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Optimizing urban tree species composition to maximize nature-based solutions

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Abstract: Nature-based Solutions (NbS) are vital for achieving sustainable urban development. While urban tree planting is one of the most important approaches to enhance NbS, current practices often concentrate on tree quantity or green coverage targets. NbS planning studies are also limited to priority identification, revealing a notable gap in both study and practice regarding NbS improvement-oriented urban tree planning. This study presents a tree species composition optimization-based framework for maximizing regional NbS by linking local demands and effectiveness of tree species through multi-objective optimization algorithm. A case study was designed in Philadelphia and the optimal tree species composition was explored on 0.25 km^2 grids. The spatial heterogeneity of local demands and varying effectiveness of tree species highlight the significance of strategic tree placement. The current tree species composition in Philadelphia is suboptimal for achieving NbS. Future greening efforts should increase the proportion of advantageous species, such as *Acer saccharinum*, *Acer rubrum*, and *Liquidambar styraciflua*. Compared with the baseline, the optimized species composition can provide substantially greater ecosystem services, for instance, about 20% more in stormwater management and up to 80% more in microclimate regulation. Two general planning recommendations are proposed: (1) maximize carbon sequestration capacity in areas with insignificant urban hazards; and (2) strategically place tree with specific advantages in targeted response to specific urban hazards. The developed framework provides guidance for efficient urban greening projects, enabling maximization of NbS under given greening quantity targets.

Introduction

Global urbanization continues to accelerate at an unprecedented rate, with approximately 57% of the world's population residing in urban areas as of 2023[1]. While urban growth is essential for economic development and social progress, it simultaneously raises significant concerns about urban ecological challenges that impact human well-being and environmental justice[2, 3]. Urban expansion usually encroaches on vast areas of natural spaces, usually resulting in loss of ecosystem services in the urban context. This trend, combined with climate change and increasing anthropogenic activities, may further exacerbate various urban environmental challenges, including urban heat stress, air pollution, and carbon sink degradation[4]. UN Sustainable Development Goal 11 (SDG 11) emphasizes the need for comprehensive improvement of urban

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environments amid intensifying urbanization and climate change, targeting a reduction in cities' per capita environmental impact by 2030[5]. Effectively addressing these urban eco-environmental challenges is crucial for achieving sustainable urban development[6].

Nature-based solutions (NbS), typically implemented through green infrastructure (GI), have been widely recognized as a critical strategy for advancing SDGs[7]. They offer a range of ecological benefits—often referred to as multifunctionality—including stormwater management, urban heat mitigation, air quality improvement, and carbon sequestration[8]. Leveraging their ability to simultaneously address diverse environmental challenges, cities worldwide have increasingly implemented NbS to mitigate the growing pressures of urbanization and climate change[9]. For instance, Berlin's City Tree Campaign aims to plant 10,000 additional roadside trees; the One Million Trees Initiative seeks to plant and conserve one million trees across metro Atlanta by 2030; and the TreePhilly Program aims to plant 300,000 trees in Philadelphia to enhance urban tree canopy. Most of urban greening initiatives, however, prioritize quantitative targets, such as increasing the number of urban trees or expanding a city's green coverage, rather than taking a more nuanced approach to leveraging urban greenery for enhanced ecological benefits[10, 11]. While numerical metrics are valuable for their measurability and visibility, they may overshadow more critical aspects such as strategic placement and ecosystem integration that could maximize trees' multifunctional benefits in addressing complex urban challenges[12].

Given both the essential role of NbS in addressing urban environmental challenges, designing effective NbS to enhance their multi-benefits and promote urban resilience has drawn increasing attention from scholars, urban planners, and policymakers[13, 14]. NbS planning has emerged as a prominent concentration, leading to the development of several models that engage with its multifunctional nature. Green Infrastructure Spatial Planning (GISP) model, for example, is particularly well-known among these planning frameworks, which integrates six criteria to capture multiple benefits[15]. GISP and similar models primarily evaluate priority locations for intervention based on spatial disparity in ecological conditions; for example, areas experiencing more severe urban heat receive higher priority for NbS implementation. The overall priority is determined by integrating separate assessment layers using various weighting methods. While subsequent studies have advanced weighting methods and assessment criteria, their primary objective remains limited to identifying priority locations through spatial disparity analysis[16, 17]. This focus makes it difficult to guide practical NbS planning, because beyond identifying demand it is also necessary to determine what measures should be taken to address these demands in order to form a complete decision-making chain. Beyond GISP-like approaches, the majority of NbS planning studies continue to focus on single benefits, such as stormwater management or urban heat mitigation, rather than incorporating multifunctionality[18-20], which is inconsistent with the multifunctional nature of NbS.

The extensive canopies of trees effectively intercept rainfall, reduce ground-level solar radiation, and capture particulate matter[21]. This makes trees dominant contributors to urban ecosystem services, including stormwater management, air quality improvement, and urban heat mitigation[22], representing the primary means by which NbS are implemented at the urban scale. Additionally, their larger biomass, longer lifespan, and greater photosynthetic capacity give trees significant advantages over shrubs and grasses in carbon sequestration[23]. NbS studies typically define NbS in terms of engineering facilities—such as green roofs, street trees, and rain gardens—while rarely considering species-specific characteristics[20, 24]. However, ecosystem services provided by NbS facilities are principally determined by their constituent plants, rather than the engineering elements — rain gardens or street trees composed of different plant species will generate varying

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ecological benefits[25, 26]. Therefore, species-specific characteristics should be considered when evaluating NbS benefits, as these characteristics largely determine the provision of ecosystem services.

Several studies have documented significant variations in ecological benefits among different tree species, even under similar physiological and growth conditions. For example, an experimental study explored how leaf attributes affect $PM_{2.5}$ capture and found that *Cinnamomum camphora* and *Osmanthus fragrans* are the most effective among ten tree species[27]; Oshio et al[28]. demonstrated that leaf quantity is the predominant factor affecting trees' microclimate regulation capacity, showing that *Zelkova serrata* provides greater cooling services than *Cinnamomum camphora*; Pérez-Cruzado et al[29]. reported that *Eucalyptus nitens* has a higher carbon sequestration rate (14.6 Mg C ha^{-1} $year^{-1}$) compared to *Pinus radiata* (8.7 Mg C ha^{-1} $year^{-1}$). Beyond these micro-perspective explorations, studies using simulation methods, such as i-Tree Eco and ENVI-met, has also demonstrated significant differences in ecological benefits between tree species[30, 31]. These findings indicate that even with identical green coverage, neglecting the effectiveness difference between species would result in varying ecological impacts.

A portion of ecosystem services provided by NbS have localized impacts, particularly the regulating services that are relevant to urban challenges, such as microclimate regulation and stormwater management[32]. This localized nature provides rationale for traditional NbS planning studies that use spatial disparity in ecological conditions to identify locations where NbS should be prioritized to implement[16]. Complex urban areas usually exhibit heterogeneous demand for NbS benefits, while different tree species provide diverse ecological functions[25]. This combination emphasizes the necessity of strategic tree placement—planting the right trees in the right locations to match the demand for NbS with the capacity to supply these ecosystem services[10]. This targeted intervention is conducive to promoting NbS efficiency—a particularly crucial consideration in metropolitan areas with limited greening space[33]. However, although scholars have recognized and highlighted the importance of strategic tree planting to promote NbS, there is currently no concrete method to achieve this goal[10].

Overall, concepts such as NbS and SDGs have gained increasing global attention, and many cities have recently launched large-scale urban greening initiatives. Current practices, however, still focus on quantitative targets, such as the number of trees planted, rather than being designed to maximize NbS outcomes. Existing studies on NbS planning also faces several limitations that reduce its practical applicability: (1) most research focus on identifying priority or demand for NbS, but do not go further to address how these demands should be met or what measures should be taken in practice; (2) NbS are frequently treated as engineering infrastructures, such as street trees, parks, or green roofs, without directly capturing the actual ecosystem service providers, namely the plants within these infrastructures; and (3) many studies tend to propose novel planning methods, but few verify the effectiveness of these methods.

Consequently, this study addresses current practical and research gaps by proposing a tree species composition optimization framework that links local NbS demand with the ecological effectiveness of species-specific trees, thereby maximizing regional NbS through planting the right trees in the right locations. To achieve this, we first quantified multiple aspects of NbS demand using machine learning, remote sensing, and downscaling approaches. We then employed the i-Tree Eco model to evaluate the ecological effectiveness of individual tree species that corresponds to local demand. On this basis, NSGA-III was applied to integrate local demand with species-specific ecological effectiveness, enabling the identification of optimal tree planning strategies that maximize regional NbS. Finally, we simulated tree-planting scenarios based on the

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study results by comparing response curves of ecosystem services to additional tree canopy cover under the optimized tree species composition with those derived from randomized control schemes. This comparison is intended to demonstrate the effectiveness of the proposed framework. A case study in Philadelphia, Pennsylvania, USA, was conducted to illustrate the applicability of this optimization framework.

Results

Spatial pattern of demand for NbS

As shown in Fig. 1a–c, where the results were divided into six categories using the Jenks natural breaks classification, the spatial distribution of NbS demand in Philadelphia varies considerably across different aspects. Overall, areas with higher demand tend to cluster in Central, North and South Philadelphia, locations characterized by intensive urban development. In contrast, neighborhoods adjacent to large green spaces (e.g., Fairmount Park, Wissahickon Valley Park) exhibit lower demand level.

Fig. 1a exhibits the demand for stormwater management. Locations with higher demand score (>0.57) are mainly concentrated in highly built-up areas, such as Central, North and South Philadelphia along the Delaware River waterfront. In these districts, the predominance of impervious surfaces, limiting rainfall infiltration, and the aging drainage system with inadequate capacity intensify stormwater runoff and heighten flood susceptibility. In comparison, lower-demand zones (<0.33) are most clustered within the northwestern and northern sections, anchored by Wissahickon Valley Park and Fairmount Park and Pennypack Park, reflecting the mitigating role of green spaces in regulating stormwater runoff.

The demand for urban heat mitigation is shown in Fig. 1b, which exhibits notable variations across Philadelphia. The highest-demand areas (>0.84) dominate large portions of Central Philadelphia and extend through South Philadelphia, underscoring the heat exposure in these dense neighborhoods. Meanwhile, moderate levels are found in the northeast, and relatively low demand appears in the northwest, around Wissahickon Valley Park. Likewise, neighborhoods along the Schuylkill River also tend to have lower demand for heat mitigation than surrounding areas, highlighting the important role of blue infrastructure in moderating urban temperatures.

As demonstrated in Fig. 1c, the demand for air quality improvement is especially pronounced on the west bank of the Schuylkill River in the southwestern section, where the demand level is generally higher than 0.54. Central Philadelphia also shows considerable need, implying the influence of high traffic volumes on air pollution. In general, the southern section of the city exhibits greater need for air quality improvement than the northern side, and areas in the northeastern and northwestern tips have the lowest demand level.

Taken together, these findings clearly show that NbS demand varies greatly across both geographic areas and thematic aspects in Philadelphia. For example, the higher-density districts, such as Central and South Philadelphia, experience more severe ecological challenges, whereas peripheral areas or those adjacent to major parks and waterways show more favorable conditions. This pronounced spatial heterogeneity highlights the importance of targeted NbS initiatives, namely planting the right trees in the right locations.

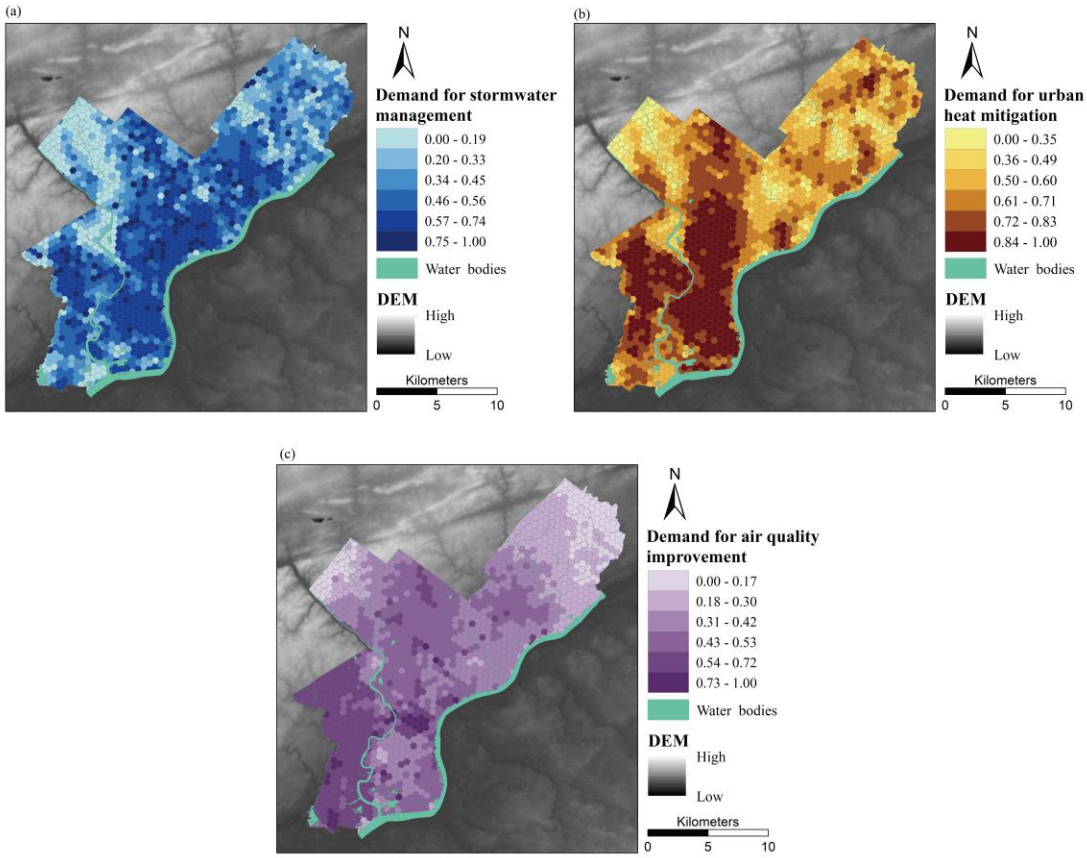


Fig. 1 | Spatial pattern of demand for NbS in Philadelphia. a Demand for stormwater management, with darker blue hexagons indicating higher demand. **b** Demand for urban heat mitigation, with dark red hexagons showing the highest demand and yellow areas the lowest. **c** Demand for air quality improvement, with darker purple hexagons representing higher demand. In all panels, water bodies are shown in cyan and are excluded from the spatial analysis. The background digital elevation model (DEM) is displayed in grayscale, where lighter shades indicate higher elevation and darker shades indicate lower elevation.

Effectiveness of species-specific urban tree

Fig. 2 illustrates the effectiveness of the 30 species-specific urban trees in four aspects. This effectiveness is based on the localized meteorological and pollution conditions in Philadelphia and has been standardized to a unit functional area. The effectiveness among tree species varies greatly. For example, the carbon sequestration of *Ginkgo biloba* is only approximately one-tenth of that of *Quercus bicolor*; *Cladrastis kentukea* achieves almost half the stormwater management capacity of *Pinus strobus* (avoided runoff); *Maackia amurensis* has less than one-third of the energy saving effectiveness compared to *Liquidambar styraciflua*. This significant variation in effectiveness suggests that neglecting tree species differences in urban greening programs could result in substantially different NbS performance, even under identical greening coverage.

Notably, among these 30 tree species, some species are outperformed by others in terms of these ecosystem service functions, that is, all four aspects are lower than those of certain other species. For instance, *Celtis occidentalis* is outperformed by *Liquidambar styraciflua*, while *Sophora japonica* is functionally

inferior to *Acer rubrum*. The gray areas of Fig. 2 represent the tree species that are Pareto-dominated by others. Furthermore, some prevalent species in the current composition, such as *Platanus* × *acerifolia* and *Pyrus calleryana* that account for 12.88% and 5.72% respectively, are functionally inferior species (Supplementary Table 3). This implies that the current tree species composition in Philadelphia has room for optimization to improve NbS performance.

There are nine tree species that are unsurpassed by others, which are considered in the optimization procedure. Each exhibits specific advantages. For example, *Pinus strobus* ranks highest among these species in $PM_{2.5}$ removal (277.7 $mg \cdot m^{-2} \cdot yr^{-1}$) and avoided runoff (17.79 $dm^3 \cdot m^{-2} \cdot yr^{-1}$); *Acer saccharum* achieves slightly lower performance in these aspects, removing 243.6 $mg \cdot m^{-2} \cdot yr^{-1}$ $PM_{2.5}$ and reducing 15.63 $dm^3 \cdot m^{-2} \cdot yr^{-1}$ runoff per functional unit, yet excels in energy savings. *Liquidambar styraciflua* demonstrates superior microclimate regulation capacity with energy savings of US1.74\cdot m^{-2} \cdot yr^{-1}$. *Quercus rubra* displays moderate but consistent effectiveness in all four categories. Although *Quercus bicolor* contributes the highest carbon sequestration at 708.4 $g \cdot m^{-2} \cdot yr^{-1}$, it ranks lower in the other three ecosystem service functions. In contrast, *Acer saccharinum* also provides substantial carbon sequestration, while demonstrating notable capability in the other three aspects.

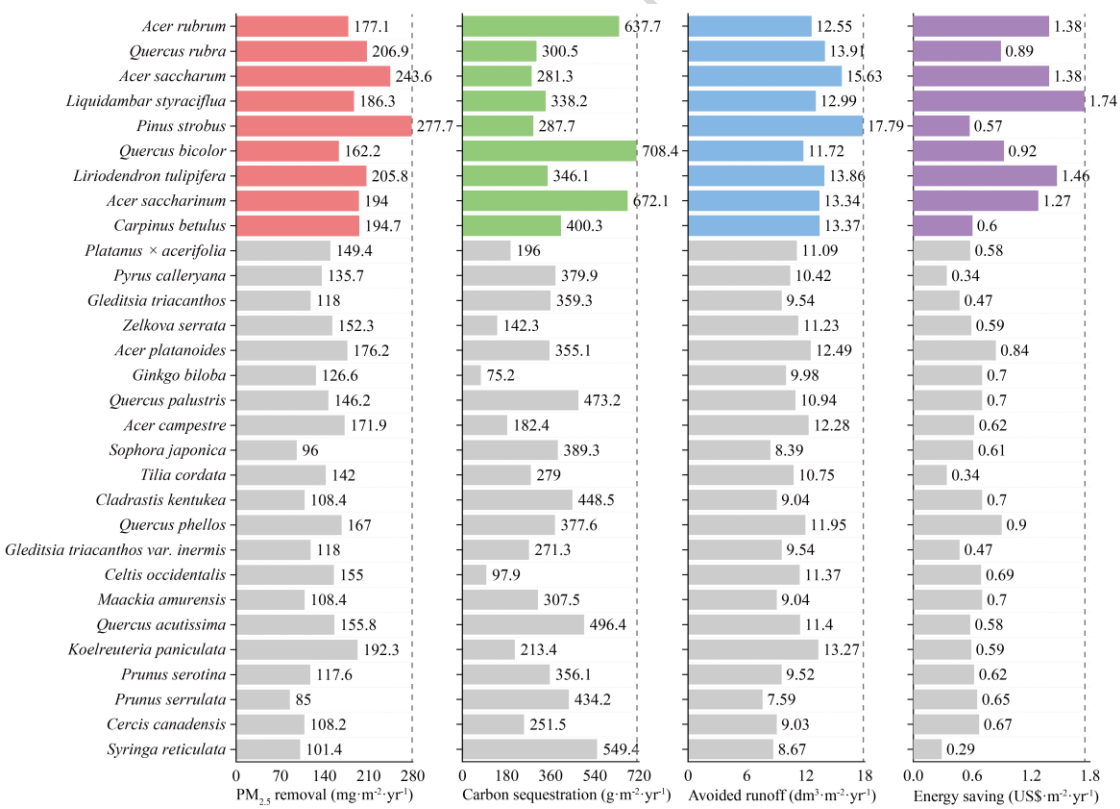


Fig. 2 | Effectiveness of species-specific trees in Philadelphia. The bar charts compare tree species in terms of four ecosystem service indicators: $PM_{2.5}$ removal ($mg \cdot m^{-2} \cdot yr^{-1}$), carbon sequestration ($g \cdot m^{-2} \cdot yr^{-1}$), avoided runoff ($dm^3 \cdot m^{-2} \cdot yr^{-1}$), and energy saving (US$$\cdot m^{-2} \cdot yr^{-1}$). Bars represent mean annual values per unit canopy area. The advantageous species are highlighted in color (red for $PM_{2.5}$ removal, green for carbon sequestration,

blue for avoided runoff, and purple for energy saving). Species shown in gray are dominated species, meaning they perform worse than at least one other species simultaneously across all four indicators. Species names are listed on the y-axis.

Pareto solution set

The Pareto solution set is illustrated in Fig. 3. Since the optimization is four-dimensional, the carbon sequestration is represented by color mapping. The Pareto solution set is a convex surface, suggesting smooth trade-offs between objectives. All solutions in the solution set are non-dominated. While each solution represents the different preference of tree species composition in each location, they are all the relatively optimal condition, indicating the most efficient tree species composition. TOPSIS was employed to identify a single compromise solution among these optimal solutions that best balances all objectives. The location of the solution with the highest TOPSIS score is also presented in Fig. 3. This compromise solution has an overall adaptability of 545.1 for stormwater management, 694.8 for urban heat mitigation, 479.3 for air quality improvement, and 524.4 for carbon sequestration, respectively. However, this study mainly concentrates the decision variables of the compromise solution instead of the objective function as they represent the tree species composition for each location.

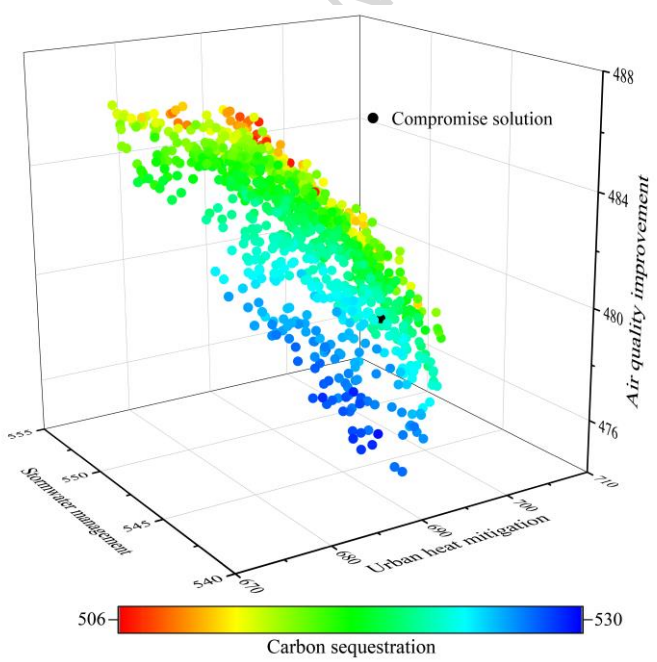


Fig. 3 | Pareto solution set for the tree composition optimization. Three-dimensional scatter plot showing the adaptability among stormwater management (x-axis), urban heat mitigation (y-axis), and air quality improvement (z-axis). Each point represents a candidate solution, with colors indicating the level of carbon sequestration adaptability (red = low, blue = high). The black point is the compromise solution that balances all four adaptability indicators.

Spatial pattern of urban tree species composition in compromise solution.

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Referring to the decision variables of the TOPSIS-based compromise solution, we identified the spatial patterns of the tree species composition for newly planted trees, as illustrated by Fig. 4 a-i. The relative frequency and percentage of each tree species for the whole city are displayed by Fig. 4j and k respectively.

On the whole, *Acer spp.* are comparatively favorable species for achieving NbS. Especially for *Acer saccharinum* and *Acer rubrum*, in nearly half of the locations, the recommended planting ratio exceeds 20% (Fig. 4a and h). Furthermore, *Liquidambar styraciflua* and *Liriodendron tulipifera* are also adaptive for the city's conditions, taking 16.6% and 11.6% respectively. These five tree species comprise 85% of the whole composition, suggesting that they should be the main selection to maximize NbS. However, the spatial patterns of the five most recommended species differ greatly. For instance, *Acer rubrum* and *Acer saccharinum* are more adaptive in the northeast and northwest parts while *Acer saccharum*, *Liquidambar styraciflua* and *Liriodendron tulipifera* are more predominant in the southern section.

Quercus rubra and *Carpinus betulus* account for only a very small fraction, playing a rather subtle role in the overall composition even though they are not dominated by other tree species (Fig. 4b and i). The two tree species show relatively weaker performance than the others. Especially for *Carpinus betulus*, planting is not recommended in almost half of the locations, except for a few scattered spots in the northern portion.

Pinus strobus and *Quercus bicolor* exhibit the most pronounced spatial heterogeneity (Fig. 4e-f). In a few areas with higher stormwater management and air quality improvement demand such as Central, North and Lower North Philadelphia, *Pinus strobus* shows high adaptability but is disadvantageous in most others. In comparison, *Quercus bicolor* is more recommended in northeastern and northwestern regions that are less developed such as Wissahickon Valley Park and its surroundings where the ecological conditions are relatively desirable. Some tree species with balanced ecosystem service functions such as *Quercus rubra* and *Liriodendron tulipifera* exhibit less heterogeneous spatial distribution.

While *Acer saccharinum*, *Acer rubrum*, *Liquidambar styraciflua*, *Acer saccharum*, and *Liriodendron tulipifera* are highly recommended for maximizing NbS, their current distribution is suboptimal. Except for *Acer rubrum*, these species are underrepresented in the current tree composition. Most notably, *Acer saccharinum*, despite being the most recommended species, comprises only 0.94% of Philadelphia's total tree population (see Supplementary Table 3), indicating significant potential for optimization of the city's urban forest composition to promote NbS.

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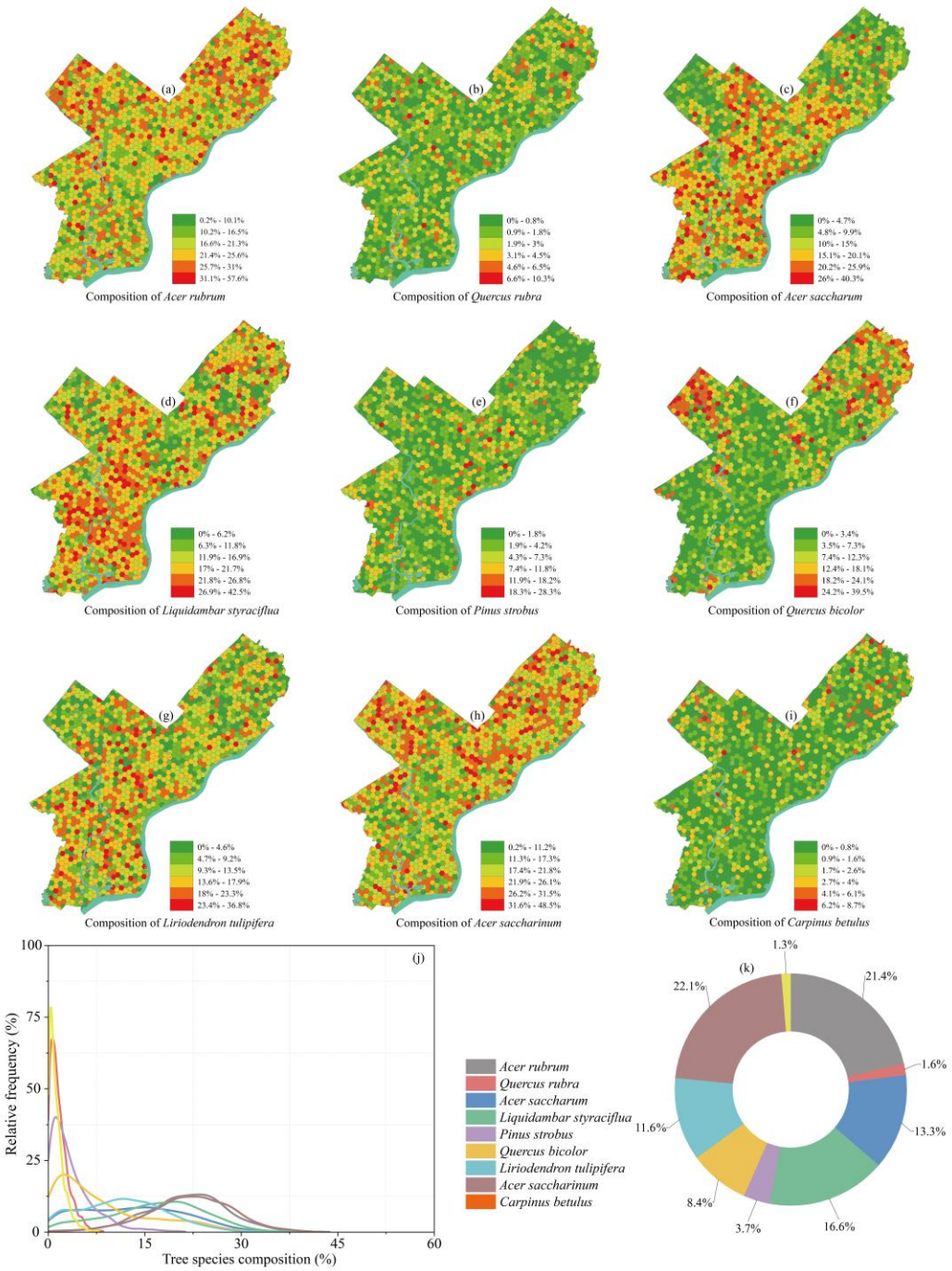


Fig. 4. Optimal tree composition in compromise solution. **a–i** Maps showing the spatial composition (%) of the nine advantageous species in Philadelphia. Colors indicate the proportion of each species within grids, from green = low to red = high. **j** Relative frequency distribution of tree species composition (%) across all grids. **k** Overall proportion of the nine species in the entire tree composition, shown as a donut chart.

Response curves of ecosystem services to additional tree canopy cover

Based on the proceeding results, including NbS demand for each location, species-specific ecological effectiveness, and the optimal species composition derived from NSGA-III and TOPSIS, we further examined the response curves of ecosystem services to additional tree canopy cover (Fig. 5).

As additional tree canopy cover increases from 0% to 25%, all ecosystem services exhibit a steady linear increase, with the optimal composition producing steeper response curves than the random baseline, demonstrating that scientific selection of species composition substantially promotes NbS associated with canopy expansion. At 15% additional canopy cover, for example, the optimal composition removes 10.43 metric tons of $PM_{2.5}$ annually, 27.8% higher than the 8.16 metric tons under the random scenario (Fig. 5a). For carbon sequestration, the difference is even greater, with 25,417 metric tons sequestered compared with 18,478 metric tons, representing a 37.6% increase (Fig. 5b). For stormwater management, the optimal composition reduces runoff by 0.71 million m^3 annually, which is 19% higher than the 0.60 million m^3 achieved by the random scenario (Fig. 5c). This relatively modest difference reflects the smaller variation among species in runoff regulation. In contrast, the difference is most pronounced in microclimate regulation. At 15% increased canopy cover, the optimal composition achieves annual energy savings of US$70.72 million, compared with US$39.94 million under the random baseline, representing a 77.1% increase (Fig. 5d). This highlights the particular importance of optimizing species composition for mitigating the urban heat island.

Overall, while expanding tree canopy cover substantially promotes NbS, optimizing species composition can further enhance the benefits by approximately 20–80%, depending on the ecosystem service considered.

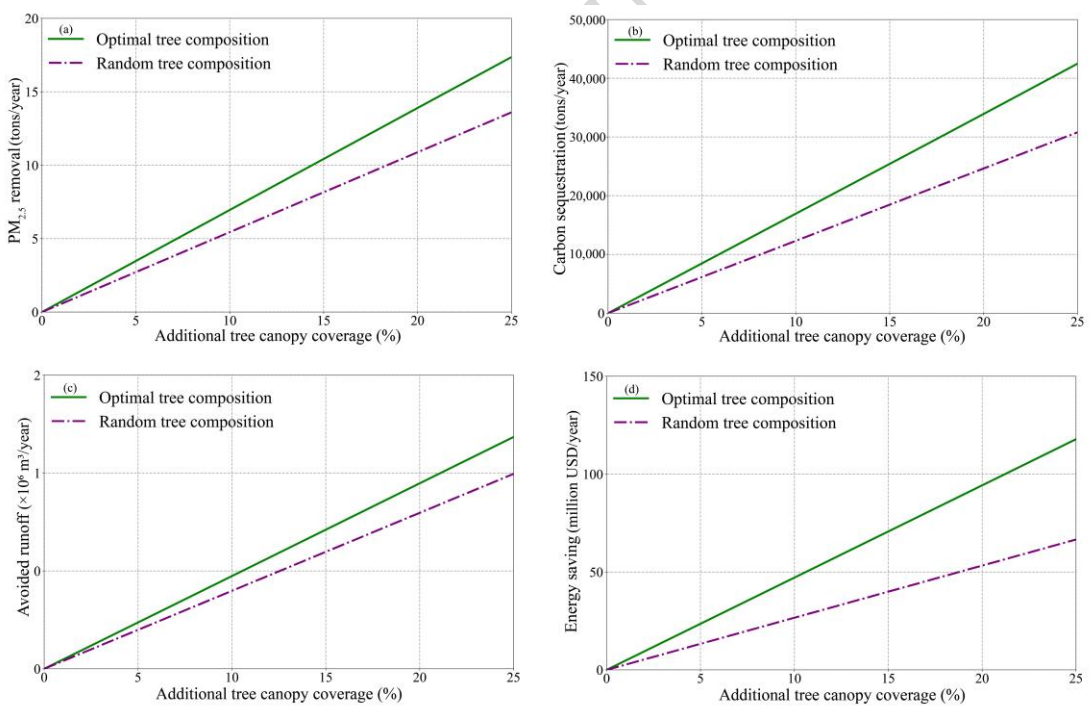


Fig. 5 | Response curves of ecosystem services to additional tree canopy cover based on the preceding results. **a–d** Comparison of ecosystem service outcomes with increasing additional tree canopy coverage (%). The green solid line represents the optimal tree composition, while the purple dashed line represents random tree composition. Ecosystem services are measured as **a** $PM_{2.5}$ removal ($tons \cdot yr^{-1}$), **b** carbon sequestration ($tons \cdot yr^{-1}$), **c** avoided runoff ($\times 10^6\ m^3 \cdot yr^{-1}$), and **d** energy savings (million $USD \cdot yr^{-1}$). In all panels, the optimal

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composition consistently outperforms the random composition across all levels of canopy expansion.

Discussion

NbS, as an important measure to promote SDGs, are receiving increasing attention. Urban greening initiatives have gained remarkable momentum across cities worldwide in recent years, with tree planting playing a prominent role, as evidenced by programs such as the London Urban Forest Plan, Le Plan Arbre 2030 (Paris), and Our Roots Chicago. While enhancing NbS is a frequently stated objective, tree planting initiatives often lack NbS-optimizing orientation, focusing instead on increases in tree quantity or green coverage (tree canopy)[10]. Methods for optimizing tree placement to maximize NbS benefits have yet to be applied in practice or thoroughly studied. In view of this, we developed a tree species composition optimization framework to link local demand and effectiveness of tree species. We identified the most adaptive tree composition for each 0.25 km^2 grid throughout Philadelphia.

The results revealed substantial differences in ecological performance among tree species. In terms of rainfall interception, for instance, we found that evergreen conifers, such as *Pinus strobus*, generally outperformed deciduous broadleaved species, such as *Acer rubrum*. This finding is consistent with previous field observations[34], which reported that *Pinus strobus* maintains a relatively high leaf area index (LAI) and stable canopy density throughout the year, thereby enabling superior rainfall interception compared with *Acer rubrum*. In addition, we identified that *Pinus strobus* also exhibited a strong $PM_{2.5}$ removal capacity. This may be attributed to the larger effective LAI for intercepting particulate matter in conifers and the waxy or sticky substances often present on their leaves, which substantially enhance particle capture[27, 35]. Overall, the species-level quantification of ecological effectiveness in this study corresponds well with general patterns observed in field and experimental research[36, 37], suggesting that the i-Tree Eco model is effective in distinguishing tree-specific ecological performance in North American contexts.

From the perspective of ecological performance, the current urban tree species composition in Philadelphia is suboptimal for promoting NbS. Except for *Acer rubrum*, other high-performing species such as *Acer saccharinum* and *Liriodendron tulipifera* are underutilized across the city, each accounting for only around 1% of total trees. While *Platanus* × *acerifolia* is the most abundant species, several other species demonstrate superior ecological effectiveness per unit. Our findings can be strategically incorporated in The Philly Tree Plan through location-specific species optimization. This includes increasing *Quercus bicolor* density in ecological zones to maximize carbon sequestration potential, expanding *Pinus strobus* presence in urban cores, and establishing effective species such as *Acer saccharinum*, *Acer rubrum*, and *Liriodendron tulipifera* as key species. This NbS improvement-oriented approach can significantly enhance the efficiency of the urban greening project and accelerate progress toward SDGs under the same tree planting quantity or green coverage targets.

Traditional multiple benefits-oriented studies are typically limited to identify priority location required NbS implementation by integrating multiple demand layers with different weighting methods[15, 38, 39]. In practice, these studies are not directly associated with NbS elements instead of reversely mapping prioritized are for NBS implementation by analyzing the spatial disparity in urban environmental conditions, which is similar to the first component of our study. Several previous studies have applied multi-objective optimization approach in NbS planning, they are almost always single benefit-based[40, 41]. Moreover, the definition of NbS

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differs from studies, but they often can be characterized into two preferences. One category usually defined NbS as an engineering facility, such as street trees, rain gardens and permeable pavements[20, 24, 42, 43]. Nevertheless, studies indicates that the ecological performance of engineering-based NBS facilities varies significantly depending on their plant species composition and design. It may lead to considerable uncertainty to evaluate ecological benefits of NbS if simply treating it as engineering facilities and neglecting the built-in plant species composition[44-46]. Another category usually relies on land use cover, taking shrub, grassland and forest as NBS elements[47, 48]. However, this is also a generalization with low precision. In particular, cropland, grassland and forest have huge differences in ecological functions. Even for the same land type, forest with different tree species compositions vary greatly in terms of carbon sequestration[49]. This evidence implies that previous NbS planning studies may fail to capture the actual effectiveness elements that provide ecosystem services.

In comparison, the tree species composition optimization framework systematically addresses the shortcomings in previous studies. Through the tree inventory analysis and i-Tree Eco model simulation, the ecological performance of NbS is directly linked to tree species instead of treating it as engineering facilities or general land-use categories; Moreover, the planning framework is not simply limited to priority identification but also recommends the optimal tree composition for each location across the city. Most importantly, this study goes beyond proposing advanced planning methods by further simulating realistic urban greening scenarios and validating the effectiveness of the proposed framework. For example, under a 15% canopy cover, the optimized tree species composition achieves 25,417 tons of CO_2 sequestration annually, 37.6% higher than the 18,478 tons under the baseline. According to the U.S. EPA, the average passenger vehicle emits approximately 4.6 tons of CO_2 per year[50]; thus, the optimized scenario offsets emissions equivalent to about 5,500 passenger cars annually, with an additional gain equivalent to 1,500 cars compared with the baseline. Across other ecosystem service dimensions, the optimized composition delivers about 20–80% greater benefits than the baseline, underscoring the importance of NbS-oriented urban greening, that is, planting the right trees in the right locations. This approach maximizes NbS delivery at a given canopy cover, which is particularly valuable for compact cities with limited greening space, such as Philadelphia.

Although this is a case study in Philadelphia, the proposed optimization framework is still highly replicable and is of great significance. The local demand for NbS benefits is mapped by remote sensing and machine learning. These methods are general and mainly dependent on open-source data, which make it easy replicate to other cities. Furthermore, the i-Tree Eco model used for tree species comparison has supported most major cities around the world[51]. However, for a more accurate assessment, we would recommend using as much locally specific data as possible. For example, the preliminary tree list for effectiveness ranking can draw from local government recommendations and existing urban forest inventories, ensuring species selected for composition optimization are well-adapted to local environmental conditions.

Based on the main findings, we propose two general planning suggestions not specific to Philadelphia: (1) maximize the carbon sequestration capacity in areas with insignificant urban hazards. Since carbon sequestration is a global benefit different with other locally-based benefits, the contribution of carbon sequestration is not tied to a specific location[52]. Therefore, we propose prioritizing tree species advantageous in carbon sequestration in areas with lower development intensity or population density, such as parks and ecological corridors, to maximize cities' carbon sequestration potential. (2) improve the proportion of tree species with specific advantages in the right locations in targeted response to specific urban hazards. For

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instance, in areas with high traffic density or around airports where air quality tends to poor, the proportion of tree species excellent at air purification should be increased. Similarly, in flood-prone lowlands or areas with aging drainage infrastructure, the proportion of tree species that excel in stormwater management should be prioritized. Such strategic placement of optimal tree species fully utilizes their local benefits, thereby maximizing NbS efficiency and enhancing urban resilience.

This study still has several practical limitations. Tree species composition optimization provides a feasible pathway to maximize NbS, yet actual urban greening initiatives are constrained by multiple factors and do not always prioritize NbS outcomes. For example, Santamour proposed the classical "10-20-30 rule", which states that no more than 10% of urban trees should belong to a single species, no more than 20% to a single genus, and no more than 30% to a single family, in order to minimize the risk of large-scale tree mortality caused by pests, diseases, or environmental stressors[53]. However, under the NbS-oriented recommendations of this study, the proportion of a single species exceeded the 10% threshold (for instance, *Acer saccharinum* was recommended at 22.1%), which appears to conflict with the rule. This may imply a trade-off that maximizing NbS could potentially reduce the overall resilience of urban forests to large-scale mortality risks. Nevertheless, the proportions recommended in this study represent a theoretically optimal scenario; in practice, decision-makers should adjust species composition to account for other considerations and balance trade-offs across multiple aspects, such as local policy, space constraint, pest resistance and maintenance cost (e.g., watering, pruning)[54, 55]. Some research also has emphasized that the 10–20–30 rule should be regarded as a flexible guideline rather than a strict threshold. In certain contexts, rigid application of this rule may result in overlooking species that provide higher ecological delivery and are well adapted to local conditions, while favoring less suitable alternatives, thereby diminishing ecosystem service provision and increasing long-term management costs[56, 57].

In addition, some communities may have aesthetic or cultural preferences that motivate them to invest in more aesthetically pleasing tree, which also limits the application of NbS-oriented greening solutions[58]. It should be noted that our assessment of NbS demand hinges almost exclusively on objective environmental indicators, overlooking key socio-economic and demographic disparities that can exacerbate environmental injustice[16]. Variations in income levels or demographic composition across different neighborhoods mean that certain communities may bear a disproportionate burden of environmental challenges while enjoying fewer benefits[59]. NbS play a pivotal role in advancing environmental justice, and future exploration should integrate broader socio-economic factors, such as income, education, and population vulnerability, into NbS demand calculations. Overall, the gap between theoretical optimization and practical implementation remains a significant challenge. How to balance these dimensions so that theoretically optimized results can be more effectively translated into practice is a key question for future exploration.

To summarize, this study presents a tree species composition optimization framework to maximize regional NbS. By quantifying local NbS demands and species-specific effectiveness, and applying a multi-objective optimization algorithm, we matched these dimensions to identify the optimal tree species composition at a fine spatial resolution. We further simulated ecosystem service outcomes as a function of increasing canopy cover under the optimized composition and validated the effectiveness of the proposed approach. The developed framework provides practical guidance for decision makers in designing efficient urban greening projects, enabling them to maximize NbS performance under specified canopy cover targets.

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Methods

Study Area and Model Overview

The demand for NbS benefits varies across cities, which is the basis of traditional planning studies to identify the priority for NbS implementation. Meanwhile, tree species exhibit distinct variations in their NbS performance. The two factors arise the significance of optimal tree placement, that is, targeting tree species with advantageous performance for high-demand areas. Integrating these two critical considerations, we developed a tree species composition optimization-based framework for maximizing regional NbS (Fig. 6).

Philadelphia was selected as case study for the optimization framework. The city has lost 6% of its tree cover in the last 10 years and is facing diverse environmental challenges under the influence of climate change, including urban heat island and flooding risk. The city's tree cover currently sits at about 20 percent, requiring an additional 10 percent of tree cover to realize urban health benefits as supported by research. In response to these challenges, Philadelphia has developed the TreePhilly Program that is a ten-year initiative and aims to plant 300,000 trees, which provides both practical context and foundation for applying the demand-driven tree species composition optimization model.

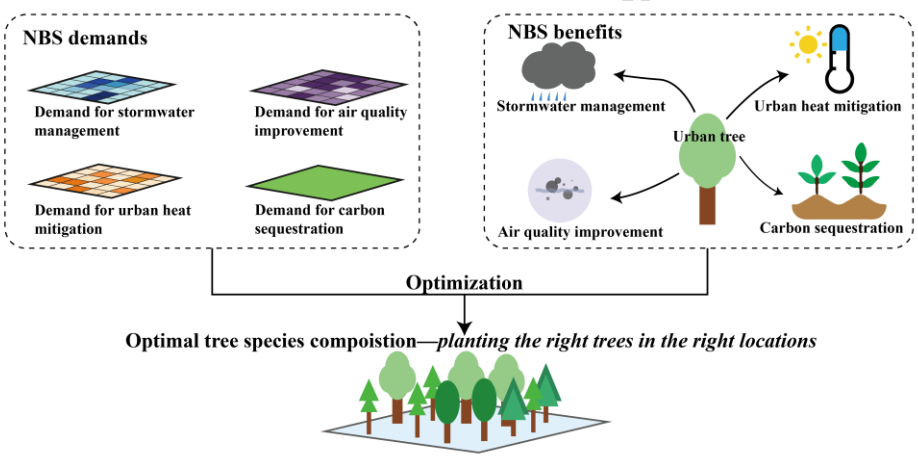


Fig. 6 | Conceptual figure of strategic tree placement to maximize nature-based solutions. The optimization process matches spatially explicit NBS demands (stormwater management, urban heat mitigation, air quality improvement, and carbon sequestration) with the corresponding benefits provided by tree species. This alignment identifies the optimal tree species composition for each location—*planting the right trees in the right locations*.

Quantification of demand for nature-based solution benefits

Local demand for NbS benefits was quantified across four aspects: stormwater management, urban heat mitigation, air quality improvement, and carbon sequestration. Following previous studies, the demand was based on the disparity of ecological conditions, where poorer local conditions indicated higher NbS demand[15, 39]. The assessment was conducted on 0.25 km² grids, with each grid serving as a basic unit for subsequent tree

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composition analysis. Water bodies were masked prior to evaluating NbS demands, as trees cannot be established in these spatial features.

Traditional NbS planning studies often use rainfall–runoff depth to indicate stormwater management demand. However, unlike other indicators perceptible to urban residents such as $PM_{2.5}$ or land surface temperature (LST), runoff depth is only one of the variables that influence whether flooding occurs and is not directly perceivable to residents. In fact, runoff depth does not represent rainfall-induced risk in urban hazard evaluation. Instead, flood susceptibility serves this role and it is equivalent in status to LST for urban heat and $PM_{2.5}$ concentration for air pollution[60]. To this end, we used flood susceptibility instead of runoff depth to determine stormwater management demand.

The flood susceptibility was quantified using a Support Vector Machine (SVM). Following previous studies[61-63], we primarily considered topographic factors, urban drainage systems, and land cover elements as predictor variables, while waterlogging points were used as the response variable. The waterlogging point data were extracted from the Philly311 Service and Information Requests dataset, which has documented non-emergency service requests submitted by residents via phone, mobile application, or web since 2014. Among the request categories are water-related issues, such as blocked storm drains or reports of surface water pooling. Because each request contains geospatial information (e.g., address or latitude and longitude coordinates) as well as a timestamp, these records can serve as proxy observations of resident-perceived flooding or waterlogging hotspots. After Hurricane Ida struck on September 1, 2021, Philadelphia experienced extensive urban flooding, with 24-hour rainfall exceeding 7 inches (approximately 180 mm) between September 1 and 2. To document flood occurrences from this event, we retrieved the Philadelphia 311 requests for the period of September 1–10, 2021, using keywords, including “inlet cleaning,” “storm inlet flooding,” and “standing water.” This search yielded 112 unique locations of reported issues, which were considered as waterlogging points and used as positive samples for the SVM model. Since SVM classifiers generally achieve higher accuracy when trained with balanced classes[64], an equal number of negative samples was generated by randomly selecting locations within the study area where no flooding had been reported.

Land cover is a key factor influencing flood occurrence, as it directly determines the proportion of rainfall that infiltrates versus the amount that accumulates and generates runoff[65]. We employed the ESA WorldCover dataset together with the Normalized Difference Vegetation Index (NDVI) to represent land cover conditions, which were incorporated as predictor variables. Topographic characteristics are also critical determinants of flooding, as they control where rainfall-induced runoff is directed and concentrated[66]. We considered several terrain-related variables, including DEM, topographic wetness index (TWI), slope, aspect. The source and calculation for these topographic features are provided in Supplementary Table 1. In addition, the capacity of the local drainage system is a critical factor influencing whether urban flooding occurs[67]. To represent this factor, we used the density of stormwater inlets as a feature.

In total, seven predictor variables together with the flood/non-flood labels were used to train the SVM model, as shown in eq (1).

$$Y = f(DEM, TWI, slope, aspect, Land\ cover, NDVI, inlet\ density) \quad (1)$$

where Y is the classification result, which is a binary value (1 for waterlogging, 0 for non-flooded).

To enhance the predictive performance of the model, we employed 5-fold stratified cross-validation combined with grid hyperparameter tuning. The optimized model demonstrated strong predictive capability, achieving a mean cross-validation AUC of 0.90 and a test set AUC of 0.86, indicating good generalization and

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limited overfitting. Based on the trained model, we predicted flood susceptibility for each location. Higher susceptibility values reflect greater demand for stormwater management. The results were normalized to a 0–1 range to represent this demand and to enable consistent comparison with other types of demand.

The demand for urban heat mitigation was mapped based on the Landsat 8 Collection 2 Level 2 product. We retrieved all imagery for 2021 through Google Earth Engine (GEE). Cloud contamination was marked using bits 3 and 4 of the quality assessment band. Then, the cloud coverage assessment was conducted using the GEE's Reduce Region method to calculate the proportion of cloud-affected pixels within the study area. Only images with less than 5% cloud coverage in the study area were reserved for further analysis, allowing for maximum data retention while ensuring quality. The acquisition date of the reserved images is documented in the Supplementary Table 2. LST was derived from Band 10 using conversion coefficients. An overall LST map was generated by compositing the maximum LST values from the temporal sequence. The LST values were then normalized, with higher values indicating greater demand for urban heat mitigation.

The demand for air quality improvement was evaluated based on an integrated air quality product and machine learning downscaling. Since air quality spatial data tends to have a coarse resolution that is usually not sufficient to support high resolution studies at the urban scale, scholars developed downscaling process, as referenced in this study[68, 69]. We employed random forest regression with multiple environmental and spatial predictors: DEM, land cover, traffic flow, MODIS-AOD (MCD19A2 550nm), and geographical coordinates. The data sources are listed in Supplementary Table 1. Initial data preprocessing involved resampling all predictors to match the GHAP resolution (1 km). As the traffic flow are vector data, it was aggregated to 1 km grid cells using zonal statistics. Before fitting the model, we carried out a multicollinearity assessment using Variance Inflation Factors, which demonstrated acceptable independence among predictors (all VIFs < 10). The relationship of the regression model can be indicated as eq (2):

$$PM_{2.5} = f(DEM,\ AOD,\ traffic\ flow,\ land\ use,\ x,\ y) \quad (2)$$

To improve model accuracy, we employed 5-fold cross-validation combined with grid hyperparameter tuning. The optimized model showed strong predictive performance, achieving R^2 values of 0.80 and 0.78 for the training and cross-validation sets, respectively. We then applied the fitted model to predictor variables resampled at 500 m resolution to generate high-resolution $PM_{2.5}$ estimates. Higher $PM_{2.5}$ concentrations indicate greater demand for air quality improvement, and the values were normalized to a 0–1 range for consistent comparison.

Carbon sequestration functions as a global benefit, primarily contributing to climate change mitigation. Given its large-scale nature, this effect tends to be relatively uniform across a city and is typically imperceptible to local residents[52]. Thus, we assumed that the demand for carbon sequestration is an average of other three demands in all locations to equally account for.

Quantification of effectiveness of species-specific urban tree

Philadelphia's tree inventory documents DBH and species information for the city's urban trees, encompassing nearly 300 distinct tree and shrub species. We mainly focused on the common and existing tree species in Philadelphia and did not intend to recommend niche species or introduce new ones. Therefore, we conducted a frequency analysis of the tree inventory to identify the 30 most common tree species already present locally for subsequent effectiveness assessments. The frequency analysis excluded species on the tree

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inventory identified only to genus level. The analysis result (tree list) can be found in Supplementary Table. 3.

The effectiveness of tree species was quantified by i-Tree Eco model. We focused on four ecosystem services, including avoided runoff, building energy saving (a proxy for microclimate regulation), air pollution removal and carbon sequestration. This category corresponds to demands for NbS mentioned in the last section. The model requires various tree characteristic as input parameters. Since we aimed to differentiate ecological effectiveness among species rather than evaluated performance of existing trees, we mainly utilized default parameters and health conditions from the i-Tree database. DBH is the minimum required setting, and we assigned 5 inches, corresponding to Philadelphia's definition of mature trees capable of providing stable ecosystem services, which is institutionally recognized in the city's Tree Preservation Credits policy for the purpose of protecting trees with DBH ≥ 5 inches during urban development activities. We applied meteorological data from station 724085-94732 and air pollution data from station 0057, which are the nearest stations to centroid of Philadelphia with fair data completeness.

Establishment of multi-objective optimization model

Some trees may provide more ecosystem services but take up more space. In the complex urban system, the space for greening is usually limited. Thus, we applied the an equal-area-based functional unit to evaluate the effectiveness of species-specific trees as eq (3)[70]. This formula aims to represent that, given equal green coverage, tree species with smaller space requirements offer enhanced ecological contributions.

$$E_{ij}^{equal-area-based} = \frac{e_{ij}}{Area_i} \quad (3)$$

where $E_{ij}^{equal-area-based}$ is the *j*th effectiveness of the *i*th tree species in equal-area-based functional unit; e_{ij} is the *j*th effectiveness of the *i*th tree species; $Area_i$ is the tree cover area of the *i*th tree species, which is output by i-Tree Eco model. To enable comparison across tree species, we further rescaled the effectiveness in equal-area-based unit to range from 0 to 1 with respect to the maximum value.

The ecosystem services provided by trees exhibit distance-decay effects, especially for regulating services that are closely tied to common urban ecological challenges. For example, trees can regulate microclimates through shade and evapotranspiration to mitigate the urban heat island, but these benefits are effective only in the immediate vicinity. Likewise, tree can help alleviate stormwater runoff by enhancing soil infiltration and water retention, yet their interception capacity is limited within their surrounding areas rather than at greater distances. Therefore, recognizing the localized nature of these regulating services, placing the most effective species in the areas where their benefits are most needed allows their strengths to be fully utilized and maximizes the regional realization of NbS. Technically, the primary objective of this study is to identify the optimal tree species composition for each location by aligning species-specific effectiveness with local demands.

We introduced adaptability to represent this degree of matching, as shown in eq (4). When tree species with stronger effectiveness are placed in locations with higher corresponding demand, the adaptability is greater.

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$$Adaptability = \sum_{j=1}^{n} E_j \cdot D_i \cdot p_{ij} \tag{4}$$

where E_j is the effectiveness of the *j*th tree species in equal-area-based functional unit; D_i is the corresponding NbS demand in the *i*th location; p_{ij} is the proportion of the *j*th tree species in the *i*th location.

We considered four aspects of demand and effectiveness. The ideal situation would be to achieve the highest adaptability across all four simultaneously. However, considering the differences in species-specific advantages, trade-offs among the four targets are inevitable. For example, increasing the proportion of species advantageous for stormwater management may help reduce flooding risk but could weaken carbon sequestration or urban heat mitigation. Therefore, we set adaptability in all four dimensions as maximization objectives, while the decision variables are the tree species compositions at each location, as expressed in eq (5).

$$\begin{cases} SWM = \sum_{i=1}^{N}\sum_{j=1}^{M} E_j^{SWM} \cdot D_i^{SWM} \cdot p_{ij} \\ UHM = \sum_{i=1}^{N}\sum_{j=1}^{M} E_j^{UHM} \cdot D_i^{UHM} \cdot p_{ij} \\ AQI = \sum_{i=1}^{N}\sum_{j=1}^{M} E_j^{AQI} \cdot D_i^{AQI} \cdot p_{ij} \\ CS = \sum_{i=1}^{N}\sum_{j=1}^{M} E_j^{CS} \cdot \overline{D} \cdot p_{ij} \end{cases} \text{subject to} \begin{cases} \sum_{j=1}^{M} p_{ij} = 1, \forall_i = 1,2,...N \\ p_{ij} \geq 0 \end{cases} \tag{5}$$

where *SWM*, *UHM*, *AQI* and *CS* are the four maximization objective functions, representing overall adaptability in stormwater management, urban heat mitigation, air quality improvement and carbon sequestration, respectively, aggregated across all units in the study area; E_j^{SWM}, E_j^{UHM}, E_j^{AQI} and E_j^{CS} are the normalized effectiveness of the *j*th tree species for stormwater management, urban heat mitigation, air quality improvement and carbon sequestration, respectively; D_i^{SWM}, D_i^{UHM} and D_i^{AQI} are the normalized demand for stormwater management, urban heat mitigation and air quality improvement in the *i*th location, respectively; $\overline{D}$ is the average of the three demands for all locations, representing the demand for carbon sequestration; p_{ij} is the decision variables, that is, the proportion of the *j*th tree species in the *i*th location.

In the optimization process, we established constraints where the proportion of each tree species in any given location must be non-negative (0,1], and the sum of all tree species proportions within each location must equal 100%.

Nondominated Sorting Genetic Algorithm III (NSGA-III) was applied for the optimization process, which is well suited for handling more than three objectives by maintaining solution diversity through a set of reference directions. To balance the optimization accuracy and time cost, the algorithm was configured with a population size of 400 and run for 500 generations. For the generation of reference directions, the outer division parameter was set to 12, which ensured a well-distributed set of solutions across the four-objective space. An adaptive operator was applied to automatically adjust other parameters such as crossover and mutation probabilities, as well as distribution indices, based on population diversity. The step size of decision variables was discrete with an interval of 0.001. We then applied the Technique for Order Preference by

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Similarity to Ideal Solution (TOPSIS) method to select a compromise solution from the Pareto frontier for visualizing the optimal tree species composition scenario. Equal weights were used in the TOPSIS analysis, assuming that the NbS target in the four aspects are of equal importance.

Estimation ecological benefits Achieved by the optimal tree species composition

In the preceding sections, we identified the spatial demand for NbS, the effectiveness of species-specific trees, and the optimal species composition. In other words, we determined where trees should be planted (NbS demand), which species should be selected (optimal composition), and the benefits expected from planting (species-specific effectiveness). In this section, we integrated these steps to further estimate the ecosystem services that can be achieved under the optimal species composition scenario. We first integrated multi-source geospatial datasets through threshold-based screening and morphological analysis to estimate the available space for urban greening at each location.

We adopted the ESA WorldCover dataset (10 m) as the baseline land cover and refined it using higher-resolution and thematically relevant datasets through a rule-based integration. Building footprint vectors were used to improve the classification of built-up areas, and 1 m canopy height data (Meta & WRI) were employed to refine tree cover. The final land cover was rasterized to 10 m resolution and categorized into nine classes: buildings, built-up land, tree cover, shrubland, grassland, cropland, bare land, water bodies, and wetlands. Based on the integrated land cover, we defined spatial constraints for additional tree cover: (1) existing tree cover, (2) water bodies and wetlands, (3) buildings, and (4) cropland were excluded. In contrast, grassland and shrubland were considered eligible for canopy expansion, consistent with vegetation succession principles.

To ensure that potential greening spaces were not only sufficient in area but also suitable in shape for tree growth, we refined the initially identified spaces using a morphological opening operation. This step aimed to remove patches too narrow or fragmented to accommodate a single tree crown. Following the previous study, we set a minimum crown radius of 4.6 m and assumed a circular crown shape. The opening operation, consisting of a 4.6 m erosion followed by a 4.6 m dilation, eliminated spaces failing to meet this threshold. Finally, the refined layer was intersected with the decision unit grids to calculate the total available area for additional canopy cover in each unit.

Subsequently, building on the preceding procedures and extracted available greening space, we examined the response curves of ecosystem services to additional tree canopy cover, as formulated in eq (6), and used them to estimate the NbS outcome under the optimal tree species composition.

$$E_k(S) = \sum_{i=1}^{N} \min(s_i^{\max}, D_i^k \lambda) \cdot (\sum_{j=1}^{M} p_{ij} \cdot E_j^k) \text{ subject to } \sum_{i=1}^{N} \min(s_i^{\max}, D_i^k \lambda) = S \quad (6)$$

where $E_k(S)$ is the achieved *k*th NbS at *S* additional tree canopy cover; $s_i^{\max}$ is the maximum available greening spaces for potential tree canopy cover; D_i^k is the demand for the *k*th NbS in the *i*th location; λ is the proportionality factor used to scale the demand, in conjunction with the constraint ensuring that the total

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allocation equals S; p_{ij} is the proportion of the jth tree species in the ith location; E_j^k is the kth effectiveness of the jth tree species.

In addition, we designed a comparison scenario to represent the NbS that could be achieved without scientific decision-making in urban greening, that is, with an almost completely random tree species composition. In this scenario, p_{ij} in eq (4) represents a random proportion of the 30 tree species rather than the optimized tree species composition. The random p_{ij} is still subject to the constraints that all values are non-negative and the sum of all proportions equals 1.

Competing Interests: The authors declare no competing interests.

Data availability: This study primarily utilizes raster and vector data, such as remote sensing data, land cover, tree cover, and digital elevation model. It also incorporates vector data, such as traffic flow, building footprint and water inlets, as well as other datasets, including the Philadelphia tree inventory and Philly311 Service and Information Requests dataset. All these datasets are open-source, with access methods and data formats detailed in Supplementary Table 1.

Code availability: The code used in this research is accessible and can be found on the provided GitHub repository: https://github.com/universe236/NBS-optimization

Author Contributions: X.D. wrote the main manuscript text, conceptualized the study, developed the methodology, and performed the formal analysis. X.D. and D.S. curated the data. D.S. conducted the investigation. Y.Y. administered the project. Y.Y., D.H., and A.L. supervised the work. All authors have read and approved the manuscript.

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