Journal of Environmental Management 279 (2021) 111718

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: http://www.elsevier.com/locate/jenvman

Research article

Planning green infrastructure placement based on projected precipitation data

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ARTICLE INFO

Keywords:
Green infrastructure
Climate change adaptation
Floods
Projected precipitation
Downscaling

ABSTRACT

Continued urbanization has led to tremendous changes on the landscape. These changes have exacerbated the effects of extreme climatic events such as flooding because of constrained water infiltration and increased surface flow. Typical runoff control measures involve sophisticated gray infrastructure that guide excess surface flow into storage and disposal sites. In a dynamic climate system, these measures are not sustainable since they cannot be easily modified to accommodate large volumes of runoff. Green Infrastructure (GI) is an adaptable technique that can be used to minimize runoff, in addition to offering an array of additional benefits (urban heat regulation, aesthetics, improved air quality etc.). Strategic placement of GI is key to achieving maximum utility. While physical site characteristics play a major role in determining suitable GI placement sites, knowledge of future precipitation patterns is crucial to ensure successful flood mitigation. In this paper, suitable GI sites within the city of Knoxville, Tennessee, were determined based on potential impact of an extreme flood event as indicated by site characteristics. Then, the relative potential likelihood of a flood event was determined based on projected precipitation data and knowledge of existing flood zones. By combining potential impact with likelihood information, low, medium, and high priority GI implementation sites were established. Results indicate that high priority sites are in the central parts of the city with priority decreasing outward. The GI prioritization scheme presented here, offers valuable guidance to city planners and policy makers who wish to exploit the GI approach for flood mitigation.

1. Introduction

With more than half of the world population living in cities (United Nations, 2014), rapid development associated with urbanization has led to tremendous changes on the landscape (Alig et al., 2004; Grimm et al., 2008). Excessive paving exacerbates the effects of extreme climatic events such as flooding because of constrained water infiltration which leads to increased surface flow (Frazer, 2005; Hollis, 1975; Konrad, 2003). Floods are primarily caused by prolonged heavy precipitation (Smith and Ward, 1998). Where applicable, accelerated snow melt, unexpectedly high tides, tsunamis, dam, or river failure may lead to flash flooding (Wehner et al., 2017). Future floods and damages are expected to intensify under rapidly changing climate conditions (Hettiarachchi et al., 2018; IPCC, 2012, National Academies of Sciences, 2019, National Research Council, 2010; Van Aalst, 2006). Managing increased flood risk in urban areas will require robust infrastructure and will demand significant proportions of public funds. Traditional flood control methods such as dams, diversion canals, river and coastal barriers may not be able to accommodate increased flood volume and cannot easily be modified to account for fluctuations in runoff volume. These facilities are overwhelmed in the event of an unexpected high precipitation event (Nie et al., 2009; Sinisi and Aertgeerts, 2010; United States Environmental Protection Agency, 2016). With rising vulnerability of urban areas to extreme climate events (Hansen et al., 2016) including floods, green infrastructure (GI) has evolved as a flood control mechanism (European Environment Agency, 2014; Thiagarajan et al., 2018) that is sustainable (Kramer, 2014) and scalable (Tahvonen, 2018).

The concept of green infrastructure (GI) is evolving and may mean different things within different disciplines or perspectives (Wright, 2011). Within the urban context, GI is conventionally used to mean a planned network of storm water management practices (Center for Neighborhood Technology, 2010), mostly plant-based systems (Gore

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https://doi.org/10.1016/j.jenvman.2020.111718
Received 11 May 2020; Received in revised form 9 October 2020; Accepted 21 November 2020
Available online 10 December 2020

et al., 2013) designed to achieve connectivity and multi-functionality (Baró et al., 2016). The system may include practices such as green roofs, vegetated swales, trees, rain gardens, and porous pavements, among others (NOAA Office for Coastal Management, 2015). On larger scales, it may include large swaths of preserved land that are adjacent to or within a city. In this paper, the term GI is described as a resilient landscape composed of any of the aforementioned practices that can underpin sustainable ecological processes, economic development and social functions without jeopardizing the resources base (Mell et al., 2009; Pauleit et al., 2011). In that regard, GI is a sustainable approach to establishing stability in the ecological system, allowing for conservation of biodiversity, soil and underground water resources, regulated runoff, improved air quality, and ultimately, a healthy population (Kramer, 2014; Ranjha, 2016). In urban areas, the effects of climate change are amplified (Kramer, 2014), partly because of the urban heat island effect, increased demand for resources especially water, increased paving and elevated vulnerability to extreme events. The concept of ecological design has come up as an integrated approach in designing sustainable systems (Van der Ryn and Cowan, 2013). At the heart of ecological design, adaptive management approaches have been defined to include GI planning (Beauchamp and Adamowski, 2013). GI can be retrofitted into new environments at neighborhood and landscape levels to promote ecosystem sustainability (Ahiablame et al., 2012; Dietz, 2007; Liquete et al., 2015; Mell et al., 2009). Planning of GI must therefore consider synergies among various GI functions and necessary trade-offs to maximize specific GI benefits (Hansen et al., 2019).

GI has been highly advocated as a sustainable climate change adaptation strategy because of its ability to mitigate climate change impacts related to the urban heat island effect, reduce building energy demand, and floods, among others (EPA, 2016; Foster et al., 2011; Pauleit et al., 2013). However, both precipitation and rising temperature can bring bigger floods. Precipitation falling on impregnable surfaces creates increased runoff (over spill) and a rising temperature can cause the atmosphere to hold and release larger volumes of water (Feng et al., 2019) (leading to more intense precipitation events). Moreover, GI is also highly vulnerable to climate change because of shifting climatic zones as patterns of precipitation and temperature change (Reynolds et al., 2019; Sarkar et al., 2018). While precipitation largely impacts water requirements for specific GI types (Radwan et al., 2010), temperature determines plant hardiness zones within which plant species can thrive. On the other hand, temperature also facilitates evapotranspiration - a process through which excess water is removed from the surface, and through which the cooling effect of vegetation occurs (Guo-yu et al., 2013; Model and Sensing, 2019). Informed GI planning must therefore consider future changes in precipitation and temperature. Most precipitation projections are based on global climate models (GCM) and are at very coarse resolutions that are not suitable for local level flood risk assessment (Flato et al., 2014). Projections based on regional numerical models are better suited for near-term responses since they do not provide long lead time (Flato et al., 2014). Integration of the two data sets allows for validation of long-term precipitation projections appropriate for urban GI planning.

A key aspect of GI is its ability for multifunctionality (Center for Neighborhood Technology, 2010; Hansen and Pauleit, 2014; Salata and Yiannakou, 2016). Other than being a flood control strategy, GI offers an array of additional benefits including regulation of the urban heat island effect and mitigating air pollution (Jayasooriya et al., 2018; Urban Climate Lab, 2016; Venter et al., 2020). These benefits are synonymous to urban ecosystem services obtained from GI (Maragno et al., 2018; Valente et al., 2020). Through these ecosystem services, GI is seen as a way to achieve resilience of cities from climate change related disasters (Meerow and Newell, 2017a). In that regard it is considered a part of a more complex urban social-ecological system (Hansen and Pauleit, 2014) that integrates human-environment interactions. A principal component of GI planning is to determine suitable placement sites that maximize the achievement of co-benefits.

Increased understanding of the collective benefits of GI has led to the development of various approaches in GI planning (Economides, 2014; Mell et al., 2017). A significant part of GI implementation therefore involves determination of suitable sites for specific GI types at various scales. The Multi-Criteria Decision Approach (MCDA) (Figueira et al., 2016) has widely been used to determine suitable GI sites based on site specific characteristics. The GIS-based MCDA (Malczewski, 2006) approach is a popular method that is used in many disciplines to evaluate the suitability of sites for various application purposes based on multiple predetermined criteria. MCDA application in GI has mostly involved selection of sites that maximize GI benefits (Meerow and Newell, 2017b; Xu et al., 2018), and that support implementation of specified GI types. Other researchers have demonstrated the applicability of flood overflow modeling techniques that simulate floods and help to identify optimal locations and measures of flood control (e.g. Loáiciga et al., 2015). Such models are more appropriate for flood monitoring, damage assessment and real time flood forecasting (Teng et al., 2017). Many implementations of GI only consider physical and socio-economic site characteristics in determining placement sites. Some researchers have included a flood hazard mitigation component by considering the proportion of impervious landcover (Li et al., 2020) in addition to precipitation observations data to model flood flow (Epps and Hathaway, 2018, 2019). While climate change presents a challenge for GI planning because of the dynamic and intensifying flood regimes, few studies have considered future precipitation patterns. Barah et al. (2020) applied a modeling approach to model optimal placement of GI to minimize runoff volume under uncertain precipitation projections, and estimated a 9.5% runoff reduction when GI practices are optimally placed within the watershed. Their approach provides for a way to account for future precipitation uncertainties and identifies optimal placement at the sub watershed level but without identifying specific available locations.

Operationalizing GI requires a comprehensive assessment of potential placement sites in addition to future precipitation patterns. This paper employs a case study approach to explore the applicability of climate projection data in the planning and design of GI as a sustainable flood control mechanism in urban areas. The study area is Knox County, Tennessee, USA. The main goal is to investigate the utility of projected precipitation data for the prioritization of GI placement sites. Here, precipitation projection acts as an indicator of flood likelihood. First, physical site characteristics are analyzed to delineate potential GI placement sites that exclude unavailable sites and those that are physically constraining. Socioeconomic characteristics are considered in determining relative vulnerability to flood events. The current approach establishes three priority levels for GI placement sites based on the relative potential impact of a flood and relative potential likelihood of a flood event. In addition to incorporating projected precipitation information thereby accounting for future precipitation patterns, this research delineates potential placement sites at the pixel level (10m by 10m) which allows for direct identification of individual parcels. Analysis at this high resolution, also allows for resolving very small but suitable parcels especially those within the city center which may not emerge at the sub-watershed level. By incorporating potential likelihood and impact of a flood event, the current approach can guide GI implementation to where they are needed most. The study provides critical information, useful for urban planners, for identification and prioritization of sites, thereby focusing finite resources where they are needed most.

2. Materials and methods

2.1. Downscaled historical and projected climate data

This project utilized temperature and precipitation data from ten GCMs (Table 1) that were statistically and dynamically downscaled to both 1 km and 4 km spatial resolutions at the Oak Ridge National

Table 1
GCM data and its characteristics.

Model	Center	AtmRes	VL in Atm	Model Components						
				a	b	c	d	e	f	g
ACCESS1-0	Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia	1.25*1.88	38	✓	✓		✓			✓
BCC-CSM1-1	Beijing Climate Center, China	2.79*2.81	26	✓	✓		✓	✓	✓	✓
CCSM4	National Center for atmospheric Research, USA	0.94*1.25	26	✓	✓		✓	✓		✓
CMCC-CM	Centro Euro-Mediterraneo sui Cambiamenti Climatici Climate	0.75*0.75	31	✓	✓			✓		✓
FGOALS-g2	State Key Laboratory Numerical Modeling for atmospheric Sciences and Geophysical Fluid Dynamics (LASG) - Institute of Atmospheric Physics, China	1.66*2.81	26	✓	✓		✓	✓	✓	✓
MPI-ESM-MR	Max - Planck - Institute Earth System Model	1.87*1.88	95	✓	✓		✓	✓	✓	✓
MRI-CGCM3	Meteorological Research Institute, Japan	1.12*1.13	48	✓	✓		✓	✓		✓
NorESM1-M	Norwegian Earth System Model	1.89*2.5	26	✓	✓	✓	✓	✓		✓
IPSL-CM5A-LR	Institut Pierre-Simon Laplace	1.89*3.75	39	✓	✓		✓	✓	✓	✓

AtmRes - Atmospheric resolution, VL in Atm - Vertical levels in atmosphere, a-Atmosphere, b-Aerosol, c-Atmospheric Chemistry, d-Land Surface, e-Ocean, f-Ocean-Bio-GeoChem, g-Sea Ice.

Laboratory (Ashfaq et al., 2016). Initial GCM outputs were dynamically downscaled to 18 km, using Regional Climate Model version 4 (RegCM4). These were then bias-corrected to 4 km grid cells using Parameter-elevation Relationships on Independent Slopes Model (PRISM) data. The 1 km resolution outputs were created by re-gridding and bias-correction of the 18 km climate data using Daymet data. Further details of the downscaling procedures can be obtained from Ashfaq et al. (2016).

At 4 km spatial resolution, the variability of Knox County's topography and its influence on local climate cannot be adequately captured (Delong et al., 2010; Wang et al., 2012). Because the two data sets (4 km and 1 km data) were bias corrected using different data, a statistical comparison was not favorable as the results would primarily depict the difference between PRISM and Daymet. The 1 km data was therefore used onward in this analysis.

2.2. Rainfall frequency spectrum (RFS)

First, RFS was analyzed for Knox County based on past and projected data to understand the general pattern and expected future changes. RFS were calculated following guidelines provided by United States Environmental Protection Agency (EPA), as part of its efforts to promote GI practices for runoff management (Clar et al., 2004a, 2004b). From gridded layers of daily precipitation data, small values (<0.1 inches) were removed because they are unlikely to create runoff as they are easily intercepted, stored in depressions, or undergo infiltration. Remaining precipitation values were ranked across an entire time period (past or future) at pixel level to isolate values that are within a predetermined percentage (75%–95%) of all values at the pixel location. Isolated values were then averaged for each pixel location to produce a raster grid of the specified percentile and averaged again across the spatial extent to produce an overall discrete value of each percentile.

2.3. Spatial precipitation patterns

Downscaled precipitation data from the 10 GCMs were summarized to show projected changes (Fig. 1). First, daily data were aggregated into monthly averages for both historical and projected periods. For each period, seasonal means were calculated at pixel level such that for each model, there were 4 outputs representing the four seasons of the year. Precipitation was quantified in two different ways (scenarios) to capture both the proportion of change in the future relative to past precipitation, and the spatial distribution of projected precipitation amount. Proportion of change was calculated as seasonal percentage change using the historical and projected seasonal means. The first scenario was represented as the median value of the seasonal percentage change of all seasons and models and the second scenario as the median value of projected seasonal means of all seasons and models.

2.4. Historical and projected temperature patterns

Minimum and maximum temperature patterns were analyzed for both the past and projected periods. Beginning with data at daily temporal coverage and data points at approximately 1 km spatial spacing, gridded files of monthly average minimum and maximum temperature were generated through pixel level calculations. These calculations were performed on data for the entire historical (1980–2005) and projected periods (2025–2050). Summary statistics for Knox County were generated, plotted, and interpreted.

2.5. GI placement

The implementation of GI in urban areas can take different forms and approaches that heavily depend on the local context (Beauchamp and Adamowski, 2013). An effective GI framework must involve careful identification and analysis of all relevant criteria for defining appropriate GI types and implementation sites. When evaluating GI for maximization of GI benefits, the potential for provision of ecological, socio-cultural, and economic benefits must be assessed (Dagenais et al., 2017). Strategic placement of GI types is key to achieving maximum utility. In addition to ameliorating runoff hazard, GI may be designed to lessen the impact of disastrous flood events by focusing on vulnerable communities. For example, Dunn (2010) advocates for policy changes that enable GI projects in poor urban neighborhoods to alleviate poverty and promote community health e.g. by improving air quality (Nowak and Heisler, 2010) and reducing the urban heat island effect (Ballinas and Barradas, 2016). Such communities are considered vulnerable to flood related disasters and they include low income groups (Garcia-Cuerva et al., 2018), young children (Chan and Hopkins, 2017), elderly persons (Maas et al., 2006), and densely populated areas (Action Contre la Faim, 2010; Cornado et al., 2017). Physical site characteristics such as high proportion of impervious surfaces or a general lack of existing green spaces also increase the vulnerability of a neighborhood to floods (Li et al., 2020). In this analysis, vulnerable areas have a high proportion of these socioeconomic and physical groups.

Potential sites must exclude unsuitable areas (Alves et al., 2018). For purposes of this research, unsuitable areas include unavailable sites such as those occupied by surface water, buildings and other structures (Conservation Advisory Council, 2015), roads and other infrastructure (Conservation Advisory Council, 2015) or those with limiting constraints such as steep slopes (Christman et al., 2018; Copeland, 2016; EPA, 2014), poorly drained soils (EPA, 2011; Shuster, 2014), shallow water table or impermeable bedrock (Chesapeake Stormwater Network, 2009; Taguchi et al., 2020). Further prioritization of potential GI sites

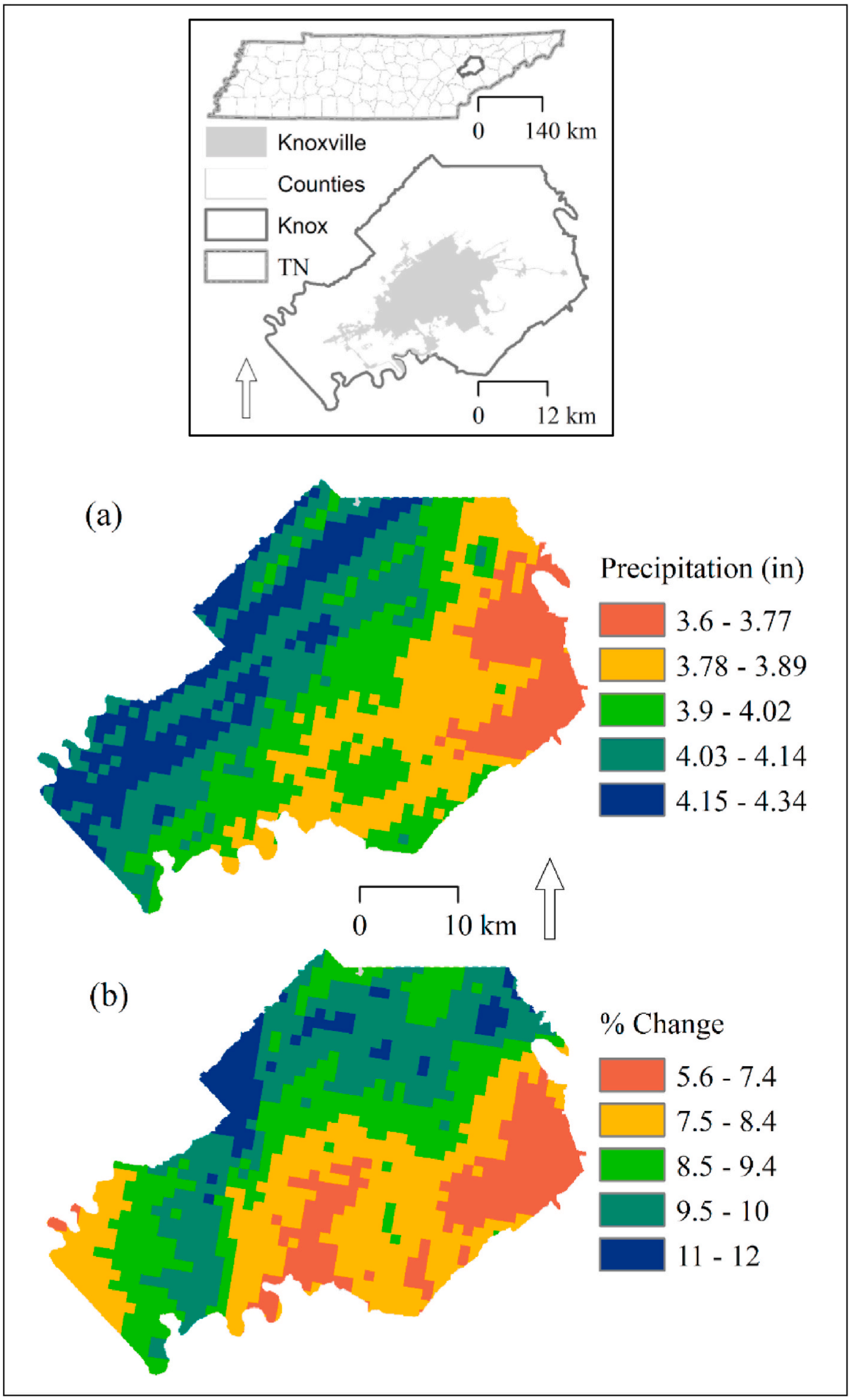

Fig. 1. Study area (top), and spatial patterns of precipitation. (a) Median of projected seasonal mean precipitation amount (b) Median of percentage change in seasonal mean precipitation.

was performed based in combination, on the potential impact of a flood event as determined cumulatively by vulnerability indicators, and on the potential likelihood of a flood event as determined by the projected spatial precipitation patterns.

2.5.1. Data

A spatial MCDA approach requires that all criteria data be represented in a geo-spatial format. For easier implementation, all the considered criteria were represented in a grid raster format. Initial preprocessing of the data involved conversion of data into spatial layers, assigning the same spatial reference system (NAD, 1983 UTM zone 16N), and resampling to 10 m spatial resolution. This ensured co-registration of grid cells among raster layers. Original data were available at varying spatial resolutions and levels of aggregation. The varying levels of aggregation were considered appropriate for the variables under the assumption that for those variables, values would naturally not vary significantly withing very small spatial extents. Data were obtained and processed according to the procedures described below. First, exclusionary criteria were used to define suitable versus unsuitable locations for GI (as summarized in Table 2)

Existing structures: GI may only be installed on available space. All land areas occupied by transportation infrastructure such as roads, railways, and buildings were excluded from consideration. Streets and roads data were obtained from the Street Lines, US, 2015, NAVTEQ database as polygon vector layers. This were converted into a grid layer at 10 m spatial resolution. Road surfaces were labeled as unsuitable with all other areas labeled as suitable. Building footprints were obtained from the state of Tennessee GIS department ([dataset] Tennessee Department of Finance and Administration, 2013). These were initially generated based on LiDAR data collected in 2008. Similar processing of the spatial polygons as with the roads data was performed to produce a grid layer.

Watershed Features: All land areas occupied by surface water were considered unavailable. Spatial layers representing lakes, dams, ponds and rivers in Knox county were extracted from the U.S. Geological Survey's (USGS) National map database ([dataset] (United States Geologic Survey)). A single grid raster was created representing surface water areas labeled as unsuitable and all other areas labeled as suitable.

Topography: Landscape topographic characteristics such as slope affect the rate of flow of runoff thus influencing infiltration. In addition, very steep slopes may not support some GI types due in part to the GI's specific nature or thinned topsoil because of erosion. Depending on the desired type of GI, various levels of slope steepness may be considered as suitable for the installation of GI. For purposes of this study, we elected to exclude all areas with slope greater than 12°. Ten-meter spatial resolution elevation data were obtained from USDA NRCS Geospatial Data Gateway ([dataset] (United States Department of Agriculture, 2014)), from which slope was calculated and a binary grid layer of suitable ($\leq 12^0$) and unsuitable ($>12^0$) areas created.

Soils and Geology: The primary role of GI in flood management is based on the ability to facilitate infiltration of runoff. It is therefore key to consider the drainage of soils. In this study, we excluded all land areas with poorly and excessively drained soils. Poorly drained soils are clogged and do not adequately support for water percolation. This may be because of a shallow water table or impermeable bedrock. Excessively drained soils may not support healthy development of GI during the dry season without extra cost of watering. Using soil drainage data obtained from the USDA NRCS Geospatial Data Gateway ([dataset] United States Department of Agriculture, 2006), a binary grid layer was generated with suitable and unsuitable areas.

Next, the relative socioeconomic impacts of floods were assessed using five vulnerability criteria (Table 3). Socioeconomic attributes including population density, projected population change, average household income and proportions of young and elderly people are significant indicators of the intensity of impacts a flood event can have. Densely populated areas have many people at risk, there is low resilience to floods in poor neighborhoods and those with a high dependency ratio. Population density data for year 2010, and projected population change up to 2030 and 2050 were obtained from the Oak Ridge National Laboratory as generated from the LandScan population mapping project (Bright et al., 2011). Household income and age data for year 2010 were obtained from the American Community Survey database (U.S. Census Bureau, 2010). Grid layers were created at 10 m spatial resolution to represent the socioeconomic attributes. Each was classified into five categories that represent relative potential impact of floods.

Table 3
Assessment criteria for relative potential impact of floods.

Criteria	Measure	Premise
Population	Population density	Densely populated areas have more people at risk of flood effects
	Projected population Increase	Future population increase may instigate more floods due to increased construction and paving.
Average household income	Population vulnerability	Low income households are more vulnerable to flood disaster.
Proportion of the young and elderly	Population vulnerability	Children (under 18 years) and elderly (over 65) are more vulnerable to flood disaster.
Proportion of impervious surface	Potential for runoff infiltration	Extensive paving inhibits infiltration of surface runoff, creating floods.
Canopy cover	Potential for infiltration and evapotranspiration	Dense canopy promotes evapotranspiration. Vegetation supports infiltration.

2.5.2. *Identification of suitable GI implementation sites*

To delineate suitable GI sites, a spatial multi-criteria decision approach (MCDA) was utilized. Based on a thorough review of literature, criteria were identified that disqualify sites from being potential areas for GI. These criteria are listed in Table 2 and discussed in section 3.5. The criteria are viewed as constraints to GI installation. For each criteria constraint (*CC*), CC_1, CC_2, CC_3, …, CC_n, spatial data were acquired and converted into grid raster layers at 10 m spatial resolution. Areas within exclusion zones were labeled with a grid value of 0 while other areas were labeled with a value of 1. These layers were then combined to form a single base layer (*BL*) by computing a pixel-based product (Equation (1)). In the resultant layer, values of 1 indicate suitable areas for GI installation.

$$BL = CC_1 \times CC_2 \times CC_3 \times \ldots \times CC_N \tag{1}$$

2.5.3. *The relative potential impact of floods*

The relative potential impact of floods for suitable GI sites was assessed using several criteria listed in Table 3 and discussed in section 3.5. These criteria were considered relevant indicators of vulnerability to impacts of floods. For each criterion, data were acquired and converted to gridded raster layers at 10 m spatial resolution. A ranking principle was then applied on each layer based on data attributes to obtain five levels of vulnerability, where a value of 1 means very low vulnerability to effects of a flood and a value of 5 means very high vulnerability. Here, vulnerability translates to potential impact of a flood. This manner of classification also allows for leveraging additional

Table 2
Exclusionary criteria used to define unsuitable sites.

Category	Consideration	Measure	Exclusion criteria
Critical infrastructure	Transportation network	Land unavailability	All land areas classified as road or rail
	Buildings	Land unavailability	All land areas occupied by buildings and those within 10 ft of buildings.
Watershed features	Lakes, dams, ponds	Land unavailability	All land classified as lakes, dams, and ponds and those within 30 ft of such surface water areas.
	Rivers	Land unavailability	All land classified as rivers and those within 30 ft of such surface water areas.
Topography	Slope	Effect on rate of surface water flow	Slope greater that 12°
Soil	Soil Drainage	Ability of soil to allow for water infiltration.	All land areas with poorly drained soils and excessively drained soils
Geology	Characteristics of bedrock	Depth of water table and permeability of bedrock	Areas with impermeable and or hazardous bedrock

benefits of GI in an area. The ranked layers were combined following a pixel-based summation algorithm (Equation (2)) to create the aggregate impact layer representing cumulative impact for each location.

$$Impact = \sum_{j}^{n} CR_j \quad (2)$$

where *Impact* is the cumulative impact rating for the location, CR_j is the criterion rating for criterion *j*, and *n* is the number of criteria considered. Unsuitable areas were eliminated from the impact layer through pixel-based multiplication with the base layer.

2.5.4. Prioritization of GI implementation sites

Our prioritization scheme (Table 4) combines the relative likelihood of floods with the relative potential impact of floods in an algebraic formulation to derive three levels of priorities. Essentially, low impact, low likelihood sites are low priority while high impact, high likelihood sites are high priority. Moderate priority sites constitute a combination of impact and likelihood levels such that impact is minimized even at high likelihood of floods.

3. Results

3.1. Rainfall frequency spectrum

Considering high precipitation events, all the models but one showed an increase in the depth of precipitation events between the 75th and 95th percentiles in the projected period (Fig. 2). FGOALS showed a slight decrease in the depth of high precipitation events. Even for high depth precipitation events, the ten models indicate comparable values during the historical period and considerable variability in the projected period. MPI, CMCC and CCSM4 show elevated precipitation depths; ACCESS, BCC, GFDL, IPSL, MRI and NorESM indicate comparable precipitation depths for all the considered percentiles and FGOALS showed lower precipitation depths. It is however evident that the depths of high precipitation events increase in the projected period.

For the historical period (1980–2005), there was little variability in total monthly precipitation among the models (Fig. 2). The projected period however showed considerable differences among the models, with the month of December showing greatest variability. During this period, a minimum and maximum range of 2 inches and 7 inches respectively in total monthly precipitation was observed among the models for all months apart from December which had a range of 25 inches. This is because CMCC and MPI showed exceptionally high values compared to the other models. A general increase in total monthly precipitation was observed in the projected compared to the historical period.

3.2. Historical and projected temperature patterns

While precipitation plays the primary role in creating floods, temperature is pivotal in the evapotranspiration process, thus facilitating removal of runoff. In Fig. 3, we show the distribution of average daily minimum and maximum temperatures from the 10 models by month. Minimum and maximum temperatures are highest in the months between May and September and both minimum and maximum temperatures are higher for the projected period relative to the historical period. With the appropriate infrastructure in place, it is expected that excess surface flow will clear up faster during the hot months of the year than in other months. This information can be useful when selecting GI types that are effective through the cold months when evapotranspiration is low, as well as through the hot months.

3.3. Spatial flood likelihood patterns

Analysis of projected precipitation showed that precipitation will increase in the future for all areas in Knox County. Based on the anticipated percentage increase relative to historical precipitation, five flood likelihood levels were generated where areas with greater percentage increase have higher likelihood. Fig. 4 shows likelihood levels based on the percentage increase and amount of expected precipitation increase. Spatial similarity between the two maps indicate that percentage increase in precipitation is somewhat proportionate to amount of precipitation increase.

3.4. GI placement

3.4.1. Potential GI sites

By eliminating all the considered GI placement constraints, suitable areas were delineated. These are areas with no known constraints to the installation of GI (Fig. 5a). Overall, 71.88% of Knox county was found to be suitable. These identified suitable areas may already have different forms of planned or unplanned GI which may be modified or changed at minimal cost. Larger and suitable contiguous parcels are located outside Knoxville city limits and smaller ones mostly within the city limits. Most areas close to downtown Knoxville are not suitable for GI installation primarily because they are occupied by buildings, transportation infrastructure and other structures. Steep slope appears to be the greatest constraint to GI placement in most parts outside of downtown Knoxville. However, GI types suited for steep slopes may be considered for these areas.

3.4.2. Relative potential impact of floods

Suitable sites were ranked according to the relative potential impact of floods. From each of the seven criteria used to describe severity of a possible flood, five impact levels were defined. These were combined to generate overall potential impact at five levels ranging from very high potential impact to very low potential impact (Fig. 5b). Greatest potential impact is in central Knox County, mostly within the Knoxville city limits and close neighborhoods. High proportions of impervious surfaces, current and projected population density are the dominant physical and socioeconomic characteristics, respectively rendering the

Table 4
Site prioritization scheme for GI installation.

		Impact				
		Very low	Low	Moderate	High	Very high
Likelihood	Very likely	Low	Moderate	High	High	High
	Likely	Low	Moderate	Moderate	High	High
	Possible	Low	Low	Moderate	Moderate	High
	Unlikely	Low	Low	Moderate	Moderate	Moderate
	Very unlikely	Low	Low	Low	Moderate	Moderate

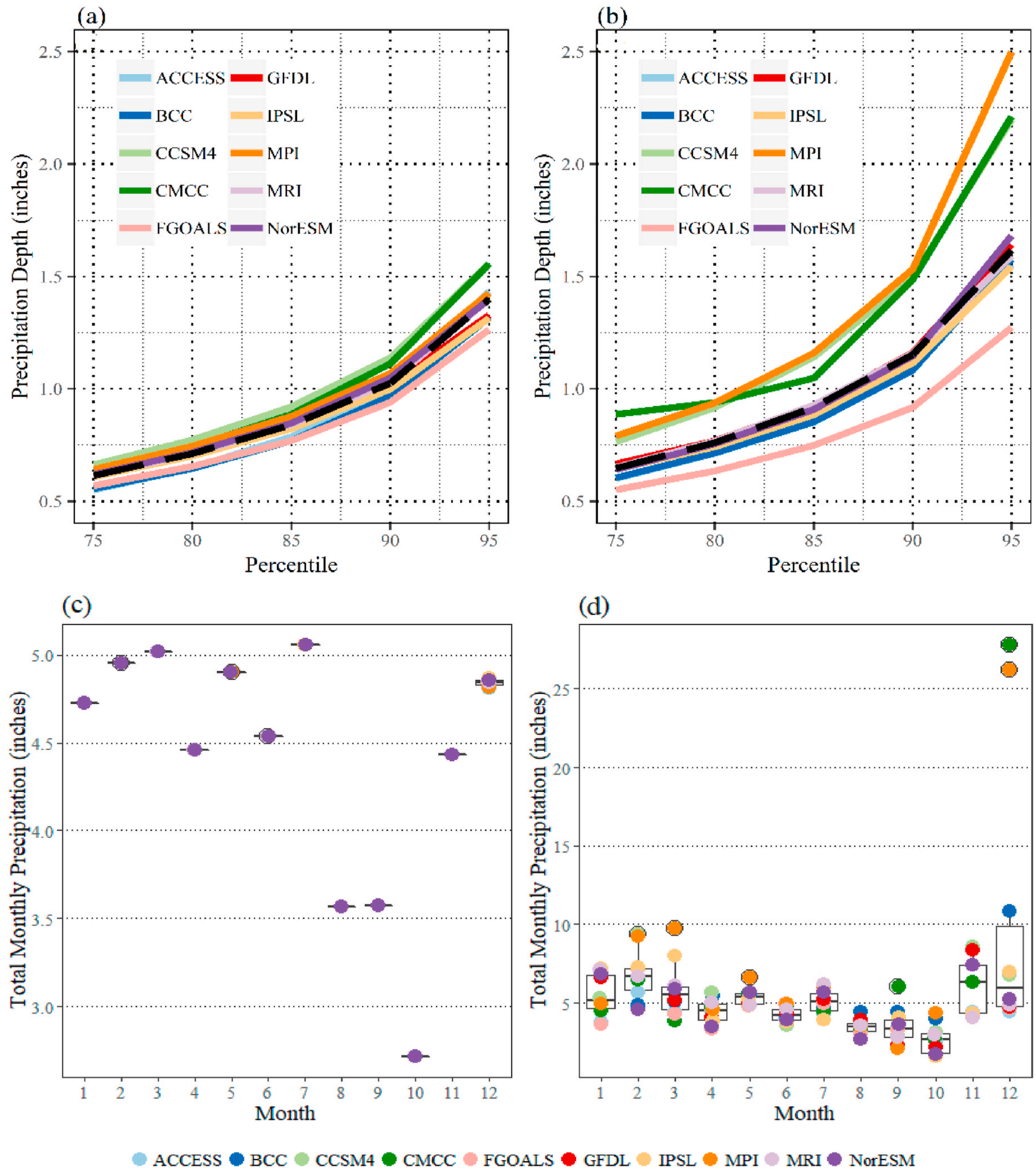

Fig. 2. Rainfall Frequency Spectrum values of precipitation events for the area of Knox County, Tennessee. Mean of precipitation events in the period 1980–2005 (a) and period 2025–2050 (b). Black dashed lines on (a) and (b) represent the median for all the models. Total monthly precipitation for each of the ten climate models for the period 1980–2005 (c) and the period 2025–2050 (d).

area a high impact zone. Proportions of canopy cover, the young and elderly, influenced pockets of high and low impact zones throughout Knox County.

3.4.3. Prioritization of GI implementation sites

The prioritization scheme for GI implementation combines potential impact of floods (Fig. 5b) with the likelihood of floods (Fig. 4) determined by projected precipitation. Generally, high priority areas are characterized by very high potential impact and very high likelihood of floods while low priority areas are characterized by very low potential impact and very low likelihood of floods. Fig. 6 shows three priority levels under two scenarios of precipitation change. In both scenarios, areas within Knoxville city limits are high priority, with priority level decreasing with distance from the city.

4. Discussion

Given the past trends and projected increase in precipitation as illustrated using the downscaled GCM data, this study has shown that additional storm water management strategies are necessary in addition to the existing gray storm water drainage infrastructure. Our case explores the use of GI as an adaptation strategy, to offset uncertainties of climate change which include precipitation increase. In addition to indicating suitable sites for GI implementation, our methodology explores relevant indicators of vulnerability to derive relative potential impact of a flood event. This is important for directing resources where

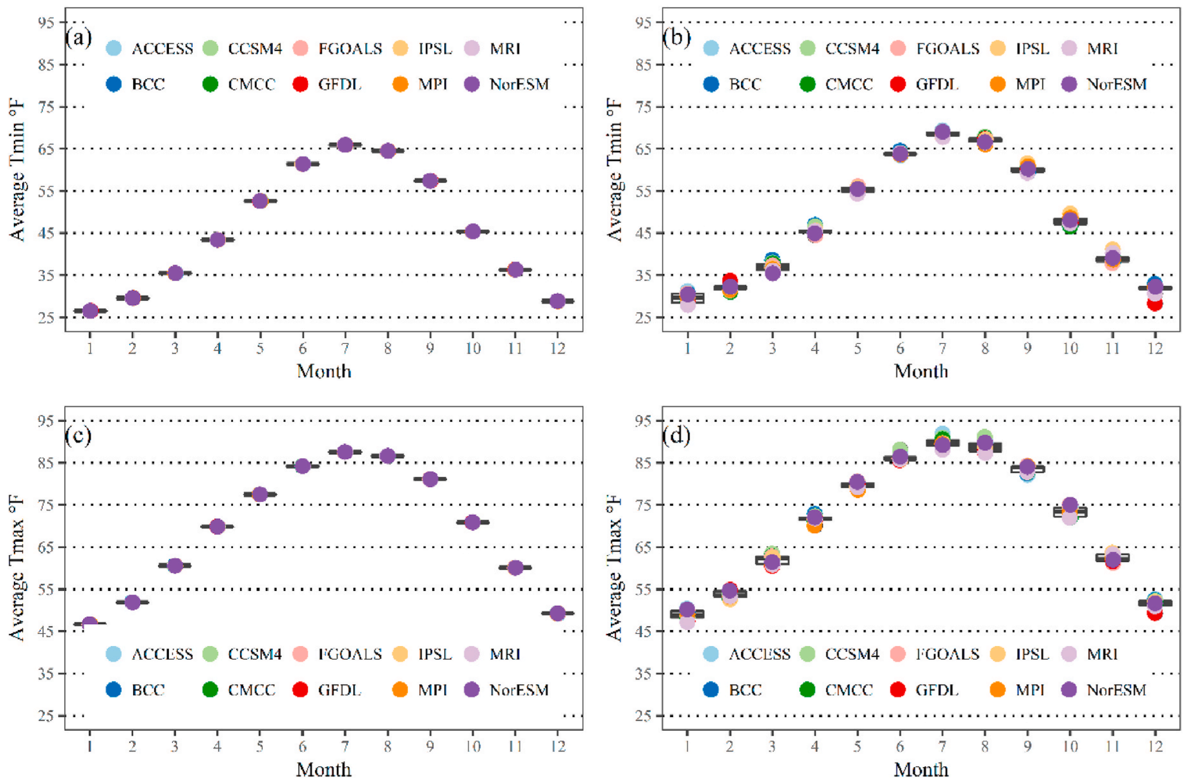

Fig. 3. Average daily minimum (a) and maximum (c) temperature for the period 1980–2005. Average daily minimum (b) and maximum (d) temperature for the period 2025–2050.

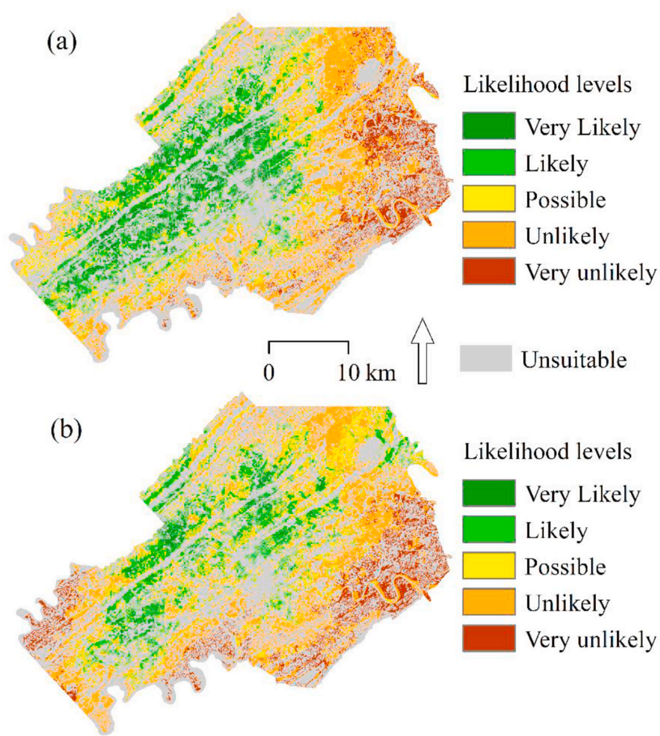

Fig. 4. Flood likelihood from projected precipitation. (a) Based on median of percentage change in seasonal mean precipitation. (b) Based on median of projected change in seasonal mean precipitation amount.

they are needed most. Effectively, there is more efficient allocation of public funds and reduced impact of extreme floods.

Recognizing the limitation of space in most urban areas, the analysis was performed at 10 m spatial resolution. This should allow for capturing all available sites including small parcels that may be appropriate for some GI types such as filter strips, canopy expansion and bioswales. Other researchers have explored opportunities for simultaneous consideration of green-blue-gray measures and recommend hybrid solutions when space is a limitation (Alves et al., 2020). The employed GIS-based multi-criteria technique for grid layers overlay is a popular method for analyzing criteria on a geographic space. Several authors have used it to assess site suitability for GI and found it to be robust (Jayasooriya et al., 2018; Kuller et al., 2019). The inclusion of socioeconomic and biophysical factors in our GI placement and site prioritization scheme is in line with suggestions by Kuller et al. (2018) on improving planning support systems that involve GI for storm water management.

There is a growing acknowledgement that change in climate will affect the ability of GI systems to support storm water management because of possible increase in precipitation (Lim and Welty, 2018) and or deteriorating condition of vegetation as plant hardiness zones shift (Sylvester et al., 2019). This study emphasizes the need to consider future changes in precipitation to counter uncertainties related to climate change in GI planning. To the best of our knowledge, there is not much that has been written about planning for GI based on precipitation projections. Recent work by Barah et al. (2020) is a good example of how precipitation projection data may be used to offset climate change uncertainties in GI planning while providing placement scenarios that reduce on implementation cost. In addition to incorporating precipitation projections, the current study follows an approach that facilitates the determination of individual placement parcels that are both suitable and high priority. Additionally, the prioritization scheme can be useful for guiding efforts and resources both to suitable areas and to where they are needed most. By performing the analysis at 10m spatial resolution

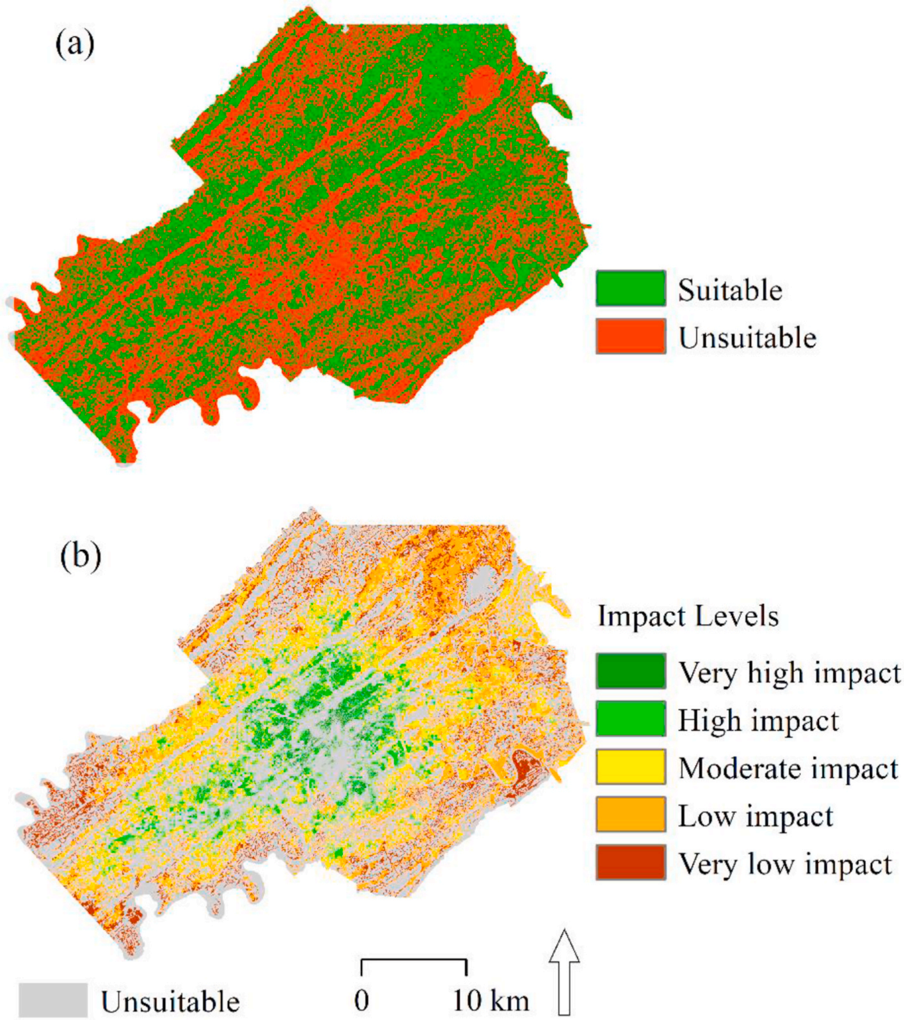

Fig. 5. (a) Potential sites for GI installation. (b) Relative potential impact of floods.

(compared to sub-watershed level as in Barah et al., 2020), the approach captures small parcels that are suitable for GI especially in dense urban areas where space is limited. This study has shown that, precipitation projection information can shape the focus of a GI implementation plan in a way that makes it more effective and cost friendly.

The consideration for projected precipitation data in GI placement for storm water management is a vital but challenging task. Lack of projected precipitation data is a major concern for many cities. Readily available projections based on GCMs are too coarse for application at the local level of a city, and the costs associated with running local numerical weather prediction models can be high. Downscaling of GCM and regional climate model data is a convenient alternative for generating the required precipitation predictions at a scale appropriate for city level planning.

Future changes in climate should be considered in selecting both placement sites and GI types. GI planning must consider ability to accommodate future changes in surface runoff. Appropriate siting should therefore coincide with high precipitation areas. In the current analysis, projected precipitation data combined with known flood zones were useful for further prioritization of vulnerable sites. The inclusion of known flood zones was particularly important in this case because the zones do not automatically coincide with high precipitation areas nor areas of projected increase in precipitation. It was found that flood zones are primarily within low lying land and flood plains adjacent to the Tennessee river. These may not always flood except in the event of historically heavy precipitation. Specific GI types such as woody vegetation suited for wetland environments may be considered for the known permanent flood zones to facilitate evapotranspiration.

When implementing the current GI placement scheme within the larger watershed extent, it is encouraged that further analysis of local hydrology be performed in order to identify surface flow pathways to guide appropriate GI types. This is expected to enhance the effectiveness GI. Such hydrologic assessment has been demonstrated in Ellis and Viavattene (2014) and found to substantially reduce surface flow. Considering the significance of the current scheme as an adaptation strategy to climate change, it is advocated for implementation within existing frameworks.

5. Conclusions

The GI prioritization scheme presented here may be viewed as a guide for effective GI placement that can easily be replicated for any other city. The current planning approach involved assessment of physical site characteristics to determine suitable sites for GI, assessment of socioeconomic variables to understand relative potential impact of floods, and analysis of precipitation projections as an indicator of likelihood of flooding. Prioritization of suitable sites is determined as a function of relative potential impact of a flood event and the likelihood of flooding.

The prioritization scheme involves a fusion of biophysical, socioeconomic and climatic data to define risk levels that assimilate potential impacts of an extreme flood event with potential likelihood of

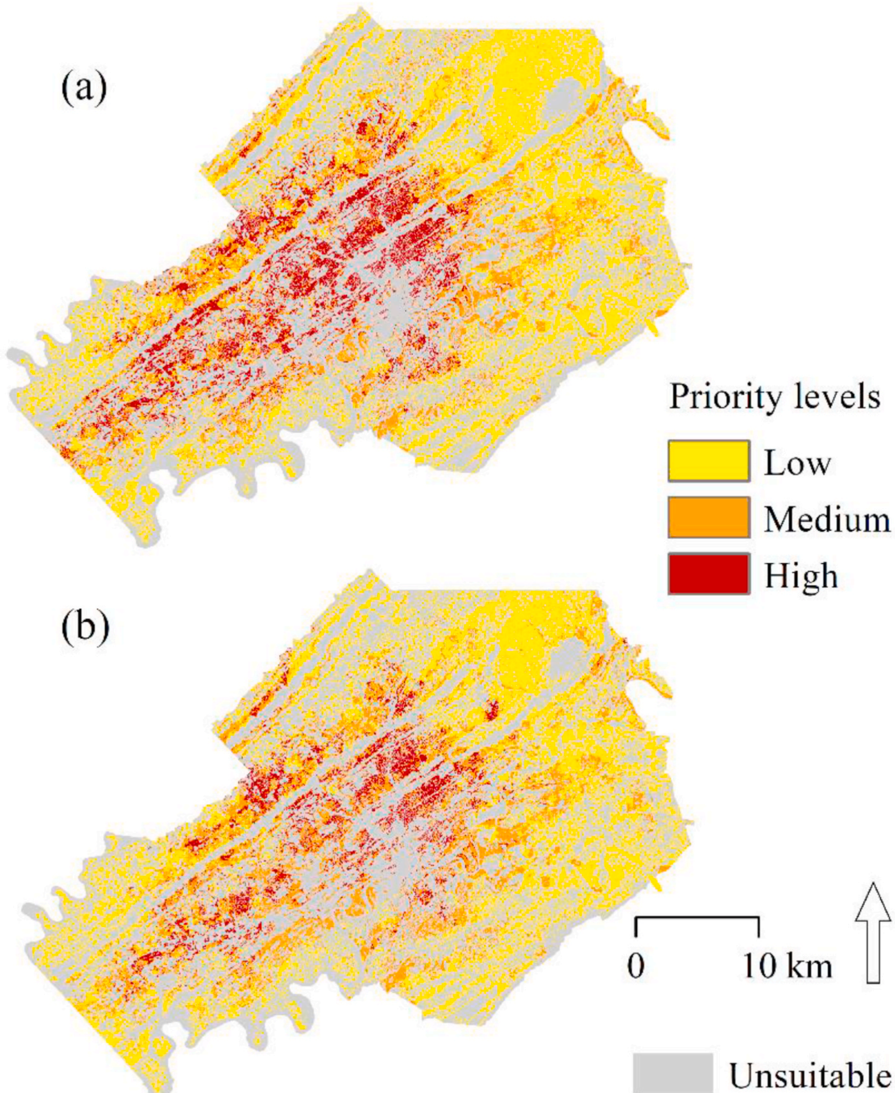

Fig. 6. Priority levels for GI implementation sites. (a) Likelihood is based on projected percentage increase in precipitation, (b) Likelihood is based on projected median increase in precipitation amount.

occurrence of the extreme event as indicated by precipitation projections. Because it integrates projected precipitation data, the current model is appropriate for exploring urban climate change adaptation strategies that can help to offset the potential impact of increased precipitation. The model emphasizes prioritization of GI placement, and therefore can be used to focus efforts and resources where they are needed most. The high spatial resolution by which the analysis was performed allows for identification of small parcels that are suitable for GI. This capability is ideal for GI implementation in dense cities or those with limited space.

The study represents projected precipitation and therefore potential likelihood of floods as a spatial map which depicts spatial variation across space. The model does not estimate potential runoff volume and their flow paths which would help to guide decisions about appropriate GI types. It is proposed that for GI implementation at watershed extents, a hydrological model should be consulted in determining specific GI types. However, it is ideal for use alongside and in sync with existing flood control plans and procedures.

Declaration of competing interest

The authors declare no competing interests.

Acknowledgements

The authors thank Linda Sylvester, Thomaz Calvahaes, Michele Thorton, Rui Mei and Parul Kaushal for their help with some of the data. The authors also thank Erin Gill and Jim Hagerman of City of Knoxville for their support of the Urban-CAT project. The authors would like to acknowledge the financial support for this research from the U.S. Government for Oak Ridge National Laboratory's Laboratory Directed Research and Development (LDRD) project number 7451. This manuscript has been authored by UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the US Department of Energy (DOE). The US government retains and the publisher, by accepting the article for publication, acknowledges that the US government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US government purposes. DOE will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (http://energy.gov/downloads/doe-public-access-plan).

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