The utilization of a recursive algorithm to determine trends of soil moisture deficits in the Mid-Atlantic United States

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Abstract

Climate change models project declining soil moisture levels across the continental US, even in regions with expected increases in annual average precipitation. Although warmer air has been shown to result in more frequent and severe precipitation events, higher vapor pressure deficits are anticipated to result in evapotranspiration rates that exceed the amount of water hitting the soil surface. Numerous analyses have shown rising degrees of aridity in many US locations, even without declining rainfall. The Mid-Atlantic region has less annual rainfall variability and seasonality relative to other areas, and an analysis is presented here examining trends from 1980 to 2019 to determine if the region has become more arid as temperatures have warmed. A comparison of evapotranspiration and precipitation trends cannot adequately answer this question, as the timing of rainfall and soil moisture levels determines how much water is absorbed into the ground and utilized by vegetation. A recursive algorithm is developed to calculate water deficits based on the previous day's conditions and amount of precipitation received during that day, excluding rainwater falling on saturated soils from being eligible to recharge the water supply available to vegetation. Trends from the algorithm show that soil moisture levels have increased over the past four decades. This equates to lower overall water demand per hectare in the municipal and agricultural sectors. While the trends may change in coming decades, unlike other US regions, the Mid-Atlantic has become wetter as defined within an agricultural and meteorological context.

Keywords Soil moisture · Drought · Precipitation · Climate change

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1 Introduction

The Mid-Atlantic region of the USA is defined loosely as the area between New England and the Atlantic coastal areas of the Southeast, including locations that are considered part of the Northeast (New York City and Philadelphia) and the Southeast (Richmond and Hampton Roads). It experiences four distinct seasons, and areas east of the Appalachian Mountains have relatively uniform average annual precipitation totals without strong seasonality (Dupigny-Giroux et al. 2018). Since nearly all Mid-Atlantic locations receive more than 1000 mm of precipitation in an average year and variability is lower than in other US regions (Fritsch et al. 1986), a higher percentage of agricultural crops in the region is rainfed, rather than irrigated, compared to the US average (Abler and Shortle 2000). In addition to cropland, the region houses diverse forests, large urban areas, and the Chesapeake Bay watershed.

Before European settlement, the Mid-Atlantic was 95% forested with a broad range of tree species that included oaks, chestnuts, beech, hemlock, hickory, black cherry, birch, ash, and magnolia (Stolte 2000). Areas of higher elevation, not included in this study, housed fir and spruce species. As of 2012, 51.1% of four states from which the observation station data was obtained for this analysis (New Jersey, Maryland, Virginia, and Delaware) remained forested (United States Department of Agriculture, Economic Research Service 2012). Nearly all the forestland is privately owned and classified as productive timberland. Cropland comprises the next largest land usage in the four states, totaling 14.0% of total land area. The three largest crops grown by area are corn, soy, and wheat, encompassing 531,000 ha, 526,000 ha, and 246,000 ha, respectively (United States Department of Agriculture, Economic Research Service 2012). Other notable crops grown in the region include cotton, tobacco, apples, stone fruit, and blueberries. Urban areas cover 13.9% of lands in the mentioned states (with the inclusion of the District of Columbia), and pasture and grasslands comprise 8.9%. The high economic productivity and vegetative diversity of the Mid-Atlantic necessitates the study of recent climatic trends to gain insight into future soil moisture levels.

The impact of anthropogenic greenhouse gas emissions on the area's average precipitation and evapotranspiration rates will determine whether the Mid-Atlantic becomes "wetter" or "drier" over the coming decades relative to its historical long-term averages. Before proceeding, the terms in quotation marks must be defined. Three classifications of metrics measure degrees of climate-related moisture: meteorological, hydrological, and agricultural (Wehner et al. 2017). An area experiencing additional rainfall would have a meteorologically defined moisture surplus, yet if evapotranspiration demand grows at a faster rate, the area would simultaneously experience an agriculturally defined moisture deficit. Hydrological conditions measure water flow and runoff, often related to precipitation intensity. This paper operates within an agricultural framework when describing moisture levels, as it measures trends and impacts on a reference grassy surface. Despite the diversity of land cover, the surface of cool season clipped fescue grass was used in the evapotranspiration estimates at all locations to provide uniformity across the area of study. As albedo and wind resistance varies widely by vegetative surface (Jensen and Allen 2016), selecting a uniform covering provides a baseline from which specialized estimates can be obtained. Such estimates are highly sensitive to seasonality (the wind resistance from a cornstalk is negligible in early May but significant in September) and management (the amount of solar energy reaching the floor of a commercially thinned forest is much higher than a natural forest) (Komatsu et al. 2012).

The next section begins with a literature survey documenting recent historical trends in the intensity, seasonality, and average annual amount of precipitation falling within the region and

includes projections from global climate models. This is then related to trends and projections of evapotranspiration demand, providing context for how the severity and duration of agricultural droughts may change. Section 3 defines the question this analysis addressed: does the region require additional irrigation water to maintain vegetation in a well-watered state? Section 4 contains an overview of the imputed data and structure of a recursive algorithm that computed trends in the supplemental water demand required for well-watered conditions at 14 Mid-Atlantic observation stations. A discussion of the results is presented and precedes Section 7.

2 Background

The Mid-Atlantic is not as vulnerable to long-term wet and dry periods as locations in the Western US (Berkowitz and Blanco 2019), but experiences frequent flooding, a comparison that is projected to hold for the remainder of the twenty-first century (Wehner et al. 2017). Except for localized areas of the Southeast, the USA has seen significant warming over recent decades, and the greatest temperature rises have occurred during winter months (Vose et al. 2017). Warmer air increases evaporation, leading to high levels of precipitable water that cause extreme precipitation events (Easterling et al. 2017). Since evapotranspiration rates also rise with higher temperatures, soil moisture levels are projected to decrease without enhanced rainfall (Seager et al. 2015; Trenberth et al. 2014).

High confidence exists in model projections for areas of the USA where average annual precipitation is expected to continue its decline as temperature warms (Prein et al. 2016). According to many studies, as climate change leads to the poleward expansion of subtropical dry zones, the Southwest US will receive less average annual rainfall. Events will become infrequent, deepening drought periods between more intense episodes of rainfall (Wehner et al. 2017), although uncertainties relating to anthropogenic impacts on large-scale circulation patterns remain (Lucas and Nguyen 2015). Regions such as California are projected to experience severe dry spells alternating with pronounced rainy periods (Cheng et al. 2016). Therefore, even though average annual precipitation trends may be stable in other regions, drought will increase in frequency and magnitude. Studies have found increasing aridification in the Plains from higher evapotranspiration rates (Seager et al. 2018), although other sources note high degrees of uncertainty in long-term drought forecasting (Lehner et al. 2017).

The Mid-Atlantic lies between areas to the North that have seen robust increases in average annual precipitation and to the Southeast which have seen modest drying (Easterling et al. 2017). As locations in Virginia are generally the only area of the Mid-Atlantic that are not usually classified as being part of the Northeast, studies of the Northeastern US are generally more applicable to the area than those of the Southeast. It is important to note, however, that analyses do not assume uniform geographic boundaries; areas that are considered part of the Northeast in one study may be omitted in another. Additional rain and snow in the Northeast are primarily attributed to higher atmospheric moisture content causing precipitation to fall at enhanced rates (Prein et al. 2016), yet a portion of the increase can be attributed to large-scale weather patterns (Stocker et al. 2013; Trenberth 2011).

Numerous studies have been published examining trends in precipitation rates and average annual amounts in the Northeast US. Horton et al. (Horton et al. 2014) found that the area has experienced the most robust growth of extreme events in the USA, with annual average amounts increasing by approximately 10 mm decade⁻¹. Walsh et al. (Walsh et al. 2014) have

shown that the highest 1% of daily events are now contributing to a greater overall share of annual totals. Using averaged data from 222 Global Historical Climate Network (GHCN) stations in the region, Guilbert et al. (Guilbert et al. 2015) analyzed the intensity of daily events in the 95th percentile and demonstrated positive trends in each month. When investigating the number of monthly consecutive dry or wet days, the authors found that consecutive wet days have increased throughout the year (using a 0.5-mm threshold), with trends of largest magnitude occurring in the spring and fall. Meanwhile, the average number of consecutive dry days was relatively flat in the winter and summer periods, positive in early spring, and negative in the fall and when averaged throughout the year. This corroborates other studies that have shown fall to be the season with the largest overall increase in measured precipitation (Easterling et al. 2017) and found a decline in the number of consecutive dry days (Griffiths and Bradley 2007).

Measuring the intensity of two-day events using a calculated extreme precipitation index (EPI) for two-, five-, and 10-year occurrence periods, Janssen et al. (Janssen et al. 2014) found a sharp uptick for the Northeast since 1990, much greater in magnitude relative to other locations. The authors deployed models from the Coupled Model Intercomparison Project 5 (CMIP5) to project that these trends would continue during the forecast period through 2100 and that higher levels of greenhouse gas emissions would increase their magnitudes. They also found that climate models loaded with historical data underestimated the increases seen in recent decades. Earlier projections utilizing alternative model ensembles had reached the same conclusions (Meehl et al. 2005). Yet, some models had diverged from these findings, showing remaining uncertainty even though confidence in a wetter future with more frequent extreme events has been increasing (Hayhoe et al. 2008).

As is the case across most of the USA, intense precipitation events in the Northeast are most commonly associated with frontal passages. In addition, tropical and extratropical cyclones comprise 35% and 16% of total accumulated extreme precipitation in the region, respectively (Kunkel et al. 2012). Therefore, different locations are, and will be, impacted differently by specific types of systems. Inland areas of the Northeast experience the most frequent events during the summertime, while in coastal areas, this occurs during the fall (Agel et al. 2015). Moreover, coastal zones have fewer precipitation days overall with higher average annual amounts, resulting in greater intensities. Anthropogenic influence on atmospheric moisture levels and large-scale weather patterns will therefore affect inland and coastal areas in different ways. For example, stronger convective events will have a greater impact on inland locations during the summer while more intense hurricanes may strike communities near the shore during the fall. Even though climatic changes are projected to reduce the frequency of summertime extratropical cyclones, higher atmospheric water vapor content will bring additional rainfall from those that do hit the region, causing uncertain impacts relating to the net amount of moisture introduced into the ground in an average year (Chang et al. 2016).

Quantifying the anthropogenic impacts on atmospheric circulations patterns that influence Mid-Atlantic rainfall remains highly uncertain (Vallis et al. 2015), and correlations between warmer global temperatures and the strength and persistence of weather patterns are of low confidence (Perlwitz et al. 2017). Detailed discussions of these patterns are outside of this paper's scope; the reader is referred to chapter 5 of the *Fourth National Climate Assessment, Volume I*. Griffiths and Bradley (Griffiths and Bradley 2007) have shown that the lowest number of consecutive dry days occurs in the region during La Niña phases of the El Niño–Southern Oscillation (ENSO) pattern combined with a neutral Arctic Oscillation (AO). During a neutral ENSO, the AO phase has a lower impact on the number of wet days, and these

correlations are more robust during the colder seasons. Related to the AO, the Atlantic multidecadal oscillation (AMO) impacts sea surface temperatures that in turn influence the amount of precipitation. Wang et al. (Wang et al. 2010) found increasing summertime precipitation variability in the Southeastern US, an area that includes Virginia, linked to higher Atlantic sea surface temperature variability, but did not establish connections to human activity.

The previous discussion of precipitation trends provides background for understanding how the region's agricultural droughts have changed over recent decades. Warmer temperatures in temperate zones lead to longer growing seasons (DeGaetano 1996), causing higher transpiration rates for vegetation over longer periods of time that increase soil moisture uptake. The higher atmospheric concentration of carbon dioxide has mixed effects on plant life: it accelerates photosynthesis yet decreases the density and apertures of leaf stomata, reducing diffusion of water vapor from leaves (Ahmed et al. 2015). Even though warm air holds high levels of moisture, analyses have documented increasing vapor pressure deficits resulting in greater atmospheric evaporative demands across both the Northeast and Southeast, although they are small in magnitude (Brown and DeGaetano 2013). Areas within the USA having positive relative humidity trends, like locations in the upper Great Plains, are thought to be influenced by the widespread adaptation of crop irrigation systems that also reduce maximum growing season temperatures (Brown and DeGaetano 2013). In the Eastern half of the USA, the combination of lower relative humidity and longer growing seasons has led to increases in average annual evapotranspiration rates, causing more water to leave the soil (Kramer et al. 2015).

In most global models, projected higher evapotranspiration rates are expected to outweigh the additional precipitation falling in an average year, causing all regions of the continental US to experience soil moisture deficiencies relative to the present state. The Interstate Commission on the Potomac River Basin, an advisory board created by the US Congress, projects a 6–8% increase in evapotranspiration rates by 2040 in the watershed that supplies municipal water to the Washington Metropolitan Area (Ahmed et al. 2013). Although there is little evidence of human influence on precipitation deficits, much higher confidence exists for anthropogenically induced soil dryness (Wehner et al. 2017). Some uncertainty remains in these forecasts, however, as large-scale climate models may exaggerate agricultural and hydrological impacts since few have detailed representations of location-specific evapotranspiration potential (De Boer et al. 2011; Williams and Torn 2015).

3 Scope

Changes in the amount, seasonality, and intensity of precipitation affect how moisture is absorbed into the ground. Trends in evapotranspiration demand determine how quickly it leaves the soil. It is therefore necessary to relate both determining factors on the same temporal scale to estimate soil moisture change. Quality-controlled data applications exist that allow for comparisons of precipitation and evapotranspiration trends (<https://giovanni.gsfc.nasa.gov/giovanni/>); however, these do not necessarily yield relevant conclusions measuring changes in soil moisture. The uncertainty also extends to projections. For example, a region anticipated to experience a robust increase in average annual precipitation and smaller increases in evapotranspiration demand may not necessarily have higher average soil moisture levels if the additional precipitation were to fall heavily

during isolated periods and flow off the surface. Ficklin et al. (Ficklin et al. 2015) have explored these issues and used the Penman-Monteith method to measure changes in the Palmer drought severity index (PDSI) over the period from 1979 to 2013. The analysis covered the continental US but showed nearly flat trends in the Mid-Atlantic (with a small decrease in drought conditions), wedged between increasing aridity in the Southeast and wetter conditions in New England. The authors do not show the magnitude of trends, instead focusing on the correlations between climatic parameters and PDSI values.

This analysis shares similarities with the PDSI study, but deploys an alternative technique whose methodology is described in the next section. The technique, also used in an earlier analysis examining a different region (Smith and Chang 2020), constructed a recursive algorithm that estimated soil moisture levels for each day in the analysis period at 14 observations locations across the Mid-Atlantic (Table 1). It then established a dryness criterion that necessitated the introduction of supplemental moisture to preserve the reference surface in a well-watered state. While the added moisture serves as a proxy for municipal water consumption to preserve landscape, modifications would allow users to calculate irrigation water demand for diverse cropland if certain characteristics, such as root depth and plant height, are known. Daily evapotranspiration of forestlands can also be estimated by the algorithm. Both applications would require knowledge of seasonal vegetative lifecycles as annual crops' roots penetrate deeper into the soil as the growing season matures while deciduous forests lose canopy coverage but gain an insulative layer of decaying leaves. Differences between this methodology and the PDSI, relating to user accessibility, applications, and interpretation of agricultural drought findings, are found in Section 6. The next section provides a concise description of the data used as parameters in the algorithm as well as its structure.

4 Method

At each location, the recursive algorithm used daily evapotranspiration (ET_0) (mm day^{-1}) estimated from the FAO-56 Penman-Monteith equation (Zontarelli et al. 2010) on a well-watered, clipped, cool season fescue grass 0.12 m in height. As mentioned, the covering is the commonly used standard and approximates a residential lawn (Wright 1993). The equation required four input parameters: wind speed (ms^{-1}), solar radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$), air temperature ($^{\circ}\text{C}$), and dewpoint temperature ($^{\circ}\text{C}$). In order to minimize the use of averaged values, the decision was made to use station-specific observations rather than blended values obtained from sites such as NASA's Giovanni database. The time period of analysis was 1 January 1980 through 31 December 2019. Non-solar data originated from two quality-controlled observation networks harbored by the National Centers for Environmental Information (NCEI), part of the National Oceanic and Atmospheric Administration (NOAA) (<https://data.noaa.gov/dataset/dataset/global-surface-summary-of-the-day-gsod>, <https://www.ncdc.noaa.gov/ghcn-d-data-access>). Daily accumulated precipitation (mm day^{-1}) was also obtained from the two networks. Since NOAA does not track solar radiation, those values were obtained from the North American Regional Reanalysis (NARR), an extension of the NCEP Global Reanalysis (<http://climateengine.org>).

The FAO-56 Penman-Monteith equation assumes growing grass, and so an adjustment was made for days during which the average temperature remained below 4.5°C and plant life was dormant: a multiplier of 0.2 was applied to the calculated ET_0 value. This value was modeled

Table 1 Locations of the 10 observation stations

Station ID	Station name	State	Latitude	Longitude	Annual average precipitation (1980–2019) (mm)
1	Washington Dulles International Airport	VA	38.93° N	77.45° W	1064
2	Wallops Island NASA Test Facility	VA	37.94° N	75.47° W	1060
3	Philadelphia International Airport	PA	39.87° N	75.23° W	1092
4	Atlantic City International Airport	NJ	39.45° N	74.57° W	1106
5	Millville Municipal Airport	NJ	39.37° N	75.08° W	1080
6	Baltimore Washington International Airport	MD	39.17° N	76.68° W	1092
7	Lynchburg International Airport	VA	37.32° N	79.21° W	1055
8	Patuxent River Naval Air Station	MD	38.30° N	76.42° W	1141
9	Washington National Airport	VA	38.85° N	77.03° W	1022
10	Richmond International Airport	VA	37.51° N	77.32° W	1123
11	Marine Corps Air Facility Quantico	VA	38.50° N	77.31° W	980
12	Davison Army Airfield	VA	38.72° N	77.18° W	1140
13	Joint Base Andrews	MD	38.82° N	76.87° W	1101
14	Dover Air Force Base	DE	39.13° N	75.47° W	1167

from the findings of studies that estimated how much moisture evaporated from the soils of silage-covered croplands (Jensen and Allen 2016).

Reference evapotranspiration (ET_0) is defined as the amount of water transferred from the grassy surface over a 24-h period. The imputation of climate parameters into the Penman-Monteith equation yielded ET_0 , the maximum rate at which moisture leaves the soil under the specified conditions. ET_0 estimates presuppose an unlimited moisture supply that allows the grass to grow at an optimal rate, maximizing transpiration, since saturated soils readily release water. Once soils become unsaturated, the grass transfers moisture at the same rate until the readily available water content (RAW) (mm) is exhausted. At that point, the vegetative water supply becomes constricted and plants no longer transpire as during optimal conditions. Without precipitation or irrigation, evapotranspiration rates continue to decline until the soil reaches its wilting point—the point at which no water can be transferred. Plants wilt well before the ground wilting point is reached, as they are no longer able to maintain turgidity.

Calculating evapotranspiration rates under moisture-stressed conditions requires knowledge of the soil at each observation location. Weighted average moisture holding capacities of the soil plots were used over a 1000-ha area, with all data collected from the USDA National Resources Conservation Service (<https://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm>). Each plot has a specific field capacity value (the total amount of water the saturated plot holds (mm)) and a wilting point (the amount of water when

moisture transfer is halted (mm)). The difference between the two values is each site's total available water (TAW) (mm). TAW levels were calculated for the top 1 m of soil at each location, the depth to which the roots of the reference grass reach. Cool season fescue draws up to 40% of the TAW before levels drop low enough to initiate moisture stress (Wright 1993). At this point, the accumulated soil moisture depletion (ASMD) (mm) exceeds RAW and the multiplier $K_{s,t}$ adjusts ET_0 to account for drought-induced stress. $K_{s,t}$ has a value of one when ASMD is equal to RAW, approaching zero as ASMD nears TAW. Reference grass begins browning at $K_{s,t}$ values of 0.7 (Rodriguez-Iturbe et al. 2001) and is heavily damaged or dies at values below 0.2 (Ferguson 1987).

$$K_{s,t} = \frac{TAW_t - ASMD_{t-1}}{(1-0.4)(TAW_t)} \text{ for all } ASMD_{t-1} > RAW_{t-1} \quad (1)$$

where (t-1) is the previous day

Whenever precipitation fell on unsaturated ground, the model assumed a 100% soil absorption rate, regardless of intensity. In order to accurately estimate the amount of intraday unabsorbed water, an hourly analysis would be required to calculate the periods when rain fell at high rates; this resolution is not currently supported by the daily algorithm and few observation locations have reliable, complete hourly data on a multidecadal scale. The algorithm assumed that precipitation replenished soil moisture deficits until field capacity was reached. At that time, excess moisture hitting the surface was lost to runoff or percolation into the water table or surrounding tributaries. The algorithm does allow for a previous day's precipitation that fell on saturated soil to meet all of that day's and the current day's evapotranspiration demand, allowing a balance to be carried forward for 1 day. This assumption does not allow rain that fell two or more days prior in an otherwise dry period to satiate demand, but it does track carryover moisture potential that occurs during periods of consecutive rainfall when the soils are at or near field capacity.

Monthly, seasonally adjusted summary data trends were calculated at each location for the parameter inputs into the FAO-56 Penman-Monteith equation as well as its output, ET_0 , over the 40-year period. Seasonal adjustment, like all trend analysis, was conducted in R Studio (<https://www.rstudio.com>), using the open source R Project for Statistical Computing. The adjustment was performed on all data and eliminated expected monthly changes in value (variability), minimizing white noise. All trends that will be presented in Section 5 use the modified parameters.

To better capture trends in time series data, autoregressive (AR) modeling was deployed. The AR process began with a simple linear regression of the parameter value against time and examined the autocorrelation function of residuals to test for statistical significance. In this analysis, statistical significance was defined as a less than 10% probability that apparent trends or correlations were actually caused by randomness. If one or more residuals displayed a correlation that exceeded the significance threshold, an alpha coefficient was added to the regression model, linking the expected value of the parameter, z_t , with the value in the previous period, z_{t-1} . AR models are defined by order p , signifying the number of significant lags. A model given as $z_t = \alpha_1 z_{t-1} + \alpha_2 z_{t-2} + w_t$ (shown without a trend component) has an order of $p = 2$. The residual autocorrelation function of each subsequent regression iteration was evaluated, and the order was increased until there was no longer a statistically significant correlation among the residuals. According to Akaike information criteria, most data was best modeled by an AR process of order two or less, although the order was as high as five for some series.

In a meteorological drought, precipitation deficits are carried across several months and therefore the estimated value of a month's rainfall can be informed by the previous month's total. This influence is separated from the time-determined trend in AR models, resulting in more precise estimates of magnitude and significance. If, for example, dry and wet periods have increased in duration and intensity for specific locations, associated time series precipitation data will be heteroskedastic, with a time-dependent variance. While heteroskedasticity preserves unbiased estimators, they are no longer efficient. In these instances, as determined by the Breusch-Pagan test, a robust standard error procedure was completed that provided correct significance levels of the regression coefficients.

The recursive algorithm calculated the moisture stress coefficient $K_{s,t}$ from the previous day's soil moisture levels and the current day's precipitation. When $K_{s,t}$ was equal to one, the well-watered grass on the soil surface transpired at its maximum rate, and moisture left the ground at a rate of ET_0 . $K_{s,t}$ reached zero at the soil wilting point. A Riemann sum measured the vertical distance between one and the value of $K_{s,t}$ for each day of the month, where t was equal to the number of days in the month, to approximate the severity of agricultural drought. The value of the Riemann sum, seasonally adjusted for months of differing lengths, could hypothetically have ranged between zero, when an unlimited moisture supply was available, and 30.4, if the soil had remained at its wilting point throughout the month.

Finally, the recursive algorithm was run to approximate the watering demand of preserving the reference grass in an esthetically acceptable state. This application of the model estimated the usage needed to prevent browning and set the threshold for the introduction of supplemental moisture at $K_{s,t} = 0.7$. When the soil moisture reached that level, 25.4 mm of water (1.0 in.) was added to raise the soil TAW and support $K_{s,t}$ values higher than 0.7. The algorithm then continued, finding the next day for which supplemental water was required. To separate irrigation water from naturally occurring precipitation, waterings were only permitted on dry days; the algorithm would find the next eligible day in instances when $K_{s,t}$ reached 0.7 on a day with recorded precipitation. This occurred on days with high evapotranspiration rates and little rainfall. The algorithm also introduced moisture on all dry days with $K_{s,t}$ levels at or below 0.7 regardless of the following day's precipitation. The qualitative criteria and constant amount of supplemental moisture was designed to mimic residential watering patterns as the reference grass appearance began to degrade. Although the criteria applied to fescue, coefficient adjustments can be made for different crops. Watering demand comparisons can also be made among variations of the same crop that have been modified for drought tolerance. There are great differences in moisture stress tolerance even among turf grasses (Carrow 1995).

5 Results

Higher air temperatures increase the rate of ET_0 unless dewpoint temperatures also rise enough to preserve relative humidity. Figure 1 shows that the region has warmed over the period from 1980 to 2019, with each station showing positive temperature trends—an expected result. Although the rates of warming and their significance levels are not uniform, the data comports with studies that have shown higher annual temperatures attributed to anthropogenic emissions. With one exception, dewpoint temperatures also have risen at each location, often at a more robust rate than air temperatures. While the changes in value over time in these two parameters are most consequential for estimating trends in ET_0 , there was also a statistically significant increase in the amount of solar radiation received at all sites. Fewer cloudy days in

an average year increase reference evapotranspiration. Even though the impact is comparatively low, more locations would have exhibited statistically significant declines in ET_0 without additional solar radiation, as Fig. 1 implies positive trends in relative humidity levels at many stations. Trends in ET_0 at each location are shown in Fig. 2, presenting the mix of direction and significance. The comparison of trends between the two figures for Stations 11–14 is a manifestation of the consequences of higher solar radiation, enhanced by positive trends in windiness, when evapotranspiration rates can rise even in more humid air.

With two exceptions, the sites show robust increases in average annual precipitation that are greater in magnitude than the positive rate of change in evapotranspiration (Fig. 3). Regressions were also run for each meteorological season, and it was found that summer and fall (1 June–31 August, 1 September–30 November) had the largest and most statistically significant trends, although locations generally showed positive changes in all seasons. The results thus far suggest that water scarcity in the Mid-Atlantic has not been exacerbated over the period of analysis, yet they cannot determine the temporal demand for supplemental water to preserve a surface covering in a well-watered state. While the trends in Figs. 1, 2, and 3 may be readily reproduced using existing databases, the recursive algorithm deployed in this analysis brings a greater understanding of how the demand for irrigation water as an agricultural drought mitigation tool has changed in the region. Rather than drawing inferences from predefined sets, the algorithm makes real-time decisions whose trends are subsequently analyzed.

Average annual precipitation from 1981 to 2019 is shown in Fig. 4, with the orange portion of each bar representing the amount of water that is not captured by the soil as estimated by the recursive algorithm (1980 is used to calibrate soil moisture levels and is not included in the subsequent trends analysis). While some of this moisture leaves the watershed, water that is captured or percolates through the soil to recharge underground aquifers and bodies of water can be utilized during dry periods. For example, the Washington Metropolitan Area obtains approximately three-quarters of its municipal water supply from the Potomac River, largely fed by runoff, interflow, and aquifers (Ahmed et al. 2015). Estimating how much water falls on saturated soils can enhance storage capability and inform infrastructure planning.

Figure 5 displays drought trends across the Mid-Atlantic, as captured by the algorithm and measures the annual change in the value of the monthly Reimann sum (as described earlier).

Fig. 1 Average daily air temperature and dewpoint temperature trends (°C year⁻¹)

Fig. 2 Average total monthly ET_0 trends (mm year⁻¹)

Thirteen out of 14 observation sites have negative trends in accumulated drought severity. This is a key finding that differentiates the region from areas that have become more susceptible to periods of drought. The figure is a measure of adjusted aggregate monthly water stress rather than severe drought occurrence. Since the units in this figure do not represent conventional measures of value, a brief interpretation is provided: as noted, values for each seasonally adjusted month can range between 0 and 30.4. The averaged 1981–2019 value of all stations is 5.26, equating to an average monthly $K_{s,t}$ value of 0.83. If a location has an annual trend of -0.02 as the change in value of the Reimann sum (roughly the sample average), its modeled 2019 $K_{s,t}$ value would be 0.03 higher than the expected 1981 average, signifying less moisture scarcity.

Annual trends in the total number of monthly waterings required to preserve well-watered grass are shown in Fig. 6. Overall, the region has experienced declines in water demand per

Fig. 3 Average total monthly ET_0 and precipitation trends (mm year⁻¹)

Fig. 4 Average annual precipitation (mm)

hectare, assuming that other factors have remained constant. The positive watering trends in Fig. 6 that occur at locations which have small negative trends in Fig. 5 are due to the algorithm's representation of supplemental water demand and variation around the $K_{s,t}$ values triggering an event due to daily rainfall. This methodology was chosen to represent sprinkling in set amounts at certain times rather than prioritizing precision; it is unlikely that a small amount of surface water would be introduced on a daily basis to exactly preserve the constant $K_{s,t}$ in any watering regimen.

Fig. 5 Change in monthly water scarcity as measured by the Reimann sum (year⁻¹)

Fig. 6 Average required monthly watering trends (year⁻¹)

Finally, Figs. 7 and 8 use the time series regression trends to compare expected supplemental water demand in the first and final years of the analysis period, 1981 and 2019, using standard units (mm). The greening of most sites in Fig. 8 signifies usage reductions, and a comparison is provided in Fig. 9. Locations that have experienced changes large in magnitude all had decreasing demand. Sites with higher water demand had small increases; they were not statistically significant. The comparison of these 2 years is not representative of the actual demand based on recorded precipitation, but rather the expected amount using modeled trends from the recursive algorithm. Averaged across all sites, there was a 23.5-mm decline in modeled average water demand in 2019 relative to 1981, representing a 9.3% decrease. Thus, the region can expect lower supplemental water usage during normal conditions, yet may still experience severe long-term droughts that heavily damage vegetation unless heavily mitigated.

6 Discussion

Positive trends in the frequency and magnitude of extreme rainfall events in the Mid-Atlantic region have been well documented in the literature as has the increasing average amount of annual precipitation. Studies also described the impact of higher temperatures from anthropogenic greenhouse gas emissions, increasing evapotranspiration rates across much of the USA and resulting in greater average annual soil moisture deficiencies even in areas that have not seen a decrease in annual rainfall. Using site-specific data from the US Government's National Centers for Environmental Information, the analysis shows that even though locations in the Mid-Atlantic are warming, dewpoint temperatures have increased at similar or more robust rates, resulting in higher relative humidity values and stable reference evapotranspiration rates that have been affected by statistically significant increases in the amount of solar radiation

Fig. 7 Modeled 1981 expected irrigation water usage for well-watered vegetation preservation (mm)

reaching the surface. The consistent rates at which moisture leaves the ground have coincided with higher annual precipitation totals, leading to a reduction of dry conditions.

To verify the hypothesis that, on average, agricultural droughts are having a diminished impact, there must be an understanding of the temporal relationship between accumulated rainfall and soil moisture deficits. The deployment of the algorithm was initiated, computing each day's soil moisture levels and making watering decisions from the determined criteria. The number of required waterings in each month was then compiled, seasonally adjusted, and run in an autoregressive least squares model to estimate the change of aridity in the Mid-Atlantic region. This approach offers novelty to an examination of historical PDSI values in important ways. PDSI is usually calculated on a monthly basis, but even weekly iterations can underestimate flash drought. With high temperatures and intense solar radiation, both of which have shown regional increases, the Mid-Atlantic can go from normal to drought conditions within a 5-day period (Ford and Labosier 2017). The FAO-56 Penman-Monteith equation deployed in this analysis has shown reliability with capturing the rapid development of drought (Peel and McMahon 2014) and the daily timescale offers sensitivity absent in weekly or monthly summaries. Soils at the 14 observation locations have lost more than 9 mm of moisture per day into the atmosphere through evapotranspiration during extreme events, which has been captured by this algorithm. Traditionally, PDSI evapotranspiration has been calculated using the Thornthwaite method, requiring fewer data parameters but presenting less realistic estimates. While studies have shown that the Thornthwaite and Penman-Monteith methods yield similar PDSI values (Schrier and Jones 2011), the irrigation decisions in this analysis are highly sensitive to the previous day's calculated

Fig. 8 Modeled 2019 expected irrigation water usage for well-watered vegetation preservation (mm)

evapotranspiration. Moreover, the PDSI is a standardized index that usually ranges from ± 4 and does not account for differences in vegetative characteristics such as root depth (Keyantash and Dracup 2002). Although PDSI offers accurate drought comparison metrics on a larger scale, this methodology can more easily be applied to diverse croplands if seasonal plant characteristics are known and the input climate parameters are captured.

As has been noted in many studies, capturing input data for the Penman-Monteith equation can be challenging. A limitation of this methodology was the small number of observation sites from which data was analyzed. The criterion for location inclusion was a near-complete record of the input parameters for the FAO-56 Penman-Monteith equation from 1980 to 2019. Each candidate site was therefore required to have Global Historical Climatology Network (GHCN) and Global Surface Summary of the Day (GSOD) coverage. GSOD data was used exclusively at two stations that did not have corresponding GHCN series, yet still had near-complete records of the required input parameters. Although a greater number of sites could have been included in the analysis, doing so would have enlarged the geographic area under review or utilized blended data since the 14-station sample exhausted all eligible sites within the core area of interest. The intent was to provide information about changes in aridity in the heart of the Mid-Atlantic region, not well captured in prior regional analyses of the Northeast and Southeast US.

Since reliable solar data was not available before 1980, a relatively brief historical record of 40 years was used. If the period began or ended with anomalous conditions, trends would be influenced by this natural variability rather than actual baseline changes. Some analyses randomize the beginning and final years of their study periods to avoid potential problems,

Fig. 9 Modeled change in irrigation water usage, 1981 vs. 2019

but such adjustments were not necessary in this case. Annual values for temperature, relative humidity, and precipitation were examined and interference with trends was not detected. While more wet years occurred after 2000, this is expected with positive precipitation trends. Only one of the 14 stations had its driest year from 1980 to 1985, so the start of the analysis period did not experience severe drought (or excess precipitation). The wettest year on record for 8 stations was 2018, but the difference at those respective stations between 2018 and the second wettest years was not large enough to result in false trends, especially since 2017 and 2019 experienced near-to-below average precipitation and 2016 was a dry year.

The limited number of sites with continuous multidecadal records does not affect this analysis' wide-ranging reproducibility for more recent data. There are 41 stations located within the geographic boundaries defined in this analysis that exceed 95% coverage for all Penman-Monteith climate parameters from 1 January 2011 to the present. If a stakeholder was to replicate this methodology on future data, he or she would have access to 95 sites in the same region that were actively reporting at the time of publication. As shown in Fig. 9, locations within relatively short distances have exhibited varying trends, and the availability of comprehensive present-day records enables the estimation of conditions at locations without referring to distant proxies. This is also important since first-order climate observation sites are rarely located in farmland, pastures, or forests. The ability of potential stakeholders to utilize several sites within a small distance from their areas of interest enhances the relevance of this methodology. Data on the physical properties of soil, necessary for K_s , t calculations, are available for any CONUS location and are not a restricting factor.

7 Conclusions

The recursive model found declining water scarcity in the Mid-Atlantic region. Future studies may closely examine vulnerability to flooding—a topic of concern given the increasing prevalence and magnitude of extreme precipitation events. While research has found that the majority of these events occur during summer and fall, the seasons during which soil moisture levels reach their minimums and absorption rates are at their maximums ((Wehner et al. 2013)); accurate measures of precipitation intensity are needed to address this vulnerability. Excess moisture is already a leading cause of crop loss in the region (Wolfe et al. 2018) and wet periods may delay scheduled plantings and reduce the number of days during which fields are workable (Tomasek et al. 2017). This algorithm used daily soil moisture levels to make determinations about water that could not be absorbed, and flooding estimates require site-specific topography to calculate the amount of water that cannot penetrate a reference plot. Such considerations are beyond the scope of this analysis, so the summary data likely overestimated the proportion of precipitation eligible to replenish moisture deficits. In order to minimize potential error attributed to runoff and ponding, all but one observation location was located within the coastal plain. This area houses most agricultural production in the study region (United States Department of Agriculture, National Agricultural Statistics Service 2019) and does not feature steep grades off of which heavy precipitation would flow. Aggregated trends of daily estimated runoff at the 14 stations showed a mix of statistically insignificant positive and negative results. In addition to more precisely capturing the proportion of intense precipitation that is not absorbed into the soil, future work also involves homogenizing and aggregating incomplete climatological data records to increase the number of eligible sites for historical trend analysis.

Use of the recursive algorithm has concluded with findings that the region, on average, has required less supplemental water to preserve reference cool season grass in a well-watered state as its climate has warmed and the growing season has lengthened. Expected moisture scarcity has decreased, due to precipitation falling in greater amounts and during periods when soil moisture levels can be replenished. Declining trends in agricultural drought for the Mid-Atlantic informs future water policies and planning, as per capita municipal and agricultural demand is expected to be lower when controlling for other parameters. Although trends may change in the coming decades, the region has become “wetter” from an agricultural perspective, with plant life experiencing less drought-induced stress over the past 40 years.

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