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The projected impacts of smart decline on urban runoff contamination levels

Rui Zhu* and Galen Newman

Abstract

There has been mounting interest about how the repurposing of vacant land (VL) through green infrastructure (the most common smart decline strategy) can reduce stormwater runoff and improve runoff quality, especially in legacy cities characterized by excessive industrial land uses and VL amounts. This research examines the long-term impacts of smart decline on both stormwater amounts and pollutants loads through integrating land use prediction models with green infrastructure performance models. Using the City of St. Louis, Missouri, USA as the study area, we simulate 2025 land use change using the Conversion of Land Use and its Effects (CLUE-S) and Markov Chain urban land use prediction models and assess these change's probable impacts on urban contamination levels under different smart decline scenarios using the Long-Term Hydrologic Impact Assessment (L-THIA) performance model. The four different scenarios are: (1) a baseline scenario, (2) a 10% vacant land re-greening (VLRG) scenario, (3) a 20% VLRG scenario, and (4) a 30% VLRG scenario. The results of this study illustrate that smart decline VLRG strategies can have both direct and indirect impacts on urban stormwater runoff and their inherent contamination levels. Direct impacts on urban contamination include the reduction of stormwater runoff and non-point source (NPS) pollutants. In the 30% VLRG scenario, the annual runoff volume decreases by 11%, both physical, chemical, and bacterial pollutants are reduced by an average of 19%, compared to the baseline scenario. Indirect impacts include reduction of the possibility of illegal dumping on VL through mitigation and prevention of future vacancies.

Keywords: Smart decline, Urban regeneration, Urban prediction modeling, Green infrastructure, Urban pollution

1 Introduction

As human interactions on the earth's surface have altered climate patterns, flood events have become more frequent (Hendricks et al., 2018). Simultaneously, flood effects have become more severe due to increases in impermeable urban area, rising sea levels, and increases in extreme precipitation events (Horney et al., 2019; Stone et al., 2019). When floods occur, cities (especially legacy cities with elevated amounts of brownfields, vacant lands, aging infrastructure, and combined sewer and stormwater systems) face increased risks of flood-related contamination (Alexandre, 2018; Desimini, 2013). Legacy cities are synonymous with shrinking (or excessively depopulating) sites in

the U.S. Rust Belt. They are postindustrial cities that suffer from continuous population decline, industrial decline, economic downturns, employment decline, and symptoms of a structural crisis such as excessive abandonment (Martinez-Fernandez et al., 2016; Tighe & Ryberg-Webster, 2019). In the U.S., urban shrinkage is primarily seen in Midwestern legacy cities. For example, cities, such as St. Louis, MO, Detroit, MI, and Baltimore, MD have experienced severe depopulation and, with this, declines in manufacturing and harsh impacts related to the 2008 U.S. housing foreclosure crisis. Because of the high rates of previous industrialization, the percentage of brownfields and toxic release sites is much higher in the Northeast and Midwest (Rustbelt) states compared to other regions (Page & Berger, 2006). A vast extent of the vacant land which arose as a byproduct of depopulation and deindustrialization in many legacy cities has not returned

* Correspondence: zr1991@tamu.edu

Department of Landscape Architecture and Urban Planning, Texas A&M University, College Station, TX, USA

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to a natural state after becoming vacant. Many such sites have become contaminated lots through the dumping of materials, pollutants from nearby active or obsolete industrial areas, or oil-based runoff from major roadway (Nassauer & Raskin, 2014). Further, when a flood occurs, suspended particulate matters, heavy-metal pollutants, and chemicals from toxic release sites, brownfields, or farms are typically drained across impervious surfaces into storm drain systems and into nearby water bodies (Ciszewski & Grygar, 2016).

To counteract the negative impacts of urban shrinkage, many declining US cities have switched from a conventional growth-oriented planning paradigm to approaches favoring 'smart decline' (Newman, Park, Bowman, & Lee, 2018). Smart decline plans for less; in such approaches, cities minimize municipal expenditures, reclaim and repurpose vacant land and abandoned buildings, adjust infrastructure and amenities to align with developmental demands of their shrinking population, and manage decline to ensure a higher quality of life of their residents (Herrmann et al., 2016; Ryan & Gao, 2019). The repurposing of vacant lots to functional and managed green space as a smart decline strategy can have a significant effect on stormwater runoff reduction, climate regulation, air quality improvement and non-point source (NPS) pollution mitigation, especially in legacy cities (Anderson & Minor, 2017; Heckert, Schilling, & Carlet, 2015; Kondo, Hohl, Han, & Branas, 2016; Shuster, Dadio, Drohan, Losco, & Shaffer, 2014; Zheng et al., 2012). However, research involving the potential impacts of limiting the transfer of hazardous substances through the greening of vacant lots during flood events in legacy cities is rare. This research asks, what effects can vacant land greening (VLRG) through smart decline help decrease pollutant loads in legacy cities undergoing excessive vacant lands amounts. To explore the probable impacts of smart decline on urban contamination levels, this research forecasts land use change, long-term runoff amounts, and non-point source (NPS) pollutant loads using the City of St. Louis, MI. Using the Conversion of Land Use and its Effects (CLUE-S) and Markov chain urban land use prediction models, we predict future land use changes for the study area. Then, we integrate the future land use predictions with the Long-Term Hydrologic Impact Assessment (LTHIA) Low Impact Development model to forecast future pollutant loads based on smart decline VLRG scenarios. The CLUE-S model was calibrated using historical land use data from 2000, 2010 and 2015, and future growth was projected out to 2025, assuming four different scenarios: (1) a baseline scenario, (2) a 10% vacant land re-greening (VLRG) scenario, (3) a 20% VLRG scenario, and (4) a 30% VLRG scenario. The baseline scenario was created based on historical land use trends

while the VLRG scenarios were designed to reduce vacant lands based on the baseline scenario.

2 Literature review

2.1 Urban shrinkage and consequential vacant land

Despite an overall increase in population globally, populations in some regions are still intensely decreasing. One in six cities worldwide over are undergoing population shrinkage (Herrmann et al., 2016). Deindustrialization, suburbanization, war, natural or human-induced disasters, aging populations, low-fertility rates, and globalization are all factors contributing to urban shrinkage in these cities (Hollander, Pallagst, & Schwarz, 2009). Some authors report that most industrial cities that have lost more than 25% of their population over the past 40 years, resulting in a built environment characterized by abandoned properties, vacancies, and blight (Schilling & Logan, 2008).

Because of globalization and deindustrialization, cities that cannot gain a foothold in the current international economic competition may eventually lose populations and, ultimately, financial resources. Since 2000, nearly 5 million manufacturing jobs have been lost in the U.S. (Xie, Gong, Lan, & Zeng, 2018). When employment falls, capital resources outflow and people who have the ability to relocate typically relocate to places with sufficient job opportunities. This increases vacancy and blight, as the spatial extent of a shrinking city does not also shrink with its population. In most shrinking cities, it is common to see aged infrastructure, such as roads, housings, and water supply, that were used when the cities were in prosperity, hence the term 'legacy city' (Herrmann et al., 2016). Moreover, the vacancy issue is contagious in that vacant land can result in more vacant land, if not treated. The condition is more likely to repeat itself through time and eventually infest adjacent areas. In essence, vacancy begets more vacancy; it is a factor contributing to itself (Newman et al., 2018; Newman, Lee, & Berke, 2016).

Relatedly, the imbalance between housing supply and demand in some shrinking cities has caused housing prices to fall significantly, but many still have trouble being sold (Hollander, 2013). Large numbers of industrial, commercial, and residential buildings have become abandoned by owners and investors in many shrinking cities (Hackworth, 2018). In neighborhoods experiencing excessive vacancy/abandonment, property values residing nearby a vacant lot can be reduced by up to 20%, causing those not relocating from the city to suffer negative economic impacts (Shetty, 2009). In addition, the physical and environmental unpleasing aesthetic of unused industrial structures can send an unwelcoming

signal to potential future residents and investors (Hackworth, 2018; (Hollander, 2013).

2.2 Flooding and industrial contamination

Flooding, the costliest disaster event globally, accounts for about 40% of the total catastrophes worldwide (Reja et al., 2017). Flooding has been associated with multiple environmental and health-related consequences such as disruption of sewage systems, contamination of drinking water sources with chemical material, damage to buildings, and the spread of water-borne disease (Euripidou & Murray, 2004; Tempark, Lueangarun, Chatproedprai, & Wananukul, 2013). Floods play a crucial role in transferring suspended particulate matters, heavy-metal pollutants, and chemicals across developed areas (Ciszewski & Grygar, 2016). Pollution transference during floods is much more considerable when industrial or agricultural lands are adjacent to residential areas (Euripidou & Murray, 2004). Global climate change and rapid urban development has made flooding more frequent and intense, increasing the potential consequences of hazardous substance transferal (Filho & Pina, 2010; Lau, Smythe, Craig, & Weinstein, 2010).

When a flood occurs, legacy cities characterized by brownfields, vacant lands, aging water infrastructure systems, and combined sewer and stormwater systems (CSS) face a larger risks of being negatively impacts by flood-related contamination (Alexandre, 2018; Desimini, 2013). As noted, the percentage of the brownfield is much higher in the US Rustbelt states (Page & Berger, 2006). Due to a lack of environmental awareness in the early decades of industrialization, most industries primarily sought high-yield production and economic growth without controlling for the release or disposal of toxic substances until environmental laws were established (Page & Berger, 2006). As a result, many soils are often polluted by the “legacy of industrial activity” in Rustbelt cities (Mersol-Barg, 2014; Wong, Gable, & Rivera-Núñez, 2018).

Often, the unmonitored nature of vacant lands makes them susceptible to becoming dumping grounds of human or industrial waste. This can also bring potential contaminants such as household waste, construction debris, unknown chemicals, oil and gas products, tires, and vehicles, asbestos, polychlorinated biphenyls (PCBs), lead, zinc, and copper. These harmful substances can accumulate for years and pose environmental and public health risks. Further, the geographic location of vacant land may influence its contamination load (Nassauer & Raskin, 2014). For example, vacant lands near active industrial areas would likely have elevated levels of chemical pollution; vacant lands closer to major roads, highways, or parking lots have a greater chance of becoming polluted by gas and oil byproducts (Nassauer &

Raskin, 2014). Additionally, in many legacy cities, the capacity of many sewer systems is insufficient to hold the amount of wastewater/stormwater necessary during major storm events, leading to untreated overflows into ecosystems, further harming natural habitats and human health (Krane, 2016).

2.3 Smart decline, vacant regreening, and impacts on pollutant load

Some shrinking US cities have switched from conventional growth-oriented planning to smart decline strategies. Smart decline plans for less development; in such approaches, cities minimize municipal expenditures, reclaim and repurpose vacant land and abandoned buildings, adjust infrastructure and amenities to align with developmental demands of their shrinking population, and manage decline to ensure a higher quality of life of their residents (Herrmann et al., 2016; Ryan & Gao, 2019). Through smart decline, cities target new development in the most promising areas or nodes; areas with low development potential are managed, repurposed through community needs or allowed to return to nature as much as possible (LaCroix, 2011). There are several strategies used in smart decline including: 1) built environment improvement, with the goal of ameliorating abandonment and vacancy; 2) community development aimed at improving the local economy and existing infrastructure; 3) administration reform, focusing on adjusting the form and function of municipal governance; and 4) civic engagement, transforming top-down planning into a grassroots approach. Built environment improvement strategies are a primary focus of smart decline, with VLRG being the most commonly used built environment strategy (Ryan & Gao, 2019).

For example, the Youngstown Neighborhood Development Corporation initiated a ‘Lots of Green’ program to repurpose vacant lands into green spaces (Kondo et al., 2016). Cleveland launched a vacant land reuse program called “Reimaging a More Sustainable Cleveland” to implement green infrastructure (GI) into vacant lots to treat stormwater runoff (Coppola, 2014; LaCroix, 2011). Philadelphia adopted a vacant greening policy to create a pocket park-like environment by cleaning up garbage and planting vegetation (Shetty, 2009). The process of vacant regreening assumes that the large extent of vacant and abandoned properties left behind by urban shrinkage still have economic, social, and ecological values (Anderson & Minor, 2017), and aims to regenerate them as part of an urban greenspace network of gardens and urban farms, pocket parks, and other park-type settings (Heckert et al., 2015).

The benefits brought by VLRG can be wide-ranging including socio-economic benefits (e.g., increasing the accessibility to green space, improving social well-being,

and increased property values), ecological benefits (e.g., carbon sequestration, decreases in energy use, air pollution and urban heat, stormwater runoff reduction, and water quality improvement), and rightsizing development (or allowing the city area to retract in size as necessary) that meets the demands of the current shrinking population without compromising the ability of future development (Anderson & Minor, 2017; Heckert, 2017).

VLRG projects can be permanent or temporary. When conditions are economically or socially unstable, such as those in shrinking cities, a property's ownership or development potential can alter significantly. Given the largely transient nature of vacant land, the temporary use of vacant lands can be more appropriate than permanent uses in depopulating cities (Anderson & Minor, 2017). Common practices of VLRG include basic cleaning and greening (e.g., removal of debris and trash, and the planting of grass, trees, and flowers), and GI implementation (e.g., stormwater runoff management, water quality improvement, and bio-remediation of contaminated sites) (Heckert et al., 2015; Kondo et al., 2016).

GI refers to a series of products, technologies, and practices that seek to reduce urban stormwater runoff and improve water quality by managing more water on-site through mimicking natural processes. GI projects can cover a wide range of elements, and can include simple small-scale treatment and stormwater drainage/storage such as lot-scaled rain gardens, community-scaled facilities such as detention/retention ponds, bioswales with complex infiltration or holding systems, and large scaled constructed wetlands to alleviate sewer overflow and provide wildlife habitat (Heckert et al., 2015; Kim, 2016; Martínez et al., 2018). It has been shown that green belts can largely mitigate stormwater runoff compared to agricultural grassed slopes; the average peak runoff was reduced by 24% by clearing and regreening five vacant lots in Northern Philadelphia (Kondo et al., 2016). In Cleveland, a study of 52 regreened vacant lots shows a positive effect on annual rainfall storage (Shuster et al., 2014). Further, robust perennial species of vegetation which can be grown in contaminated soils have been shown to be cost-effective when remediating soil contamination and improving groundwater quality (Anderson & Minor, 2017; Heckert et al., 2015; Zheng et al., 2012).

2.4 Integrating prediction modeling and the long-term hydrologic impact assessment model

Water quality and nonpoint source (NPS) pollution models are essential for simulating the land use management practice impacts on stormwater runoff and nonpoint source (NPS) pollutants reduction. Well-known models are Long-Term Hydrologic Impact Assessment (L-THIA), Estimating Pollutant Load (STEPL), GIS Pollutant Load (PLOAD), ArcView Soil and Water

Assessment Tool (AVSWAT-X), Soil and Water Assessment Tool (SWAT), and Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) (Nejadhashemi & Mankin, 2007; Yuan, Sinshaw, & Forshay, 2020). To assess the future impacts of land use changes on urban runoff contamination levels, these water quality and NPS pollution models can be combined with land use prediction models. For example, by combining urban growth predictions using the (LTM) with land use performance metrics using the Long-Term Hydrologic Impact Assessment (L-THIA) model, Tang et al. (2005) forecasted future land use changes and measured their probable environmental impact. Dams, Woldeamlak, and Batelaan (2008) assessed the impacts of land use changes on groundwater quantity by using the CLUE-S model in conjunction with both the WetSpa and MODFLOW groundwater flow tools. Wilson and Weng (2011) applied the Land Change Modeler (LCM) in combination with the SWAT hydrologic and water quality model to simulate the impacts of future land use changes and climate changes on surface water quality. While these combinations are rare, they are growing in popularity.

Among these water quality and nonpoint source (NPS) pollution models, L-THIA stands out as a powerful tool for enhancing NPS pollution management by identifying environmentally sensitive areas and assessing different land use scenarios (Bhaduri, Engel, Harbor, Jones, & Lim, 1999). As one of the most simple-to-use model for simulating the hydrologic impacts of the land use change for planners and natural resource managers, the L-THIA has gained extensive attention in recent years (Li et al., 2013). Woonsup (2007) applied L-THIA to evaluate the impacts of future urban growth in the Richland Creek basin, Illinois, on direct runoff, NPS total nitrogen, total suspended particles, and total phosphorous loads. Through L-THIA model, Li, Bai, Han, and Zhang (2016) explored the contributions of different land use type to local hydrology and non-point source pollution in Bao'an District in Shenzhen, China from 1988 to 2014. Newman, Kim, Joshi, and Liu (2020) also assessed the probable impacts of resilient community design on flood risk and pollutant loads in Tampa, FL using the L-THIA, finding significant decreases in pollutant loads as the percentage of green land uses increased.

2.5 Land use/land cover modeling in shrinking cities

Land use/land cover (LULC) modeling has become a widely used technique for understanding complex of land use dynamics, assessing the environmental impacts of land use policies, and predicting future circumstances for guiding land management practices (Hu, Zheng, & Zheng, 2013; Veldkamp & Lambin, 2001; Verburg & Overmars, 2009). Through scenario-based approaches,

LULC modeling helps inform planners of the potential environmental, social, and economic impacts of different land use policies and the possible implications of future urban growth/land use changes. The most widely used LULC models are SLEUTH, Cellular Automata Model, Artificial Neural Network (ANN) such as the Land Transformation Model (LTM), Agent-based Model, Markov, and CLUE-S (Kim & Newman, 2019; Wu et al., 2012).

Contrary to most land use prediction models, the CLUE-S model is a regional scaled dynamic model which is able to simulate multiple land-use types simultaneously by dynamically simulating the competition between land use types (Verburg et al., 2002). Once future land uses are projected, the outputs can be used to assess the relationships between land use change and the driving factors contributing to such change. Further, one can explore the impacts of different land use scenarios at different spatial scales (Hu et al., 2013). Because the CLUE-S model combines top-down and bottom-up algorithms, unlike other spatially explicit prediction models, it can project land use change when the demands of different land use types change, thus it can dramatically avoid the inaccuracy of land use simulation and prediction. (Hu et al., 2013; Verburg et al., 2002). The CLUE-S model consists of spatial module and non-spatial module (Hu et al., 2013). Both modules require external models to assist in the completion. In spatial module, outputs of a logistic regression calculated from other statistical packages used as inputs of the CLUE-S model to aid it in the land use allocating process. The Markov chain model, used as a stochastic model, has been recognized as the most suitable model for non-spatial module of the CLUE-S model, because it predicts land use changes from one status to another status between discrete time periods, which is in line with the rule of land use changes (Hu et al., 2013; Iacono, Levinson, El-Geneidy, & Wasfi, 2015; Muller & Middleton, 1994).

The ability of the CLUE-S to accurately simulate land use changes has made it widely used in many studies. Xu, Li, Song, and Yin (2013) used the CLUE-S model to simulate different land use scenarios in Guangzhou, China, to study the impact of future urban sprawl on land ecosystems. Hu et al. (2013) simulated future land use scenarios from 2010 to 2020 in Beijing, China by using land-adaptive, regional spatial, and socio-economic driving factors, and the future urban pressure was discussed from the perspective of ecological and cultivated land protection. Grigorescu et al. (2019) assessed future urban sprawl in Romania using the CLUE-S.

As noted, the CLUE-S model, like other LULC models, is primarily used to predict urban growth patterns. LULC modeling has been rarely applied in shrinking

cities, and the common variables used to predict land use dynamics usually do not often consider the forecasting variables for vacant land. Until recently, few scholars have explored urban vacancy dynamics using LULC models. Newman et al. (2016) utilized the land transformation model (LTM) to test the effectiveness of vacant land forecasting variables in vacant urban land prediction, paving the way to LULC modeling in shrinking cities. Lee and Newman (2017) then tested urban land use change model in Chicago, Illinois, USA, predicting future urban decline in the city. In 2018, Lee et al. used the same methodology to make comparisons in vacant land amounts between growing and shrinking cities.

3 Literature gaps and research objectives

While most LULC studies concentrated on vacant land solely focus on vacant land prediction or conversion, different land use change processes mutually influence one other simultaneously (Verburg & Overmars, 2009). The CLUE-S model serves as a proven solution for simulating multiple land-use types simultaneously. This research advances the Lee and Newman (2017) model by more accurately predicting the vast array of multiple future land uses in shrinking cities rather than simply predicting for future vacant land only. It also couples these outputs with impact models to project effects on hazardous substance increase or decrease.

There are few LUCC models targeting land use change prediction in shrinking cities, while most of them are mainly focus on urban growth prediction. Relatedly, while there has been mounting research interest about how green space can help reduce stormwater runoff and improve water quality, few studies have explored the effects of greening through smart decline to reduce stormwater runoff and improve water quality nor have they projected such effects over the long-term (in this case, 15 years). These gaps in the research are the primary focus of this study. In this research, ask, what effects can VLRG through smart decline help decrease pollutant loads in legacy cities undergoing excessive vacant lands amounts? With flood occurrence frequency increasing in legacy cities with a large degree of brown-fields, vacant lands, toxic release sites, and outdated sewer systems, this research is both timely and necessary. To understand the potential urban contamination reduction services that VLRG can provide to legacy cities, is essential to effectively support planning or management through smart decline for shrinking cities. This paper sheds light on the long-term impacts of smart decline on stormwater management and urban contamination levels and is important to land use decision-makers, whose policies support urban regeneration and multi-exposure risk evaluations for urban populations.

4 Methods

4.1 Study area description and data

To understand the VLRG effects on stormwater runoff reduction and nonpoint source pollution mitigation, we evaluate a legacy city with a declining population, excessive amounts of vacant land, and one which also faces flood issues. The city of St. Louis, MO, the study area of this research, has lost 64% of its residents since 1950 (Page & Berger, 2006). Based on population change from 2009 to 2018, St. Louis is ranked as a top 3 shrinking U.S. city among cities with 250,000 and above in population with a 2.5% increase in vacant housing units (Kim & Newman, 2020).

Additionally, the numerous small and oddly shaped vacant parcels in St. Louis make it a unique study area. From 1995 to 2015, the area of vacant land in St. Louis actually decreased from about 2400 to 1700 ha, while the number of vacant parcels increased significantly (see Fig. 1). This characteristic of vacant land makes it difficult to regenerate or repurpose for traditional development (Németh & Langhorst, 2014). The geographic location of St. Louis also makes it vulnerable to flooding (see Fig. 1). St. Louis is nestled below the confluence of the Missouri and the Mississippi rivers, two of the largest and most powerful rivers in the U.S. Combined with the Meramek river, these three rivers nearly completely encircle the city. Historically, the Great Flood of 1993 occurred on the Missouri and Mississippi rivers, ravaging nearly the entire city of St. Louis (Kousky & Kunreuther, 2010). From 1973 to 2017, St. Louis experienced 12 severe flood events and the frequency of flooding also has increased recently (St. Louis County, Missouri, 2020). The pollutants in the resultant

stormwater runoff, such as chemicals, oil, suspended solids, and disease-causing bacteria, primarily come from industrial sites, parking lots, streets, vacant lands, and unkempt infrastructure in declining neighborhoods. Unlike domestic wastewater, the polluted stormwater directly enters the water system without any treatment.

The methodological approach follows three primary steps: 1) application of the CLUE-S model to predict future land uses of St. Louis by 2025; 2) development and application of greening proportions for different smart decline scenarios; and 3) calculation of stormwater runoff and the nonpoint source pollutant loads under each different scenario. Parcel data from 2000 to 2015 was obtained from the City of St. Louis Open Data (City of St. Louis, MO Open Data, 2020). The parcel data contains detailed information such as zoning codes, land use codes, land vacancy status, land value, and land improvement value. There are 24 types of zoning codes and 852 land use types in the data. Land use types were condensed to 7 classifications – single-family, multi-family, industrial area, commercial area, green space, vacant land, and other land uses. Green space comprises forest parks, public gardens, golf courses, water areas, and other outdoor entertainment areas. Vacant lands, according to the datasets, were defined as any place with a vacant status, regardless of whether it has building structure on the land. In addition, others land uses include institutional facilities, governmental services, and transportation utilities. Each land use category accounts for more than 5% of the city's total area. Since all parcel data were downloaded as vector data, which does not meet the CLUE-S model requirement, we used the Vector to Raster tool in ArcGIS 10.8 to convert vector data

Fig. 1 Vacant land changes from 1995 to 2015 in the City of St. Louis

to raster data. In St. Louis, the average size of a land parcel is about 900 m², so a spatial resolution of 30 m was utilized in the raster conversion process.

4.2 Future scenarios development

As noted, although the area of vacant land in St. Louis has declined, the number of vacant parcels is increasing. Instead of permanent solutions, flexible, incremental, and temporary responses are necessarily incorporated into the urban vacant land regeneration programs for these small and odd shaped vacant lots (Németh & Langhorst, 2014). Németh and Langhorst (2014) suggested that some regeneration strategies, such as the Adopt-A-Lot and the Clean and Green approaches, have shown promising outcomes for temporary uses. Moreover, VLRG offers an alternative to the traditional method of directing stormwater runoff simply into sewers and rivers. Generally speaking, the vacant conversion rate in cities using VLRG strategies is about 10% to 30% within the range of city's capacity according to available projects that have been completed. For example, the Clean & Green program conducted by the Genesee county land bank annually maintains around 10% (1000 lots) of vacant residential lots in Flint, MI (Genesee County Land Bank - Vacant Land, 2020). In Philadelphia, PA, The LandCare program initiated by the Pennsylvania Horticultural Society (PHS) annually cleans, greens, and maintains approximately 30% (12,000 lots) of vacant lots (Loesch, 2018). In order to understand how VLRG has an effect on reducing stormwater pollutions, a set of vacant regeneration scenarios are created based on the feasible vacant land conversion scope mentioned above: 1) a baseline scenario, which is created to predict the future land use based on historical trends; 2) a 10% VLRG scenario, which is aimed to reduce 10% of the vacant land based on the baseline scenario with the balance of vacant land primarily compensated by green spaces; 3) a 20% VLRG scenario, which is designed to reduce 20% of the vacant land based on the baseline scenario with the balance of vacant land is primarily compensated by green spaces; and 4) a 30% VLRG scenario, which is the same as the above two scenarios, but the goal is to reduce 30% of the vacant land through regreening.

4.3 CLUE-S model

As noted, in this research, we adopted the CLUE-S model to forecast future land use and generate different vacant regreening scenarios. The CLUE is a dynamic model which integrates environmental modeling with geographical information systems. It was developed at Wageningen University and first published in 1996 (Veldkamp & Fresco, 1996). As one of the most widely used land use prediction models globally, the model's applications have primarily focused on understanding

and exploring the land use dynamics of agricultural intensification, deforestation, land abandonment, and urbanization (Verburg & Overmars, 2007). Because the CLUE model was initially developed for study areas with a large extent, such as national and continental levels, the model has been modified to adapt to finer-scaled extent (now called the CLUE-S model) (Verburg et al., 2002).

The overview of the CLUE-S modeling process is shown in Fig. 2. The CLUE-S model consists of two distinct modules: spatial and non-spatial analysis. There are two processes which are required to be completed in the spatial module. One is to select the land use with the highest preference. To determine preferred land use for each location, it is necessary to consider the suitability of the location itself, land use conversion elasticity, and the competitive advantage of land use types (Hu et al., 2013). To determine the suitability of the land use location, the logistic regression results of each land use type are required to be entered into the CLUE-S model. Logistic regression can only be conducted in other statistic packages, such as STATA. Its equation is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} \dots + \beta_n X_n$$

Where P_i is the probability of a grid cell to have a certain type of land use. X_1 represents one of the driving factors. β_0 is the constant and β_1 is the coefficient of variable X_1 . The values of conversion elasticity should be in the range from 0 (easy to convert) to 1 (cannot be converted). Land use types with a low capital investment can be easily shifted to other types if there are few demands, and vice versa. During each iteration, the competitive advantage can be modified based on the balance of the allocated area and the land demand. If the allocated area is not equal to the land demand, the competitive advantage of different land use types will be modified so that the land use with unmet demand will have higher preference. Another process in the spatial module is to check if the conversion is allowed. Spatial policies and restrictions need to be defined in the CLUE-S model to allow for certain areas to remain unchanged, influencing the pattern of the land use change. In addition, the conversion matrix is used to understanding the land use temporal characteristics, that is how possible the land use type of the area can be changed to another land use type. If a land conversion is possible, set it to 1, if not, set it to 0 (Verburg & Overmars, 2007). For example, it is almost impossible to convert agriculture land into forest, while it is very easily to convert it to grassland. Thus, the agriculture land to forest conversion should be value 0, and the agriculture land to

Fig. 2 Overview of the CLUE-S modeling procedure

grassland conversion should be value 1. The non-spatial module needs to be assisted by other specific models, like the Markov chain model, to calculate the land demands for all land use types each year. The results of the non-spatial module are treated as direct input of the land allocation module.

4.4 Markov chain prediction model

We used the Markov chain model to predict temporal land use change for 2025 using historical data from 2000 to 2010. After calculating the land demands for baseline scenario, the land use demands were adjusted according to the requirements of VLRG scenarios as described in future scenarios development section. Markov chain models have been commonly used to simulate land use/cover changes (Al-sharif & Pradhan, 2014; City of St. Louis, MO Open Data, 2020; Muller & Middleton, 1994; Zheng, Shen, Wang, & Hong, 2015). They are used as a stochastic model to project land use changes from one status to another status between discrete time periods. The probabilities of the land transition are assumed to be no memory, that is, the future state of land use depends only on the current state of land use, not the previous state (Iacono et al., 2015; Muller & Middleton, 1994), or mathematically as following:

$$x_{t+1} = f(x_t)$$

Where x_t is the land use at the beginning time t and x_{t+1} is the land use at the end time $t+1$. The Markov chain model predicts the quantity of future land use in the way that is subject to the nature of land use transition. Land use change can be viewed as a multi-directional process. In theory, a given piece of land may transfer from one type of land use to any other at any time. The transition probability matrix representing all the multi-directional land use changes between all mutually exclusive land use categories must be provided before implementing the Markov chain analysis (Muller & Middleton, 1994). Below is the expression of the transition probability matrix representing the land use changes occurred from time t to time $t+1$:

$$p = (p_{xy}) = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \quad (x, y = 1, 2, 3, \dots, n)$$

In the above, p_{xy} indicates the transition probability from previous x th land use status to future y th land use status. n is the total number of land use type of study area. The row of the probability matrix must add up to one, as below:

$$\sum_{x=1}^n p_{xy} = 1$$

$$(x, y = 1, 2, 3, \dots, n)$$

4.5 Variable selection

To determine the preferred land use for each location, the relationship of location driving factors and different land uses was considered. All driving factors were selected based on proven models to represent the complexity of the land use system, covering physical, demographic, socioeconomic, and proximity aspects. The driving factors of general land use types came from a proven model used by Zheng et al. (2015), including slope, elevation, distance to CBD, distance to park, distance to school, population density, etc. Using these factors, they successfully simulated changes in commercial, residential, industrial, green space, vacant, and other land uses in urban renewal areas of Hong Kong. To compensate the lack of driving factors for vacant land change in the model of Zheng et al., specific vacant land forecasting variables were derived from studies on forecasting urban vacancy dynamics in shrinking cities (Lee & Newman, 2017; Newman et al., 2016), including parcel size, population change, education rate, employment rate, minority rate, poverty rate, vacant unit rate, and distance to vacant land.

4.6 Model calibration

Relative operating characteristic (ROC), kappa, quantity disagreement, allocation disagreement, and overall agreement were used to calibrate the model. ROC is utilized to evaluate the performance of the logistic regression model. A 0.5 ROC value represents the assignment probability is due to chance, and 1.0 of a ROC value indicates perfect probability (Alsharif & Pradhan, 2014). To calibrate the CLUE-S model, three different periods of land use need to be provided, at minimum. In this study, we used 2000 and 2010 land use data to predict land use in 2015 and then compared the predicted land use in 2015 with the actual land use in 2015. The kappa statistic is the most widely used method to measure the magnitude of agreement between observations (Cohen, 1960). The mathematical expression of the kappa statistic is following:

$$k = \frac{p_o - p_e}{1 - p_e}$$

Where p_o represents the actually observed agreement and p_e indicates the expected chance agreement. A perfect agreement gives a kappa value of 1.0; whereas a kappa value of 0 indicates the agreement is very weak, only equivalent to chance (Cohen, 1960). However, since

the kappa statistic can sometimes be misleading for practical applications, Pontius and Millones (2011) recommended researchers to replace kappa indices with a more straightforward and useful calculation process that provides two components of disagreement between maps – quantity disagreement and allocation disagreement. To ensure the reliability of this research, we utilized both kappa statistic, quantity disagreement, and allocation disagreement measurements. By using the Raster Calculator tool in ArcGIS, four different conditions can be calculated based on predicted and real maps (see Fig. 3). The formulas for quantity disagreement, allocation disagreement, and overall agreement are as follows (Newman et al., 2016):

$$\text{Quantity disagreement} = \frac{|\{(1+3) - (2+3)\}|}{(0+1+2+3)}$$

$$\text{Allocation disagreement} = \frac{(1+2)}{(0+1+2+3)}$$

$$\text{Overall agreement} = \frac{(0+3)}{(0+1+2+3)}$$

4.7 L-THIA model

The L-THIA model was used to estimate the long-term average annual runoff and nonpoint source pollution for each different scenario. The L-THIA, developed by Purdue University, sheds light on the hydrologic impacts of the land use change for planners and natural resource managers. In order to prevent catastrophic flooding and improve public health, it is critical to understand how land use changes have an impact on surface runoff, ground water recharge, and pollution loading. The inputs of the L-THIA model include location, type and size of land uses, and hydrologic soil type. The outputs of the L-THIA are composed of two components; one is stormwater runoff results and the other is nonpoint source pollutant results. The SCS curve number method is a core component of the L-THIA model to assess the long-term hydrological impacts of land use change. Different area's hydrologic soil group, land use, treatment, and hydrologic condition are all related to the curve number (Li et al., 2013). The following formula shows its equation:

$$CN = 1000 / (10 + S)$$

Where CN is curve number, which is found from the table and ranges from 0 to 100. High curve numbers

		Predicted Values	
		Negative	Positive
Actual Values	Negative	<p>Ture Negative (TP)</p> <p>0 = no real and no predicted transition</p>	<p>False Negative (FN)</p> <p>1 = no real but predicted</p>
	Positive	<p>False Positive (FP)</p> <p>2 = real but no predicted</p>	<p>Ture Positive (TP)</p> <p>3 = both real and predicted transition</p>

Fig. 3 Contingency table for four different conditions of predicted and actual values

indicate high runoff potential (Golberg, 2015). S is the potential maximum retention at a certain time (inches) (Yang, Ma, Guo, & Bai, 2008). When S is known, we can calculate the direct runoff. The mathematic expression for runoff is

$$Q = (P - 0.2S)^2 / (P + 0.8S)$$

Where Q is direct runoff (acre-ft), and P is precipitation (inch). Based on the stormwater runoff results and coefficients associated with different land use types, the nonpoint source pollutant results are estimated (Lim et al., 2006).

The average annual NPS pollution for 15 pollutants are calculated based on an amount of runoff and event mean concentration (EMC). EMC refers to a flow-weighted average concentration of a specific pollutant in a rainfall-runoff event from a particular land use type within a watershed (Mirzaei, Solgi, & Salmanmahiny, 2016; Yusop & Chow, 2008). During the simulation period, the annual average pollutant loads of the entire study area are calculated. Therefore, the L-THIA is different from typical export coefficient models (ECM), which calculate the pollutant load without considering runoff (Wang, Choi, & Deal, 2005). In L-THIA model, the non-point source pollutant load is calculated by following equation:

$$L = E \times Q_{-}(n) \times k$$

where L represents the non-point source pollutant load (kg or millions of coliform), E is the EMC, $Q_{-}(n)$ is the annual runoff volume (m³) and k is a unit conversion factor (Li et al., 2016).

5 Results

5.1 Land demands

The Markov chain model was used to predict the land demand for the baseline scenario in 2025. Before using the Markov chain model, the land conversion probability from 2000 to 2010 must be provided. Based on this historical land conversion probability, we used Markov chain model to calculate the probability of land conversion in 2025 (see Table 1), which can be multiplied by 2010 land use to calculate the land demand under the baseline scenario in 2025. The land requirement of VLRG scenarios were calculated based on the demand of the baseline scenario with adjustments according to different land requirement of each VLRG scenario (see Table 2).

5.2 Spatial allocation

In the spatial analysis module of the CLUE-S model, land use conversion elasticity, driving factors of location, the conversion matrix, and spatial restriction settings are required as inputs. The conversion elasticity of the baseline scenario was calculated based on historical trends

Table 1 Matrix of conversion probability for 2025

2010	2025						
	Others	Vacant land	Industrial	Green space	Commercial	Single-family	Multi-family
Others	0.69	0.09	0.21	0.00	0.00	0.00	0.00
Vacant land	0.03	0.71	0.15	0.01	0.02	0.02	0.06
Industrial	0.04	0.06	0.82	0.02	0.04	0.00	0.02
Green space	0.00	0.00	0.00	0.02	0.97	0.00	0.00
Commercial	0.01	0.06	0.21	0.00	0.70	0.00	0.01
Single-family	0.00	0.00	0.03	0.01	0.00	0.00	0.95
Multi-family	0.00	0.08	0.03	0.00	0.01	0.00	0.86

from 2000 to 2010. From the results, vacant land has the lowest elasticity among all land use types, due to its low capital investment. For VLRG scenarios, the vacant land utilization should be larger than the baseline scenario; therefore, we further reduced the elasticity of vacant land to simulate a smart decline strategy, which manages vacant land through transforming it into green space. Because there are no restrictions on conversion between each land use type, the values in the conversion matrix are tabulated as 1. In terms of the spatial restriction, forest parks and historical district were considered unchangeable under any circumstances. Table 3 lists the estimated coefficients for the selected spatial factors and the different land use types related to their different driving factors.

5.3 Model calibration

Table 4 shows the ROC, kappa value, quantity disagreement, allocation disagreement, and overall agreement of each land use type. All of the values of the ROC are above 0.7, which signifies that these driving factors are able to explain the distribution of each land use type (Mandrekar, 2010). Each kappa value falls within the range of 0.8 to 0.9, indicating a substantial agreement (Viera & Garrett, 2005). Typically, the acceptable overall agreement should be above 85% (Newman et al., 2016). In this study, all the land use types' overall agreements meet the requirement of more than 85%. There are some minor quantity and allocation disagreements, but all of them are within an acceptable range.

5.4 Simulation results for different scenarios

The land use patterns of the four scenarios for 2025 were simulated after running the calibrated CLUE-S model with different land demands and conversion elasticity (see Fig. 4). From the results of the simulation scenarios (see Fig. 5. and Table 5.), the loss of vacant land in the VLRG scenarios significantly increases and the newly vacant land decreases, compared with the baseline scenario. Under the 30% VLRG scenario, the vacancy rate is reduced by 5% compared to the baseline scenario; existing and newly gained VL also dropped by 24.6% and 7.4% respectively, while the VL regeneration rate increased by 31.9%. The conversion rate of vacant land to green space increases as the percentage of regreening increases under the VLRG scenario type (see Fig. 6). Table 6 indicates the conversion rate of vacant land and green space increase from 8% to 25.6% as the percentage of green space increases under the VLRG scenario. Additionally, there are still 88.3% of vacant land that persist in the baseline scenario, while only 63.3% in the 30% VLRG scenario.

5.5 L-THIA results for different scenarios

When applying the L-THIA, the climate data of St. Louis was input as a first step to help assess runoff amounts. For next step, there are eight land use types and four soil types (A, B, C, and D) available to choose from. The soil type A means the soil is has high infiltration, whereas type D represents impermeable soil. According to the current web soil survey (WSS) conducted by the USDA Natural Resources Conservation Service (Web Soil Survey - Home, 2019), the average soil

Table 2 Land use demands of different scenarios in 2025 (unit: ha)

2025	Others	Vacant land	Industrial	Green space	Commercial	Single-family	Multi-family
Baseline	791.12	1973.64	2728.59	1082.03	679.63	2775.72	2161.39
Regeneration (10%)		1776.27		1279.4			
Regeneration (20%)		1578.91		1476.76			
Regeneration (30%)		1381.54		1674.13			

Table 3 Estimated coefficients of binary logistic regression for different land use types

	Driving factors	Others	Vacant	Industry	Green space	Commercial	Single-family	Multi-family
Physical	Parcel size	−0.0218	−0.0158	−0.014	0.0312	−0.1391	−0.0109	−0.0963
	Elevation		−0.0071				−0.0086	
	Slope							
Demographic	Population change							−0.0121
	Population density	−0.0123		−0.0141				−0.01
	Minority rate	0.0037	0.0056	0.0063			0.0057	
Socioeconomic	Education rate (high school graduate or higher)	−0.0268						
	Employment rate	0.0334	−0.0172		0.0581			
	Poverty rate (Under 1.00)	0.0125	−0.007	−0.0063				
	Vacant unit rate	−0.0237		−0.0146	0.0434			0.0178
	Land value				−0.0063	0.0015	0.003	
	Land improvement			0.0002		0.0002		−0.0004
	Household income (Less than \$10,000)	−0.0423		0.0139	0.0444	0.0303	−0.0444	
Proxy	Distance to school	0.0007		−0.0006		−0.001	−0.0015	−0.0019
	Distance to CBD	−0.0005	−0.0003					0.0006
	Distance to floodplain	−0.0007				0.0004		0.0003
	Distance to historical district	0.0002	−0.0003	−0.0002	−0.0003	−0.0005	−0.0004	−0.0012
	Distance to hospital	−0.0003				0.0002		−0.0004
	Distance to park	0.001	0.0003				0.0006	
	Distance to major road	−0.0003		0.0002		−0.0004	0.0012	
	Distance to vacant land	0.0042		0.0011	0.0021	−0.0001	0.0049	0.002
	constant	0.8343	−0.7243	−2.7929	−10.6525	−4.6121	−6.0852	−0.8118

type in St. Louis is type C. Therefore, we used type C soil to represent the soil type for each land use. Also, because vacant land, green space, and others land use types are not options in the L-THIA, we used other similar land use types as substitutes. For example, we use the low-density residential land uses to replace vacant land, the commercial land use to replace others, and the forest to replace green space. Table 7 shows the runoff results of vacant land transition under different scenarios in 2025. Both the runoff and pollutant loads within the runoff significantly decreased with more vacant lands converted to green spaces (see Table 8.) The reduction

levels of the annual runoff volume and the physical/chemical pollutants are very close for the 10% VLRG scenario and the 20% VLRG scenario, with a difference of only 1% and 2%, respectively. The biggest difference between the 10% VLRG scenario and the 20% VLRG scenario are the amount of bacterial pollutants, which reaches 5%. The performance of the 30% VLRG scenario on the annual runoff volume and the non-point source pollutants is much better than other scenarios. In the 30% VLRG scenario, the annual runoff volume is decreased by 11% which is 3% higher than that of the 20% VLRG scenario and 4% higher than that of the 10%

Table 4 ROC, kappa, quantity disagreement, allocation disagreement, and overall agreement outputs

Parameter	Others	Vacant land	Industrial	Open space	Commercial	Single-family	Multi-family
ROC	0.88	0.74	0.70	0.93	0.84	0.92	0.92
Kappa	0.93	0.84	0.86	0.97	0.94	0.99	0.94
QD ^a	0.21	0.86	1.13	0.04	0.12	0.10	0.10
AD ^b	0.98	4.44	4.51	0.40	0.71	0.24	1.72
OA ^c	99.02	95.56	95.49	99.60	99.29	99.76	98.28

^aQD quantity disagreement, ^bAD allocation disagreement, ^cOA overall agreement

VLRG scenario. Moreover, the physical/chemical pollutants of the 30% VLRG scenario is reduced by 19% compared to the baseline scenario, which is 6% higher than that of the 20% VLRG scenario and 8% higher than that of the 10% VLRG scenario. Furthermore, the bacterial pollutants are reduced more than twice than that of the 10% VLRG and 20% VLRG scenarios in the 30% VLRG scenarios. In all the VLRG scenarios, all the nonpoint source pollutants significantly decrease except Chromium. The content of Chromium actually increases slightly in the 30% VLRG scenario.

6 Discussion

We combined the CLUE-S and the Markov chain prediction models with the L-THIA performance model

in this research to forecast the environmental impacts of land use changes related to urban contamination levels both spatially and temporally. The parameters of the prediction models were drawn from historical land use data from 2000 to 2010 and we validated models by comparing simulated land use with actual land use in 2015. ROC, kappa, quantity disagreement, allocation disagreement, and overall agreement outputs all indicated an acceptable or above reliability. Results show that smart decline has positive direct and indirect impacts on flood mitigation and pollutant removal.

Table 5 Vacant land gains and losses under different scenarios in 2025

	Baseline	10% VLRG	20% VLRG	30% VLRG	Difference
Vacancy rate	16%	15%	13%	11%	−5%
persistence	73.0%	63.8%	57.0%	48.4%	−24.6%
Losses	7.6%	22.9%	30.8%	39.5%	31.9%
Gains	19.5%	13.3%	12.2%	12.1%	−7.4%

6.1 The direct impacts of smart decline on urban runoff contamination levels

Directly, it is shown that, as more vacant lands are converted to green spaces, stormwater burdens on the sewer system are lessened, resulting in a significant reduction in the stormwater runoff and non-point source pollutants. The reduction of non-point source pollutants is due not only to the decrease in stormwater runoff but also to the capability of increased vegetation to help remediate soil contamination. From the results, we noticed that while all three VLRG scenarios have positive impacts on urban runoff and contamination levels, these levels do not decrease proportionally as the increase in the VLRG rate. The levels of the annual runoff volume and the non-point pollutants of the 20% VLRG scenario are only slightly lower than that of the 10% VLRG scenario. However, the 30% VLRG scenario has a much better performance on urban runoff and non-point source pollutant reduction than the other scenarios. This implies that converting 30% or more of vacant lands to green spaces could also be more cost-effective. The more vacant lands are regreened, the more it can help city form a larger, less fragmented, and more interconnected green network, which is more likely to reduce the average annual peak runoff (Kim & Park, 2016).

In our study, we found that all the nonpoint source pollutants significantly decrease through VLRG.

Suspended solids, heavy metals such as Lead, Zinc, Copper and Cadmium, phosphorus, and nitrogen are effectively removed by vegetation and phytoremediation (Hatt, Fletcher, & Deletic, 2009; Read, Wevill, Fletcher, & Deletic, 2008). Fine particulates and dissolved pollutants can be trapped and removed by being adsorbed into the filter medium, being up-taken by plants or microbial components of the plant-soil environment as stormwater infiltrates through the planted filter media (Read et al., 2008). In the 30% VLRG scenario, there is a slight increase in Chromium. The reason for this increase may be related to the CLUE-S model itself. In the CLUE-S model, in order to balance land supply (spatial analysis module) and land demand (non-spatial analysis module), it may modify the competitive advantage of different land use types so that the land use with unmet demand will have higher preference. As the land demand for green space increases in each VLRG scenario, the transition rate of vacant land uses to other land uses is influenced. Therefore, more vacant lands are also transformed to industrial land and other land uses in the 30% VLRG scenario.

6.2 The indirect impacts of smart decline on urban runoff contamination levels

In addition to the direct impacts of regreening vacant lots, indirectly, VLRG through smart decline can play a

Table 6 Vacant land transition under different scenarios in 2025

	Baseline	10% VLRG	20% VLRG	30% VLRG
Others	0.2%	1.4%	1.4%	2.2%
Industrial	9.0%	1.5%	1.9%	2.3%
Green space	0.0%	8.0%	16.2%	25.6%
Commercial	0.0%	0.0%	0.0%	0.0%
Multi-family	2.5%	7.5%	7.5%	6.6%
Single-family	0.0%	0.0%	0.0%	0.0%
Persistence	88.3%	81.5%	73.0%	63.3%

large role in vacant land reduction and reuse. The unappealing and unregulated aesthetics associated with most vacant land can make such lots a hotspot for illegal dumping. While the effects of illegal dumping on urban contamination levels take long periods of time to present themselves, there are myriad of potential environmental risks. Because of no built-in monitoring system, illegal dumping, unlike regulated sanitary landfills, may contaminate soil and water, destroy wildlife habitat, and increase negative human health issues. Both the people who violate the law can be affected by the risks of illegal dumping, as well as all those who share the environment with them.

Through our simulation results, we see an obvious effect on vacant land reduction. Based on the prediction outputs, by 2025, the vacancy rate of the baseline scenario is 16%, of which 73.0% of vacant land remains, 7.6% vacant land is lost, and 19.5% of vacant land is added. However, under the 30% VLRG scenario, the vacancy rate is reduced by 5% compared to the baseline scenario; existing and newly gained VL also decreases by 24.6% and 7.4% respectively, while the VL regeneration rate increased by 31.9%. Without regreening interventions, the vacancy issue is more likely to get worse and, as the literature shows, have a negative ripple effect on the surrounding areas, leading to issues related to urban decline (Newman et al., 2016; Newman et al., 2018). Long term existence of excessive vacant land attracts illegal dumping of debris, increased crime activities, and can drive down property values of adjacent parcels (Nassauer & Raskin, 2014). The disheveled appearance of vacant land also decreases quality of life perception levels and further undermine social capital (Nassauer & Raskin, 2014). As a result, more people, especially upper- and middle-class residents, often relocate to other places in search of a higher-quality living environment. As they

leave, social isolation can result, foreclosure crises can develop, and the vacancy issue becomes more severe (Cortese, Haase, Grossmann, & Ticha, 2014; Nassauer & Raskin, 2014). Inversely, successful VLRG can reduce the negative externalities associated with vacant land, help stabilize declining neighborhoods, boost economic markets, reduce violent crimes, mitigate the impacts of a changing climate, and, as shown in this research, decrease pollutant loads in stormwater runoff.

6.3 Health benefits from reduced urban runoff contamination levels

This research indicates that effects of smart decline on urban runoff contamination, both in the short- and long-term, can significantly improve health of residents in shrinking legacy cities. Ethnic minorities, low incomes, and disabled, usually concentrated in communities prone to floods and high vacancy rates, are more vulnerable to flooding and flooding-related contamination than others (Du, FitzGerald, Clark, & Hou, 2010; Hajat et al., 2003). Through applying smart decline to clean up brownfields, improve land infiltration, make up for inadequate drainage system, and strengthen water treatment, all immediate health effects (downing, physical injuries, and animal bites) and secondary health effects (water contamination and waterborne diseases).

Reducing peak stormwater runoff can decrease fatal drowning and injuries caused by flash flooding. Physical injuries usually caused by sharp debris and wildlife contained in floodwaters can also be lessened. Even after floods, the unstable building condition and broken electrical power cables can cause injuries, even death, during the cleanup process (Du et al., 2010; Hajat et al., 2003). In addition to the immediate health benefits of smart decline VLRG to individuals, its benefits on larger populations are also worth mentioning. Especially in legacy cities, floods can stir historically contaminated areas and bring chemicals and other contaminants into ecosystems. Contaminants accumulated and deposited in human activity areas may lead to food insecurity and threaten human health (Du et al., 2010; Euripidou & Murray, 2004). This study shows that Cadmium, Zinc, and Suspended Solids are the primary non-point source pollutants reduced by VLRG. Typically, Zinc and Cadmium are concentrated in brownfields as traces of industrial land uses (Gallagher, Pechmann, Bogden, Grabosky, & Weis, 2008). It can be extremely harmful to human health when such contaminants are directly discharged to the environment and this discharge area is

Table 7 Runoff results of vacant transition under different scenarios in 2025 (per ha)

	Baseline	10% VLRG	20% VLRG	30% VLRG
Runoff results (avg. annual runoff volume m3)	2394.773	2235.810 (− 7%)	2212.590 (− 8%)	2136.280 (− 11%)

The value in parenthesis is the difference between VLRG and baseline scenario

Table 8 Nonpoint source pollutant results (per ha) of vacant transition under different scenarios in 2025

	Pollutant	Baseline	10% VLRG	20% VLRG	30% VLRG
Physical & Chemical	Cadmium (kgs)	0.002	0.002 (0%)	0.001 (−50%)	0.001 (−50%)
	Zinc (kgs)	0.258	0.185 (−28%)	0.185 (−28%)	0.178 (−31%)
	Suspended Solids (kgs)	106.194	89.462 (−16%)	86.345 (−19%)	80.070 (−25%)
	Nicked (kgs)	0.022	0.021 (−5%)	0.019 (−14%)	0.017 (−23%)
	Lead (kgs)	0.023	0.019 (−17%)	0.018 (−22%)	0.018 (−22%)
	Phosphorous (kgs)	1.245	1.204 (−3%)	1.114 (−11%)	0.995 (−20%)
	BOD (kgs)	56.402	54.000 (−4%)	50.752 (−10%)	45.843 (−19%)
	Nitrogen (kgs)	4.126	3.929 (−5%)	3.738 (−9%)	3.448 (−16%)
	COD (kgs)	117.590	106.097 (−10%)	105.643 (−10%)	99.656 (−15%)
	Copper (kgs)	0.023	0.019 (−17%)	0.019 (−17%)	0.020 (−13%)
	Oil & Grease (kgs)	4.667	3.748 (−20%)	4.152 (−11%)	4.206 (−10%)
	Chromium (kgs)	0.006	0.006 (0%)	0.006 (0%)	0.007 (17%)
	Sum (kgs)	290.559	258.692 (−11%)	251.992 (−13%)	234.459 (−19%)
Bacterial	Fecal Coliform (millions of coliform)	436.103	422.326 (−3%)	387.670 (−11%)	343.586 (−21%)
	Fecal Strep (million of coliform)	1136.019	1097.628 (−3%)	1065.582 (−6%)	936.824 (−18%)
	Sum (millions of coliform)	1572.123	1519.954 (−3%)	1453.252 (−8%)	1280.409 (−19%)

The value in parenthesis is the difference between VLRG and baseline scenario

expanded during flood events. While Zinc is an essential component of the human body (in small doses), long-term exposure to excessive amounts can suppress the absorption of copper and iron (Cherfi, Abdoun, & Gaci, 2014). Long-term exposure to Cadmium may increase the risk of bone disease (especially for women) (Järup, Berglund, Elinder, Nordberg, & Vanter, 1998), nephrotoxicity, and lung cancer (Schoeters et al., 2006) for adults. For children, it may influence their motoric and perceptual behavior (Schoeters et al., 2006). Suspended solids are a primarily factor leading to serious ecological degradation of environment for fish and aquatic life through altering the physical, chemical and biological properties of water bodies. Physically, high concentrations of suspended solids can lead to poor aesthetics and higher water treatment costs. Chemically, it can release heavy metals, nutrients and pesticides to environment causing serious public health problems. Biologically, when the organic content of suspended solids is too high, it can cause hypoxia which will kill fish (Bilotta & Brazier, 2008). Moreover, suspended soil particles containing bacteria, Giardia, Cryptosporidium, and other microorganisms can flow into water bodies by inflows of runoff, leading to an increased in acute gastrointestinal illness (Gaffield, Goo, Richards, & Jackson, 2003). Waterlogging issues also provide an ideal breeding areas of mosquitoes carrying dengue hemorrhagic fever, West Nile virus, and other infectious diseases (Gaffield et al., 2003; Nasci & Moore, 1998). Due to the accumulation of sediment and lack of sunlight, stormwater drainage pipelines and channels can become breeding grounds for bacteria (Gaffield et al., 2003).

Through VLRG, the above-mentioned situations can be greatly alleviated. Green infrastructure, such as rain gardens, bio-swales, and bio-retention areas, converted from vacant lands, can act as a sponge to soak up stormwater runoff and capture water for reuse, reducing peak runoff volumes and waterlogging (Li, Li, Huang, & Liu, 2020). Because green infrastructure mimics the natural processes of purifying stormwater, pollutants can be absorbed through natural ecological processes, and bacteria can be destroyed by ultraviolet rays from sunlight.

6.4 Planning practice recommendations for St. Louis and other shrinking cities

While the application of smart decline can adjust the trajectory of growth for St. Louis (or other cities) compared to historical growth patterns, the results of the simulations in this research can be valuable for guiding future related planning processes. Spatially, vacant-to-green conversion will not occur evenly across St. Louis. The results of the simulation maps illustrate that vacant land in affluent areas has a better chance of being converted to green space. Because of settlement patterns, St. Louis has been somewhat divided demographically between the northern and the southern areas. The northern portion, predominantly African American, has remained largely marginalized and has large tracts of vacant land. In the 10% and 20% VLRG scenarios, the vacant-to-green conversion occurs primarily in the southern portion of the city, with a small proportion occurring in the periphery of northern portion of St. Louis. Further, in the 30% VLRG scenario, very little

vacant lands are converted into green spaces in the urban core, where vacancy is a serious problem.

This phenomenon is commonly existing in most of shrinking cities, not only for St. Louis. The top-down manner of historic planning approaches more or less left to smart decline strategy (Ryan & Gao, 2019). Community engagement is still one of the weaknesses of smart decline. Without intervention, less affluent areas, which face environmental inequality, are more likely to be ignored during the planning process. Generally speaking, vacant land in lower-income areas are more likely to remain fallow and unused for longer than in affluent areas, due to a lack of attractiveness for private developers and public investments from governmental authority (Maantay & Maroko, 2018). For vacant lands that have been contaminated by a legacy of industrial growth, there can oftentimes be little willingness to regenerate them without outside private investment or projected profit (Maantay & Maroko, 2018). More likely, the poor are longest suffering victims of catastrophic flooding and urban contamination. Therefore, VLRG through smart decline must need to ensure greater inclusivity and equitability.

While this research is specifically evaluated in regards to St. Louis, its generalizability can be linked to many legacy and shrinking cities undergoing similar circumstances. There are some planning practice recommendations for St. Louis and other shrinking cities. First, Smart decline-based planning processes must be transparent and value multiple voices to encourage residents to understand and question the future development of their communities (Hollander & Németh, 2011). The biggest contribution the community engagement can bring is to let voices of disadvantaged neighborhoods be heard, so as to prevent them from continuing to live in neighborhoods with great risks of flood and contamination. Also, community participation processes can contribute to vacancy prevention, further reducing urban runoff contamination levels indirectly (Anderson & Minor, 2017). By incorporating residents into the planning and vacant regreening processes, community spirit and commitment can be awakened, and ultimately the social capital of these communities can be rebuilt (Kim, 2016; Schilling & Logan, 2008). Increases in social capital may reduce illegal dumping by improving people's consciousness and encouraging mutual supervision between neighbors, and may even further prevent population decline by promoting neighborhood stability and security (Jennings, Baptiste, Osborne Jelks, & Skeete, 2017; Nassauer & Raskin, 2014; Sadler & Pruett, 2017). Second, gentrification threats due to regreening should be monitored in lower-income areas. While green efforts can improve the living environment, reduce vulnerabilities of contamination hazards, and increase social capital, the rising cost of

living may cause upper-class populations to replace the original neighborhood residents and local businesses (Curran & Hamilton, 2012). When this occurs, lower-income people could be pushed to a more deteriorated area, worsening disproportionate exposure to environmental hazards.

7 Limitations and future research

While the proposed model in this research is valuable for guiding VLRG through smart decline and avoiding possible mistakes in the planning process, more precise simulations will need to be developed to further explore spatial impacts. Models that can adjust spatial parameters based on policy would have more far-reaching significance on understanding and monitoring the long-term impacts of land use policies and can provide planners and policymakers more acute decision-making directions. In addition, the application of CLUE-S model has a basic assumption, that, the final result of land use change is achieved by balancing land supply (spatial analysis module) and land demand (non-spatial analysis module). The simulation results of CLUE-S can only reflect the land use pattern at a certain point in the "equilibrium" state, and there is no method to measure the process and effects of changes in land use before reaching this state. But, in practice, since land use changes and economic and social development cannot be completely synchronized, whether this "equilibrium" state fully exists is worthy of further study (Wu et al., 2012). Moreover, field investigations should be conducted in the future to know the condition of vacant lands in order to improve the accuracy of the simulation. Another limitation of this study is that all vacant converted green spaces are treated as the same in the L-THIA model. There is no present way to differentiate the type or quality of green space it is converted, as they are all based on the same algorithm.

Code availability

Not applicable.

Authors' contributions

Rui Zhu and Dr. Galen Newman contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript. The author(s) read and approved the final manuscript.

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The author declares that they have no competing interests.

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