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Multifunctional retention pond for stormwater management: A decision-support model using Analytical Network Process (ANP) and Global Sensitivity Analysis (GSA)

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A R T I C L E I N F O

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A B S T R A C T

The ever-growing impervious and contaminated surfaces in urban areas result in severe floods, degraded waterways, and stormwater. Water-sensitive strategies and water-sensitive urban design and planning can manage stormwaters through multifunctional retention ponds; however, urban professionals seek an assessment model that evaluates and quantifies the performance of multifunctional retention ponds on stormwater management. This research has developed the Urban Retention Pond Index (URPI) assessment model, a universal multi-layered decision-support tool that constitutes three criteria (C1. Geotechnical functions, C2. Water quality and treatment, and C3. Structural and physical landscaping functions), and twenty sub-criteria. Employing Analytical Network Process (ANP) has determined the weights of indicators, which formulated the URPI index. The ANP result indicated soil investigation ($W_{C1.1} = 0.170$), soil retention ($W_{C2.1} = 0.156$), and infiltration rate ($W_{C1.2} = 0.108$) could extensively impact to the performance of multifunctional retention ponds. To validate the model, it was implemented in the Boneyard Creek retention pond using the Weighted Sum Method. The assessment analysis assigned grade A to this site, meaning, Boneyard Creek pond manages stormwater mainly through Soils Investigation ($W_{C1.1} = 0.150$), Soil retention ($W_{C2.1} = 0.144$), and Infiltration Rate ($W_{C1.2} = 0.091$). Furthermore, Global Sensitivity Analysis (GSA) was conducted to analyze the URPI model's input–output uncertainty and effect of variations, through a series of methods; Cumulative Distribution Functions (CDF), Probability Density Function (PDF), Scatterplot-Histogram Plot, Box-Whisker Plot, and Parallel Coordination. GSA could support the dominant controls and robust decision-making of the URPI model. GSA results determined that model outputs are empirically distributed with minor regression variance to the theoretical distribution. Most of the outputs fall within the intervals where the mean and median are more significant than the mode. The multiple regression analysis has shown that the three criteria are positively and linearly correlated. The Box-Whisker plots revealed the behaviors of the four mentioned measures are similar. Notably, the Box-Whisker standard error plots indicated the minor errors of the outputs in the whole network of the URPI model. Meanwhile, the Parallel Coordination indicated the largest centrality degrees by the spillway and landscape habitat retention sub-criteria and the largest Eigenvector centralities by soil retention and soil investigation sub-criteria in the whole network.

1. Introduction

The world faces a water crisis based on the World Water Council report, not because of the amount of water, but due to its management that is particularly affected severely by the environment and population (UN-Water, 2016). Water health management and urban water management play critical roles in providing quality water resources and protecting urban population health worldwide; for instance, the Healthy

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Cities movement initiated by Canada in 1984 and approved by WHO (World Health Organization), which is promoting the water health management worldwide since 1986 (Ashton et al., 1986). Also, the Sustainable Development Goals (SDGs) were released by the United Nations over the local and global dynamics of water usage and water availability (Bhaduri et al., 2016). In particular, SDG112 and SDG61emphesize sustainable urban water management for resilient cities (Pusalkar et al., 2020). Integrated Urban Water Management (IUWM) supports the drinking water planning and implicates sustainable development goals (SDGs) (including waste management, nutrient losses, Greenhouse Gas emission reduction, energy generation, life cycle costs, etc.). Purposefully, a new paradigm of water management infrastructures and policies was developed as the Urban Water Strategies, motivating a broader collaboration of stakeholders, citizenship, and governance. The urban water strategies can manage climate variability, population growth challenges, and uncertainties through technocratic and engineering solutions while maintaining ecological and social values (Shafaghat et al., 2017; Buurman and Padawangi, 2018; Kösters et al., 2020). On the other hand, these strategies can significantly control climate change, impacting the cities by natural disasters, such as floods, typhoons, storms, heatwaves, or through gradual ruins, such as weather changes, microclimate change, temperature increase, sea-level rise, and so on.

In the past few decades, different terms have been used for water management, such as water-sensitive city, Water Sensitive Urban Design (WSUD), Sustainable Urban Drainage Systems (SUDS), Green Infrastructure (GI), Low Impact Development (LID), and Stormwater Best Management Practices (BMPs) (Lerer et al., 2015). The water-sensitive city is under the umbrella of sustainable urban water management and urban water security. The water-sensitive city is also dominant in Climate Sensitive Urban Design (CSUD, known as Climate Responsive Design or Bio-climatic Design-CRDBD). CSUD is a bio-climatic design seizing harmony in nature and a mechanism for the human thermal comfort in urban and building scales. The water sensitive city has three key drivers (Wong and Brown, 2009); including 1) developing varieties of water sources development in which the city resilience is promoted through different and independent water recourses while minimizing water loss, such as recycled wastewater/stormwater and rainwater harvesting, 2) developing urban ecosystem services in which the water resilience of the city needs specific rules and regulations, technologies and urban design standards for using the green infrastructure properly and 3) strengthening the institutional capacities to enable the cities for the transition of water-sensitive urban development through a new culture across multiple parties, which can guarantee the successful implementation of new socially-wised technologies, strategies, and policies for the environment and ecosystem preservation. Meanwhile, the natural hydrological recovery problem is deemed to the regional performance through the concepts of Water Sensitive Urban Design (WSUD) (Melbourne Water Authority, 2017; U.S. National Research Council, 2009), Low-Impact Urban Design and Development (LIUDD) (Ignatieva et al., 2008). These concepts are practically implemented in several large-scale urban planning projects, say the City Council of Oakland and Canada, establishing water-saving urban design (Wellington City Council, 2020). Also, De Urbanisten-Turenscape Landscape Architecture has used these concepts for water and green systems creation (Kazantsev et al., 2020).

In particular, incorporating WSUD provides the water-sensitive streetscapes, water visible within the urban landscape, and urban forms, which consequently supports the sustainable urban environment (Smith et al., 2020). WSUD is also commonly known as Sustainable Urban Drainage Systems (SUDS) in UK and Low Impact Development (LID) in the USA. The mechanism of WSUD supports the Climate Sensitive Urban Design (CSUD) by promoting local-scale and microclimate, surface cooling, and evapotranspiration while limiting Urbanheat Island (UHI) intensities (Coutts et al., 2013; Taslim et al., 2015). WSUD is also a paradigm that focuses on providing innovative, informative, and engaging landscape design solutions within communities and neighborhoods (Wong, 2006) that is increasingly used in both urban renewal developments and new urban greenfield development. Specifically, WSUD copes with stormwater management through treatment, collection, and storage of stormwater via wetlands, porous pavements, bioswales rainwater tanks, and vegetated bio-retention systems (Fletcher et al., 2008). WSUD comprises a few key principles (Wong, 2006; Keyvanfar et al., 2014; Kamyab et al., 2016) as follow;

i. using the water-efficient appliances to reduce potable water demand and pursuing alternative water sources (e.g., treated wastewater, treated rainwater),
ii. reducing wastewater generation while improving wastewater treatment to the standard level and reusing opportunities at buildings,
iii. improving the stormwater treatment to the standard level for discharging or reusing the surface waters, and
iv. maximizing the recreational visual amenity of the environment and urban landscape by integrating the infrastructure of the stormwater and water cycle management to urban design.

WSUD is also known as stormwater best management practices (BMPs) in the United States (USEPA, 2009), and Sustainable Urban Drainage Systems (SUDS) in the United Kingdom (Duffy et al., 2013). In this case, BMPs have different types, including

i. BMPs for urban land-use practices, in which common land-use can control the runoff quality and quantity. The most well-known practice is higher density development with lower runoff per housing, which serves social, environmental, and economic goals (Carmon and Shamir, 2010). USEPA (2009) has reported that the low-density land-use produces 3.8 times more runoff per housing unit than the high density and 3.0 times more than the medium density. High-density areas can protect regional water quality better than low-density areas (Carmon and Shamir, 2010). Hence, the mixed land-use is appreciated by the minimum area for sidewalks, streets, and parking lots
ii. BMPs for the land cover design in which it is a mean for transforming up to 90% runoff from rainfall generated by rainstorm events into a water resource. It has an acceptable level of contamination used for irritation and landscaping purposes or recharging the groundwaters (Carmon and Shamir, 2010). This stormwater infiltration approach is highly recommended in countries with limited water resources for recharging groundwater, especially in semi-arid countries.

Water Sensitive Planning (WSP) is an approach parallel to WSUD with a broader view considering water management through urban and regional planning. Similar to WSUD, WSP supports synergistically sustainable development and construction. The primary principle of WSP is to replace open spaces according to the natural hydro-geographic layout within a natural stream system through the retention and detention of stormwater (Musiake et al., 1999; France, 2002). The replacement planning needs to be started by spatial planning before land-use planning. The open spaces have different roles and functions in a city (including air-refresher, stormwater receptors, flood mitigator, runoff infiltrator, leisure activities, etc.); hence, they have diverse forms and sizes from the private yard to large parks (Burmil et al., 2003). WSP might manage the stormwaters of the open spaces by serving as landscape elements or by irrigation purposes (Burmil et al., 2003).

Currently, stormwater management through flood control or water quality improvement is performed (Proverbs et al., 2008). Stormwater harvesting is a mechanical mechanism for collecting and storing urban runoff. State-of-the-art stormwater management approaches have been performed in many countries in the last two decades, e.g., and it was started in the U.S. in 1970 to protect the water quality of lakes and streams and control the pollution of overland flows (USEPA, 2009). The landscape architects, planners, and drainage engineers could improve each discipline (e.g., Konrad et al., 1995). Recently, they have developed some integration approaches, such as compact development and increased housing density (USEPA, 2009), limiting imperviousness (Moglen and Kim, 2007), and Low Impact Development (LID) (USEPA, 2009). For instance, USEPA estimated that implementing LID BMPs could save 15–80% of cost compared to the conventional methods (USEPA, 2009). The UK has mainly focused on the sustainable urban drainage system (Andoh and Iwugo, 2002). It has expanded the scope to sustainable water and wastewater integrated into land-use planning. Canada has initiated a new stormwater management approach called ADAPT (Agree Design Act Plan Test) for a stormwater catchment in basins in various rainfall events and different scales as site, neighborhood, watershed, or regional scales. The Canadian Water Balance Model simulates and makes different planning alternatives. Japan has also investigated the regulating effect of infiltration, detention, and retention of runoff discharge (Musiake et al., 1999). New Zealand has established integrated and comprehensive stormwater management and conservation of water resources for both urban and rural areas (Van Welie et al., 2018). Furthermore, the National Water Agency of Singapore has initiated the Active, Beautiful and Clean (ABC) waters program in 2006, focusing on water security and integrated blue-green infrastructure (BGI) strategic initiatives.

The stormwater can be controlled in many forms, such as ponds, streams, lakes, cascades, and fountains. Retention pond design is one of the WSUD trustable solutions to get rid of flooding problems, tackle monsoon, and creating livable water-based urbanism (Siddiqua, 2020). The retention ponds are basins that catch water-runoffs transferred from higher elevation areas to the newly populated areas covered by newly developed buildings, parking lots, and roads. The retention pond is known as a permanent pool allowing the deposition of sediments and diminishing pollutant concentration (Miguez et al., 2015). It is also known as a wet detention pond (or preservation pond) as a part of a drainage system designed to contour water flow during rainstorms and trap contaminated solid particles of the run-offs along the highways, motorways, and urban areas (Lee et al., 1997; Rae et al., 2019). The retention pond also acts as a construction control measure for reducing or even avoiding the flood damages. It holds up the storm-runoff in a drainage system for a particular time and limits the peak discharge to a convenient level (Verstraeten and Poesen, 1999). The other significant function of the retention pond is to store the muddy floods. Birx-Raybuck et al. (2010) has stated that retention ponds can collect contaminants of stormwater runoff, which are not suitable for pollution sensitive species and habitats in the ecosystem and green spaces (such as parks, gardens, urban forests, landfills). The retention pond offers water quality and flood control through a natural process and provides the most effective stormwater treatment for removing the total mass of pollutants from heavy rainfalls (Maniquiz-Redillas et al., 2014; Che et al., 2014). The treatment trains treat the runoff by providing quality multi-usage water through bio-filtration systems. Aquifer Storage and Recovery is an advanced system that uses artificial underground aquifers for stormwater bio-filtration through permeable media or via direct injection and channeling water runoffs into trenches, densely vegetated basins, or retention ponds (FAWB, 2009; Coutts et al., 2013). In retention ponds, hydraulic, hydrologic, and botanic designs are integrated and interconnected for long-term sustainable outcomes (Wong, 2006). The compartmentalization of stormwater retention ponds operates the by-pass high flows to the detention storages within the required detention time and inter-event periods. Pond shapes, vegetation layout, and bathymetry affect its hydraulic efficiency (Wong, 2006). Collectively, it was expressed that; i) improper designs of retention ponds make abundant residential areas and environments, and ii) unsuitable filtering plantings and vegetation along the retention ponds make tragically polluted water flows (Kim et al., 2009; Hussein, 2014).

2. Problem statement

The Water Centric Sustainable Communities, Sustainable Blue-green Urbanism, and the concept of future cities may seem a dream today; however, the future is constructed by the new incremental activities and discoveries from now. Accordingly, there is a need for multi-disciplinary research to solve multi-dimensional water problems (Novotny et al., 2010). Water sensitive city paradigm tries to integrate the ecological, sociological and environmental aspects into water sensitive programs and policy-making, which might be different in countries with specific management policy (Van Welie et al., 2018). The water-sensitive city strategy is currently practicing in many developed countries, such as the U.S., Singapore, Australia, but not safely and reliably in some others as Indonesia (Kösters et al., 2020). These countries face the lack of low water security caused by infrastructural deficiencies, high vulnerability, high hazard exposure, institutional & stakeholders challenges, and governmental structures and mechanisms (Hoekstra et al., 2018; Ramos-Mejía et al., 2018). Meanwhile, WSUD can considerably connect urban water streams and human activity; however, there is a paucity of integrated connection between urban water quality and human health and consciousness (Wong, 2006).

A multifunctional stormwater management system can make the retention pond more naturally effective (Adam et al. 2016). A multifunctional pond can fulfill ecological, economic, cultural, historical, and aesthetical dimensions (Birx-Raybuck et al., 2010; Keyvanfar et al., 2018; Zhou et al., 2020). Integrating stormwater management and urban landscape design provides a mechanism for promoting urban climates and urban communities' health and well-being. One of these approaches is to design the retention pond-park. The retention pond-park can fluctuate with the water levels throughout the year in seasonal variation, where local users may incorporate environmental and biodiversity within their living environment. In retention pond-parks, rushes, reeds, or other indigenous plants can treat water as filters and purifiers, which would then use for aquaculture, irrigation, potable water, or mixed with groundwater (Menetrey et al., 2011; Yang et al., 2013; Zhou et al., 2020). Siddiqua (2020) states such a system can be integrated with water-based recreational facilities or water-based public places (e.g., water parks in local and city scales). Therefore, the multifunctional pond (i.e., retention pond-park) can play a key role in sustainable urban development and water-sensitive urban design by creating a multifunctional land-use and built environment.

However, urban ecologists and landscape planners seek an assessment model to quantify and evaluate the diverse functions of retention pond-parks. According to the literature, a few decision making models and tools have been developed that assist the WSUD implementation while focusing on the analytical estimation of multifunctional pond stormwater management. These tools carry different goals as sustainability assessment, water quality impact assessment, or cost-benefit analysis (Bach et al., 2014). These decision-making methods have been remarkably used to the minimum extent in retention pond assessment and evaluation. Regarding the anthropogenic effects and pollution on the quality of pond water, the multivariate statistical decision-making methods have been applied, such as Artificial Neural Networks (ANN), Artificial Intelligence (AI), Principal Component Analysis-PCA (Saxena and Gangal, 2010), and Geographic Information System (GIS) (Al-Adamat, 2008). These methods assist the environment planners in controlling the pond stormwater treatment through site management and sites selection for water harvesting (Al-Adamat, 2008), soil preservation, remedial actions (Taner et al., 2011), and wastewater treatment and waste stabilization (Garfí et al., 2017; Li et al., 2018). While a few researchers have studied the ecological quality assessment of the ponds associated with the socio-environmental aspects (e.g., Williams and Cary, 2002), some have focused on the ecological-biodiversity integrity in pond preservation and rehabilitation assessment (e.g., Biggs et al., 2005; Duelli et al., 2007). Regarding the hydrological assessment of ponds, Hong (2008) has established a numerical model for the hydrological continuity evolution of the detention ponds based on routing phenomena. His model calculates the maximum detention volume of the pond based on different shapes, inflow hydrograph, and outflow devices. Bolte et al. (2000) have developed a decision support software for assessing and analyzing the ecological and economic impacts of different decisions on aquaculture production of the ponds. This software is used for manipulating pond aquaculture facilities using a series of mini-databases and several knowledge-based components. Vezzulli et al. (2006) have applied MATLAB software for infrastructure planning and management of Phyto-treatment ponds to manipulate criteria and gross estimation of their effects on environmental and biological nitrogen removal efficiency. According to Sharma et al. (2016), several tools and models have been developed to achieve WSUD objectives in retention pond design and development. However, these tools should be able to locally applicable and adaptable to the target site covering all ecological, biological, hydrological, physical, and environmental dimensions.

Accordingly, the current research highlights a paradigm shift in multifunctional retention pond-park design practices and stormwater management philosophies and principles. The research delivers ecologically, biologically, and sustainably water-sensitive urban design and planning, aiming to develop a decision support tool for quantifying and evaluating the stormwater management performance of the multifunctional retention ponds in urban areas, so-called Urban Retention Pond Index (URPI) assessment model. The current research has conducted two research phases to achieve its objectives. Phase one is to develop and validate the URPI assessment model. After identifying the features (i.e., criteria and sub-criteria) of the URPI assessment model through a critical literature review, applying Analytical Network Process (ANP) to measure the weights of features and formulate the URPI index equation. Implementing the URPI model in a case study has validated the model while conducting the Weighted Sum Method (WSM) and a series of expert input studies. Phase two has conducted the Global Sensitivity Analysis (GSA) to analyze the uncertainty and effect of the variation of URPI inputs to variation of its outputs and to investigate the non-influential input factors while improving the predictive capabilities of the model.

3. Materials and methods

3.1. Features of the URPI assessment model

Urban ecologists move quickly towards adopting multifunctional retention pond design, integrating quantity and quality objectives in stormwater management. The URPI assessment model comprises the features of a retention pond design extracted through a critical literature review on water-sensitive city strategies and policies; in particular, Water Sensitive Urban Design (WSUD), Water Sensitive Planning (WSP), Sustainable Urban Drainage Systems (SUDS), Green Infrastructure (GI), Low Impact Development (LID), and Climate Sensitive Urban Design (CSUD). Accordingly, the features cover the functional and structural performance of multifunctional retention ponds for stormwater management, which clustered into three criteria (C1.Geotechnical functions, C2.Water quality and treatment, and C3.Structural and physical landscaping functions) series of sub-criteria. To develop the URPI assessment model, the weights of features will be measured, as explained in the next sections.

- *C1. Geotechnical Functions:*

  C1.1. Soils Investigation: Soil investigation is required for any type of retention facilities and the location. Each soil log should extend a minimum of 1.5 m below the bottom of the facility, describe the soil series, the textural class of the soil horizon(s) through the depth of the log, and note any evidence of high groundwater level, such as mottling.

  C1.2. Infiltration Rate: It equals one-half of the infiltration rate found from the soil textural analysis.

  C1.3. Runoff Quality Treatment: Runoff from the three-month ARI design storm is to be treated entirely before discharge to the basin.

  C1.4. Drawdown time: Recharge basins shall be designed to completely drain the intended stored runoff within one day following the ten-year ARI, 24 h design storm, and two days of the hundred-year ARI, 24-hour design storm with appropriate correction factors.

  C1.5. Backfill Material: The aggregate material shall consist of a clean aggregate with a minimum diameter of 30 mm and a maximum diameter of 70 mm. A void space for these aggregates is assumed to be in the range of 30 to 40 percent.

  C1.6. Overflow Route: An overflow route must be identified if the retention facilities' capacity is exceeded. It should be designed to meet the minimum requirement of preservation of natural drainage systems within erosive velocities.

  C1.7. Seepage Control: It needs to prevent any possible adverse effects of seepage zones when nearby building foundations, basements, roads, parking lots, or slopping sites. Developments on sloping sites often require the use of extensive cut and fill operations.

  C1.8. Groundwater mound: The maximum groundwater mound under the center of the basin is limited to 1.5 m below the basin's base.

- *C2. Water Quality and Treatment:*

  C2.1. Soil retention: The cultivation systems shape limiting surface runoff by improving the soil structure, agricultural drainage, liming, proper agro-techniques, proper crop rotation, and increasing organic matters in the soil.

  C2.2. Spillways: The spillway is only applied for the infiltration basin. The bottom elevation of the low-stage orifice should be designed to coincide with the one-day infiltration capacity of the basin.

  C2.3. Soil and groundwater aquifers: The aquifers are for; cultivation, limiting surface runoff; increasing soil filtration capacity, anti-erosion, Phyto-drainage, agro-drainage measures, the regulated outflow from the drainage system, and ponds and infiltration wells for storage of rainwater from sealed surfaces

  C2.4. Surface waters control: Hydro-technical systems of division and storage of water are for; regulation of outflow from ponds and small reservoirs, water storage in drainage ditches and channel, retention of water outflowing from drainage systems, and increasing the valley retention including the construction of polders.

  C2.5. Pollutant Filtration system: The pond allows road particles to settle and prevent them from entering the environment. The pollutant concentration needs to be diminished, and the sediments have to be dispositioned.

- *C3. Structural and Physical Landscaping Functions:*

  C3.1. Observation Well: It shall be recommended for every on-site retention pond, and also shall be required for every community retention. It indicates how quickly the trench dewaters following a storm and should be located in the canter of the structure.

  C3.2. Outlets: The bottom elevation of the low-stage orifice controls the release control from pond and coincides with the prescribed one-day infiltration capacity of the basin.

  C3.3. Slope control: The community detention facilities should be a minimum of 20 m from any slopes greater than 15 percent. A geotechnical report should address the potential impact of the basin infiltration upon the steep slope.

  C3.4. Pedestrian trails: The trails within the retention pond area provide a secondary path system for pedestrians to experience the pond natural landscape and habitat. In some areas, trails will provide a pathway connection between the retention pond onsite and outside.

C3.5. Facilities for pollutant and flow-rate control: On-site retention facilities shall be located 3 m from building foundations. Community retention facilities should be a minimum of 50 m upslope and 7 m downslope from any building.

C3.6. Vegetation: The embankments, emergency spillways, spoil and borrow areas, and another disturbed area shall be stabilized and planted following the Minimum Requirement of Erosion and Sediment Control.

C3.7. Landscape habitat retention: The habitat and ecosystem shape the proper structure of the land use through; arable fields, grasslands, forest, ecological lands and ponds, afforestation, creation of protective belts, woodlots shrubs, bruises and terraces, wetlands, and swamps.

3.2. Analytic Network Process (ANP) method

Analytic Network Process (ANP) is a decision-making method developed by Saaty (2005) for complex and complicated decision-making problems and networks. It can be used for developing a decision support tool. ANP is an advanced method of AHP that resolves the limitations of dependency among variables in a system by dividing them into different decision criteria and embedded sub-criteria (Saaty, 2005). ANP makes a connection network between criteria and sub-criteria, indicating the dependencies (either inner or outer dependencies). In a criterion, the dependencies among components (i.e., nodes) show the inner dependencies, while among the sub-criteria in a criterion (and other criteria) show the outer dependencies (Chemweno et al., 2015; Fazli et al., 2015). This research has used the ANP-solver v1.0.1 software, conducted the following ANP steps:

Step 1: Pairwise comparison; This step compares the interactions of components (i.e., nodes) pair-wisely using the ANP-based questionnaire. The questionnaire collects the experts' judgments on a nine-point rating scale (1 is equally important, to 9 extremely important).

Step 2: **S**upermatrix development; In this step, the supermatrix will be developed, which indicates the priorities of the pair-wised comparisons. The supermatrix of current research is shown in Equation 1, where w_{ij} is the principal eigenvector of the influence of the components (criteria and sub-criteria).

$$W_{URPI} = \begin{bmatrix} w_{1.1} & w_{1.2} & w_{1.3} & \cdots & w_{1.20} \\ w_{2.1} & w_{2.2} & w_{2.3} & \cdots & w_{2.20} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{20.1} & w_{20.2} & w_{20.3} & \cdots & w_{20.20} \end{bmatrix}$$

Step 3: Weighted supermatrix calculation; This step calculates the unweighted supermatrix and normalizes the weights to enhance data integrity while reducing data redundancy. The normalized unweighted supermatrix entails organizing the column of the matrix to ensure that data integrity limitations appropriately implement the components' dependencies. Next, the weighted supermatrix is calculated by multiplying the corresponding priority of each criterion to the unweighted values.

Step 4: Limit supermatrix calculation; As the final step, the weighted supermatrix will be raised to the sufficient power k by using Eq. (2) until it is stable enough to obtain overall priorities or donated ANP weight.

$$\lim_{k \to \infty} w^k \tag{2}$$

3.3. Weighted Sum method (WSM)

The research has validated the URPI model by implementing a study area (i.e., Boneyard Creek retention pond) and applying the Weighted Sum Method (WSM). Boneyard Creek pond is one of six watersheds within Champaign in the United States (Fig. 1). It is the oldest part of the city, including downtown and Campustown (a business area adjacent to the University of Illinois campus) as a public open space during the unflooding seasons. It is a daily stormwater management facility for Illinois and stream restoration for natural ecology habitat. This site is to provide the hundred-year flood protection downstream, revitalization of the neighborhoods, and recreational amenities and to enhance water circulation between the campus town and downtown. Boneyard Creek pond is a highly channelized and engineered waterway that flows through Champaign, draining much of the stormwaters of the city, including the central business district and the University of Illinois Campus town area. The low water quality and flooding issues have prompted the city and university to develop a seven-phase redevelopment master plan. Phase two of the master plan has considerably increased the stormwater storage capacity and enhanced ecological functions while creating new spaces for recreation and enjoyment.

WSM is a multi-criteria decision-making method for evaluating a series of alternatives based on several decision criteria (and sub-criteria) and several experts in decision-making problems (Lamit et al., 2013;

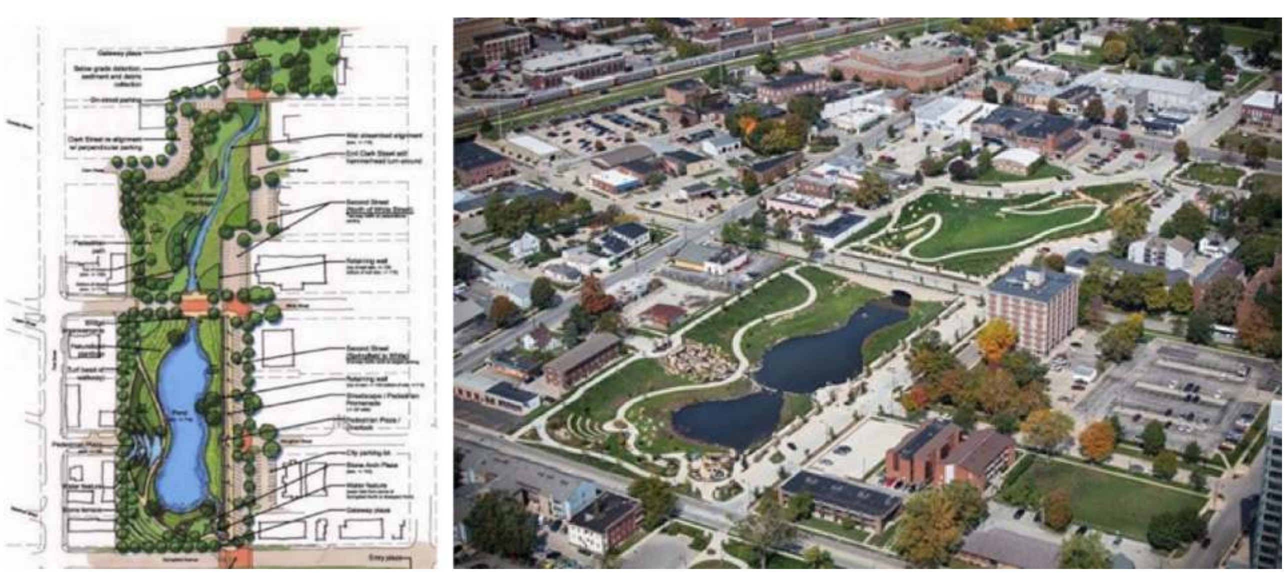

Fig. 1. Aerial photo of Boneyard Creek retention pond. (Source: http://landscapeperformance.org/case-study-briefs/boneyard-creek-restoration).

Kohar, 2018). Based on the WSM's purposive sampling method, the group of five experts attended in the ANP process were invited to the WSM process (experts in pond design, environmental planning, and stormwater management). A self-reporting questionnaire was answered by the experts who rated all the criteria and sub-criteria based on WSM's 5-point Likert scaling (1 is weak, five is excellent). The following WSM equations have been applied to get the approval weights of each sub-criterion through the judgments of experts (Eqs. (3) and (4)).

$$WSM(a_i) = (\sum_{j=1}^{n} w_j)a_i(for\ i = 1,2,3,\cdots,m) \quad (3)$$

where,

'w_j', it refers to the assigned weight by an expert in the WSM discussion for the sub-criterion 'j.'

'a_i', it is sub-criterion of WSM discussion with the given ordering number of 'i'.

$$WSM(a_i)/WSM(a)_{max} = \text{Consensus in } \% \quad (4)$$

where, $WSM(a)_{max}$, it refers to the maximum sum of possible weight given for the sub-criterion 'j.'

3.4. Global Sensitivity Analysis (GSA)

The research has conducted Global Sensitivity Analysis (GSA), which constitutes a series of statistical techniques to evaluate the effect of variability and uncertainty of the input factors on the outputs of a decision-making model (Saltelli et al., 2008; Vrugt et al., 2008; Baroni and Tarantola, 2014). GSA is used for various purposes, such as model verification, model calibration, model simplification, or diagnostic evaluation (Nossent et al., 2011; Butler et al., 2014; Wagener and Pianosi, 2019). Accordingly, GSA has diverse approaches to support robust decision making, reducing uncertainties, and evaluating the dominant controls (Anderson et al., 2014). GSA conducts the Monte Carlo simulation, Regional Sensitivity Analysis, and other input–output post-processing analysis (Noacco et al., 2019). In particular, it calculates the sensitivity indices of the model's input factors. It provides a series of setup options for users, in which each setup is suitable for a specific study. These options impact the reproducibility and transparency of the robust results of GSA, such as estimated sensitivity indices, detecting non-influential parameters (i.e., screening), consequent ordering of the most prominent parameters (i.e., ranking), and variance cutting (Vanuytrecht et al., 2014; Noacco et al., 2019). Also, GSA can apply mapping methods (e.g., Classification and Regression Trees (CART), Patient Rule Induction Method (PRIM)) for uncertainty analysis, which explores the space of possible variability of the model parameters (e.g., natural resources, land use, etc.) (Lempert et al., 2008). It might increase the vulnerability thresholds of a model or measure the links between the vulnerability resources in the model and its properties (Prudhomme et al., 2013).

In the current research, GSA aims to verify and validate the reliability of URPI assessment behavior and to assess the robustness of results across the model assumptions and uncertain inputs. GSA measures the performance of the URPI assessment model through a series of simulations and a set of sensitivity indices and forecasts, e.g., the sum of squared errors and aggregate statistics of parameters. GSA produces scalar output metrics, such as statistics or performance metrics. Therefore, the model needs to translate the time distributed outputs or space distributed outputs to a scalar output metric (Homma and Saltelli, 1996; Hartmann et al., 2013). The output sensitivity analysis techniques are chosen based on the goals of URPI model; therefore, the current research has applied the ranking approach, which supports the space-dependent and decision-making nature of the outputs of the URPI model. The GSA ranking approach indicates the order of the input factors based on their comparative and cumulative effects on the output. Definitely, this approach can assist us in detecting dominant controls of the behaviors of URPI, prioritizing the actions for uncertainty reduction, and mightily to understand better and support the URPI model development.

GSA tools have been developed and available in different sources; such as MATLAB, GUI-HDMR MATLAB by Ziehn and Tomlin (2009), Sensitivity Analysis package by Pujol et al. (2014), the Cþþ-based PSUADE software by Gan et al. (2014), and Fortran functions by Joint Research Centre (2014), and so on. This research has used the SAFE R1.1 toolbox (Sensitivity Analysis For Everybody), as well as, XLMiner Data Visualization toolbox, and Analytic Solver, and Microsoft Excel for the Global Sensitivity Analysis of the URPI model. The SAFE toolbox has several platforms of sensitivity analysis; i) using multiple GSA methods to validate and complement an individual result, ii) providing several visualization tools, and iii) providing multiple revision choices for the user, particularly for robust estimation of sensitivity indices.

4. Analysis and results

4.1. Developing the URPI assessment model

To develop the URPI model, the research had to determine the weights of all criteria and sub-criteria. The ANP method was applied to determine the weights of three (3) retention pond design criteria and their sub-criteria. Firstly, the ANP-decision-making construct of the model was created based on the interactions between criteria and sub-criteria. This research has employed the ANP-Solver software to construct the decision construct and compute the supermatrics (see Fig. 2).

The ANP-Solver software is an established platform developed by a group of researchers at the University of the Aegean to conduct the ANP method. Using this software, the pairwise comparison matrices were designed, presented to experts for ratings. The research has K experts and n criteria. The output from each expert in direct relation of an $n \times n$ matrix was designated as x_{ij}^{k}, where ij is the influence level of criterion i on criterion$j$. According to Dehdasht et al. (2017), "there is not any general rule for the number of responding in MCDM techniques such as ANP, but, it is theatrically valid that MCDM does not require a big sample." This statement was also supported by Kuo and lu (2013), and Uygun et al. (2015). The research conducted the pairwise comparison step inviting five experts who had knowledge and experience in urban Ecology, landscape design and planning, and Environment planning and Environment management. Referring to the ANP method, an example of a pairwise comparison question was "To C1. Geotechnical functions, C1.1. Soils Investigation is (between 1 and 9) more important than C1.2. Infiltration Rate". After completing all pairwise comparisons, the unweighted supermatrix and weighted supermatrix were calculated. Then the limited supermatrix was computed, which determines the normalized weights of each criterion and sub-criterion in the URPI model.

ANP-solver software has computed the weighted supermatrix of the criteria (C1.Geotechnical functions, C2.Water quality and treatment, and C3.Structural and physical landscaping functions) (see Table 1) based on the entries of the pairwise comparisons. Next, the software has computed the weighted supermatrix of the sub-criteria for sub-criteria (see Table 2).

After computing the weighted supermatrices, the software has computed the limited Supermatrix of sub-criteria, as shown in Table 3. Table 3 presents the final weigh of each sub-criterion. Among the sub-criteria, the sub-criterion Soil Investigation has received the highest weight ($W_{C1.1} = 0.170$), followed by the Soil retention ($W_{C2.1} = 0.156$), and Infiltration Rate ($W_{C1.2} = 0.108$). In contrast, both facilities' development and vegetation sub-criteria have received the lowest weights (0.004).

Using the outputs of the limited Supermatrix (Table 3), the URPI index model was developed (see Eq. (5)). This is a linear index model

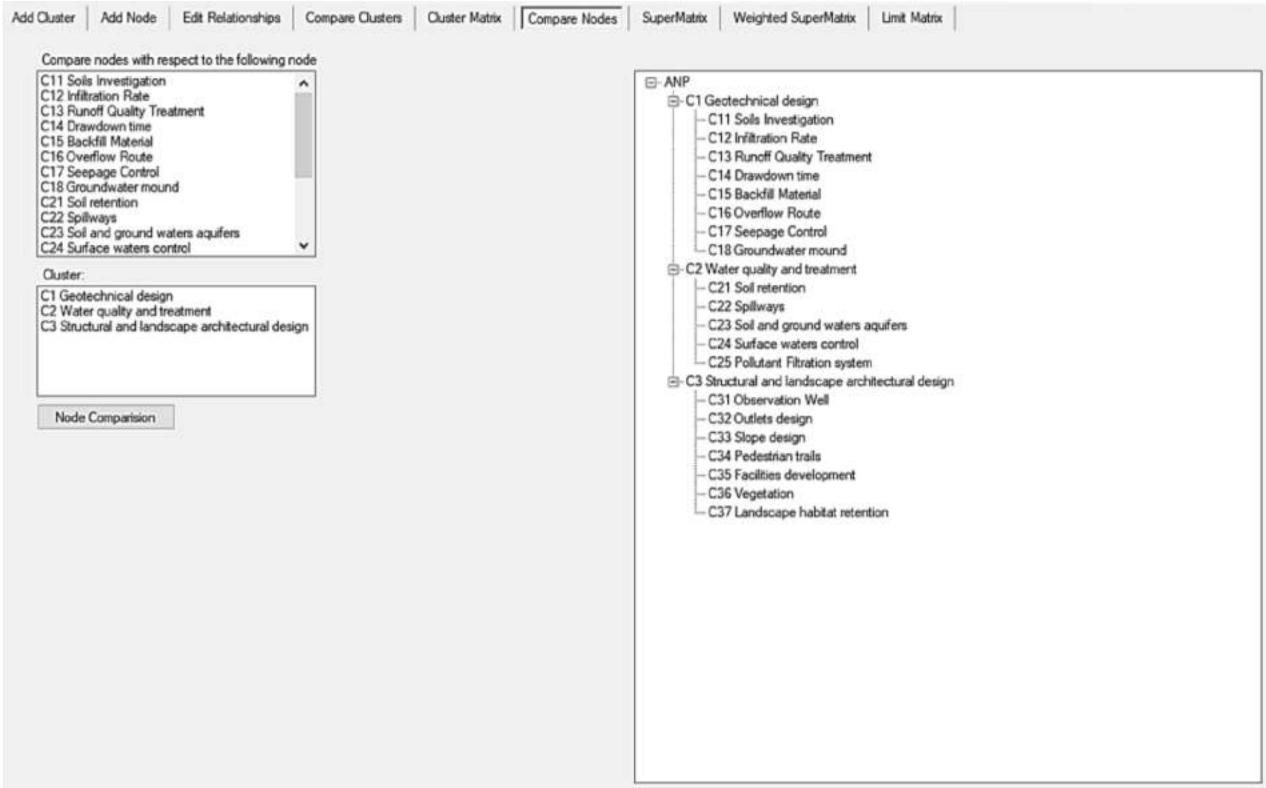

Fig. 2. The ANP construct of URPI assessment model using ANP-Solver software.

involving all the sub-criteria and their corresponding values.

$$\textit{Urban Retention Pond Index (URPI)} = \sum \textit{Index Geotechnical Functions} + \sum \textit{Index Water Quality} + \sum \textit{Index Structural and Physical Landscaping Functions} = \sum_{i=1}^{8} a_i X + \sum_{j=1}^{5} a_j Y + \sum_{k=1}^{7} a_k Z \tag{5}$$

where,

a; consistent value of sub-criterion extracted from Table 3
i; sub-criterion of the criterion Geotechnical functions (for i: 1,2,3, …,8)
j; sub-criterion of the criterion Water quality and treatment (for j:1,2,3, …,5)
k; sub-criterion of the criterion Structural and physical landscaping function (for k:1,2,3,…,7)
X; WSM-based rate of the sub-criterion 'i' assigned by the model-user (s) in the case study
Y; WSM-based rate of the sub-criterion 'j' assigned by the model-user (s) in the case study
Z; WSM-based rate of the sub-criterion 'k' assigned by the model-user (s) in the case study

Table 1
Normalized Weighted Supermatrix of URPI assessment model's criteria.

Criteria	C1	C2	C3
C1	0.586	0.551	0.633
C2	0.353	0.382	0.304
C3	0.061	0.066	0.063

Note: C1. Geotechnical Functions, C2. Water Quality and Treatment, and C3. Structural and Physical Landscaping Functions.

4.2. Implementing the URPI assessment model in a study site

The URPI assessment model was implemented in the Boneyard Creek retention pond. The experts have evaluated the site across the URPI model features. They have rated all criteria and sub-criteria for this target site based on WSM 5-point Likert scaling. WSM has computed the final consensus values of sub-criteria for this site. According to Table 4, the Final-WSM column shows that the experts have consensus more than 70% in most of the sub-criteria, where Soil retention and Soil and ground waters aquifers have received the most extensive consensus (0.922). Next, Soils Investigation and Drawdown time have earned 0.883 consensuses. The limited weighted values resulted in Table 3 have been multiplied to the final-WSM consensus values to obtain the actual-limited weighted values for each sub-criterion in the Boneyard Creek retention pond. The actual-limited weighted values were imported to the URPI index (Eq. (5)). As a result, the Boneyard Creek retention pond has received a 0.809 index score.

Table 2
Normalized Weighted Supermatrix of URPI assessment model's sub-criteria.

Nodes	C1.1	C1.2	C1.3	C1.4	C1.5	C1.6	C1.7	C1.8	C2.1	C2.2	C2.3	C2.4	C2.5	C3.1	C3.2	C3.3	C3.4	3.5	C3.6	C3.7
C1.1	0.153	0.175	0.152	0.169	0.177	0.213	0.205	0.172	0.154	0.190	0.181	0.189	0.166	0.173	0.177	0.182	0.185	0.194	0.176	0.176
C1.2	0.103	0.102	0.106	0.118	0.114	0.114	0.109	0.110	0.095	0.110	0.116	0.107	0.131	0.130	0.130	0.129	0.127	0.127	0.141	0.132
C1.3	0.102	0.076	0.113	0.098	0.096	0.083	0.083	0.103	0.082	0.075	0.08	0.069	0.083	0.097	0.094	0.085	0.089	0.089	0.083	0.094
C1.4	0.066	0.064	0.06	0.062	0.042	0.041	0.042	0.051	0.052	0.05	0.038	0.047	0.043	0.053	0.064	0.067	0.049	0.06	0.059	0.054
C1.5	0.05	0.043	0.042	0.037	0.051	0.033	0.04	0.05	0.053	0.039	0.044	0.043	0.037	0.046	0.041	0.043	0.049	0.054	0.042	0.044
C1.6	0.041	0.042	0.039	0.038	0.027	0.027	0.026	0.036	0.039	0.026	0.027	0.033	0.027	0.035	0.035	0.035	0.035	0.031	0.036	0.034
C1.7	0.036	0.042	0.04	0.032	0.039	0.037	0.04	0.032	0.038	0.031	0.032	0.031	0.03	0.05	0.046	0.046	0.052	0.039	0.046	0.049
C1.8	0.036	0.042	0.034	0.032	0.039	0.037	0.04	0.032	0.038	0.031	0.033	0.031	0.036	0.05	0.046	0.046	0.047	0.039	0.05	0.049
C2.1	0.161	0.154	0.155	0.152	0.161	0.15	0.162	0.155	0.14	0.167	0.168	0.183	0.183	0.142	0.135	0.119	0.151	0.127	0.129	0.139
C2.2	0.059	0.081	0.091	0.069	0.078	0.087	0.079	0.08	0.083	0.088	0.075	0.076	0.081	0.058	0.076	0.069	0.067	0.081	0.082	0.079
C2.3	0.056	0.049	0.045	0.069	0.051	0.048	0.046	0.047	0.08	0.053	0.059	0.05	0.048	0.05	0.044	0.054	0.045	0.045	0.041	0.04
C2.4	0.047	0.03	0.031	0.037	0.035	0.032	0.032	0.032	0.043	0.041	0.045	0.037	0.034	0.032	0.032	0.037	0.026	0.026	0.031	0.026
C2.5	0.031	0.039	0.031	0.027	0.029	0.036	0.034	0.039	0.036	0.033	0.034	0.037	0.036	0.023	0.018	0.025	0.015	0.024	0.021	0.02
C3.1	0.02	0.024	0.024	0.02	0.02	0.019	0.019	0.017	0.021	0.021	0.022	0.022	0.017	0.02	0.021	0.021	0.019	0.019	0.019	0.022
C3.2	0.013	0.013	0.013	0.013	0.011	0.012	0.01	0.013	0.016	0.016	0.016	0.016	0.015	0.013	0.016	0.015	0.012	0.012	0.014	0.014
C3.3	0.011	0.009	0.009	0.01	0.009	0.009	0.011	0.009	0.009	0.012	0.01	0.01	0.012	0.01	0.01	0.009	0.011	0.01	0.009	0.01
C3.4	0.005	0.004	0.004	0.004	0.007	0.005	0.005	0.006	0.005	0.006	0.007	0.006	0.007	0.006	0.005	0.006	0.007	0.007	0.007	0.006
C3.5	0.004	0.003	0.003	0.004	0.005	0.006	0.005	0.006	0.004	0.004	0.005	0.005	0.006	0.004	0.005	0.004	0.005	0.005	0.004	0.004
C3.6	0.004	0.004	0.003	0.004	0.004	0.005	0.004	0.004	0.006	0.004	0.004	0.004	0.005	0.004	0.003	0.004	0.004	0.004	0.004	0.004
C3.7	0.005	0.004	0.004	0.005	0.005	0.005	0.006	0.005	0.005	0.003	0.004	0.004	0.005	0.005	0.004	0.004	0.004	0.005	0.005	0.004

Note: C1.1. Soils Investigation, C1.2. Infiltration Rate, C1.3. Runoff Quality Treatment, C1.4. Drawdown time, C1.5. Backfill Material, C1.6. Overflow Route, C1.7. Seepage Control, C1.8. Groundwater mound, C2.1. Soil retention, C2.2. Spillways, C2.3. Soil and ground waters aquifers, C2.4. Surface waters control, C2.5. Pollutant Filtration system, C3.1. Observation Well, C3.2. Outlets, C3.3. Slope control, C3.4. Pedestrian trails, C3.5. Facilities for pollutant and flow-rate control, C3.6. Vegetation, C3.7. Landscape habitat retention.

Table 3
Limited Weighted Supermatrix of URPI assessment model's sub-criteria.

Nodes	C1.1	C1.2	C1.3	C1.4	C1.5	C1.6	C1.7	C1.8	C2.1	C2.2	C2.3	C2.4	C2.5	C3.1	C3.2	C3.3	C3.4	3.5	C3.6	**C3.7**
C1.1	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170
C1.2	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108
C1.3	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089
C1.4	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055
C1.5	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045
C1.6	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036
C1.7	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
C1.8	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
C2.1	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156
C2.2	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077
C2.3	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056
C2.4	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038
C2.5	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033
C3.1	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021
C3.2	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014
C3.3	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
C3.4	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
C3.5	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
C3.6	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
C3.7	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005

Note: C1.1. Soils Investigation, C1.2. Infiltration Rate, C1.3. Runoff Quality Treatment, C1.4. Drawdown time, C1.5. Backfill Material, C1.6. Overflow Route, C1.7. Seepage Control, C1.8. Groundwater mound, C2.1. Soil retention, C2.2. Spillways, C2.3. Soil and ground waters aquifers, C2.4. Surface waters control, C2.5. Pollutant Filtration system, C3.1. Observation Well, C3.2. Outlets, C3.3. Slope control, C3.4. Pedestrian trails, C3.5. Facilities for pollutant and flow-rate control, C3.6. Vegetation, C3.7. Landscape habitat retention.

Table 4
WSM data collection and analysis of implementing the URPI assessment model in the Boneyard Creek retention pond.

Criteria	Expert Panels					$WSM(a)_{max}$ of Criterion	Cons.	Sub-criteria	Expert Panel					$WSM(a)_{max}$ of Sub-criteria	Cons.	Final WSM Cons. of Sub-criteria	Applied Limited Weighted Value to Final-WSM Cons. of Sub-criteria
	EX_1	**EX_2**	EX_3	EX_4	EX_5				EX_1	EX_2	EX_3	EX_4	EX_5				
C1. Geotechnical Functions	5	4	4	5	4	25	0.92	C1.1. Soils Investigation	5	5	4	5	4	25	0.96	0.883	0.150
								C1.2. Infiltration Rate	5	5	4	4	5	25	0.92	0.846	0.091
								C1.3. Runoff Quality Treatment	4	5	4	5	5	25	0.92	0.846	0.075
								C1.4. Drawdown time	5	5	5	4	5	25	0.96	0.883	0.049
								C1.5. Backfill Material	3	4	4	4	3	25	0.72	0.662	0.030
								C1.6. Overflow Route	5	4	2	2	4	25	0.68	0.626	0.023
								C1.7. Seepage Control	4	4	5	4	2	25	0.76	0.699	0.026
								C1.8. Groundwater mound	4	5	4	4	5	25	0.88	0.810	0.030
C2. Water Quality and Treatment	4	5	4	5	5	25	0.96	C2.1. Soil retention	5	5	4	4	5	25	0.96	0.922	0.144
								C2.2. Spillways	4	5	4	3	5	25	0.92	0.883	0.068
								C2.3. Soil and ground waters aquifers	5	5	4	5	4	25	0.96	0.922	0.052
								C2.4. Surface waters control	5	5	3	4	5	25	0.88	0.845	0.032
								C2.5. Pollutant Filtration system	4	3	5	4	3	25	0.76	0.730	0.024
C3. Structural and Physical Landscaping Functions	5	5	4	4	3	25	0.84	C3.1. Observation Well	5	4	5	5	3	25	0.88	0.739	0.016
								C3.2. Outlets	4	5	4	3	5	25	0.92	0.773	0.011
								C3.3. Slope control	5	4	4	3	5	25	0.84	0.706	0.007
								C3.4. Pedestrian trails	5	4	5	4	5	25	0.92	0.773	0.004
								C3.5. Facilities for pollutant and flow-rate control	3	4	4	4	4	25	0.76	0.638	0.003
								C3.6. Vegetation	3	4	4	3	4	25	0.68	0.571	0.002
								C3.7. Landscape habitat retention	5	5	4	5	4	25	0.96	0.806	0.004

Note. EX: Expert; Cons.: refers to consensus calculated based on Eq. (4).

Urban Retention Pond Index $(\text{URPI})_{\text{Implementation}} = \sum \text{Index}_{\text{Geotechnical Functions}} + \sum \text{Index}_{\text{Water Quality}} + \sum \text{Index}_{\text{Structural and physical Landscaping functions}}$

$\text{URPI}_{\text{Implementation Geotechnical Functions}} = (0.170 * 0.883) + (0.108 * 0.846) + (0.089 * 0.846) + (0.055 * 0.883) + (0.045 * 0.662) + (0.036 * 0.626) + (0.037 * 0.699) + (0.037 * 0.810) = 0.444$

$\text{URPI}_{\text{Implementation Water Quality}} = (0.156 * 0.922) + (0.077 * 0.883) + (0.056 * 0.922) + (0.038 * 0.845) + (0.033 * 0.730) = 0.320$

$\text{URPI}_{\text{Implementation Structural and physical Landscaping functions}} = (0.021 * 0.739) + (0.014 * 0.773) + (0.010 * 0.706) + (0.005 * 0.773) + (0.004 * 0.638) + (0.004 * 0.571) + (0.005 * 0.806) = 0.046$

Urban Retention Pond Index $(\text{URPI})_{\text{Implementation}} = 0.444 + 0.649 + 0.046 = 0.809$

The UPRI assessment model has five (5) grading levels. Grade A has the maximum index grading score, while grade E has the lowest index grading score. The calculation of maximum (*Max.*) and minimum (*Min.*) grades are presented bellow. For the maximum grading score, if WSM weights of all sub-criteria are appointed as 1, then the maximum score equals to 1.000. The minimum (*Min.*) grading score is 0.2 of the maximum (*Max.*) grading score; hence, the minimum score equals 200.

$\text{URPI model}_{\text{Max}} = 0.577 + 0.360 + 0.063 = 1.000$

$\text{URPI model}_{\text{Min}} = \text{URPI model}_{\text{Max}} * 0.2 = 1.000 * 0.2 = 200$

According to the URPI model's gradings, the Boneyard Creek retention pond has earned Grade A (i.e., Superior); meaning, it is a well-designed retention pond executing stormwater management and treatment appropriately, and simultaneously, performing effectively as a social park.

This study has measured CDF, which is the probability of the variance and standard deviation for the probability distribution of the URPI model's outputs. In CDF, the value of sub-criterion is equal or less than x; $F(x) = Pr[X \leq x] = \alpha$. For discreteoutput distributions, CDF uses the equation; $F(x) = \sum_{i=0}^{x} f(i)$, where F (Cumulative Distribution Functions) is determined from f (Probability Density Function). The probability was calculated through; $P(X = b) = F_x(b) - \lim_{x \to b^-} F_X(x)$, where X is the variable with an x value of b. The CDF of the URPI model was compared to the normal distribution curve to measure whether derivatives exist (see Fig. 3). As shown in Fig. 3, the URPI model has an exponential cumulative distribution, a continuous analog of the geometric distribution with a constant average rate. The CFD curve has 0.05 mean (μ) and 0.0490 standard deviations (σ). The maximum point of the graph has the largest ANP normalized weighted value (W) 0.213 (with 1.000 standard deviations (σ) to the mean), and 0.9995 normal standard deviations (z). The CFD and normal curves have an intersection in point 0.102, where z equals to 0.8601. Comparing the goodness-of-fit lines of CDF and the normal distribution curve shows that they have 98% similarity ($y_F = 5.2753x + 0.2375$, $y_N = 5.3558x + 0.1914$, respectively), and the regression variance of the curves are considerably close to each other; $R_F^2 = 0.8009$ and $R_N^2 = 0.9424$, respectively. It indicates that outputs of the URPI model have a proper empirical distribution with a minor variance to the theoretical distribution.

The research has computed the Kolmogorov–Smirnov test (KS test) to compare the distribution of the model's outputs with the normal (ideal) probability distribution, using the equation; $D_x = sup_x |F_n(x) - F(x)|$; where sup_x is the Supremum (i.e., maximum absolute differences between the values of empirical and ideal distributions) of the set of distances, and D_n converges to 0in the limit when $n \to \infty$. The KS test can effectively provide the rate of output convergence. The KS test has implemented twenty conditional samplings (n) for each of twenty input factors (i.e., 400 total sampling size). The output values were standardized to compare with the normal null distribution based on the supremum value. Accordingly, the KS test indicated the graph has 0.1924 (or 19.24%) supremum, while the probability of supremum is 3.849%.

$$\text{URPIIndexGrading Score (S)} : \begin{cases} 800 < S \leqslant 1.000 : \text{Grade A: Superior; Well - designedurbanretention pondwhere treats the stormwater effectively.} \\ 600 < S \leqslant 800 : \text{Grade B: Good; Urbanretention pondtreats the stormwater effectively, but minor improvements are needed.} \\ 300 < S \leqslant 600 : \text{Grade C: Fair; Usableurbanretention pond wheretreats the stormwater, but major improvements are needed.} \\ 150 < S \leqslant 300 : \text{Grade D: Poor; Urbanretention pondtreats the stormwater, but serious improvements are needed.} \\ 0.0 < S \leqslant 150 : \text{Grade E: Very Poor; Non - usableurbanretention pond.} \end{cases}$$

5. Global Sensitivity Analysis (GSA) of URPI assessment model

The research has conducted different methods and techniques for sensitivity analysis of the URPI assessment model; Cumulative Distribution Functions (CDF), Probability Density Function (PDF), Scatterplot-Histogram Plot, Box-Whisker Plot, and Parallel Coordination. Since each GSA method estimates a specific aspect of output distribution, this research has applied these methods to validate one another.

5.1. Cumulative Distribution Functions (CDF)

The Regional Sensitivity Analysis (RSA) (or Monte Carlo filtering) can detect the specific regions in the input space with specific values of the output (Spear and Hornberger, 1980). The RSA method can divide the input data according to the corresponding output threshold position (i.e., below or above the threshold) through the Cumulative Distribution Functions (CDF) method and Kolmogorov Smirnov statistic. The visual inspection of distributions can give specific information, such as variability ranges of the outputs.

5.2. Probability Density Function (PDF)

The moment-independent sensitivity indices do not rely on a specific moment and shape of output distribution to measure the uncertainty. This method is called the density-based method, which measures the Probability Density Function (PDF) of outputs and their variances. The PDF can be computed either two approaches; i) conditional PDF is induced by fixing one input factor according to a prescribed value, and ii) unconditional PDF is induced by divergency and varying all factors (Ahmed and Singh, 2020). PDF detects the specific regions in the input space with specific values of the URPI model outputs.

CDF and PDF are the exceptional cases of the lognormal distribution, which is the maximum entropy probability distribution for the multivariate variables (X), where mean is the division of parameterization

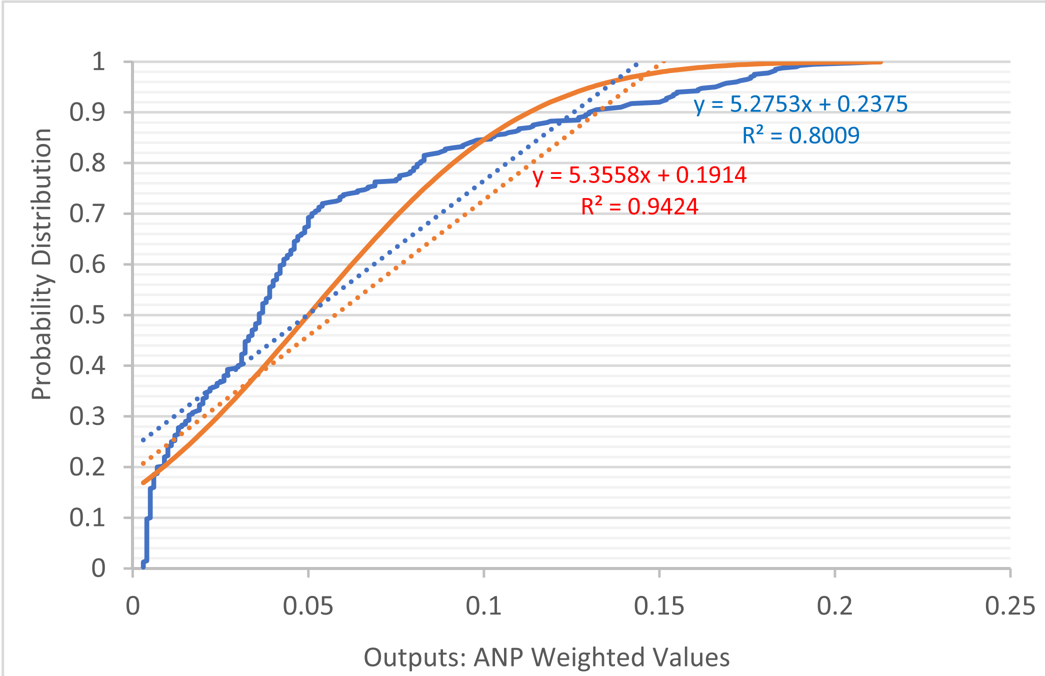

Fig. 3. Cumulative Distribution Function (CDF) of the URPI assessment model.

shape to rate (α/β) and is more significant than zero. This study has measured PDF of the URPI model's outputs ($n = 400$) to measure the probability of the continuous distributions of them. PDF has a discrete distribution function of the variate X (i.e., sub-criterion) with the value x, and is shown as; $f(x) = Pr[X = x]$. Since the URPI model's outputs have the lognormal distribution, PDF was computed through; $f(x) = \frac{1}{x\omega\sqrt{2\pi}} exp\left[-\frac{(In(x)-\theta)^2}{2\omega^2}\right]$; where $0 < x < \infty$, θ is mean, and ω^2 is variance.

Also, we have analyzed the standard normal distribution curve using the function; $y = \frac{1}{\sigma\sqrt{2\pi}} e^{-1/2Z^2}$. In this regard, the research has computed the histogram of the outputs (i.e., ANP normalized weighted values). The histogram diagram has distributed the outputs into 22 groups. Then, the normal distribution curve was calculated, which has 0.05 mean (μ), 0.036 median (x), 0.004 mode ($\hat{x}$), 0.049 standard deviation (σ), and 0.002 variances of the distribution (σ^2). Considering 95% confidence

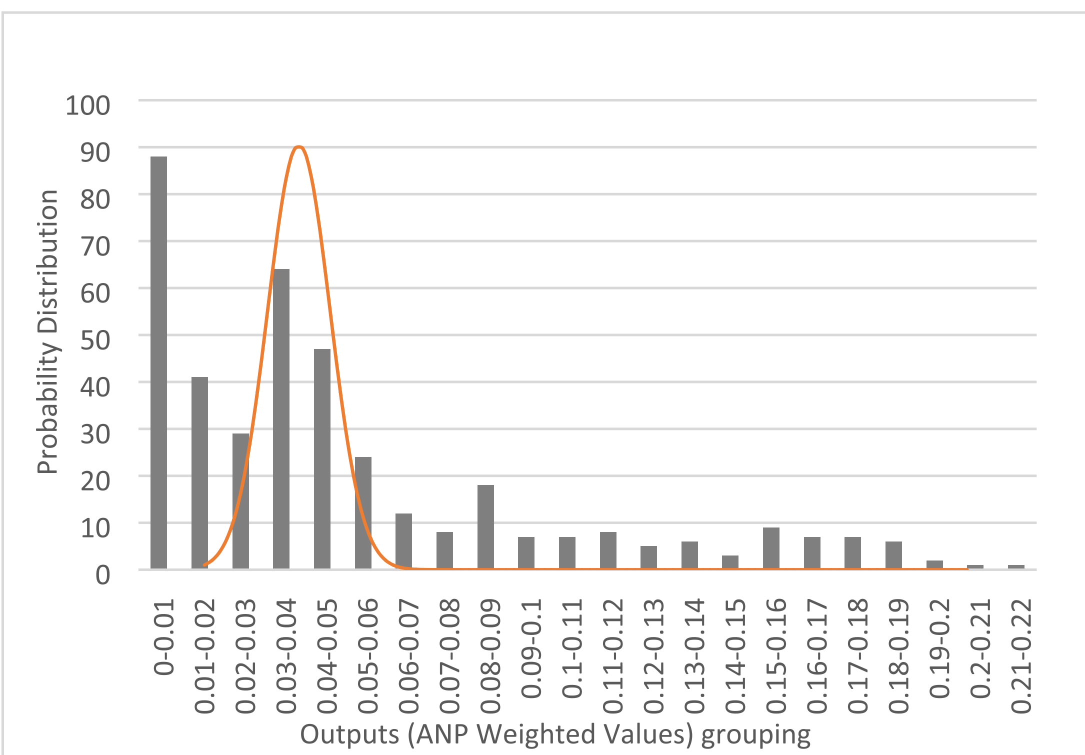

Fig. 4. Probability Density Function (PDF) of the URPI assessment model.

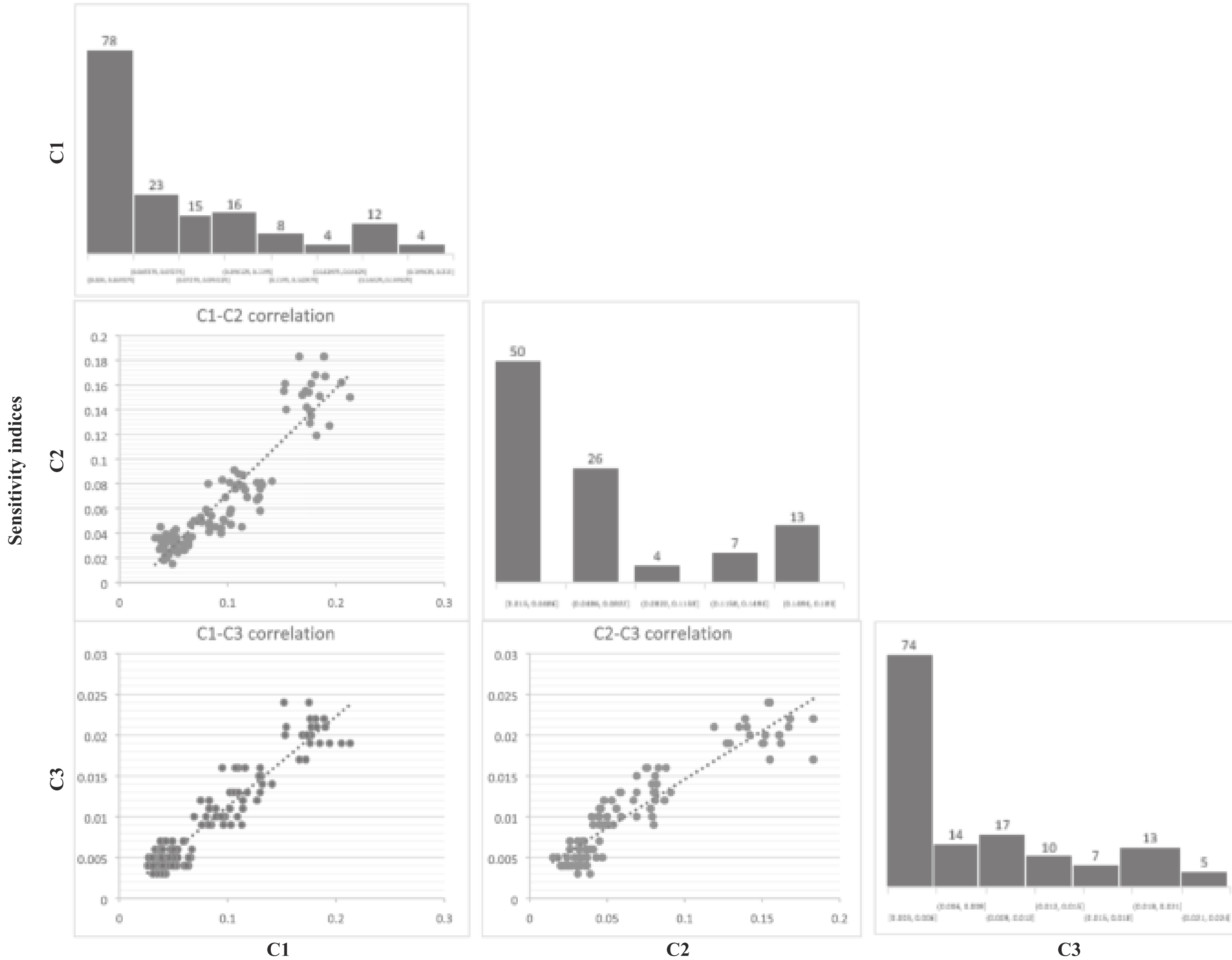

Fig. 5. Sensitivity indices: Three pair-wise regression analysis and three individual histogram analysis of the URPI assessment model's criteria (C1. Geotechnical functions, C2. Water quality and treatment, and C3. Structural and physical landscaping functions).

level, the confidence interval equaled to 0.0048 (upper level 0.0548, and lower level 0.0451). Fig. 4 shows the PDF plot embedding the normal distribution curve. As can be seen, the URPI assessment model has a lognormal distribution with 1.376 positive skewness and 1.099 kurtoses. The middle of the distribution curve is more congested, while most of the data fall within intervals, and most of the outputs distributed after the mean.

5.3. *Multiple regression analysis and histogram analysis*

GSA conducts the correlation and regression analysis using Monte Carlo simulation to measure the sensitivity of the linear or non-linear relationship between input factors and outputs based on; Partial correlation coefficient (or Spearman rank correlation coefficient), Pearson correlation coefficient, or Canonical Correlation Analysis (Minunno et al., 2013). The acceptability degree of monotonicity assumption, linearity between inputs and outputs, and visual inspection can determine the choice of alternatives (Singh et al., 2014). GSA uses Standardized Regression Coefficients (SRC) for the input factors with various units. Concurrently, Classification And Regression Trees (CART) as a non-linear regression method can significantly cope with non-numerical inputs and outputs suitable for both mapping and ranking sensitivity analysis (Singh et al., 2014).

Accordingly, the current research has conducted the regression analysis through scatter-plot technique and computing the Pearson correlation coefficient (r) for the URPI model, which has three criteria linearly correlated. According to Fig. 5, positive slopes of regression functions show that all criteria are positively and linearly correlated. Referring to the C2-C3 correlation function ($y = 0.1189x + 0.0027$), they are strongly correlated than the other two pairs. Regression statistics in Table 5 show that the C2-C3 correlation has a −0.981642 lower level and 14.43372 upper level for their 95% confidence intervals. The C1-C2 correlation is statistically significant, with a 0.99 person regression coefficient (r) and 0.8593 coefficient of determination (r^2). In contrast, the C2-C3 is not significantly correlated ($r = 0.39$, $r^2 = 0.85$), although the slope of the best-fit trendline is the largest (0.1189) among all three pairs. The C1-C3 correlation has received the acceptable p-value 0.0456 (i.e., $P < 0.05$); however, the other correlation pairs (i.e., C1-C2 and C2-C3 correlations) have gained a p-value more than the threshold, which means that the null hypothesis is true.

The sensitivity indices plot consists of the histogram analysis as well (Fig. 5), showing the distribution of each criterion's outputs. In each histogram, the number of bins was defined based on the number of sub-criteria embedded in that corresponding criterion (e.g., C1 histogram has eight bins) to understand the frequency distribution of each criterion properly. For this reason, the group width of criteria varies; C1 has 0.023 group width, C2 and C3 have 0.033 and 0.003 group widths, respectively. According to the histograms, all three criteria have unimodal shapes skewed right. In the C1 histogram, 48.7% of outputs (78 as the count of entries in the first histogram group (i.e., bin) is divided to 160 as

Table 5
Pair-wise regression analysis of the URPI assessment model's criteria.

C1-C2						
Multiple R	0.997439146					
R^2	0.8593					
Adjusted R^2	0.994600675					
Standard Error	0.000300037					
Observations	20					
ANOVA	df	SS	MS	F	Significance F	
Regression	1	0.000315164	0.000315164	3500.958161	4.45659E-22	
Residual	18	1.6204E-06	9.00222E-08			
Total	19	0.000316784				
Trendline	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.0136	0.00074948	157.9500415	9.76549E-30	0.116805759	0.119954956
X Variable 1	0.8547	0.010871991	−59.16889522	4.45659E-22	−0.666124889	−0.620442479
C1-C3						
Multiple R	0.451603922					
R^2	0.9059					
Adjusted R^2	0.159720886					
Standard Error	0.003742974					
Observations	20					
ANOVA	df	SS	MS	F	Significance F	
Regression	1	6.46069E-05	6.46069E-05	4.611534285	0.045626381	
Residual	18	0.000252177	1.40099E-05			
Total	19	0.000316784				
Trendline	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.0003	0.020681692	5.734007731	1.95195E-05	0.07513836	0.162039606
X Variable 1	0.1102	2.299733724	−2.14744832	0.045626381	−9.770120591	−0.106998054
C2-C3						
Multiple R	0.396673335					
R^2	0.8544					
Adjusted R^2	0.110535831					
Standard Error	0.005971084					
Observations	20					
ANOVA	df	SS	MS	F	Significance F	
Regression	1	0.000119839	0.000119839	3.361175257	0.083341824	0.916658176
Residual	18	0.000641769	3.56538E-05			
Total	19	0.000761608				
Trendline	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.0027	0.032993044	0.249195731	0.806030762	−0.061094088	0.077537539
X Variable 1	0.1189	3.668714117	1.833350827	0.083341824	−0.981642286	14.43372241

Note: C1. Geotechnical Functions, C2. Water Quality and Treatment, C3. Structural and Physical Landscaping Functions.

the sample size of C1) is placed in the first group (lower limit: 0.026, upper limit: 0.0493), which was estimated almost similarly to C3 that 56.9% of the outputs (74 divided to130) are in the first group (lower limit: 0.003, and upper limit: 0.006). In the C2 histogram, 50% of outputs have occupied the first group (lower limit: 0.015, upper limit: 0.0486). Referring to Table 2 (Normalized Weighted values of sub-criteria), some sub-criteria significantly affected the ANP limited weighted values of their corresponding criteria, as well as the whole network. For example, the sub-criteria C1.4, C1.5, C1.6, C1.7, and C1.8 (which are more than half of the total sub-criteria in C1), have received the normalized weighted values <0.064, while the maximum normalized weighted values of C1 is 0.213. As mentioned earlier, the low normalized weighted values were derived due to receiving low ranking rates during the ANP pair-wise comparisons. Hence, these sub-criteria do not significantly affect either C1 or the whole network. The same justification is applied to C2 and C3.

5.4. Box-Whisker plot

Box-Whisker method is based on the variance decomposition that can evaluate the contribution of input factors' variations to the variance of outputs (Moges et al., 2016). The current research has computed the first-order (main) sensitivity index, which estimates the variances generated by an individual input factor's variation; so, the variance estimation excludes the interaction of a single input factor with other input factors. Box-Whisker method can compare the output of histograms gained by altering the input factors concurrently (Moges et al., 2016). In this research, the Box-Whisker method plots sensitivity indices based on the numerical data and their quartiles. Box-Whisker also plots the variation of the URPI model's outputs without assuming the basic statistical distribution.

$$Q_2 \text{ is the middle line calculated through } Q_2 = [Q_1 - 1.5IQR, Q_3 + IQR];\ \textit{Interquartile Range}\ (IQR) = Q_3 - Q_1$$

where,

Q_1, is the lower quartile
Q_2, is the entries median
Q_3, is the upper quartile (MathBootCamp, 2020).

The spacing between these three quartiles indicates skewness and degree of dispersion (spread) of data. This research has studied different sensitivity indices on the URPI model's outputs; included median (x), mean ($\bar{x}$), standard deviation (σ), and standard error of the mean ($\sigma_{\bar{x}}$). The following presents the findings of Box-Whisker plots across these metrics.

5.4.1. Bootstrapping resampling

Before mapping the Box-Whisker plots, the research has performed bootstrapping resampling. The research has conducted bootstrapping resampling by simulating the original sampling of the URPI model.

Table 6

Box-Whiskers Plot of the URPI assessment model for diverse indices; including, median (x), mean ($\bar{x}$), standard deviation (σ), and standard error of the mean ($\sigma_{\bar{x}}$).

Criteria	C1								C2					C3						
Sub-criteria	**C1.1**	**C1.2**	**C1.3**	**C1.4**	**C1.5**	**C1.6**	**C1.7**	**C1.8**	**C2.1**	**C2.2**	**C2.3**	**C2.4**	**C2.5**	**C3.1**	**C3.2**	**C3.3**	**C3.4**	**C3.5**	**C3.6**	**C3.7**
Max. (Upper extreme)	0.213	0.141	0.113	0.067	0.054	0.042	0.052	0.05	0.183	0.091	0.08	0.047	0.039	0.024	0.016	0.012	0.007	0.006	0.006	0.006
Quartile 3 (Lower Quartile)	0.186	0.12925	0.09625	0.0605	0.04925	0.0365	0.046	0.046	0.16125	0.08125	0.05325	0.037	0.036	0.02125	0.01525	0.01025	0.007	0.005	0.004	0.005
Quartile 2 for Median	0.1765	0.115	0.087	0.0525	0.043	0.035	0.039	0.0385	0.153	0.079	0.0485	0.032	0.031	0.02	0.013	0.01	0.006	0.0045	0.004	0.005
Quartile 2 for Mean	0.17795	0.11755	0.08870	0.05320	0.04405	0.03345	0.03940	0.03940	0.15165	0.07695	0.05100	0.03430	0.02940	0.02035	0.01365	0.00995	0.0057	0.00455	0.00410	0.00455
Quartile 2 for Std. Dev.	0.01577	0.01252	0.01085	0.00917	0.00567	0.00522	0.00693	0.00657	0.017220	0.00877	0.00948	0.00603	0.00734	0.00200	0.00200	0.00100	0.00100	0.00100	0.00100	0.00100
Quartile 2 for Std. Error	0.0012	0.0010	0.0009	0.0007	0.0004	0.0004	0.0005	0.0005	0.0017	0.0009	0.0009	0.0006	0.0007	0.0002	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001
Quartile 1 (Upper Quartile)	0.17125	0.1085	0.08275	0.046	0.04075	0.027	0.032	0.03375	0.13975	0.0735	0.045	0.031	0.02375	0.019	0.01275	0.009	0.005	0.004	0.004	0.004
Min. (Lower extreme)	0.152	0.095	0.069	0.038	0.033	0.026	0.03	0.031	0.119	0.058	0.04	0.026	0.015	0.017	0.01	0.009	0.004	0.003	0.003	0.003

Note: C1. Geotechnical Functions, C2. Water Quality and Treatment, and C3. Structural and Physical Landscaping Functions. C1.1. Soils Investigation, C1.2. Infiltration Rate, C1.3. Runoff Quality Treatment, C1.4. Drawdown time, C1.5. Backfill Material, C1.6. Overflow Route, C1.7. Seepage Control, C1.8. Groundwater mound, C2.1. Soil retention, C2.2. Spillways, C2.3. Soil and ground waters aquifers, C2.4. Surface waters control, C2.5. Pollutant Filtration system, C3.1. Observation Well, C3.2. Outlets, C3.3. Slope control, C3.4. Pedestrian trails, C3.5. Facilities for pollutant and flow-rate control, C3.6. Vegetation, C3.7. Landscape habitat retention.

Bootstrapping is a resampling method beneficial for complex estimators of the distribution parameter (θ). Bootstrapping produces the simulated resamples, where the distribution could approximate the characteristics of the original samples' distribution and confidence intervals (Pappalardo et al., 2020). The bootstrapping method designates the measures of accuracy, such as prediction error and bias, confidence intervals, and variances. It is also a very accurate method for standard intervals estimation (rather than using normality of sample variance) to asymptotically control the analysis results (Banjanovic and Osborne, 2016). In the current research, the bootstrap resampling has derived the distribution of $\bar{X}$ based on the bootstrap mean (μ^*). C_1 has 160 original sample size (n_1), and C_2 and C_3 have 100 and 140 original sample sizes, respectively. The Monte Carlo algorithm was applied for bootstrapping to draw new samples from the empirical samples with replacement with size *n*. The bootstrapping produced a total 1200 number of resamples data based on the mean bootstrapping approach. θ statistic for each bootstrapping sample was estimated, and then bootstrapping distribution was computed.

Accordingly, conducting bootstrapping to θ value of 200 resampling size (n) in C1, 95% confidence intervals for the median equaled to $0.07312 < x < 0.07906$. Also, conducting bootstrapping to θ value of 200 resampling size (n), 95% confidence intervals for the mean equaled to $0.07256 < \bar{x} < 0.07584$ (so, C1 mean bootstrap is 0.07420, which is very close to the mean of C1 original sample data (0.074212)). The bootstrapping Standard Error (SE) was calculated through $\frac{\sigma^*}{\sqrt{n^*}}$, where n^* is the resampling size and σ^* is the bootstrapping standard deviation. Bootstrapping Standard Error (SE) for C1 has been measured as 0.00006094, which is much lower than the Standard error of the C1 original sample data (i.e., 0.000913041). The same procedure was applied to C2 and C3. In C2, conducting bootstrapping to θ value of resampling data ($n^* = 500$), the 95% confidence interval for the median equaled to $0.0608 < x < 0.0708$, and for the mean equaled to $0.06556 < \bar{x} < 0.07178$ (so, C2 mean bootstrap is 0.068658, which is very close to the mean of C2 original sample data (0.06866)). The bootstrapping Standard Error (SE) for C2 has been estimated as 0.00005998, which is lower than the Standard error of C2 original sample data (0.00091304). For C3, using bootstrapping to θ value of resampling data ($n^* = 500$), the 95% confidence interval for the median of the C3 equaled to $0.00871 < x < 0.00914$, and for the mean equaled to $0.009143 < \bar{x} < 0.00881$ (hence, the C3 mean bootstrap is 0.008928, which is very close to the mean of C3 original sample data (0.0089857)). The bootstrapping Standard Error (SE) for C3 has been estimated as 0. 0.000003535, which is lower than the Standard Error of C3 original sample data (0.000008349).

The similar procedure was conducted to other bootstrapping metrics; bootstrapping median (x^*), bootstrapping mean ($\bar{x}^*$), bootstrapping standard deviation (σ^*), and bootstrapping standard error of the mean ($\sigma^*_{\bar{x}}$), as presented in Table 6.

i. median Box-Whisker plot:

According to Table 6 and Fig. 6, C1.1 has the largest maximum value (0.213) in C1 (although it is the outlier of the box); in contrast, C1.6 has the least minimum value (0.026). C1 plot shows that C1.1. has the most extensive total variation (i.e., data covered between Max-Min) (0.213–0.152 = 0.061), contrary to C1.6 (0.016). Among all sub-criteria, C1.2 has the largest level of variation (0.020), as 50% of entries are covered within the upper and lower quartiles of the box (Q_1:0.109–Q_3:0.129). Contrary, C1.5 has the smallest level of variation (0.008) among all sub-criteria (Q_1:0.041–Q_3:0.049). C1 plot also determines that most of the sub-criteria have skewness and inconsistent spread of data. For instance, C1.6 has the largest skewness (0.0015 left skewness), as 25% of data is covered within Q_3 (0.0365) and Q_2

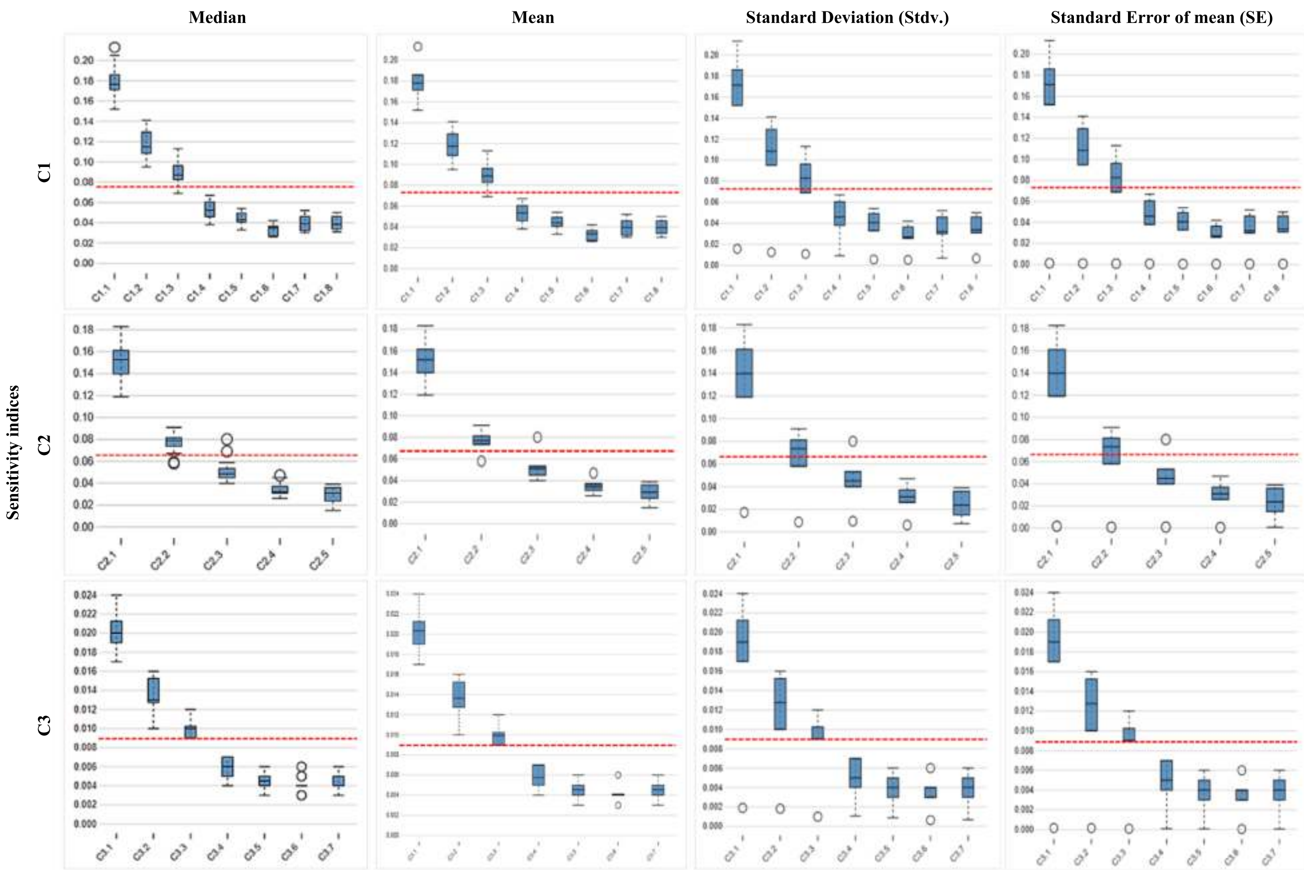

Fig. 6. Sensitivity indices (median ($\tilde{x}$), mean ($\bar{x}$), standard deviation (σ), and standard error of the mean ($\sigma_{\bar{x}}$)) using Box-Whiskers plot technique on the URPI assessment model based on bootstrap resampling (Note: C1. Geotechnical functions, C2. Water quality and treatment and C3. Structural and physical landscaping functions).

(0.0350). However, C1.7 has almost symmetrical data spread as Q_2 ($\tilde{x}$ = 0.039) placed precisely in 25% of the interquartile range. Referring to the Box-Whisker plot for C2, C2.1 has the largest maximum value (0.183) and also has the largest total variation (0.183–0.119 = 0.064), which is even greater than C1.1 (i.e., 0.061). In C2, C2.3 has the smallest total variation (0.040), while both the upper extreme and lower extreme are the outliers. Also, this plot determines that C2.1 has the largest level of variation (0.0215) as the upper-lower quartiles have the largest interquartile range (Q_1:0.1398–Q_3: 0.1613). The level of variation of C2.1 is even larger than C1.1 (0.020). In opposite, C2.4 has the smallest level of variation (0.006), which is even smaller than C1.5 (0.008). Although all sub-criteria in C2 has skewness, C2.4 has a significant skewness compared to other sub-criteria. C2.4 has right skewness where 25% of the data is covered within Q_1 and Q_2 (0.0010), which even smaller than the skewness of C1.6 (0.0015). The median Box-Whisker plot of C3 reveals that C1.3 has the largest total variation (0.007), while C3.6 has the smallest total of variation (0.003). C3.2 has the largest level of variation (0.0025), while C3.6 has the smallest level of variation (0.000). Exempt to C3.6, C3.7 has the significant skewness (0.000 left skewness), then C3.3 with 0.003 left skewness.

ii. mean Box-Whisker plot:

According to Fig. 6 and Table 5, all criteria have almost similar behaviors in their median, mean, Standard Deviation, and Standard Error Box-Whisker plots. All criteria have consistent IQRs and total variations in their plots; for instance, in all Box-Whisker plots of C1, C1.1 has the largest maximum value (0.213), and C1.6 has the least minimum value (0.026). In all plots of C2, C2.1 has the largest maximum value (0.183), and C2.5 has the lowest value (0.015). Meanwhile, each criterion observes slightly different behaviors of mean, Standard Deviation, and Standard Error plots. The mean Box-Whisker plot of C1 shows similar skewnesses to the median plot's skewnesses, although the median plot has slightly higher skewnesses. The median plot of C1.6 had the largest skewness (i.e., 0.0015 left skewness). Similarly, C1.6 has the largest skewness (0.0031) in the mean plot, as 25% of its data is covered within Q_3 (0.0365) and Q_2 (0.0334). C2 also has similar behavior of median and mean Box-Whisker plots. Some of the sub-criteria in C2 (i.e., C2.4 and C2.5) have even smaller skewness; for instance, C2.4 has a significantly smaller mean skewness (Q_2:0.032–Q_1:0.031 = 0.001) than its median skewness (Q_2:0.0343–Q_1:0.031 = 0.0013). In opposite to C1 and C2, sub-criteria of C3 have slightly higher consistency in the mean plots than their median plots. It is highly observable in the case of C3.2. It has median right skewness (Q_2:0.0130–Q_1:0.0127 = 0.0003), which is higher in the mean plot (Q_2:0.0136–Q_1:0.0127 = 0.0006; right skewness).

iii. standard deviation Box-Whisker plot:

In general, Standard Deviation and Standard Error plots have similar behaviors in all criteria. Standard Deviation (σ) is generated based on the mean value using the equation $\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}}$; where, μ is the mean., N is sampling size, and x_i is the entry values (i.e., ANP normalized weighted values). Hence, the middle line in the Standard Deviation box is the mean. Referring to Table 6, calculating Standard Deviation (σ) as the 2nd quartile of each box has shown that Standard Deviation (σ) of most of the sub-criteria has been represented as outliers (see Fig. 6). For instance, Standard Deviation (σ) of six sub-criteria in C1 are outliers (exempt to C1.4 and C1.7), which indicates that most of the sub-criteria have deviations to their means. It was similarly observed in C2 and C3.

iv. standard Error of the mean Box-Whisker plot:

According to Fig. 6, the Standard Errors (SEs) were mostly represented as outliers. According to the Standard Error equation, $SE = \frac{\sigma}{\sqrt{n}}$, where, $\sigma$is the standard deviation and n is the sample size, SE is a portion of the mean. Hence, the middle lines in the Standard Errors boxes are associated to mean. According to Table 6, in all three criteria, outliers have very small values and lied on zero-value lines, meaning all outputs have likely zero errors.

5.5. Parallel coordination

The research has conducted parallel coordination to validate the results of Box-Whisker plots. The parallel coordination is such a sensitivity visualization method useful for high-dimensional datasets. The parallel coordination visualizes the data through a series of data points on an n-dimensional space in n-parallel vertical profiles spaced equally (Achtert et al., 2013). The parallel coordination measures the quantization level for each data point through a dynamic normalization. Ordering, scaling, and rotation of the axis are the critical features of the parallel coordination plot. The method is relatively a time-series visualization method; however, its parallel profiles (i.e., axis) do not follow the natural time order, while the axis follows the instructive order of data and interpolation of consecutive pairs of criteria (Moustafa and Wegman, 2006; Inselberg, 2009). The series of data points on an n-dimensional space make a polyline with vertices on the parallel profiles, where “the position of the vertex on the *ith* profile corresponds to the *ith* coordinate of the point” (Wikipedia, 2020).

The research has plotted the parallel coordination for each criterion separately. The method has reordered the entries for each axes from minimum entry to maximum entry. Each profile presents a sub-criterion, and the points are the ANP normalized weighted values extracted from Table 2. According to Fig. 7a, the parallel coordination plot of C1 was blushed based on C1.1, which has the largest normalized weighted value ($W_{C.1.1} = 0.213$) in the group of eight sub-criteria. In this regard, the upper-half subset of data (range: 0.183–0.213) was selected on C1.1 axes. According to the selected subset data, the blushed polylines were distributed with different behaviors in other sub-criteria axes. It was mirrored as the middle of C1.2 axes, the lower-half of C1.3 axes, while discretely spread along other axes. Fig. 7a shows that the density of data spread in the C1.2 axis is significantly more than other axes, with 6 data points in the range of $0.127 < W < 0.131$. It is similarly observed in the C1.1 axis but with 5 data points in the range of $0.166 < W < 0.185$. Referring to Fig. 7b, the plot of C2 was blushed based on C2.1, comprising the largest normalized weighted value ($W_{C.2.1} = 0.183$) in the group of five sub-criteria. According to Fig. 7b, selecting a subset data range of 0.120 to 0.138 has resulted in the most concentrated group of polylines throughout the C2 plot. According to Fig. 7b, the density of data distribution is mainly observed in C2.1 axes covering 5 data points in the range of $0.152 < W < 0.161$. Next, density occurred in C2.2 axes with a smaller range covering 11 data points ($0.75 < W < 0.083$). The plot of C3 was blushed based on C3.1, which has the largest normalized weighted value ($W_{C.3.1} = 0.024$) in the group of seven sub-criteria (see Fig. 7c). The data points are wide-spread; meanwhile, the C3.7 axis has the largest densities, especially for the 0.05 normalized weighted value, covering 10 points, followed by the 0.04 normalized weighted value covering 8 points.

6. Discussion

Rapid urban growth and environmental degradation persuade urban ecologists and urban designers to utilize water resources for sustainable land development. It needs a superior understanding of land management for incorporating natural land–water resources in the built environment while ensuring the hydro-ecological, environmental and biological benefits. These issues encourage urban professionals to establish alternative design strategies for water problems in local and global scales. The Water Sensitive Urban Design (WSUD) is one of the trustable solutions and strategies in many cities of the world. WSUD can mitigate the effects of urban heat island (UHI), climate change, and uncomfortable thermal environment (Huong and Pathirana, 2013). WSUD significantly retains water in the urban landscape and improves stormwater management through stormwater harvesting techniques, soil infiltration, and moisture technologies to support ecological, environmental, and social needs (Coutts et al., 2013). WSUD technologies can handle a trade-off between urban climate degradation and water consumption (Mitchell et al., 2006); however, the capacity of stormwater harvesting and stormwater management depends on the water demand policy of the region and its climate. Accordingly, the current research attempted to promote the ecological and environmental dimensions of WSUD through multifunctional retention pond design and development in residential communities.

The research findings indicate that the vegetated filter, grass swales, and buffer strips are the most practical solutions in multifunctional retention pond design, particularly for a retention pond with a seasonal park function. Such solutions act similarly for serving stormwater slowly down, which improves evapotranspiration and microclimate. In well-irrigated green spaces (such as retention ponds and retention basin parks), the evapotranspiration rates are three times more than its surrounding residential neighborhoods, and the rate of oasis effect is higher (especially in warm and dry weather cities) (Oke, 1987; Coutts et al., 2013). Therefore, the multifunctional retention pond can increase the soil capacity as a heat sink while reducing the temperature of the lower surfaces (exempt to the water-resistant surfaces) through evaporative cooling. Besides, the surface, canopy air temperature, and soil of an irrigated retention pond can be cooler during the day because of the evapotranspirational cooling phenomenon. Significantly, the multifunctional retention pond in dry seasons (while acting as a park) can reduce the local air temperatures through evaporative cooling. The reduction in extreme heat weather is 0.5 to 1 K. Notably, this condition may have higher humidity than normal conditions, and also, higher soil moisture than normal heat capacity (Grossman-Clarke et al., 2010). It may cause the soil to cool not rapidly as dry soils at night-time. Spronken-Smith and Oke (1998) state that water irrigation of green spaces in the parks (along with shade and surface albedo) is an important control of surface temperature through the intensity of PCI (park cool island) and evaporative effects, especially during the day. This issue is also an essential concern to the multifunctional retention ponds.

The URPI assessment model can potentially modulate the pond space microclimate by reducing the impact of UHI, supporting the natural air ventilation, therefore, stabilizing diurnal temperature. Using the URPI model can manage and control the effects of hydroclimatic and bioclimatic variabilities of land-cover changes (such as soil drought), dust hazards, and wind-borne air pollution. Also, using the URPI assessment model can significantly increase the land biodiversity by protecting the land’s aquatic ecosystem, improving rich biotopes to nurture flora and fauna. Meanwhile, it creates a public space for exercise, recreation, and social activities with neighbors and communities; besides, it improves aesthetic attractiveness, mental health, physical health, and affinity with nature. Collectively, the URPI model promotes the resilience, livability, and adaptability of neighborhoods and urban infrastructures through water-sensitive strategies and water-sensitive urban design. It may promote property values and the real estate and housing market of the communities as well.

The URPI assessment model was implemented in the Boneyard Creek retention pond. It is such a multifunctional pond that focuses on stormwater management, transforming the wasted space effectively into the recreational park, and providing functional facilities and amenities

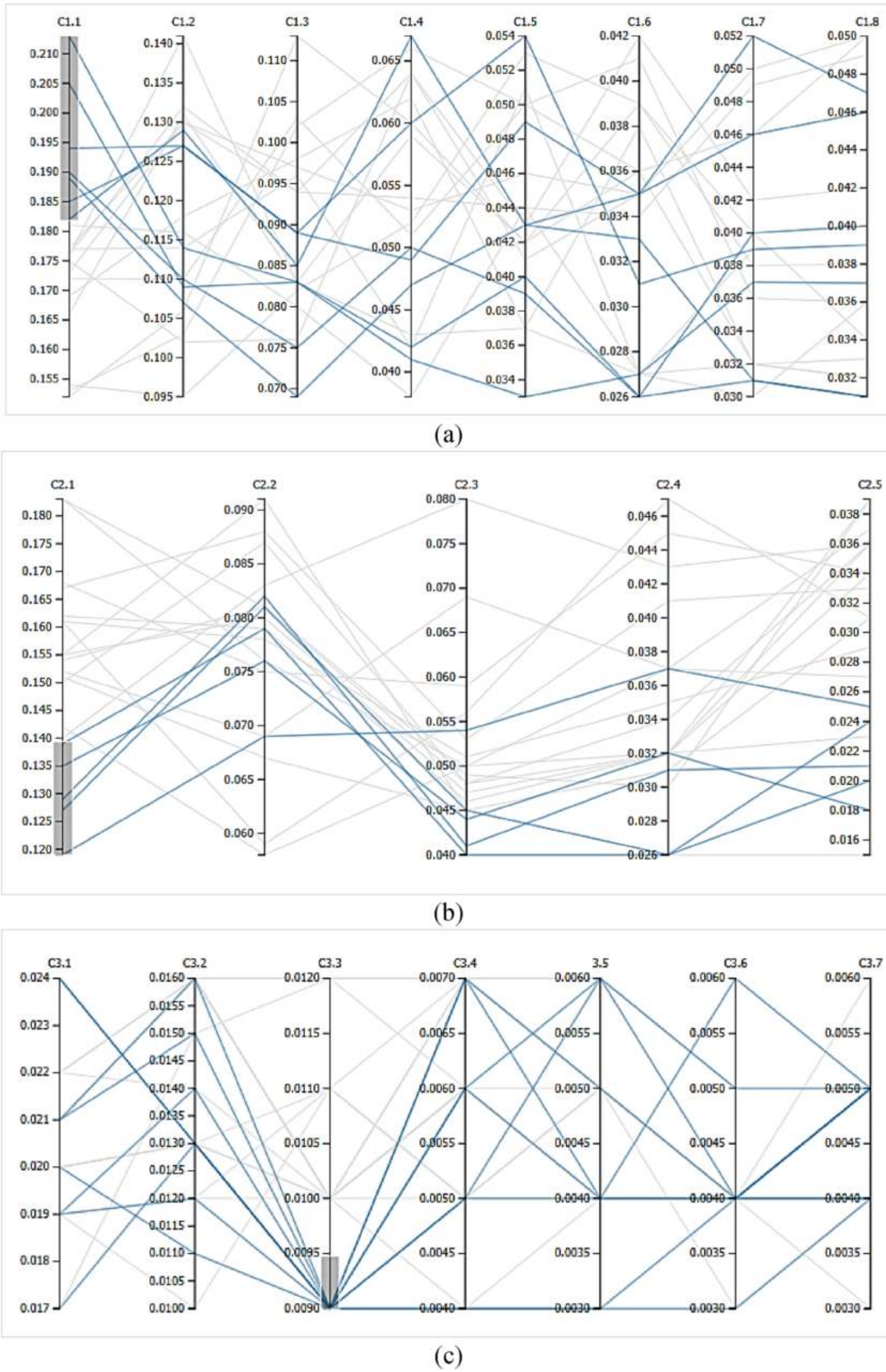

Fig. 7. The parallel coordination of the URPI assessment model; a) C1. Geotechnical functions, b) C2. Water quality and treatment, and c) C3. Structural and physical landscaping functions.

for surrounding residential areas. The Boneyard Creek retention pond has a subtropical climate and almost uniform rainfall patterns throughout the year. It has a great demand for irrigation that coincides with a large rainfall storage capacity. By completing the model implementation and case evaluation, it has received <70% consensus for a few sub-criteria. So, the Boneyard Creek pond must be improved in terms of backfill material ($WSM_{C1.5} = 0.662$), overflow route ($WSM_{C1.6} = 0.626$), seepage control ($WSM_{C1.7} = 0.699$), facilities for pollutant and flow-rate control ($WSM_{C1.7} = 0.638$), and vegetation ($WSM_{C1.7} = 0.571$). The group of experts has suggested the following recommendations to rectify the weaknesses observed at the Boneyard Creek pond;

- It needs to improve the hydro-technics and drainage system to delay the surface water runoff to small water reservoirs, raise the water level and channels, and drainage water retention from surrounding streets to allow percolation of water in adjacent unsealed areas. Then the site can store and release the flow gradually through outlet control structures.
- Proper spatial use of catchment is important in the water management of the Boneyard Creek pond. Creating spatial order in the rapid outflow of rainwater is possible through developing arable fields, grasslands, and swamps, and also creating protective plant belts like shrubs and trees.
- It needs a deep penetration root system that can grow up to 3 m in length. Long roots are useful in improving the stability of earth slope, providing reinforcement by holding the soil particles together, and removing subsoil mixture and detrimental to slope stability.
- Riparian vegetation also helps protect the riverbank, providing a breeding ground for aquatic life, and temporarily holding overflow while trapping sediments and pollutants.

In the second phase of the research, the sensitivity and uncertainty of the URPI model's outputs have been investigated by applying the Global Sensitivity Analysis (GSA) methods and techniques. GSA has a vulnerability-based and bottom-up approach for estimating uncertainties of the decision-making models. GSA can predict the effects of management actions, assisting the robust decision-making concerning the assumptions and inputs of the uncertain models (Saltelli and D'Hombres, 2010; Wilby and Dessai, 2010). The GSA sensitivity indices vary, such as output distribution statistics and the correlation between inputs and output. Indeed, computing all these indices may not be possible for most of the models; therefore, GSA measures the sensitivity indices approximated from a sample input for output estimation (Saltelli et al., 2008; Noacco et al., 2019). GSA methods selection directly impacts the sensitivity results; hence, using multiple methods for GSA is highly recommended. In this regard, the current research has applied a series of sensitivity analysis methods and techniques using various tools and toolboxes (i.e., SAFE toolbox, XLMiner Data Visualization toolbox, Analytic Solver, and Microsoft Excel). This research has measured the following GSA sensitivity indices; Cumulative Distribution Functions (CDF), Probability Density Function (PDF), Scatterplot-Histogram Plot, Box-Whisker Plot, and Parallel Coordination. As each GSA method estimates a specific aspect of the model's outputs distribution, these methods were applied validating the results of one another as well. The research has conducted the bootstrapping resampling in computing the sensitivity indices since the bootstrapping method can deliver an accurate analytical inference of inputs-outputs correlation and interactions in the whole network of the URPI model.

Cumulative Distribution Functions (CDF) indicated that the outputs of the URPI model are properly and empirically distributed ($R^2 = 0.8009$), with minor regression variance to the theoretical distribution ($R^2 = 0.9424$). Also, the Kolmogorov-Smirnov (KS) test was conducted to understand whether the actual (empirical) distribution curve is the proper representative of the standard distribution curve. KS test resulted that the average maximum vertical distance between the two curves is 3.8491 as an acceptable value. Probability Density Function (PDF) has shown that the normal distribution curve of the outputs is lognormal with 1.376 right skewness and 1.099 kurtoses. The considerable skewness and kurtosis indicate that most of the URPI model's outputs fall within the intervals; however, the mean and median of the outputs were more significant than the mode. It occurred because most of the sub-criteria have been rated within the higher ranges (±3 to ±6) of ANP pair-wise comparisons, indicating no significant correlation among them. However, according to PDF results, the variability of sub-criteria is significant (close to 90%) in the first group. In ANP, the higher rating ranges determined the lower inter-dependency between two sides of a pair. For instance, C3.3 Slope control, C3.4 Pedestrian trails, and C3.7 Landscape habitat retention have received lower dependency rates in most of their all pair-comparisons and therefore gained smaller limited weighted values. The results of WSM also support this finding (see Table 4), where the low limited weights of C3.3, C3.4, and C3 sub-criteria have resulted in lower Final-WSM consensuses. The research has analyzed the regression of criteria pair-wisely, to measure the degree of linear correlation. The multiple regression analysis has shown that all three criteria are positively and linearly correlated and have a proximate coefficient of determination (r^2) (0.8593, 0.9059, 0.8544, respectively). The histogram analysis supports these findings. According to histogram analysis, the data distributions in the three criteria are almost similar. However, the first group in the three histograms is the most dominant. The observed similarity is due to the higher rating range (±3 to ±6) selected by the model evaluators during ANP pair-wise comparisons, which shows the insignificant correlation among sub-criteria.

Furthermore, using an input–output sample and employing the Monte Carlo simulation can approximate the sensitivity indices (Noacco et al., 2019). Indeed, variance-based indices have some computational limitations. If the output distribution is highly-skewed or multi-modal, the variance would not be a practical indicator. For this reason, this research has selected the Box-Whisker technique as an appropriate method for variance-analysis of URPI model outputs. Meanwhile, the sampling size plays a critical role in GSA. It should be accurately defined to achieve a great balance between the robust result (considering sample independent) and the computational cost of GSA (Pianosi et al., 2016; Wagener and Pianosi, 2019). Hence, the research has conducted the bootstrapping resampling for sensitivity analysis of the Box-Whisker method. The research demonstrated that the original sample size ($n = 400$) and bootstrapping resampling ($n^*=1200$) were large enough to obtain reliable and robust results. According to Box-Whisker median plots, the water quality and treatment (C2) has the largest total variation (0.064) for soil retention (C2.1), where 60% of outputs in C2 are below the average median bootstrapping threshold ($\widetilde{x}_{C2}^* = 0.0658$). After the water quality and treatment (C2), geotechnical functions (C1) has the largest total variation (0.061) for soil investigation (C1.1), where 56% of outputs are below the average median bootstrapping threshold ($\widetilde{x}_{C1}^* = 0.0760$). It was similarly observed in the criterion structural and physical landscaping functions (C3) for the sub-criterion Outlets with a 0.0089 bootstrapping threshold ($\widetilde{x}_{C3}^*$). It indicates that the outputs of all three criteria have been equally fallen into both sides of the median. However, according to histogram analysis, the outputs are lognormally distributed, and the mean is shifted to the left. It occurred because most sub-criteria have received ANP higher rates (i.e., ±3 to ±6) during pair-wise comparisons, which induced lower limited weights. Furthermore, the research found that water quality and treatment (C2) has the largest level of variation (0.0215) for soil retention. It was followed by geotechnical functions (C1) with a 0.0200 level of variation derived by soil investigation. The vegetation (C3.6) is the most significant consistent sub-criterion in the URPI model, since it has equal upper quartile (Q_3) and lower quartile (Q_1) (0.004), meaning that it was rated consistently during ANP pair-wise comparisons. The behaviors of Box-Whisker mean plots are very similar to the median plots. It is also observed that bootstrapping values for the median and the mean are proximate in all three criteria. The research found more than 60% of outputs have placed below the average mean bootstrapping threshold in all three criteria. Notably, the sub-criteria below the mean bootstrapping threshold are significantly consistent than the upper threshold sub-criteria in all three criteria. Moreover, the behaviors of Box-Whisker standard deviation (σ) and standard error (SE) plots are very similar. As both standard deviation (σ) and standard error (SE) measures are mean derivatives, the same bootstrapping thresholds were plotted for each criterion. In compassion to Box-Whisker median and mean, the standard deviation and standard error plots have many outliers, representing the standard deviation and standard error values. It was expected since the IQRs of each criterion are consistent (see Table 6), so the small values of standard deviations (σ) and standard errors (SE) have placed out of the IQRs.

The results of Parallel Coordination have determined that data density in soil investigation (C1.1) and infiltration rate (C1.2) are expressively more than the other axes in the criterion geotechnical function. In the water quality and treatment criterion, the density of data distribution was principally observed in soil retention (C2.1) and spillways (C2.2). It was observed in the landscape habitat retention (C3.7) axis in the Structural and physical landscaping functions (C3). Comparatively, data spread in the three criteria are diverse. Spillway (C2.2) and landscape habitat retention (C3.7) axes have covered eleven data points and ten data points, respectively. It determines they are the most central nodes in the whole network of the URPI model because they have the largest centrality degrees in the whole network. With a considerable gap, data spread is much lower in the following sub-criteria; infiltration rate (C1.2) with six data points, soil investigation (C1.1) with five data points, and soil retention (C2.1) with five data points. Hence, C1.2, C1.1, and C2.1 have moderate centrality degrees in the whole network of the URPI model. Besides, the data range of blushed zones varies in the three criteria. The largest data range was observed in the soil retention (C2.1) axis for the range of $0.119 < W < 0.183$. According to the normalized weighted values (see Table 2), soil retention (C2.1) has the largest Eigenvector centrality in the whole network. Hence, it is the most connected and effective sub-criterion impacts other sub-criteria and criteria in the URPI model's network. Next, the largest data range was observed in the Soils Investigation (C1.1) axis for the range of $0.152 < W < 0.213$. In contrast, the smallest data range was observed in the slope control (C3.3), pedestrian trails (C3.4), and landscape habitat retention (C3.7) axis, with 0.003 Eigenvector centrality. It indicates that these sub-criteria affect minor other sub-criteria and criteria of the network.

7. Conclusion

Despite the massive pressure on the ecosystem and natural environment, rapid urban development provides opportunities for water-sensitive urban design and planning. Unlike conventional water supply approaches, incorporating water-sensitive urban design and planning aids us to depart from the conventional urban community design to such a sustainable urban preserving natural environment and ecosystem. In particular, water-sensitive strategies and WSUD can enhance urban resilience and protect such water-sensitive neighborhood design and community development against negative impacts of UHI, climate change, climate variability, and population growth. WSUD is the cross-section of water resources, land-use planning, urban planning, spatial planning responses to climate change, flood and GHG emission adaptation, and mitigation strategies, while guaranteeing people well-being, urban livability, and a healthy city. WSUD should be comprehensive, ranging from a straightforward approach to complicated plans supporting green infrastructure towards sustainability. Complementing the Sustainable Urban Drainage System (SUDS) and Low Impact Development (LID) programs can enhance the impacts of WSUD in both water quality and management.

This research has developed the Urban Retention Pond Index (URPI) assessment model for measuring and quantifying the performances and capabilities of the multifunctional retention ponds in stormwater management. The research has promoted knowledge in natural water purification through retention ponds and surroundings based on WSUD principles. WSUD cannot be a single program, but it is set off with other programs to consolidate local or global impacts. Therefore, using the URPI model aids the local and state authorities to implement WSUD beyond a strategy or policy. It aids in making revisions or improvements to their regulatory urban design and planning guidelines while promoting the fundamentals of stormwater management (i.e., ecological, biological, recreation, and aesthetic). The URPI model is a universal decision support tool that aids urban planners and ecologists to assess and enhance the retention pond's ecosystem and its built environment by offering environmental, habitat, and recreational benefits. The URPI model has clustered the design features of multifunctional retention ponds into three criteria; Geotechnical functions, Water quality and treatment and Structural and physical landscaping functions. Each criterion involves a series of sub-criteria, a total of twenty sub-criteria. The URPI model has used the ANP method to measure and determine the limited weight of each sub-criterion. The research has found that soil investigation has gained the largest limited weight (0.170), followed by soil retention (0.156) and infiltration rate (0.108). Despite using the URPI model in any urban ponds worldwide, it was implemented at the Boneyard Creek retention pond in Illinois, the U.S. The model implementation has shown that the Boneyard Creek retention pond has earned grade A, meaning it can manage stormwater efficiently and effectively.

The research has conducted GSA on the URPI model to estimate its dominant controls and decision-making performance. The URPI is such a qualitative-based decision-making tool; hence, the GSA ranking-based sensitivity analysis methods and techniques have been employed for this study. Two approaches of sensitivity analysis were applied in this study; i) Main effect index (it is to measure the direct effect of any single input factor), and ii) Total effect index (it is to measure the direct effect and interaction effects of any single input factor on other input factors). The main-order indices and total-order indices are associated through the output variance decomposition and independent input factors, which signifies the URPI model's structure. The research has applied Box-Whisker Plot and Parallel Coordination methods, which induce the Main effect indices. Besides, the research has conducted the Cumulative Distribution Functions (CDF), Probability Density Function (PDF), and Scatter-histogram plot with the total-effect approach.

CDF determined that model outputs are empirically distributed with minor regression variance to the theoretical distribution. The KS test demonstrated the average maximum vertical distance between the two empirically, and theoretical curves are acceptable. PDF resulted that the normal distribution curve of the model outputs is lognormal. The significant skewness and kurtosis of the PDF's normal curve indicated that most of the outputs fall within the intervals where the mean and median are more significant than the mode. It occurred since most of the sub-criteria have received higher rates during ANP pair-wise comparisons, which results in a lower inter-dependency between two sub-criteria. The PDF determined the insignificant correlations among the sub-criterion in the whole network of the URPI model. The results of WSM support these findings, where the lower limited weights of some sub-criteria induced the lower Final-WSM consensuses. The research has conducted GSA multiple regression analysis, while it might not be powerful and accurate enough for complex interactions among input factors. Therefore, this study has conducted the Box-Whisker technique to validate the results more accurately. The multiple regression analysis resulted in a proximate coefficient of determinations, and consequently, confirmed that three criteria are positively and linearly correlated. The histogram analysis supported these findings, where outputs distributions of three criteria are almost similar. It occurred because these sub-criteria were mostly rated in higher ranges (± 3 to ± 6) in ANP pair-wise comparisons, which resulted in a lower inter-dependency among sub-criteria either in criterion or the whole network.

Furthermore, the research has conducted the Box-Whisker sensitivity analysis technique for output distribution variance analysis of the URPI model. Accordingly, the research has conducted four Box-Whisker sensitivity indices; median (x), mean ($\bar{x}$), standard deviation (σ), and standard error of the mean ($\sigma_{\bar{x}}$) using bootstrapping resampling. The Box-Whisker median plots have shown that the sub-criterion for soil retention made the criterion water quality and treatment the largest total variation and the largest level of variation in the whole network of the URPI model. It was followed by the geotechnical function (based on the soil investigation sub-criterion), and structural and physical landscaping functions (for the outlet design sub-criterion). It indicates the outputs of each criterion have been equally fallen into both sides of their median. Meanwhile, vegetation is the most significant consistent sub-criterion in the URPI model due to receiving consistent ratings during ANP pair-wise comparisons. The research found that the behaviors of Box-Whisker mean plots are very similar to the median plots. The Box-Whisker mean plots have shown that, generally, the sub-criteria below the mean bootstrapping threshold are significantly consistent than the upper threshold in all three criteria. The behaviors of Box-Whisker standard deviation (σ) and standard error (SE) plots are also very similar. These plots have shown the standard deviation and standard error values as outliers lied on the zero lines, meaning the outputs of the whole network as zero errors.

The results of Parallel Coordination have determined that data density of the criterion geotechnical function is the largest, followed by water quality and treatment and Structural and physical landscaping functions, respectively. It was found that the data density of the soil investigation and infiltration rate are expressively more than other sub-criteria in the criterion geotechnical function. Meanwhile, soil retention and spillways have the most dens data distribution in the criterion water quality and treatment and Structural, and the sub-criterion landscape habitat retention of the Structural and physical landscaping functions. Moreover, the research found that data spread in the three criteria are comparatively diverse. The spillway axis (of the 2nd criterion) and landscape habitat retention axes (of the 3rd criterion) have covered the largest numbers of data points, eleven and ten data points, respectively. It determined that Spillway and landscape habitat retention are the most central nodes in the whole network of the URPI model and have the largest centrality degrees. Next, the infiltration rate, soil investigation, and soil retention have moderate centrality degrees in the whole network. Additionally, the research found that the data range of blushed zones varies in the three criteria, as the largest data range was observed in the soil retention axis (in the 2nd criterion) and soils investigation (in the 1st criterion), which indicates they have the largest Eigenvector centralities in the whole network. Hence, these sub-criteria are the most connected sub-criterion affecting other sub-criteria and criteria in the URPI model's network.

The UPRI model emphasizes on the collaborative team of experts practicing water-sensitive urban design and planning, as well as, collaborative cooperation among stakeholders, local authorities, and the government. Using the URPI model, the urban designers and ecologists can evaluate the characteristics, opportunities, and threats of the retention pond site across water-sensitivity disciplines (ecology, landscape architecture, drainage engineering, biology, etc.) local and regional levels. Accordingly, the model user can operate the most suitable Best Management Practice (BMP) of stormwater management and infrastructure planning (such as the local design of housing layout, road layout, public space, parking space, streetscape, etc.).

In future works, the Climate Sensitive Urban Design (CSUD) of multifunctional retention ponds can be investigated, such as water quality, surface energy balance, climate variability, vegetation types, landscaping, as well as evapotranspiration and heat-storage. In this regard, an optimal design of multifunctional retention ponds can be studied, which maximizes the cooling and evapotranspiration capacities. Furthermore, multi-disciplinary research is noteworthy. Integrating sociology, energy efficiency, food production, and low-carbon emission disciplines in multifunctional retention ponds design may provide a more comprehensive WSUD platform for the URPI model. Future studies can also focus on the rural and suburban areas that face floods, water pollution, and soil runoff frequently. Besides, ANP can be coupled with other decision-making methods to reduce the inconsistencies and uncertainties of the URPI model, while increasing accuracy and validity. Finally, future research can conduct the calibration sensitivity analysis of the model to detect limitations making uncertainties in the network of sub-criteria.

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Ali Keyvanfar: Conceptualization, Data curation, Formal analysis, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Arezou Shafaghat:** Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Nurhaizah Ismail:** Investigation, Writing - original draft. **Sapura Mohamad:** Conceptualization, Methodology, Project administration, Resources, Supervision. **Hamidah Ahmad:** Conceptualization, Resources.

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.

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