ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Climatic controls on the hydrologic effects of urban low impact development practices

ENVIRONMENTAL RESEARCH
LETTERS

OPEN ACCESS

RECEIVED
4 December 2020

REVISED
31 March 2021

ACCEPTED FOR PUBLICATION
27 April 2021

PUBLISHED
21 May 2021

LETTER

Climatic controls on the hydrologic effects of urban low impact development practices

Carolyn B Voter* and **Steven P Loheide II**

University of Wisconsin-Madison, Department of Civil and Environmental Engineering, Madison, WI 53706, United States of America
* Author to whom any correspondence should be addressed.

E-mail: cvoter@wisc.edu

Keywords: urban hydrology, aridity index, climate, stormwater, low impact development, green infrastructure, ecosystem services

Supplementary material for this article is available online

Abstract

To increase the adoption and reliability of low impact development (LID) practices for stormwater runoff management and other co-benefits, we must improve our understanding of how climate (i.e. patterns in incoming water and energy) affects LID hydrologic behavior and effectiveness. While others have explored the effects of precipitation patterns on LID performance, the role of energy availability and well-known ecological frameworks based on the aridity index (ratio of potential evapotranspiration (ET) to precipitation, PET:P) such as Budyko theory are almost entirely absent from the LID scientific literature. Furthermore, it has not been tested whether these natural system frameworks can predict the fate of water retained in the urban environment when human interventions decrease runoff. To systematically explore how climate affects LID hydrologic behavior, we forced a process-based hydrologic model of a baseline single-family parcel and a parcel with infiltration-based LID practices with meteorological records from 51 U.S. cities. Contrary to engineering design practice which assumes precipitation intensity is the primary driver of LID effectiveness (e.g. through use of design storms), statistical analysis of our model results shows that the effects of LID practices on long-term surface runoff, deep drainage, and ET are controlled by the relative balance and timing of water and energy availability (PET:P, 30 d correlation of PET and P) and measures of precipitation intermittency. These results offer a new way of predicting LID performance across climates and evaluating the effectiveness of infiltration-based, rather than retention-based, strategies to achieve regional hydrologic goals under current and future climate conditions.

1. Introduction

As recently as 1950, only 30% of the world population resided in urban areas but this has grown to over 55% today and is projected to rise to 68% by 2050 (The United Nations 2018). This increased population density intensifies the demand for water and other resources and transforms natural, vegetated areas into urban landscapes dominated by man made surfaces such as buildings, parking lots, and roads, with serious consequences for water and energy balances. Rainfall that can no longer infiltrate into the ground due to paved surfaces is instead routed through storm water drainage networks to downstream waterbodies, leading to 'flashy' flows and degraded waterways (Walsh *et al* 2005). When the capacity of these drainage systems is overwhelmed, as is common in both aging and rapidly expanding cities, flooding occurs in city streets before it can even reach streams (Rosenzweig *et al* 2018). Vegetation loss during landcover change leads to reduced evapotranspirative cooling which, in tandem with the lower-albedo of built surfaces, causes 'urban heat islands' where persistently higher temperature increases the dangers of heat waves and extreme heat (Harlan *et al* 2006, Rizwan *et al* 2008, Schatz and Kucharik 2015). Where groundwater is the main water supply, intensified demand can outpace groundwater recharge, lead to groundwater declines, and trigger a cascade of additional issues including land subsidence (Zektser

et al 2005, Zhang *et al* 2014). Climate change is further exacerbating these unintended ecohydrologic consequences of urbanization. Intense rainfalls which overwhelm drainage systems and cause flooding are beginning to occur more frequently (Moore *et al* 2016, Rosenzweig *et al* 2018), dangerous heat waves are projected to arrive more often (Seneviratne *et al* 2014), and demand for water is increasing (Vörösmarty *et al* 2010). As urban areas continue to grow under a changing climate, so too will the need to find sustainable solutions for reducing surface runoff, increasing evapotranspiration (ET) and cooling, enhancing groundwater recharge, and managing other ecohydrologic fluxes holistically.

One way cities are beginning to address these challenges is by moving away from a centralized approach to urban water management with a narrow focus on stormwater conveyance toward a philosophy that embraces distributed, multi-functional low impact development (LID) practices (also called green infrastructure, see Fletcher *et al* (2015) for other terms). With encouragement from world regulatory, policy, and research agencies including the U.S. Environmental Protection Agency (Hopkins *et al* 2018), the European Commission (Lafortezza *et al* 2018), the Australian and New Zealand Environment and Conservation Council (Roy *et al* 2008), and China's Sponge City Initiative (Li *et al* 2017), LID practices (e.g. rain gardens, green roofs) and non-structural LID strategies (e.g. impervious disconnection) were initially adopted as a means of managing runoff volumes from small, frequent storms to minimize nonpoint sources of pollution and combined sewer overflows (McPhillips and Matsler 2018). Recently, additional ecosystem services (Millennium Ecosystem Assessment 2005) such as increasing groundwater recharge (Bhaskar *et al* 2018), cooling the urban heat island via increased ET (Koc *et al* 2018), improving human health and wellness (Tzoulas *et al* 2007), increasing property values (Mazzotta *et al* 2014), and boosting willingness-to-spend in business districts (Wolf 2005) have grown in importance as motivators for LID adoption (McPhearson *et al* 2016, McPhillips and Matsler 2018). Unfortunately, because of the novelty of this type of managed urban ecosystem (Groffman *et al* 2017), we lack a scientific understanding of the relationships among individual LID co-benefits and the geographic variability of these LID ecosystem services. So far, LID co-benefits have typically been evaluated in isolation (Prudencio and null 2018) or in one city, rather than as a suite of ecosystem services across a geographical gradient of conditions (McPhearson *et al* 2016). This absence of general principles describing the ecohydrologic benefits of LID makes it difficult to advise cities on what co-benefits they can expect from LID, particularly if they are not among the handful of cities that have been well-studied due to their status as leaders in LID adoption (Garrison and Hobbs 2011, Li *et al* 2017, Cook *et al* 2019).

While many factors drive LID performance, climate (i.e. patterns of incoming water and energy) exerts a particularly strong control on the range of possible ecohydrologic outcomes. One way of describing climate is to calculate the ratio of potential ET (i.e. available energy) to precipitation (i.e. available water) (PET:P, or 'aridity index'). The empirical Budyko curve (Budyko 1974), a relationship between the aridity index and the ratio of actual ET to precipitation, shows remarkable consistency across natural landscapes and climates. Vegetation type (Zhang *et al* 2001, Donohue *et al* 2007), soil type (Milly 1994, Wolock and McCabe 1999, Troch *et al* 2013), and other location-specific factors (Roderick and Farquhar 2011) can explain deviations from this empirical Budyko curve, but the aridity index is understood to be the primary driver of actual ET and runoff in catchments all around the world (Padron *et al* 2017). While natural gradients in soil type and vegetation type are muted in urban areas due to construction activities which import fill and topsoil (Schifman *et al* 2018) as well as widespread landscaping preference for turfgrass (Milesi *et al* 2005, Larson *et al* 2009), continental-scale gradients in precipitation and incoming solar energy—and, by extension, the aridity index—are difficult to manipulate locally and largely unaltered by urban development.

Despite the importance of the aridity index in theory of water budget dynamics in natural ecosystems, it is conspicuously absent from the scientific literature on LID practices. When the role of climate on LID performance has been considered, the focus has been almost exclusively on rainfall (i.e. water availability), within-storm characteristics (e.g. intensity) and how these control event-scale runoff, without consideration of energy availability or between-storm characteristics such as interstorm duration which may control how the long-term water balance responds (Holman-Dodds *et al* 2003, Hood *et al* 2007, Gautam *et al* 2010, Gallo *et al* 2012, Qin *et al* 2013, Bhaskar *et al* 2018). For example, out of seven factors considered in a recent review of the effects of climate on LID practices, only one was related to energy (temperature) and one to interstorm dynamics (antecedent soil moisture) (Sohn *et al* 2019). The emphasis on event scale hydrologic performance of LID in the scientific literature parallels the engineering practice of stormwater infrastructure design which utilizes a design storm approach to size facilities to accommodate events of a given magnitude (Watt and Marsalek 2013). While event-scale performance is critical for mitigating flood risk, an understanding of the long-term partitioning of hydrologic fluxes is also needed to assess impacts on other ecosystem services that are controlled by deep drainage (DD) and evapotranspirative fluxes. Studies which have more

broadly assessed the relative roles of climate and land use change on water and energy balances typically focus on statistical analyses of large catchments (Jiang *et al* 2015, Zipper *et al* 2018, Wang *et al* 2019) and cannot untangle the relative importance of climate and individual LID practices on ecohydrologic fluxes. Describing the performance of LID practices across a gradient of aridity indices is a critical step toward developing the generalizable principles that are needed to advise cities on expected ecosystem services of LID practices beyond event-scale runoff reduction.

We used a two-step approach to systematically explore how climate alters LID effectiveness at manipulating the long-term urban water balance. First, we used a process-based hydrologic model, ParFlow.CLM, to simulate the effects of infiltration-based LID strategies on a single-family parcel. We examined how climatic conditions (represented by 1 year of hourly meteorological forcing from the 50 largest U.S. cities plus Madison, WI) affected the difference in total annual surface runoff, DD, and ET between a baseline single-family parcel and a low impact single-family parcel with disconnected impervious surfaces (downspouts, walkways, sidewalk), microtopography, and amended soil (compacted soils augmented by soils with a higher infiltration capacity). Second, we developed a partial least squares regression (PLSR) statistical model to (a) identify which climate metrics best described variations in LID performance, and (b) extend predictions of LID performance to a multi-decadal period with variable weather conditions. We explored:

(a) How does climate alter the reduction in runoff resulting from infiltration-based LID practices?
(b) When runoff is reduced due to infiltration-based LID practices, how does climate alter the partitioning of increased infiltration between ET and DD?

2. Methods

2.1. Single-family development scenarios

We modeled a single-family residential parcel under two development conditions: a baseline and a low impact scenario. Here, we evaluate the combined effect of multiple infiltration-based practices, but for detailed exploration of the relative effectiveness of these practices see Voter and Loheide (2018). Key features in both versions of the single-family parcel include a house (133.5 m^2) with an attached garage (3 × 6 m), driveway (3 × 9.5 m), front walk (0.5 m wide) and sidewalk (1.0 m wide). In the baseline scenario (identical to the 'highly-compacted baseline' layout in Voter and Loheide 2018), all impervious surfaces are connected to the drainage network via slopes that drain runoff directly off the domain. In the yard, the soil is a compacted silt loam with porosity reduced by 10% and saturated hydraulic conductivity reduced by a factor of ten compared to mean natural parameters. The lawn slopes away from the house at 2% in all directions. In the low impact scenario (identical to the 'lowest-impact' layout with all five low impact interventions considered by Voter and Loheide 2018), we disconnect all impervious surfaces through adjustments to site topography: roof pixels drain to the yard via downspout outlets, a 2 m grass curb strip separates the sidewalk from the street, and a transverse slope (2%) allows lateral flow from the driveway and sidewalk to the yard. In the yard, we decompact the soil by using natural silt loam soil hydraulic parameters and add microtopography by superimposing randomly generated deviations in elevation to the baseline elevation at every pixel. For additional details about the single-family parcel design, see Voter and Loheide (2018). While we recognize that many features of this parcel, including soil type, vegetation type, and parcel type may vary among cities, we keep these parameters constant in order to isolate the effect of climate in our modeling scenarios.

2.2. Climate scenarios

To systematically explore a range of climate conditions, we forced a physically based model representing both versions of the single-family parcel with hourly weather data from the 50 largest U.S. cities (US Census Bureau 2010) plus Madison, WI. For each city, we used the city coordinates (see SI data, table S1) to retrieve hourly meteorological inputs for the 2014 water year from the North American Land Data Assimilation System (NLDAS-2) (NASA 2015). We could have sampled a range of climatic conditions by simulating ten cities for 5 years or five cities for 10 years, but we chose to model 51 cities for one year in order to maximize variability and minimize computation time on a high-throughput computing system. We know that some cities had anomalously wet or dry years in WY2014, so we also examined climatic conditions at each city from WY1981 to WY2010 by developing a statistical model to predict expected long-term behavior of LID practices.

2.3. Physically-based model simulations

We performed all physically-based model simulations using ParFlow.CLM, a hydrologic model that couples the three-dimensional, time-dependent, variably saturated subsurface flow equation to the kinematic wave overland flow equation via a continuity of pressure boundary condition (Ashby and Falgout 1996, Jones and Woodward 2001, Kollet and Maxwell 2006). The coupled surface-subsurface flow model is linked to the Community Land Model for vegetation processes and a land surface energy balance (Dai *et al* 2003, Maxwell and Miller 2005, Kollet and Maxwell 2008). The model domain has a horizontal resolution

of 0.5 m and a variable vertical discretization with the top 15 elements at 0.1 m, followed by two elements at 0.25 m, 12 elements at 0.5 m, six elements at 0.25 m, and the bottom five elements at 0.1 m. Boundary conditions are the same as used in Voter and Loheide (2018) and include a constant pressure head of zero at the bottom of the domain (10 m below the surface), no flow boundaries on all four sides, and a continuity of pressure head boundary linked to kinematic wave overland flow at the surface. We developed initial conditions for each weather and development scenario by forcing a 1D model of turfgrass with (a) compacted and (b) decompacted soil (for each development scenario) with 300 years of hourly meteorological inputs (ten loops of WY1981-WY2010) for each city. Initial conditions throughout the parcel were set to the vertical pressure head profile on October 1 of the last simulated year. Models returned hourly, spatially distributed outputs of water fluxes and soil moisture which we summarized spatially and temporally to obtain the overall (annual) water balance for each simulation.

2.4. Climate metrics

We examined 89 climate metrics to determine which aspects of climate affect the ability of LID practices to alter the long-term urban water balance via reductions in stormwater runoff and increases in DD and/or ET (see SI data, table S4 (available online at stacks.iop.org/ERL/16/064021/mmedia) for complete list of climate metric definitions). These climate metrics capture a wide range of potentially influential factors and include measures of the balance and timing of water availability and energy availability (e.g. PET:P, 30 d correlation between PET and P), measures of precipitation intermittency (e.g. percent of time raining, burstiness and memory, interstorm duration), measures of within-storm characteristics (e.g. storm depth, duration, and intensity) and dozens of thresholds of precipitation or storm intensity (e.g. percent of storms with storm depth >1 in, percent of total precipitation falling at >1 in h^{-1}). Burstiness and memory may be less familiar metrics; they represent the time between precipitation events (burstiness) and the autocorrelation of times between precipitation events (memory) (Schleiss and Smith 2015). For storm metrics, we defined storms as having a minimum precipitation depth of 2.5 mm and counted periods of rain separated by less than 6 h as one storm.

2.5. Partial least squares regression (PLSR) models

To develop PLSR models that relate climate metrics to the LID-induced reduction in runoff and partitioning of reduced runoff into ET and DD, we used the pls package in R (Mevik and Wehrens 2007). All predictor and response variables were centered on their mean and scaled by their standard deviation. First, we pruned the 89 climate metrics via backward selection, using the variable importance in prediction (VIP) score to eliminate variables with the lowest predictive power one by one until all variables had a VIP of at least 0.9. From the variables that remained, we selected the combination that yielded the lowest root mean square error (RMSE) in a cross-validated PLSR model. For all PLSR models, we withheld six cities (∼10%) for external validation, performed internal cross-validation with ten segments, and selected the final number of components using the built-in one-sigma method (Mevik and Wehrens 2007). We evaluated final PLSR model performance using measures of accuracy (RMSE), bias (percent bias; PBIAS), precision (coefficient of determination; R^2), and an aggregate measure commonly used in hydrologic modeling (Nash–Sutcliffe efficiency; NSE).

In addition to using these PLSR models to identify which climate metrics best describe variations in LID performance, we also used the PLSR models to extend predictions of LID performance to additional years with variable weather conditions beyond what we simulated with our physically based hydrologic model (ParFlow.CLM). We did this by first calculating all climate metrics for each city for each of the 30 water years between WY1981 and WY2010. We then used these metrics as inputs in the PLSR models to predict the reduction in runoff and partitioning angle due to LID practices in each of those years. We evaluated expected long-term behavior of LID practices by summarizing the number of years reduction in runoff was >25%, 15%–25%, or <15% and the number of years LID practices mostly increased DD, increased both DD and ET, or mostly increased ET.

3. Results and discussion

3.1. Water balance impacts of LID

Climate-dependent patterns emerge when we compare annual water balances for a baseline single-family parcel (typical residential development) and a single-family parcel with infiltration-based LID under climatic conditions for 51 US cities (figure 1(a), modeled after water balance triangle in Eger *et al* (2017)). Under all climatic conditions considered, infiltration-based LID practices reduce annual runoff; the vector connecting the baseline (circles) and LID scenarios (triangles) for each modeled city points away from the lower left corner where runoff is 100% of the balance. However, in some cases the reduced runoff is partitioned mostly to DD (vector is nearly parallel to the runoff axis, angle is nearly $\pi/3$, indicates no change in ET) and in others it is partitioned mostly to ET (vector is nearly parallel to the ET axis, angle is nearly zero, indicates no change in DD). This vector angle, or partitioning angle, therefore provides a useful means of quantifying the degree to which LID practices mostly increase DD (angle $\geqslant 2\pi/9$),

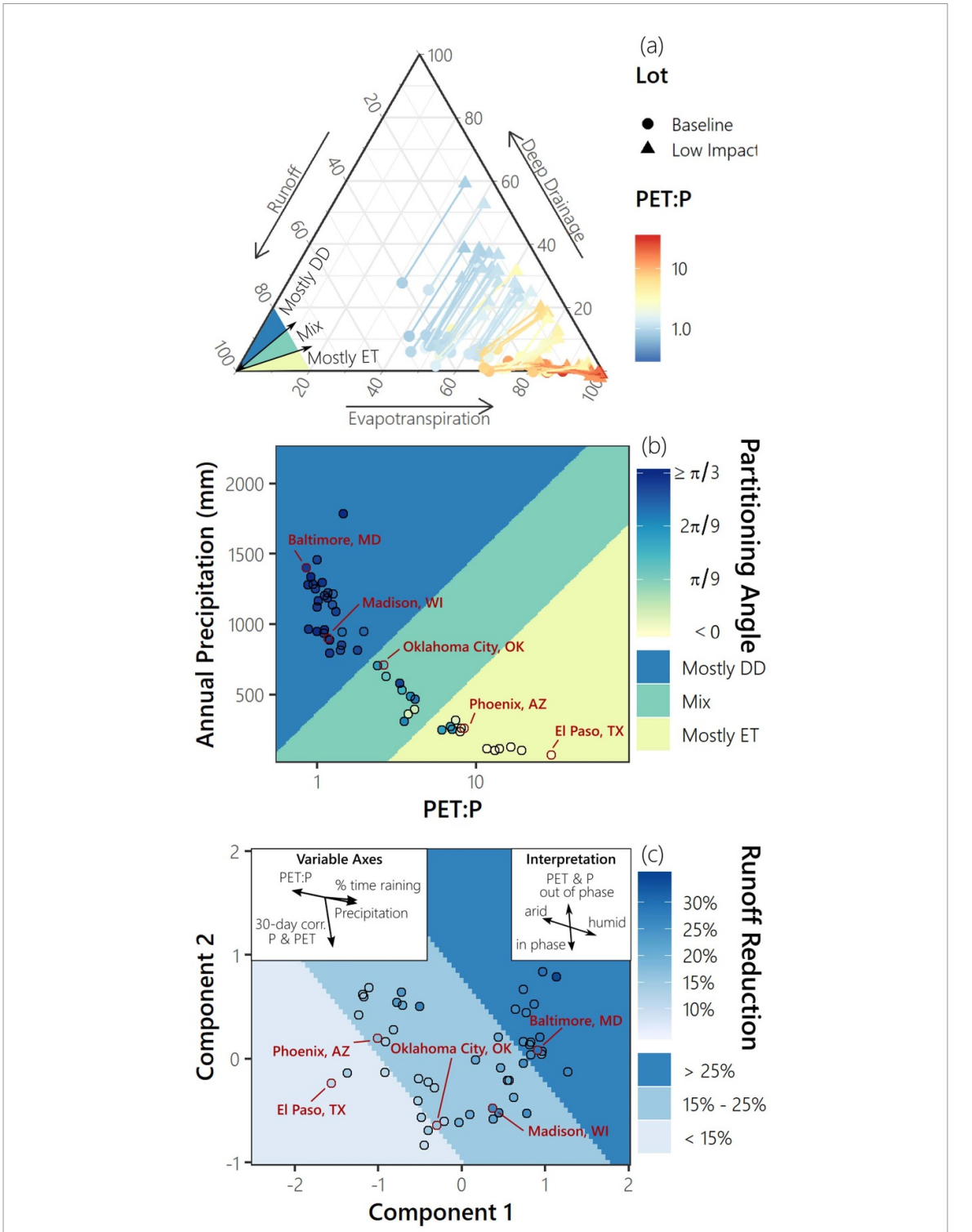

Figure 1. (a) A ternary diagram highlights the shift in partitioning among annual surface runoff, evapotranspiration, and deep drainage between baseline (circles) and low impact (triangles) development conditions for all climate scenarios; (b) all cities (circles) colored by the partitioning angle between deep drainage (DD) and evapotranspiration (ET) as a function of the two variables used in the one component included in the PLSR model: PET:P vs total annual precipitation (mm); (c) all cities (circles) colored by the reduction in runoff as a percent of precipitation due to LID practices as a function of the two components included the PLSR model. Inset indicates direction of increase for the variables represented by these components.

ET (angle $\leqslant \pi/9$), or both (angle $\pi/9$–$2\pi/9$) (see interpretation in lower left corner of figure 1(a)). We excluded change in soil moisture from our analysis since it becomes negligible over long time periods, but we note that this term is non-negligible for some of the 1 year climate scenarios presented here and causes some partitioning angles to be slightly negative (see SI data, tables S2 and S3 for detailed water balances). Coloring each vector by PET:P illustrates that both the energy and water components of climate drive differences in how the water balance shifts in response to infiltration-based LID.

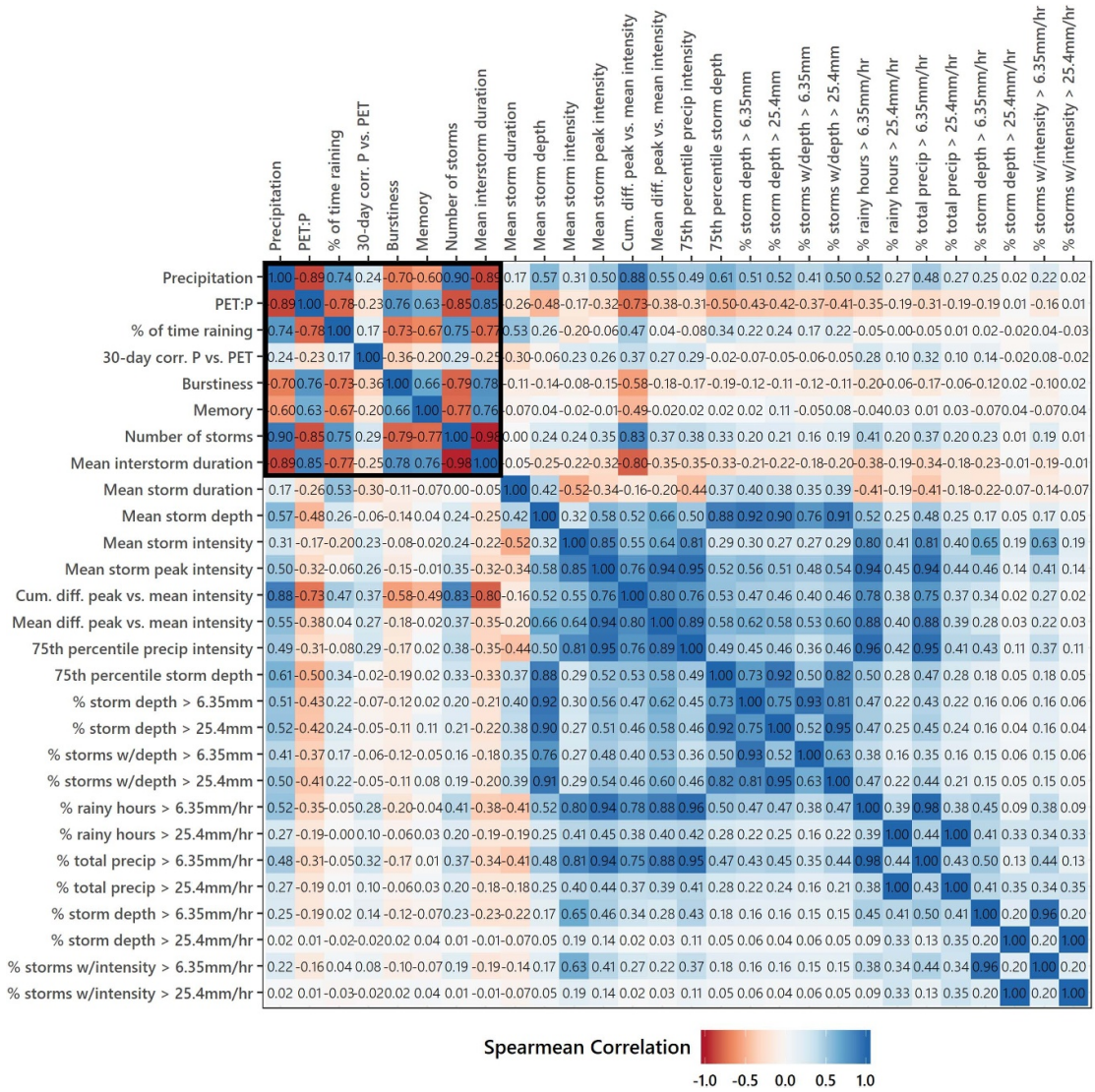

Figure 2. Correlations matrix for key climate metrics examined for use in PLSR models. The eight metrics with predictive power for one or both PLSR models have bolded text and are outlined in the upper left. Final runoff PLSR model uses the top four variables; final partitioning angle PLSR model uses the top two variables.

3.2. Climate metrics important to LID performance

From an initial list of 89 climate metrics (see SI data, table S4), only eight had predictive power in PLSR models relating climate metrics to the reduction in annual runoff and the partitioning angle (i.e. how the urban water balance is altered by infiltration-based LID practices). These eight metrics included: (a) total precipitation, (b) PET:P, (c) percent of time raining, (d) 30 d correlation between PET and P, (e) burstiness (a measure of time between precipitation events; Schleiss and Smith (2015)), (f) memory (autocorrelation of time between precipitation events; Schleiss and Smith (2015)), (g) number of storms, and (h) mean interstorm duration. Although the current literature on climate and LID performance has a heavy focus on within-storm characteristics and how they control episodic runoff and recharge (Holman-Dodds *et al* 2003, Hood *et al* 2007, Gallo *et al* 2012, Bhaskar *et al* 2018, Sohn *et al* 2019), no metric explicitly describing within-storm behavior (e.g. storm depth, storm duration, many metrics related to precipitation intensity) was important in the PLSR models describing changes in the annual water balance. Within-storm metrics were also not well-correlated with metrics that were selected for inclusion (figure 2). Instead, selected metrics describe overall water availability (total precipitation), the balance of energy availability and water availability (PET:P), the relative timing of energy availability and water availability (30 d correlation between PET and P), and the intermittency of precipitation (percent of time raining, burstiness, memory, number of storms, mean interstorm duration).

Many combinations of the top eight climate metrics yielded acceptable PLSR models but the best PLSR models (selected based on RMSE and parsimony) included only 2–4 metrics. The final PLSR model describing the reduction in annual runoff due

Table 1. PLSR model performance.

Model	Validation	RMSE	PBIAS	R^2	NSE
Partitioning angle	Int. Cross-Validation	0.19 rad	0	0.79	0.79
	Ext. Validation	0.13 rad	−4.56	0.93	0.90
Reduction in runoff	Int. Cross-Validation	3%	0	0.76	0.76
	Ext. Validation	2%	−3.09	0.74	0.55

to LID practices included: (a) PET:P, (b) total precipitation, (c) percent of time raining, and (d) 30 d correlation between PET and P (figure 1(c)). The final PLSR model describing the partitioning angle due to LID practices included: (a) PET:P, and (b) total precipitation (figure 1(b)). Performance metrics for these final PLSR models (table 1) meet common thresholds for an 'acceptable' fit in hydrologic modeling based on RMSE (1.7*RMSE < SD), PBIAS < 5%, coefficient of determination ($R^2 > 0.7$), and NSE > 0.65 (Ritter and Muñoz-Carpena 2013).

3.3. Using LID to reduce runoff

Infiltration-based LID yields the greatest reductions in runoff in humid areas with abundant, frequent precipitation where PET and precipitation are out of phase with one another (PET and energy availability are high when precipitation and water availability is low and vice versa) (figure 1(c)). In humid environments, runoff is a larger component of the baseline water balance (figure 1(a)) so more gains are possible and reductions due to LID practices are proportionally larger (figure 1(c)). All three metrics describing humid environments (low PET:P, high total precipitation, high percent of time raining) are well-correlated (figure 2), but the relative timing of PET and P can drive LID performance to be more or less effective than the first three metrics might indicate. For example, Phoenix, AZ is more arid than Oklahoma City, OK based on PET:P (8.4 vs 2.6), total precipitation (258 mm vs 711 mm), and percent of time raining (2% vs 5%) (figure 3), which indicates Phoenix may experience a lower reduction in runoff due to LID. However, PET and P are out of phase in Phoenix (30 d correlation of −0.22) and are strongly in phase at Oklahoma City (30 d correlation of 0.70) which results in Phoenix actually experiencing a slightly higher reduction in runoff compared to Oklahoma City (17% vs 15% as a percent of precipitation).

We note that at the scale of individual storm events, reduction in runoff due to LID practices is influenced by within-storm characteristics like storm intensity and duration, as others have found (see supplemental information for event-scale analysis; Holman-Dodds *et al* 2003, Hood *et al* 2007, Gallo *et al* 2012, Bhaskar *et al* 2018, Sohn *et al* 2019). However, other ecosystem services which may benefit from LID practices are unrelated to discrete flood events and instead depend on the long-term shift of water away from runoff and to other components of the urban water balance such as ET (e.g. for urban cooling) and DD (e.g. for groundwater recharge and water supply). To understand the potential of LID practices to holistically address multiple urban challenges, it is therefore important to examine how runoff is reduced as a percent of the annual urban water balance and how much water can be made available to enhance these other hydrologic fluxes, as is our focus here.

Geographically, our PLSR models and hourly weather data from WY1981-WY2010 indicate that reduction in annual runoff as a percent of annual precipitation is consistently high (>25%) in the Pacific Northwest, a humid region known for frequent rainfall and winter rainy seasons (i.e. out of phase PET and P) where others have demonstrated that LID practices are especially effective (Gallo *et al* 2012) (figure 4(a)). Runoff reduction is often high in the temperate cities east of the Mississippi River Valley as well, but cities in this region that experience in-phase PET and P are more likely to see years with slightly lower LID effectiveness (runoff reduction 15%–25%). This includes cities in the Midwest U.S., where summer atmospheric energy drives high PET and intense convective thunderstorms, and along the U.S. Eastern Seaboard, where summer hurricanes and tropical storms are common (figure 4(a), see SI data tables S6 and S7). Although no explicit measure of precipitation intensity was an important predictor of runoff reduction in our study (figure 2), these geographic patterns indicate that the relative timing of PET and P may be a proxy for prevailing storm characteristics (also see supplemental information on event-scale response). All other cities tend to exhibit consistently intermediate response in runoff (reduction 15%–25%), though some cities in the Rockies (with moderate climate but frequently in-phase PET and P) and cities in the Southwest (with arid climates) experience years with lower reduction in runoff (<15%).

While there are clear climate-dependent differences in the extent to which infiltration-based LID can reduce runoff, locations with more arid climates or strongly in-phase PET and P can still benefit from adopting infiltration-based LID practices. For example, El Paso, TX was the most arid city in the study (PET:P of 29.5) and had slightly in phase PET and P (30 d correlation of 0.11), but it still experienced a reduction in runoff of 11% of annual precipitation due to infiltration-based LID practices (figure 3). However, for these cities to achieve high reductions in runoff, we suggest that managers

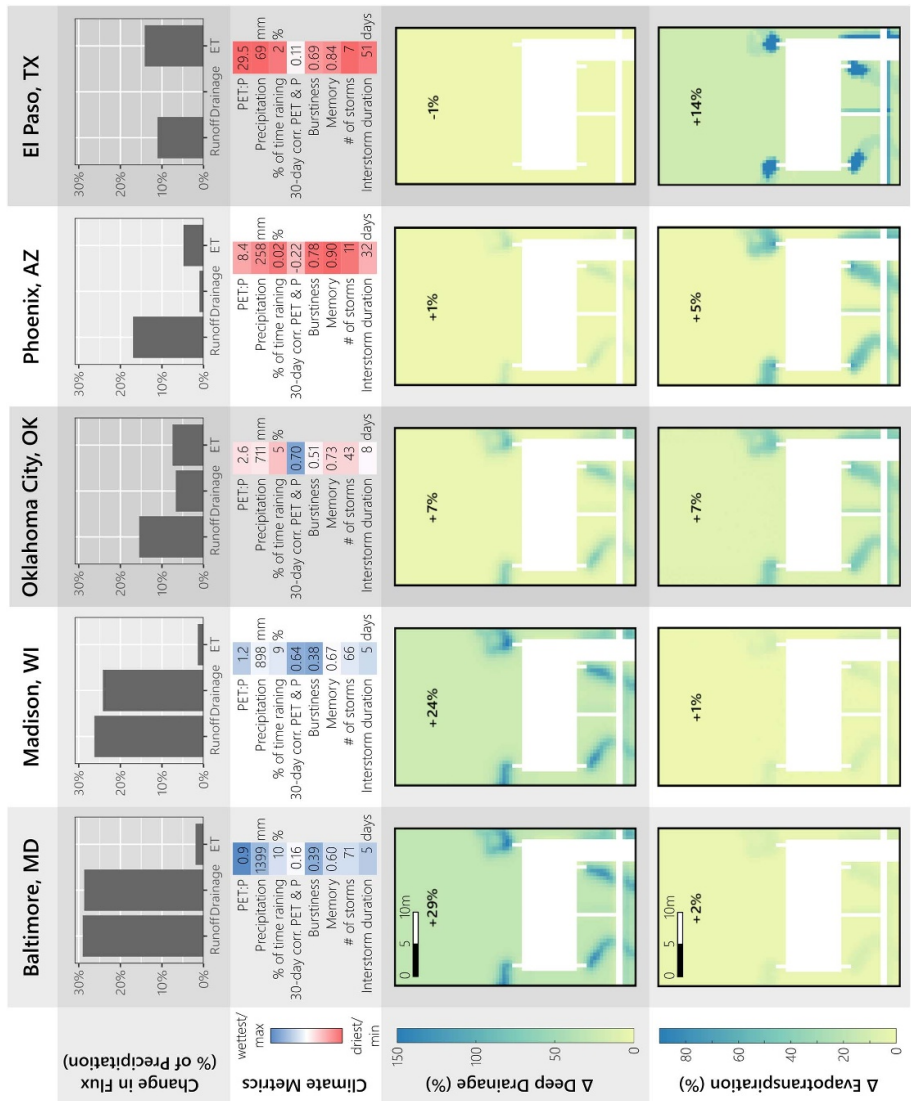

Figure 3. Five exemplar cities which illustrate the range of climate and LID response seen across all 51 cities. Top panel displays the change in total runoff, deep drainage, and evapotranspiration as a percent of precipitation. Second panel displays the eight climate metrics shown to be important by the PLSR model (only the top four are included in the final PLSR models). Lower two panels display the spatial distribution of the cumulative changes in deep drainage and evapotranspiration due to LID practices.

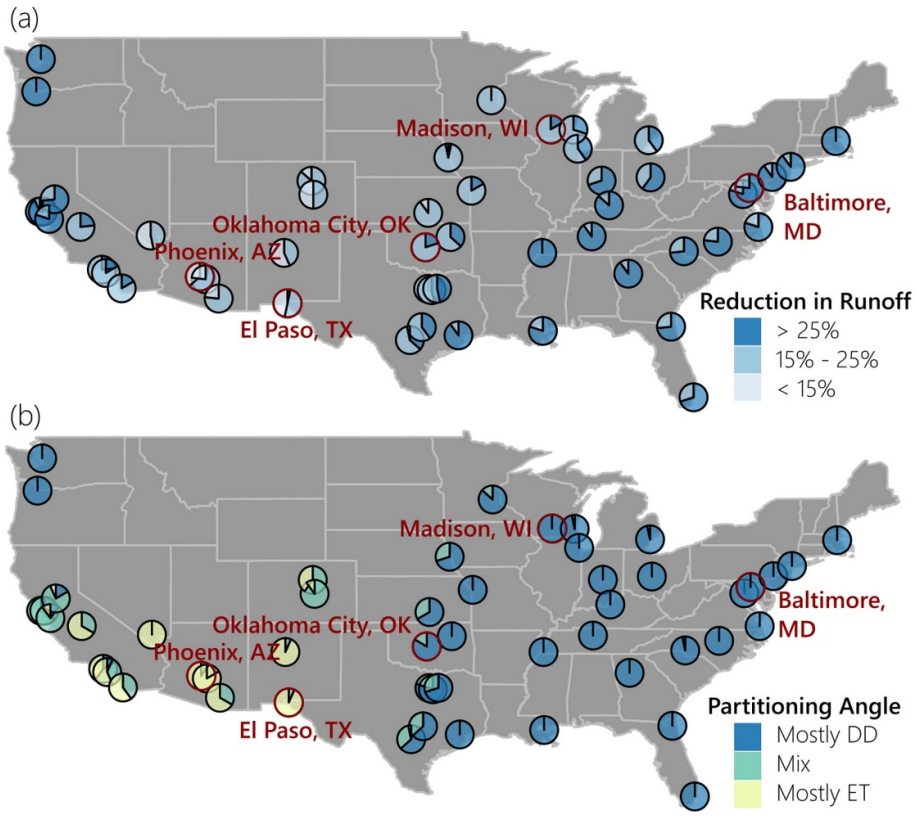

Figure 4. For each city, pie charts indicate the number of years from WY1981-2010 that PLSR models indicate LID practices would (a) lead to a reduction in runoff (as a percent of precipitation) >25%, 15%–25%, or <15%, and (b) mostly increase deep drainage, increase both, or mostly increase ET.

augment infiltration-based practices with additional strategies. Harvest- or retention-based LID practices such as cisterns, green roofs, as well as bioswales with high storage capacities are logical complements (Askarizadeh *et al* 2015, Deitch and Feirer 2019), especially if placed in series with infiltration-based techniques (Gilroy and McCuen 2009).

3.4. Using LID to manipulate deep drainage and evapotranspiration

Partitioning of increases in DD vs increases in ET due to infiltration-based LID is controlled by PET:P and total precipitation, with LID practices mostly increasing DD in humid areas but mostly increasing ET in arid and semi-arid areas (figure 1(b)). Geographically, infiltration-based LID practices consistently increase DD but rarely or never increase ET in nearly all the temperate cities in the Southeast, Northeast, Midwest, and Pacific Northwest (figure 4(b)). By contrast, in Southern California and the Southwest, infiltration-based LID practices mostly increase ET and rarely or never increase DD. A few cities in the Bay Area of California and in the Rockies regularly see increases in both DD and ET, but this variable response from year to year is less common.

This relationship between the aridity index and partitioning behavior can also be seen as larger shifts in ET:P at higher values of PET:P on a Budyko plot (figure 5(a)) as well as larger DD:P shifts at low values of PET:P (figure 5(b)). The Budyko curve (Budyko 1974) describes the steady state water balance dynamics of natural ecosystems and is controlled by two asymptotes: the energy limit (1:1 line) and the water limit (horizontal line at ET:P = 1). These two asymptotes meet at PET:P = 1.0, where evapotranspirative demand due to incoming energy is perfectly balanced by incoming precipitation. At higher ratios of PET:P, the Budyko curve approaches the water limit where evaporative demand exceeds precipitation availability and any increase in precipitation increases ET (maintains an ET:P ratio of 1.0). At lower ratios of PET:P, the Budyko curve approaches the energy limit where precipitation exceeds evapotranspirative demand and an increase in precipitation cannot increase ET, but instead increases runoff or DD (decreases the ratio of ET:P). When infiltration-based LID practices transfer runoff from impervious surfaces to nearby pervious areas, they increase effective precipitation on the pervious areas of a parcel. Because of this lateral transfer of water, LID practices can increase ET within the pervious portion of a parcel and increase overall parcel ET:P when PET:P is high (Budyko curve approaches water limit) but cannot increase ET and instead increase DD when PET:P is low (Budyko curve approaches energy limit) (figure 5). In regions where PET:P is near 1 and the Budyko curve shows

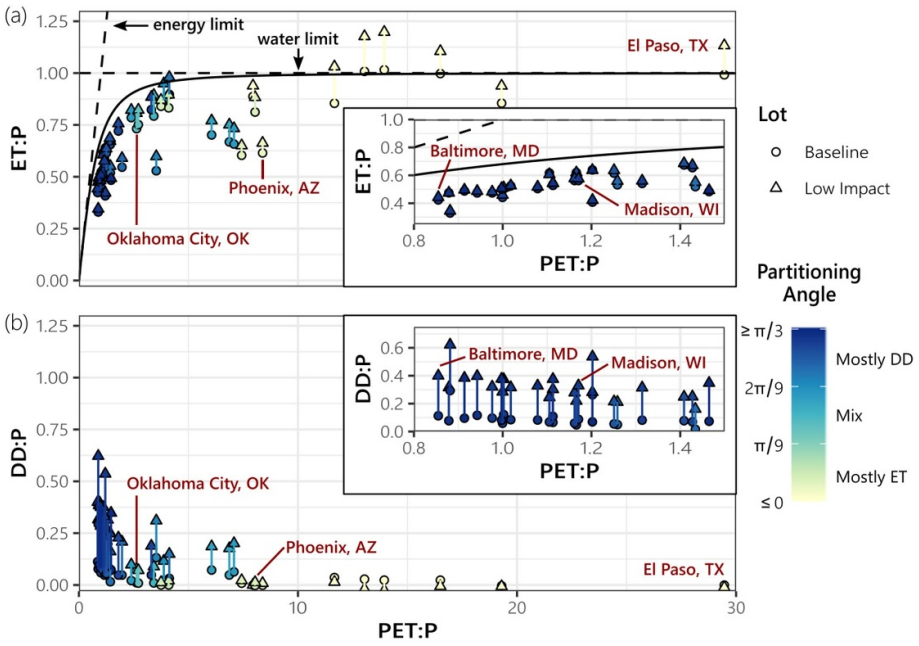

Figure 5. Relationship between aridity index (PET:P) and (a) actual evapotranspiration as a fraction of precipitation (ET:P), and (b) deep drainage as a fraction of precipitation (DD:P). Baseline (circles) and low impact (triangles) results are colored by the partitioning angle for each city. Longer connections indicate greater increases due to LID practices. On (a), the Budyko curve is the solid black line, the theoretical energy limit is the dashed 1:1 line, and the theoretical water limit is the horizontal dashed line.

the greatest curvature, we observe a mixed response in the partitioning of water between DD and ET. Locations which plot above the water limit (ET:P = 1) experienced a decrease in soil moisture over the 1 year simulation, which provided an additional source of water (see SI data, tables S2 and S3 for complete water balances).

We also see this explanation for observed partitioning behavior in the spatial maps of cumulative DD and ET for five example cities, which include all three urban sites represented in the NSF Long-Term Ecological Research Network (figure 3; Baltimore, MD; Madison, WI; Phoenix, AZ). Humid locations like Baltimore, MD and Madison, WI (PET:P of 0.8 and 1.1, respectively) show strong hot spots of increased DD near disconnected impervious features and little sign of increased ET. A city with a more moderate climate like Oklahoma City, OK (PET:P of 2.6) experiences equal increases in DD and ET. The more arid cities of Phoenix, AZ and El Paso, TX (PET:P of 8.1 and 29.5, respectively) instead show strong hot spots of increased ET with little increase in DD. As in Voter and Loheide (2018), parcel-scale changes in DD and ET are not uniformly distributed, but are instead driven by hot-spots of infiltration at the interfaces between impervious and pervious surfaces. This indicates that in humid environments, wetting fronts at impervious-pervious interfaces can regularly penetrate past the root zone and result in strong hot spots of DD, but are not strong enough to do the same in more arid locations where infiltrated water instead remains in the root zone until transpired by vegetation. Increases to DD and/or ET are not as immediate as reductions in runoff and continue long past the end of individual storms, so we did not attempt to evaluate event-scale response but focused exclusively on cumulative annual differences.

These results indicate that infiltration-based LID practices are well-suited for increasing groundwater recharge in humid locations and for cooling the urban heat island in arid locations, but it is rare to realize both ecosystem services from these interventions. If managers in arid locations desire increased DD, we suggest concentrating runoff from a larger impervious source area than exists on this example single-family parcel, e.g. by using focused infiltration basins which collect runoff from several residential parcels (Göbel *et al* 2004, Bhaskar *et al* 2016). To increase ET and affect the urban heat island in humid areas, we suggest managers focus on replacing impervious surfaces with transpiring surfaces or otherwise increasing the percent vegetation cover. De-paving, green roofs, and street trees which overhang pavement are all more likely to achieve this effect in humid areas than the infiltration-based practices explored in this study.

While increasing DD is often a desired outcome of LID practices, we recognize this is not always the case. In areas with a shallow water table, increasing DD is both less feasible (due to weaker vertical gradients in pressure head) and less desirable (due to concerns about basement flooding). Increasing DD may also be less desirable where groundwater contamination is a concern. To limit the degree to which infiltration-based LID practices increase DD in humid areas, we suggest distributing infiltration over

a larger area to minimize hot spots at impervious-pervious interfaces and/or relying on LID practices which have underdrains, though we note that the latter will also reduce the effectiveness of LID practices at reducing runoff (Wright *et al* 2018) unless paired with a harvest-based LID practice.

3.5. Implications for current theoretical frameworks

Our modeling results indicate that the balance of energy availability and water availability (the aridity index, PET:P) is a key control on water balance response to LID practices, just as it is a primary driver of long-term water balance dynamics in natural ecosystems (Budyko 1974). In natural ecosystems at steady state, water balance dynamics will tend to plot on the Budyko curve (figure 5(a)), with ET:P limited by energy availability when and where PET:P < 1 and ET:P limited by water availability when and where PET:P > 1 (Budyko 1974, Roderick and Farquhar 2011). Urbanization causes predictable deviations from the original Budyko curve: by replacing transpiring land with impervious cover, urbanization lowers ET and causes baseline urban development to plot below the original Budyko curve (Roderick and Farquhar 2011) (figure 5(a)). We show that routing water from impervious areas to pervious areas with infiltration-based LID practices augments water availability, which allows some recovery of ET in arid cities where water—in addition to the amount of transpiring land—limits ET (PET:P > 1). However, infiltration-based LID practices cannot alter ET in urban areas where water is abundant (PET:P < 1) because they do not restore transpiring land cover; instead, these practices increase DD (figure 5(b)).

These findings are consistent with theory used by natural ecosystem hydrologists, but it is exceedingly rare for PET:P or other energy-related metrics such as drying time between storms or rainfall intermittency (figure 2) to be considered as drivers of LID effectiveness in urban areas. It is far more common for studies that explore the role of climate on LID effectiveness to focus solely on water availability (Askarizadeh *et al* 2015) and within-storm characteristics (Holman-Dodds *et al* 2003, Hood *et al* 2007, Gallo *et al* 2012, Bhaskar *et al* 2016), even in studies which incorporate PET and dynamic ET into model physics (Wright *et al* 2018). This is partly because stormwater runoff and flooding occurs in response to discrete storm events and LID practices were initially designed as a response to this particular challenge. Insights into how LID performance varies with rainfall characteristics have had clear implications for stormwater regulations since engineers have a long history of tying stormwater ordinances to 'design storms,' which characterize the within-storm characteristics (intensity, duration, and frequency) that stormwater infrastructure must be able to accommodate (Watt and Marsalek 2013). Thus, LID effectiveness is also commonly evaluated with event-based approaches. However, in our analysis at the annual scale, the extent to which LID alters the larger urban water balance is not predicted by any metric describing within-storm behavior. Instead, the relative balance and timing of water and energy availability (PET:P, 30 d correlation of PET and P) and measures of precipitation intermittency are stronger controls. As we expand the use of LID practices to address multiple urban ecohydrologic challenges in addition to stormwater runoff, it will become more important to incorporate PET:P and long-term analysis into predictions of LID performance.

3.6. Future directions

In this study, we intentionally isolated the effect of climate on infiltration-based LID practices and found that the relative balance and timing of water and energy availability (e.g. PET:P, 30 d correlation of PET and P) and precipitation intermittency (e.g. percent of time raining) are the best predictors of the reduction in runoff and partitioning of increases to DD vs ET due to LID practices. However, we recognize that climate co-varies with many other geographic drivers of LID performance, including soil type, landscaping preferences (e.g. for xeriscaping or irrigation), depth to groundwater, regulatory environment, and typical parcel size or layout. Just as soil-vegetation-climate parameters interact to modify water balance dynamics in natural systems, (Troch *et al* 2013) city characteristics may do the same in urban systems. Future work should explore what synergistic or antagonistic effects exist with other urban parameters along climate gradients. In addition, it would be useful to upscale soil moisture storage effects to characterize storm-level effectiveness and account for changes in interannual variability in effectiveness due to sequencing of wet and dry years. Data from these simulations could also be used to improve our understanding of the how LID practices reduce runoff at the scale of individual storm events as well as which types of storms are common in different cities. Ultimately, continued exploration of how geographic gradients affect LID performance will further improve site-specific predictions of LID ecosystem services and thus lead to greater effectiveness and adoption of LID practices for stormwater management tailored to regional climate.

Data availability statement

Model input data to replicate results is included in tables and references in this paper and in the SI; input data, processing scripts, and summary output data are also posted publicly on github (https://github.com/cvoter/low-impact-lot-climate).

Acknowledgments

Funding was provided by the University of Wisconsin Sea Grant Institute (2016-2020 R/RCE05), Wisconsin Water Resources Institute (WR12R002), and the National Science Foundation Northern Temperate Lakes Long-Term Ecological Research (DEB 1440297). Models were run using the computational resources and assistance from the UW-Madison Center for High Throughput Computing in the Department of Computer Sciences.

ORCID iDs

Carolyn B Voter https://orcid.org/0000-0002-4023-7390
Steven P Loheide II https://orcid.org/0000-0003-1897-0163

References

Ashby S F and Falgout R D 1996 A parallel multigrid preconditioned conjugate gradient algorithm for groundwater flow simulations *Nucl. Sci. Eng.* **124** 145–59
Askarizadeh A *et al* 2015 From rain tanks to catchments: use of low-impact development to address hydrologic symptoms of the urban stream syndrome *Environ. Sci. Technol.* **49** 11264–80
Bhaskar A S, Hogan D M and Archfield S A 2016 Urban base flow with low impact development *Hydrol. Process.* **30** 3156–71
Bhaskar A S, Hogan D M, Nimmo J R and Perkins K S 2018 Groundwater recharge amidst focused stormwater infiltration *Hydrol. Process.* **32** 2058–68
Budyko M 1974 *Climate and Life* (New York: Academic)
Cook S, Van Roon M, Ehrenfried L, LaGro J and Yu Q 2019 Chapter 27—WSUD 'best in class'—case studies from Australia, New Zealand, United States, Europe, and Asia *Approaches to Water Sensitive Urban Design* ed A K Sharma, T Gardner and D Begbie (Woodhead Publishing) pp 561–85 (available at: www.sciencedirect.com/science/article/pii/B9780128128435000277)
Dai Y *et al* 2003 The common land model *Bull. Am. Meteorol. Soc.* **84** 1013–23
Deitch M J and Feirer S T 2019 Cumulative impacts of residential rainwater harvesting on stormwater discharge through a peri-urban drainage network *J. Environ. Manage.* **243** 127–36
Donohue R J, Roderick M L and McVicar T R 2007 On the importance of including vegetation dynamics in Budyko's hydrological model *Hydrol. Earth Syst. Sci.* **11** 983–95
Eger C G, Chandler D G and Driscoll C T 2017 Hydrologic processes that govern stormwater infrastructure behaviour *Hydrol. Process.* **31** 4492–506
Fletcher T D *et al* 2015 SUDS, LID, BMPs, WSUD and more—the evolution and application of terminology surrounding urban drainage *Urban Water J.* **12** 525–42
Gallo C, Moore A and Wywrot J 2012 Comparing the adaptability of infiltration based BMPs to various U.S. regions *Landsc. Urban Plan.* **106** 326–35
Garrison N and Hobbs K 2011 *Rooftops to Rivers II: Green strategies for controlling stormwater and combined sewer overflows* (National Resources Defense Council) (available at: www.nrdc.org/sites/default/files/rooftopstoriversII.pdf)
Gautam M R, Acharya K and Stone M 2010 Best management practices for stormwater management in the desert southwest *J. Contemp. Water Res. Educ.* **146** 39–49
Gilroy K L and McCuen R H 2009 Spatio-temporal effects of low impact development practices *J. Hydrol.* **367** 228–36
Göbel P *et al* 2004 Near-natural stormwater management and its effects on the water budget and groundwater surface in urban areas taking account of the hydrogeological conditions *J. Hydrol.* **299** 267–83
Groffman P M *et al* 2017 Moving towards a new urban systems science *Ecosystems* **20** 38–43
Harlan S L, Brazel A J, Prashad L, Stefanov W L and Larsen L 2006 Neighborhood microclimates and vulnerability to heat stress *Soc. Sci. Med.* **63** 2847–63
Holman-Dodds J K, Bradley A A and Potter K W 2003 Evaluation of hydrologic benefits of infiltration based urban storm water management *J. Am. Water Resour. Assoc.* **39** 205–15
Hood M J, Clausen J C and Warner G S 2007 Comparison of stormwater lag times for low impact and traditional residential development *J. Am. Water Resour. Assoc.* **43** 1036–46
Hopkins K G, Grimm N B and York A M 2018 Influence of governance structure on green stormwater infrastructure investment *Environ. Sci. Policy* **84** 124–33
Jiang C, Xiong L, Wang D, Liu P, Guo S and Xu C Y 2015 Separating the impacts of climate change and human activities on runoff using the Budyko-type equations with time-varying parameters *J. Hydrol.* **522** 326–38
Jones J E and Woodward C S 2001 Newton–Krylov-multigrid solvers for large-scale, highly heterogeneous, variably saturated flow problems *Adv. Water Resour.* **24** 763–74
Koc C B, Osmond P and Peters A 2018 Evaluating the cooling effects of green infrastructure: a systematic review of methods, indicators and data sources *Sol. Energy* **166** 486–508
Kollet S J and Maxwell R M 2006 Integrated surface-groundwater flow modeling: a free-surface overland flow boundary condition in a parallel groundwater flow model *Adv. Water Resour.* **29** 945–58
Kollet S J and Maxwell R M 2008 Capturing the influence of groundwater dynamics on land surface processes using an integrated, distributed watershed model *Water Resour. Res.* **44** W02402
Lafortezza R, Chen J, van den Bosch C K and Randrup T B 2018 Nature-based solutions for resilient landscapes and cities *Environ. Res.* **165** 431–41
Larson K L, Casagrande D, Harlan S L and Yabiku S T 2009 Residents' yard choices and rationales in a desert city: social priorities, ecological impacts, and decision tradeoffs *Environ. Manage.* **44** 921–37
Li H, Ding L, Ren M, Li C and Wang H 2017 Sponge city construction in China: a survey of the challenges and opportunities *Water* **9** 594
Maxwell R M and Miller N L 2005 Development of a coupled land surface and groundwater model *J. Hydrometeorol.* **6** 233–47
Mazzotta M J, Besedin E and Speers A E 2014 A meta-analysis of hedonic studies to assess the property value effects of low impact development *Resources* **3** 31–61
McPhearson T, Pickett S T A, Grimm N B, Niemelä J, Alberti M, Elmqvist T, Weber C, Haase D, Breuste J and Qureshi S 2016 Advancing urban ecology toward a science of cities *BioScience* **66** 198–212
McPhillips L E and Matsler A M 2018 Temporal evolution of green stormwater infrastructure strategies in three US cities *Front. Built Environ.* **4** 26
Mevik B H and Wehrens R 2007 The pls package: principal component and partial least squares regression in R *J. Stat. Softw.* **18** 1–23
Milesi C, Running S W, Elvidge C D, Dietz J B, Tuttle B T and Nemani R R 2005 Mapping and modeling the biogeochemical cycling of turf grasses in the United States *Environ. Manage.* **36** 426–38
Millennium Ecosystem Assessment 2005 *Ecosystems and Human Well-being: Current State and Trends* (Washington, DC: Island Press)
Milly P C D 1994 Climate, soil water storage, and the average annual water balance *Water Resour. Res.* **30** 2143–56
Moore T L, Gulliver J S, Stack L and Simpson M H 2016 Stormwater management and climate change: vulnerability

and capacity for adaptation in urban and suburban contexts *Clim. Change* **138** 491–504
NASA 2015 Goddard earth sciences data and information services center (available at: http://disc.sci.gsfc.nasa.gov/hydrology/data-holdings)
Padron R S, Gudmundsson L, Greve P and Seneviratne S I 2017 Large-scale controls of the surface water balance over land: insights from a systematic review and meta-analysis *Water Resour. Res.* **53** 9659–78
Prudencio L and Null S E 2018 Stormwater management and ecosystem services: a review *Environ. Res. Lett.* **13** 033002
Qin H, Li Z and Fu G 2013 The effects of low impact development on urban flooding under different rainfall characteristics *J. Environ. Manage.* **129** 577–85
Ritter A and Muñoz-Carpena R 2013 Performance evaluation of hydrological models: statistical significance for reducing subjectivity in goodness-of-fit assessments *J. Hydrol.* **480** 33–45
Rizwan A M, Dennis Y C L and Chunho L 2008 A review on the generation, determination and mitigation of Urban Heat Island *J. Environ. Sci.* **20** 120–8
Roderick M L and Farquhar G D 2011 A simple framework for relating variations in runoff to variations in climatic conditions and catchment properties *Water Resour. Res.* **47** W00G07
Rosenzweig B R, McPhillips L, Chang H, Cheng C, Welty C, Matsler M, Iwaniec D and Davidson C I 2018 Pluvial flood risk and opportunities for resilience *Wiley Interdiscip. Rev. Water* **5** e1302
Roy A H, Wenger S J, Fletcher T D, Walsh C J, Ladson A R, Shuster W D, Thurston H W and Brown R R 2008 Impediments and solutions to sustainable, watershed-scale urban stormwater management: lessons from Australia and the United States *Environ. Manage.* **42** 344–59
Schatz J and Kucharik C J 2015 Urban climate effects on extreme temperatures in Madison, Wisconsin, USA *Environ. Res. Lett.* **10** 094024
Schifman L A, Tryby M E, Berner J and Shuster W D 2018 Managing uncertainty in runoff estimation with the U.S. environmental protection agency national stormwater calculator *J. Am. Water Resour. Assoc.* **54** 148–59
Schleiss M and Smith J A 2015 Two simple metrics for quantifying rainfall intermittency: the burstiness and memory of interamount times *J. Hydrometeorol.* **17** 421–36
Seneviratne S I, Donat M G, Mueller B and Alexander L V 2014 No pause in the increase of hot temperature extremes *Nat. Clim. Change* **4** 161–3
Sohn W, Kim J H, Li M H and Brown R 2019 The influence of climate on the effectiveness of low impact development: a systematic review *J. Environ. Manage.* **236** 365–79
The United Nations 2018 World urbanization prospects: the 2018 revision: population facts (available at: https://population.un.org/wup/Publications/Files/WUP2018-PopFacts_2018-1.pdf)
Troch P A, Carrillo G, Sivapalan M, Wagener T and Sawicz K 2013 Climate-vegetation-soil interactions and long-term hydrologic partitioning: signatures of catchment co-evolution *Hydrol. Earth Syst. Sci.* **17** 2209–17
Tzoulas K, Korpela K, Venn S, Yli-Pelkonen V, Kaźmierczak A, Niemela J and James P 2007 Promoting ecosystem and human health in urban areas using Green Infrastructure: a literature review *Landsc. Urban Plan.* **81** 167–78
US Census Bureau 2010 Annual estimates of the resident population: April 1, 2010 to July 1, 2017 US Census Bureau, Population Division (available at: https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml)
Vörösmarty C J *et al* 2010 Global threats to human water security and river biodiversity *Nature* **467** 555–61
Voter C B and Loheide S P 2018 Urban residential surface and subsurface hydrology: synergistics effects of low-impact features at the parcel scale *Water Resour. Res.* **54** 8216–33
Walsh C J, Roy A H, Feminella J W, Cottingham P D, Groffman P M and Morgan R P 2005 The urban stream syndrome: current knowledge and the search for a cure *J. North Am. Benthol. Soc.* **24** 706–23
Wang J, Zhang S and Guo Y 2019 Analyzing the impact of impervious area disconnection on urban runoff control using an analytical probabilistic model *Water Resour. Manage.* **33** 1753–68
Watt E and Marsalek J 2013 Critical review of the evolution of the design storm event concept *Can. J. Civ. Eng.* **40** 105–13
Wolf K L 2005 Business district streetscapes, trees, and consumer response *J. For.* **103** 396–400
Wolock D M and McCabe G J 1999 Explaining spatial variability in mean annual runoff in the conterminous United States *Clim. Res.* **11** 149–59
Wright O M, Istanbulluoglu E, Horner R R, DeGasperi C L and Simmonds J 2018 Is there a limit to bioretention effectiveness? Evaluation of stormwater bioretention treatment using a lumped urban ecohydrologic model and ecologically based design criteria *Hydrol. Process.* **32** 2318–34
Zektser S, Loáiciga H A and Wolf J T 2005 Environmental impacts of groundwater overdraft: selected case studies in the southwestern United States *Environ. Geol.* **47** 396–404
Zhang L, Dawes W R and Walker G R 2001 Response of mean annual evapotranspiration to vegetation changes at catchment scale *Water Resour. Res.* **37** 701–8
Zhang Y, Gong H, Gu Z, Wang R, Li X and Zhao W 2014 Characterization of land subsidence induced by groundwater withdrawals in the plain of Beijing city, China *Hydrogeol. J.* **22** 397–409
Zipper S C, Motew M, Booth E G, Chen X, Qiu J, Kucharik C J, Carpenter S R and Loheide S P II 2018 Continuous separation of land use and climate effects on the past and future water balance *J. Hydrol.* **565** 106–22