Permeable Pavement Hydrological Model to Assess the Long-Term Efficiency of Maintenance using High-Resolution Temperature and Rainfall Data

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Abstract

Permeable Pavements (PP) are one of the most flexible stormwater facilities to mimic pre-development flow conditions in urbanized areas. They provide multiple benefits as (a) runoff storage and slowly release, (b) pollutant treatment and (c) reduce heat island effect due to evaporative cooling. Assessing PP long-term efficiency require a continuous model to simulate flow routing, evaporation, clogging, and maintenance using high-frequency rainfall and temperature data. The purpose of this article is to develop a PP continuous model and assess the trade-offs among Permeable Asphalt (PA), Permeable Concrete (PC) and Permeable Interlocking Concrete Pavers (PICP) using the observed climate of San Antonio – Texas for 1975-2000. The objective functions to assess the long-term effectiveness were the (a) month average treated volume, (b) the month average evaporated volume and (c) the drainage layer cost. Solutions were assessed for different scenarios of diameter and number of underdrains and drainage layer depth (i.e., cost), as well as the type of the pavement. Results indicate that PA and PC have nearly the same long-term efficiency and PICP typically provides less evaporation but can provide more treated volume for more expensive solutions. A PP design with a drainage layer of 30 cm and a 4-inches underdrain was assessed and results indicate that it can provide, in average, 45 mm of treated volume in October. For this design, no significant difference in seasonality performance was found varying the type of the pavement, indicating that it may only provide marginal benefits for designs with relatively small drainage layer depths.

Introduction

In last decades, many studies were developed to mitigate the impacts of urbanization and climate change in the water cycle of the built environment. Several principles for
stormwater management have been proposed such as Best Management Practices (BMP), Low Impact Development (LID), Water Sensitive Urban Design (WSUD), Sustainable Urban Drainage (SUDs), Green Infrastructure (GI) and the Alternative Techniques or Compensatory Techniques (CTs) (Fletcher et al., 2015). In this article, we focused on LID as stormwater control measures designed to restore the hydrologic flow regime to pre-development levels by enhancing infiltration and evaporation, and providing water treatment. Typically, LID practices can be defined in three major spatial scales: (a) lot scale (e.g., green roofs, bioretention, lot scale reservoirs, infiltration wells, infiltration and/or detention trenches and other), (b) neighbourhood scale (wetlands, larger bioretention, permeable pavements and other) and at c) catchment scale (e.g., detention and retention ponds, parks, green rivers and etc). Which LID technique is more appropriate than other is not a trivial problem, and multi-criteria algorithms coupled with hydrological models can be applied to enhance decision-making.

One of the most common LID technique used in urbanized areas is the Permeable Pavement (PP). PPs are structures that capture precipitation and stormwater runoff, infiltrating water through permeable materials to an underground reservoir, and provide multiple hydrological benefits for stormwater quantity and quality. Two of the main benefits include enhancing water quality and decreasing runoff volume through evaporation, which also indirectly help alleviate heat island effects in cities. PP are highly adaptable to high density urban centers due to be applicable into urban environment as streets, sidewalks, garages, backyards, and parking lots. One of the main issues of PP is the clogging of surface and drainage reservoir (Brunetti et al., 2016; Lee et al., 2015; Yong et al., 2013). Clogging is associated with accumulation of pollutants, especially total suspended solids in the voids of the permeable material. To avoid the loss of performance, PP require recurrent maintenance in the form of sweeping and/or vacuuming that typically clean the surface of the pavement and restore to some extend the hydraulic performance of the porous material.

Estimating the long-term efficiencies of PP is a difficult problem because of high uncertainties regarding the clogging, maintenance and the mechanical behavior of the porous materials that can change over time once subjected to high mechanical loads. Modeling clogging typically require long-term field observations and maintenance. Investigations showed that some properties of stormwater runoff, such as (a) particle average diameter, (b) viscosity of the runoff, and (c) particle size distribution can play a significant role in clogging (Huang et al., 2016). This study showed that exponential functions can model clogging and maintenance and provide relatively good agreement between simulated and observed clogging over time.

The goal of this article is to present a computational modeling framework to simulate PP systems. The model was used to assess the long-term performance of three types of permeable materials subjected to long term cycles of clogging and maintenance. The evaluated PP are Permeable Asphalt (PA), Permeable Concrete (PC) and Permeable Interlocking Concrete Pavers (PICP). The analysis evaluated trade-offs between different designs, including number of underdrains and reservoir storage, its costs, and the hydrologic benefits of volume of treated runoff and evaporation. The model was applied for the historical climate of the City of San Antonio – Texas for period of 1975 to 2000.

Material and Methods

Conceptual Model

The proposed conceptual model for a hydrologic model of PP represents the infiltration, storage, lateral surface runoff, outflow trough underdrains, given a continuous time series of rainfall and temperature. Figure 1 shows the processes of the conceptual model. In this model,
we consider a side channel as an emergency drainage structure designed to convey excess of saturation flow. In this conceptual model, $L$ and $Q_c$ is the length and flow of the channel, $P$ is the precipitation, $E$ is the evaporation, $Q_o$ is the underdrain outflow, $h_{surf}$ is the depth of the surface of the pavement, $L_d$ is the length of the drainage layer and $\Phi$ is the diameter of the underdrain.

![Diagram of conceptual hydrological model to estimate permeable pavement flow dynamics](image)

**Figure 1 - Conceptual hydrological model to estimate permeable pavement flow dynamics**

**Simplified Evaporation Model**

In reviewed literature, there is a lack of physically based models to estimate evaporation in PP. Estimating evaporation is important to assess the long term efficiency of PP because it not only alter the PP water balance but also reduces heat island effect due to evaporative cooling (Li et al., 2014; Starke et al., 2010). Some recent studies addressing evaporation investigation and monitoring had been found, however, little effort for modeling evaporation is seen (Li et al., 2014; Liu et al., 2018; Nemirovsky et al., 2013). Key governing parameters, such as permeability and air void content were found to be positively correlated with evaporation rate, whereas the depth of water level from surface showed negative correlations, but they can change according to the design of the permeable pavement (Li et al., 2014; Starke et al., 2011). The physical process of evaporation requires energy and is influenced by wind speed, relative humidity, temperature, and other physical variables. These variables can be monitored and are available in some regions of U.S in high-frequency time series. However, in several other regions data is missing.

Simplified methods to model evaporation include regression models or simplified functions of temperature. The Thornthwaite equations (CW, 1948) is a simple model that only uses temperature as input data, even though its estimation is for evapotranspiration. The model had been extensively applied for rural catchments to estimate evapotranspiration in semi-arid regions. To consider differences in incoming radiation, coefficients for different latitudes were proposed. Using these factors, the potential evapotranspiration can be estimated as a function of temperature. In this paper, the Thornthwaite model is compared to pan and gross evaporation measurements in further sections and an empirical adjustment in its equation is proposed. Equations (1)-(3) describes the evapotranspiration (ETP) model. The ETP is corrected according to latitude, and for San Antonio, the correction factors are showed in Table 1. The actual evapotranspiration is calculated as the minimum value between the potential evaporation and the available water to be evaporated (function of internal storage of the PP reservoir).
\[ ETP(t) = \frac{16}{30} \left( \frac{10T_t}{I} \right)^a \]  
\text{(Eq. 1)}

\[ I(y_r) = \sum_{i=1+(y_r-1)12}^{12y_r} \left( \frac{T_i}{5} \right)^{1.514} \]  
\text{(Eq. 2)}

\[ a(y_r) = \frac{6.75 \times 10^{-7}I(y_r)^3 - 7.71 \times 10^5 \times I(y_r)^2 + 1.792 \times 10^{-2} \times I(y_r) + 0.49239}{127} \]  
\text{(Eq. 3)}

where \( ETP \) is the potential average evapotranspiration in mm.day\(^{-1}\), \( T_t \) is the average monthly temperature (Celsius degrees), \( a \) and \( I \) are constants for each year \( y_r \).

Table 1 - San Antonio ETP correction factors

<table>
<thead>
<tr>
<th>Latitude</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>29°N</td>
<td>0.88</td>
<td>0.93</td>
<td>1.00</td>
<td>1.07</td>
<td>1.14</td>
<td>1.17</td>
<td>1.15</td>
<td>1.10</td>
<td>1.03</td>
<td>0.95</td>
<td>0.89</td>
<td>0.86</td>
</tr>
</tbody>
</table>

**Surface Water Balance**

Permeable pavements are typically designed to treat the water quality volume of incoming precipitation at its surface and/or for small drainage areas (SARA, 2019). Since PP drainage layers are designed with high drainage reservoir, it is assumed that the water that infiltrates at the surface goes directly to the bottom by gravity. This assumption is typically valid due to high average saturated hydraulic conductivity of permeable pavers. The rainfall-runoff model to estimate the available stormwater runoff for treatment or to overflow can be derived using the runoff coefficient, according to Equation (4), especially because the drainage areas are relatively small. Other models such as Green-Ampt (Green & Ampt, 1911) can also be assumed as loss model but would require more parameters.

\[ I_{p \, t+1} = I_{c \, t} + (C_{pp}P_{c \, t}^f - E_{c \, t})A_{pp} \]  
\text{(Eq. 4)}

where: the subscript \( p \) and \( c \) indicates the permeable pavement and the catchment respectively, \( t \) is the time step index and indicates the number of time steps \( t \), \( I \) is the inflow (L\(^3\)T\(^{-1}\)), \( P \) is the precipitation rate (L.T\(^{-1}\)), \( A_{pp} \) is the permeable pavement area (L\(^2\)) and \( C \) is the runoff coefficient. The inflow from the catchment can be assumed either as an input data, zero or calculated using a rainfall-runoff model for the catchment.

**Stage-Discharge Relationships**

The PP outflow is modeled using an orifice and channel stage-discharge relationships (Lee et al., 2015). Usually, two types of overflow can be expected in PP. The most common is due to clogging in the surface or bedding layer. The other, however, recent models had neglected, and it is the outflow due to larger inflow rates when the reservoir capacity is already reached, called excess of saturation (Fry & Maxwell, 2018). The excess of saturation causes the failure of the PP when all internal volume is filled, and the inflow is larger than the outflow capacity. We assume this hypothesis in the model to estimate the outflow though the lateral channel.

It is assumed that all ponded area conveys overland flows directly to the lateral channel with no lag time. This assumption can be applied because of the high velocities in the PP surface due to (a) smooth surface (i.e., small Manning’s roughness coefficient \( \sim 0.013 \)) and (b) slopes (i.e., \( \sim 1 \) to 3\%). Therefore, the maximum head pressure in the orifice is equal the PP total depth (surface + bedding reservoir depth). Equations (5) and (6) express the maximum orifice flow and the channel stage-discharge relationship, assumed as the Manning’s equation.
\[ Q_o(h_0) = \sum_{i=1}^{n} n^i_o \delta_i A_{e,i} \sqrt{2g(h_o - e_i)} \quad \text{(Eq. 5)} \]

\[ Q_c(h_c) = \frac{1}{n} \left( bh_c \left( \frac{b + h_c}{b + 2h_c} \right)^{\frac{2}{3}} \right) \quad \text{(Eq. 6)} \]

where: \( \delta \) is the hydraulic transient coefficient, \( n^i_o \) is the number of orifices, \( A_e \) is the effective drainage area of the orifice (L²), \( e \) is the orifice elevation from the bottom (L) \( g \) is the gravitational acceleration (LT⁻²), \( h_o - e_i \) is the head pressure in the orifice (L), \( h_o \) is the stored water level (L), \( n \) is the manning coefficient (TL⁻¹/₃), \( b \) is the width of the channel (m), \( h_c \) is the depth of water in the channel (m) and \( S \) the slope (LL⁻¹).

The outflow of the system (pavement + channel) is a function of the amount of water stored (i.e., internal water stored in the pavement and the accumulated volume in the channel for a particular time) and the hydraulic capacities of the control devices (i.e., diameter of the outlet pipe and the channel routing properties). Assuming a control volume including the PP and the channel, the water budgeted in the system follow as (7).

\[ I_p^t - O_s^t = \frac{dS_s}{dt} \quad \text{(Eq. 7)} \]

where: the subscript \( s \) indicates the system composed by the pavement and the channel.

To solve Equation (7), an approach similar to the level-pool routing method often used for flood routing in reservoirs is to develop. Function relating the outflow of the system with respect to the volume − \([k(h) = f(O_s(h))]\) are used. In a finite difference scheme, Equation (7) can be solved for the 1-dimentional case assuming the initial boundary conditions of the system’s accumulated volume. The basic format for these stage-discharge-storage relationships can be written according to Equation (8):

\[ \frac{k(h)}{\Delta t} \left( \frac{2S_s(h)}{\Delta t} + O_s(h) \right) = f[O_s(h)] \quad \text{(Eq. 8)} \]

where: \( k(h) \) is the auxiliary factor (L³T⁻¹) \( O_s \) is the sum of the permeable pavement and channel outflows. Figure 2 shows a schematic auxiliary graph to solve the water balance equation.

Figure 2 - Auxiliary graph relating a storage factor that depends on stage-discharge relationship and outflow from the outlet hydraulic devices.
**Clogging and Maintenance**

To estimate the internal storage volume in the PP, the average porosity is used. The porosity, however, can decrease over time due to sediment entrapment. Several studies had shown that not only the surface layer but also bedding layers can clog during the first years of PP lifespan service (Huang et al., 2016; Lee et al., 2015). The EPA Stormwater Management Model SWMM assumes a linear relationship with the accumulated volume (Rossman & Huber, 2016) to model clogging in terms of accumulated volume.

One of the main challenges to assess long-term efficiency of permeable pavements is to model clogging and maintenance. Huang et al., (2016) estimated these processes establishing exponential empirical parameters to model clogging based on analysis of surface and drainage layer porosities. Assessing these properties before and after maintenance and fitting exponential functions to the observations, the authors were able to model maintenance effect on porosity, and to model TSS accumulation in the layers of the permeable pavement. These parameters are sensitive to site specific conditions of pollutants and rainfall patterns. However, not assuming clogging and maintenance in long term efficiency assessment may not represent the real efficiency of the system. Equation (9) shows the temporal evolution of the average porosity of the PP in terms of the porosity of the bedding layer and the surface layer.

\[
n(t) = n_c(t) = n_0 - \frac{1}{L_d} \left[ h_{surf} K_s \exp(-a_s t) + h_b K_b \exp(-a_b t) \right]
\]

(Eq. 9)

where: \( n_c(t) \) is the average porosity before the first maintenance, \( n(t) \) is the average porosity, \( n_0 \) is the initial average porosity, \( h_{surf} \) is the depth of the surface layer, \( K_s, a_s, K_b, a_b \) are fitted parameters for the surface (s) and drainage reservoir (b).

Similarly, the maintenance can be modeled assuming exponential coefficients that increase the porosity of the surface layer at the maintenance time. The maintenance time provides in the porosity function a cyclical effect that restore the porosity right after the maintenance. The porosity at a specific time \( t^* \) larger than the maintenance time \( t_m \) can be modeled as following Equation (10).

\[
n(t)_{t \geq t_m} = \frac{1}{L_d} \left[ h_{surf} K_{s,m} \exp[-a_{s,m}(t - k t_m)] + n_b(t) \right]
\]

(Eq.10)

where: \( k \in \mathbb{N}^* \) and \( k = \frac{t}{t_m}, a_{s,m} \) and \( K_{s,m} \) are fitted parameters after maintenance.

In this investigation, three types of PP were evaluated, including the PA, PC and PICP. The temporal evolution of clogging and maintenance can be determined using parameters showed in Table 2 and maintenance is assumed to occur once every 12 months.

Table 2 – Typical porosity parameters for the surface and drainage layers for PA, PC, and PICP concrete pavers. Parameters assumed according to (Huang et al., 2016).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Permeable Asphalt</th>
<th>Permeable Concrete</th>
<th>PICP</th>
</tr>
</thead>
<tbody>
<tr>
<td>( K_s )</td>
<td>19.64</td>
<td>25.17</td>
<td>10.45</td>
</tr>
<tr>
<td>( K_{s,m} )</td>
<td>17.83</td>
<td>21.62</td>
<td>9.9</td>
</tr>
<tr>
<td>( a_s )</td>
<td>0.08</td>
<td>0.07</td>
<td>0.24</td>
</tr>
<tr>
<td>( a_{s,m} )</td>
<td>0.05</td>
<td>0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>( K_b )</td>
<td>30.68</td>
<td>30.68</td>
<td>30.68</td>
</tr>
<tr>
<td>( A_b )</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
</tr>
</tbody>
</table>
Flow Routing

At the first time-step, the left side of Equation 8 is known. In our proposed approach, auxiliary curves are built for the initial porosity \(n_0\) to determine the flows for the second time step. The auxiliary curves are created in a two-steps process: first, the orifice flow is calculated only using the hydraulic head pressure in the permeable pavement for internal water levels smaller than the depth of the PP \((h_t)\). After water level reaches \(h_t\), the net depth is assumed to be only in the channel. The minimum auxiliary value to start channel routing can be determined implying the PP internal depth equal \((h_t = L_d + h_{surf})\). Equation (11) shows the conditions to build the auxiliary graph for a specific time.

\[
\begin{cases}
\text{If } k^{t+1} \leq \frac{2S_{pp}(h_t)}{\Delta t} + O_s(h_t), h_{t+1}^{c+1} = h_{t+1}^{p+1}, h_{t+1}^c = 0 \quad \rightarrow Q_{o}^{t+1} = O_s(h_{t+1}^p) \rightarrow Q_{c}^{t+1} = 0 \\
\text{Otherwise} \quad h_{t+1}^{p+1} = h_t \rightarrow h_{t+1}^{c+1} = h_{t+1}^{c} - h_{t} \quad \rightarrow Q_{o}^{t+1} = Q_o(h_t) \rightarrow Q_{c}^{t+1} = Q_c(h_{t+1})
\end{cases}
\]

(Eq.11)

The functions to calculate \(Q_o\) and \(Q_c\) are described in Equations (5) and (6). The auxiliary tables are refreshed each time according to the porosity changes to capture the variation in stage-discharge-storage relationship due to clogging. Therefore, the water depth inside the permeable pavement are calculated assuming the infiltrated depth corrected by the average porosity. A schematic example of an auxiliary curve for time \(t\) is showed in Figure 3.

![Schematic example of an auxiliary curve](image)

Figure 3 - Generical example of an auxiliary graph and calculations of k and O for times \(t\) and \(t+1\).

Optimization Problem

In this paper, three main objectives were selected to assess solutions using an extensive modeling approach. Other alternative such as the multi-objective genetic algorithm NSGA-II (Deb et al., 2002) could be applied; however, the decision space is reduced due to construction boundaries (i.e., commercial underdrain and its quantity and drainage layer depth). Therefore, the decision space was discretized according to reasonable discretization parameters for these variables. The objective functions are (i) the average monthly treated volume, followed by (ii) the average monthly evaporated volume; and the (iii) bedding reservoir cost. The equations and assumptions of these objective functions are showed in Table 3.

Three decision variables were selected to assess the problem (orifice diameter, reservoir depth and number of orifices). Other initial parameters, such as the surface and/or bedding reservoir porosity and recurrence of maintenance could also be defined as decision variables.
However, they are usually specified by local regulations and have typically small ranges of variation. The optimization problem is defined in Equation (15).

Table 3 - Objective functions of the optimization problem, where $T$ is the number of steps.

<table>
<thead>
<tr>
<th>Equation</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_m = \frac{1}{n_m} \sum_{t=1}^{T} Q_o^t \Delta t$ (Eq.12)</td>
<td>This objective function was selected to assess the potential water treatment provided by the permeable pavement. It is assumed that the treated volume is the amount of the inflow that infiltrates in the pavement and, therefore, passes through the outlet underdrain, according to Equation (5).</td>
</tr>
<tr>
<td>$E_m = \frac{1}{n_m} \sum_{t=1}^{T} E t A_{pp} \Delta t$ (Eq.13)</td>
<td>Similarly to the first objective function, this one measures the average month evaporated volume using the evaporation time series of the model.</td>
</tr>
<tr>
<td>$C = \frac{59.55}{m^2 \times m} \times A_{pp} L_d$ (Eq.14)</td>
<td>Since surface layer is primary determined by structural design, it is pre-defined and the variation in the permeable pavement cost will be a function of the bedding layer reservoir. To estimate this cost, it was used the SARA (2009) manual costs for bedding materials of permeable pavements.</td>
</tr>
</tbody>
</table>

where: $V_m$ is the average month treated volume (mm/month or L/m$^2$/month), $n_m$ is the number of months in the analyzed time series, $T$ is the total number of time-steps, $t$ is the accumulated time-steps varying from 1 to $T$, $E$ is the evaporated volume in mm/month and $C$ is the reservoir costs.

$$\min[-\bar{V} ; -\bar{E} ; C ]$$

subject to

$$1/2" \leq \phi \leq 6"$$

$$1 \leq n_0 \leq 3$$

$$\min(1.5 \times \phi_0) \leq L_d \leq 0.5 \text{ m}$$

(Eq.15)

Evaporation Formulation

Some studies reported evaporation from different PP design compared PP evaporation to pan evaporation (Kuang et al., 2011; Li et al., 2014; Liu et al., 2018; Nemirovsky et al., 2013; Starke et al., 2010, 2011). Li et al., (2014) reported PC field analysis showing that PPs provide, in average, 30% of the evaporation rate of a bare water (pan evaporation), indicating that a higher hydraulic resistance was found to evaporate internal volume in the PP. The authors also reported that pan evaporation had a good correlation with PP evaporation, although larger evaporation rates in the permeable pavement was observed.

Data collected from San Antonio – Texas were used to compare gross lake evaporation with evapotranspiration calculated by the Thornthwaite method (NOAA National Centers for Environmental information, Climate at a Glance: National Time Series, 2020). The time series used gathered observations from January of 1954 to January of 2020 and was used to obtain a general trend relationship between these two variables. Figure 4 shows the comparison between (a) gross evaporation and month average temperature, and (b) gross evaporation and ETP estimation.
The results indicate good correlations of gross evaporation with month average temperature and modeled ETP. This relationship, however, showed a lag of approximately 60 mm in a month, which represents a daily difference of 2 mm/day between gross evaporation and ETP from Thornthwaite method. The Thornthwaite equation can represent variation trends according to changes in average temperatures ($R^2 = 0.99$) but lagged of 2 mm.day$^{-1}$. Therefore, we assume a newer empirical evaporation equation for PP according to Equation (16):

$$E = \beta (ETP + \alpha)$$

(Eq.16)

where: $\beta$ is a factor that converts gross evaporation into evaporation in the permeable pavement (dimensionless) assumed as 0.3, and $\alpha$ is a linear parameter assumed 2 mm.day$^{-1}$.

![Image of graphs showing correlations](Figure 4)

Figure 4 - (a) is correlation between gross evaporation and month average temperature, (b) is the correlation between gross evaporation and ETP estimation by Thornthwaite equation and (c) is the correlation between the Thornthwaite ETP and 50% of the gross evaporation.

**Data acquisition**

Rainfall and monthly average temperature data were collected from July 1975 to July 2000 in the station (RANDOLPH AFB, TX US, COOP:417422, LAT/LONG - 29.5325°, -98.2623°). The 15-min rainfall intensity is showed in Figure 7. This selected period characterises past climate and is long enough to represent the lifespan of PP system.

**Model Application**

The model is applied for 3 of the 4 types of pavements at the recreational facility to be built at the Classen-Steubing Ranch, San Antonio, under the 2017-2022 Bond Proposition 3 (www.sanantonio.gov/2017Bond). Each permeable pavement cell has an area of approximately 348 m$^2$ and a schematic is presented in Figure 5. The modeling routine is developed in Matlab ®.

**Parameter Estimation**

To assess the hydrological processes using the developed model, a set of initial parameters were assumed. Reasonable values for the (a) outlet and lateral channel routing parameters and (b) time and space discretization were assumed based on literature and expertise and are showed in Table 4.
Figure 5 - Schematic of the PP layouts

**PP Long-Term Performance for 1975 to 2000**

Because the relatively small size of the decision space, the developed model was run for a possible combinations of number of drains, underdrain diameter and size of reservoir storage. The total number of simulation runs was 810. However, some solutions presented instabilities for a 15-min time-step and others did not satisfy the last boundary condition in Equation (15). The modeling results of this extensive analysis are showed in Figure 6, which depicts the tradeoffs between cost (color), number of underdrains (symbol), monthly average evaporation (mm/month), and average treated stormwater volume (mm/month) for the three types of PP.

The pavers PA and PC had nearly the same general efficiency due to similar average porosities. Increasing the number of underdrains, in general, decreases evaporation due to rapid outflow but does not necessarily provide more treated runoff for these pavements. Moreover, considering only evaporation and treated volume, one trade-off curve per cost can be observed, indicating that the problem has 3 objectives that conflict each other. Typically, the non-dominated solutions of evaporation and treated volume represent the larger costs (i.e., larger drainage layer) with varying underdrain diameters.

![Figure 6 - Modeling results where (x) is using 1 underdrain, (+) using 2 and (*) using 3.](image-url)

Figure 6 – Modeling results where (x) is using 1 underdrain, (+) using 2 and (*) using 3.
The results indicate that PICP presented a relatively lower efficiency with respect to evaporation. This is due to lower average porosity which leads to less stored volume. Figure 7 shows the changes on average porosity for the three PP. The PICP was able to produce a larger average monthly treated volume, even though it had the smaller average storage volume. It may be due to model 1-D simplification that theoretically lumps the pavement and the reservoir into only one average porosity. This assumption produces larger stored depths in the PICP reservoir, that ultimately increases the pressure in the orifices for relatively small stored volumes. We hypothesized that this effect changed the dynamics of outflow in such a way that increase the treated volume. Another pattern identified among all pavements is that solutions with only 1 underdrain are more effective to enhance evaporation, due to reduced outflow rates which maintains more storage and opportunities for water to evaporate.

Table 4 - Parameter estimation for hydrologic modeling.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Unit</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δt</td>
<td>15</td>
<td>min</td>
<td>Time-step of simulation</td>
</tr>
<tr>
<td>C</td>
<td>0.95</td>
<td>m³/m³</td>
<td>Runoff coefficient</td>
</tr>
<tr>
<td>h_c,max</td>
<td>0.15</td>
<td>m</td>
<td>Channel height</td>
</tr>
<tr>
<td>n_c</td>
<td>0.018</td>
<td>s.m⁻¹/³</td>
<td>Manning’s roughness coefficient</td>
</tr>
<tr>
<td>w_c</td>
<td>0.3</td>
<td>m</td>
<td>Width of the channel</td>
</tr>
<tr>
<td>l_c</td>
<td>41</td>
<td>m</td>
<td>Length of the channel</td>
</tr>
<tr>
<td>C_d</td>
<td>0.5</td>
<td></td>
<td>Discharge coefficient</td>
</tr>
<tr>
<td>t_m</td>
<td>12</td>
<td>months</td>
<td>Maintenance cycle</td>
</tr>
<tr>
<td>Δh</td>
<td>0.001</td>
<td>m</td>
<td>Height-step for auxiliary graphs</td>
</tr>
</tbody>
</table>

**Discretization**

Φ* [3/4” 1” 5/4” 3/2” 5/2” 3” 4” 5” 6”]

n_o [1 2 3]

L_d [0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40 0.45 0.50]

Φ* is the nominal diameter and is corrected to internal diameter in the modeling and L_d is in (m).

Figure 7 - Temporal evolution of porosity and rainfall during 1975-2000. Data from San Antonio Airport
Seasonality Performance

One solution with reservoir depth of \( L_d = 30 \text{ cm} \), with 1 underdrain of \( \Phi = 4\)-inches was selected for further analysis. This solution would require less maintenance (i.e., only one underdrain) and also satisfy local standards for permeable pavements in San Antonio (SARA, 2019). Figure 8 shows the seasonality behaviour of the design using the PA. The seasonality analysis is built based on all data from the continuous simulation of the permeable pavement. A monthly summary of the results is performed for each year of the scenario 1975-2000 and computations of standard deviations, 25th and 75th percentiles and median values are calculated for precipitation, temperature, \( V_m \) and \( E_m \).

October is the month with higher potential water to be treated, reaching long-term averages of approximately 45 mm/month or 1.77 inches. The evaporation, however, had two peaks occurring in May and September. Even though May has not the maximum average temperature, it has an average monthly precipitation large enough to provide available stored water to evaporate. Moreover, the variability (i.e., standard deviation) of evaporation in this month is high, indicating that larger temperatures can also occur and combined with rainfall can increase evaporation. No significant differences in seasonality variation were found for PC and PICP compared to PA. This result suggests that the difference in the pavements surface might not be very relevant for long-term assessment of treated volume and evaporation.

![Figure 8 Seasonality effects for observed data (1975-2000) in permeable asphalts](image)

Conclusions

A hydrological model to simulate long-term efficiency of permeable pavements were developed and tested for observed climate of San Antonio with 15-min rainfall data. An extensive modeling discretizing the drainage layer depth, number and diameter of underdrains were performed. Moreover, a seasonality analysis of potential treated volume and evaporation were assessed for a design condition that satisfy local standards. Based on the results, we concluded:

- The model is flexible enough to perform continuous simulations of permeable pavements.
- Evaporation mechanisms and modeling is still a gap. The adopted empirical formulation can provide good results if extensive gross evaporation data is available.
Permeable Asphalt and Permeable Concrete had nearly same long-term efficiency. PICP had a superior average month treated volume for more expensive solutions.

The designed permeable pavement can provide approximately 45 mm of potential treated volume in October and has the evaporation peaks in May and September for the climate of the City of San Antonio – Texas.

Although most parameters of the model are physically based, significant more testing and calibration with observed rainfall-flow is needed. A sensitivity analysis and a varying time-step can enhance the model capabilities, computational efficiency and decrease instability. The model was developed in Matlab® and can include parallel computing for time-consuming analysis of long terms scenarios or optimization.

**References**


Li, H., Harvey, J., & Ge, Z. (2014). Experimental investigation on evaporation rate for


