Ecosystem Services 59 (2023) 101500

Contents lists available at ScienceDirect

Ecosystem Services

journal homepage: www.elsevier.com/locate/ecoser

Full Length Article

Comparing three spatial modeling tools for assessing urban ecosystem services

C.J. Veerkamp [a,b,*,1], M. Loreti [a,1], R. Benavidez [c,d], B Jackson [c,d], A.M. Schipper [a,e]

[a] PBL Netherlands Environmental Assessment Agency, PO Box 30314, 2500 GH The Hague, the Netherlands
[b] Institute for Science in Society, Radboud University, PO Box 9010, 6500 GL, Nijmegen, the Netherlands
[c] BEEA Limited, PO Box 28105, Wellington 6150, New Zealand
[d] School of Geography, Environment and Earth Sciences, Victoria University of Wellington, PO Box 600, Wellington 6140, New Zealand
[e] Department of Environmental Science, Radboud Institute for Biological and Environmental Sciences (RIBES), Radboud University, PO Box 9010, 5600 GL Nijmegen, the Netherlands

ARTICLE INFO

Keywords:
Model uncertainty
Green and blue infrastructure
Cities
InVEST
LUCI
NC-Model

ABSTRACT

The (re)integration of nature into cities has been a progressively promoted strategy to foster sustainable urbanization. To quantify the ecosystem services (ES) provided by urban nature, spatially explicit ES modeling is a key method. However, particularly in absence of independent validation data, there is a clear need for multi-model assessments in order to better understand uncertainties in model outcomes. Here we applied three commonly used open-source ES models (i.e., InVEST, LUCI, NC-Model) to quantify three key urban ES (i.e., local temperature regulation, flood protection and global climate regulation) using the city of The Hague (The Netherlands) as a case study. We quantified the three ES for the current situation and under two hypothetical scenarios representing changes in the amount of vegetation within the city. We found mostly positive correlations between the estimates for a given ES (Spearman's ρ from 0.11 to 0.84). Yet, our comparison also revealed systematic differences in the ES indicator values between the ES models, as well as different responses to the scenarios. These differences may stem from differences in model structure (i.e., differences in biophysical processes accounted for) and model parameterization (i.e., differences in the value used to quantify a given biophysical process). To further advance urban ES modeling, we recommend i) to improve the representation of urban nature (e.g., green roofs, bioswales, gardens) and urban-specific conditions and processes (e.g., drainage systems, building patterns, soil characteristics) in urban ES models and ii) to systematically account for uncertainty in (urban) ES assessments (e.g., through multi-model assessments).

1. Introduction

Urbanization is one of the key societal processes of the 21st century. Today, more than half of the global human population lives in cities, with most urban areas expected to continue to grow in both size and numbers (Seto et al., 2011, UN, 2019). It is expected that by 2050, nearly 70 % of the global population will live in cities, with an additional 2.5 billion city dwellers (UN, 2019). Urbanization is generally associated with economic growth, poverty reduction and increased human development (UN, 2019), but it also puts pressure on urban dwellers and their living environment. For example, many cities are characterized by poor water and air quality (Sarzynski, 2012, Teurlincx et al., 2019, Khomenko et al., 2021) and many inhabitants have limited access to nature, which may affect their mental and physical health (Van den Berg et al., 2010, Kondo et al., 2018, Ventriglio et al., 2021). Moreover, impervious surfaces can lead to flooding during heavy rainfall (Du et al., 2015), and built-up areas increase the risk of heat stress (Lemonsu et al., 2015; Manoli et al., 2019). With further global climate change, the urban population will face additional exposure to heat stress, floods and drought (IPCC, 2022), bringing forth substantial challenges to maintain or create healthy, resilient and livable urban environments.

A progressively promoted strategy to foster sustainable urbanization is the (re)integration of nature into cities as a means to address environmental, economic and social challenges (Kabisch et al., 2017; Van den Bosch and Sang, 2017; Liu and Jensen, 2018; Faivre et al., 2017; Xie and Bulkeley, 2020). This strategy – captured by the umbrella term

* Corresponding author at: PBL Netherlands Environmental Assessment Agency, PO Box 30314, 2500 GH The Hague, the Netherlands.
E-mail address: clara.veerkamp@pbl.nl (C.J. Veerkamp).

[1] C. J. Veerkamp and M. Loreti contributed equally to this work.

https://doi.org/10.1016/j.ecoser.2022.101500
Received 15 June 2022; Received in revised form 7 October 2022; Accepted 9 December 2022
Available online 4 January 2023

nature-based solutions (NBS) - is based on the capacity of nature to provide multiple ecosystem services (ES). For example, an urban park offers physical and mental health benefits by providing opportunities for recreation, contributes to water infiltration, carbon sequestration and air cooling, and provides habitat for birds and insects (Nielsen et al., 2014, Mexia et al., 2018, Veerkamp et al., 2021). Numerous policy targets acknowledge the importance of nature in urban planning (e.g., Goal 11 of the Sustainable Development Goals (UN, 2015), New Urban Agenda (UN, 2017), post-2020 Global Biodiversity Framework (CBD, 2021)), and enhancing urban NBS has been encouraged particularly by the European Commission (EC, 2013; 2015; 2020; Faivre et al. 2017, Lafortezza et al. 2018).

To consider nature more systematically in urban planning and development, practitioners and decision makers need quantitative evidence on the ES provided by urban nature (Haase et al., 2014, Veerkamp et al., 2021). Spatially explicit modeling is a common methodology to quantify urban ES, particularly across relatively large extents (e.g., an entire city or region) or in scenario studies (Veerkamp et al., 2021). Examples include assessments of flood protection services in Hyderabad (India) (Kadaverugu et al., 2021), local temperature regulation in Addis Ababa (Ethiopia) and Dar es Salaam (Tanzania) (Cavan et al., 2014) and urban nature scenario studies in Amsterdam (the Netherlands) (Paulin et al., 2020a), Great Metropolitan Area of Costa Rica (Chen et al., 2021) and Trento (Italy) (Cortinovis and Geneletti, 2018). Quantifying and understanding the uncertainties in these model outputs is critical for assessing the robustness and credibility of the conclusions (Refsgaard et al., 2007, Bryant et al., 2018, Willcock et al., 2020). Ideally, uncertainties in model outcomes are quantified by comparing them with independent measurements. However, particular when empirical data on ES are sparse, an alternative approach to address model uncertainty is needed.

In model-based environmental assessments related to land cover change, climate change and biodiversity, model uncertainty is increasingly being tackled through model intercomparisons and multi-model approaches (Rosenzweig et al., 2013, Warszawski et al., 2013, Alexander et al., 2017, Thuiller et al., 2019). Model intercomparisons are less common in ES modelling (IPBES, 2016; Willcock et al., 2020; Pereira et al., 2020; Rosa et al., 2020), although there have been a few efforts (Bagstad et al., 2013a, Schulp et al., 2014, Sharps et al., 2017, Dennedy-Frank et al., 2016, Veerkamp et al., 2020). For example, Sharps et al. (2017) compared outputs of three ES modeling tools (LUCI, ARIES, InVEST) and identified differences related to model approaches and underlying assumptions. Similarly, Dennedy-Frank et al. (2016) used two ES modeling tools (InVEST, SWAT) and illustrated substantial differences between some of the model outcomes as a result of different model structures (e.g. complex or simple representation of hydrological processes). Uncertainties are also characterized through scenario-based modeling. For example, Veerkamp et al. (2020) used two modeling frameworks (GLOBIO-ES, CLIMSAVE) to project future trends of ES under different scenarios, which facilitated nuanced and contextualized insights with respect to possible ES futures. More recently, the biodiversity and ecosystem services scenario-based inter-model comparison project (BES-SIM) was established to assess uncertainties in ES model projections more systematically (Kim et al., 2018, Rosa et al., 2020).

Despite the growing attention for multi-model approaches as a means to convey uncertainties in ES assessments, there is a considerable lack of ES model intercomparison studies for the urban context. This may reflect that urban ES modelling is a relatively new research area, and methods used are often not yet fully developed or extensively tested (Haase, et al., 2014, Veerkamp et al., 2021). Many existing ES models were originally designed for the rural context, without consideration of specific urban characteristics, such as specific types of urban green infrastructure and the fine-scale heterogeneity that is specific to urban areas (Delpy et al., 2021, Hamel et al., 2021). In absence of context-specific parameterization and validation data, it is unknown to what extent such simplifications or omissions introduce uncertainty in model outcomes. This limits credibility and may lead to possible misinterpretations of model outcomes by end users, such as urban planners and policy makers. These issues emphasize the need to increase our understanding of urban ES models and their associated uncertainties by comparing the outcomes of multiple models for the same ES and study site(s).

Here we applied three ES modeling tools to quantify three key urban ES based on the city of The Hague (The Netherlands) as a case study. First, we identified suitable ES models applicable to the urban environment. We selected three commonly used open-source ES modeling tools (InVEST, LUCI, NC-Model) and applied them to quantify three ES (local temperature regulation, global climate regulation and flood protection) and changes therein under two hypothetical scenarios representing reductions in the amount of urban green. We quantified similarities and differences in both the city-average outcomes and the spatial patterns of ES provision as generated by the different models and discuss these in the light of similarities and differences in model structure and parameterization.

2. Material and methods

2.1. Selection of models for urban ecosystem service assessments

To identify ES models applicable to the urban environment, we first compiled an initial list of commonly used ES models based on previous reviews and model intercomparison studies (Bagstad et al., 2013b, Harrison et al., 2018, Van Oijstaeijen et al., 2020, Delpy et al., 2021, Veerkamp et al., 2021) and online platforms of available ES assessment tools (Ecosystems Knowledge Network (2021), Urban Nature Navigator (NATURVATION, 2021)). We focused on stand-alone models specifically designed to provide quantitative outputs of ES delivery. Hence, we excluded biophysical models that merely assess biophysical factors controlling ES supply rather than the ES itself (e.g., hydrological SWAT model), and integrated assessment models, which account for feedbacks between different sectors and ecosystem components (e.g., IMAGE-GLOBIO, CLIMSAVE). Next, we searched for additional ES models in Google Scholar and Web of Science, with the terms 'ecosystem service assessment tools' and 'ecosystem service assessment methodologies'. The screening resulted in a list of 28 ES modeling tools, potentially applicable to generate spatially explicit assessments of multiple ES delivered by urban green and blue infrastructure. While we acknowledge that this list is not necessarily complete, it does represent a set of models commonly encountered in the literature. In order to evaluate the models' usefulness for urban ES assessment supporting urban planning and decision-making, we applied a set of selection criteria to each model including i) applicable to an urban context, ii) enabling city-wide ES assessment, iii) providing spatially explicit outcomes, iv) enabling scenario analyses, v) including multiple ES, vi) open access, and vii) peer reviewed. For a full explanation of the criteria and evaluation of the 28 ES modeling tools, see Tables A-1 and A-2. Based on these criteria, we selected three ES modeling tools for our analysis, namely the Integrated Valuation of Ecosystem Services and Trade Offs (InVEST; Sharp et al., 2020), the Land Utilisation and Capability Indicator tool (LUCI; LUCI, 2019) and the Natural Capital Model (NC-Model; Remme et al., 2018, Paulin et al., 2020b) (**Box 1**).

Box 1: Overview of the three selected ES modeling tools for the model comparison.

InVEST is a software suite of open-source ES models for mapping and valuing ES provided by terrestrial and aquatic ecosystems, developed by the Natural Capital Project and Stanford University (Sharp et al., 2020, Natural Capital Project, 2022). The model aims to support decision makers by assessing trade-offs between ES associated with alternative management choices and by identifying areas where investment in nature can enhance human development and nature conservation. InVEST models are spatially explicit, combining land use and land cover (LULC) data with additional information (e.g., soil type, climate) to provide ES output values in biophysical and/or economic units. While InVEST provides a stand-alone user interface, additional spatial mapping software (e.g., ArcGIS) is needed to view the results. Originally developed for assessing ES in natural and rural areas, InVEST was recently extended to include also urban-specific models (Grafius et al., 2016, Bosch et al., 2021, Hamel et al., 2021). Currently, InVEST includes nine ES models, of which seven models are applicable to both natural or rural and urban landscapes (e.g., carbon sequestration and storage, pollination), and three were particularly developed for the urban context (i.e., urban cooling, urban stormwater retention and urban flood risk mitigation) (Hamel et al., 2021).

The **NC-Model** is a suite of spatially explicit models for quantifying and mapping ES, developed by a consortium of Dutch knowledge institutes (Remme et al., 2018, Paulin et al., 2020b). The NC-Model aims to support the integration of ES within spatial planning and policy making to meet Dutch and international environmental policy targets and has been applied to various study areas in the Netherlands, including the city of Amsterdam (Paulin et al., 2020a). ES output maps, describing ES in biophysical and/or economic units, are produced by combining empirical model relationships (including look-up tables) with customizable, readily available input data (including standardized sets of spatial data and reference values). As the model does not provide a separate user interface, users need knowledge of spatial modeling and coding (Python) to customize and run the model for the area of interest. Model outputs need to be viewed in a mapping software (e.g., ArcGIS). The NC-Model estimates multiple ES, of which there are currently six particularly applicable to the urban environment (i.e., air quality regulation, contribution of urban nature to physical activity, property value attributed to urban nature, urban cooling, urban health improvement and water storage) (Paulin et al., 2020a).

LUCI is a spatially explicit modeling tool designed to assess the consequences of land use change for various ES, aiming to support city and landscape planners to understand the impact of possible changes or interventions (Sharps et al., 2017; LUCI, 2019, 2022). LUCI has been applied in several countries, but most extensively in rural areas of the United Kingdom and New Zealand (Sharps et al., 2017, Trodahl et al., 2017). Recently it has also been applied to urban settings (Delpy et al., 2021, Nguyen et al., 2021). LUCI quantifies multiple ES and compares current ES with potential future ES due to interventions (land use and management change), based on absolute values (e.g., changes in ton carbon per grid cell stored) and/or color-coded output maps (default palette using a system with green: improvements in/existing provision of ES; red: decrease in/potential opportunities for ES). The model incorporates biophysical processes (e.g., hydrology) and uses look-up tables. The tool comes in the form of a GIS toolbox embedded within the ArcMAP or ArcPro user interfaces and has in-app data manipulation capabilities. To date, LUCI includes six ES models applicable to both natural or rural and urban environments (i.e., carbon sequestration, agricultural production, erosion risk reduction, flood mitigation, habitat suitability/connectivity and water quality) (Delpy et al., 2021, Nguyen et al., 2021).

2.2. Ecosystem services models and indicators

We selected three ES that were included in at least two of the three selected ES modeling tools: local temperature regulation, global climate regulation and flood protection (Table 1). While the models use the same indicators for local temperature regulation and global climate regulation, LUCI's indicator of flood protection differs from the flood protection indicators in InVEST and the NC-Model, but outputs are

Table 1
Selected urban ES and indicators used by the three ES modeling tools.

Urban Ecosystem Services	Brief description	ES model	Indicator (unit)	Model approach
Local temperature regulation	Mitigation of the urban heat island (UHI) effect by urban vegetation and water	InVEST – urban cooling model	Air temperature reduction (°C)	The cooling effect is modeled as a function of air temperature, shade, evapotranspiration, albedo, and the additional cooling potential of larger urban green areas.
		NC-Model - urban cooling model	Air temperature reduction (°C)	The cooling effect is modeled as a function of air temperature, vegetation cover (trees, shrubs/bushes, low vegetation), water cover, impervious cover, population density (as a proxy of building density) and wind speed.
Global climate regulation	Reduction of atmospheric carbon dioxide concentration due to the sequestration and storage of carbon in living and dead organic matter (vegetation and soil)	InVEST - carbon sequestration & storage model	Carbon storage (metric ton C /m^2)	Carbon storage is modeled as a function of LULC and associated carbon stocks in four pools (aboveground biomass, belowground biomass, soil and dead organic matter).
		LUCI – carbon stocks and fluxes model	Carbon storage (metric ton C /m^2)	Carbon storage is modeled as a function of soil types and LULC combinations and associated carbon stocks at different soil depths.
Flood protection	Reduction of urban flood risk as rainfall is intercepted and retained by vegetation and soil	InVEST - urban stormwater retention model[1]	Avoided water runoff (m^3/m^2)	Flood risk reduction is modeled as a function of rainfall, distance to roads and impervious areas, and the infiltration capacities of soil and LULC combinations.
		NC- Model – urban water storage model	Avoided water runoff (m^3/m^2)	Flood risk reduction is modeled as a function of rainfall and the vegetation's capacity to store rainwater.
		LUCI – flood mitigation model	Flood mitigation class (% of area)	The model simulates water flow accumulation as a function of the actual rainfall, elevation and flow direction, evapotranspiration and infiltration capacities of soil and LULC.

[1] InVEST includes two flood protection models: an urban stormwater retention model and a flood risk mitigation model. For this study, we selected the urban stormwater retention model because it is more similar to the other flood protection models in terms of input data and biophysical processes and accounts for urban-specific processes (presence of a drainage network).

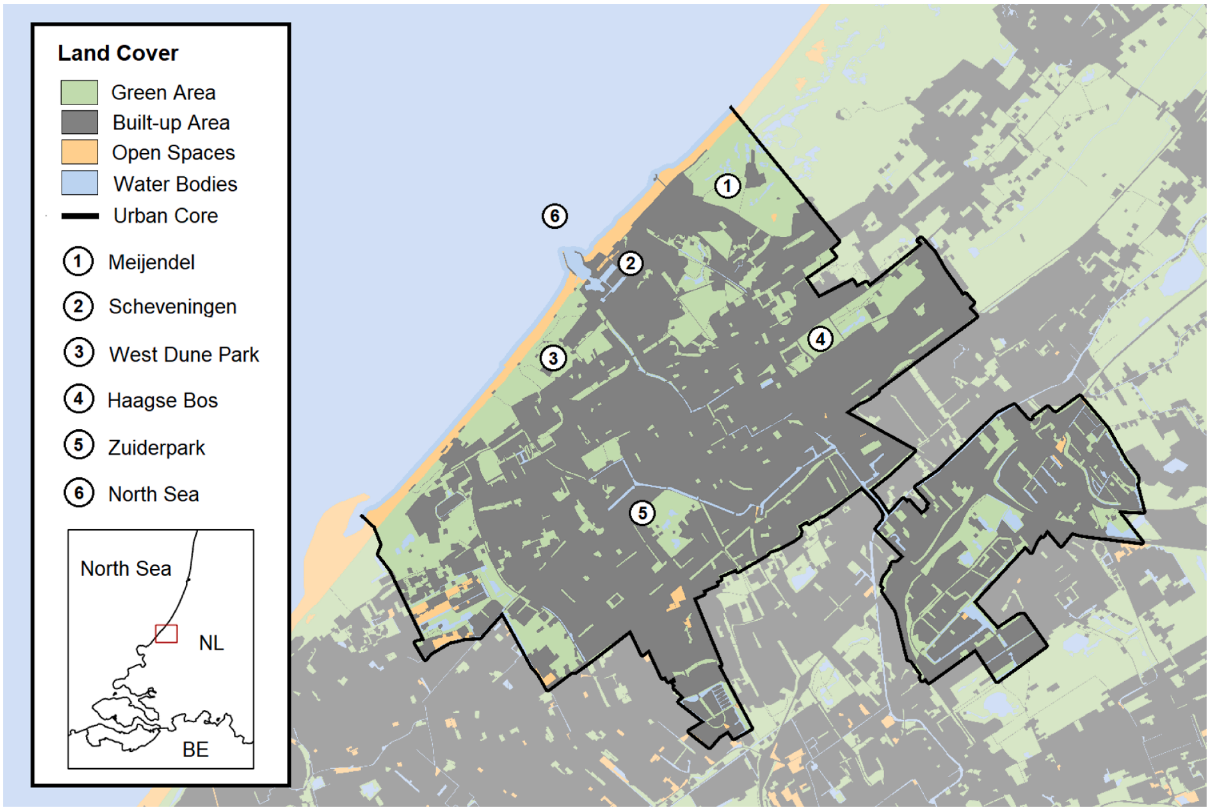

Fig. 1. Green, blue, open and built-up areas within the city of The Hague and the city's location in the Netherlands. The land cover data is retrieved from the Urban Atlas (EEA, 2018a). Numbers indicate sites referred to in the text. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

conceptually similar.

2.3. Model parameterization

We parameterized the models for the city of The Hague, located in the west of the Netherlands (Fig. 1). With nearly 550,000 inhabitants, The Hague is the most densely populated city and the third largest municipality of the Netherlands, covering an area of 9,813 ha (CBS, 2020; 2021, Statista, 2020). The city is characterized by its close proximity to the North Sea, bordering the city over a distance of 11 km to the west. It contains a large share of built up area and infrastructure (e.g. roads) (71 %) interspersed with extensive (semi-)natural areas (24 %), including coastal nature reserves (West Dune Park, Meijendel), urban forests (Haagse Bos) and parks (Zuiderpark), particularly towards the outskirts of the city (Fig. 1, Fig B-1). Heat stress, drought and peak rainfall events are regular challenges (Gemeente Den Haag, 2022).

To parameterize the models, we used a consistent set of input data from publicly available sources. For identical input variables (e.g., LULC, soil type, tree cover, climate data) we used the same input across all ES models. For example, all models require a LULC map, which we obtained from the European Urban Atlas dataset of the Copernicus Land Monitoring Service (EEA, 2018a). This LULC map distinguishes 27 urban LULC classes (e.g., urban fabric, green urban areas, forests, roads, water bodies) at a resolution of 10 m. Some input data, however, needed to be translated to fit the model's specific classification system. For example, we reclassified the Dutch soil type map to LUCI's soil classification system and to InVEST's hydrological soil groups. In addition, each model also required specific input data (e.g., hydrological network, human population density, wind speed, water cover). Where possible, we tailored these input data to the study area (e.g., albedo and crop coefficient in InVEST, sealed surface in the NC-Model), otherwise we relied on the default values suggested by or built-in in the models (e.g., water storage capacity values in the NC-Model, soil carbon values in LUCI, relative weights of factors contributing to the cooling capacity index in InVEST). We parameterized all the models based on a 10 by 10 m spatial resolution, as further detailed below, using a resampling approach if the input data was of a lower spatial resolution.

2.3.1. Local temperature regulation

InVEST's local temperature regulation model requires values of shade, crop coefficient and surface albedo per LULC class. To estimate shade, we obtained tree cover density from the Copernicus Land Monitoring Service (EEA, 2018b), representing tree cover in a range from 0 to 100 % per 10 by 10 m grid cell, and calculated an average tree cover (shade) value per LULC class. We retrieved crop coefficient and surface albedo values per LULC class from the literature (Table B-2). InVEST further requires a city-wide value of potential evapotranspiration, which we obtained from a global climate database (Trabucco and Zomer, 2019). To estimate the urban heat island (UHI) effect, InVEST requires air temperature data, which we obtained from nine weather stations with open-access data located within the city of The Hague and its surrounding (rural) areas. We selected measurements for the hottest day in August 2019 (Table B-3), representative of a day during a summer heatwave when cooling demands are highest. We defined the magnitude of the UHI as the difference between the urban and rural mean temperatures (i.e., 5.3 °C).

The local temperature regulation module of the NC-Model requires the average urban temperature, for which we used measurements from the same day in August 2019 (i.e., 34.3 °C). To estimate the UHI effect, the NC-Model further requires data on the presence of sealed surfaces, which we obtained from the LULC map (Table B-4), and wind speed and human population density (as a proxy of the density of built-up area), both included in the default settings of the model (Remme et al., 2018) and tested in earlier NC-Model application studies in the Netherlands

(Paulin et al., 2020b). Moreover, the NC-Model requires vegetation coverage per grid cell, in addition to LULC types, to estimate UHI reduction capacities (Table B-4). For shrub/grass and low vegetation, we used national vegetation maps included in the default settings in the model (Remme et al., 2018). For trees, we used the tree cover density data from Copernicus Land Monitoring Service (EEA, 2018b).

2.3.2. Global climate regulation

InVEST requires values of carbon pools for each LULC type, which we derived from the literature (Bouwer et al., 2018, Table B-6). LUCI's global climate regulation model requires LULC and soil type information to estimate carbon pools. Because LUCI is primarily parameterized for the United Kingdom and New Zealand, it was necessary to match the European Urban Atlas LULC classes (EEA, 2018a) and soil types from the Dutch soil map (Anon, 2014) to the classification system supported by LUCI (i.e., UK LULC map LCM2007BH, Table B-7; UK soil map NATMAP, Table B-8).

2.3.3. Flood protection

For the flood protection models (InVEST, NC-Model, LUCI), we obtained the annual precipitation sum for The Hague (i.e., 847 mm) from a public accessible global climate database (Climate Data.org., 2021), using the mean over a 20 year period (1999 – 2019). All flood protection models also require input on urban green, either as vegetation and tree cover density maps (NC-Model) or as a LULC map (InVEST, LUCI). In addition, both InVEST and LUCI require a map with soil types and associated hydrological properties. We retrieved soil types from the Dutch Soil Map (Anon, 2014) and reclassified these into the types distinguished by LUCI and InVEST (Tables B-8, B-10). InVEST further requires information on impervious LULC classes and road networks, as a proxy for the presence of the artificial drainage network, which we obtained from the LULC map (e.g., roads, urban fabric), as well as the coverage of tree and impervious surface per LULC to estimate runoff coefficients per each LULC and soil type combination (Table B-11). LUCI requires elevation data to simulate the flow of water through the landscape, which we obtained from the Dutch digital elevation model (Actueel Hoogtebestand Nederland (AHN3); PDOK, 2020) as well as potential evapotranspiration rates per grid cell, which we retrieved from a global climate database (Trabucco and Zomer, 2019).

More detail on the parametrization of each model (including assumptions, input variables, sources used and GIS model flow charts) is available in Appenidx A. Supplementary data (Table B-1, B-5 and B-9 and Figure B-1, B-2, B-3, B-4).

2.4. Model simulations

In order to compare the models' responses to changes in input values, we applied a scenario-based approach. The scenarios served as a means to understand how the different ES models react to changes in urban vegetation cover, and why. We designed two hypothetical scenarios representing situations with lower amounts of vegetation when compared to the current situation (reference). In the No-Park scenario, all urban parks (any urban green space of >2 ha) are removed, while the No-Green scenario represents a situation where any vegetation (including in parks or forests, street trees, shrubs) is largely removed from the city. We simulated these scenarios by replacing the respective vegetated urban LULC classes by the class 'open space with little to no vegetation' (see Table B-12 for the changes in LULC and vegetation classes per scenario). We preferred this class over other classes in order to prevent confounding effects of increasing the sealed surface. In the No-Park scenario, the cover of trees is reduced from 16 % to 9 % and green LULC (e.g., green urban areas, forests) from 24 % to 9 % of the total urban area. In the No-Green scenario, the cover of trees is reduced to 7 % and green LULC to 5 % of the total urban area. With more vegetation removed, the No-Green scenario is expected to result in larger declines in urban ES than the No-Park scenario. We implemented the scenarios via changes in urban LULC classes and associated LULC characteristics (e.g., shade, crop coefficient, impervious surface, runoff coefficients) when compared to the reference. We assumed no changes to water bodies and the vegetation of the coastal dunes (Appendix A. Supplementary data).

2.5. Analysis of the results

To reveal similarities and differences between the models, we first compared spatially explicit model outputs for the reference situation. We quantified the degree of agreement between model outputs for the same ES (in the same unit) from pairs of models using the Mean Absolute Error (MAE) (i.e., average absolute difference between the values) and the Spearman's rank correlation coefficient (ρ) based on the grid-specific values (10 m $\times$ 10 m resolution), considering that the higher the MAE and the lower Spearman's ρ, the higher the model uncertainty. Then, we estimated the relative changes in the indicator values for the two scenarios when compared to the reference, as

$$ES\ change\ (\%) = \frac{(X_{scenario} - X_{reference})}{X_{reference}} * 100 \qquad [1]$$

where X represents the city-average ES indicator value. Finally, we tested for possible systematic differences in ES indicator values between the outputs of two models and three scenarios (reference, No-Parks, No-Green) using the Kruskal-Wallis test with a post-hoc Dunn test (p-values adjusted with Holm method). We used the model-scenario combination as a grouping factor, allowing us to identify differences between models for a given scenario as well as differences between scenarios for a given model. We performed the analyses in the R environment (R version 4.2.0, R Core Team, 2022), including the FSA package for the Kruskal-Wallis test with post-hoc test (Olge et al. 2022), the *multcompView* and *rcompanion* packages for analysis and visualization of paired comparisons (Graves et al. 2019, Mangiafico, 2022), the *dplyr* and *tidyr* packages for data transformation (Wickham et al., 2022, Wickham and Girlich, 2022), and the *ggplot2* and *ggpubr* packages for data visualization (Wickham, 2016; Kassambara, 2020). Statistical analyses were limited to those models capable of producing identical output indicators (ES values in the same unit), thus the flood protection outputs of the LUCI model were not included.

3. Results

3.1. Local temperature regulation

For the reference situation, InVEST and the NC-Model produced output maps with similar spatial patterns in air temperature reduction (Fig. 2, Fig. 5**a**, $\rho = 0.84$, MAE = 0.31 °C). Both models estimated the lowest air temperature reduction for centrally located neighborhoods and the harbor area (Scheveningen), while attributing larger cooling effects to (semi-)natural areas (e.g., the coastal nature reserve Meijendal and West Dune Park and the Zuiderpark, Fig. 1). However, the models estimated significantly different temperature reduction values on average (InVEST 1.62 °C; NC-Model 1.78 °C, Fig. 6**a**).

The scenarios revealed slightly lower similarities between the two models ($\rho = 0.72$ and MAE = 0.69 °C for the No-Park scenario, $\rho = 0.76$ and MAE = 0.45 °C for the No-Green scenario) (Fig. 5b+c, Fig. 6a, Fig. C-1). In the No-Park scenario, the NC-Model projected a 4 % lower temperature reduction compared to the reference, while for InVEST the temperature reduction was 37 % lower, reflecting that InVEST attributes additional cooling capacities to parks. The removal of all vegetation (No-Green scenario) resulted in more similar changes in ES between the two models, with decreases in temperature reduction of 59 % (InVEST) and 42 % (NC-Model) compared to the reference situation. InVEST estimates generally higher cooling values for residential areas than the NC-Model, even when nearly all vegetation was removed (Fig. C-1), which may

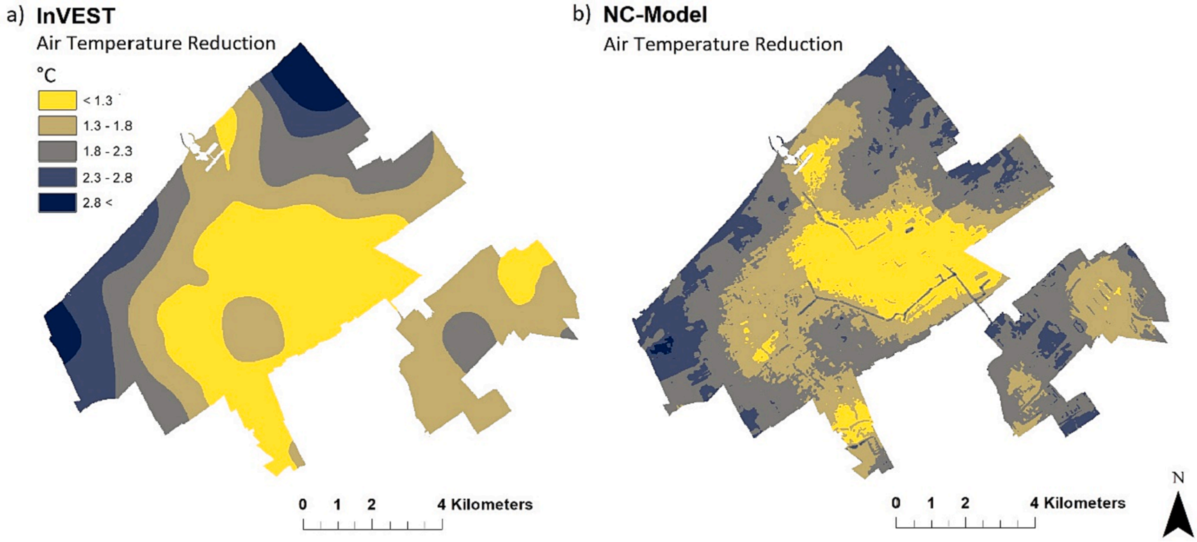

Fig. 2. Air temperature reduction (in °C) for (a) InVEST and (b) the NC-Model.

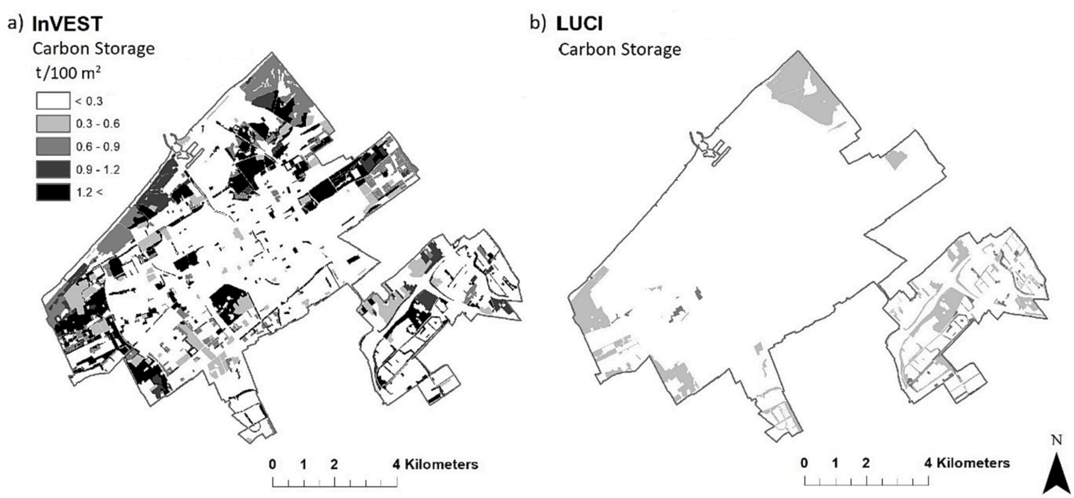

Fig. 3. Carbon storage in metric ton/100 m^2 for (a) InVEST and (b) LUCI model.

reflect the inclusion of the albedo effect associated with grey surfaces (e.g., buildings, paved areas, roads) (Fig. B-2). In contrast, the NC-Model accounts for an additional cooling potential of water bodies, and temperature reduction values for water bodies estimated by the NC-Model were always higher than those estimated by InVEST (Fig. C-1).

3.2. Global climate regulation

We found positive but only weak correlations between the carbon storage outputs of InVEST and LUCI ($\rho = 0.31$, MAE = 0.39 metric ton/100 m^2, Fig. 3, Fig. 5d). While LUCI attributes carbon storage mostly to the larger urban green areas, InVEST also accounts for carbon storage in (partially) built-up LULC classes. This difference is also reflected by a relatively larger systematic difference in city average outcomes (InVEST: 0.42 metric ton/100 m^2; LUCI: 0.04 metric ton/100 m^2) (Fig. 6b).

The correlation between the outputs decreased in the scenarios ($\rho = 0.11$ and $\rho = 0.19$ for the No-Park and No-Green scenario, respectively) (Fig. 5e+f, Fig. C-2). InVEST projected stronger declines in carbon storages than LUCI. In the No-Park scenario, InVEST projected a loss of nearly 50 % of the carbon stored compared to the reference, while in the No-Green scenario a reduction of 83 % was estimated. In contrast, LUCI calculated a smaller and non-significant reduction of 10 % and 13 % in the No-Park and No-Green scenario, respectively (Fig. 6b).

3.3. Flood protection

Although LUCI's flood protection model uses a different ES indicator than the flood protection models of InVEST and the NC-Model (Table 1), the output maps for the reference situation revealed similar spatial patterns among the three models (Fig. 4). In general, (semi-)natural areas (e.g., coastal dunes and nature reserves (Meijendal and West Dune Park), urban park (Zuiderpark), forest (Haagse Bos)) showed the highest flood protection, while centrally located, predominantly built-up areas were characterized by the lowest flood protection values (lowest avoided water runoff for InVEST and the NC-Model, non-mitigated flood prone land for LUCI). LUCI classified 22 % of city's area as land receiving flood mitigation, due to the presence of flood mitigating land (15 % of the urban area). The outputs of InVEST and the NC-Model were moderately correlated ($\rho = 0.44$, MAE = 22.5 m^3/100 m^2, Fig. 5g, Fig. C-3) but average avoided water runoff estimates were significantly higher for InVEST (38 m^3/100 m^2 versus 19 m^3/100 m^2 for the NC-Model).

Differences in model outcomes become more evident in the scenarios (Fig. 6c+d). The agreement between InVEST and the NC-Model outputs decreased, with no correlation in the No-Park scenario ($\rho = 0$) and the

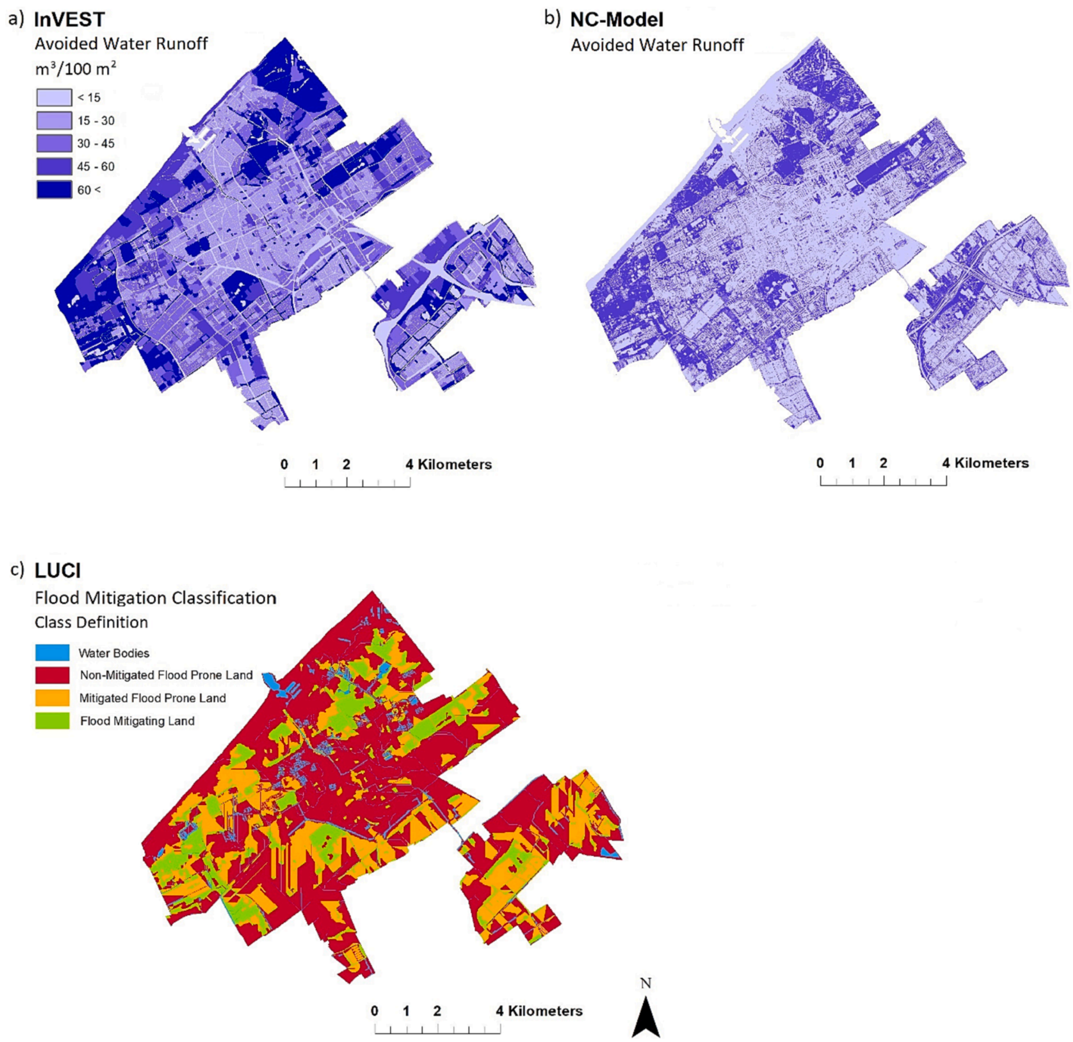

Fig. 4. Flood protection expressed as (a) annual avoided water runoff ($m^3/100\ m^2$) by InVEST, (b) annual avoided water runoff ($m^3/100\ m^2$) by the NC-Model, (c) and flood mitigation classes by the LUCI model.

highest MAE between model outputs in the No-Green scenario (MAE = 34.7 $m^3/100\ m^2$) (Fig. 5h+i, Fig. C-3). The NC-Model estimated average decreases in city-wide flood protection of 33 % and 90 % in the No-Park and No-Green scenarios, respectively (Fig. 6c), reflecting that the NC-Model defines flood protection by the vegetation's capacity to intercept rainwater (Table 1). In the No-Green scenario, LUCI projected similar changes as the NC-Model, including a nearly complete loss of mitigated flood prone land (91 % due to a 99 % loss of flood mitigating land) (Fig. 6d). The much more moderate decline in flood protection services in the No-Park scenario (i.e., 35 %, although 83 % of the flood mitigating land is lost) illustrates LUCI's spatially explicit and configuration-sensitive flow retention routing (i.e., remaining mitigating features (e.g., dunes) can take up runoff from upstream). In contrast, InVEST projected only little and non-significant changes in flood protection (−2,0 % and −2.4 % for the No-Park and No-Green scenario, respectively), reflecting InVEST's emphasis on runoff retention provided by soil infiltration (which remained unchanged in the scenarios).

4. Discussion

4.1. Understanding similarities and differences between the models

Our model intercomparison based on three urban ES (local temperature regulation, global climate regulation and flood protection) estimated by three commonly used ES modeling tools (InVEST, NC-Model and LUCI) applied to the city of The Hague, revealed mostly positive correlations between the estimates for a given ES. The local temperature regulation models showed the highest degree of agreement, but we found similarities also among the outputs of the flood protection models and carbon storage models. Moreover, Van Oorschot et al. (2021) recently estimated flood protection and local temperature regulation services for the same city, using different models, and reported spatial patterns similar to ours, with higher ES values in the less densely built-up areas of the city. The similarities in the model outputs reflect that they all rely on a LULC or vegetation map to quantify ES, whereby specific service-providing properties are assigned to different LULC or vegetation classes. For example, both local temperature models (NC-Model and InVEST) build upon cooling capacities assigned to urban nature, and the global climate regulation models (LUCI and InVEST) are both based on carbon stocks in biomass. As a result, the output maps of the different models reflect the spatial configuration of (larger) urban green areas.

Yet, our comparison also identified significant differences in ES indicator values among the ES models (Fig. 5, Fig. 6, Fig C-1+2+3). Differences were particularly evident in the scenarios, which generally resulted in larger differences (higher MAE) and lower correlations (lower Spearman's rho) between ES indicator values from different

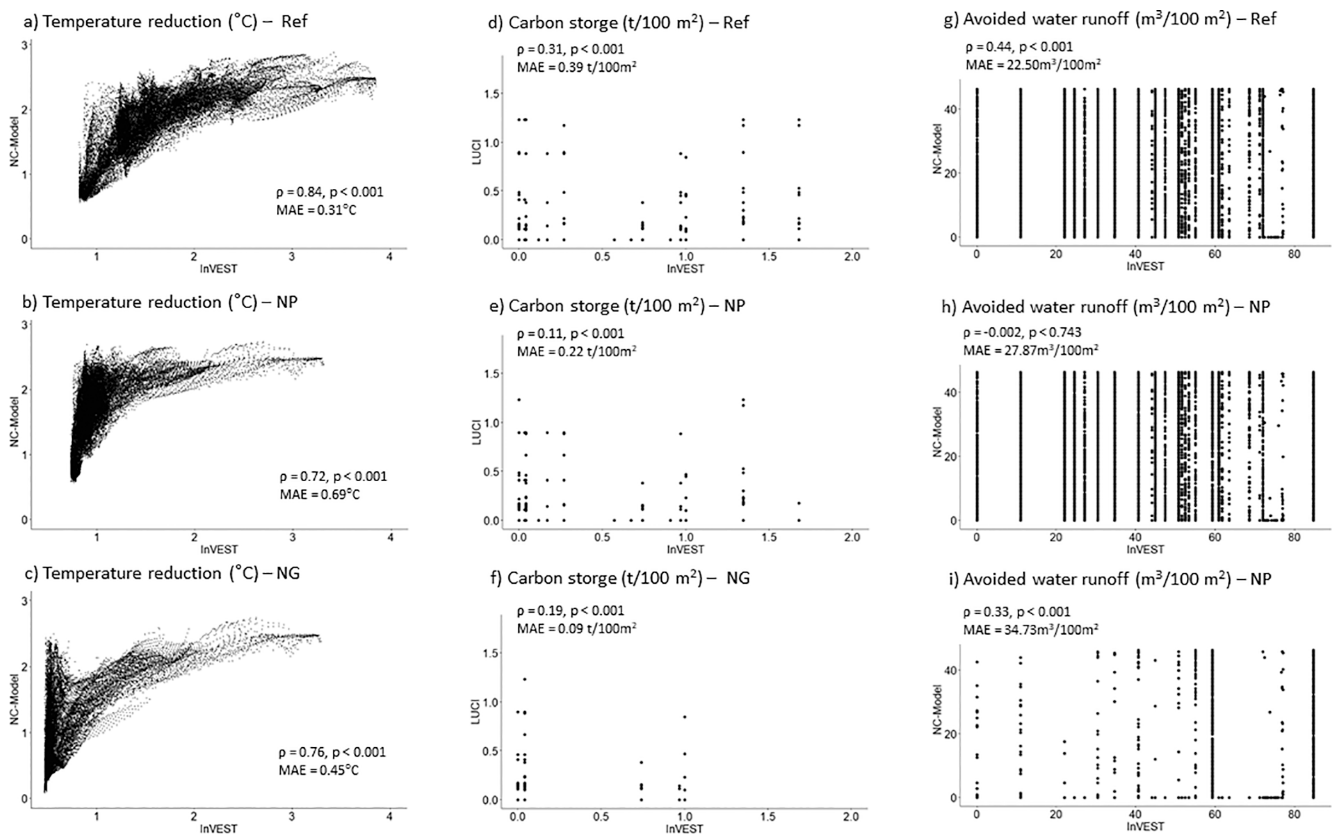

Fig. 5. Pairwise model comparison of ES values per grid-cell, with associated correlation coefficient (Spearman's rho, ρ), p-value and mean absolute error (MAE), for the reference (Ref) and the two scenarios (NP, NG referring to No-Park and No-Green scenario respectively) including a - c) local temperature regulation (air temperature reduction, °C) estimated by InVEST and the NC-Model; d - f) global climate regulation (carbon storage, metric ton/100 m^2) estimated by InVEST and LUCI; and g - i) flood protection (avoided water runoff, m^3/100 m^2) estimated by InVEST and the NC-Model.

models. These differences may stem from differences in model structure (i.e., differences in biophysical processes accounted for) and model parameterization (i.e., differences in the value used to quantify a given biophysical process), in line with two commonly recognized sources of uncertainties in environmental modelling (Refsgaard et al., 2007), and have distinct implications for model outputs (Table C-1). For example, InVEST accounts for an additional cooling effect of large green spaces (>2 ha) on surrounding areas, hence projects a stronger decrease of local temperature regulation services than the NC-Model, particularly in the No-Park scenario (Fig. 6**a**). Moreover, the two urban cooling models differ in how the cooling effect of urban nature is quantified, leading to different temperature reduction values. For instance, the NC-model accounts for the cooling capacity of water bodies and distinguishes between different vegetation types (i.e., trees, shrubs/bushes, grass) in addition to distinction between LULC classes (Table B-4). In contrast, InVEST assigns cooling primarily to shading by trees and includes the cooling effect of other vegetation types and water bodies only via surface albedo and evapotranspiration estimates per LULC class (Table B-2), which may explain the generally lower city-average temperature reduction values for InVEST than for the NC-Model.

We found pronounced differences in model parameterization also in the global climate regulation models. LUCI calculates carbon stocks for different soil and LULC combinations based on spatial LULC, soil data and look-up tables based on IPCC Tier 1 protocols on climate change, and assumes no carbon stock values for residential vegetation and soils. In contrast, InVEST calculates carbon stocks based on user-defined look-up tables (Table B-11), allowing to account also for carbon stocks in (partially vegetated) urban fabric LULC classes. As a result, city-average carbon storage values estimated by InVEST are larger than those modeled by LUCI and show a stronger decrease in response to the scenarios (Fig. 6b). Differences between the models become smaller when the amount of vegetation decreases, and the models showed the highest agreement in the No-Green scenario, reflecting the similar underlying model structure (i.e., assigning carbon pools to green LULC).

Differences in model structure and parametrization were also evident for the flood protection models. While the NC-Model estimates water interception by vegetation only, InVEST accounts also for additional water retention through infiltration in the soil and water flow to neighbouring grid cells (within a certain retention radius). Hence flood protection services estimates were generally higher for InVEST than for the NC-Model, and InVEST was less sensitive to the scenarios (Fig. 5c), which did not affect the soil structure. Compared to InVEST, LUCI simulates the flow of water through the urban areas more accurately, building on detailed hydrological and topographic information. This allows LUCI to account for the downstream effect of flood mitigating features (i.e., features that intercept rainfall such as parks, forests, dunes) beyond the grid cell level. As a result, the loss of flood mitigating features affects not only the grid cell itself (as for the NC-Model), or the neighboring grid cells (as for InVEST), but also grid cells further downstream, hence LUCI estimates more profound changes in ES loss than the NC-Model and InVEST when vegetation is reduced (Fig. 5c+d).

4.2. Future research implications

Spatially-explicit modelling approaches for quantifying the role of nature in addressing urban societal challenges are vital to better support urban planning and decision making in the light of current policy developments (e.g., city greening initiatives such as European Green City Accord). Yet, the availability of ES models tailored to the urban context is rather limited, as highlighted by our initial selection process (Table A-

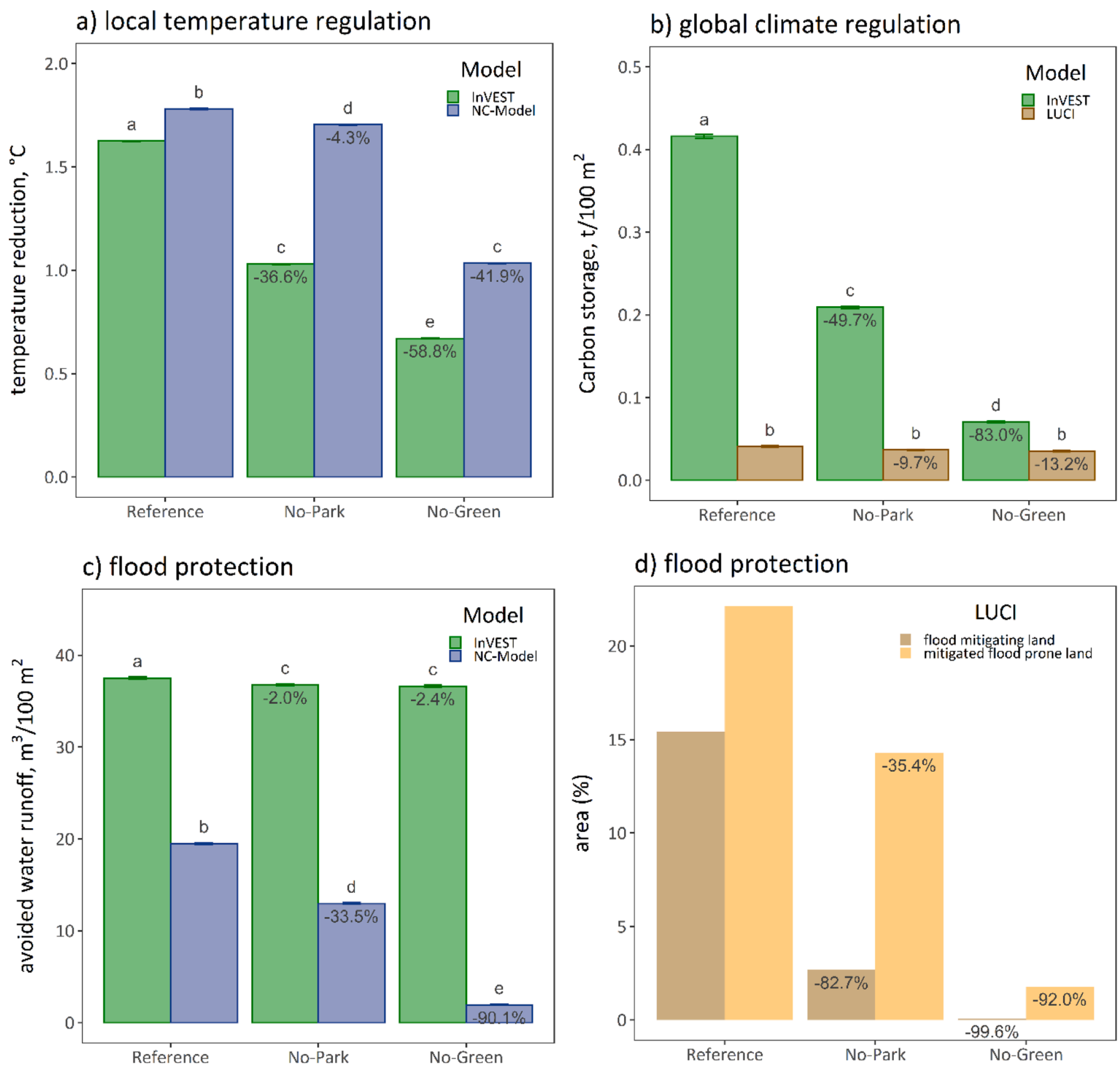

Fig. 6. City-average ES values per model for the reference and the two scenarios including a) local temperature regulation (air temperature reduction, °C), b) global climate regulation (carbon storage, metric ton/100 m^2), c) flood protection by InVEST and the NC-Model (annually avoided water runoff, m^3/100 m^2), and d) flood protection by LUCI (area receiving and providing flood mitigation, %). Bars show the standard error, percentages in the bars reflect changes in the scenario relative to the reference, and letters above the bars represent the results of the statistical analysis. Different letters reflect that model-scenario combinations were significantly different ($p < 0.05$) according to the Kruskal-Wallis test with Dunn's test.

1) as well as earlier studies (Delpy et al., 2021, Hamel et al., 2021). We recommend further development of urban ES models by improving the representation of the urban nature, as we were limited in capturing small-scale natural elements. For example, we could not account for nature-based solutions integrating nature into the built environment (i. e., permeable parking lots, bioswales along roadsides, green roofs on buildings) or urban green consisting of highly heterogenous vegetation (e.g., allotment gardens, backyards), which may have resulted in an underestimation of the full potential of nature in cities (Derkzen et al., 2015, Kain et al., 2016, Shafique et al., 2018, Chen et al., 2021). Part of this limitation lies in the spatial and thematic resolution of the LULC map that we used as input for all models and a more fine-grained representation of the urban LULC than applied here may improve the accuracy of ES estimates (Grafius et al., 2016; Hamstead et al., 2016; Rioux et al., 2019; Zawadzka et al., 2021). However, urban ES models can also be improved through a better representation of urban-specific conditions and processes influencing actual ES delivery. Examples include the presence of underground drainage networks, which strongly modify urban hydrology hence actual surface runoff (Guo et al., 2021), and building patterns and the height of buildings, which influence shading, wind and solar radiation (Norton et al., 2015, Wu et al., 2019), hence actual temperature values. Although some of these aspects were included in the models we used here (e.g., the NC-Model included a proxy of building density to estimate the UHI effect), further refinements would allow to quantify ES delivery more adequately. We also recommend to advance the parameterization of urban ES models based on data specific to cities. Urban soils in residential areas, for example, can store and sequester large amounts of soil organic carbon, potentially larger than agricultural or natural soils due to the absence of regular soil disturbance (Vasenev and Kuzyakov, 2018; Pouyat et al., 2006). The two models applied here (LUCI, InVEST), however, had limited opportunities to account for carbon stocks of urban soils, due to default settings within the models. Finally, future work should be done on how to better incorporate the effects of climate change into ES modeling as climate change affects not only climatic variables (e.g., temperature, rainfall) but also biophysical factors and processes, such as the cooling effect of urban green space (e.g., trees, parks) (Manoli et al., 2019; Kraemer and Kabisch, 2022), or the carbon uptake by vegetation and soil (Melillo et al., 2011). There are models available that assess the biophysical factors controlling certain urban ES supplies in more detail, such as hydrological models (e.g., Storm Water Management Model (SWMM), Model for Urban Stormwater Improvement Conceptualisation (MUSIC)),

microclimate models (e.g., ENVI-met model, RayMan model), or models focusing on specific urban nature types (e.g., i-tree model) (Table A-2), which can provide valuable elements to further advance urban ES models.

In order to increase confidence in urban ES assessments, models can be parameterized and validated with local field-sampled values from the study area of concern. Bosch et al., (2021), for instance, compared the outputs of the InVEST cooling model with air temperature observation data, demonstrating similar spatial patterns, thus increasing confidence in the model outcomes. Similar, Delpy et al., (2021) conducted a field analysis on land cover features (e.g., small-scale green space) to evaluate LUCI outputs of seven ES (e.g., flood mitigation), and showed that model outputs can be improved by parameterization based on local field data. However, validation of models is often not possible due to lack of observational data, in particular for large-scale assessments or scenario applications. Especially in these cases, multi-model assessments serve as a valuable strategy to better understand the models and quantify associated uncertainties (IPBES, 2016, Leclère et al., 2020, Rosa et al., 2020). Multi-model assessments offer insights into characteristics of different models, identify options for model improvement, and help to evaluate the applicability of specific models for particular decision-making or research contexts (Dennedy-Frank et al., 2016, Sharps et al., 2017, Veerkamp et al., 2020, Delpy et al., 2021). Using multiple models also allows for additional or complementary dimensions of ES to be quantified, either by highlighting a different aspect of the same ES (e.g., the different flood protection indicators used in this study) and by quantifying different ES (Veerkamp et al., 2020). This will provide valuable insights into the emergence of potential synergies and trade-offs between ES, and help to identify priority areas for interventions (e.g., green infrastructure development) (Sylla et al., 2020, Van Oorschot et al., 2021). Finally, multi-model assessments are crucial to quantify uncertainties related to differences in model structure and parameterization. This is particularly important when models are used to support policy and decision-making, as conclusions drawn from a single model may not fully inform end-users (e.g., urban planners, decision-makers) about the possible effectiveness of a given measure or strategy (e.g., city greening schemes).

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Acknowledgements

The research leading to this article has received funding from PBL Netherlands Environmental Assessment Agency as part of the GLOBIO project (www.globio.info). Funding was also received from the European Union's H2020 research and innovation program under the grant agreement no 730423 (NATURVATION, www.naturvaton.eu). The authors also would like to thank the NC modelling team, in particular Dr. Remon Koopman, and the InVEST modelling team, in particular Dr. Roy Remme for their help to get the models running, and Dr. Alexander van Oudenhoven and Prof. Bram Bregman for helpful discussions about urban ES assessments.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoser.2022.101500.

References

Alexander, P., Prestele, R., Verburg, P.H., Arneth, A., Baranzelli, C., Batista e Silva, F., Brown, C., Butler, A., Calvin, K., Dendoncker, N., 2017. Assessing uncertainties in land cover projections. Glob. Change Biol. 23, 767–781. https://doi.org/10.1111/gcb.13447.

Anon. 2014. Map of the soil structure in the Netherlands 1:50,000 under INSPIRE, download service. Available at: http://data.europa.eu/88u/dataset/dd414384-0bcb-4188-86e2-2843e12a579e (Accessed 20 May 2020).

Bagstad, K.J., Semmens, D.J., Winthrop, R., 2013a. Comparing approaches to spatially explicit ecosystem service modeling: a case study from the San Pedro River. Arizona. Ecosyt. Serv. 5, 40–50. https://doi.org/10.1016/j.ecoser.2013.07.007.

Bagstad, K.J., Semmens, D.J., Waage, S., Winthrop, R., 2013b. A comparative assessment of decision-support tools for ecosystem services quantification and valuation. Ecosyst. Serv. 5, 27–39. https://doi.org/10.1016/j.ecoser.2013.07.004.

Bosch, M., Locatelli, M., Hamel, P., Remme, R.P., Chenal, J., Joost, S., 2021. A spatially explicit approach to simulate urban heat mitigation with InVEST (v3.8.0). Geosci. Model Dev. 14, 3521–3537. https://doi.org/10.5194/gmd-14-3521-2021.

Bouwer, L., Capriolo, A., Chiabai, A., Foudi, S., Garrote, L., Harmáčková, Z.V., Iglesias, A., Jeuken, A., Olazabal, M., Spadaro, J., Taylor, T., Zandersen, M., 2018. Chapter 4 - Upscaling the impacts of climate change in different sectors and adaptation strategies. *In:* Adapting to climate change in Europe. Sanderson H., Hildén M., Russel, D., Penha-Lopes, G., Capriolo A., (Eds.) 173-243. https://doi.org/10.1016/B978-0-12-849887-3.00004-6.

Bryant, B.P., Borsuk, M.E., Hamel, P., Oleson, K.L., Schulp, C., Willcock, S., 2018. Transparent and feasible uncertainty assessment adds value to applied ecosystem services modeling. Ecosyt. Serv. 33, 103–109. https://doi.org/10.1016/j.ecoser.2018.09.001.

Cavan, G., Lindley, S., Jalayer, F., Yeshitela, K., Pauleit, S., Renner, F., Gill, S., Capuano, P., Nebebe, A., Woldegerima, T., 2014. Urban morphological determinants of temperature regulating ecosystem services in two African cities. Ecol. Indic. 42, 43–57. https://doi.org/10.1016/j.ecolind.2014.01.025.

CBD 2021. First draft of the post-2020 global biodiversity framework. (CBD/WG2020/3/3). Secretariat of the UN Convention on Biological Diversity.

CBS. 2020. Voorlopige bevolkingsaantallen, 1-1-2020. Available at: https://www.cbs.nl/nl-nl/maatwerk/2020/11/voorlopige-bevolkingsaantallen-1-1-2020?msclkid=0502d287cf6d11eca11d0ec1bf10b7e5 (Accessed 6 April 2022).

CBS. 2021. Land use; all categories, municipalities. Available at: https://www.cbs.nl/en-gb/figures/detail/70262eng?msclkid=3c168544cf6d11ec81da545fdf10c3e4 (Accessed 6 April 2022).

Chen, V., Bonilla Brenes, J.R., Chapa, F., Hack, J., 2021. Development and modelling of realistic retrofitted Nature-based Solutions scenarios to reduce flood occurrence at the catchment scale. Ambio 50, 1462–1476. https://doi.org/10.1007/s13280-020-01493-8.

Climate Data.org. 2021. Climate The Hague. Available at: https://en.climate-data.org/europe/the-netherlands/south-holland/the-hague-2101/ (Accessed 15 June 2021).

Cortinovis, C., Geneletti, D., 2018. Mapping and assessing ecosystem services to support urban planning: a case study on brownfield regeneration in Trento, Italy. One Ecosyst. 3, e25477.

Delpy, F., Pedersen Zari, M., Jackson, B., Benavidez, R., Westend, T., 2021. Ecosystem services assessment tools for regenerative urban design in Oceania. Sustainability. 13, 2825. https://doi.org/10.3390/su13052825.

Dennedy-Frank, P.J., Muenich, R.L., Chaubey, I., Ziv, G., 2016. Comparing two tools for ecosystem service assessments regarding water resources decisions. J. Environ. Manage. 177, 331–340. https://doi.org/10.1016/j.jenvman.2016.03.012.

Derkzen, M.L., van Teffelen, A.J.A., Verburg, P.H., 2015. Quantifying urbane ecosystem services based on high-resolution data of urban green space: an assessment for Rotterdam, the Netherlands. J. Appl. Ecol. 52, 1020–1032. https://doi.org/10.1111/1365-2664.12469.

Du, S., Shi, P., Van Rompaey, A., 2015. Quantifying the impact of impervious surface location on flood peak discharge in urban areas. Nat. Hazards. 76, 1457–1471. https://doi.org/10.1007/s11069-014-1463-2.

EC (European Commission). 2013. Green Infrastructure (GI) - Enhancing Europe's Natural Capital. Communication from the Commission to the European Parliament, the Council, The European Economic and Social Committee and the Committee of the Regions, COM (2013) 249 final, Brussels.

EC (European Commission, Directorate-General for Research and Innovation). 2015. Towards an EU Research and Innovation policy agenda for Nature-Based Solutions and Re-Naturing Cities. Final report of the Horizon 2020 Expert Group on ́ Nature-Based Solutions and Re-Naturing Cities (full version). Publication Office. https://data.europa.eu/doi/10.2777/479582.

EC (European Commission, Directorate-General for Research and Innovation). 2020. Nature-based solutions: state of the art in EU-funded projects. Bulkeley, H., Naumann, S., Voijnovic, Z., Calfapietra, C., Whiteoak, K., (eds.) Available at: https://data.europa.eu/doi/10.2777/236007.

EEA (European Environment Agency). 2018a. Urban Atlas 2018. Available at: https://land.copernicus.eu/local/urban-atlas/urban-atlas-2018 (Accessed 1 June 2020).

EEA (European Environment Agency). 2018b. Tree Cover Density 2018. Available at: https://land.copernicus.eu/pan-european/high-resolution-layers/forests/tree-cover-density/status-maps/tree-cover-density-2018 (Accessed 24 July 2020).

Faivre, N., Fritz, M., Freitas, T., de Boissezon, B., Vandewoestijne, S., 2017. Nature-Based Solutions in the EU: innovating with nature to address social, economic and environmental challenges. Environ. Res. 159, 509–518. https://doi.org/10.1016/j.envres.2017.08.032.

Gemeente Den Haag (2022) Den Haag Klimaatatlas. https://denhaag.klimaatatlas.net/ (Accessed 17 May 2022).

Grafius, D.R., Corstanje, R., Warren, P.H., Evans, K.L., Hancock, S., Harries, J.A., 2016. The impact of land use/land cover scale on modelling urban ecosystem services. Lands. Ecol. 31, 1509–1522. https://doi.org/10.1007/s10980-015-0337-7.
Graves, S., Piepho, H-P., Dorai-Raij S., Selzer L., 2019. multcompView: Visualizations of Paired Comparisons. R package version 0.1-8, https://cran.r-project.org/web//packages/multcompView/index.html.
Guo, K., Guan, M., Yu, D., 2021. Urban surface water flooding modelling – a comprehensive review of current models and future challenges. Hydrol. Earth Syst. Sci. 25, 2843–2860. https://doi.org/10.5194/hess-25-2843-2021.
Haase, D., Larondelle, N., Andersson, E., Artmann, M., Borgström, S., Breuste, J., Gomez-Baggethun, E., Gren, Å., Hamstead, Z., Hansen, R., 2014. A quantitative review of urban ecosystem service assessments: concepts, models, and implementation. Ambio 43, 413–433. https://doi.org/10.1007/s13280-014-0504-0.
Hamel, P., Guerry, A., Polasky, S., Han, B., Douglass, J., Hamann, M., Janke, B., Kuiper, J., Levrel, H., Liu, H., 2021. Mapping the benefits of nature in cities with the InVEST software. NPJ Urban Sustain. 1, 1–9. https://doi.org/10.1038/s42949-021-00027-9.
Hamstead, Z.A., Kremer, P., Larondelle, N., McPherson, T., Haase, D., 2016. Classification of the heterogeneous structure of urban landscapes (STURLA) as an indiactor of landscape function applied to surface temperature in New York City. Ecol. Indic. 70, 574–585. https://doi.org/10.1016/j.ecolind.2015.10.014.
Harrison, P.A., Dunford, R., Barton, D.N., Kelemen, E., Martín-López, B., Norton, L., Termansen, M., Saarikoski, H., Hendriks, K., Gómez-Baggethun, E., 2018. Selecting methods for ecosystem service assessment: a decision tree approach. Ecosyst. Serv. 29, 481–498. https://doi.org/10.1016/j.ecoser.2017.09.016.
IPBES 2016. Summary for Policymakers of the Methodological Assessment of Scenarios and Models of Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. IPBES secretariat.
IPCC. 2022. Summary for Policymakers. In: Climate Change 2022: Mitigation of climate change. Contribution of working group III to the sixth assessment report of the Intergovernmental Panel on Climate Change. P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, (Eds.), Cambridge University Press, Cambridge, UK and New York, NY, USA. doi: 10.1017/9781009157926.001.
Kabisch, N., Korn, H., Stadler, J., Bonn, A. (Eds.), 2017. Nature-based solutions to climate change adaptation in urban areas: Linkages between science, policy and practice. Springer Nature. doi: 10.1007/978-3-319-56091-5.
Kadaverugu, A., Rao, C.N., Viswanadh, G., 2021. Quantification of flood mitigation services by urban green spaces using InVEST model: a case study of Hyderabad city, India. Model. Earth Syst. Environ. 7, 589–602. https://doi.org/10.1007/s40808-020-00937-0.
Kain, J.-H., Larondelle, N., Haase, D., Kaczorowska, A., 2016. Exploring local consequences of two lan-use alternatives for the supply of urban ecosystem services in Stockholm year 2050. Ecol. indic. 70, 615–629. https://doi.org/10.1016/j.ecolind.2016.02.062.
Kassambara, A., 2020. Ggpubr: 'ggplot2' Based Publication Ready Plots. R package version 0.4.0. https://cran.r-project.org/web/packages/ggpubr/index.html.
Khomenko, S., Cirach, M., Pereira-Barboza, E., Mueller, N., Barrera-Gómez, J., Rojas-Rueda, D., de Hoogh, K., Hoek, G., Nieuwenhuijsen, M., 2021. Premature mortality due to air pollution in European cities: a health impact assessment. Lancet Planet. Health. 5, e121–e134. https://doi.org/10.1016/S2542-5196(20)30272-2.
Kim, H., Rosa, I., Alkemade, R., Leadley, P., Hurtt, G., Popp, A., Van Vuuren, D.P., Anthoni, P., Arneth, A., Baisero, D., 2018. A protocol for an intercomparison of biodiversity and ecosystem services models using harmonized land-use and climate scenarios. Geosci. Model Dev. 11, 4537–4562. https://doi.org/10.5194/gmd-11-4537-2018.
Ecosystems Knowledge Network. 2021 https://ecosystemsknowledge.net/?msclkid=1506594bcf6e11eca109d7e9c2d10b0d. (Accessed 12 March 2021).
Kondo, M.C., Fluehr, J.M., McKeon, T., Branas, C.C., 2018. Urban green space and its impact on human health. Int. J. Environ. Res. Public Health 15, 445. https://doi.org/10.3390/ijerph15030445.
Kraemer, R., Kabisch, N., 2022. Parks under stress: air temperature regulation of urban green space under conditions of drought and summer heat. Front. Environ. Sci. https://doi.org/10.3389/fenvs.2022.849965.
Lafortezza, R., Chen, J., Konijnendijk van Den Bosch, C., Randrup, T.B., 2018. Nature-based solutions for resilient landscapes and cities. Environ. Res. 165, 431–441. https://doi.org/10.1016/j.envres.2017.11.038.
Leclère, D., Obersteiner, M., Barret, M., Butchart, S. H. M., Chaudhary, A., De Palma, A., DeClerck, F. A. J., Di Marco, M., Doelman, J. C., Dürauer, Freeman, R., Harfoot, M., Hasegawa, T., Hellweg, S., Hilbers, J. P., Hill, S. L. L., Humpenöder, Jennings, N., Krisztin, T., Mace, G. M., Ohashi, H., Popp, A., Purvis, A., Schipper, A. M., Tabeau, A., Valin, H., van Meijl, H., van Zeist, W-J., Visconti, P., Alkemade, R., Almond, R., Bunting, G., Burgess, N. D., Cornell, S. E., Di Fulvio, F., Ferrier, S., Fritz, S., Fujimori, S., Grooten, M., Haarwood, T., Havlik, T., Meyer, C., Nel, D., Newbold, T., Schmidt-Traub, G., Stehfest, E., Strassburg, B. N., van Vuuren, D. P., Ware, C., Watson, J. E. M., Wu, W., Young, L., 2020. Bending the curve of terrestrial biodiversity needs an integrated strategy. Nature. 585:551-556. https://doi.org/10.1038/s41586-020-2705-y.
Lemonsu, A., Viguie, V., Daniel, M., Masson, V., 2015. Vulnerability to heat waves: impact of urban expansion scenarios on urban heat island and heat stress in Paris (France). Urban Climate. 14, 586–605. https://doi.org/10.1016/j.uclim.2015.10.007.
Liu, L., Jensen, M.B., 2018. Green infrastructure for sustainable urban water management: practices of five forerunner cities. Cities 74, 126–133. https://doi.org/10.1016/j.cities.2017.11.013.
LUCI. 2019. Land Utilisation Capability Indicator (LUCI) Help Documentation. Available at: https://lucitools.org/assets/Uploads/LUCI-Documentation-as-of-April-2019.pdf.
LUCI, 2022. LUCI Land Utilisation Capability Indicator. Available at: https://www.lucitools.org/. (Accessed 23 May 2022).
Mangiafico, S., 2022. Rcompanion: Functions to Support Extension Education Program Evaluation. R package version 2.4.15. https://cran.csail.mit.edu/web/packages/rcompanion/index.html.
Melillo, J. M., Butler, S., Johnson, J. Mohan, J., Steudler, P., Lux, H., Burrows, E., Bowles, F., Smith, R., Scott, L., Vario, C., Hill, T., Burton, A., Zhou, Y.-M., Tan, J., 2011. Soil warming, carbon-nitrogen interactions, and forest carbon budgets. 108:9508-9512. https://doi.org/10.1073/pnas.1018189108.
Manoli, G., Fatichi, S., Schläpfer, M., Yu, K., Crowther, T.W., Meili, N., Burlando, P., Katul, G.G., Bou-Zeid, E., 2019. Magnitude of urban heat islands largely explained by climate and population. Nature 573, 55–60. https://doi.org/10.1038/s41586-019-1512-9.
Mexia, T., Vieria, J., Principe, A., Anjos, A., Silva, P., Lopes, N., Freitas, C., Santos-Reis, Correira, O., Branquinho, C., Pinho, P., 2018. Ecosystem services: Urban parks under a magnifying glass. Environ. Res. 160, 469–478. https://doi.org/10.1016/j.envres.2017.10.023.
Natural Capital Project, 2022. InVEST. Available at: https://naturalcapitalproject.stanford.edu/software/invest. (Accessed 23 May 2022).
NATURVATION. 2021. Urban Nature Navigator. Available at https://naturvation.eu/result/urban-nature-navigator.html (Accessed 26 March 2021).
Nguyen, T.T., Meurk, C., Benavidez, R., Jackson, B., Pahlow, M., 2021. The effect of blue-green infrastructure on habitat connectivity and biodiversity: a case study in the Ōtākaro/Avon River catchment in Christchurch, New Zealand. Sustainability 13, 6732. https://doi.org/10.3390/su13126732.
Nielsen, A.B., van den Bosch, M., Maruthaveeran, S., van den Konijnendijk, C., 2014. Species richness in urban parks and its drivers: a review of empirical evidence. Urban Ecosyst. 17, 305–327. https://doi.org/10.1007/s11252-013-0316-1.
Norton, B.A., Coutts, A.M., Livesley, S.J., Harris, R.J., Hunter, A.M., Williams, N.S.G., 2015. Planning for cooler cities: a framework to prioritise green infrastructure to mitigate high temperatures in urban landscapes. Landsc Urban Plan. 134, 127–138. https://doi.org/10.1016/j.landurbplan.2014.10.018.
Olge, D.H., Doll, J.C., Wheeler, P., Dinno A., 2022. FSA: Fisheries Stock Analysis. R package version 0.9.3, https://github.com/fishR-Core-Team/FSA.
Paulin, M., Remme, R., de Nijs, T., Rutgers, M., Koopman, K., de Knegt, B., van der Hoek, D., Breure, A., 2020a. Application of the natural capital model to assess changes in ecosystem services from changes in green infrastructure in Amsterdam. Ecosyst. Serv. 43, 101114 https://doi.org/10.1016/j.ecoser.2020.101114.
Paulin, M., Remme, R., Van der Hoek, D., De Knegt, B., Koopman, K., Breure, A., Rutgers, M., de Nijs, T., 2020b. Towards nationally harmonized mapping and quantification of ecosystem services. Sci. Total Environ. 703, 134973 https://doi.org/10.1016/j.scitotenv.2019.134973.
PDOK 2020. Actueel Hoogtebestand Nederland (AHN3). Available at: https://www.pdok.nl/introductie/-/article/actueel-hoogtebestand-nederland-ahn3- (Accessed 11 June 2020).
Pereira, H. M., Rosa, I. M. D., Martins, I. S., Kim, H., Leadley, P., Popp, A., van Vuuren, D. P., Hurtt, G., Anthoni, P., Arneth, A., Baisero, D., Chaplin-Kramer, R., Chini, L., Di Fulvio, F., Di Marco, M., Ferrier, S., Fujimori, S., Guerra, C. A., Harfoot, M., Harwood, T. D., Hasegawa, T., Haverd, V., Havlík, P., Hellweg, S., Hilbers, J. P., Hill, S. L. L., Hirata, A., Hoskins, A. J., Humpenöder, J., Janse, J. H., Jetz, W., Johnson, J. A., Krause, A., Leclère, D., Matsui, T., Meijer, J. R., Merow, C., Obsersteiner, M., Ohashi, H., Poulter, B., Purvis, A., Quesada, B., Rondinini, C., Schipper, A. M., Settele, J., Sharp, R., Stehfest, E., Strassburg, B. N. B., Takahashi, K., Talluto, M. V. Thuiller, W., Titeux, N., Visconti, P., Ware, C., Wolf, F., Alkemade, R., 2020. Global trends in biodiversity and ecosystem services from 1900 to 2050. bioRxiv (Preprint) https://doi.org/10.1101/2020.04.14.031716.
Pouyat, R.C., Yesilonis, I.D., Nowak, D.J., 2006. Carbon storage by urban soils in the United States. J. Environ. Qual. 35, 1566–1575. https://doi.org/10.2134/jeq2005.0215.
R Core Team, 2022. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process – A framework and guidance. Enviro. Model. Softw. 11, 1543–1556. https://doi.org/10.1016/j.envsoft.2007.02.004.
Remme R., de Nijs, T., Paulin, M., 2018. Natural Capital Model. Technical documentation of the quantification, mapping and monetary valuation of urban ecosystem services. RIVM report 2017-0040. 10.21945/RIVM-2017-0040.
Rioux, J.-P., Cimon-Morin, J., Pellerin, S., Alard, D., Poulin, M., 2019. How land cover spatial resolution affects mapping of urban ecosystem service flow. Front. Environ. Sci. https://doi.org/10.3389/fenvs.2019.00093.
Rosa, I.M.D., Purvis, A., Alkemade, R., Chaplin-Kramer, R., Ferrier, S., Guerra, C.A., Hurtt, G., Kim, H., Leadley, P., Martins, I.S., 2020. Challenges in producing policy-relevant global scenarios of biodiversity and ecosystem services. Glob. Ecol. Conserv. 22, e00886. https://doi.org/10.1016/j.gecco.2019.e00886.
Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., Jone, J.W., 2013. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. PNAS 11, 3268–3273. https://doi.org/10.1073/pnas.1222463110.
Sarzynski, A., 2012. Bigger is not always better: a comparative analysis of cities and their air pollution impact. Urban Stud. 49, 3121–3138. https://doi.org/10.1177/0042098011432557.

Schulp, C.J.E., Burkhard, B., Maes, J., Van Vliet, J., Verburg, P.H., 2014. Uncertainties in ecosystem service maps: a comparison on the European scale. PLoS One 9, e109643. https://doi.org/10.1371/journal.pone.0109643.
Seto, K.C., Fragkias, M., Güneralp, B., Reilly, M.K., 2011. A meta-analysis of global urban land expansion. PLoS One 6, e23777. https://doi.org/10.1371/journal.pone.0023777.
Shafique, M., Kim, R., Rafiq, M., 2018. Green roof benefits, opportunities and challenges – a review. Renew. Sustain. Energy Rev. 90, 757–773. https://doi.org/10.1016/j.rser.2018.04.006.
Sharp, R., Douglass, J., Wolny, S., Arkema, K., Bernhardt, J., Bierbower, W., Chaumont, N., Denu, D., Fisher, D., Glowinski, K., Griffin, R., Guannel, G., Guerry, A., Johnson, J., Hamel, P., Kennedy, C., Kim, C.K., Lacayo, M., Lonsdorf, E., Mandle, L., Rogers, L., Silver, J., Toft, J., Verutes, G., Vogl, A. L., Wood, S., Wyatt, K., 2020 InVEST 3.10.2 User's Guide. The Natural Capital Project, Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund.
Sharps, K., Masante, D., Thomas, A., Jackson, B., Redhead, J., May, L., Prosser, H., Cosby, B., Emmett, B., Jones, L., 2017. Comparing strengths and weaknesses of three ecosystem services modelling tools in a diverse UK river catchment. Sci. Total Environ. 584, 118–130. https://doi.org/10.1016/j.scitotenv.2016.12.160.
Statista 2020. Population density of the most populated cities in the Netherlands 2019. Statista Research Department.
Sylla, M., Hagemann, N., Szewrański, S., 2020. Mapping trade-offs and synergies among peri-urban ecosystem services to adress spatial policy. Environ. Sci. Policy. https://doi.org/10.1016/j.envsci.2020.06.002.
Teurlincx, S., Kuiper, J.J., Hoevenaar, E.C., Lurling, M., Brederveld, R.J., Veraart, A.J., Janssen, A.B., Mooij, W.M., de Senerpont Domis, L.N., 2019. Towards restoring urban waters: understanding the main pressures. Curr. Opin. Environ. Sustain. 36, 49–58. https://doi.org/10.1016/j.cosust.2018.10.011.
Thuiller, W., Guéguen, Renaud, J., Krager, D.N., Zimmerman, N.E., 2019. Uncertainty in ensembles of global biodiversity scenarios. Nat. Commun. 10:1-9. https://doi.org/10.1038/s41467-019-09519-w.
Trabucco, A., Zomer, R., 2019. Global Aridity Index and Potential Evapotranspiration (ET0) Climate Database v2. Figshare. Available at: https://doi.org/10.6084/m9.figshare.7504448.v3.
Trodahl, M.I., Jackson, B.M., Deslippe, J.R., Metherell, A.K., 2017. Investigating trade-offs between water quality and agricultural productivity using the Land Utilisation and Capability Indicator (LUCI)–A New Zealand application. Ecosys. Serv. 26, 388–399. https://doi.org/10.1016/j.ecoser.2016.10.013.
UN 2017. New Urban Agenda (A/RES/71/256). United Nations, Habitat III Secretariat.
UN 2019. World Urbanization Prospects: The 2018 Revision (ST/ESA/SER.A/420). United Nations, Department of Economic and Social Affairs, Population Division, New York.
UN, 2015. Transforming Our World: The 2030 Agenda for Sustainable Development. United Nations, New York.
Van den Berg, A.E., Maas, J., Verheij, R.A., Groenewegen, P.P., 2010. Green space as a buffer between stressful life events and health. Soc. Sci. Med. 70, 1203–1210. https://doi.org/10.1016/j.socscimed.2010.01.002.
Van den Bosch, M., Sang, Å.O., 2017. Urban natural environments as nature-based solutions for improved public health–A systematic review of reviews. Environ. Res. 158, 373–384. https://doi.org/10.1016/j.envres.2017.05.040.
Van Oijstaeijen, W., Van Passel, S., Cools, J., 2020. Urban green infrastructure: a review on valuation toolkits from an urban planning perspective. J. Environ. Manage. 267, 110603 https://doi.org/10.1016/j.jenvman.2020.110603.
Van Oorschot, J., Sprecher, B., van 't Zelfde, M., van Bodegom, P.M., van Oudenhoven, A.P.E., 2021. Assessing urban ecosystem services in support of spatial planning in the Hauge, the Netherlands. Landsc. Urban Plan. 214:104195. https://doi.org/10.1016/j.landurbplan.2021.104195.
Vasenev, V., Kuzyakov, Y., 2018. Urban soils as hot spots of anthropogenic carbon accumulation: review of stocks, mechanisms and driving factors. Land Degrad. Dev. 29, 1607–1622. https://doi.org/10.1002/ldr.2944.
Veerkamp, C.J., Dunford, R.W., Harrison, P.A., Mandryk, M., Priess, J.A., Schipper, A.M., Stehfest, E., Alkemade, R., 2020. Future projections of biodiversity and ecosystem services in Europe with two integrated assessment models. Reg. Environ. Change. 20, 1–14. https://doi.org/10.1007/s10113-020-01685-8.
Veerkamp, C.J., Schipper, A.M., Hedlund, K., Lazarova, T., Nordin, A., Hanson, H.I., 2021. A review of studies assessing ecosystem services provided by urban green and blue infrastructure. Ecosyst. Serv. 52, 101367 https://doi.org/10.1016/j.ecoser.2021.101367.
Ventriglio, A., Torales, J., Castaldelli-Maia, J.M., de Berardis, D., Bhugra, D., 2021. Urbanization and emerging mental health issues. CNS Spectr. 26, 43–50. https://doi.org/10.1017/S1092852920001236.
Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., Schewe, J., 2013. The inter-sectoral impact model intercomparison project (ISI-MIP): project framework. PNAS. 111, 3228–3232. https://doi.org/10.1073/pnas.1312330110.
Wickham, H., 2016. Ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag, New York.
Wickham, H., François, R., Henry, L., Müller, K., 2022. Dplyr: A Grammar of Data Manipulation. R package version 1.0.9. https://cran.r-project.org/web/packages/dplyr/index.html.
Wickham, H., Girlich, M., 2022. Tidyr: Tidy Messy Data. R package version 1.2.0. https://cran.r-project.org/web/packages/tidyr/index.html.
Willcock, S., Hooftman, D.A.P., Blanchard, R., Dawson, T.P., Hickler, T., Lindeskog, M., Martinz-Lopez, J., Reyers, B., Watts, S.M., Eigenbrod, F., Bullock, J.M., 2020. Ensembles of ecosystem service models can improve accuracy and indicate uncertainty. Sci. Total Environ. 747 https://doi.org/10.1016/j.scitotenv.2020.141006.
Wu, Z., Dou, P.D., Chen, L., 2019. Comparative and combinative cooling effects of different spatial arrangements of buildings and trees on microclimate. Sustain. Cities Soc. 51, 101711 https://doi.org/10.1016/j.scs.2019.101711.
Xie, L., Bulkeley, H., 2020. Nature-based solutions for urban biodiversity governance. Environ. Sci. Policy. 110, 77–87. https://doi.org/10.1016/j.envsci.2020.04.002.
Zawadzka, J.E., Harris, J.A., Corstanje, R., 2021. Assessment of heat mitigation capacity of urban greenspaces with the use of InVEST urban cooling model, verified with day-time land surface temperature data. Landsc Urban Plan 214, 104163. https://doi.org/10.1016/j.landurbplan.2021.104163.