Landscape Architecture

ARTICLE

Scale-Resolved Indicator Weighting for Climate-Responsive Green Infrastructure Optimisation

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Abstract

Urban green infrastructure controls heat, stormwater, air quality, biodiversity, energy use, and human well-being via vegetation, soil, water, and interconnectivity. This paper constructs IMPACT-GI, an approach to scale-resolved weightage for climate-smart green infrastructure design. The data comprise 290 instances of indicators concerning air quality, biodiversity and ecological sustainability, energy performance, human well-being, heat-island mitigation, and water management; 66 instances of objective-scale and 60 instances of model-use. The balance of the indicators is evaluated based on normalised entropy of green-infrastructure indicators, specific to objectives and geospatial factors. Scale dispersion is calculated with respect to building scale, street scale, district scale, and urban scale. In heat-island mitigation, the indicator balance (0.987), scale dispersion (0.953), and transfer caution (0.040) values indicate high cross-scales. Energy efficiency has maximum transfer caution value of 0.607 because all scale observations are at building scale only. These weights help in replicable indicator selection, algorithm choice, and scale interpretation for urban green infrastructure planning.

Keywords: green infrastructure; climate adaptation; multi-objective optimisation; indicator weighting; entropy; spatial scale; artificial intelligence; urban resilience

1. Introduction

Climate adaptation in cities becomes more and more dependent on the ability of green infrastructure systems to provide multiple environmental and socio-economic benefits. Green streets, rooftops, urban parks, natural wetlands, bioswales, ecological corridors, and porous land surfaces affect heat exchange, stormwater flow, pollutant concentrations, ecological connectivity, accessibility for recreation, energy consumption, and human wellbeing. Their significance does not lie in only one aspect. Vegetation cover, soils, waters, and interconnected open spaces have always been known as means of regulating local temperature, water flow, habitat creation, and human activities simultaneously [10, 25, 35]. The same vegetative strip could provide cooling effect, facilitate pedestrians' movements, mitigate surface runoff, increase habitat connectivity, and control air pollutant concentrations. The same multifunctional quality has made green infrastructure indispensable for urban planning but has also made optimization more complicated since each of these functions has its specific characteristics, restrictions, and spatial dimensions.

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The six objective classes are presented on Figure 1 by examples of common urban spaces where the same green infrastructure system plays its multiple roles.

Figure 1. Multi-scale green infrastructure functions associated with the six optimisation objectives included in the analysis. The photographic composition links street trees, parks, green roofs, public open space, heat-mitigation landscapes, and water-retention areas to air quality, biodiversity and ecosystem security, energy efficiency, public health, heat-island mitigation, and water management.

The literature on green infrastructure emphasises the connection between its component ecological resources as much as its physical presence in space [2, 7]. Green infrastructure studies in urban ecosystems reveal the potential of green areas in terms of contributions to human well-being, ecological function, and environmental regulation, provided they are integrated within land-use plans and urban designs [10, 25, 35, 54]. Research in climate adaptation adds an important operational constraint on this integration: green infrastructure must work under rising thermal pressure, flood risk, air pollution exposure, and other stresses [18, 23, 38]. Such constraints raise multiple competing objectives that need to be satisfied. The location of optimal vegetation for cooling might differ from the optimal location for runoff. The site offering the highest cooling effect might lack accessibility. The most effective planting might enhance shade but reduce the effectiveness of canyon streets. The application of optimisation becomes relevant here, but solely when the appropriate indicators and scale of observation match the objective.

Most green infrastructure studies start with choosing a model family, such as genetic algorithm, non-dominated sorting genetic algorithm, particle swarm optimisation, simulated annealing, random forest, neural network, support vector machine, or linear regression. Such methods have shown their value as tools for solving complex problems, making predictions, and finding solutions that satisfy multiple objectives [12, 14, 17, 21, 24, 27, 32, 33, 57]. However, no algorithm can solve the problem if the input data do not properly reflect the planning context. Roof geometry, sun exposure, building geometry, building envelope performance, shading conditions, cooling load, and vegetation coverage are crucial to building energy efficiency optimisation. Landscape cover, habitat connectivity, habitat fragmentation, resistance to fragmentation, road density, elevation, and temperature data become critical for biodiversity and ecosystem security at city level. Rainfall, runoff, drainage, soil quality, slope, water quality, and retention capacity are needed for managing the water cycle. Environmental stressors alone will not suffice for public health optimisation; accessibility and vulnerability indicators are needed too. When such criteria are poorly correlated, there is a risk of solving a problem that is irrelevant to urban planning needs.

This task becomes difficult in light of disparities in numerical representation among objective classes. Some objective classes show balanced representation in indicators, green infrastructure, and geospatial variables. Other objective classes include numerous indicators but are strongly dominated by one kind of variable. While some objective classes have been tested at building, street, district, and city scales, the remaining objective classes can only be studied at a limited range of scales. These distinctions are relevant because they define whether the results can be used in a new scale of observation and whether the optimisation models include enough variables to define the intervention.

The present article applies IMPACT-GI, which uses scale-resolved weighting to optimise climate-responsive green infrastructure. Scale-resolved weighting consists of calculating transfer-caution scores and constructing indicator-weighting tables based on indicator balance, scale dispersion, and scale-observation support. Indicators balance refers to division between green infrastructure descriptors, objective-specific variables, and geospatial variables. Scale dispersion refers to the degree of diversity in observations among building, street, district, and city scales. Scale-observation support reflects the amount of numerical data related to a specific scale of observation for each objective. These metrics are aggregated into two measures – a transfer-caution score and an indicator-weighting table, which helps select models matching the numerical profile of the objective.

The analysis is applied to six objective classes – air quality, biodiversity and ecosystem security, energy efficiency, public health, heat-island mitigation, and water management. Each of these classes corresponds to major climate functions attributed to green infrastructure in urban planning. The analysis shows that heat-island mitigation is the most numerically well-founded candidate for cross-scale optimisation, whereas energy efficiency should be carefully converted from building-level optimisation to larger-scale units of planning. Water management has the largest number of indicators but requires a stronger presence of green infrastructure descriptors. Public health needs more alignment between environmental stressors and exposure-related geospatial variables. Intermediate positions are taken by air quality and biodiversity objectives.

2. Data and methods

2.1. Objective classes and numerical observations

The numerical basis includes four counts of observations – by indicator relevance and objective; by model use and algorithm family; by objective and spatial scale; and by objective, green infrastructure, and planning scale. The counts are arranged by objective to ensure that all calculations are performed according to the same logic for each objective. All scores in the paper can be reproduced from the data given in Tables 1–5.

The six objective classes are denoted by

$$O = \{AQ, BIO, EE, PH, HI, WM\},$$

where AQ represents air quality, BIO represents biodiversity and ecosystem security, EE represents energy efficiency, PH represents public health, HI represents heat-island mitigation, and WM represents water management. Indicator relevance is denoted by

$$R = \{GI, OBJ, GEO\},$$

where GI represents green-infrastructure descriptors, OBJ represents objective-specific variables, and GEO represents general geospatial variables. The spatial levels are denoted by

$$L = \{\text{building, street, district, city}\}.$$

These categories are broad enough to compare objectives while remaining specific enough to preserve the planning meaning of the counts.

The indicator observations total 290. Water management has 72 observations, heat-island mitigation has 59, biodiversity and ecosystem security has 50, air quality has 47, public health has 36, and energy efficiency has 26. The spatial-scale observations total 66, with water management contributing 17, heat-island mitigation 16, biodiversity and ecosystem security 14, air quality 9, public health 6, and energy efficiency 4. The algorithm-use profile contains 60 observations, dominated by general or modified optimisation algorithms, non-dominated sorting genetic algorithms, and genetic algorithms. These numerical totals provide the empirical basis for the entropy and weighting calculations.

The distribution of the 290 indicator observations is shown visually in Figure 2. The figure places the six objectives beside their three indicator classes and representative variables, making clear why the same optimisation method cannot serve all objectives equally.

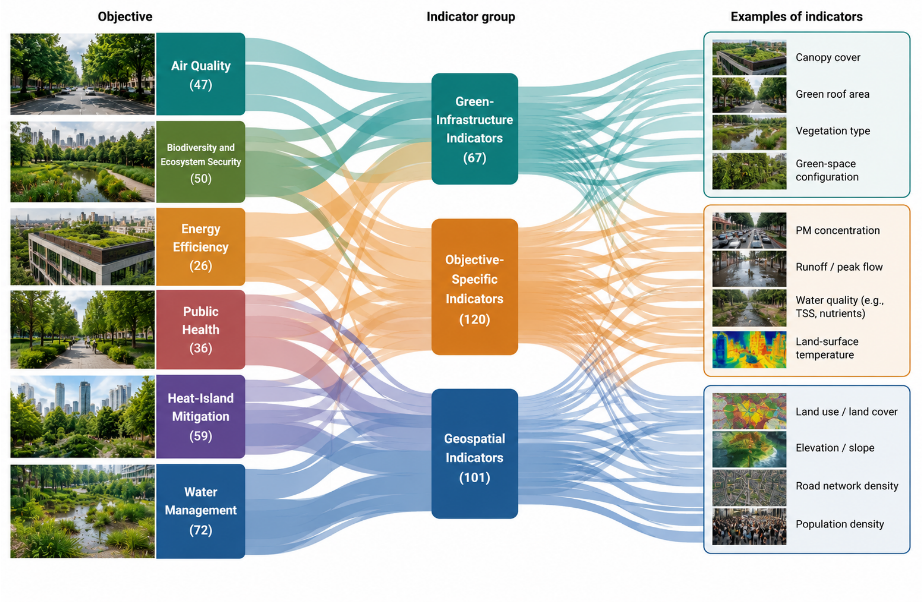

Figure 2. Indicator composition used for objective-level weighting. The figure groups the six optimisation objectives with green-infrastructure descriptors, objective-specific variables, and geospatial variables, while the accompanying text and tables provide the exact counts used in the calculations.

2.2. Indicator balance and scale dispersion

For each objective o, the proportion of indicator observations assigned to relevance class r is calculated as

$$p_{or} = \frac{I_{or}}{{}_{r \in R} I_{or}},$$

where I_{or} is the count for objective o and relevance class r. Indicator balance is calculated with normalised Shannon entropy, following the use of entropy as a measure of distributional evenness and information content [16, 51]:

$$B_o = -\frac{{}_{r \in R} p_{or} \log p_{or}}{\log 3}.$$

A value close to 1 indicates a balanced distribution across green-infrastructure descriptors, objective-specific variables, and geospatial variables. A lower value indicates concentration in one relevance class. This calculation is important because a high indicator count can still be narrow if most variables describe only one part of the planning problem.

Spatial scale is evaluated in the same way. For each objective o, the proportion of scale observations assigned to scale l is

$$q_{ol} = \frac{S_{ol}}{{}_{l \in L} S_{ol}},$$

where S_{ol} is the count for objective o and spatial level l. Scale dispersion is calculated as

$$H_o = -\frac{{}_{l \in L} q_{ol} \log q_{ol}}{\log 4}.$$

A value close to 1 indicates representation across building, street, district, and city scales. A value close to 0 indicates concentration at one scale. This score is used to identify whether a modelling result is likely to support transfer across planning levels or whether it should remain tied to a particular scale.

Scale-observation support is calculated as

$$C_o = \frac{{}_{l \in L} S_{ol}}{\max_{o \in O} {}_{l \in L} S_{ol}}.$$

This term compares the total scale-related count for each objective with the largest objective-level scale count. It prevents a balanced but numerically small class from being interpreted in the same way as an objective represented by a larger count.

2.3. Transfer-caution scoring and shrinkage weighting

The transfer-caution score combines indicator imbalance, scale concentration, and scale-observation support:

$$P_o = \frac{1 - B_o \;\; 1 - H_o \;\; 1 - C_o}{3}.$$

A higher value indicates that model transfer should be handled cautiously. The score does not measure objective importance. It records whether the numerical representation is less balanced, less spatially distributed, or weakly supported by scale observations.

Indicator weights are calculated with shrinkage toward equal representation:

$$w_{or} = \lambda p_{or} \;\; 1 - \lambda \frac{1}{3},$$

where $\lambda = 0.65$. Shrinkage prevents a dominant indicator class from fully controlling future optimisation. It also preserves space for low-count but planning-critical variables. Similar safeguards are used in multi-criteria decision analysis and sensitivity-oriented model appraisal when variable dominance may distort interpretation [31, 40, 47]. This is essential in green infrastructure analyses because a variable can be conceptually necessary even when it appears less frequently. Vegetation morphology may be underrepresented in water-management counts, yet it remains necessary for distinguishing a vegetated retention strategy from a conventional drainage strategy. Vulnerability indicators may appear less frequently in public-health optimisation, yet they are essential for equitable climate adaptation.

Figure 3 summarises the calculation sequence. Indicator aggregation, spatial-scale distribution, entropy calculation, support calculation, and objective-specific weighting correspond directly to the equations above.

Figure 3. Analytical sequence used to convert objective-level indicator and scale counts into balance, dispersion, support, priority, and shrinkage-based indicator weights. The image provides a compact visual guide to the calculation steps in the Methods section.

3. Results

3.1. Objective-wise indicator composition

Table 1 shows the indicator counts and entropy scores for the six objective classes. Air quality has the highest indicator-balance score at 0.997, with 14 green-infrastructure descriptors, 16 objective-specific variables, and 17 geospatial variables. Heat-island mitigation is also highly balanced, with 24 green-infrastructure descriptors, 19 thermal-objective variables, and 16 geospatial variables, producing a score of 0.987. Energy efficiency has fewer total observations, but the distribution of 13, 7, and 6 across the three relevance classes gives a score of 0.945. Water management has the largest indicator count at 72, but its score is the lowest at 0.729 because 44 of the 72 observations are objective-specific hydrological variables.

Table 1. Objective-level indicator composition and normalised indicator-balance scores.

Objective	GI indicators	Objective indicators	Geospatial indicators	Total	B_o
Air quality	14	16	17	47	0.997
Biodiversity and ecosystem security	7	12	31	50	0.832
Energy efficiency	13	7	6	26	0.945
Public health	8	22	6	36	0.850
Heat island	24	19	16	59	0.987
Water management	3	44	25	72	0.729

Figure 4 depicts similar information from a compositional perspective. Objectives closer to the centre of the diagram are more evenly weighted between green-infrastructure, objective-specific, and geospatial indicators, while objectives closer to one edge rely heavily on a specific indicator class.

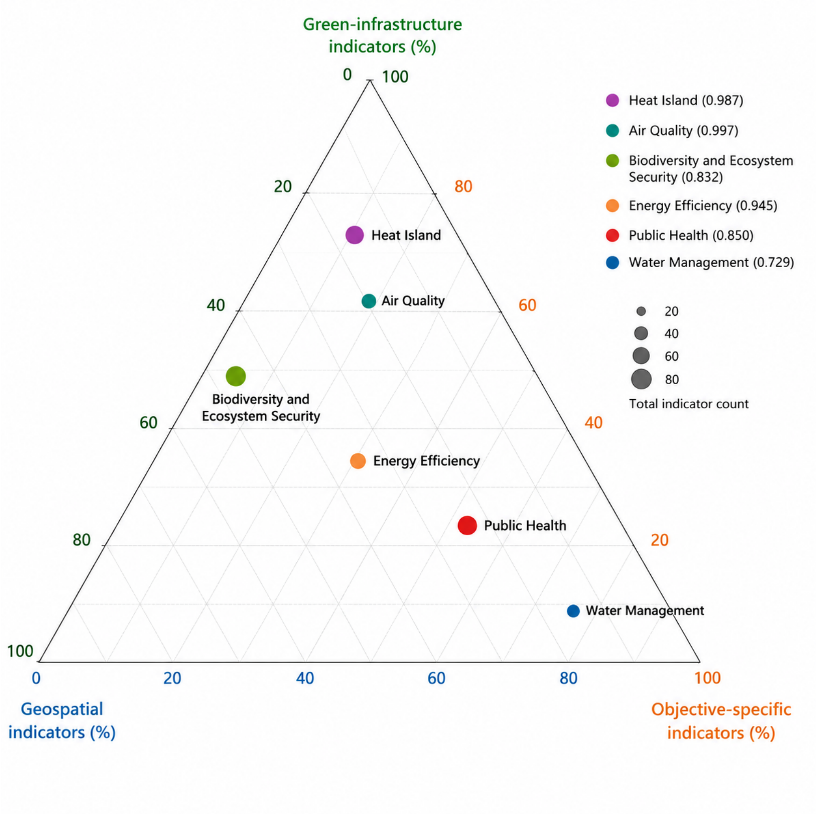

Figure 4. Ternary representation of indicator composition across the six objectives. The plotted positions show the proportions of green-infrastructure descriptors, objective-specific variables, and geospatial variables, while the labelled values refer to the indicator-balance scores listed in Table 1.

The results for the air-quality objective show that this objective is evenly represented among indicator categories of intervention description, pollutant exposure, and spatial setting. This is an important finding because air-quality optimisation cannot be performed solely based on vegetation area. Vegetation affects pollutant exposure depending on pollutant concentration, vehicle movement, vegetation canopy, land use, population distribution, and built form [1, 19, 41, 42, 50, 55]. Balanced representation thus improves the basis of air quality optimisation for integration of exposure and intervention form.

The two dominant indicator categories of the biodiversity objective are geospatial variables and objective-specific variables. The observation count for geospatial variables is 31, which is higher than the 7 green-infrastructure variables and the 12 objective-specific variables. This reflects the landscape ecology of planning, with variables such as land cover, elevation surfaces, temperature surfaces, nighttime light, road networks, population density, and points of interest representing habitat pressure and spatial connectivity [6, 8, 22, 37, 49]. This relatively low observation count for green-infrastructure indicators suggests that vegetation type, vegetation patch quality, vegetation species composition, canopy attributes, and ecological functions should be better represented when optimising biodiversity objectives. Failure to do so may lead to identification of a suitable spatial location but inadequate understanding of the ecological quality of the intervention.

Energy efficiency has the lowest observation count but an equal representation among indicator categories. The higher proportion of green-infrastructure indicators relates to the direct links between energy consumption and vegetation placement, shading, and roof greening in building-level analysis [4, 5, 13, 46, 52]. A low entropy score thus shows internal balance within a narrow observational base. However, it does not imply that the result is generalisable to broader scales because the scale analysis indicates that energy-efficiency observation is highly concentrated at building scale. Therefore, the generability of energy-efficiency optimisation will be constrained by this observational scale concentration.

The public-health objective has 22 objective-specific indicators, 8 green-infrastructure indicators, and 6 geospatial variables. Objective-specific indicators include those related to heat, air pollution, noise, water pollution, and climate-health impact variables, all of which are associated with proven linkages between urban nature, environmental stressors, restoration, and health outcomes [26, 28, 30, 34, 36, 56]. This shows that public-health objective optimisation is more advanced in terms of environmental stressor measurements than environmental stressor generators. A health-focused green infrastructure model therefore needs to incorporate indicators related to the social and spatial contexts of environmental stressors. It is not enough to measure improvement in the mean environmental stressors; rather, factors that generate environmental stressors should also be considered, including accessibility, vulnerable population distribution, housing density, mobility patterns, and the spatial form of green space.

Water management has the largest volume of indicators, although 44 of the 72 observations fall under the objective variable category. Variables such as rainfall, runoff, drainage, soil type, slope, water quality, and flood risk are important in hydrological performance, which works through mechanisms such as infiltration, water storage, delayed conveyance, and pollutant removal [3, 9, 20]. The problem with this objective class is not the high number of objective-specific variables but rather the low number of green-infrastructure indicators. There are only 3 observations classified as green-infrastructure variables. Optimisation of hydrological performance based on this indicator profile would provide good representation of hydrology but poor representation of the green/permeable infrastructure that provides hydrological performance. Future water-management objectives therefore need to include indicators for green roof type, bioswale geometry, wetland geometry, infiltration surface, vegetation structure, and maintenance capacity.

3.2. Spatial scale distribution

Table 2 shows scale counts and scale-dispersion scores. The objective with the most balanced scale representation is the heat-island mitigation objective, with 4 building-scale observations, 2 street-scale observations, 6 district-scale observations, and 4 city-scale observations, resulting in a scale-dispersion score of 0.953. The air quality objective has an intermediate dispersion score of 0.723 with observations at each of the four scales, but mainly at the city scale. The objective with the most observations overall is the water management objective, with 17 observations at the district and city scales, producing a scale-dispersion score of 0.489. The objective with the lowest dispersion score is the energy efficiency objective, with a score of 0.000 and all observations at building scale.

Figure 5 translates these counts into a scale profile. The pattern is visually distinct across objectives: heat-island mitigation is distributed across all four planning levels, energy efficiency is concentrated at building level, and water management is concentrated at district and city levels.

Of all the objectives considered here, the heat-island effect represents the best fit for cross-scale optimisation since the goal is expressed at multiple spatial scales. Indeed, urban heat involves roof temperature, street shape, tree shadows, neighborhood green networks, and city land surface patterns [11, 43, 48, 53]. Thus, a heat-island optimiser will relate local shading, neighborhood thermal control, and city priority surfaces provided the uncertainty and the appropriate spatial resolution at each scale level are accounted for.

Table 2. Objective-level scale distribution and normalised scale-dispersion scores.

Objective	Building	Street	District	City	Total	H_o	Dominant scale
Air quality	1	1	1	6	9	0.723	City
Biodiversity and ecosystem security	1	0	1	12	14	0.367	City
Energy efficiency	4	0	0	0	4	0.000	Building
Public health	0	0	1	5	6	0.325	City
Heat island	4	2	6	4	16	0.953	District
Water management	0	0	10	7	17	0.489	District

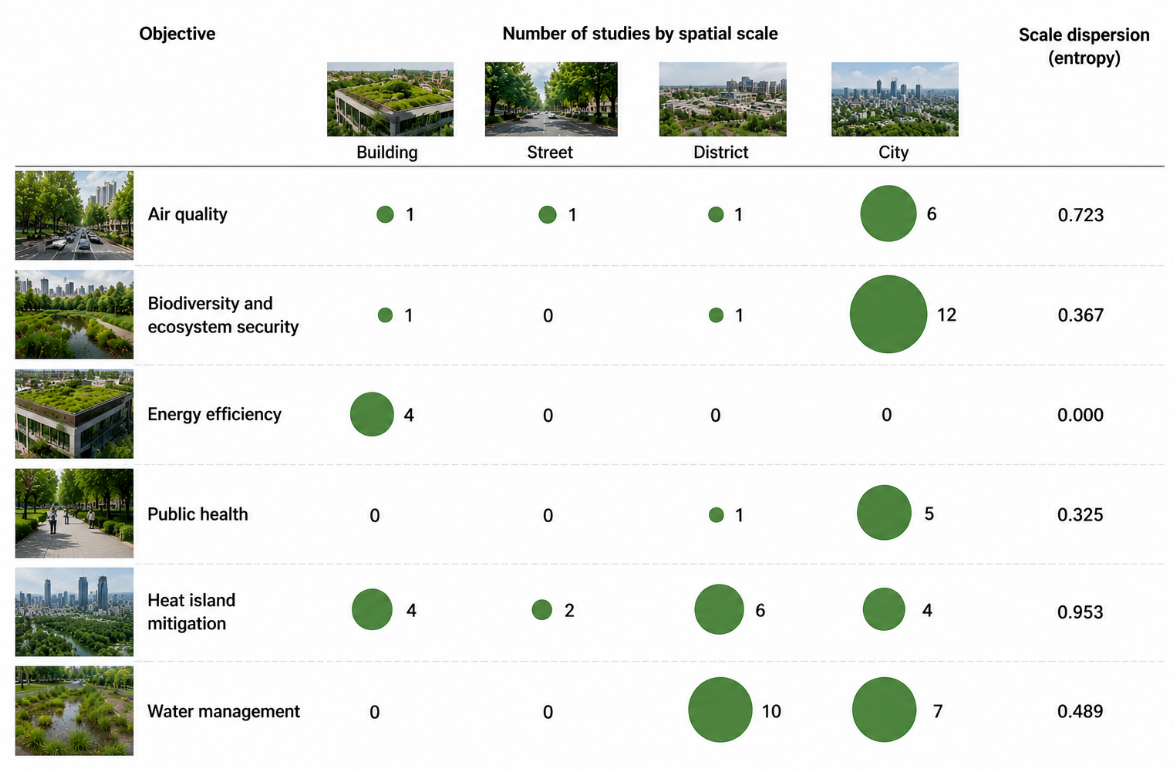

Figure 5. Spatial distribution of objective observations across building, street, district, and city scales. Bubble size represents the observations at each scale, and the right-hand values give the scale-dispersion scores listed in Table 2.

In turn, energy-efficiency is represented by building scale observations only. This scale is physically justified by the fact that energy demand depends on building form, material characteristics of the walls and roof, solar radiation impact, cooling requirements inside the building, and the nearby arrangement of vegetation [4, 5, 13, 46]. However, the observed pattern does not allow us to translate observations directly into the district scale in an optimisation task. In order to do that, it is necessary to start with estimating building energy response using simulation and then apply the obtained response function at the broader spatial scale. This way, it will be possible to preserve the physical meaning of the building energy response function and consider various urban configurations for planners.

Water management interventions have to be planned primarily at district and city scales since runoff, drainage, catchment routing, flood risk zone, and land use mosaic operate above the individual parcels [3, 9, 20]. Nevertheless, the lack of building and street scale observations is still significant for green infrastructure applications as many of them intercept water at or near the location. Thus, water management optimisations should include connecting local interception of water with district catchment routing and city-scale flood mitigation.

Biodiversity and public health interventions have to be made primarily at the city scale because biodiversity has 12 out of 14 scale observations at the city scale implying reliance on large landscapes [8, 22, 37]. It is helpful for connectivity and habitat pressure analyses; however, it could lead to neglecting more precise ecological indicators such as plant community composition, canopy and patch quality. At the same time, public health indicators are mostly located at the city scale (5 of 6), which is useful for urban exposure mapping but might not account for differences in streets regarding shade, walkability, noise, and access to various facilities [28, 36, 56].

3.3. Algorithm-use profile

Table 3 summarises the model-use counts.

Table 3. Model-use profile for green infrastructure optimisation.

Model category	Model family	Count
Evolutionary algorithm	Artificial immune system	1
Evolutionary algorithm	Annealing algorithm	3
Evolutionary algorithm	Genetic algorithm	10
Evolutionary algorithm	Evolutionary algorithm	1
Evolutionary algorithm	Non-dominated sorting genetic algorithm	12
Evolutionary algorithm	Particle swarm optimisation	4
Heuristic algorithm	Heuristic algorithm	1
Machine learning	Artificial neural network	1
Machine learning	Linear regression	2
Machine learning	Random forest	2
Machine learning	Support vector machine	1
Optimisation algorithm	General or modified optimisation algorithm	19
Other optimisation method	Piecewise linear model	1
Other optimisation method	Taguchi method	1
Other optimisation method	Three-dimensional spatial optimisation model	1

General or modified optimisation approaches are the most common group, with a frequency of 19. Non-dominated sorting genetic algorithms have a frequency of 12, genetic algorithms have a frequency of 10, particle swarm optimisation has a frequency of 4, and annealing algorithms have a frequency of 3. Models related to machine learning are less common: linear regression and random forests both have a frequency of 2, while artificial neural networks and support vector machines both have a frequency of 1. From the profile, one can observe that the field of green infrastructure optimisation relies mostly on search-based approaches than prediction.

Figure 6 represents a concise illustration of the above model use profile.

The above distribution reflects the nature of green infrastructure optimisation. In many cases, decisions entail allocations in physical space, discrete candidate sites, nonlinear interactions, and trade-offs among the effects of cooling, runoff, costs, accessibility, ecosystem function, and land availability. Non-dominated sorting genetic algorithms can be applied in situations where the planner cannot reduce multiple non-commensurable outcome metrics to one [14, 17, 21, 57]. Genetic algorithms can still prove helpful where discrete choices about locations and configurations are concerned and where constraints are irregularly shaped [24]. PSO can be used in cases where decision variables are described by continuous allocations or weights [32]. Simulated annealing is applicable in spatial rearrangement problems involving multiple local optima [33].

In contrast, machine-learning approaches play a more selective role and can be recommended only if predictions, response surface estimation, feature selection, or sensitivity analysis is required. Random forests allow one to capture complex interactions between environmental covariates as well as to rank the importance of the latter

[12]. The classic linear regression model is still useful where interpretability of estimates is key. Artificial neural networks and support vector machines can be used for high-dimensional prediction, although such application requires careful validation because of out-of-range predictions [15, 27, 45]. In green infrastructure optimisation, machine learning works best when coupled with a search algorithm that explores the feasible solution space while guided by a predictive environmental model.

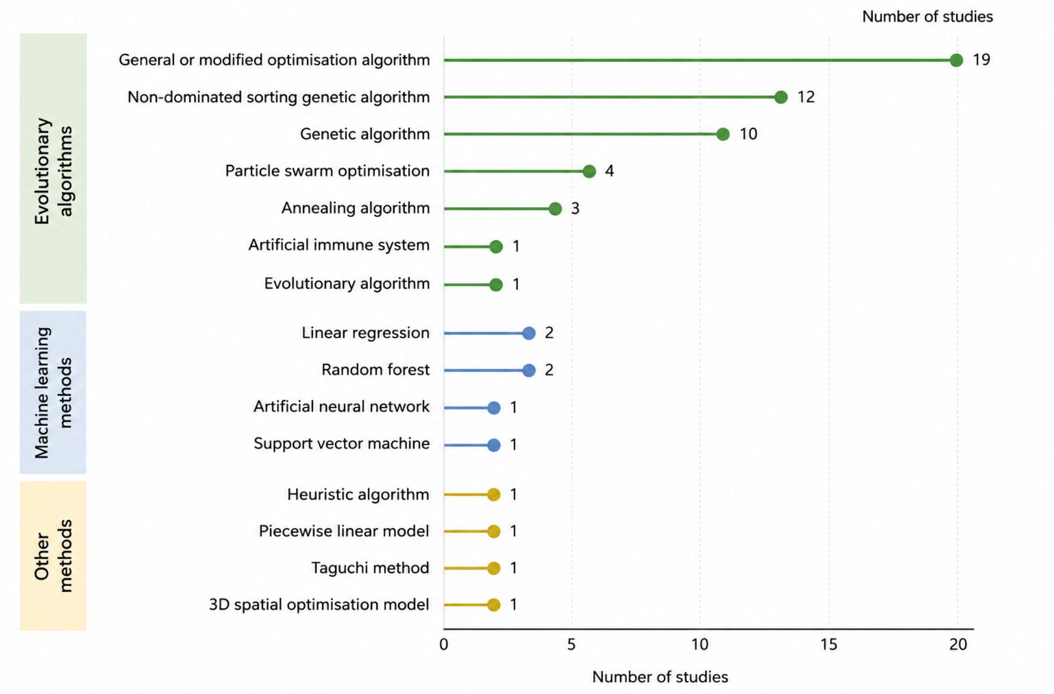

Figure 6. Frequency profile of optimisation and prediction methods used in green infrastructure optimisation literature. The ranked lollipop layout groups methods by algorithmic family and lists the count for each model type.

3.4. Transfer-caution score and indicator weights

In Table 4, one can find the combined transfer-caution score. Heat-island mitigation attains the smallest transfer-caution score (0.040) owing to the optimal combination of indicator balance, scale dispersion, and observation scale coverage. Air quality obtains a relatively small transfer-caution score (0.250) because of the very strong indicator balance and moderate scale dispersion. Water management receives a score of 0.261, even though its number of indicators is large, because it includes mostly hydrological indicators and is strongly focused on scales of districts and cities. Energy efficiency attains the highest score (0.607), whereas public health obtains 0.491.

Table 4. Transfer-caution score derived from indicator balance, scale dispersion, and scale-observation support.

Objective	Balance B_o	Dispersion H_o	Support C_o	Caution P_o
Air quality	0.997	0.723	0.529	0.250
Biodiversity and ecosystem security	0.832	0.367	0.824	0.326
Energy efficiency	0.945	0.000	0.235	0.607
Public health	0.850	0.325	0.353	0.491
Heat island	0.987	0.953	0.941	0.040
Water management	0.729	0.489	1.000	0.261

Figure 7 integrates the three numerical dimensions into a single comparative map. Objectives in the upper-right region combine stronger indicator balance with broader scale dispersion; bubble size reflects support, and the plotted transfer-caution values follow Table 4.

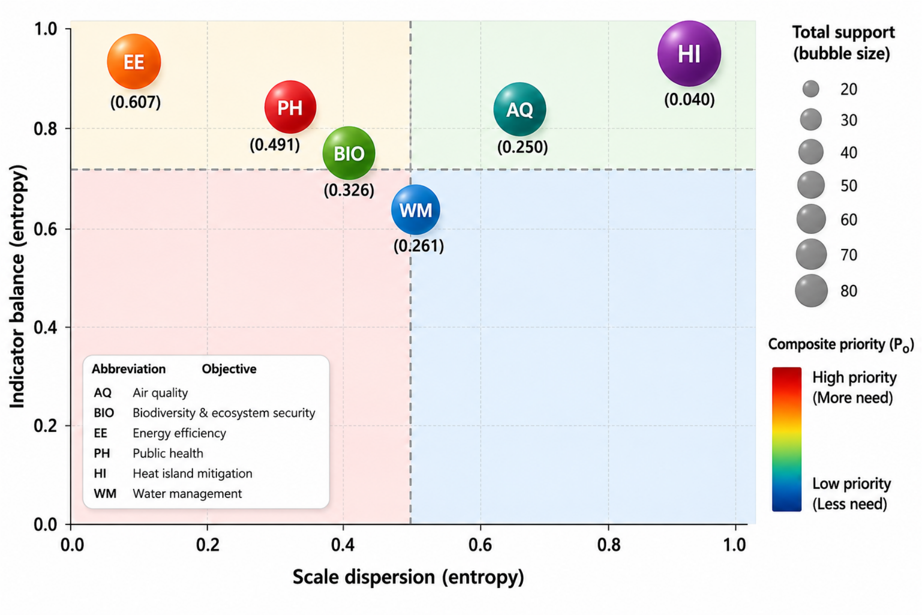

Figure 7. Integrated objective map showing indicator balance, scale dispersion, scale-observation support, and the transfer-caution value for the six optimisation objectives. Heat-island mitigation occupies the strongest cross-scale position, whereas energy efficiency has high indicator balance but no scale dispersion because its observations are building-scale only.

Count totals do not account for the order. Water management has the most indicators, and it also has the highest scale count; however, its uneven concentration means that its transfer-caution factor is higher than that of heat-island mitigation. Energy efficiency has a relatively balanced set of indicators, but no observations at all are beyond the building scale. Public health is characterized by urban-scale concentration as well as objective-oriented indicator profiles with many objective variables. Heat-island mitigation serves as a clear example of a multi-scale issue due to its high balance of indicators, dispersion of scales, and significant support.

The shrinkage weights for each of the three indicator categories can be seen in Table 5. While preserving the core of each objective, these weights ensure that none of the classes will be neglected. In particular, for water management, the weight for the objective variable remains relatively high at 0.514, while the green infrastructure descriptor weight is increased to 0.144 instead of using the raw count of 0.042. The public health objective variable weight is equal to 0.514, while the green infrastructure and geospatial variables have a weight of 0.261 and 0.225, respectively. In biodiversity, the geospatial weight equals 0.520, while the green infrastructure variables still have a weight of 0.208.

Table 5. Shrinkage-based indicator weights for objective-level optimisation.

Objective	GI weight	Objective-variable weight	Geospatial weight
Air quality	0.310	0.338	0.352
Biodiversity and ecosystem security	0.208	0.273	0.520
Energy efficiency	0.442	0.292	0.267
Public health	0.261	0.514	0.225
Heat island	0.381	0.326	0.293
Water management	0.144	0.514	0.342

4. Discussion

Figure 8 summarises the objective-specific modelling routes that follow from the numerical results. The figure is placed in the discussion because it translates the indicator and scale findings into practical modelling decisions for each objective.

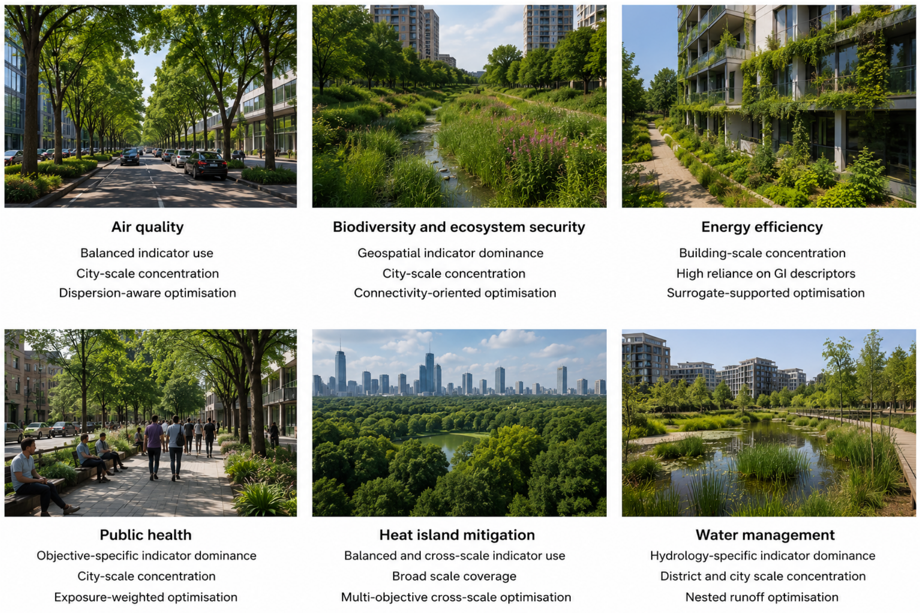

Figure 8. Objective-specific modelling routes derived from the indicator composition, spatial concentration, and support values. Each photographic panel links one objective to its dominant indicator tendency, spatial concentration, and suitable optimisation mode.

4.1. Indicator representation and planning reliability

From the indicator-balance results we can see that count total and analytical completeness are two separate qualities. The largest number of indicators in water management is caused by large numbers of hydrological indicators that describe intervention needs and intervention performance [3, 9, 20]. Hydrological characteristics do not define what kind of intervention should be applied – green roof, wetlands, bioswale, rain garden, permeable corridor, detention landscape, or vegetated mixed system. The intervention decision depends on vegetation structure, form, construction possibilities, area, maintenance needs, and co-benefits. The shrinkage weights retain hydrological dominance but require a minimum representation of the intervention form class.

For public health a separate correction should be developed. The high concentration of environmental objective-specific indicators in the numerical profile means that there are enough variables describing the problem of urban environmental exposures and risks. Optimisation, however, cannot be based solely on stressor-reducing effects. One should consider also who is exposed, where vulnerable population lives, along which routes people travel, what kinds of access people have to green spaces, and whether interventions actually reach people who have the greatest need [29, 36, 56]. The relatively low frequency of geospatial and green-infrastructure indicators suggests that for public-health objectives accessibility, deprivation, age structure, housing density, and movement variables should be included.

For biodiversity and ecosystem security scale dispersion is appropriate. This is due to the nature of fragmentation and landscape pressure estimation. However, biodiversity outcomes cannot be explained by mapped locations alone [6, 8, 49]. Even if a corridor looks spatially connected, it can be environmentally unfriendly due to poor vegetation structure, low species richness, poor edge and patch width, and bad maintenance. Therefore, biodiversity optimisation should retain strong geospatial representation but have a considerable portion of the intervention-form class.

Both air quality and heat-island mitigation demonstrate good indicator balance. Air quality has a balanced distribution between vegetation, pollutants, and spatial context [1, 19, 55]. Heat-island mitigation has a similar balanced distribution caused by the dependence of urban heat on surface materials, shadow and vegetation cover, morphological characteristics, and regional thermal regime [43, 48, 53]. Both objective classes are better prepared for optimisation due to relatively balanced numerical profiles.

4.2. Spatial scale and model transfer

Scale dispersion helps in assessing how confidently the optimisation can be translated to other planning levels. Strongest scale distribution is achieved for heat-island mitigation objective, making it possible to develop hierarchical models that link building shading, street-canyon thermal effects, district-cooling networks, and urban thermal surfaces [11, 43, 48]. While strong scale distribution ensures confidence in model development, it is still required that scale-specific uncertainty should be visible. Thermal properties at building, district, and city level are different and cannot be easily converted from one scale to another.

Energy efficiency is the clearest case of restrictive scale distribution. Building concentration is the consequence of physics of energy consumption but limits the applicability of energy optimisation to district and city planning. An energy model for larger areas cannot simply copy energy savings of individual buildings but should translate building simulations into functions of vegetation cover and response to land use [13, 46, 52]. This approach will enable building physics to become part of the model and will help in broader application.

In water management spatial nesting is essential. The need to account for catchments, surface water and stormwater pipes, surface flow routing, and land-use mosaic is responsible for district and city scale observations. On the other hand, much of water management takes place on building and street levels, and the optimisation design should include connections between local infiltration and retention and downstream water flows. An intervention site may turn out to be unimportant at local scale but significant after being aggregated with other sites in a catchment. Similarly, a big intervention site can turn out to be inefficiently placed within a catchment.

For air quality, biodiversity, and public health combined scale considerations are needed. Air quality needs city-scale environmental exposures and land use information but also requires street morphology close to major streets [1, 50, 55]. Biodiversity needs spatial connectivity at city scale but also requires good habitat quality [6, 8, 37]. Public health needs vulnerability maps at city scale but also requires street- and neighbourhood-level assessment of green space accessibility, walkability, service proximity, and exposure [28, 30, 34, 56]. In each case spatial scale distribution should guide model development and validation.

4.3. Algorithm selection for green infrastructure optimisation

The results of the model-use survey suggest continued use of search-based optimisation in green infrastructure planning. Non-dominated sorting genetic algorithms should be applied when it is necessary to keep several objectives as separate elements of optimisation, such as cooling, runoff reduction, costs, accessibility, biodiversity, and land availability [14, 17, 39, 57]. Genetic algorithms are appropriate for discrete intervention siting and allocation problems. Particle swarm optimisation can be applied for continuous intervention intensity and suitability weights. Simulated annealing is helpful for rearrangement of spatial interventions and irregular search surface.

Machine learning algorithms should be considered in connection with other modelling tools. Predictive models can be estimated from relevant environmental variables. For example, random forest models can be used to estimate cooling responses from canopy cover, surface temperature, building density, and land use [12, 27]. Once cooling response is estimated, non-dominated sorting genetic algorithm can allocate interventions within cost and access limitations [12, 17]. A similar strategy can be used to estimate runoff, exposure to contaminants, energy savings, or biodiversity suitability from relevant variables.

Objective-specific algorithmic strategies follow from the numerical results. Heat-island mitigation can be approached through multi-objective evolutionary optimisation with validation across multiple spatial scales. Optimisation in water management should take advantage of hydrology-constrained search with intervention form and flow routing. In energy efficiency surrogate-assisted optimisation with links to building simulation is applicable. Public health problems should be solved with exposure-sensitive optimisation with weighted population. Biodiversity requires connectivity-oriented optimisation with habitat quality variables. For air quality dispersion-aware optimisation is suitable.

4.4. Analytical limits and reproducibility

The analysis relies on counts extracted from tables and not on the original data matrices. This is a way to assess representation, indicator balance, and scale dispersion. Environmental effects are not estimated here, as frequency may be driven by publication preferences, data availability, disciplinary focus, or ease of measuring. Sensitivity to such factors becomes crucial when numerical weights are used to inform planning [47]. To avoid such sensitivity a shrinkage correction was introduced in IMPACT-GI. The highest count could overshadow low-count variables that are essential for planning purposes.

The analysis separates indicator and scale categories, but real urban ecosystems are complex and interactive. Heat mitigation reduces energy consumption and improves public health. Water management affects biodiversity and health. Vegetation influences air quality and thermal exposure. In future a further application of IMPACT-GI could estimate co-benefits and trade-offs between objective classes. A planner could learn which interventions perform well under several objectives and at which places one objective negatively impacts others.

It is possible to reproduce results only if the equations are provided [44]. This paper offers indicator counts, scale counts, model-use counts, equations for entropy estimation and support calculation, transfer-caution index, and shrinkage weights. All of this is required to understand and replicate the weights. A city facing severe flood risk could deliberately assign larger shares of hydrological variables while a city suffering from heat waves could put higher weights on thermal exposure. Reproducible calculation is enabled by published formulae.

5. Conclusions

Three hundred observations of indicator, scale, and model use provide a scale-resolved weighting method for climate responsive green infrastructure optimisation. The tool evaluates six objective classes with respect to their indicator balance, scale dispersion, scale observation support, transfer-caution, and shrinkage-based weights. The resulting weights give a basis for selecting the most appropriate indicators and algorithms before developing a model.

Heat-island mitigation is best supported numerically by balanced indicator distribution, scale distribution, and transfer-caution. This objective is suitable for multi-objective evolutionary optimisation that connects building, street, district, and city scale elements. Energy efficiency has the most restrictive scale distribution since all observations are at building scale, although indicator balance is quite high. Optimisation should include translation from building scale to higher scales using surrogate modelling.

Water management has the largest number of indicators (72) and scale observations (17) but indicator balance is dominated by hydrological variables. The shrinkage weights attribute 0.514, 0.342, and 0.144 to the objective-specific, geospatial, and intervention form classes. High weight of the hydrological class implies that more attention should be paid to intervention form and vegetation. Public health is the second most restrictive objective since its transfer-caution value is equal to 0.491, while geospatial and green infrastructure classes remain underrepresented.

Both air quality and biodiversity have mid-ranking indicator and scale distributions. Air quality shows high indicator balance while biodiversity shows strong geospatial distribution. Climate-responsive green infrastructure optimisation should start with the choice of indicators and scales that correspond to each objective class. Once selected, objective and algorithm choice become easy with IMPACT-GI.

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