RESEARCH PAPER

From Retrospective Association to Predictive Integration: A Review of AI-Based Temporal Forecasting of Urban Greenery and Its Implications for Urban Happiness

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Abstract. Urban greenery is increasingly recognised as a non-pharmacological, nature-based intervention for subjective well-being and mental health. However, most existing research is retrospective: it assesses the impact of greenery on people's happiness today. Urban planning and preventive public health need to know how greenery will affect residents' happiness in the future (for instance, in ten years). This article asks whether existing studies can answer that question. The review is based on 35 studies published between 2018 and 2026 in environmental psychology, remote sensing, artificial intelligence and urban planning. It covers four major aspects: the pathways through which greenery supports happiness, how greenery "exposure" or dose is measured, how AI technologies can help predict the dose–response effect of greenery on happiness, and statistical methods and study design. The review finds that forecasting studies seldom consider human outcomes, while well-being studies rely almost entirely on observed rather than forecasted exposure. It also identifies a problem of metric translation: indicators that closely reflect experienced greenery rarely have reliable predictive models. The article uses Ahmedabad, India, as a case to develop an approach suited to hot, rapidly developing Global South cities with limited evidence and misleading local vegetation patterns. It proposes a six-stage framework, from satellite observation through forecasting and scenario modelling to pathway-based happiness modelling, which treats greenery as a measurable, deliverable preventive health resource. It closes with a research agenda.

Keywords: Urban greenery forecasting, Subjective well-being, Happiness, Spatio-temporal deep learning, NDVI, Structural equation modelling, Scenario planning, Decision support

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1. Introduction

Indian cities are growing faster than their tree cover. Every year, peri-urban farmland, scrub and informal groves are converted into housing, roads and commercial land. In hot and semi-arid cities, the impacts of such a phenomenon can be perceived directly as heat and dust and over time as the deterioration of locations where people can find places to rest, socialize, or walk. The World Health Organization synthesis of the latest evidence shows that having access to green and blue spaces contributes to mental health. It also suggests that such spaces should be considered as a part of a city's health infrastructure rather than amenities [1]. Urban green infrastructure provides numerous co-benefits starting from local cooling and biodiversity to social cohesion and overall well-being, thus demonstrating the increasing importance of the listed advantages in sustainability planning processes [2].

The last ten years have witnessed a surge in research into nature and well-being, with various methods used to measure exposure, including residential access, available green space in neighborhoods, and visibility from the road [3]. There is now a well-documented dose-response relationship, one notable example being the discovery that spending roughly two hours a week in nature improves people's self-reported health and quality of life [4]. Certain psychological theories of these effects have also been developed, especially "soft fascination" in directed attention theory [5]. Systematic reviews focused on happiness and subjective well-being (SWB) conclude that the association between urban greenery and happiness is generally positive. They also find it varies with population, setting and the quality of the green space [6–8].

Almost all of this evidence, however, is retrospective. A typical study relates the greenery around a person's home today to how satisfied that person feels today. Planning decisions look the other way. A municipal corporation deciding whether to protect a tree belt, or approve a dense township, needs some estimate of what greenery the city will have in ten years and what that will mean for its residents. Two bodies of work are relevant but rarely meet. Remote sensing and artificial intelligence (AI) have produced increasingly capable models for predicting vegetation dynamics. Well-being research has produced increasingly careful estimates of how greenery relates to happiness. A recent deep-learning study linked segmented greenery types to life satisfaction but did not consider how that greenery would change [9]. A recent spatio-temporal transformer produced accurate multi-year NDVI forecasts but did not consider who lives under the forecast pixels [10].

Existing literature provides examination of several portions of the domain of AI-powered prediction modeling for sustainable urban development [11], mechanisms behind governance of green space and mental health [12] and conceptual frameworks for green space and SWB [13]. However, none of these reviews brings an insight into the question tackled by the present paper: whether and how time-based forecasts of urban greenery process can be related to the quantitative modeling of happiness which permits

evaluations of future outcomes of well-being depending on different planning solutions. This literature review is structured around the four guiding questions:

RQ1. Through which pathways does urban greenery influence happiness, and why do temporal dynamics matter for these pathways?

RQ2. Which greenery metrics and data sources can support long, consistent time series, and how well do they represent the greenery people actually experience?

RQ3. Which AI model families are used to forecast vegetation and land change, and what are their strengths and limitations as inputs to well-being models?

RQ4. What would an integrated pipeline from satellite observation to scenario-based happiness prediction require, and what gaps currently prevent it?

This research makes three significant contributions. Firstly, it provides the field of forecasting as well as happiness studies an integrated methodology where their methods are compared with one another. Secondly, it provides an integrated framework for combining greenery forecasting with structural happiness modeling and scenario modeling as well as a detailed mediation and moderation mechanism. Third, it examines how the framework would need to be adapted for rapidly urbanizing Global South cities, which are under-represented in the existing evidence, using Ahmedabad, India, as an example. Section 2 describes the review approach. Sections 3–6 address RQ1–RQ3 and the modelling of greenery–happiness relationships. Section 7 presents the integrated framework, and Section 8 considers its applicability to Global South cities. Section 9 sets out the research gaps and agenda, Section 10 draws out implications for policy and practice, and Section 11 concludes.

2. Review Approach

This is a structured integrative review. An integrative design suits the question because the relevant evidence spans study types that a single systematic protocol would struggle to compare: epidemiological cohorts, cross-sectional surveys, experiments, remote sensing benchmarks and machine learning papers. The literature was searched in Scopus, Web of Science, IEEE Xplore and Google Scholar. arXiv was also searched, because several of the most relevant 2024–2026 forecasting models first appeared as preprints. Two families of search strings were combined. The first targeted well-being: ("urban green*" OR "green space" OR NDVI OR "street view greenery") AND (happiness OR "subjective well-being" OR "life satisfaction" OR "mental well-being"). The second targeted prediction: (NDVI OR vegetation OR "land use change") AND (forecast* OR predict* OR simulat*) AND ("deep learning" OR LSTM OR transformer OR "cellular automata" OR "foundation model").

Studies were included if they were published between 2018 and 2026, written in English and reported in peer-reviewed outlets or as widely used preprints. They also had to contribute substantively to at least one of four thematic strands, and describe their data and methods clearly enough to be compared. Studies of purely agricultural or non-urban vegetation were excluded unless their method was directly transferable to urban settings, as were commentaries without empirical or methodological content. Searches were supplemented by backward and forward citation tracking from two anchor studies, chosen because each represents one half of the problem: a deep-learning analysis of greenery and life satisfaction [9] and a spatio-temporal transformer for long-term NDVI forecasting [10].

The final corpus of 35 sources was coded by study type, region, greenery metric, well-being measure, model family and temporal design (cross-sectional, longitudinal or predictive). The sources were then grouped into four strands: (A) theory and well-being evidence, (B) greenery measurement and data platforms, (C) AI forecasting and modelling, and (D) planning, equity and decision support. Figure 1 shows how the corpus is distributed. Well-being evidence forms the largest strand. AI forecasting work is concentrated after 2020, and 37% of the corpus was published in 2024–2026, which indicates how quickly the integrated question is becoming answerable.

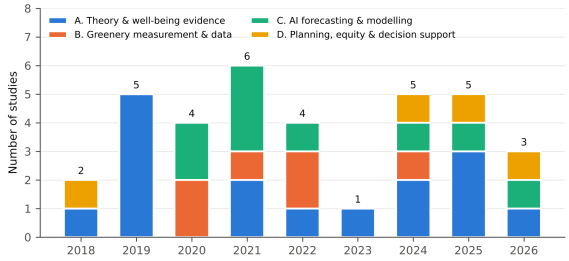

Figure 1. Distribution of the 35 reviewed studies by publication year and thematic strand (2018–2026).

Each study was appraised against four questions rather than scored on a single quality scale, because a common scale would penalise either the epidemiological or the computational studies unfairly. Is the greenery exposure defined explicitly, including its spatial unit and buffer? Is the temporal design stated, and does it allow any inference about change? Are variables like income, age, and types of housing included in research regarding well-being? In modelling studies, were results presented based on databases that were kept reserved from an analysis rather than simply split randomly into parts? Answers to those questions were marked during data coding and should be reflected in the corresponding limitations section of Table 2 and design columns of Table 3. The synthesis was thematic. Results were informed on a functional basis and different studies within the same strand were examined to find discrepancies in findings which could be explained by different methodologies employed. No meta-analysis was attempted as the data types are too dissimilar and thus do not allow for meta-analysis.

The analysis has its own limitations. The study is restricted to English-language documents and limited to 35 items to ensure the study remains focused. Hence, some relevant regional literature especially municipal

planning reports from India is missing from the study. Pre-prints are listed only when they provide full method description and results, however these documents are not peer-reviewed yet, and their results should be regarded accordingly.

3. Theoretical Foundations: Why Greenery Shapes Happiness, and Why Time Matters

3.1 Restorative and stress-reduction pathways

Two psychological accounts underpin most research on greenery and well-being. Attention restoration theory holds that natural settings hold attention effortlessly, through "soft fascination", and so let the directed attention used in demanding urban life recover. Recent work refines this by linking restoration to the mental bandwidth that a setting leaves free for reflection [5]. Stress reduction theory emphasises a faster, affective response, in which unthreatening natural scenes lower physiological arousal and improve mood. The WHO evidence review treats these two mechanisms, together with increased physical activity and social contact, as the main routes from green space to mental health [1]. A recent synthesis of 93 empirical studies expands this to six interconnected pathways: attention restoration, stress recovery, behavioural activation, physiological regulation, social cohesion and environmental buffering. It also documents a methodological shift from static vegetation indices towards dynamic, mobility-aware exposure measures [12].

The ways in which these mechanisms function differ from each other in terms of duration of time. Recovery from stress is evident within just a matter of minutes. Social bonding takes place after some time, usually months or years after repeated utilization. Environmental factors such as cooling and cleanliness of air totally depend on the development of the canopy which takes quite a lot of time.

3.2 From quantity to quality and context

The other line of research challenges the notion that an abundance of greenery is conducive to improved well-being. A framework for analysing green spaces with respect to subjective well-being identifies three interacting actors: individuals, characteristics of green spaces, and the overall spatial context[13]. According to research, the quality of green spaces has an impact on mental health regardless of the amount of green space available [8]. Moreover, a larger study of public spaces showed that there are 64 factors that come from 8 different areas that make a space important to people, one of which is vegetation [14]. Studies among the elderly show that the advantages are represented in the type of vegetation and the fact that it is close enough to be usable [7].

3.3 Temporal dynamics: lags, adaptation and accumulation

Though most of the theories discussed above do not refer to time, a forecasting framework must. There are three temporal mechanisms that need to be explicitly highlighted. Lag is the first mechanism. A newly planted avenue will show its effects in NDVI after one or two growing seasons, but it takes many years for it to provide shade, an image of closure and location, so the emotional response to greening is likely to lag behind the satellite signal. Adaptation is the second mechanism. People learn to adapt their expectations to the environment, so the loss of greenery may be noticed sharply, but quickly becomes neglected. The next one is accumulation. Years of repeated exposure can embed in cohorts recoveries and social relationships, which one snapshot of the current state cannot capture. The suggested framework allows for time-varying relationships since [13]. In real life, however, there have hardly been any analyses that were built to disentangle these mechanisms. In terms of predictions, this means that the same forecast of the green wave would have different well-being trajectories.

Asymmetry is a related issue. Losing a mature tree canopy is not simply the reverse of gaining a young one. The loss is immediate, while the replacement takes decades to deliver comparable shade and visual mass. Forecasting models that treat NDVI as a symmetric quantity will therefore understate the well-being cost of scenarios in which mature vegetation is cleared and replaced with new planting of similar measured greenness.

3.4 A pathway model for prediction

To carry out forecasting, the above insights can be presented in a structural pathway model as shown in Figure 2. The change in urban green spaces, which is expressed by NDVI, green cover rate or accessibility index, acts as an exogenous driver with respect to happiness; the influence of the former takes place partly due to four mediators environmental quality, perceived quality of green spaces, stress relief and social interaction. The strength of influence also depends on four moderators: income, age, education, and population density. The result is SWB, which can be measured with certain already validated instruments for instance, WHO-5 and the life satisfaction scale. Studies provide confirmation for each component of this model. Data from different countries demonstrate that the green space effect on happiness depends on the level of social support and is influenced by the economic situation [15]. In Switzerland the positive impact of greenery on life satisfaction was true only for older people [9]. In Beijing the connection between greenery and health was different for areas with low and high vegetation cover [16]. There are four hypotheses that can be tested. Greenery positively influences happiness (P1), while the positive effect is mediated by the quality of the environment (P2) and by the level of stress (P3). Economic status has an influence on the green space-happiness relationship (P4).

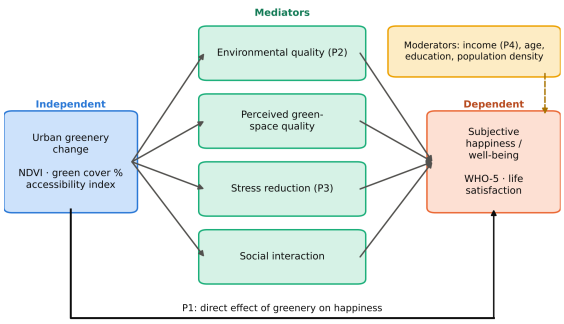

Figure 2. Structural pathway model linking urban greenery change to subjective happiness through mediators, conditioned by moderators (propositions P1–P4).

4. Measuring Greenery Through Time

Any forecasting pipeline is limited by the greenery metric it forecasts. Table 1 compares the main families of metrics on their temporal depth, their resolution and how closely they represent the greenery people experience.

4.1 Satellite vegetation indices and land cover

The Normalised Difference Vegetation Index (NDVI), and related indices such as EVI and SAVI, remain the workhorses of urban greenery research because they can be computed consistently from Landsat archives going back to the 1980s and from Sentinel-2 at 10 m since 2015. Cloud platforms such as Google Earth Engine have made multi-decadal, city-wide processing routine. They host the full Landsat and Sentinel catalogues alongside climate reanalyses such as ERA5 [17]. Near-real-time land cover products extend this further. Dynamic World provides 10 m class probabilities, including trees, grass, crops and built area, for every Sentinel-2 scene, which allows greenery to be tracked at sub-annual frequency [18]. The weakness of these metrics is that they measure photosynthetic activity from above. NDVI saturates over dense canopy, cannot separate a private lawn from a public park, and mixes seasonal crops with permanent vegetation, which is a serious problem for district-scale analyses in India.

4.2 Eye-level and fine-grained greenery

Street view images help resolve the problem of perspective by quantifying greenery from the perspective of the pedestrian in the form of a Green View Index based on semantic segmentation [19]. In a study in Beijing, it was found that deep learning street view green and blue views reduced depressive symptoms in older people [20]. Another investigation undertaken in Guangzhou directly compared satellite images to street views as measures of greenery. The two methods examined different parameters of greenery with different links to mental health [21]. Deep segmentation of high-resolution images enables the classification of trees, grass and parks into specific types, making this classification more informative with respect to life satisfaction than the indicator “total green cover” [9]. The problem with such data sources is that, being irregular and costly, neither of them can be applied for building long datasets for predictions.

4.3 Condition, quality and accessibility

The third set of measures pertains to the health of vegetation and accessibility of green spaces. A review of monitoring tools indicates the possibility of monitoring tree condition, i.e. not only its existence but also its health using remote sensing, sensors and public observations [22]. The studies conducted in Beijing indicate that using and perceiving residential green spaces interacts with health differently than coverage measures [16]. Accessibility measures based on network distance to the nearest park significantly rely on the buffer distance and spatial unit used, which is the main source of inconsistency in research efforts as indicated by a systematic review [3].

4.4 Building consistent time series

A forecasting model learns from the history it is given, so the construction of that history is a modelling decision in its own right. Several practical steps recur in well-designed studies. Clouds and cloud shadows must be masked using quality bands before compositing, in monsoon climates this can remove most observations between June and September. Reflectance from different sensors must be harmonised, because the Landsat 8 and 9 sensors have narrower spectral bands than their predecessors, and uncorrected NDVI can jump at sensor transitions. Annual composites, such as the median or a seasonal maximum, should be built from a consistent seasonal window so that a wet year is not mistaken for greening. Cloud platforms make each of these steps scriptable and repeatable at city scale [17]. Land cover probabilities can then be used to separate permanent vegetation from cropland and seasonal grass [18]. Finally, the series should be masked to a fixed urban extent, or to an extent that expands with the city, depending on whether the question concerns existing neighbourhoods or the city as it grows. These choices rarely appear in published greenery–happiness studies, yet they can change the sign of a trend at district scale, as discussed in Section 8.

Table 1. Comparison of greenery metrics by temporal depth, resolution and relevance to happiness modelling

Metric	Typical data source	Resolution / temporal depth	What it captures	Main limitation for happiness modelling	Ref.
NDVI / EVI / SAVI	Landsat 5–9, Sentinel-2 processed in Google Earth Engine	10–30 m; Landsat since 1984, Sentinel-2 since 2015	Photosynthetic greenness seen from above	Saturates in dense canopy; mixes crops and parks; not what residents see	[17]
Land-cover class probabilities	Dynamic World (Sentinel-2)	10 m; per scene since 2015	Trees, grass, crops, built area	Class confusion in mixed urban pixels; short archive	[18]
Green View Index	Street view imagery with semantic segmentation	Street-level points; irregular years	Eye-level greenery experienced by pedestrians	Irregular capture dates; road-biased sampling	[19, 20]
Segmented green types	Very-high-resolution imagery with deep learning	<1–2 m; few epochs	Trees, grass, gardens and parks separately	Costly; limited time series	[9, 23]
Vegetation condition	Remote sensing, ground sensors, citizen data	Variable	Tree stress and vitality	Patchy coverage; not standardised	[22]
Perceived quality and use	Surveys and site audits	Neighbourhood; mostly cross-sectional	Maintenance, safety, facilities, use	Rarely available as time series; subjective	[8, 16]
Accessibility / proximity	Park polygons and road networks	Address or ward; largely static	Opportunity to visit green space	Sensitive to buffer size and spatial unit	[3]

The comparison in Table 1 exposes what this review calls a metric translation problem. The metrics that can be forecast reliably, namely satellite indices and land cover, are not the metrics most closely tied to happiness, which are eye-level greenery, quality and use. An integrated pipeline therefore needs an explicit bridge, for example a model that maps forecast NDVI and land cover to expected street-level greenery, calibrated where both are observed. Figure 3 positions the metrics in Table 1 on these two dimensions.

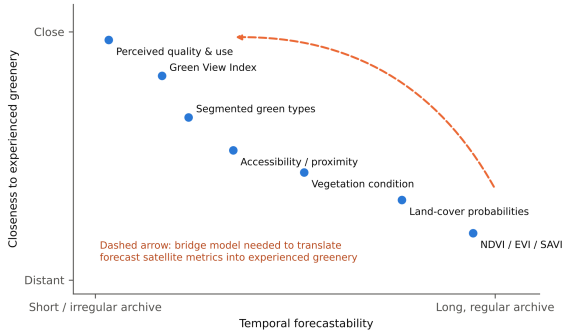

Figure 3. Conceptual positioning of greenery metrics by temporal forecastability and closeness to experienced greenery (qualitative, based on Table 1).

5. AI Models for Temporal Greenery Forecasting

Forecasting urban greenery means predicting a spatial field several years ahead from its own history and from drivers such as climate, population growth and land

policy. Figure 4 summarises how the methods have developed, and Table 2 compares representative studies.

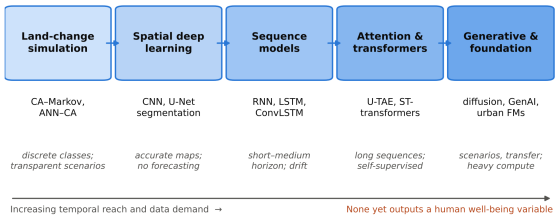

Figure 4. Evolution of AI and simulation methods for temporal greenery prediction, with typical models and characteristic trade-offs.

5.1 Land-change simulation

Before deep learning, the standard tool for projecting urban land change was the cellular automata–Markov chain (CA–Markov) model. A Markov matrix predicts the amount of land shift from one class to another while the spatial allocation of such changes is achieved through cellular automata based on certain suitability and neighborhood rules. Using artificial neural networks to define those suitability surfaces allows for improved allocation accuracy [24]. Despite their shortcoming in the sense that they predict discrete classes rather than continuous greenness, and do not involve a gradual process, meaning that their strength lies in the transparency of their scenarios, CA-Markov models are popular among planners.

5.2 Convolutional and recurrent networks

Convolutional neural networks (CNNs) transformed the extraction of vegetation information from imagery, outperforming pixel-based classifiers in mapping species, canopy and vegetation structure [23]. Across environmental remote sensing more broadly, deep learning has improved retrieval and gap-filling, but the evidence also shows persistent difficulties with limited labels, physical interpretability and transfer between regions [25]. For temporal prediction, recurrent networks, particularly long short-term memory (LSTM) models, became the default. In a study of urban overheating, ANN, RNN and LSTM models were trained on field measurements across microclimate zones with different vegetation levels, and the LSTM gave the best predictions. The trained model was then driven with warming scenarios for 2050 and 2090. Tree-covered zones were projected to avoid extreme heat stress even under high warming [26]. This design, a learned local response driven by external scenarios, is directly transferable to greenery–happiness forecasting.

5.3 Spatio-temporal video prediction

Treating a satellite time series as a video allows models to forecast whole image patches rather than single pixels. The term "guided video prediction" was coined by the EarthNet2021 challenge to describe the task of predicting future accurate Sentinel-2 frames using previous frames and future weather information as predictors [27]. ConvLSTM and other convolutional LSTM architectures are effective in forecasting for short periods but yield unreliable predictions when the forecast period is longer than a few months.

5.4 Attention and transformers

Attention mechanisms let a model weigh every past time step directly, rather than passing information along a recurrent chain. The U-TAE architecture combined a convolutional encoder with temporal self-attention to segment satellite image time series, and showed that attention handles irregular acquisition dates and cloud gaps well [28]. The most relevant recent advance is a spatio-temporal transformer for long-term NDVI forecasting. It processes multi-scale spatial patches and temporal sequences of up to 20 years, is pre-trained in a self-supervised way on unlabelled Landsat data, and achieved a mean absolute error of 0.033 and R^2 of 0.84 for next-year NDVI over heterogeneous Mediterranean landscapes. It outperformed LSTM baselines [10]. It is, however, a vegetation model. It was not tested in dense cities and does not output any variable with a human interpretation.

5.5 Generative and foundation models

Two newer directions widen the scope of what can be predicted. Generative models can generate plausible future urban spaces. In one study, 15 AI-generated greening designs for 5 public spaces were evaluated in terms of visual greenness, function and stakeholder preference, and vegetative density alone could not account for people preferences among those designs [29]. Urban foundation models, pre-trained on large multimodal corpus of images, mobility, text, and points of interest, promise transferability of representations across cities and tasks [30]. Both directions remain computationally expensive and largely untested on greenery prediction. A review of AI in sustainable urban development also notes recurring concerns about data quality, bias and governance that apply with particular force to these large models [11].

5.6 Interpretability and evaluation

It is necessary that predictions are not only accurate but also sensible. The use of Shapley additive explanations (SHAP) for the interpretation of gradient boosting regressions reveals spatial variability similar to the geographically weighted regression (GWR) technique [31]. The above mentioned aspects make it possible to identify predictors (for instance, distance from roads, population increase, precipitation) determining vegetation prediction in different neighborhoods. Moreover, evaluation standards are not consistent across the existing studies included in the review. Correct evaluation implies MAE, RMSE and R^2 statistics should be obtained not according to the random separation or randomization, but for the years under consideration, spatial block cross-validation should be applied in order to minimize the information leakage due to the adjacent pixels, while comparison with over-simplified persistence or climatology benchmarks is neglected by a lot of studies.

Table 2. Survey of AI model families for temporal greenery and urban environmental prediction

Model family	Representative study	Inputs	Output and horizon	Strengths	Limitations for happiness integration
ANN–CA–Markov	Gharaibeh et al. [24]	Land-use maps, driver layers	Discrete land-use classes; multi-year	Transparent, scenario-friendly	No continuous greenness; no human outcome
CNN (spatial)	Kattenborn et al. [23]; Yuan et al. [25]	Single-date imagery	Vegetation maps (not forecasts)	High mapping accuracy	No temporal prediction; label-hungry
ANN / RNN / LSTM	Zou et al. [26]	Field microclimate data, warming scenarios	Thermal stress (UTCI) for 2050 and 2090	Scenario-driven long-term projection; LSTM best	Single site; heat rather than well-being
Guided video prediction	Requena-Mesa et al. [27]	Sentinel-2 sequences and weather	Future image frames; weeks to months	Conditioned on known drivers	Short horizon; error accumulates
Temporal attention (U-TAE)	Garnot & Landrieu [28]	Irregular Sentinel-2 time series	Parcel segmentation	Handles irregular dates and clouds	Classification, not forecasting
Spatio-temporal transformer	Farantet al. [10]	Landsat NDVI, up to 20 years	Next-year to multi-year NDVI (MAE 0.033, R^2 0.84)	Long sequences; self-supervised; beats LSTM	Non-urban test areas; no human link
Generative AI	Annan et al. [29]	Text prompts and site images	Visual greening scenarios	Rapid design alternatives; stakeholder testing	Not temporal; density does not predict preference
Urban foundation models	Zhang et al. [30]	Multimodal urban data	General-purpose representations	Transfer across tasks and cities	Heavy compute; untested for greenery forecasting
Interpretable ML (XGBoost + SHAP)	Li [31]	Tabular spatial covariates	Predictions with local explanations	Spatially varying explanations	Not a sequence model

5.7 Comparative assessment for greenery–happiness applications

The table presented indicates that there is no optimal model family that can be used in the integrated task. The selection of the model depends on 4 important criteria that are of special importance when a forecasting model is used for feeding the Well-being model. First, horizon: planning concerns range of a couple of years up to a 20-year period when both recurrent models and video-prediction models lose their predictive power and give way to transformers and scenario simulations. Second, scenario capabilities: the model must accept the control levers for further processing. CA–Markov models do this

automatically due to transitions. Deep models, however, require explicit signal channels, e.g., climate scenarios used in the study of overheating [26]. Third, output granularity: happiness models work on the level of individuals and neighborhoods, while the pixels must be shifted towards or buffers without losing the distinction of the greenery. Finally, degree of interpretability is important since models will be used to argue for or against some development if they can be explained to non-professionals.

When it comes to these requirements, hybrid design proves to be the most attractive option. A spatio-temporal deep model (CNN-LSTM or transformer) learns the trend and everything related to climate response. The scenario layer taken from land-change modeling then specifies the limitations of the policy on the vegetation loss or gain. Interpretable surrogate models used alongside the main model help to interpret the resulting maps. This approach provides all the advantages of deep learning combined with all the transparency required by planners in land change scenarios.

6. Modelling the Greenery–Happiness Relationship

6.1 What the evidence shows

The empirical evidence linking greenery to happiness is consistent in direction but varied in strength and mechanism (Table 3). At the largest scale, satellite-derived green space across 90 cities in 60 developed countries was associated with city-level happiness, mainly among the wealthiest countries, and the association was mediated by social support [15]. In a national Swiss sample, deep-learning-segmented trees and grass in gardens and parks were associated with higher life satisfaction for older residents only [9]. In England, a threshold of about 120 minutes a week in nature separated people more likely to report good health and high well-being from those less likely to [4]. An experimental study in Chile used photo-simulations of street-level green interventions and found that all intervention types raised perceived happiness and lowered perceived stress, with effect sizes that differed by type and scale [32]. Reviews of this literature agree on the positive direction of the association. They also note that most studies come from Europe, North America and East Asia [6, 14].

6.2 Analytical designs

Most studies are cross-sectional regressions of a well-being score on a greenery measure, adjusted for individual and area covariates. Mediation analysis is increasingly common, and SEM is the natural framework when several pathways operate together. A study of young adults in Bulgaria showed why careful specification matters. Testing mediators one at a time suggested different conclusions from testing them in a serial model, in which restorative quality led to more physical activity and social cohesion and these in turn improved mental health. In that study, objectively measured greenspace had no direct effect at all [33]. Similarly, the Guangzhou study found that the mediating pathways differed depending on whether greenery was measured from satellites or from street view [21]. For forecasting, the implication is direct. If predicted greenery is fed into a mis-specified pathway model, the predicted happiness effect will be wrong even if the greenery forecast is accurate.

Panel designs with individual fixed effects, which compare the same person before and after greenery changes, provide the strongest observational evidence. However, they remain rare because few surveys can be linked to annual greenery data at the address level. Experimental and quasi-experimental designs, such as the photo-simulation approach, offer a complementary way to estimate the effect of specific, planned changes before they are built [32].

6.3 Measuring happiness

The outcome side is less standardised than the exposure side. Studies use single-item life satisfaction, multi-item satisfaction scales, the WHO-5 Well-Being Index, positive and negative affect scales, depressive symptom inventories and self-rated health. These capture related but distinct constructs: evaluative well-being (life satisfaction), hedonic well-being (affect) and mental health. Greenery may influence each differently. Short-term affect responds quickly to exposure, while life satisfaction is more stable and is likely to respond only to sustained change. For a predictive framework, WHO-5 and life satisfaction are attractive outcomes because they are short, widely translated and suitable for repeated administration, so they can be tracked over time.

6.4 Heterogeneity

Three moderators recur across the evidence. Age modifies the effect, which is strongest among older adults, who spend more time near home [7, 9]. National or household income conditions it, with greenery mattering more once basic needs are met, or alternatively compensating more where private space is scarce [15]. Baseline vegetation conditions it, so that additional greenery may matter less where coverage is already high [16]. A review of green space access in the Global South found complex patterns of inequity and comparatively little research [34]. As a result, effect sizes estimated in wealthy, temperate cities cannot be assumed to transfer to hot, dense and unequal cities such as Ahmedabad.

Table 3. Representative empirical studies of the greenery–happiness relationship

Study	Setting	Greenery measure	Well-being outcome	Design	Key finding	Predicted greenery?
Kwon et al. [15]	90 cities, 60 developed countries	Sentinel-2 green space score	National happiness	Cross-sectional with mediation	Positive in the 30 richest countries; mediated by social support	No
White et al. [4]	England, about 20,000 adults	Weekly time in nature	Self-rated health and well-being	Cross-sectional survey	Threshold near 120 min per week	No
Helbich et al. [20]	Beijing, older adults	Street-view green and blue (deep learning)	Depressive symptoms	Cross-sectional, multilevel	More eye-level greenery, fewer symptoms	No
Wang et al. [21]	Guangzhou, adults	NDVI vs street-view greenery	Mental well-being	Multiple-pathway mediation	Pathways differ by greenery metric	No
Dzhambov et al. [33]	Plovdiv, Bulgaria, ages 15–25	Objective greenspace measures	General mental health	Parallel vs serial mediation	No direct effect; serial restorative pathways	No
Navarrete-Hernandez & Laffan [32]	Chile, biennale visitors	Photo-simulated interventions	Perceived happiness and stress	Experiment	All interventions raised happiness; size varied	Simulated
Bahr [9]	Switzerland, 2,755 participants	Deep-learning green types (VHR)	Life satisfaction	Cross-sectional regression	Effect only for older residents	No
Huang et al. [16]	Central Beijing	Coverage rate, perception, use	Self-rated health	Correlation by coverage group	Associations differ by coverage level	No

6.5 From association to prediction: requirements for the happiness model

Table 3 shows that none of the reviewed empirical studies used predicted greenery, and only one, using simulated photographs, estimated the effect of a specified future change. Using these models for prediction places demands on them that association studies do not face. First, the exposure must be measured in the same units that the forecasting model produces. A coefficient estimated on street-view greenery cannot be applied directly to forecast NDVI without the bridge described in Section 4. Second, the relationship must be allowed to be non-linear. The evidence of a weekly exposure threshold [4] and of differences across coverage levels [16] both suggest diminishing or threshold effects. A linear coefficient extrapolated to large forecast changes would then

overstate gains in already green areas and understate losses in sparse ones. Thirdly, the model needs to be robust enough to pass through time. The coefficient estimated in 2025 will be utilized in estimating greenery levels as of 2035, which means that no change is assumed in the link between greenery and happiness until then. This assumption must at least be verified by estimating the model on successive waves of the survey. Fourthly, the model must generate a distribution and not just a point estimate.

SEM meets several of these requirements. It can include latent constructs, such as perceived quality, measured by several indicators. It can test serial and parallel mediation explicitly, a distinction shown to change substantive conclusions [33]. Multi-group estimation can also show whether coefficients differ by income or age group. Its weakness for prediction is that it is usually linear and cross-sectional. Extensions with interaction terms for moderators, piecewise specifications for thresholds and estimation on panel data where available would make it a more reliable link in a predictive chain.

7. Towards Integrated Prediction: A Framework from Forecast to Happiness Scenario

Sections 4–6 show that the components of an integrated pipeline exist but are developed in separate communities. Figure 5 assembles them into a six-stage framework.

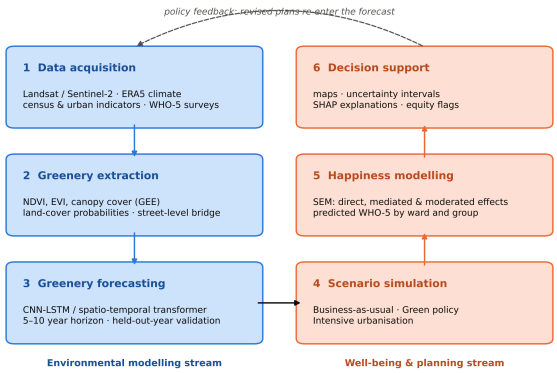

Figure 5. Proposed six-stage framework integrating greenery forecasting, scenario simulation and happiness modelling for decision support.

Stage 1 (data acquisition) assembles Landsat and Sentinel-2 imagery, climate reanalysis, census and urban indicators, and repeated well-being surveys. Stage 2 (greenery extraction) computes NDVI, EVI and canopy cover in Google Earth Engine, and uses land cover probabilities and, where available, street-level greenery to build the metric bridge described in Section 4. Stage 3 (forecasting) trains a spatio-temporal model, such as a CNN-LSTM or transformer, to project greenery forward over a 5–10 year horizon. Stage 4 (scenario simulation) generates alternative greenery futures. Stage 5 (happiness modelling) passes each future through an SEM estimated on historical data to obtain predicted well-being by neighbourhood and population group. Stage 6 (decision support) presents the results with their uncertainty and explanations to planners.

7.1 Designing scenarios

Three scenarios are commonly used in land-change studies and translate naturally to this setting. Business-as-usual extrapolates recent trends. Green policy imposes protection of existing canopy and planned additions. Intensive urbanisation raises the conversion rate of vegetation to built land. The overheating study shows how externally defined scenarios can drive a trained model [26], and CA–Markov transition matrices show how policy rules can be written directly into allocation [24]. Two further lessons come from the design literature. First, scenarios should specify the type and quality of greenery as well as its quantity, because people's preferences are not explained by vegetation density alone [29]. Second, photo-simulation of specific interventions can provide ex-ante estimates of well-being change that complement model-based projections [32].

7.2 Propagating uncertainty

A happiness prediction inherits the error of every stage before it. Greenery forecast error, the uncertainty of the metric bridge and the sampling uncertainty of SEM coefficients all compound. A responsible framework should propagate these through Monte Carlo simulation or ensemble forecasting and report predicted well-being as intervals. A scenario difference whose interval spans zero should be reported as inconclusive rather than as a recommendation.

7.3 Validating the integrated pipeline

Integrated forecasting cannot be validated through the test of time, however, it can be validated on history. A back-casting method entails that the forecasting model uses data accumulated until a certain cut-off year, for instance, 2018 and makes predictions about greenery in the following years, which are compared to the actual greenery measured. If there are wellbeing surveys conducted at the same time, the calculated greenery can then be used in the happiness model enabling comparisons between wellbeing estimates and actual survey results. As the available survey data is quite limited, back-casting cannot be realized for all wards. Still, the impact of a little quantity of matched units can reveal how errors are accumulated or canceled. Moreover, studies should investigate if the pipeline is capable of ensuring the same ranking of the scenarios.

7.4 Explainability and governance

Planners will not act on forecasts they cannot interrogate. Local explanation methods such as SHAP can show, for each ward, which drivers produce the predicted greenery loss [31]. The decomposition of SEM effects into direct, mediated and moderated components shows why that loss is expected to matter for well-being and for whom. These outputs must sit within governance arrangements that address data quality, privacy and the risk of reinforcing existing inequities [11]. Recent proposals call for AI-enabled decision support that explicitly prioritises vulnerable populations and equitable access [12].

8. Applicability to Rapidly Urbanising Global South Cities

The evidence reviewed in Sections 3–6 comes largely from Europe, North America and East Asia [6]. Cities in the Global South differ in ways that matter for every stage of the framework. A systematic review of green space access in these cities found complex and context-specific patterns of inequity, and comparatively little research [34]. Hot, semi-arid Indian cities illustrate the point. In Ahmedabad, for example, satellite analyses have shown that land surface temperature is strongly related to vegetation, built-up area, soil and water surfaces, with marked differences between summer, monsoon and winter [35]. In such settings, the cooling function of greenery is likely to be a more prominent pathway to well-being than in temperate cities. Environmental quality in the pathway model would therefore need to include thermal comfort explicitly as a mediator.

Data conditions also differ. City- or district-wide vegetation averages in Indian metropolitan regions combine dense urban cores with peri-urban agriculture, whose greenness depends on monsoon rainfall and irrigation. A rising regional NDVI can therefore coexist with stable or declining greenery inside the city, if gains in irrigated farmland offset losses to construction. Year-to-year changes are further affected by sensor transitions and data gaps in the Landsat record. Turning such series into evidence planners can use requires the steps described in Sections 4 and 7. These include masking to the urban extent, separating permanent from seasonal vegetation with land cover probabilities [18], disaggregating to the ward level, and linking with well-being surveys that match these units in time and space. None of the reviewed greenery–happiness studies was conducted in an Indian city. The effect sizes needed for Stage 5 must therefore be estimated locally rather than borrowed from wealthier, temperate contexts [15].

In a city of this kind, the framework in Figure 5 would proceed as follows. A ward-level greenery series would be constructed for the municipal area, separating tree canopy, grass and cropland. A spatio-temporal model would be trained on the earlier part of the record, validated on the most recent years and then run forward a decade under the three scenarios. The data collected from the household survey utilizing the WHO-5 index, perceived green space quality, a stress measure and social contact, along with the moderators mentioned in Figure 2, would provide inputs to calculate the pathway model. A prediction of "happiness for the city" is not expected from this exercise. Rather, the data output would produce a number of maps at ward level showing where, when measured against the business-as-usual scenario, and there their wellbeing dips below a certain threshold, as well as the population groups living in the area. This type of evidence represents a solid foundation for a planning authority.

9. Research Gaps and Future Directions

Table 4 consolidates the gaps identified across the four strands and links each to a concrete research direction.

Table 4. Research gaps and proposed directions for integrated greenery–happiness prediction

Gap	Evidence from the review	Proposed direction
G1. Retrospective exposure	Happiness studies use observed greenery; forecasts ignore people [9, 10]	Couple forecasts with SEM on shared spatial units; repeated, geocoded surveys
G2. Metric translation	Forecastable NDVI differs from experienced greenery [19, 21]	Bridge models mapping NDVI and land cover to street-level greenery and quality
G3. Temporal misalignment	Dense satellite series versus sparse survey waves [13, 18]	Annual or seasonal panels; mixed-frequency models
G4. Heterogeneity and equity	Age, income and coverage moderate effects; Global South under-studied [9, 15, 34]	Group-specific predictions; local effect estimation in Indian cities
G5. Causal identification	Cross-sectional designs dominate; results sensitive to specification [33]	Natural experiments, difference-in-differences, fixed-effects panels
G6. Model transfer and benchmarks	Transformers and foundation models untested in dense semi-arid cities [10, 30]	Open greenery–well-being benchmark with temporal and spatial splits
G7. Uncertainty and explainability	Point forecasts and opaque models [11, 31]	Ensemble or Monte Carlo propagation; SHAP plus SEM effect decomposition

The most basic difference is that studies of green spaces and happiness are based on the observed data of green spaces, while predictive studies only use the data of green spaces [9, 10]. To eliminate this gap, it is not enough to use both models sequentially. One needs a common spatial unit (e.g., ward or a grid) and the same time resolution for green space data and happiness measure. Practically, this means designing well-being surveys with repeated waves geocoded to the same units used for the forecast, rather than relying on one-off cross-sections.

The metric translation problem identified in Section 4 is the next most important. Forecasting models are built on NDVI and land cover because these have long, regular archives [17, 18]. The evidence on happiness, however, points to eye-level greenery, quality and use [8, 21]. Research is needed on models that predict expected street-level greenery and quality from forecast satellite variables, validated wherever both are observed.

Third, the moderators that the evidence identifies, such as age, income, density and baseline coverage, are rarely carried into prediction. A forecast of average well-being change can hide large differences between groups, and the residents most exposed to greenery loss are often those with the least private green space [34]. Group-specific predictions should be standard outputs, not optional extensions.

Fourth, causal identification remains weak. Most effect sizes come from cross-sectional data, and the Bulgarian study shows that conclusions about mechanisms depend on model specification [33]. Natural experiments created by new parks, metro corridors or tree-felling for road widening offer opportunities for difference-in-differences designs linked to satellite time series.

Fifth, more stringent evaluation of its potential should be carried out in case of AI approaches. The use of transformer-based and foundation algorithms awaits the appraisal of the performance both in tropical and semi-arid cities [10,30]. Urban vegetation in people's well-being is not yet addressed by any database open to the public. That is why there is a chance to get more significant advances compared to any other algorithm. Additionally, all components should report uncertainty and provide explanations [31] if the support for decision-making is to gain people's confidence and strength to contradict it [11,12].

There are ethical questions that arise with technical questions. Geocoded well-being mapping with detailed photography can give sensitive information about people and households, so aggregation, consent and security must be built-in right from the start. Predictions may also be self-fulfilling. A map that states that an area is likely to see a decline in greenery may reduce property values or invites development pressure. Deliberation with local citizens and committees through scenarios and interpretation of the result, has been the beginning of stakeholder evaluations of greening design [29].

10. Implications for Policy and Practice

Even though the integrated pipeline is not functioning at the moment, it nevertheless endorses some useful suggestions for urban authorities in expanding cities. First of all, greenery should be tracked over time rather than through sporadic surveys. Free satellite archives which are available online mean that it is possible to produce annual assessments of greenery on a ward basis for very little cost [17, 18]. The well-being and cooling benefits are concentrated in trees [9, 26], and an aggregate index can hide the replacement of old trees with lawns. Third, routine well-being measurement using a short, validated instrument such as WHO-5 could be added to existing municipal or smart city surveys, geocoded to wards. This would create, within a few years, the linked panel data that the research community lacks. Fourth, master plans and development approvals could be accompanied by greenery scenarios, much as environmental impact assessments now require pollution or traffic projections. Even simple CA–Markov scenarios would make the expected change in green cover explicit [24]. Finally, distributional analysis should be standard. Plans should report which groups gain or lose access to greenery, because the evidence consistently shows that benefits and losses are unevenly shared [15, 34].

For researchers, the most valuable near-term contribution may be less a new model than a well-documented case study. One city, with a reproducible greenery time series, a repeated well-being survey and a transparent scenario analysis, would show what the integrated approach can and cannot deliver, and would provide a template that other Global South cities could adapt.

11. Conclusion

In this review, the question was raised if research can provide the answer to how greenery would impact the residents' happiness in any given city. The answer is still negative, but the parts are available. Theory and evidence suggest the process through which greenery has an impact on SWB, the mediators and moderators taking shape in the process. AI models, from CA–Markov hybrids and LSTMs to spatio-temporal transformers, can project those series forward with increasing accuracy. Structural equation models can estimate how greenery translates into well-being, and for whom. What is missing is the integration: a shared spatial and temporal frame, a bridge between the metrics that can be forecast and those that people experience, locally estimated effect sizes, and transparent propagation of uncertainty into scenario comparisons.

The discussion of Global South cities illustrates both the opportunity and the caution required. A greening trend in a regional vegetation index is only the starting point for asking whether the city's residents are gaining or losing the greenery that supports their well-being. The framework proposed here, from satellite observation through forecasting, scenario simulation and pathway-based happiness modelling to explainable decision support, offers a structure for answering that question. Its development would move urban greenery research from describing associations to informing choices, which is what planners in rapidly urbanising cities need most.

Author Contributions

Piyushkumar Patel: Conceptualisation, Methodology, Literature search and curation, Formal analysis, Visualisation, Writing – original draft. Rajeev Mathur: Conceptualisation, Supervision, Validation, Writing – review and editing. Both authors have read and approved the final manuscript.

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Data Availability
No new data were generated or analysed in this study. All sources reviewed are cited in the reference list.

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