dataset benefits from the spatial resolution of MODIS coupled with blending the accuracy of the MOD16 algorithm and GLEAM-b dataset, delivering a complete $ET_a$ dataset for Indiana. This dataset is created from all of the available data from 2003.

d. Variability in $ET_{ref}$, $ET_a$, and agricultural/hydrological components

A time series of $ET_a$ from selected ET databases is generated and is shown in Fig. 9. No significant increasing or

![Fig. 10. Spatial distribution of season means of reference ET values (1989–2019) for winter (December–February), spring (March–May), summer (June–August), and autumn (September–November) across Indiana generated using adjusted gridMET products and the ASCE Penman–Monteith equation.]

### Table 5. Accumulated $ET_a$, $ET_{ref}$, rainfall, and $P – ET$ amount for different climate divisions of Indiana through a growing season.

<table>
<thead>
<tr>
<th>Division</th>
<th>CD1</th>
<th>CD2</th>
<th>CD3</th>
<th>CD4</th>
<th>CD5</th>
<th>CD6</th>
<th>CD7</th>
<th>CD8</th>
<th>CD9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ET_{ref}$ (mm) Mean</td>
<td>668.32</td>
<td>671.60</td>
<td>650.23</td>
<td>678.75</td>
<td>673.94</td>
<td>674.61</td>
<td>702.87</td>
<td>682.97</td>
<td>668.26</td>
</tr>
<tr>
<td>$ET_a$ (mm) Mean</td>
<td>471.73</td>
<td>476.70</td>
<td>449.92</td>
<td>541.59</td>
<td>474.03</td>
<td>471.84</td>
<td>601.60</td>
<td>622.37</td>
<td>588.53</td>
</tr>
<tr>
<td>Std dev</td>
<td>64.98</td>
<td>51.09</td>
<td>48.50</td>
<td>63.66</td>
<td>76.45</td>
<td>43.67</td>
<td>66.00</td>
<td>76.75</td>
<td>55.72</td>
</tr>
<tr>
<td>Rainfall ($P$) (mm) Mean</td>
<td>549.69</td>
<td>521.98</td>
<td>497.81</td>
<td>532.82</td>
<td>537.79</td>
<td>516.17</td>
<td>565.79</td>
<td>568.29</td>
<td>547.12</td>
</tr>
<tr>
<td>Std dev</td>
<td>11.95</td>
<td>17.11</td>
<td>20.41</td>
<td>17.96</td>
<td>11.99</td>
<td>14.87</td>
<td>21.17</td>
<td>15.62</td>
<td>20.71</td>
</tr>
<tr>
<td>$P – ET_{ref}$ (mm) Mean</td>
<td>-169.20</td>
<td>-198.32</td>
<td>-200.27</td>
<td>-194.34</td>
<td>-183.48</td>
<td>-205.30</td>
<td>-179.77</td>
<td>-150.31</td>
<td>-155.47</td>
</tr>
<tr>
<td>Std dev</td>
<td>13.43</td>
<td>17.43</td>
<td>13.74</td>
<td>28.88</td>
<td>15.27</td>
<td>16.28</td>
<td>28.45</td>
<td>13.46</td>
<td>23.74</td>
</tr>
<tr>
<td>$P – ET_a$ (mm) Mean</td>
<td>80.61</td>
<td>46.59</td>
<td>48.17</td>
<td>-12.62</td>
<td>63.54</td>
<td>45.35</td>
<td>-33.66</td>
<td>-53.82</td>
<td>-39.67</td>
</tr>
<tr>
<td>Std dev</td>
<td>65.85</td>
<td>49.36</td>
<td>51.77</td>
<td>65.40</td>
<td>76.95</td>
<td>45.23</td>
<td>64.16</td>
<td>76.44</td>
<td>58.83</td>
</tr>
</tbody>
</table>
decreasing trend is found for ET<sub>a</sub>. For ET<sub>ref</sub> and rainfall, the trend analysis showed a positive slope (0.013 and 0.01 mm yr<sup>-1</sup>, respectively) over Indiana during the course of study as it aligns with the numerous climate assessments of increasing temperature and precipitation. These trends over the Indiana state, however, is not statistically significant within our climatological review period. A climatological assessment of ET over a regional domain (e.g., U.S. Midwest) from 1895 to the present would likely better highlight the statistically significant shifts in ET but is outside the scope of this paper. The relatively constant rate of these variables results in a stable water cycle trend considering the analysis of precipitation minus ET (Fig. 9). With the positive average P – ET<sub>a</sub> value, it can be inferred that the net state water balance is in a stable positive state (+383 mm annually) with sustainable soil moisture availability. Averaging the annual values for the state (Table 4), accumulated ET<sub>ref</sub> is computed as 1110 mm (with constant mean of 3.08 mm day<sup>-1</sup>), ET<sub>a</sub> is computed as 708 mm (with constant mean of 1.97 mm day<sup>-1</sup>), and precipitation is computed as 1091 mm (with constant mean of 3.03 mm day<sup>-1</sup>).

The resulting seasonal average ET<sub>ref</sub>, ET<sub>a</sub>, and rainfall maps for the state are shown in Figs. 10–12, respectively, and the monthly data are provided in figures in the online supplemental material. Indiana’s ET<sub>ref</sub> starts from 0.85 mm day<sup>-1</sup> in January, and with increasing temperature and radiation peaking in summer, maximizes at 5.34 mm day<sup>-1</sup> in June. Higher ET<sub>ref</sub> rates are observed in southern climate divisions (CD; Table 5) (i.e., CDs 7 and 8, with accumulated amounts of 703 and 683 mm during the growing season, respectively) while the northeastern region (CD 3, in particular) witnesses lower ET<sub>ref</sub> values (650 mm during the growing season). ET<sub>ref</sub> shows less statewide variability relative to ET<sub>a</sub> and rainfall. The spatial distribution of ET<sub>a</sub> is also not significantly different across Indiana during the cold months of January–March and October–December (nongrowing season). However, during an average growing season, the ET<sub>a</sub> values increase with crop stage and vegetative greenness. The mean ET<sub>a</sub> rate starts from 0.33 mm day<sup>-1</sup> in January and reaches its maximum in June at 3.90 mm day<sup>-1</sup>. The southern part of the state, more heavily forested than other regions shows higher ET<sub>a</sub> rates (CD 8 with 623 mm during the growing season; Table 5) as compared with other divisions primarily covered in cultivated crops. Urbanized areas are marked in the maps with zero to low values (e.g., the city of Indianapolis in climate division 5).

With regard to rainfall, the wettest month for Indiana is June with an average rainfall of 4.4 mm day<sup>-1</sup>, and September and January are the driest months with an average rainfall of 2.5 mm day<sup>-1</sup>. Statewide distribution of rainfall shows that CD...
3 receives the lowest annual rainfall amount with 498 mm and CDs 7 and 8 receive the highest annual rainfall amount with 567 mm during the growing season (Table 5).

The resulting seasonal maps of $P - ET_{ref}$ are shown in Fig. 13, and monthly maps are provided in figures in the online supplemental material. The increase in $ET_{ref}$ rate is higher than the rainfall amount during frost-free months (end of April until October), and consequently, $P - ET_{ref}$ reaches negative values and maximizes during July and August. Considering the spatial extent of the negative values, a southwest–northeast gradient is identified. Deviations from this pattern are particularly useful in identifying temporal evolution and potential for drought intensity propagation over the state. Accordingly, cultivated areas in these regions (particularly, CDs 3, 6, and 7) are likely at a higher risk of drought impact on yield and crop condition.

Seasonal $P - ET_a$ maps are shown in Fig. 14 and monthly maps are provided in figures in the online supplemental material. The maps indicate that the net state water balance remains in a positive condition for much of the year and becomes negative during July and August. The negative water balance signifies enhanced potential for impacts due to soil moisture deficiency. Lack of available soil moisture below a certain threshold (which is soil and crop dependent) could place the agricultural and forested areas in a water-stress condition during these months. The total value of the negative $P - ET_a$ relationship during July and August is computed as $-20$ mm. However, it is typically compensated during the next two months (September, October). According to the National Agricultural Statistics Service (NASS) data, July and August coincide with the growing stage of “blooming to set pods” for soybeans and “silked” for corn. These stages have been highlighted as sensitive to soil moisture deficiency (Mansouri-Far et al. 2010; Maleki et al. 2013), and water stress during these stages has been documented to result in significant yield loss (Prasad et al. 2008).

The negative $P - ET_a$ in July and August indicate that irrigation demands will be, on average, higher during these months. A representative modeling and observation of $ET_a$, as well as accurate soil moisture monitoring, is suggested, particularly for in CDs 4, 7, 8, and 9. The information on the spatial distribution of negatively impacted areas (Fig. 14) serves to help crop growers adjust planting dates, manage irrigation schedules, and handle water management tasks. Conversely, the spatial areas with positive $P - ET_a$ values may be associated with a higher risk of erosion and runoff risk during heavy rainfall events (e.g., CDs 1 and 5). Additional assessment focusing on the soil-specific information (e.g., moisture availability and soil properties including hydraulic conductivity, soil storage capacity, vegetation cover and type, slope) is required to further address flood and drought risk in the CDs with positive $P - ET_a$ values.
4. Conclusions

An ET$_{ref}$ and ET$_a$ climatology for Indiana is developed and presented as a regional water management tool to enhance the best management practices of agricultural production. Thirty years of ET$_{ref}$ data computed from ET gauge measurements at Purdue Mesonet locations across Indiana are analyzed using the standard Penman–Monteith equation as the representative equation for assessing ET$_{ref}$ estimates for the state. Primary inputs for the equation were surface meteorological data from gridMET to create statewide ET$_{ref}$ maps.

Different remotely sensed ET$_a$ datasets including MODIS (MOD16), SSEBop, NLDAS (Noah and VIC), and GLEAM (3.3a and 3.3b) are evaluated against in situ observations at two AmeriFlux sites of differing vegetation cover in the state. MODIS and GLEAM (3.3b) are found to have higher accuracy for capturing the magnitude and variability of ET$_a$ over the state. The higher spatial resolution of MODIS is found to be best suited for the development of a state ET$_a$ dataset, with gaps in the data filled using GLEAM 3.3b.

Precipitation data are also analyzed, and spatial P – ET$_{ref}$ and P – ET$_a$ maps are presented. The P – ET maps have a direct application for agriculture and water use. These include drought assessment, drainage construction, cropping practices, cultivar selection, planting dates, irrigation schedules, and assessing crop stress and/or damage. Identifying climate divisions in the state with high, positive accumulated P – ET values can help mitigate damage from possible flood events by helping identify regions with potential drainage issues due to saturated soils and inadequate tile drains. Alternatively, negative P – ET values can be a risk marker for increased interannual drought vulnerability.

The maps of P – ET$_{ref}$ show a southwest–northeast gradient that can be used for identifying temporal evolution and drought propagation over the state. Accordingly, cultivating areas in these regions (CDs 3, 6, and 7) poses a higher risk of drought damage. Additionally, from the P – ET$_a$ maps, a negative water balance status recognized during July and August supports the need for accurate soil moisture monitoring and the potential need for irrigation during these two months for agricultural areas in CDs 4, 7, 8, and 9. Despite the negative water balance identified during July and August, the water cycle in Indiana has had a positive balance during the last 30 years with an accumulated ET$_{ref}$ of 1110 mm, ET$_a$ of 708 mm, and precipitation of 1091 mm.

![Figure 13](https://via.placeholder.com/150)
Climatological maps of ET$_a$ across the state provide a simple yet informative tool that stakeholders can apply to water supply management, flood and drainage management, or crop management to make more robust and sustainable decisions in the state. The findings are of interest for drought monitoring and water shortage task studies that the state is continually reviewing. Future application of this work includes developing a near-real-time drought assessment tool utilizing the data presented herein to assist regional water resources planning activities. It is highlighted that while the study focuses on Indiana, the findings are of relevance to different agriculture-dominated regions and can serve as a possible template for other regional assessments.

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Data availability statement. The data associated with this paper will be publicly accessible through the online, collaborative data-sharing platform of Purdue University Research Repository (PURR; https://purr.purdue.edu/) to support data citation, quality, and reuse by the scientific community.

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