



Assessment of Spatial and Temporal Variation of Potential Evapotranspiration Estimated by Four Methods for South Carolina

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Abstract. Given South Carolina's ongoing water planning efforts, in this study, we evaluated seasonal and annual potential evapotranspiration (PET) using measured Class A pan evaporation (PE) and 3 widely used estimation methods for the state with 3 distinct physiographic regions (Coastal, Piedmont, and Mountain). The methods were temperature-based Hargreaves-Samani (H-S), radiation-based Priestley-Taylor (P-T), and process-based Penman-Monteith (P-M). The objectives of the study were to (a) describe seasonal and temporal distribution of PET by all methods, (b) quantify differences among PET methods, and (c) identify relationships between monthly PE and estimated PET by each method. Daily weather variables from 59 National Oceanic and Atmospheric Administration weather stations distributed in the 3 regions of South Carolina (SC) were used to estimate daily PET for an 18-year period (1998–2015). Net radiation was estimated using modeled solar radiation values for weather stations. The average annual H-S PET values adjusted with the empirical radiation factor (KT) and the average annual P-T PET values for 1998–2015 were $1,232 \pm 9$, $1,202 \pm 11$, and $1,115 \pm 10$ mm and $1,179 \pm 10$, $1,137 \pm 11$, and $1,082 \pm 11$ mm, respectively, for the Coastal, Piedmont, and Mountain regions. Both the mean annual H-S and P-T PET for the Mountain region were significantly ($\alpha = 0.05$) lower than for the Coastal and Piedmont regions. The mean annual P-T PET for the Coastal region was significantly ($\alpha = 0.05$) greater than that for the Piedmont. Regional differences showed that estimated PET for 1998–2015 was greatest in the Coastal and lowest in the Mountain region. Comparison of all 3 methods using only common 8-year data showed mean annual P-M PET, varying from 1,142 mm in the Piedmont to 1,270 mm in the Coastal region, was significantly higher than both the H-S and P-T PET in both regions. The greatest mean monthly H-S and P-T PET values were observed in June and July. Statistical evaluation using Nash–Sutcliffe efficiency and percent bias showed a slightly better agreement of H-S PET with both the measured PE as well as the P-M method, followed by the P-T. However, the P-T method yielded a close to unity slope and slightly higher R^2 than the H-S PET when compared with the PE. The P-T PET method that uses both the temperature and radiation data may be preferred for SC with a humid climate dominated by forest land use, given more rigorous ground-truthing of modeled solar radiation as data become available. Surface interpolation algorithm, inverse distance weighted, was used to spatially map both the distributed H-S and P-T PET for the state. Results from this study can be used to support several components of the ongoing water planning efforts in SC.

INTRODUCTION

Evapotranspiration (ET) is a major component of the water cycle and influences runoff, soil water storage, groundwater recharge, biodiversity, and the global climate system (McMahon et al., 2013; Tegos et al., 2015; Sun et al., 2011). Potential evapotranspiration (PET) is a common measure of evaporative demand defined as the rate of evaporation that would occur from soil and plant surfaces

with unlimited water supply and no resistance to transfer of water (Hember et al., 2017). Numerous methods and models for estimating PET have been developed that range from pan evaporation (PE) to the parameter-intensive, physically based Penman-Monteith (P-M; Monteith, 1965) method to temperature-only-based methods to many other methods of varying complexity (McMahon et al., 2013).

Some of the widely-used temperature-based PET methods, which rely on temperature as the primary

climate variable to estimate PET directly or indirectly, include Thornthwaite (1948), Hamon (1963), and modified Hargreaves–Samani (H-S; Hargreaves & Samani, 1985). Because PET is also controlled by other climatic variables like solar radiation, humidity, and wind speed, and owing to advances in computing technology, there has been a tremendous effort in the last few decades to develop process-based PET models (Allen et al., 1998; Marek et al., 2016). Furthermore, the interaction of vegetative parameters like leaf area index and stomatal conductance with the microclimate including aerodynamic resistance has also been shown to be important for addressing the PET for a given surface resistance in the process-based PET models (Brauman et al., 2012; McKinney & Rosenberg, 1993). In recent years, the U.N. Food and Agricultural Organization (FAO)-56 Penman–Monteith model (Allen et al., 1998), which is a slight modification of the original P-M method, has been used globally as a reference ET (REF-ET or ET_0) for a standard grass from which to compare crop ET of all other crops under nonstressed conditions (Allen et al., 1998; Allen et al., 2006; Amatya & Harrison, 2016; Amatya et al., 1995; Cai et al., 2007; FAO, 1990; Lima et al., 2013; Lopez-Moreno et al., 2009; McMahon et al., 2013; Rao et al., 2011; Wang et al., 2015; Raziei & Pereira, 2013). Shevenell (1996) used measured temperature and the calculated ratio of total to vertical radiation to estimate monthly PET at 125 weather stations in Nevada, most of which are near valley floors at elevations ranging from 393 to 2,287 m. The author reported that the calculated values were found to be well correlated ($R^2 = 0.91\text{--}0.99$, slopes near 1.0) with monthly PE measurements at 8 sites in Nevada.

There have been only limited studies conducted to assess the short- or long-term PET for South Carolina. Barker and Pernik (1994) noted that although regional maps of actual ET were not available, 2 published maps of PET were available that covered the Southeastern Coastal Plain aquifer system including South Carolina. The first one, by Geraghty et al. (1973), provided a PET map used by the U.S. Department of Agriculture (USDA) Forest Service to estimate ET from the oak–hickory–pine forests in the southeastern United States. Their estimates indicated that PET ranges from 36 in. (900 mm) per year along the northern edge to 40 in. (1,000 mm) along the southern edge. The second one is Hamon's (1963) map of PET based on air temperature, saturation vapor pressure, and daytime hours for the eastern United States. Barker and Pernik (1994) used the Hamon's PET method to estimate ET for their study areas in the Southeastern Coastal Plain aquifer system because they found that the Hamon's results were close to those estimated from the Thornthwaite (1948) and Penman (1948) methods. Young (1968) documented a 3-year estimate of Thornthwaite-based PET using temperature data at the USDA Forest Service's Santee Experimental Forest (SEF) headquarters in coastal

South Carolina. Lu et al. (2005) contrasted 6 commonly used PET models and quantified the long-term PET across a physiographic gradient of 36 watersheds in the southern United States including 1 at the SEF. Three temperature-based (Hamon, 1963; H-S, Hargreaves & Samani, 1985; Thornthwaite, 1948) and 3 radiation-based (Makkink, 1957; P-T, Priestley & Taylor, 1972; Turc, 1961) PET methods were compared. The authors concluded that, in general, the P-T, Turc, and Hamon methods performed better than the other PET methods and that the ET values with temperature-based methods were more variable than those obtained from solar radiation-based methods. Later, Harder et al. (2007) compared 3 methods (Hamon, 1963; P-M, Monteith, 1965; Thornthwaite, 1948) to estimate PET using data from a standard weather station above a grass reference also at the SEF. The authors also found that the temperature-based Thornthwaite and Hamon methods yielded results close to those by the P-M method. Amatya and Harrison (2016) evaluated 5 different methods (H-S, Hargreaves & Samani, 1985; P-M, Monteith, 1965; P-T, Priestley & Taylor, 1972; Thornthwaite, 1948; Turc, 1961) to estimate daily and monthly PET for a pine and hardwood forest in coastal South Carolina and found P-T and H-S PET matching closely with the P-M PET. Similarly, the P-M based reference ET estimates using 9-year (2001–2009) data were recently reported for 21 stations in South Carolina for their potential use in agricultural water management by the Natural Resources Conservation Service (NRCS, 2016).

All of these studies were more site specific and with limited data. Furthermore, most of the aforementioned PET studies have been conducted for a well-watered standard grass reference that may not well represent evaporation from large, open-water bodies like reservoirs and lakes often used for multipurpose water management (Rosenberry et al., 2007). A pan coefficient is generally applied to measurements of PE from a National Weather Service Class A pan to account for heat transfer through the sides and bottom of the pan for estimating open water evaporation (OWE; Hember et al., 2017) of large water bodies with deep storage (Jensen et al., 1990). There are some empirical methods in the literature to derive pan coefficients using some measured climatic variables like wind speed, relative humidity, and upwind fetch distance (Grismer et al., 2002; Irmak et al., 2002). Phillips et al. (2014) compared remote sensing estimates of lake evaporation with PE measurements along the Savannah River Basin and attributed seasonal variabilities in lake evaporation to seasonal variations in temperatures. Recently, CDM Smith (2016) reported a long-term assessment of H-S-based PET compared with pan and OWE for some limited locations in South Carolina.

As the issues of water supply, reservoir water management, drought, irrigation and crop water use, and land use change are becoming of a societal concern given the pressures

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of urbanization and climate change (Lackstrom et al., 2016; Mizzell et al., 2014; Roehl & Conrads, 2015), there is a growing need for more reliable operational methods and tools to assess long-term ET and PET to support sound management decisions on water resources. Therefore, our objectives in this study were to (a) describe spatially distributed seasonal and annual PET by 3 widely used methods (H-S, originally developed for cool-season grass in subhumid to arid western United States; P-T, originally developed for rain-fed grassland in Australia and United States; and P-M, for a standard 12-cm-high grass at all locations), (b) quantify differences in computed PET among the 3 methods in each region and among 3 regions for each PET method, (c) compare each of the H-S and P-T PET methods with the standard grass reference-based P-M PET for all sites, and (d) examine the relationships between monthly PE and PET by each of the 3 methods for the state of South Carolina. Although the H-S and P-T PET methods were originally developed for only 7- and 10-day

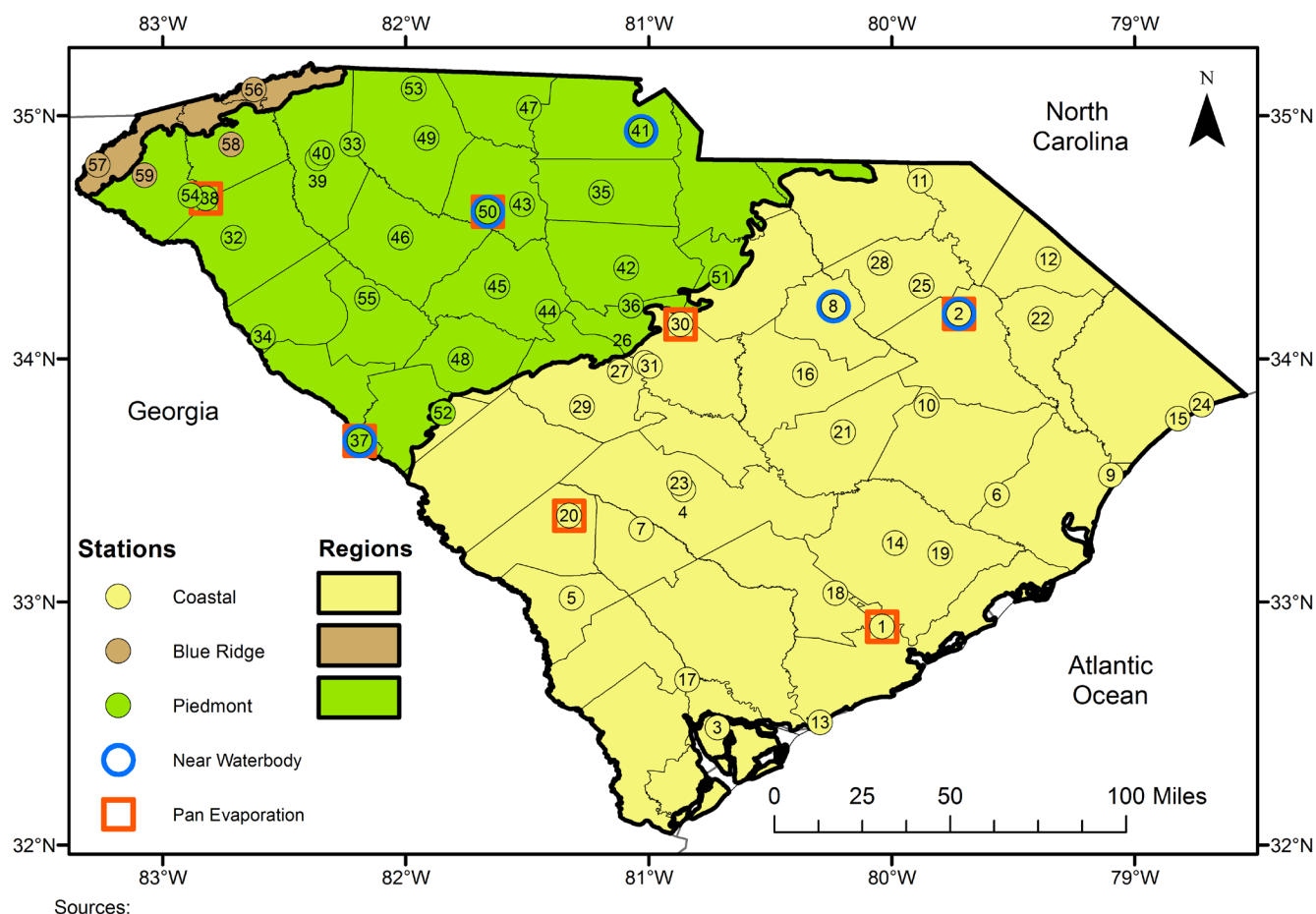
periods, respectively (Jensen et al., 1990), calculations on a daily time step were performed to obtain the monthly values for all the 3 methods in this study. Spatially interpolated GIS maps were developed using both the H-S and P-T methods.

MATERIALS AND METHODS

STUDY SITES

The climatological (weather) stations used as study sites for the spatiotemporal assessment of PET are shown in Figure 1; their names and characteristics are listed in Table 1.

A total of 59 stations distributed across the physiographic areas (Coastal, 31; Piedmont, 24; Mountain, 4) are maintained by National Oceanic and Atmospheric Administration (NOAA). The ranges of elevation (above mean sea level) were approximately 2.4–137.2 m, 70.1–319.4 m, and 298.7–975.4 m, for stations in the Coastal, Piedmont, and Mountain regions, respectively, whereas



Sources:

Menne, Matthew J., Imke Durre, Bryant Korzeniewski, Shelley McNeal, Kristy Thomas, Xungang Yin, Steven Anthony, Ron Ray, Russell S. Vose, Byron E. Gleason, and Tamara G. Houston (2012): Global Historical Climatology Network - Daily (GHCN-Daily), Version 3.21. NOAA National Climatic Data Center. doi:10.7289/V5D21VHZ [6/25/2015].

Omernik, J.M. and G.E. Griffith. 2014. Ecoregions of the conterminous United States: evolution of a hierarchical spatial framework. *Environmental Management* 54(6):1249-1266.

Figure 1. Spatial distribution of 59 National Oceanic and Atmospheric Administration weather stations selected for this study. Circled stations are near open water bodies (lakes and reservoirs).

Table 1. NOAA weather stations and their characteristics in Coastal (C), Piedmont (P), and Mountain (M) regions.

Station	City	Lat, °N	Long, °W	Elev, m	Station ID (US)	Reg	H-S PET, mm	P-T PET, mm
1. Charleston AP ^a	Charleston	32.90	-80.04	12.2	W00013880	C	1,206 ± 6 ^b	1,205 ± 11 ^c
2. Florence AP ^a	Florence	34.19	-79.72	44.5	W00013744	C	1,210 ± 9	1,168 ± 11
3. Beaufort MCAS ^d	Beaufort	32.48	-80.72	11.3	W00093831	C	1,199 ± 9	1,235 ± 11
4. Orangeburg MU AP	Orangeburg	33.46	-80.86	60	W00053854	C	1,251 ± 17	1,203 ± 11
5. Allendale 2 NW	Allendale	33.02	-81.32	54.9	C00380126	C	1,305 ± 11	1,231 ± 11
6. Andrews	Andrews	33.44	-79.57	10.7	C00380184	C	1,224 ± 10	1,164 ± 11
7. Bamberg	Bamberg	33.30	-81.03	50.3	C00380448	C	1,241 ± 14	1,187 ± 12
8. Bishopville 1ENE	Bishopville	34.22	-80.24	75.9	C00380736	C	1,216 ± 10	1,158 ± 11
9. Brookgreen Gardens	Murrells Inlet	33.52	-79.10	6.1	C00381093	C	1,109 ± 9	1,194 ± 11
10. Cades 4W	Lake City	33.81	-79.86	24.4	C00381241	C	1,291 ± 10	1,183 ± 10
11. Dillon	Dillon	34.41	-79.36	35.1	C00382386	C	1,224 ± 16	1,159 ± 11
12. Edisto BE ST PA	Edisto Beach	32.51	-80.29	2.4	C00382730	C	1,067 ± 11	1,232 ± 10
13. Moncks Corner 4N	Moncks Corner	33.24	-79.99	14.9	C00385946	C	1,242 ± 9	1,216 ± 11
14. Myrtle Beach ^d	Myrtle Beach	33.75	-78.82	11.9	C00386153	C	1,089 ± 10	1,171 ± 11
15. Sumter	Sumter	33.94	-80.36	53.9	C00388440	C	1,199 ± 13	1,151 ± 11
16. Yemassee	Yemassee	32.68	-80.84	13.4	C00389469	C	1,409 ± 8	1,183 ± 13
17. Summerville 4W	Summerville	33.04	-80.23	19.8	C00388426	C	1,257 ± 12	1,180 ± 10
18. Santee ^f	Cordesville	33.20	-79.80	14		C	1,390 ± 21	1,132 ± 17
19. Blackville 3W ^e	Blackville	33.36	-81.33	96.6	W00063826	C	1,252 ± 21	1,182 ± 11
20. Manning	Manning	33.70	-80.20	30.5	C00385493	C	1,272 ± 13	1,186 ± 11
21. Marion	Marion	34.17	-79.39	22.9	C00385509	C	1,214 ± 13	1,165 ± 10
22. Orangeburg	Orangeburg	33.49	-80.87	54.9	C00386527	C	1,303 ± 13	1,201 ± 11
23. N. Myrtle Beach AP ^d	Myrtle Beach	33.81	-78.72	9.8	W00093718	C	1,062 ± 11	1,157 ± 11
24. Darlington ^d	Darlington	34.30	-79.88	45.7	C00382260	C	1,245 ± 10	1,174 ± 11
25. Columbia Met. AP ^d	Columbia	33.95	-81.12	68.6	W00013883	C	1,230 ± 10	1,171 ± 12
26. Hartsville	Hartsville	34.40	-80.05	56.4	C00383990	C	1,233 ± 11	1,137 ± 11
27. Pelion 4N	Pelion	33.80	-81.27	137.2	C00386775	C	1,244 ± 10	1,167 ± 11
28. Sandhill Research ^a	Elgin	34.14	-80.87	134.1	C00387666	C	1,234 ± 9	1,166 ± 11
29. Columbia Owens AP ^d	Columbia	33.97	-81.00	64.6	W00053867	C	1,223 ± 11	1,180 ± 12
30. Cheraw	Cheraw	34.73	-79.88	42.7	C00381588	C	1,181 ± 9	1,117 ± 11
31. Columbia University	Columbia	33.98	-81.02	73.8	C00381944	C	1,324 ± 10	1,203 ± 12
Mean						C	1,232 ± 9	1,179 ± 10*
32. Cedar Creek 2E	Blythewood	34.22	-81.07	103	C00381479	P	1,280 ± 14	1,121 ± 10
33. Anderson Co. AP	Anderson	34.50	-82.71	231.6	W00093846	P	1,164 ± 11	1,154 ± 11 ^c
34. Greenville-Spartanburg AP ^d	Greer	34.88	-82.22	287.4	W00003870	P	1,138 ± 11	1,133 ± 12
35. Calhoun Falls	Calhoun Falls	34.09	-82.59	161.5	C00381277	P	1,210 ± 11	1,158 ± 11
36. Chester 1SE	Chester	34.68	-81.20	170.7	C00381633	P	1,201 ± 10	1,109 ± 11
37. Clarks Hill 1W ^e	Clarks Hill	33.66	-82.19	115.8	C00381726	P	1,280 ± 20	1,174 ± 11
38. Clemson Univ. ^e	Clemson	34.66	-82.82	251.2	C00381770	P	1,172 ± 11	1,147 ± 11
39. Greenville	Greenville	34.82	-82.36	292.6	C00383735	P	1,093 ± 9	1,115 ± 11
40. Greenville D AP ^d	Greenville	34.85	-82.35	319.4	W00013886	P	1,122 ± 10	1,151 ± 11
41. Winthrop Univ.	Rock Hill	34.94	-81.03	210.3	C00389350	P	1,162 ± 10	1,139 ± 11

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Station	City	Lat, °N	Long, °W	Elev, m	Station ID (US)	Reg	H-S PET, mm	P-T PET, mm
42. Winnsboro	Winnsboro	34.37	-81.09	161.5	C00389327	P	1,205 ± 12	1,130 ± 10
43. Santuck		34.64	-81.52	158.1	C00387722	P	1,206 ± 12	1,141 ± 12
44. Little Mountain	Little Mountain	34.19	-81.41	216.7	C00385200	P	1,159 ± 11	1,150 ± 11
45. Newberry	Newberry	34.30	-81.62	145.1	C00386209	P	1,227 ± 14	1,134 ± 11
46. Laurens	Laurens	34.50	-82.02	179.5	C00385017	P	1,221 ± 15	1,131 ± 12
47. Ninety-Nine Islands	Blacksburg	35.03	-81.49	152.4	C00386293	P	1,170 ± 11	1,094 ± 11
48. Saluda	Saluda	34.00	-81.77	146.3	C00387631	P	1,254 ± 11	1,147 ± 11
49. Spartanburg 3SSE	Spartanburg	34.91	-81.91	185.9	C00388188	P	1,243 ± 11	1,118 ± 11
50. Union 8S ^c	Union	34.61	-81.66	146.3	C00388786	P	1,233 ± 14	1,118 ± 11
51. Wateree Dam	Lugoff	34.33	-80.70	70.1	C00388979	P	1,244 ± 11	1,143 ± 10
52. Johnston 4SW	Johnston	33.78	-81.85	189	C00384607	P	1,303 ± 15	1,160 ± 12
53. Clemson Oconee Co. AP	Clemson	34.67	-82.89	271.6	W00053850	P	1,142 ± 14	1,171 ± 11
54. Greenwood Co. AP ^d	Greenwood	34.25	-82.16	192.3	W00053874	P	1,208 ± 12	1,155 ± 11
55. Chesnee 7WSW	Chesnee	35.11	-81.97	228	C00381625	P	1,211 ± 14	1,100 ± 9
Mean						P	1,202 ± 11	1,137 ± 11
56. Caesars Head	Caesars Head	35.11	-82.63	975.4	C00381256	M	986 ± 14	1,012 ± 12
57. Long Creek	Long Creek	34.80	-83.27	502.9	C00385278	M	1,095 ± 11	1,083 ± 12
58. Pickens	Pickens	34.88	-82.72	354.2	C00386831	M	1,176 ± 11	1,121 ± 10
59. Walhalla	Walhalla	34.75	-83.08	298.7	C00388887	M	1,201 ± 14	1,113 ± 11
Mean						M**	1,115 ± 10	1,082 ± 11

Note. Mean Hargreaves-Samani (H-S) and Priestley-Taylor (P-T) potential evapotranspiration (PET) for 18 years (1998–2015). Lat = latitude; Long = longitude; Elev = elevation; Reg = region; Co. = County; AP = airport; MU = municipal, BE = beach; ST = state; PA = park; Met. = metropolitan; D = downtown.

^a Stations with pan evaporation and Penman–Monteith (P-M) PET. ^b H-S PET for 1996–2015. ^c P-T PET for 1998–2015. ^d Stations with P-M PET. ^e Stations with pan evaporation. ^f Data for Santee 2006–2015.

* Coastal P-T mean PET value significantly greater than for the Piedmont and Mountain. **Mountain (M) mean PET values significantly lower ($\alpha = 0.05$) than values for Coastal (C) and Piedmont (P) regions for both methods. *

latitudes and longitudes were 32.48°–34.73°, 33.66°–35.11°, and 34.75°–35.11° and 78.72°–81.33°, 80.70°–82.89°, and 82.63°–83.27°, respectively (Table 1). Based on the NOAA site information, there were 6 stations near airports, 1 near a university, and 4 near water bodies in the Coastal region and 5 stations near airports, 2 near universities, and 3 near water bodies in the Piedmont region.

PAN EVAPORATION MEASUREMENTS AND ANALYSIS FOR OPEN WATER PAN EVAPORATION

We obtained Class A PE data from the National Climatic Data Center's Global Historical Climatology Network website (<https://www.ncdc.noaa.gov/cdo-web/search>) for only 7 stations within the Coastal and Piedmont regions (no data for the Mountain) in South Carolina. The years for PE data varied from 1948 to 2014. In some cases data had gaps preventing us from calculating the annual values. The report by CDM Smith (2016) made available to us by South Carolina Department of Natural Resources also used data from the same site. For

water reservoirs like shallow lakes, OWE was calculated by multiplying measured PE data by pan coefficients (Jensen & Allen, 2016; Singh, 2016) obtained from NOAA Technical Report NWS-33 (Farnsworth et al., 1982) to the raw PE data. Annual pan coefficients typically range from 0.65 to 0.85, whereas monthly values can vary from 0.3 to 1.7, depending on water body characteristics, such as depth, turbidity, and potential for heat storage (Singh, 2016). The values unique for each station varying from 0.72 to 0.76 as reported by CDM Smith (2016) were also used in our study. These values closely agree with those developed by Phillips et al. (2016) for individual lakes due to their geographical and geometric (in shape and size) differences at the Savannah River site in South Carolina, except for the Coastal Plain region, with as high as 0.77 (McCuen, 1989). Although pan coefficients may bring uncertainties in estimates of OWE while calibrating PET estimates, the PE method is the only one that represents the measured evaporative demand for the study sites (McMahon et al., 2013).

MODIFIED HARGREAVES-SAMANI (H-S; HARGREAVES & SAMANI, 1985) PET METHOD

Daily H-S PET was calculated using Eq. 1:

$$H - S \text{ PET (mm d}^{-1}) = \frac{[0.0135(KT)(R_a)(T_{av}+17.8)(T_{max}-T_{min})^{0.5}]}{\lambda}, \quad (1)$$

where T_{av} , T_{min} , T_{max} , and λ represent daily average, minimum, and maximum temperatures in °C, and factor for converting radiant energy flux in MJ m² d⁻¹ to mm d⁻¹, respectively. The term $((KT)(R_a)(T_{max}-T_{min})^{0.5})$ in Eq. 1 represents daily solar radiation (R_s) as suggested by Hargreaves-Samani (1982)

$$R_s = (KT)(R_a)(TD)^{0.5}, \quad (2)$$

where R_a is daily extraterrestrial radiation (MJ m⁻² d⁻¹) calculated using standard formulas following Allen et al. (1998) for given latitude and Julian day, and the term $(T_{max} - T_{min})$ is the temperature difference (TD). Hargreaves and Samani (1985) also provided the following field-based empirically calibrated equation for calculating KT:

$$KT = 0.00185 (TD)^2 - 0.0433 (TD) + 0.4023; \\ (R^2 = 0.70, SE = 0.0126). \quad (3)$$

In this study, KT, the empirical radiation adjustment factor, was calculated through trial and error by minimizing the average daily error obtained as a difference between the calculated daily solar radiation (using the assumed KT) and the actual measured daily solar radiation for a 5-year (2005–2009) record. Daily maximum and minimum temperature data for the same period were used for TD in Eq. 2. The estimated KT for the ten stations (5 from Coastal and 5 from Piedmont) ranged from 0.148 to 0.171; too few stations were available to perform this function for the Mountain region. After identifying no significant difference ($\alpha = 0.05$) between the Coastal and Piedmont mean KT values (mean KT for Coastal: 0.157, very similar to the values [0.15–0.16] obtained by Amatya et al. (2000) for 3 coastal North Carolina sites using the self-calibration approach recommended by Allen, 1997; mean KT for Piedmont: 0.154), we used the average value (0.155) to compute adjusted H-S daily PET using Eq. 1 for each of the 59 stations. A mean value of KT = 0.154 was obtained in the H-S PET estimates for humid areas of Iran (Raziei & Periera, 2013).

PRIESTLEY-TAYLOR (P-T; PRIESTLEY & TAYLOR, 1972) METHOD

Daily P-T PET was calculated using Eq. 4:

$$P - T \text{ PET (mm d}^{-1}) = \left[1.26 \left(\frac{\Delta(R_n - G)}{\Delta + \gamma} \right) \right] / \lambda, \quad (4)$$

where R_n and G represent daily net radiation (MJ m⁻² d⁻¹) and daily soil heat flux (MJ m⁻² d⁻¹), respectively, and γ is psychrometric constant (kPa °C⁻¹) = (specific heat of air × atmospheric pressure)/(0.622 × λ), where atmospheric pressure (kPa) = 101.3 – 0.01055 × elevation (m). The parameters λ is latent heat of vaporization (MJ kg⁻¹) = 2.501 – (0.002361 × T) and Δ is slope of vapor pressure-temperature

curve [kPa °C⁻¹] = 0.2 × (0.00738 × T + 0.8072)⁷ – 0.000116, where T = daily average air temperature (°C). The constant 1.26 is a calibration factor that accounts for aerodynamic effects for wet or humid conditions.

PENMAN-MONTEITH (P-M; MONTEITH, 1965) MODIFIED BY ALLEN ET AL. (1998) AS FAO-56 METHOD

Daily P-M PET was calculated using Eq. 5 at stations where full data were available:

$$P - M \text{ PET (mm d}^{-1}) = \frac{0.408 \Delta (R_n - G) + \gamma \left(\frac{C_n}{T + 273} \right) u_2 (e_s - e)}{\Delta + \gamma (1 + C_d u_2)}, \quad (5)$$

where, R_n , G , T , u_2 , and $(e_s - e)$ represent net radiation (MJ m⁻² d⁻¹), soil heat flux (MJ m⁻² d⁻¹), daily average temperature (°C), wind speed (m s⁻¹) adjusted to 2-m height above ground, and vapor pressure deficit (kPa), respectively. The psychrometric constant (γ), slope of vapor pressure-temperature curve (Δ), numerator constant for reference type and calculation time step (C_n), and denominator constant for reference type calculation time step (C_d) were 0.0583 kPa °C⁻¹, 0.1501 kPa °C⁻¹, 900, and 0.34, respectively. Soil heat flux on a daily basis was estimated to be negligible in both the P-T and P-M methods (Allen et al., 1998; Amatya & Harrison, 2016).

All the daily PET values using H-S, P-T, and P-M methods were calculated directly in MS Excel spreadsheets using these equations with downloaded daily weather variables described next for multiple stations for the 1998–2015 period for the first 2 methods and 2002–2009 for the P-M method.

WEATHER DATA ACQUISITION FOR PET ESTIMATES

Air temperature (T). The daily temperature (minimum and maximum) data for all stations, except for Santee (<https://www.srs.fs.usda.gov/charleston/santee/>), were downloaded from the NOAA website (<https://www.ncdc.noaa.gov/cdo-web/search>) and used to obtain the daily average temperature to compute daily H-S PET using Eq. 1 for the 1998–2015 period. In the case of a missing value between dates, the average of the previous and subsequent daily temperature value was used. For situations where more than 1 consecutive date had missing values, 1-km gridded temperature data downloaded from the Oak Ridge National Laboratory's DayMet website (<https://daymet.ornl.gov/singlepixel>) were used to fill the data gap because of its good agreement with measured data ($R^2 > 0.90$) and a near unity slope (0.97 to 1.03) with a small bias for randomly selected 4 stations (2 from Piedmont and 2 from Coastal).

Solar radiation (R_s). Daily solar radiation (R_s) data were used for calculation of net radiation for P-T (Eq. 4) and P-M (Eq. 5) PET methods because measured net radiation data were only available for the Santee Station (Coastal region). Actual field measured solar radiation data were available for only a very few Coastal stations (Santee, Savannah River site, and North Inlet); therefore, we used the National Solar Radiation

(NSR) database website (<https://nsrdb.nrel.gov>) to download modeled hourly solar radiation data on 10-km grid for all 59 stations for the period 1998–2015. The hourly data were processed to compute daily values. For this study, we did not directly use the daily solar radiation obtained from these modeled hourly measurements for computing net radiation for the P-T and P-M PET estimates. We first selected stations with actual measured daily solar radiation and regressed with daily data obtained from the downloaded hourly data for all of those selected stations to obtain a combined calibration equation that was used for all stations without measured data. Because the calibration Eq. 6 obtained by a bootstrap regression (Ssegane et al., 2017; that potentially reduces the effects of autocorrelation in daily values) was significant, we chose it to correct the bias in daily solar radiation data ($\text{Mj m}^{-2} \text{d}^{-1}$) from the downloaded hourly data for all the stations.

$$\begin{aligned} R_s &= \text{NSR data} \times 0.98 - 1.59 \\ (R^2 &= 0.88; P < 0.001; \\ \text{RMSE} &= 1.89 \text{ Mj m}^{-2} \text{d}^{-1}), \end{aligned} \quad (6)$$

where, RMSE = root mean square error.

Net radiation (R_n). Daily net radiation ($\text{Mj m}^{-2} \text{d}^{-1}$) needed for computing the daily P-T and P-M PET (Eqs. 4 and 5) was calculated following the FAO (1990) and Archibald and Walter (2014) methods based on modeled (where measured was not available) daily solar radiation and temperature:

$$R_n = (1 - \alpha) R_s - C \epsilon_n \sigma T_k^4, \quad (7)$$

where, α is albedo (= 0.23 for grass), C is cloudiness factor, ϵ_n is net emissivity (= atmospheric emissivity – vegetation emissivity), σ is Stephan–Boltzman constant = $4.89\text{E-}^{09} \text{ Mj m}^{-2}\text{K}^{-4}\text{d}^{-1}$, and T_k is temperature in Kelvin (= $T \text{ }^\circ\text{C} + 273.3$)

One slight modification we made was in computing the cloudiness factor (C):

$$C = (a_c \times R_s/R_a + b_c), \quad (8)$$

in which the constants a_c and b_c recommended in the FAO (1990) method were optimized to 0.72 and 0.28, respectively, by minimizing the difference between daily calculated net radiation by the FAO method and the measured data from the USDA Forest Service SEF Station for a 10-year (2006–2015) period. This maximized the highest Nash–Sutcliffe coefficient (in this case, $N-S = 0.93$). The calibrated constants were used to compute cloudiness as required for calculating net radiation at each station. Measured net radiation data were available for only the Coastal SEF station starting from 2006 to 2015. Daily calculated net radiation using the FAO (1990) method yielded a strong significant relationship ($R^2 = 0.94$; $P = 0.02$; $\text{RMSE} = 1.21 \text{ Mj m}^{-2} \text{d}^{-1}$) obtained using a block bootstrap geometric linear regression with the measured data at the SEF station. The ϵ_n , net emissivity was calculated from the Eq. 9:

$$\epsilon_n = 0.261 \text{ EXP}(-7.77 \times 10^{-4} T^2) - 0.02. \quad (9)$$

Relative humidity and wind speed. Measured hourly wind speed (u) and relative humidity (RH) data were available only for 11 stations (Charleston Airport [AP], North Myrtle Beach AP, Florence AP, Myrtle Beach Air Force Base, Beaufort Marine Corps Air Station, Darlington County AP, Columbia Metropolitan AP, Columbia Owens AP, Greenville Downtown AP, Greenwood County AP, and Greenville–Spartanburg AP) from NOAA's NCEI website (<https://www.ncdc.noaa.gov/cdo>). Missing data were gap filled using the same procedure described for the air temperature. Hourly values were further processed to obtain the daily values. Daily humidity values were used for calculation of vapor pressure deficit (as shown next), which together with the daily wind speed was used in calculating P-M PET in Eq. 5.

Vapor pressure deficit. The vapor pressure deficit was calculated using the maximum ($T_{\max}$) and minimum ($T_{\min}$) temperature and maximum ($\text{RH}_{\max}$) and minimum ($\text{RH}_{\min}$) relative humidity as follows following the procedure by Jensen et al. (1990):

$$\begin{aligned} \text{Maximum vapor pressure, } e_o(T_{\max}) &= \text{EXP}[(16.78 \times T_{\max} \\ &\quad - 116.9) / (T_{\max} + 273.15)]; \\ \text{Minimum vapor pressure, } e_o(T_{\min}) &= \text{EXP}[(16.78 \times T_{\min} \\ &\quad - 116.9) / (T_{\min} + 273.15)]; \\ \text{Saturated vapor pressure, } e_s &= [e_o(T_{\max}) + e_o(T_{\min})] / 2; \\ \text{Actual vapor pressure, } e_a &= 0.5 \times \{[\text{RH}_{\min} / 100 \times e_o(T_{\max})] \\ &\quad + [\text{RH}_{\max} / 100 \times e_o(T_{\min})]\}; \\ \text{Vapor pressure deficit (VPDC)} &= e_s - e_a \end{aligned} \quad (10)$$

DATA PROCESSING AND STATISTICAL ANALYSES

First, we used the daily weather variables (temperature, humidity, and solar radiation) to compute daily net radiation (Eq. 7) and vapor pressure deficit (Eq. 10). As a next step, we used daily weather data to calculate daily PET by each of the prior 3 methods (Eqs. 1, 4, and 5), although PET estimates from weather data at the monthly scale have been reported to be acceptable by some studies for assessing water yield of stream or river basins (CDM Smith 2016; Hember et al., 2017; Lu et al., 2003; Rao et al., 2011; Shevenell, 1996). Daily PET values were integrated to obtain the monthly and annual means for each of the stations in each of the 3 regions. Then the annual means were averaged to obtain the mean annual value, and similarly, monthly means for each year were averaged to obtain the mean monthly value at each of the stations. Regional mean monthly and mean annual values by each of the PET methods were derived by averaging station mean values in each of the 3 regions. The same procedure was repeated for the OWE data obtained from the PE stations to summarize mean monthly and mean annual values. Standard deviations and standard errors were also reported.

The significance in differences in mean annual PET among the regions by each method (H-S, P-T, and P-M) and among the methods in each region were identified using analysis of variance with Tukey test ($\alpha = 0.05$) in R software (R Core Team, 2017). For example, we tested whether there was a difference among mean annual P-T PET in Coastal, Piedmont, and Mountain regions and also whether there was a difference in mean annual PET by H-S, P-T, and P-M methods in Piedmont region. Regressions between H-S PET (1996–2015), P-T PET (1998–2015), and P-M PET (2002–2009) were developed to identify the strength of relationships between each pair, particularly for the H-S and P-T PET with the standardized P-M PET.

Scatter plots and ordinary least squares lines were fitted to examine the association between the monthly PE and monthly PET by each of the 3 methods for all regions together. Unlike with daily values, it was assumed that monthly model relationship would have a negligible effect of autocorrelation. Statistical criteria of coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), percent bias (PBIAS), and root mean square error normalized by dividing by standard deviation (RSR) following Moriasi et al. (2007) were used to evaluate the model performance.

GIS SPATIAL ANALYSES FOR INTERPOLATED PET MAPS

The above analyses provided seasonal and annual estimates of PET for 59 stations spread across South Carolina (Figure 1). However, these stations may not yet adequately describe the PET estimates for some specific sites of interest due to their location which may be much further away than desired. In such circumstances an accurate spatial interpolation of the PET from the spatially distributed station data is needed, and the method of interpolation between plays an important role, as with any other hydrologic data (Chen et al., 2017).

Among several interpolation methods available in the literature, IDW surface interpolation scheme available in ArcGIS 10.5 tool was used to develop spatial PET distribution maps for South Carolina. IDW uses the influence of a measured point by weighing it according to the distance from the sampled point (in our case, the PET values of NOAA weather stations) to the estimated point.

The mean monthly and mean annual PET calculated by P-T and H-S methods for all 59 NOAA weather stations in the state were added to the weather station shape file. The IDW scheme created the spatial distribution raster, which was masked to the state boundary and classified into 5 class ranges to provide the visual distributed map of PET in the state. An automated geospatial model was developed in ArcGIS ModelBuilder to streamline the entire working process and make the job efficient.

More details on the weather stations, metadata, data gap, data filling and extrapolation, relationships of climatic data with PE, calculation of daily PET by each method and

their parameters, statistical methods used for PET model evaluation, and GIS maps for the mean annual and mean monthly PET by both the H-S and P-T PET methods are given in the Final report of this project being submitted to South Carolina Department of Natural Resources.

RESULTS AND DISCUSSION

SPATIAL AND TEMPORAL DISTRIBUTION OF PET

The 18-year (1998–2015) mean annual PET with their standard errors of the mean using H-S and P-T methods are presented in Table 1 for stations in each of the 3 regions, with year-to-year variability shown in Figures 2A and 2B. However, a comparison among all the 3 methods was also done for 11 stations in common in the Coastal and Piedmont regions (Table 2) for an 8-year (2002–2009) period for which complete data for the P-M method were available.

The highest mean annual PET was computed for the P-M method followed by the H-S PET and the P-T PET for both the Coastal and Piedmont regions. The difference in mean annual means between the H-S PET and P-T PET was less than 2% compared with more than 7% between the P-T and the P-M methods.

When the mean annual PET values were correlated to elevation across regions, both the H-S and P-T PET significantly ($P < 0.05$) decreased with increasing elevation from Coastal to Mountain (not shown), consistent with findings in Shevenell (1996). The mean annual H-S PET for Piedmont and Mountain regions significantly decreased ($P < 0.05$) with increase in elevation unlike the Coastal region with only a small gradient (not shown). The mean annual PET trends for the regions also followed the temperature and net radiation data (not shown); the increase of which correlated to an increase of PET.

Comparison of 3 PET methods in each region. Calculated annual mean PET for each of the 3 regions varied as high as about 1,300 mm for the H-S PET and 1,250 mm for the P-T PET for the Coastal region to as low as 1,000 mm for the P-T method to 1,020 mm for the H-S PET in the Mountain region (Figures 2A and 2B). Clearly, annual mean H-S PET was higher than the P-T PET in each of the 3 regions. Although both methods yielded similar annual trend, the high and low PET values did not necessarily coincide for all the years. Furthermore, the difference in Coastal and Piedmont regions was smaller for the H-S method compared with the P-T method. This was attributed to the effects of only temperature on the H-S and both the temperature and radiation in the P-T method.

The mean annual H-S PET for Coastal, Piedmont, and Mountain regions were 1,232 mm, 1,202 mm, and 1,115 mm, respectively, compared with 1,179 mm, 1,137 mm, and 1,082 mm, respectively, for the P-T PET (Table 1).

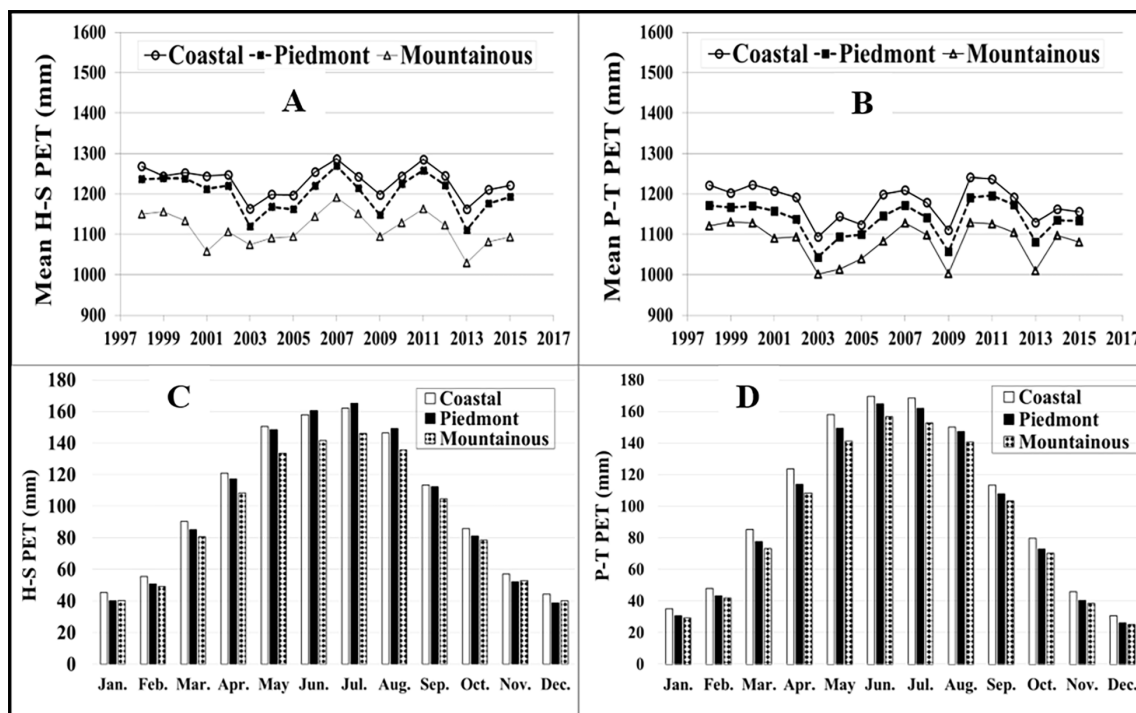


Figure 2. Annual mean and monthly mean (A and C) Hargreaves–Samani (H-S) potential evapotranspiration (PET) and (B and D) Priestley–Taylor (P-T) PET for the Coastal, Piedmont, and Mountain regions.

Table 2. Comparison of mean annual Hargreaves–Samani (H-S), Priestley–Taylor (P-T), and Penman–Monteith (P-M) potential evapotranspiration (PET; in mm).

Station	Reg	H-S PET _a ± SE (COV)	P-T PET _a ± SE (COV)	P-M PET ± SE (COV)
Charleston AP	C	1,197 ± 10 (0.02)	1,178 ± 15 (0.04)	1,270 ± 25 (0.05)
North Myrtle Beach AP	C	1,044 ± 11 (0.03)	1,128 ± 15 (0.04)	1,165 ± 23 (0.05)
Florence Airport	C	1,187 ± 14 (0.03)	1,142 ± 17 (0.04)	1,244 ± 26 (0.06)
Myrtle Beach AFB	C	1,091 ± 19 (0.05)	1,164 ± 17 (0.04)	1,248 ± 24 (0.05)
Beaufort MCAS	C	1,181 ± 15 (0.04)	1,214 ± 16 (0.04)	1,239 ± 22 (0.05)
Darlington Co. AP	C	1,250 ± 20 (0.04)	1,147 ± 16 (0.04)	1,267 ± 36 (0.06)
Columbia Met. AP	C	1,207 ± 15 (0.04)	1,139 ± 16 (0.04)	1,252 ± 26 (0.06)
Columbia Owens AP	C	1,203 ± 15 (0.03)	1,152 ± 19 (0.05)	1,149 ± 34 (0.07)
Average for C		1,170	1,158	1,229
Greenville D AP	P	1,107 ± 16 (0.04)	1,125 ± 18 (0.04)	1,142 ± 31 (0.07)
Greenwood Co. AP	P	1,192 ± 20 (0.05)	1,127 ± 16 (0.04)	1,240 ± 41 (0.07)
Greenville–Spartanburg AP	P	1,130 ± 20 (0.05)	1,109 ± 20 (0.05)	1,213 ± 38 (0.09)
Average for P		1,143	1,120	1,198

Note. Reg = region; COV = coefficient of variation; AP = airport; AFB = Air Force Base; MCAS = Marine Corps Air Station; Met. = metropolitan; C = Coastal; D = downtown; P = Piedmont. Mean annual PET for the period, 2002–2009. No Mountain weather station had more than temperature data, preventing the multiple-model comparison.

^aSignificantly different ($\alpha = 0.05$) from P-M PET.

Mean annual H-S PET was significantly ($P < 0.05$) greater than P-T PET for all 3 regions. Mean annual H-S PET values varied from 1,062 mm for North Myrtle Beach to 1,409 mm for Yemassee in southern Coastal South Carolina, with a mean of 1,232 mm for the Coastal region (Table 1); however, the P-T values had a much smaller variability in mean annual PET with 1,132 mm for Santee to 1,235 mm for Beaufort, with a mean of 1,179 mm. In the Piedmont H-S PET varied from 1,093 mm in Greenville to 1,324 mm in Columbia, with a mean of 1,202 mm, whereas the P-T PET ranged from 1,094 mm at Ninety Nine Islands to 1,203 mm in Columbia, with a mean of 1,137 mm. Similar observations were found with results from the 2 methods for the limited 4 stations in the Mountain, with the lowest at Caesar Head by both the methods to highest at Walhalla by the H-S method and at Pickens by the P-T method. Perhaps because of interaction of both the temperature and net radiation the P-T method did not necessarily yield higher PET for the southern stations than the north in each region (Table 1). Annual H-S PET also had a larger coefficient of variance than the P-T method at all stations. This was likely due to wider variation in air temperatures between stations from the south to the north (reflected in the H-S PET estimates) compared with the solar radiation (used in the P-T PET method) that did not vary as much. Mean annual P-T PET was lower than the H-S PET for the 18-year period (Table 1).

When compared among all 3 methods using only the short 8-year data (Table 2), P-M method varied from 1,142 mm at the Piedmont station to 1,270 mm at the Coastal. Similar pattern was observed for P-T from 1,109 mm at Piedmont to 1,214 mm at Coastal. However, it did not hold for the temperature only based H-S method, with both the lowest and highest PET occurring at the Coastal stations. P-M mean annual PET was the highest for all stations in the 2 regions, except for the Columbia Owens station in the Coastal where H-S PET yielded the highest. The H-S PET and P-T PET for Coastal and Piedmont were significantly ($P < 0.05$) lower than P-M PET (Table 2). The coefficients of variation were the highest for the fully process-based P-M method with multiple variables followed by the P-T and H-S method with only the temperature variable.

Monthly mean PET for the H-S and P-T PET for each of the 3 regions are presented in Figures 2C and 2D, respectively. The monthly mean P-T PET consistently yielded highest values for the Coastal followed by the Piedmont and Mountain regions, unlike the H-S PET which did not indicate any pattern. Again this may likely due to both decreasing temperature and radiation from Coastal to Mountain.

The mean monthly H-S PET for Coastal, Piedmont, and Mountain regions were 102 mm, 101 mm and 94 mm, respectively, which were very similar to the mean monthly P-T PET of 102 mm, 95 mm and 91 mm, respectively, for

the 3 regions. The highest monthly mean PET for both the H-S and P-T methods (as high as 171 mm for the P-T in the Coastal) were observed in June and July and the lowest PET in December (as low as 25 mm for the P-T method in the Mountain) in each of the 3 regions (Figure 4).

Interestingly, the temperature-based H-S monthly mean PET were higher than the P-T PET during the fall-winter and early spring in contrast with the P-T PET, which yielded higher PET than the H-S method during the May–August summer months when both the radiation and temperature included in the P-T method are generally higher than the rest of the months. Garcia et al. (2004) reported large variations of energy between summer and winter with the greatest radiation energy occurring in summer in Bolivian highlands. Sumner et al. (2017) analyzed REF-ET data for stations in Florida, and they reported that monthly ET peaked in June and July and that the greatest variabilities were observed in spring and summer, with less variability for the winter months. Amatya et al. (1995) reported for a site in eastern North Carolina that peak P-T PET values occurred in summer (June and July) and that those peak values were in close agreement with results from P-M PET. Amatya and Harrison (2016) documented that the peak monthly PET occurred in June and July at the SEF weather station, and were associated with the peak values of the energy component and leaf area index at the same period.

The observed differences in calculated PET by these 3 different methods for both the mean monthly and annual periods was likely due to different variables used in the methods from process based P-M method that uses all variables like temperature, net radiation, wind speed and relative humidity to somewhat simpler temperature only based H-S method. In cooler months, wind speed is likely to be more important than solar radiation as opposed to the solar radiation in the summer months, potentially indicating importance of the P-M method. It is also important to note that only the H-S method uses complete measured data (temperature) in contrast with the P-T and P-M methods that also use modeled radiation data potentially increasing some uncertainty.

Regional comparison of PET by each method. The mean annual H-S PET of 1,115 mm for Mountain region was significantly ($P < 0.05$) lower than for the Coastal (1,232 mm) and Piedmont (1,202 mm) regions (Table 1), likely due to the lowest temperatures observed for the Mountain region. There was no significant difference in H-S PET between Coastal and Piedmont regions (Figure 2A). The mean annual P-T PET of 1082 mm for Mountain region was significantly ($P < 0.05$) lower than for the Coastal (1,179 mm) and Piedmont (1,137 mm; Figure 2B), also likely due to both significantly lower temperature and slightly lower net radiation (not shown).

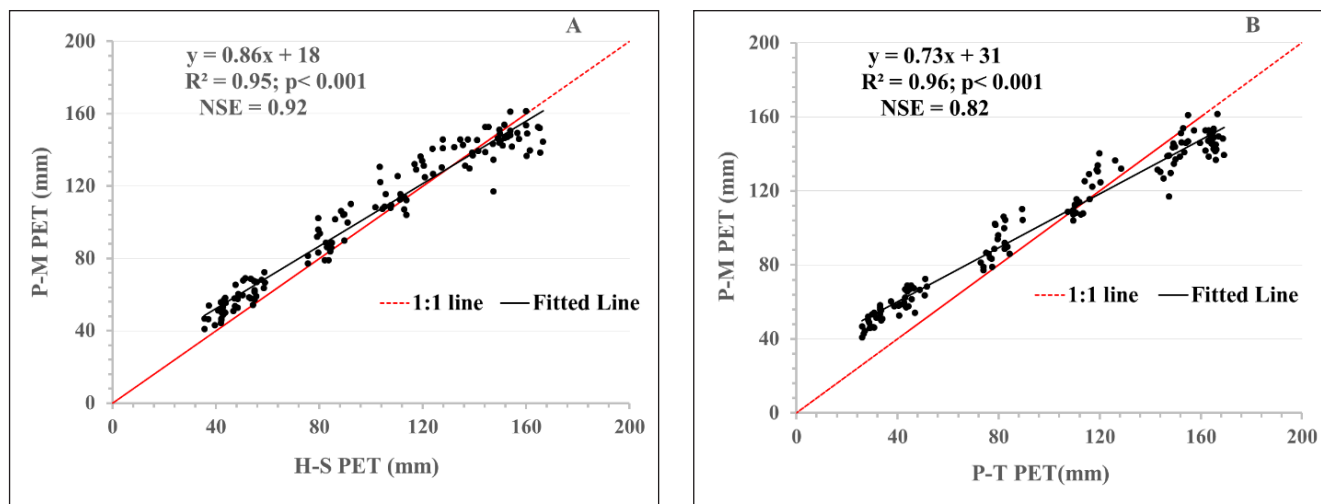


Figure 3. Relationships between monthly (A) Penman–Monteith (P-M) and Hargreaves–Samani (H-S) potential evapotranspiration (PET) and (B) P-M and Priestley–Taylor (P-T) PET.

The P-T PET for Coastal region was significantly ($P < 0.05$) greater than for the Piedmont region (Figure 2B).

The mean annual P-M PET (1,229 mm), obtained using data from only limited stations (Table 2), for the Coastal region was not significantly ($P > 0.05$) different from the Piedmont region (1,198 mm), likely due to no significant differences in weather variables (not shown). However, the H-S PET and P-T PET for both the Coastal and Piedmont were significantly ($P < 0.05$) lower than the P-M PET based on data from these limited stations (Table 2).

Our estimates of the mean annual standard P-M PET (mean annual for Coastal: 1,229 mm; mean annual for Piedmont: 1,198 mm) are somewhat smaller (within 6%) than those recently reported by NRCS (2016; mean annual for Coastal: 1,266 mm; mean annual for Piedmont: 1,270 mm) using data from 2002 to 2009 for 14 stations (out of the 59 in this study). However, we could not verify the source of weather variables the NRCS study used in their P-M PET estimate for those stations. Future study should verify results from these 2 studies using the same P-M PET method for those 14 stations.

The regional differences in weather variables (e.g. sunshine hours, temperature, humidity, radiation, rainfall and cloud cover) during different seasons contributed most to the seasonal variability in H-S and P-T PET results (Figures 2C and 2D), consistent with past studies (Chattopadhyay & Hulme, 1997; Hember et al., 2017; Shukla & Mintz, 1982; Thomas, 2000). For example, increases in temperature led to increases in both the H-S PET and P-T PET in Coastal, Piedmont, and Mountain regions. Hember et al. (2017) documented that the increases and decreases of PET with weather variables like temperature are more pronounced at shorter time intervals. Barik et al. (2016) found greater PET values calculated during clear days.

Figure 3 shows the relationship between monthly H-S PET and P-M PET, as well as the relationship between the monthly P-T PET and the P-M PET using data from stations in both the Coastal and Piedmont regions (Table 2), as there was inadequate data with only 3 stations for the Piedmont region to analyze it separately. Both the slope and the NSE for the H-S PET method (0.86; 0.92) were higher than that for the P-T method (0.73; 0.82). Similarly, the PBIAS (−0.04%) for the H-S PET was lower than that for the P-T method (−0.16%). However, the RSR value was higher (0.22) for the H-S method compared with 0.19 for the P-T method. These evaluation statistics for performance of both the H-S and P-T PET methods compared with the standard P-M method for monthly PET estimates can clearly be rated as “very good” based on the Moriasi et al. (2017) recommended criteria of $0.00 < \text{RSR} < 0.50$, $0.75 < \text{NSE} < 1.00$, and $\text{PBIAS} \leq \pm 10$ for monthly streamflow estimates. Based on this evaluation and the fact that the mean monthly PET between the H-S and P-T PET were also similar, either of the method can be used.

COMPARISON OF PET METHODS WITH PAN (PE) AND OPEN WATER EVAPORATION (OWE)

Examination of relationships between the measured mean monthly PE and the PET calculated using H-S and P-T with 84 observations from 7 stations and with P-M PET with only 24 observations from 2 stations where the data was available in Figure 4, yielded the R^2 values of 0.92, 0.94, and 0.97, respectively, with under predictions of PET (as much as by 28 mm for the P-M method) by all 3 methods as shown by their slopes > 1 . This shows that the calculated PET values by all 3 methods are somewhat realistic because evaporation measured from pans is generally greater than from nearby vegetated areas (Grismer et al., 2002; Shevenell, 1996). For instance, reference crop evaporation is typically lowered by multiplying the PE value by 0.65 to 0.85 for annual and 0.3

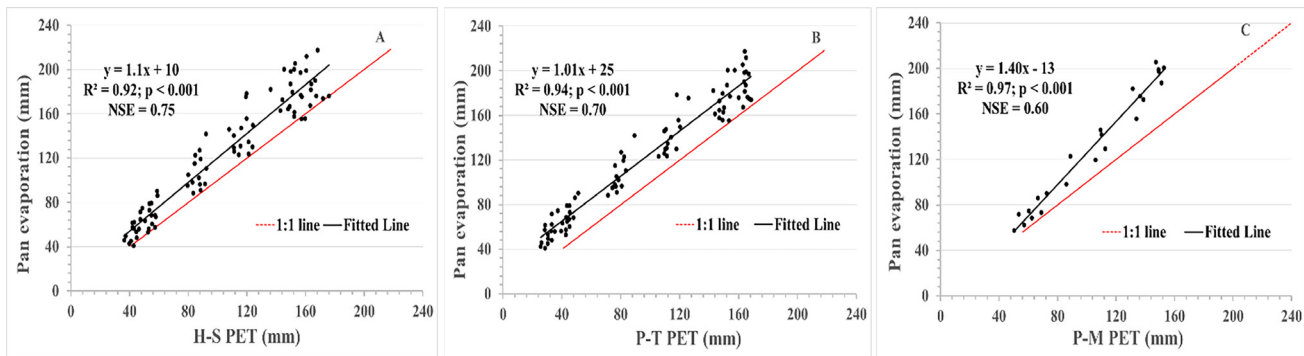


Figure 4. Relationships between mean monthly pan evaporation and (A) Hargreaves–Samani (H-S) potential evapotranspiration (PET), (B) Priestley–Taylor (P-T) PET using all 7 stations’ data in Table 3, and (C) Penman–Monteith (P-M) PET using only 2 stations’ data.

to 1.7 for monthly, depending on wind speed, and the fetch of wet versus dry crop (Maidment, 1993; Singh, 2016). The clustering of points, particularly in plots of Figure 4A and 4B, indicates the effects of seasonal climatic variables on PET by both the H-S and P-T methods. Based on the highest NSE of 0.75 and the smallest RSR of 0.21 and PB of 16.7% compared with 2 other methods, H-S method was found to be most closely associated with the mean monthly pan data. The P-T method was the second most closely associated (NSE = 0.70; RSR = 0.23, PB = 24.6%) followed by the P-M method (NSE = 0.60; NRMSE = 0.24; PB = 19.3%) using only the limited data. Because the H-S method generally overestimates the PET in the humid regions (Amatya et al., 1995; Dai et al., 2013) its close association with the pan data is expected. Flint and Childs (1991) reported $\alpha = 1.26$ in the P-T method could represent OWE estimate for humid regions.

Mean annual PET estimated by each of the 3 methods was compared with the OWE obtained from the measured PE for 7 stations, with 2 in Coastal and 5 in the Piedmont (Table 3; Figure 1). The OWE values ranged from 1,095 mm to 1,272 mm for the Coastal and 970 mm to 1,071 mm for the Piedmont, indicating higher values for the Coastal than the Piedmont. This shows that the PET estimates discussed earlier by all 3 methods with higher values in Coastal than the Piedmont are consistent with the measured weather variables as well as the PE data used to obtain OWE values. The average annual percent deviations of H-S PET and P-T PET from OWE for the 7 stations were 13.5 and 6.6, respectively (Table 3). The smaller average deviation yielded by the P-T method is consistent with other studies (Rosenberry et al., 2007; Winter et al., 1995). Although the H-S PET had closer association with measured PE data, the higher mean percent deviation from the OWE was likely due to use of annual pan coefficients, varying from 0.72 to 0.76, obtained from the CDM Smith (2016) report. The estimated OWE were consistently lower than the PET estimated by either of the H-S or P-T methods in the region.

Table 3. Comparisons of mean annual open water evaporation (OWE) versus calculated potential evapotranspiration (PET), and percentage deviation of calculated value from corrected measured values.

Station	Reg	OWE, mm	H-S PET, mm	P-T PET, mm	Deviation, %	
					H-S PET	P-T PET
Charleston	C	1,271.5	1,201	1,205	−6.6	−5.5
Florence	C	1,094.7	1,206	1,168	10.2	6.3
Sandhill	C	1,207.0	1,234	1,166	2.3	−3.5
Clarks Hill	P	969.8	1,290	1,174	33.0	17.4
Clemson	P	1,046.5	1,166	1,147	11.4	8.8
Blackville	P	1,070.6	1,260	1,182	17.7	9.4
Union	P	969.5	1,229	1,118	26.8	13.3
Average		1,090	1,227	1,166	13.5	6.6

Note. Reg = region; H-S = Hargreaves–Samani; P-T = Priestley–Taylor; C = Coastal; P = Piedmont. Source for OWE: CDM Smith report 2016. Source for H-S PET (1998–2015): this study. Source for P-T PET (1998–2015): this study.

Some uncertainties exist in derived pan coefficients due to pan type (screened/unscreened), ground cover, evaporative conditions within the fetch of the pan, presence of plants and foreign materials, microclimatic conditions surrounding the pan (i.e., freezing), and the level of maintenance. Future study should evaluate mean monthly pan coefficients developed using climatic data at the stations (Grismar et al., 2002; Irmak et al., 2002) and estimate ET_0 using these coefficients with measured PE data to recompare them against ET_0 estimates obtained by the H-S and P-T PET methods.

DISCUSSION ON H-S AND P-T PET METHODS

These results on the comparisons between the H-S and P-T methods in each region and comparisons of all 3 methods including the P-M with the measured PE lead us to conclude that the H-S PET method is most likely the best method followed by the radiation-based P-T for application in the

state of South Carolina. However, Amatya et al. (1995) found the P-T method superior to H-S method, which consistently overpredicted PET by the standard P-M method for the North Carolina Coastal Plain site. However, when making management decisions about applying either method, it may also be important to consider some other factors including the data availability and quality and land use. The fact that the radiation data used to estimate P-T PET for 59 stations in this study were modeled and calibrated with data from a few Coastal stations might have also influenced its results. The land use/land cover in river basins of South Carolina is composed of about 60% forests, on average. Amatya and Harrison (2016) showed a closer agreement of the P-T PET with the forest-reference based P-M PET for a coastal forest in South Carolina. Similarly, Rao et al. (2011) found higher correlation between simulated and measured monthly streamflow using the P-T PET than even the P-M PET in their hydrologic model applied on upland forests in western North Carolina. Lu et al. (2005) also found the P-T method performing better than the H-S method for 36 forested watersheds in the southeast. Archibald and Walter (2014) also found a stronger correlation of the P-T method with measured ET during periods of maximal ET than the fully empirical Hargreaves, Hamon and Oudin methods. Furthermore, literature suggests that P-T method also performs better than the temperature-based methods in estimating OWE (McMahon et al., 2013; Rosenberry et al., 2007; Winter et al., 1995). However, a recent study by Amatya et al. (2016) also found a satisfactory performance in predicting monthly streamflow of a coastal forest watershed in South Carolina when the H-S based PET adjusted to match the P-M PET was applied to simulate ET in a hydrologic water balance model. One reason for a better agreement of

the H-S method with the P-M method in our study compared with other studies is likely due to adjustment of the original H-S method with the KT factor (0.155) calibrated based on measured solar radiation from 5 Coastal and 5 Piedmont stations and applied to all the stations. This is consistent with a recent study by Raziei and Periera (2013). Therefore, based on all these facts, we recommend using the P-T method for South Carolina if and when measured radiation data are available; otherwise, the H-S method adjusted for the KT parameter in this study should be adequate for monthly water balance, crop water requirements, and surface and groundwater modeling purposes. That said, both H-S and P-T PET could be used for these conditions with PE data to develop mean monthly correction factors for application in lake/OWE analyses.

The mean annual H-S and P-T method-based spatially distributed PETs are presented in Figure 5(left) and 5(right), respectively.

The monthly mean H-S and the P-T-based PET results for 59 stations within 3 regions shown in Figure 1 were used for creating spatially interpolated GIS-based monthly mean PET maps for the whole state of South Carolina, as shown in Figures 6 and 7, respectively. The greatest interpolated monthly PET values were observed in the Coastal region followed by Piedmont and smallest values or the Mountain region for both the methods. The interpolated mean monthly PET range was 40–47 mm for the month of January to 154–170 mm for July for the P-T method. The PET ranges increased from January and peaked in June and there after exhibited a decreasing trend to December. The variability in monthly ranges could be due to variability in both the temperature and net radiation. We also developed the maps of 95% confidence limits of the mean (not shown).

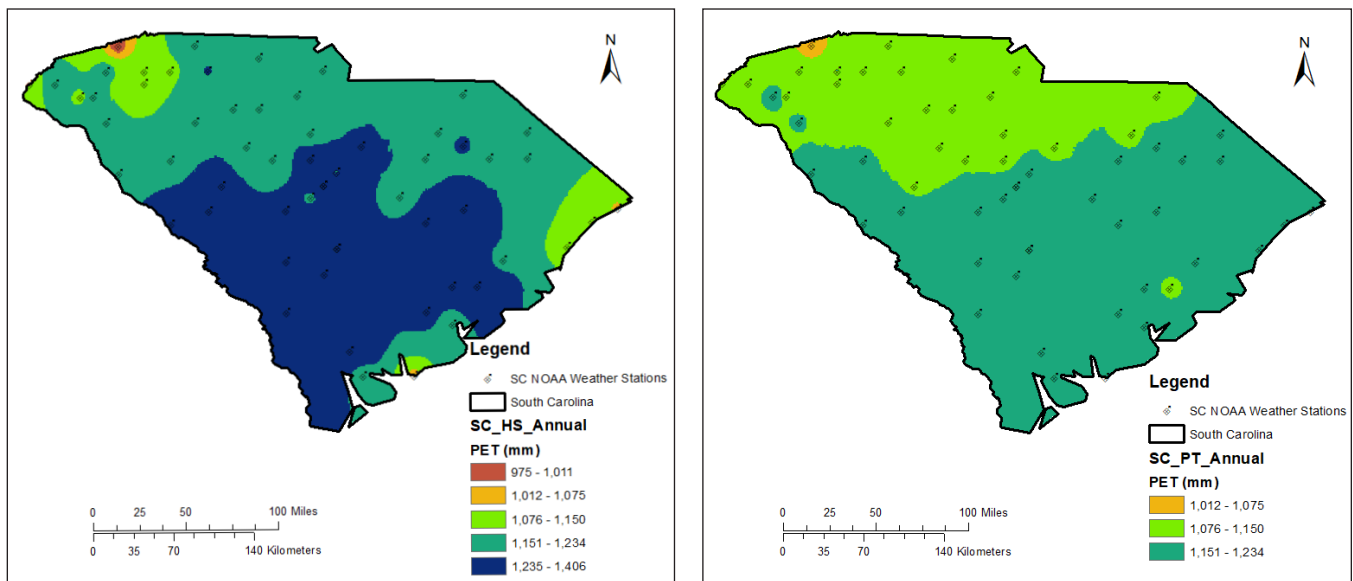


Figure 5. Interpolated mean annual Hargreaves-Samani (H-S) PET model for years 1996-2015 (left) and Priestly-Taylor (P-T) PET model for years 1998-2015 (right) determined from analysis of weather data at stations across South Carolina. Note the upper-most and lower-most ranges are not present for the P-T model because of the smaller variance in the results. The range-in-value bins are the same for both maps.

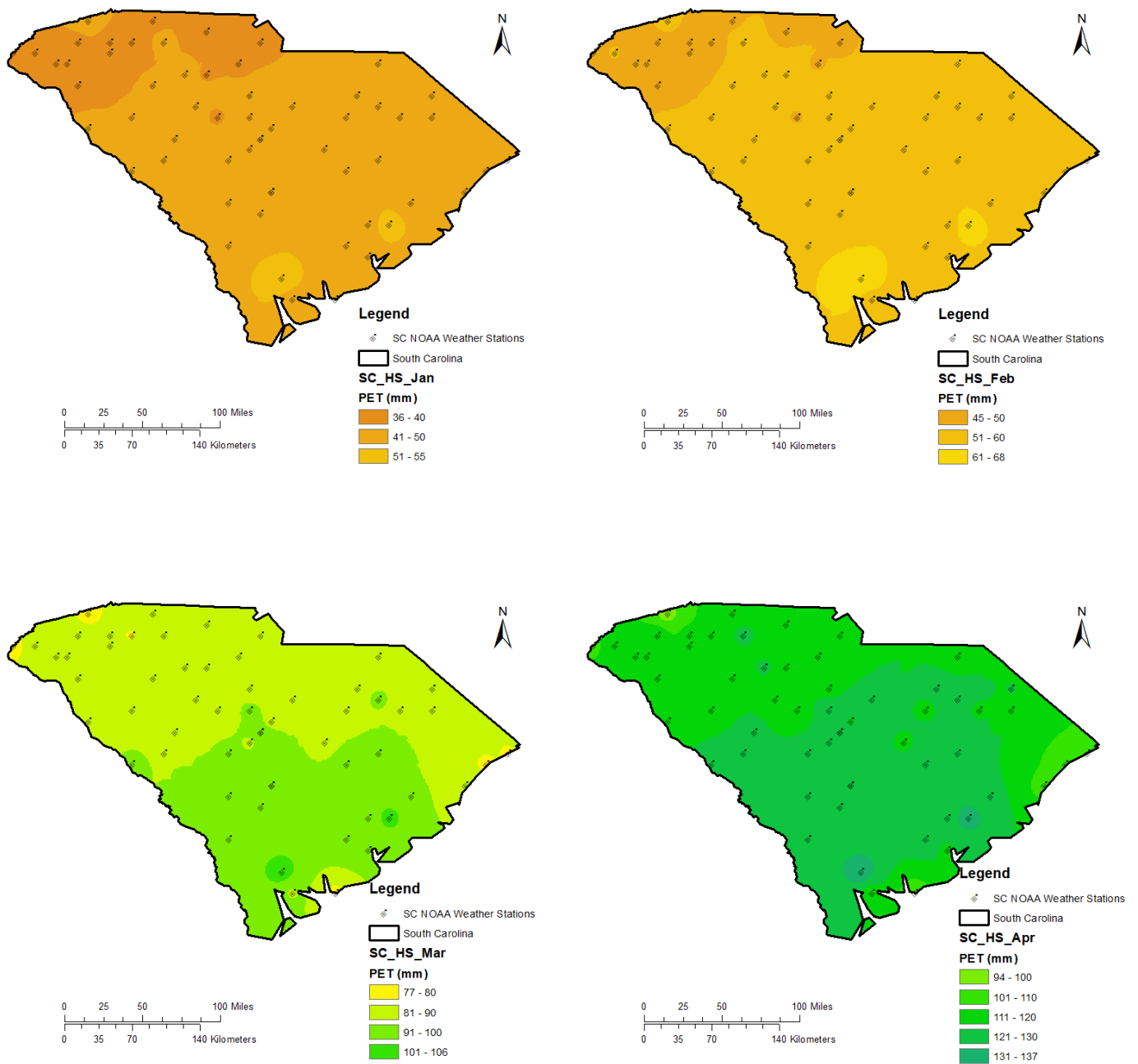


Figure 6a. Interpolated mean monthly H-S PET for January and February (top row) and March and April (bottom row). Data period of analysis is 1996-2015.

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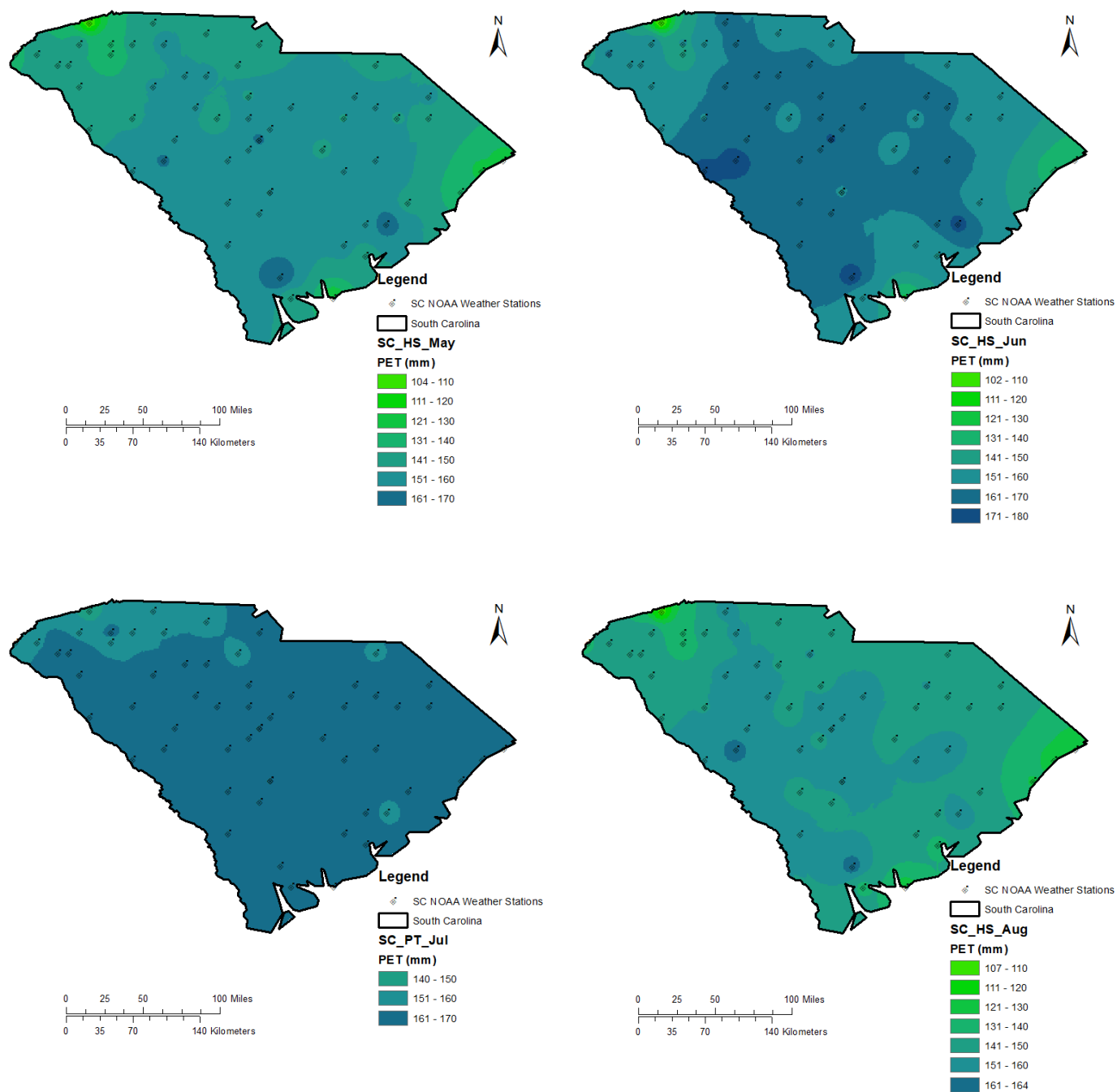


Figure 6b. Interpolated mean monthly H-S PET for May and June (top row) and July and August (bottom row). Data period of analysis is 1996-2015.

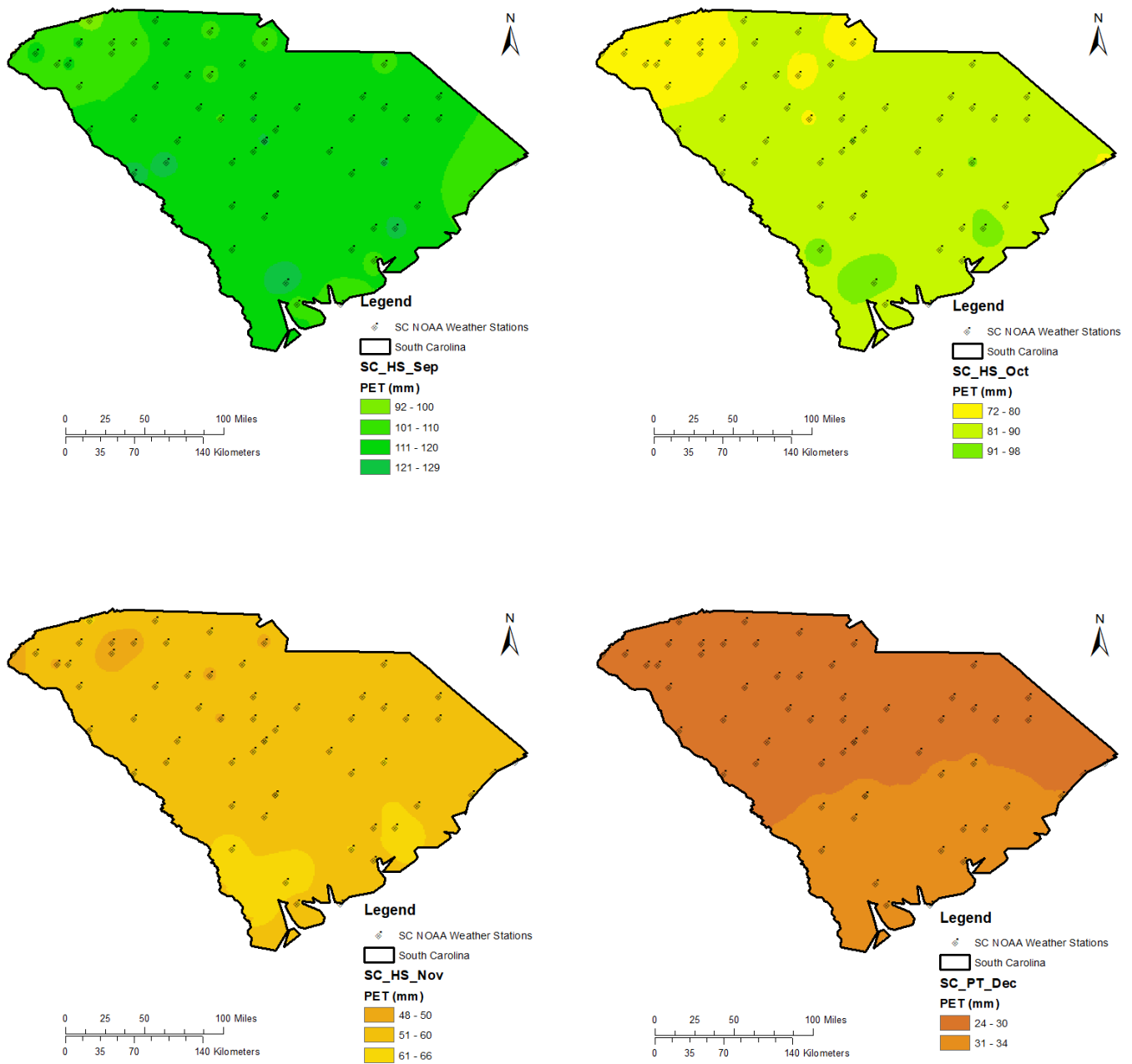


Figure 6c. Interpolated mean monthly H-S PET for September and October (top row) and November and December (bottom row). Data period of analysis is 1996-2015.

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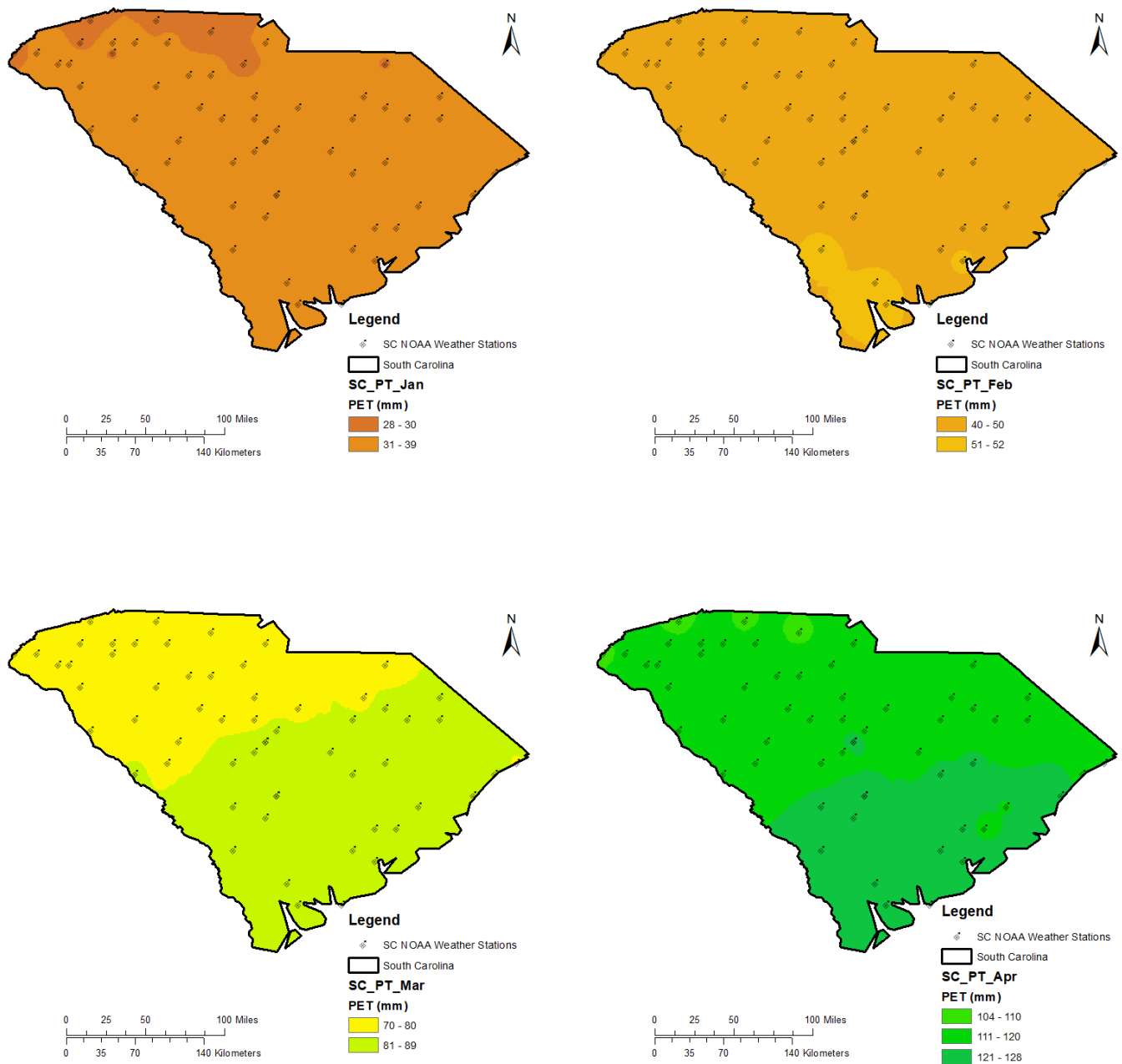


Figure 7a. Interpolated mean monthly P-T PET for January and February (top row) and March and April (bottom row). Data period of analysis is 1998-2015.

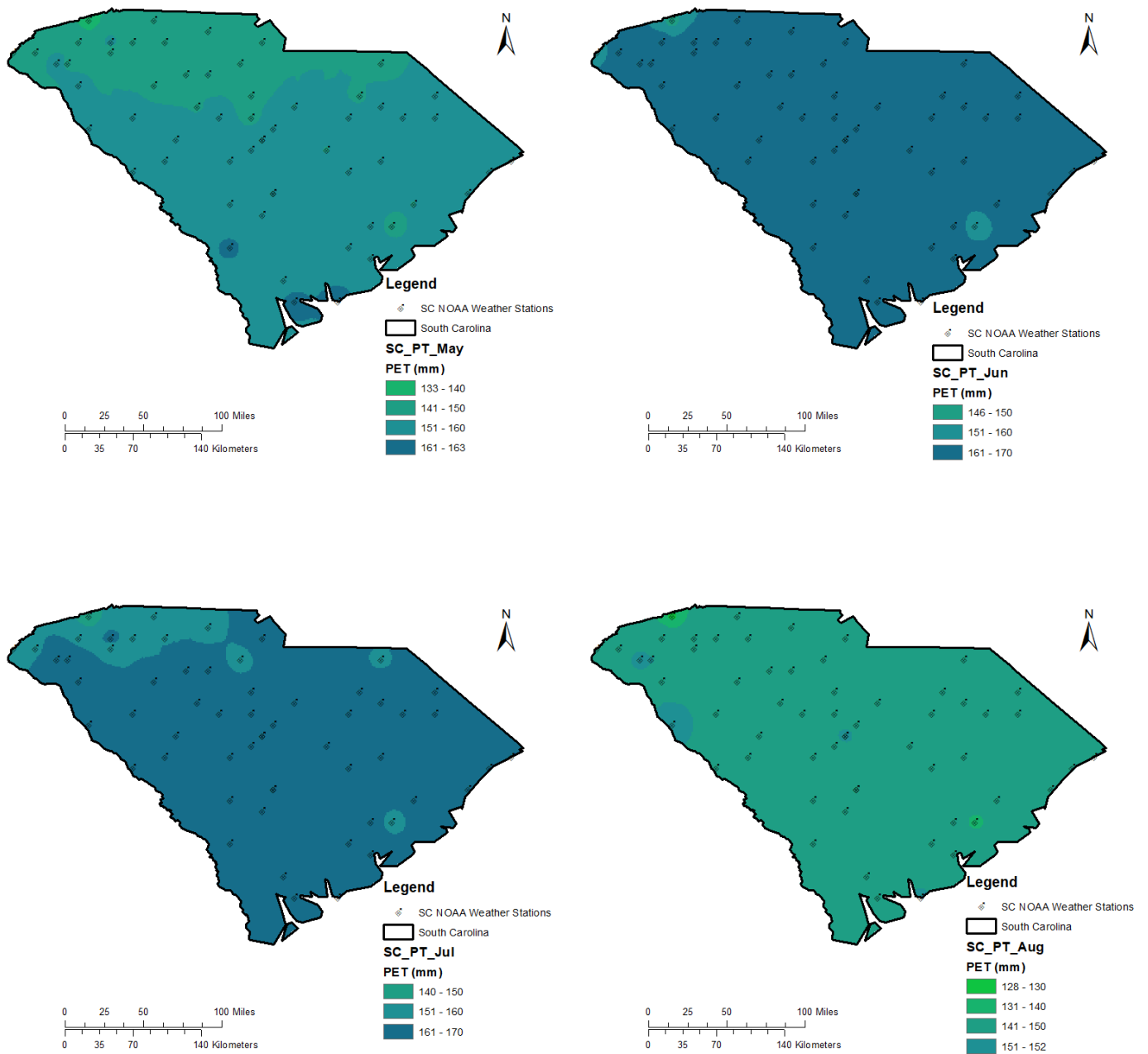


Figure 7b. Interpolated mean monthly P-T PET for May and June (top row) and July and August (bottom row). Data period of analysis is 1998-2015.

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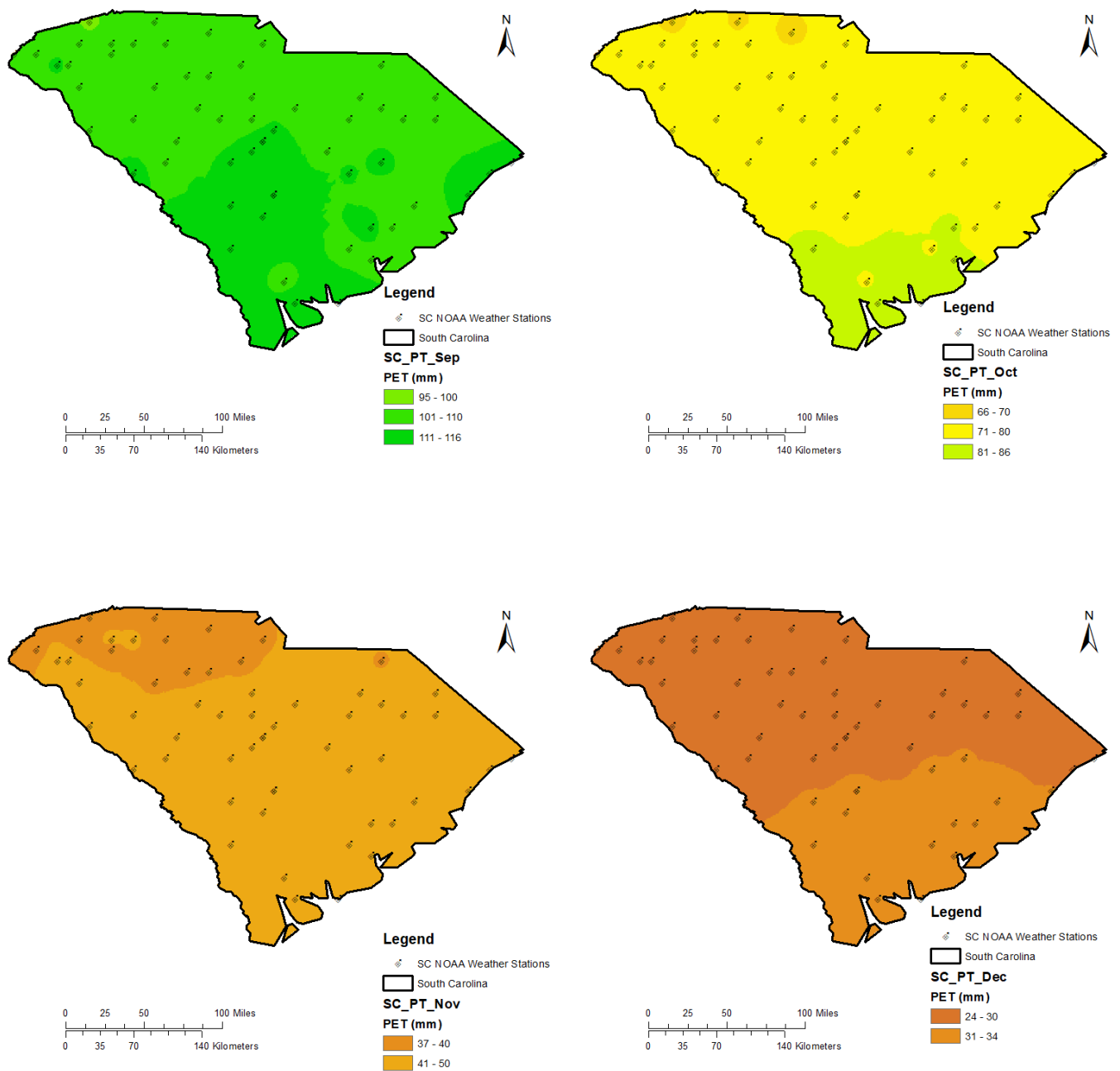


Figure 7c. Interpolated mean monthly P-T PET for September and October (top row) and November and December (bottom row). Data period of analysis is 1998-2015.

SUMMARY AND CONCLUSIONS

Based on the long term (1998–2015) data, both the mean annual calculated H-S and P-T PET for Mountain region were significantly ($P < 0.05$) lower than for the Coastal and Piedmont regions. There was no significant difference in H-S PET between Coastal and Piedmont regions. The observed spatial annual mean PET trend, Coastal > Piedmont > Mountain, by each of the 3 methods (H-S, P-T, and P-M) using shorter term (2002–2009) data, was similar to measured weather variables (air temperature, solar radiation, and relative humidity) trend, with the highest and the lowest PET observed during summer and winter months, respectively. The mean annual P-M PET was found to be larger than both the H-S and P-T PET in both the Coastal and Piedmont regions based on the limited site-year data. Thus regional differences in weather variables and their influences found on estimated PET by 3 widely used methods will give water managers and policy-makers valuable information for water resource management and planning in South Carolina. However, based on the NSE and PBIAS evaluation statistics it was concluded that the adjusted H-S method performed better than the P-T when compared with the standardized P-M PET (REF-ET) as well as PE in this study, although a slope closer to unity and slightly higher R^2 was found for the P-T than for the H-S PET when compared with the PE. Limited stations with short-term record of complete dataset prevented us from concluding about the standard P-M PET method in this study. At the same time, considering the forest as dominant land use in South Carolina and changing climatic pattern in the southeast, energy-balance-based P-T method may ultimately be a choice for regional water management decisions including for OWE from lakes as the PET is strongly influenced by radiation also besides the air temperature used in the H-S method. However, more rigorous ground-truthing of publically available modeled solar radiation data used in this method is warranted as more data becomes available for its operational application. Furthermore, future studies should also test the reliability of these PET methods either by using simple water balance from gauged catchments or using hydrologic models. It is also recommended that the pan factors be derived using widely recommended empirical formulas involving climatic variables measured at the PE stations for assessing open water evaporation.

Results from this study can be used to support several components of the ongoing water planning efforts in South Carolina. For example, improved estimates of OWE on reservoirs can be incorporated into surface water modeling applications such as the simplified water allocation model, the model currently being used to help assess surface-water availability in the 8 major river basins in the state. Similarly, estimates of PET as reference ET can be used to estimate crop

irrigation requirements for estimating future water demands and also possibly as inputs for the groundwater flow models being developed in the Coastal Plain to assess groundwater availability. These findings and the associated methods are easily transferrable to other states and regions that have similar needs and available data.

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