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Review

Sustainable Urban Drainage System (SUDS) modeling supporting decision-making: A systematic quantitative review

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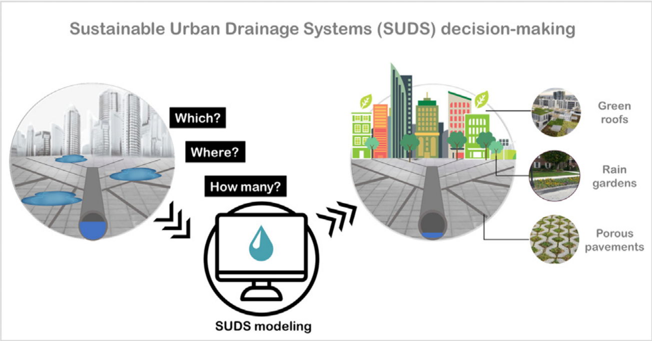
HIGHLIGHTS

- This paper aims to quantitatively analyze how SUDS-DSS are being build and applied.
- The question was "What is the role of SUDS models on the decision-making process?"
- Database and snowballing searches methods were used to appraise the papers.
- The research focus has shifted from simple representations to more sophisticated tools.
- There are some aspects that require special attention for SUDS-DSS development.

GRAPHICAL ABSTRACT



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ABSTRACT

Decision Support Systems (DSS) for Sustainable Urban Drainage Systems (SUDS) are a valuable aid for SUDS widespread adoption. These tools systematize the decision-making criteria and eliminate the bias inherent to expert judgment, abridging the technical aspect of SUDS for non-technical users and decision-makers. Through the collection and careful assessment of 120 papers on SUDS models and SUDS-DSS, this review shows how these tools are built, selected, and used to assist decision-makers questions. The manuscript classifies the DSS based on the question they assist in answering, the spatial scale used, the software selected, among other aspects. SUDS-DSS aspects that require more attention are identified, including environmental and social considerations, SUDS trains performance and criteria for selection, stochasticity of rainfall, and future scenarios impact. Suggestions for SUDS-DSS are finally offered to better equip decision-makers in facing emerging stormwater challenges in urban centers.

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Contents

1. Introduction

Sustainable Urban Drainage Systems (SUDS) are an integrated network of engineered vegetated areas and open spaces (i.e., green roofs, rain gardens, porous pavements, etc.) used to protect natural ecosystem principles and functions and to offer a wide variety of benefits to people and wildlife (Tang et al., 2021). SUDS are a complement to centralized conventional sewer systems infrastructure to minimize the hydrological urbanization impacts and increase resilience to extreme rainfall events in urban centers (Zhu et al., 2019). These structures have the ability to attenuate extreme rainfall events (Tang et al., 2021) and are known for providing multiple environmental benefits (Liao et al., 2013), including climate change impacts reduction (Coutts and Hahn, 2015; Jones and Somper, 2014; Ghodsi et al., 2020; Roseboro et al., 2021), along with ecological and social benefits and other potential monetizable benefits in the long term (Wolf, 2003; Hamann et al., 2020).

SUDS are usually referred to using several other terms, including Best Management Practices (BMPs), Green Infrastructure (GI) (Benedict et al., 2006), blue-green systems (Bozovic et al., 2017), Low Impact Development (LID), source control (Hamel et al., 2013), sponge city (Xia et al., 2017), nature-based solutions (Kabisch et al., 2016; Oral et al., 2020), and Water Sensitive Urban Design (WSUD) (Wong, 2006), among others (Fletcher et al., 2015; Chatzimentor et al., 2020). This set of terms is not static since, as described in Fletcher et al. (2015), they respond to evolving technologies and the incorporation of other fields into the urban drainage practice, and have (some subtle, others drastic) differences in scope and principles. For the purpose of this review, terms referring to 'nature-based stormwater management solutions' will be unified under 'SUDS', and the difference in the scope they encompass will be overlooked.

SUDS selection, design, and location is a high-level complexity problem that relies on tools that systematically introduce relevant information, usually based on the best available representation of the urban drainage system. In such a complex endeavor, modeling is necessary to predict the behaviour of SUDS configurations (type, design, and location) and appraise their impact in the urban system. Modeling, along with other tools like multi-criteria matrices and optimization tools are put together on frameworks to aid SUDS decision-making frequently referred to as Decision Support Systems (DSS).

The applicability of DSS in diverse fields results on numerous definitions, which although well-established in a particular niche, are confused when applied to an interdisciplinary field. Provided that SUDS are part of both the urban and environmental systems, the term DSS tends to be used interchangeably with others such as Environmental Decision Support Systems (EDSS) (Poch et al., 2004; Matthies et al., 2007; Reichert et al., 2015) and Planning Support Systems (PSS) (Klosterman, 1997). For a discussion of the usage of these terms, refer to Kapelan et al. (2005) and Te Brömmelstroet (2013).

In the field of SUDS, the above-mentioned terms are hardly separable since SUDS-DSS can be classified into both highly complex systems (EDSS - as defined in Poch et al. (2004)) and planning-actions-related (PSS). Building upon the DSS definition provided by Fox and Das (2000), in this study the term SUDS-DSS is used to refer to "*an structured set of tools (e.g., optimization, artificial intelligence, numerical models, statistical methods, Geographical Information Systems (GIS)) to assist decision makers and provide recommendations on SUDS design and spatial deployment*".

DSS is a valuable aid for SUDS widespread adoption. They systematize the decision-making criteria and eliminate the bias inherent to expert judgment. By making SUDS decision-making less technical, SUDS-DSS encourage their adoption and increase their impact at the local, regional, and global scale (Baptista et al., 2005). Available SUDS-DSS generally aim to solve problems of two natures 1) SUDS design (preliminary or detailed) and 2) SUDS spatial location (selection and placement), seeking the best SUDS implementation scenarios in terms of, at least, water quantity/quality and having ideal margins of cost-benefit (Veith et al., 2003).

Because the primary SUDS objective is the attenuation of the hydrological cycle disturbances, SUDS-DSS rely on the best available hydrological representation of the study area and the SUDS structure. Urban Drainage Models (UDM) with SUDS modeling capabilities are commonly used for this purpose, (Krebs et al., 2013; Kong et al., 2017). While mechanistic approaches are generally preferred for hydrological representations, there are other simplified approaches used in SUDS-DSS, chosen for practical reasons (e.g., fast convergence or straightforward coupling with other DSS modules). Calibrated UDMs are ideal for building a robust and reliable SUDS-DSS (Haris et al., 2016; Beck et al., 2017; Ellis, 2013; Iffland et al., 2021) but they are not always available. Furthermore, future scenario projections considering urbanization trends and climate change are desirable but not always included (Wang et al., 2020).

Some SUDS-DSS emphasize the exploitation of SUDS environmental benefits, aiming to find the best configuration to maximize one or more objectives. Also, despite stakeholders' relevancy, these actors are seldom included in the early steps of the decision-making process, resulting in SUDS designs and locations that do not adjust to the expectations of those who will benefit from the structure (Raei et al., 2019). Many of these limitations result from the reactive approach in which SUDS-DSS are conceived and built. When a DSS-SUDS responds to the particularities of the case study and its temporal necessities, the resulting DSS 1) fails in capturing a holistic and unbiased perspective and 2) its applicability is constrained to the case study that motivated its development (i.e., Torres et al. (2016); Kuller et al. (2017)).

In a rapidly (regionally-focused) evolving field like the SUDS-DSS, it is necessary to make periodical assessments of the state-of-art to internationalize regional experiences and bring forward new perspectives for the development and use of SUDS-DSS. This paper presents a quantitative and critical discussion on how modeling-based SUDS-DSS are being used to support decision-making. Through a two-year-long (2019-[March]2021) appraisal of articles introducing or applying urban drainage models to assist SUDS-related planning actions, the current state of the art was quantitatively evaluated with the key objectives of:

- Analyze and update the state of the art and latest-trends in modeling-based SUDS-DSS research.
- Quantify and map the development and implementation of modeling-based SUDS-DSS.
- Understand the (modeling) practices employed when using SUDS-DSS.

The next sections of this article are structured as follows. Section 2 summarises previous reviews. Section 3 describes each step of the systematic quantitative review. Section 4 is divided into six subsections that report the quantitative results and discuss implications. Finally, Section 5 provides a critical perspective and suggests future research directions.

2. Previous reviews

From a dedicated revision of previous reviews, it was evidenced how the SUDS research concerns and directions have been shaped by the development of interdisciplinary research, the broadening of SUDS understanding as providers of multiple benefits, and the late inclusion of urban planning in the stormwater management field (Kuller et al., 2017). Among the many reviews available, those tackling specifically SUDS modeling or SUDS-DSS and published in the last two decades (1997–[March] 2021) were considered.

2.1. SUDS modeling

First urban stormwater models lacked the ability to model SUDS (see Burton et al. (2001) and Zoppou (2001) for a review). SUDS modeling gained sharper attention after their reported success in managing runoff. In 2007, Elliott and Trowsdale (2007) presented the first SUDS modeling review and proposed a classification based on their purpose: planning, preliminary or detailed design. Their review pointed out the importance of temporal and spatial resolution (particularly the limited ability of stormwater models to predict the flow rates from small catchments), runoff generation, and pollutants transport modeling. Two of their main findings were that *i)* only half of the SUDS models had a groundwater/baseflow component, and *ii)* there was a deficiency of tools that operate effectively at a large spatial scales.

Ahiablame et al. (2012) provided a detailed review of SUDS representation in computational methods. By focusing on 4 SUDS types, they identified two modeling approaches: a process representation (e.g., infiltration, sedimentation, settling) and a practice representation, which uses an aggregation method to model the practice as a unit. They identified as areas of future research the scaling of SUDS practices from lot to watersheds and regional scales.

The further refinement of SUDS models' physical processes representation (Kaykhosravi et al., 2018) was impulsed by the widening of SUDS models' usage for urban planning and decision-making. Kaykhosravi et al. (2018) compared stormwater models' capabilities of representing the hydrological and hydraulic SUDS processes and pointed out the need to develop more comprehensive SUDS models allowing various applications (i.e., research, conceptual, preliminary and detailed design, and operational support).

With Ahiablame et al. (2012), it was evidenced that research grew on SUDS models' applicability for urban planning and policy-making. The authors promote the development of easy-to-use SUDS-DSS that effectively support decision makers and involve stakeholders, regulators, and policy-makers. As discussed previously, the attractiveness of SUDS for stormwater management is their ability to provide environmental benefits beyond the hydrological dimension (Caparrós-Martínez et al., 2020). Consequently, many SUDS-DSS are developed to help decision-makers incorporate additional criteria for placement and design.

There are informative reviews that tackled a broader perspective of modern stormwater management and UDMs. For example, Salvadore et al. (2015) stated that many modeling approaches target specific objectives and that the level of detail in representing physical processes is not consistent. Other examples are the works by Bach et al. (2014) and Maftuhah et al. (2018), who focused on integrated urban water systems modeling. While Bach et al. (2014) classified integrated UDMs at one of four degrees of integration, Maftuhah et al. (2018) performed a classification considering social aspects, institutional dynamics, technical innovation, and local contexts. These bigger-picture reviews focused on drainage systems integration and interaction with other urban systems rather than focusing exclusively on SUDS.

2.2. SUDS-DSS

Lerer et al. (2015) classified the SUDS-DSS according to the question it assists in answering: "How Much", "Where", and "Which". Torres et al. (2016) focused on the geographical distribution of SUDS-DSS and the stormwater dimensions considered (e.g., quantity, quality, ecosystem services). Both reviews found case study specificity and lack of flexibility were drawbacks of most SUDS-DSS. On the other hand, Zhang and Chui (2018) reviewed SUDS-DSS for spatial decision-making and concluded that its generic structure couples a detailed UDM and an optimization tool, which communicate iteratively until a stop criterion is met.

Other reviews on SUDS-DSS include the works by Zhou (2014) and Jayasooriya et al. (2020). Zhou (2014) made a comparison of modeling approaches and decision-aid tools for assessing SUDS alternatives. The author classified DSS into types of assessment tools: *i)* Economic, *ii)* Social, *iii)* Environmental, *iv)* Life-Cycle Assessment, and *v)* Health. Additionally, Zhou (2014) highlighted the importance of climate change and urbanization impacts in SUDS design, and stated that the future of the field are solutions that pursue a balance between the cost of investment and efficient performance (Zhou, 2014).

More recently, Jayasooriya et al. (2020) revisited the importance of balancing environmental and economic goals and showed that despite many studies have recognized stakeholders' involvement importance, none have extensively studied the relevancy of their participation. Finally, the authors listed SUDS implementation barriers, including land ownership and lack of interest in negotiating land areas for SUDS placement.

A seminal review that showed the importance of SUDS as part of the urban form is the work by Kuller et al. (2017). The authors proposed that SUDS location should not be considered a one-way process, but rather a two-sided problem. By defending that "*WSUD (SUDS) needs a place* as much as *a place needs a WSUD*", they proposed the first-of-a-kind suitability framework for SUDS planning. Kuller et al. (2017) went beyond in classifying PDSS into their approach towards SUDS, as a part of (a) the urban water cycle, (b) the urban form, and (c) the water governance.

Elliott and Trowsdale (2007), Ahiablame et al. (2012) and Kaykhosravi et al. (2018) extensively explored key aspects of SUDS modeling while Zhou (2014), Lerer et al. (2015), Torres et al. (2016), Zhang and Chui (2018), Jayasooriya et al. (2020) and Kuller et al. (2017) focused on SUDS-DSS taxonomy and good practices for SUDS-DSS development. This review does not attempt to cover in detail topics already discussed in previous reviews, but to build upon these recommendations to *quantitatively* analyze how modeling-based SUDS-DSS are being build and applied. For example, what questions are more frequently being answered with SUDS-DSS? How models are being used in practice (scale of the cases of study, time steps, modeling windows, calibration procedures, etc.). How SUDS-DSS development and usage are spread geographically?

3. Methodology

A systematic quantitative literature review locates, appraises, and synthesizes evidence of a specific issue limiting bias by deciding specific criteria to include and exclude studies (Petticrew, 2001). The two most widely used techniques to systematically collect publications were used: database and snowballing searches (Badampudi et al., 2015). In the first, a combination of keywords was used to search in different databases (Scopus, Web of Science -WOS, and Google Scholar); and in the latter, new pertinent papers were identified through the reference list (backward) and citations (forward) of a seed-set of influential papers (Jalali and Wohlin, 2012; Fontecha et al., 2021).

The review question addressed in this study was "*What is the role of SUDS models on the decision-making process?*" The objectives were to *i)* understand which SUDS models/software are more frequently used and how they are deployed for decision-making, *ii)* determine which questions the SUDS-DSS assist in answering (e.g., Which SUDS? Where? How many?), *iii)* analyze the DSS capabilities (e.g., optimization, stakeholders inclusion, uncertainty analysis).

Table 1 lists the search terms used in the databases. Papers whose title have at least three words in different keyword sets were included in the review. In this way, the inclusion of the key eligibility criteria was guaranteed: "decision/tool", "SUDS", "modeling", and "stormwater". The best effort was carried out to include a comprenhensive set of key search terms for the papers appraisal, but it is not guarantee that all terms have been included given the proliferation and volatility of local terminology. Similarly, it is acknowledged that much of the literature on SUDS-DSS applications is written in languages different to English, leaving out of the review applications of non-English-speaking countries.

Once a first potential seed-set of significant papers was gathered, the inclusion criteria of the search were that the paper must be *i)* useful for decision-making (i.e., a tool or case study, not a framework, review, or experience report), *ii)* specific for stormwater (although other urban water cycle elements may be present), and *iii)* include SUDS modeling. All papers that answer the review question and fulfill the inclusion criteria were collected. If the review question was not answered after reading the whole document or/and the inclusion criteria were not fulfilled, the paper was withdrawn. The data extracted from each paper was stored by filling fields in a review tool developed in Excel Visual Basic (VB) to ease the information withdrawal.

Table 1
Sets of keywords used for search. Papers whose title have at least three words in different keyword sets were considered for review.

Set 1	Set 2	Set 3	Set 4
Decision/tool keywords	SUDS keywords	Modeling keywords	Stormwater keywords
Assess*	Best management practice* (BMP)	Model*	Runoff
Effective*	Sustainable urban drainage systems (SUDS)	–	Storm*
Cost*	Green infrastructure (GI)	–	Urban
Heuristic*	Low impact development (LID)	–	Flood*
Management	Water sensitive urban design (WSUD)	–	Pluvial
Optim*	Nature based solutions	–	Rainfall
Objective*	Blue green systems	–	–
Planning	Sponge cities	–	–
Support*	Bioretention	–	–
Tool*	Infiltration	–	–
Decision*	Retention	–	–
–	Detention	–	–

*Any word containing the root-word signaled by * also makes part of the set. For example, "assess*" includes the words "assesing", "assessed", and "*objective" includes "multi-objective" or "multiobjective".

Approximately 270 papers were collected using the keywords in the search engines and subsequent snowball forward and backward procedures. Only 120 articles met the inclusion criteria and were studied in depth. The following subsections summarize the results extracted from these 120 manuscripts, but only some will be referenced as part of the bibliography of this document. For a complete list of the papers, please refer to Appendix 1.

4. Results and discussion

4.1. Categorization and historical overview

Two broad categories were identified in the preliminary assessment of the articles, each creating differentiated research outcomes: 1) a SUDS model or 2) a DSS relying on a SUDS model. There are inputs and outputs in both categories, but the first refers to isolated modeling generally to assess SUDS performance, while the latter couples the SUDS model with other modules to include costs, stakeholders, and secondary benefits, for example. Another essential difference is the nature of the outputs. While the stand-alone SUDS model delivers runoff series, pollutants reductions, or any other performance measure, the DSS provides answers to decision-makers questions (i.e., Which SUDS is recommended or the best? What locations are suitable/optimal for SUDS? Which SUDS meets the pollutant reduction target?). Fig. 1 illustrates the relation between the two article categories and shows the count for SUDS models (category 1) and SUDS-DSS (category 2), the number of articles that address the questions *Which?*, *Where?*, *How many?*, or assists the design of individual SUDS and trains. A single paper can assist in answering more than one question, so a manuscript can be counted several times in Fig. 1 (once per question assisted).

The total reviewed articles spanned the period comprised between 1997 and 2021. The number of articles had an increasing trend, starting with just a couple of publications per year, from 1997 to 2012, and then continued increasing from 2015 to 2020. The type of output was diverse (i.e., the question the tool assists in answering). Notice in Fig. 2(a), that SUDS-DSS commonly answered a single question, while since 2012, there is more output diversity; observe that since 2015, the outputs include 5 categories. These observations reflect both the diversification of SUDS-DSS users and the broadening of perspective from SUDS "units" to SUDS "systems".

SUDS trains were only included in DSS from 2015, which can be explained by the evolved capability of models to simulate flow among connected SUDS structures. Similarly, the "SUDS design" question predominated the early development of the tools, but with time this

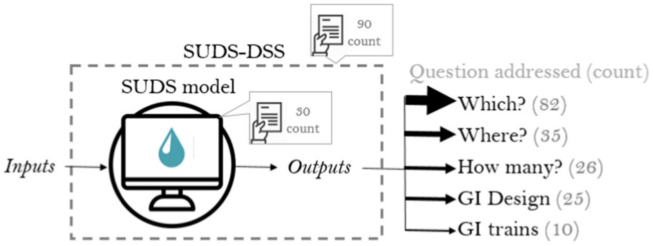
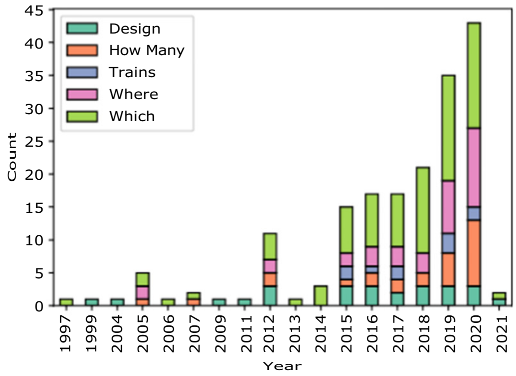
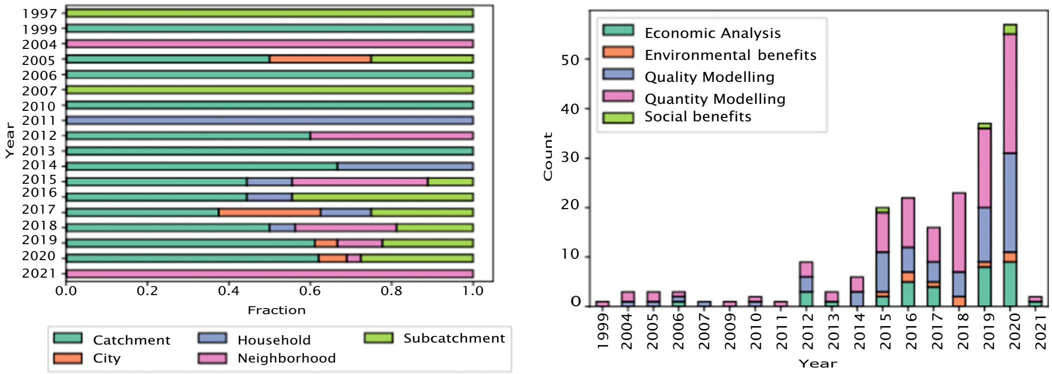


Fig. 1. SUDS models embedded in a SUDS Decision Support System (DSS).



(a) Question addressed over time (count).



(b) Spatial scale modeled over time (proportion)

(c) Dimensions over time (count)

Fig. 2. Research interest evolution over time. Categories in panel (a) defined as follows: Design (preliminary or detailed design), How Many (number of suitable/optimal structures), Trains (order of interconnected typologies), Where (spatial allocation of SUDS), Which (optimal/suitable SUDS typologies). Panel (c) shows the aspects (dimensions) considered for SUDS decision-making using a timeline. Observe that early years focused exclusively in quantity and quality modeling.

interest declined, giving space to other aspects, such as “which”, “where” or “how many” SUDS were suitable or optimal. This observation is tied to the change in the study scale interest and dimensions under study. Fig. 2(b) shows that larger study areas (i.e., subcatchment and catchment) gained attention over the last years in comparison with smaller scales, while the number of studies focusing on household and neighborhood scales has decreased over the last 6 years. The city-scale decision-making appeared for the first time in 2005 with the study developed by Makropoulos and Butler (2005), which used non-structural SUDS for potable water consumption reduction. This shift in the spatial scale can be explained by the exponential growth of computational capabilities (Burger et al., 2014), which allowed the modeling softwares to include bigger spatial scales over time without incurring in longer processing times. When appraising the papers, it was consistently found as a recommendation for future studies the development of SUDS-DSS capable of assisting decision-making at the city-scale (Makropoulos and Butler, 2005; Chen et al., 2017; Zubelzu et al., 2020). Furthermore, these articles pay special attention to the importance of including optimization and stakeholders bargaining models for decision-making at watershed and city-scales, and also make a special highlight on the importance of including economic, social and environmental dimensions. Similarly, Fig. 2(c) shows that the dimensions considered in decision-making diversified with time. In 2006, SUDS-DSS were already considering the economic aspect along with the runoff quantity and quality, while the environmental and social dimension appeared more recently and continue gaining importance (Alves et al., 2020).

4.2. Geographical spread

Fig. 3 shows that the majority of the studies were developed in Asia, with 58% of the articles, followed by North America (27%), Europe with (14%), Oceania with (6%) and South America (6%). The countries with the largest contributions were China, United States of America (USA), Iran and Australia, with 28%, 20%, 11%, and 5% respectively. The rest of the countries had a lower count (less than 3% from the total) and 36% when aggregated. Based on these numbers, it was possible to identify the urgent need for less-developed countries to increase the SUDS-DSS scientific productivity (Ferrans et al., 2018), considering there is a high potential for existing models to be implemented in these countries (McClymont et al., 2020). Developed countries can contribute to closing this gap through collaborative international projects (e.g. Resource Brandia, euPOLIS, euPOLIS, 2020, etc.), where other countries' expertise can accelerate their learning curve.

As expected, the question the tool assists in answering and the SUDS aspects considered in each country are diverse. While more-developed countries, like the USA, Canada, and Australia included more aspects besides runoff quantity and quality, less-developed countries focused almost exclusively on these two. An exception is China, with several included aspects, and Brazil, which put special attention to the social

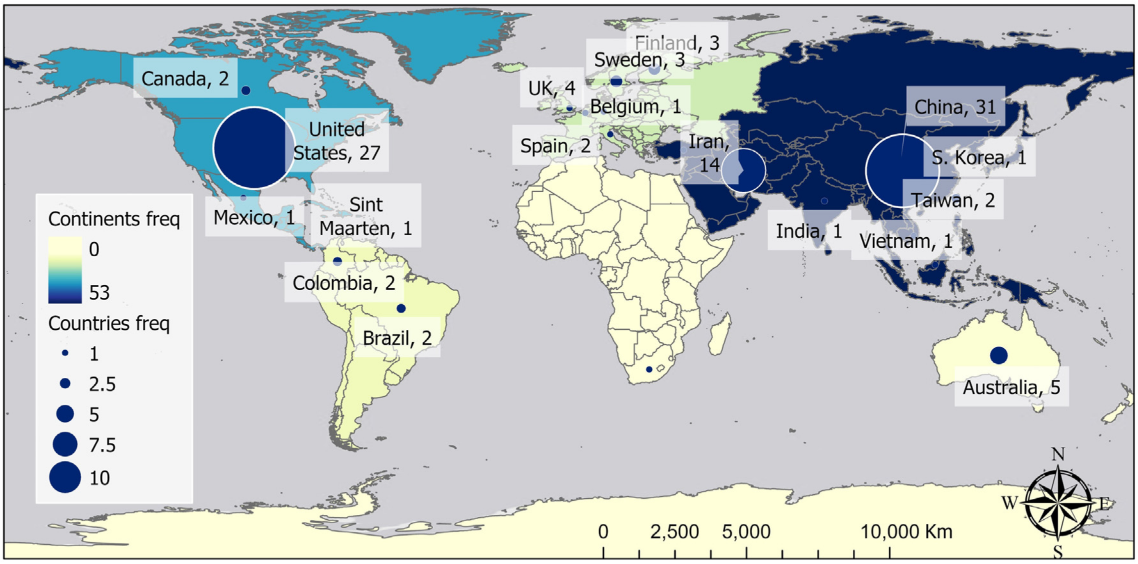


Fig. 3. Literature geographical distribution.

aspect. This finding is explained by the urgent challenges (e.g., urban flooding and receiving water bodies quality impairment) that are still to overcome in less-developed countries. Once again, these results reinforce the need for developed countries to generate collaborative environments in which there is room to share experiences and gather information.

4.3. Case study scale, typologies, spatial and temporal modeling resolution

In recent years, there has been a rapid development of computational capabilities, which allowed the representation of detailed processes at larger scales. For SUDS models, these advances permitted refinements in process representation and finer spatial and temporal resolution. Previously, it was shown that the spatial scale focus has shifted in time, partially because the modeling capabilities have allowed the inclusion of more detail and more complexity, but also because decision-makers needs have evolved. Every day, decision-makers rely more upon software to make decisions, while expert judgment has been gradually replaced by systemic procedures that reduce the amount of bias and manual work, generally speeding up the process (Hattab et al., 2020).

From the appraised papers, 55% used a catchment-scale, 22% a subcatchment-scale, followed by neighborhood-, household-, and city-scale, with 12%, 6%, and 5%, respectively. Fig. 4(a) shows that the study area has a range of 6 orders of magnitude, with a minimum value of 0.01 hectares (ha), a maximum value of 650,000 ha, and a standard deviation of 80,000 ha. The catchment-scale has the largest range and number of outliers (comprising 6 orders of magnitude). Fig. 4(a) shows that the area is not determinant of the spatial unit of analysis, since the same study area (e.g., 100 ha) can be classified into city, catchment, sub-catchment, or neighborhood. The smallest scale found was the household, with a mean area of 0.1 ha and the largest was the city-scale, with a mean of 1000 ha.

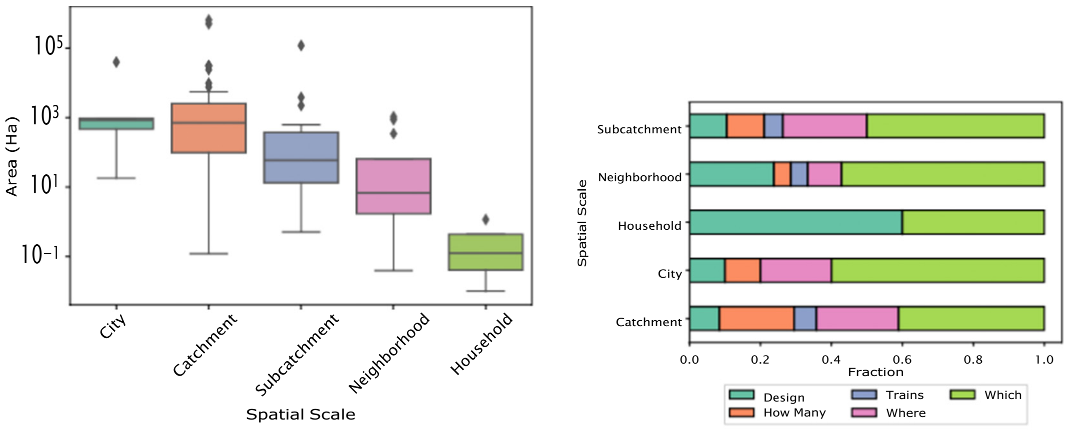
Fig. 4(b) shows that most DSS answered the question "Which SUDS", disregarding the scale. In general, all questions can be answered at a neighborhood-scale or bigger, while for the household-scale, the only questions addressed were "Design" (detailed dimensioning and location) and "Which SUDS". The household-scale has a larger proportion of "Design", which was expected considering that smaller areas makes it more attainable to reach a higher level of detail.

Fig. 4(c) shows the frequency of the most common SUDS typologies found in the review. Curiously, the most used typology is one that does not use green areas directly (permeable pavements), followed by grassed swales, bio-retention cells, and rain barrels. In total, nearly 30 articles included SUDS in their models, but do not specify which type (e.g. Jia et al., 2012; Raei et al., 2019; Rodríguez-Sinobas et al., 2018). It was found that all typologies had similar proportions with respect to the question they assist in answering (Fig. 4(c)), showing that the tools do not differentially address the questions depending on the typologies they include. Fig. 4(e) shows that (as expected) some of the typologies are more frequently used in large scales: constructed wetlands, detention and infiltration basins, dry detention, and bio-retention ponds; while some other typologies have more flexibility to be used in large, medium, and small scales: storage tanks, rain barrels, infiltration trenches, and grassed swales. Specifically for the household-scale, the most popular typologies were green roofs, rain gardens, permeable pavements, and bio-retention strategies. Contrary to the scale, the land use (e.g., commercial, industrial, residential, recreational open space) showed no trends regarding typologies; all typologies were present in similar proportion. Only 4% of the articles (5 papers) allowed the inclusion of SUDS trains (typologies sequentially interconnected) despite the literature recommends trains to increase the structures' efficiency in managing runoff (e.g., Bastien et al., 2010). Those articles that did consider SUDS trains, selected the train components based on experts knowledge and the reported efficiency of individual SUDS to control target pollutants (e.g., Xu et al., 2017; Jayasooriya et al., 2016; Zafra et al., 2017), instead of following an standard procedure.

The time step used for the calculations showed a high variability among the different studies, ranging from 1 min to 2 h. Fig. 4(d) shows a scatter plot of the size of the study area and the modeling time step, using color codes for the softwares. The outlier in Fig. 4(d) (30 days time step) corresponds to Chang et al. (2011), who performed an own-developed model based on water balance equations with a simulation period of 50 years.

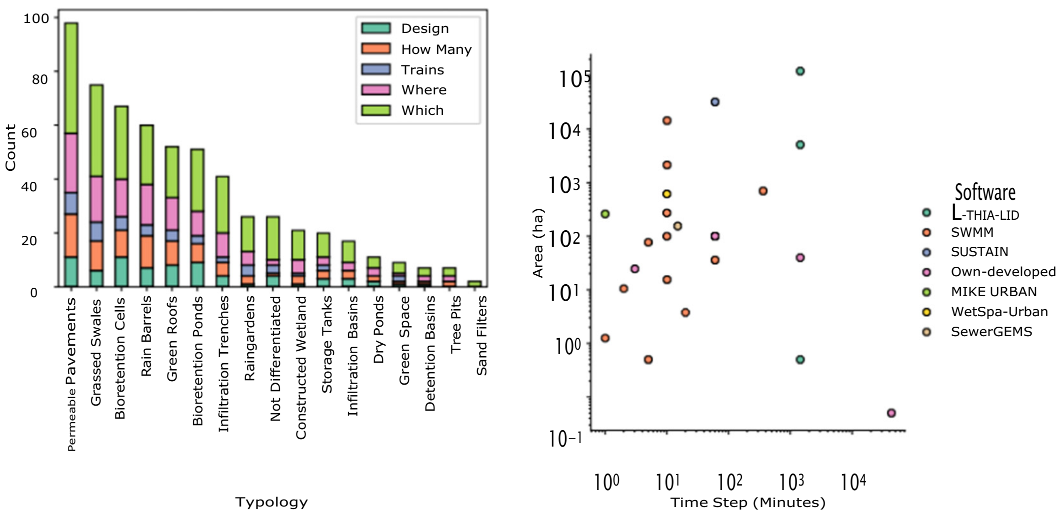
Disregarding the software, there is no evident area-time trend in Fig. 4(d). This can be attributed to differences in the models complexity even when the same software is used. The figure shows that the SWMM software is scattered along the two axis, as opposed to other softwares that are clustered in areas of the plot (e.g. L-THIA-LID is found in large areas and large time steps only).

A previous study, Salvadore et al. (2015) reviewed 100 UDMs to compare the space-temporal resolutions. The authors identified two clusters: catchment-scale applications (larger temporal resolutions) and small-size cases of study. The authors found the finest temporal



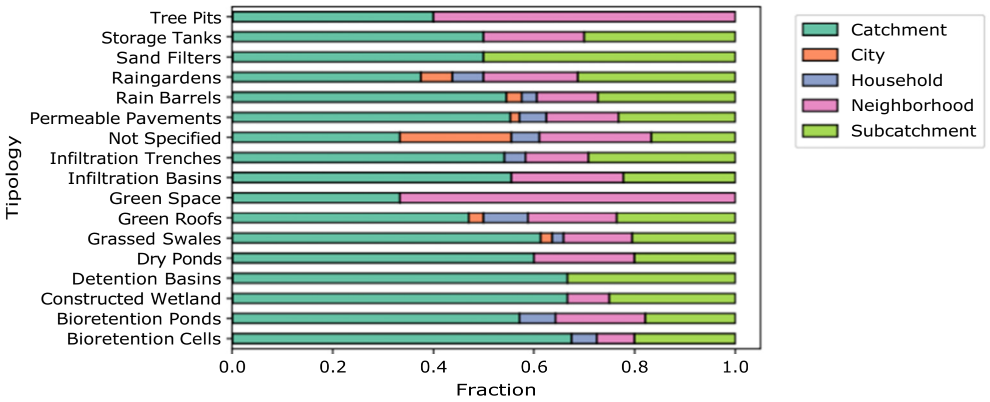
(a) Area (ha) vs. spatial scale

(b) Spatial scale vs. question addressed



(c) SUDS typologies frequency

(d) Area (ha) vs. modeling time step (min) color-coded by Software



(e) Spatial scale per SUDS typology

Fig. 4. Case study (land use and typologies) and temporal resolutions per spatial scale. Categories in panels (b, c) defined as follows: Design (preliminary or detailed design), How Many (number of suitable/optimal structures), Trains (order of interconnected typologies), Where (spatial allocation of SUDS), Which (optimal/suitable SUDS typologies).

and spatial resolutions to be 1 s and 10 m^2, but these UDMs did not have the capabilities of modeling SUDS. When comparing our results to Salvadore et al. (2015), it was evidenced that category 2 articles (studies developing/applying a DSS) were only being implemented in what these authors call "catchment-scale applications," meaning that SUDS-DSS are still in the larger scale of urban drainage modeling in terms of temporal and spatial modeling granularity. As will be discussed in Section 4.4, the decision on the temporal and spatial resolution is also related to SUDS model capabilities and the selection of event-based or continuous simulation.

4.4. Modeling methodologies: software and events selection

The Storm Water Management Model (SWMM) (Rossman, 2010) developed by the US Environmental Protection Agency (EPA) was the most frequently used in the papers appraised (46% of the studies). The second most common software were own-developed non-commercial models, with 16% of the studies, followed by L-THIA-LID (Purdue-University, 2016) (4%) and SUSTAIN (Shoemaker et al., 2009) (2%). The rest of the studies, which represent the 20% of the total articles, used other software (e.g., MIKE URBAN (DHI, 2008), MUSIC (eWater, 2020), SUDSLOC (Viavattene et al., 2011), GISP (Meerow and Newell, 2017), ReVISIONS (Hargreaves et al., 2019), SSANTO (Kuller et al., 2019), UrbanBEATS (Bach et al., 2013), WSCT (Zhang et al., 2020), etc.) each representing less than 2% of the total number of publications. SWMM, MIKE URBAN, and L-THIA-LID were the only software capable of modeling SUDS trains (see Fig. 5(a)). SWMM and the own-developed models were used in similar proportions to address all questions, while the other softwares were used to tackle more targeted questions.

The most basic approaches used in own-developed models consisted of water balance calculations, statistical analyses, or GIS-based tools (Wang and Wang, 2018; Zhen et al., 2006; Lee et al., 2010; Yang and Best, 2015). Others opted for numeric algorithms to solve hydrological and hydraulic differential equations (e.g., Beck et al., 2017; Perez-Pedini et al., 2005; Gülbaz and Kazezyılmaz-Alhan, 2017; Wright et al., 2018). Finally, some studies relied on linear programming to embed the hydrological equations in the optimization model. This last approach requires a simplified representation of the processes occurring in the SUDS structure. For example, Sebti et al. (2016) estimated SUDS impact using a variant of the Improved Rational Hydrograph method (IRH), and Chang et al. (2011) and Torres et al. (2020) used water balance equations. Regardless of the complexity in these studies, it was identified that the necessity of developing own models and tools is driven by the lack of flexibility of the available software, in particular when data is limited and its format incompatible with the required inputs.

Regarding the type of temporal simulation, 58% of the studies used event-based simulations, 28% used continuous simulation, and 14% performed a comparison analysis using both approximations. Fig. 5 (b) shows the proportion of continuous/event-based approaches for each spatial scale; as the spatial scale decreases, the proportion of studies performing continuous simulation grows. Disregarding whether event-based or continuous, 88% of the studies appraised used a deterministic approach, 9% a stochastic approach, 3% did a comparative analysis of both approaches. These results evidence that the computational resources needed to perform time- and resource-consuming simulations (continuous and stochastic approaches) are available in seldom cases.

Fig. 5(c) and (d) presents box-plots with the number of events (event-based) or the number of years (continuous-simulation) analyzed for each DSS question addressed. For event-based, the number of events ranged between 1 and 10, with outliers up to 20 and a maximum value of 53. It was found that 56% of the studies used design rainfall events with return periods (ranging from 5 to 50 years), 37% used representative historical rainfall events, 6% employed synthetically generated events, and only 3% based their analyses on forecasted events. On the other hand, Fig. 5(d) shows that the majority of the studies using continuous-simulation analyzed from 1 to 25 years. Fig. 5(e) presents a stacked bar plot differentiating the type of simulation performed per question addressed. The "Design tools" used continuous simulation in a higher proportion than the rest of the categories, with 46% of the studies using a continuous simulation. The myriad of modeling settings and precipitation events selection evidence that there is still no consensus on good practices for modeling-based SUDS decision-making.

4.5. Categories, processes modeled, and stakeholders

Table 2 shows that 82% of the studies included water quantity, 53% water quality, 28% economic analysis, and only 8% and 3% included environmental and social benefits. Within the environmental aspects, the most common are air quality and energy savings (e.g., Chang et al., 2011) and in the social aspect the recreation, acceptability, and amenity (e.g., Jia et al., 2012). Table 3 shows the processes more frequently modeled in the quantity and quality dimensions besides the rainfall-runoff process (which was included in all the articles). Not surprisingly, the processes more frequently modeled are infiltration and evapotranspiration since these two are responsible for the runoff volume reduction and the peak flow flattening. Of secondary importance were the groundwater flow and sedimentation processes. The first is frequently neglected, despite its proven importance in SUDS efficiency (Zhen et al., 2004; Xu et al., 2020b), because of the lack of local data, while the latter is less included in proportion to other processes given that it is irrelevant in runoff quantity assessments.

The majority of the SUDS-DSS appraised had scenario modeling (65%) (i.e., comparing SUDS spatial configurations using performance metrics). However, most of the studies did not consider climate change nor urbanization trends projections (only 12% had this capability). It is highly recommended to re-direct efforts to include future projections in SUDS-DSS since it is expected that climate change and urbanization rates will play a major role in future urban hydrology, particularly in large urban centers (Xu et al., 2020a; Saldarriaga et al., 2020).

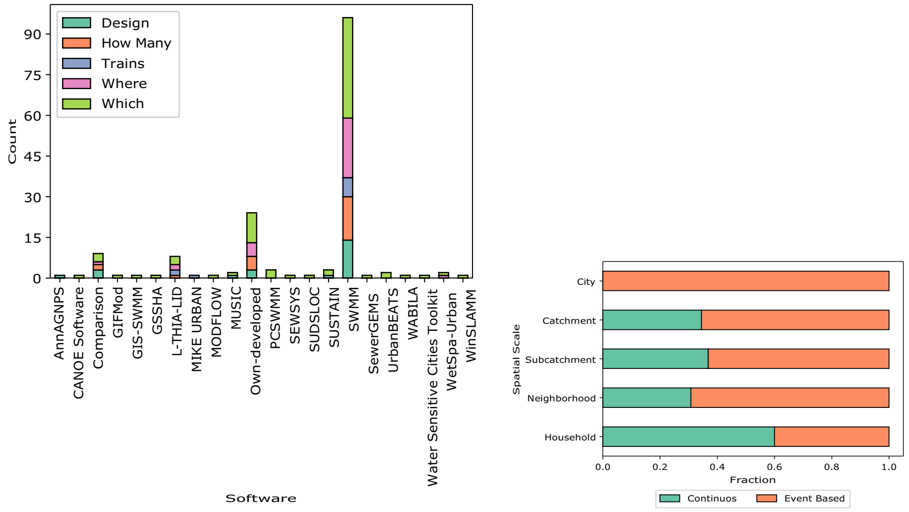
Previous works identified that a key aspect to guarantee a successful decision-making process is the early inclusion of stakeholders perspectives and preferences (e.g., Jayasooriya et al., 2020; Ahiablame et al., 2012; Torres et al., 2020). However, it was found that 87% of the studies do not include stakeholders. Table 4 shows that from the 13% (16 articles out of the 120 reviewed) that did consider one or several stakeholders, the most common are local authorities (31%), utilities (13%), neighbors (13%), politicians (6%), and Environmental Agencies (EA) (6%); 31% of the articles include at least one stakeholder, but do not state which one. From the papers reviewed, none considered the opinion/preferences of the community members, who ultimately are impacted by the decisions. It is highly recommendable that the stakeholders' positions are included for decision-making, particularly the communities.

4.6. DSS inputs, outputs and general framework

4.6.1. Inputs and outputs

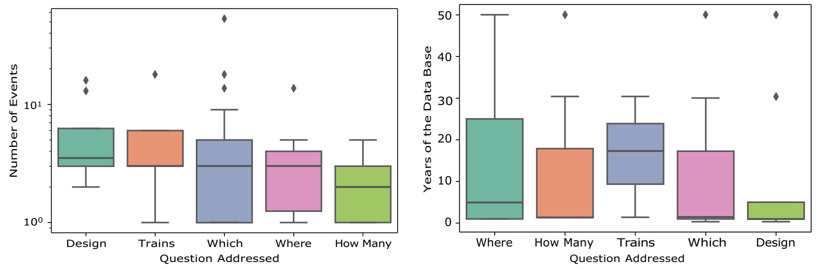
This subsection is dedicated to the articles in category 2, DSS relying on a SUDS model and including additional dimensions besides the hydrological. A total of 83 articles lie in this category, compiling 4 types of input variables: hydro-meteorological (e.g., precipitation, runoff, temperature or evapotranspiration), study-site (e.g., land uses, impermeability, slope, infiltration rate, presence of conventional drainage systems), water quality (e.g., loads of pollutants like nutrients, organic matter, solids, and heavy metals), and economic (e.g., SUDS and land costs and monetary quantification of environmental services).

The most frequent input variable to SUDS-DSS are the hydro-meteorological variables, with a percentage of inclusion between 40 and 60%. The study site features also presented high percentages of inclusion (30-50%). The runoff quality (build-up and wash-off



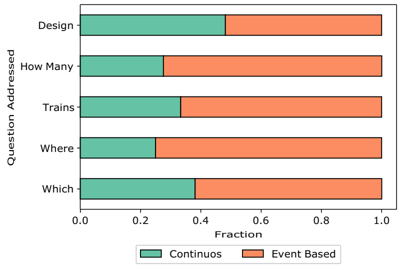
(a) Question addressed among the different software

(b) Temporal simulation among the different spatial scales



(c) Number of events simulated for each questions addressed

(d) Years simulated for each questions addressed.



(e) Type of simulation for the different questions addressed.

Fig. 5. Software, simulation, and temporal resolution for each question addressed.

parameters) variables had a lower frequency: 25%, 13%, 12% and 2% for total suspended solids, total phosphorus, total nitrogen, and heavy metals, respectively. Finally, among the economic input variables, SUDS costs were included in 40% of the studies, but other economic indicators (e.g., economic return, net present value, etc.) exhibit percentages of inclusion lower than 2%.

Regarding the evolution over time of the input variables, it was noticed that from 2000 to 2010 the most frequently included category was the study site aspects, with some reduced usage of economic indicators. From 2010 forward, the water quality inputs started to be included, showing an increasing trend over the years. The economic aspects also showed an increasing trend over time. The hydro-meteorological variables showed a steady trend of inclusion over time. These trends reflect both the increased data availability and the driving interest on SUDS from a more holistic perspective.

Table 2
Percentage of modeled dimensions.

Dimension	Percentage (%)
Quantity modeling	82
Quality modeling	53
Economic analysis	28
Environmental benefits	8
Social benefits	3

Percentage calculated from the total number of articles assessed.

Table 4
Percentage of stakeholders inclusion.

Stakeholder	Percentage (%)
Not specified	31
Local authorities	31
Utilities	13
Neighbors	13
Politicians	6
Environmental Agencies (EA)	6

Percentages calculated from the number of articles that include stakeholders.

4.6.2. SUDS-DSS framework

Most of the reviewed articles followed a two-stage structure. First, an evaluation of topographic, hydrologic and hydraulic parameters to pre-select SUDS alternatives. And second, the SUDS selection from the pre-selected options based on predefined criteria (e.g., Zhen et al., 2004; Scholz, 2007). Some of the most common tools/software used to perform these two-steps include GIS-based models (e.g., Makropoulos and Butler, 2005), Excel spreadsheets, Matlab and Simulink (MathWorks, 2018) (e.g., Makropoulos et al., 2008), optimization search algorithms (e.g., Lee et al., 2012), fuzzy sets (method that evaluates the grade of membership of the elements to given sets (e.g., Zimmermann, 2011), and multi-criteria evaluations (e.g., Makropoulos et al., 1999).

Despite the variability identified in SUDS-DSS, it is possible to extract some "building blocks" typically interconnected sequentially or iteratively. A DSS can be represented as a black box that receives data with particular spatio-temporal resolution using previously loaded SUDS databases (such as estimated costs and efficiencies) and passes the data through a set of "sub-tools" that reduce the number of possible solutions until a unique (or a set) of suggested solution(s) is provided. Some of the "sub-tools" found in the review are: weighting tools that assign importance to objectives or benefits provided by SUDS, screening tools that eliminate from the analysis the less attractive SUDS options, sustainability evaluation tools that score the proposed solution, stakeholder engagement tools that include opinions and engage involved agents, GIS to carry out spatial analyses, urban drainage modeling (UDM), feasibility analyses, optimization, and life-cost analysis.

SUDS-DSS can be further classified by the format in which the results are presented, which are intertwined with the method selected to suggest a (or several) SUDS configuration(s). On one hand, studies performing simulations of a few SUDS configurations of interest (resulting from feasibility analyses or expert judgment) deliver the results by presenting a ranking or detailed comparison of the best performing solutions. On the other hand, simulation-optimization approaches present results in the form of Pareto fronts (for multi-objective optimization) and/or a single best solution when only one objective is considered. This review gathered 90 SUDS-DSS, from which 30% correspond to the first classification and 70% to the latter, showing that current research attention is mostly directed towards the integration of optimization approaches to determine SUDS selection, location, and design.

4.6.3. SUDS-DSS involving optimization

These SUDS-DSS counted on a calculation engine to determine the hydrological performance of a proposed SUDS configuration and an optimization component (Zhang and Chui, 2018). The calculation engine is frequently a UDM with SUDS modeling capabilities, but some SUDS-DSS replace the UDM with simplified approaches like look-up-tables or empirical equations to assess the goodness of a solution. The replacement of the UDM is generally undesired since it is the best available representation of the system and will yield the most accurate estimation of the SUDS performance. Nonetheless, integrating UDM simulations in the SUDS-DSS is computationally expensive, in particular for long-term continuous simulations, which may hinder the overall effectiveness of the solution process.

Table 3
Percentage of modeled processes.

Process	Percentage (%)
Runoff quantity	100
Runoff quality	43
Cost analysis	32
Infiltration	27
Evaporation	14
Groundwater flow	6
Sedimentation	2
Climate change scenarios	0.1

Percentage calculated from the total number of articles assessed.

In this review, three structures for coupling the optimizer and the calculation engine were found. The most common is the use of UDMs as calculation engines and coupling them with metaheuristics such as evolutionary algorithms to find optimized solutions (Lee et al., 2012; Macro et al., 2019; Saldarriaga et al., 2020). Metaheuristics iteratively search for new potential solutions (i.e., SUDS configurations) by applying small local changes to the parameters until no further improvements can be made. The generic framework is shown in Fig. 6. Part A of the optimization tool generates and updates the parameters, and part B evaluates if the stop criteria is reached. The process starts with an "starting solution", usually defined by the modeler, which contains proposed SUDS sites, typologies, and sizes. The input parameters are fed to run the UDM, and the simulated results are transferred to the optimization tool (part A), which defines whether the proposed solution is satisfactory. If it is not, the evolutionary algorithm generates new parameters (representing an alternative SUDS configuration) to be fed back into the UDM. This cycle is repeated until a satisfactory solution is found.

Since the loop is repeated multiple times to explore different regions of the solution space (i.e., all possible SUDS configurations), it is desirable to run as many iterations as possible for this framework to be effective. However, considering that testing each new solution requires running a new simulation of the UDM, solving the problem using these methods often requires several days or even weeks to be completed (Zhang and Chui, 2018; Wang and Wang, 2018).

As discussed previously, SUDS planning requires the involvement of the stakeholders during multiple stages of the process to evaluate critical aspects such as runoff quantification (quantity and quality), social and environmental benefits of the SUDS installations. For this reason, requiring long-running times to identify good solutions may render this type of approach unpractical in collaborative environments. This is particularly critical in cases where the stakeholders and/or decision-makers require to evaluate the SUDS performance under different system settings and weather conditions; or when there is a need for comparing alternative solutions to identify potential trade-offs. In such cases, performing extensive runs each time there is a new SUDS configuration, as shown in Fig. 6, is not appropriate.

Two alternative approaches were found which reduced the execution time while attempting to maintain a good calculation engine accuracy. Fig. 7 shows the three ways of connecting the UDM with the optimizer found in this review. The previously mentioned UDM-and-heuristic approach is represented with a dashed line. A second alternative is the use of classical optimization techniques like linear, integer, and dynamic programming by modeling directly the dynamics of the systems as components of mathematical formulations (e.g., Sample

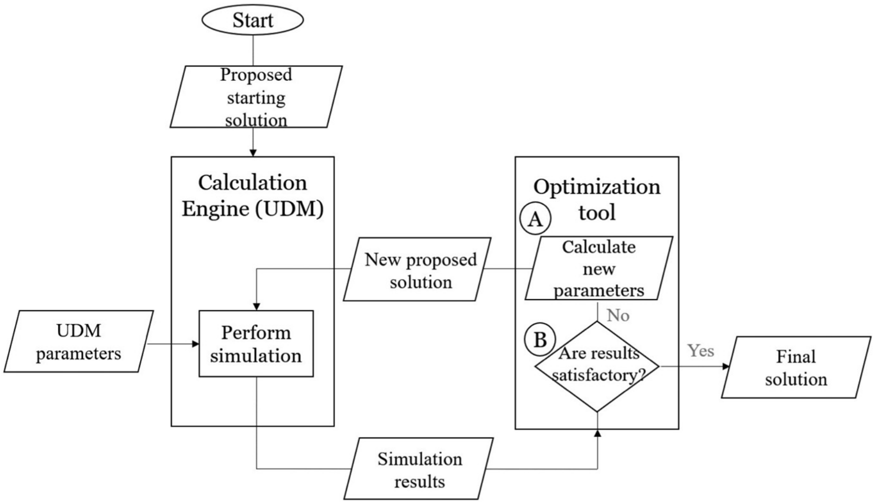


Fig. 6. DSS loop - UDM and heuristic optimization.

et al., 2001; Sebti et al., 2016; Torres et al., 2020; Limbrunner et al., 2013) (see the dotted lines in Fig. 7). The third approach (represented with a continuous line in Fig. 7) is the build up of a surrogated model from repeated executions of the UDM to completely replace the UDM with a faster-converging simplified version (e.g., Raei et al., 2019; Torres et al., 2021; Shojaeizadeh et al., 2021). A key advantage of second and third approaches is that they can often be solved significantly faster than the time it takes to complete even a single run of a UDM simulation. The downside however is that the accuracy of these formulations is often limited when compared to the UDM simulations, as they can only capture a simplified version of the complex hydrological dynamics of the system. Selecting the appropriate approach for SUDS planning comes with a critical trade-off between the desired precision and the speed and flexibility.

5. Conclusions and perspectives

The decisions that the SUDS-DSS assist are classified into 5 groups: "Where", "How Many", "Which", "Design" or "Trains". Starting from this fact, a quantitative and critical review was developed, regarding the current state of the art of how models are being used to address each question. Models are the mainstay of decision-making since they allow evaluating a diversity of potential solutions without incurring expenses. Hence, the selection of the SUDS model and the DSS should meticulously consider, among others, the modeling software, spatial and temporal resolution, dimensions and processes modeled, and potential SUDS typologies depending on the land use and the spatial scale.

There has been a wide development of SUDS models, aiming to tackle hydrological and hydraulic aspects. Literature in SUDS models and SUDS-DSS is clustered in a few countries, which does not surprisingly correspond to those with a larger history and investments in SUDS implementation. However, it is still necessary to develop a common framework to select SUDS models and tools to ultimately assist decision-making. This framework should include aspects that have not been rigorously studied, such as environmental and social aspects (e.g., public perceptions (Rodriguez-Valencia et al., 2021; Vallejo-Borda et al., 2020)), SUDS trains performance, models uncertainty analysis for stochastic approximations, urbanization and climate change scenarios, and stakeholders inputs. In particular, integrated urban drainage models would benefit from a pragmatic representation of SUDS and its effect in the urban water system (e.g., sedimentation load changes and risk of sediment-relament failures in the sewer system (Fontecha et al., 2020, 2021; Montes et al., 2021)). As pointed out by Bach et al. (2014) and Maftuhah et al. (2018), parsimonious, comprehensive, and high-degree-of-integration models are a mainstay to transitioning towards more resilient urban centers.

There is a large number and great variability of SUDS-DSS. It is hypothesized that the main cause of these tools' diversity is the lack of

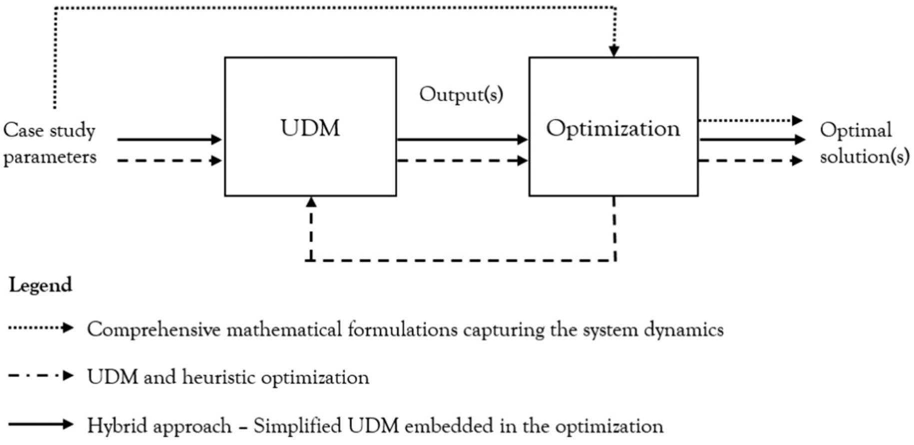


Fig. 7. Three different approaches to couple UDMs and optimization to build SUDS-DSS.

transferability to other study cases. While SUDS-DSS have diverse building blocks and structures, they frequently have a standardized iterative configuration. Most reviewed works use evolutionary algorithms and hydraulic drainage models. This trend is partially explained by the current advances in computational power -more cores and threats that increase the capacity of performing a large number of simulations even using complex urban drainage models. However, it should be mentioned that remarkable improvements have been achieved in the exact optimization programming solvers (Bixby, 2012) during the last decades, opening the possibility of incorporating these powerful techniques to the SUDS selection and design problem (e.g., Torres et al., 2020).

The computational time and power required by the SUDS-DSS are closely related to the spatial discretization of the UDM. The spatial resolution of obtained results is settled upon the selection of the UDM. Hence it is important to keep in mind the trade-off between computational demand and the desired results spatial resolution. For example, a distributed model will specify the cells in the mesh (or grid) in which the SUDS should be installed. The mesh resolution requires special consideration when implementing a distributed model: increasing the mesh resolution intensifies the computation requirements and increases the time required to reach a solution.

The role that the increasing data availability will play in urban drainage model development is of relevancy for SUDS-DSS development. Studies point out that more data-driven novel methodologies for water management are becoming available, increasing the efficiency and functionality of existing models (Eggimann et al., 2017). Despite there is a trade-off between the cost and benefits provided, it is expected that increased data availability will provide diverse and better-spatially distributed information useful for decision-making. Data availability increases the efficiency and accuracy in urban water areas such as real-time control, early pollutant detection, and early-flood warning systems (Eggimann et al., 2017). SUDS also benefit from increased data availability, as have been proved by SUDS smart technologies such as sensing, controls, communications, and computing (Meng and Hsu, 2019).

SUDS-DSS will have a critical role in the future in allowing the incorporation of a new paradigm in which simplicity and stationarity are no longer assumed. These tools must include the complexity and future changes and be capable of analyzing hybrid systems (centralized/decentralized) to better address future challenges in cities. SUDS-DSS conception and development have necessarily to be permeated with current urban water innovations and respond adaptively to the emergent needs of our society (Franco-Torres et al., 2020).

In particular, SUDS-DSS need to be equipped for modeling and predicting the impact of water governance, management, and infrastructure swifts (i.e., the current trend towards participatory approaches, circular systems, and ecosystem services, respectively) (Franco-Torres et al., 2020). These new paradigms will undoubtedly impact SUDS decision-making and need to be incorporated to provide concrete guidance that truly reflects up-to-date societal priorities. To achieve this, SUDS-DSS require an interdisciplinary team of practitioners and scholars, which can provide the state-of-art in the different SUDS dimensions (i.e., economic, environmental, social).

To conclude, SUDS-DSS have the potential to serve as meeting spaces between different actors so that they abridge the gap between SUDS as "emerging practices" to be fully appropriated in practice (Wong et al., 2020). Such transition is needed to different extents in both more developed and less-developed countries. One suggestion to ease such transition is to make SUDS-DSS publicly available and to create a community of scholars and practitioners that more actively share experiences, successes and failures, and historical monitoring data regarding SUDS planning, deployment, and performance in accessible databases. Online database repositories such as The International BMP DataBase (Clary et al., 2020) have already begun data compilation and sharing but are still in need of less-developed countries' participation to fill the gaps of non-reported globe locations (Clary et al., 2020).

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.150447.

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