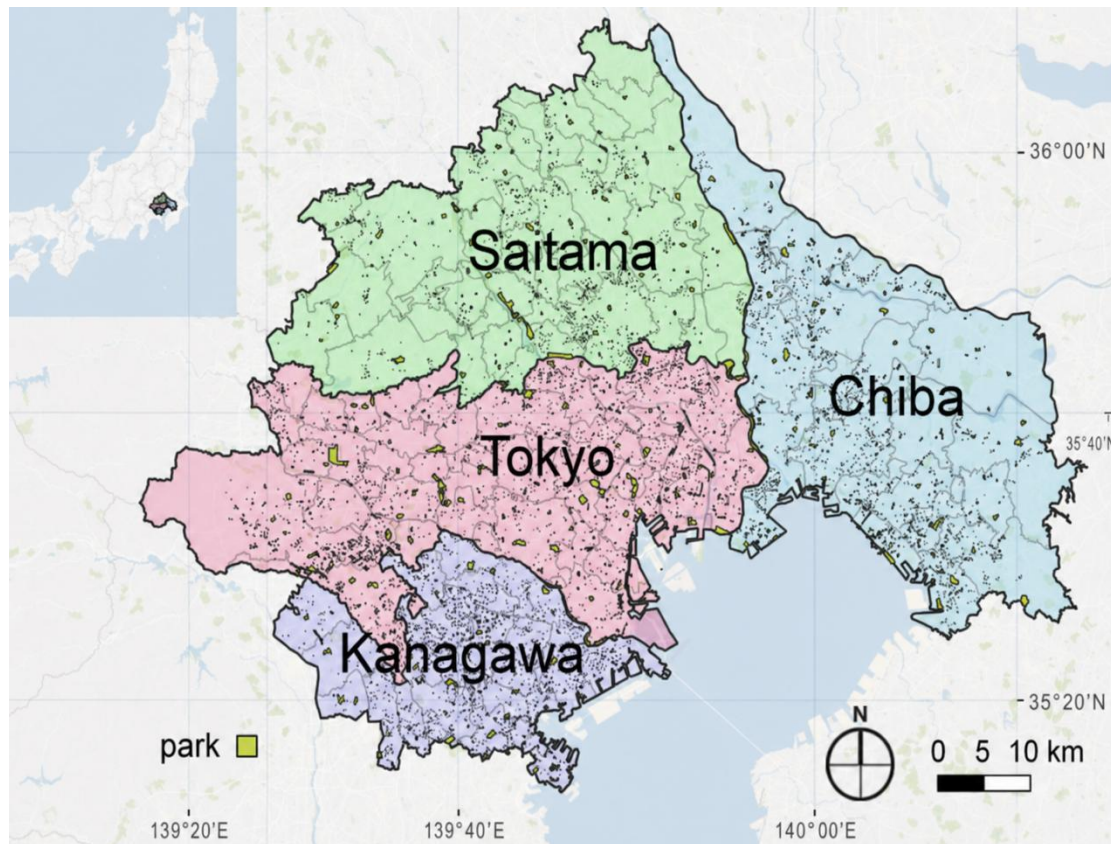


Supplementary information

Supplementary methods S1: Study area

We conducted a retrospective observational study to quantify park-attributable, walking-related health benefits and to assess park-level economic payback under a unified 2019 accounting framework. The study area comprised the full administrative extent of Tokyo Metropolis and the surrounding prefectures of Chiba, Saitama and Kanagawa. Analyses covered 1 January to 31 December 2019. The analytical sample was restricted to parks within the study boundary and to users with sufficient mobility records to support inference of a primary residential location for residence-based distance analyses.



Supplementary Fig. 1. Study area and urban-park locations across Tokyo Metropolis and the surrounding prefectures of Saitama, Chiba and Kanagawa.

Supplementary methods S2: Stay location extraction and Park visitation estimation.

To detect visitors of the urban parks and the visitors' residential locations, we first extract the stay location from the individual's raw human trajectory based on the method developed in the former work . Here we introduce it succinctly. The stay location of an individual's raw mobility trajectory is a series of consecutive points that represent the user staying at a location, while the moving location represents the user moving. The stay locations represent the places that a user spends a considerable amount of time, for example, home, workplace, restaurant, market, gym, park, etc. we extracted the stay location according to the distance Δl and time spam Δt of temporal

neighboring points which are less than the threshold. If $X_u = \{x_{t1}, x_{t2}, x_{t3}, \dots, x_{ti}, \dots\}$ denotes a set of GPS locations of user u where x_{ti} is the location at time t_i , $\{x_{ti}, x_{ti+1}, x_{ti+2}, \dots, x_{tm}\}$ that are within Δl and $t_m - t_i \leq \Delta t$ are grouped as a stop. The ones which are greater than the threshold are identified as moving segments. The noise points are removed according to the mean and standard deviation of Gaussian distribution. By implementing this process, we determine the travel state of each user during each period and obtained the stay location which allows life pattern detection next step. We use $S_u = \{S_1, S_2, S_3, \dots, S_i\}$ to represent the user u 's stay location history. Each stay point S_i represents a stay location. It retains the arrival time ($S.arvT$) and the leaving time ($S.leiT$) which respectively equals to the timestamp of the first and last GPS point constructing this stay point.

The urban park boundary polygons and stay points that were overlapping spatially are identified. In our research, stay points within the park boundary of each and stayed longer than five minutes are defined as a 'park visit'. The five-minute criterion is applied to exclude those who were simply passing through the parks since those parks which located closer to a transportation hub or crowded streets are more likely to have a higher number of 'passers-through'. Besides, the accuracy error of GPS records is in general at a minimal level of 10–30 m in optimal conditions where no obstructions existed. In the urban environment, the error margin can be higher because some tall structures can affect the accuracy of location detections. Therefore, we exclude park visitors whose primary residential locations are within the park boundaries or less than 10 meters from the park boundaries. To reduce the bias caused by data sparseness, parks with less than 5 visitors throughout the year are also excluded.

Supplementary methods S3: Residential locations estimation of visitors.

To detect the residential location of the visitors, we conduct the spatial clustering of stay location. Due to the uncertainty of human movements, two stay points in the same places may have different spatial coordinates. Thus, we need to cluster different stay points with the same semantic meaning. The centroid of the cluster was considered as a significant place (e.g., home, workplace, other) which represents the individual's typical activity. Here, DBSCAN (Density-Based Spatial Clustering of Applications with Noise) was utilized for spatial clustering. DBSCAN has been adopted in many mining applications of spatial data. It is a highly popular clustering method in determining the zones regularly visited by the individuals and has been proved to have a good performance among other techniques. Two parameters are required in DBSCAN method: the minimum number of points that can form a cluster ($minpts$) and the maximum distance within which two points belong to a cluster (eps). Points with a neighborhood eps more than $minpts$ are categorized as core points, and points reachable by a core point are border points of the cluster. Both core points and border points are considered as the clustered points. Points not within the eps search radius of any core point are treated as noise. Then, we identify residential locations from significant places. Here, we assume that every person has his/her own home and most people return homes at the end of a day. Although there are exceptions in the real world, this assumption simplifies the way we identify the residential locations from unlabeled GPS data and allows us to estimate residential locations justifiably. The residential location identification criteria included (1) Of all

the significant places, users spend the longest time at this place from 20:00–06:00 (2) at least four days a week for more than half of the total records. This estimation enabled us to execute the analyses on residential locations distribution of park visitor.

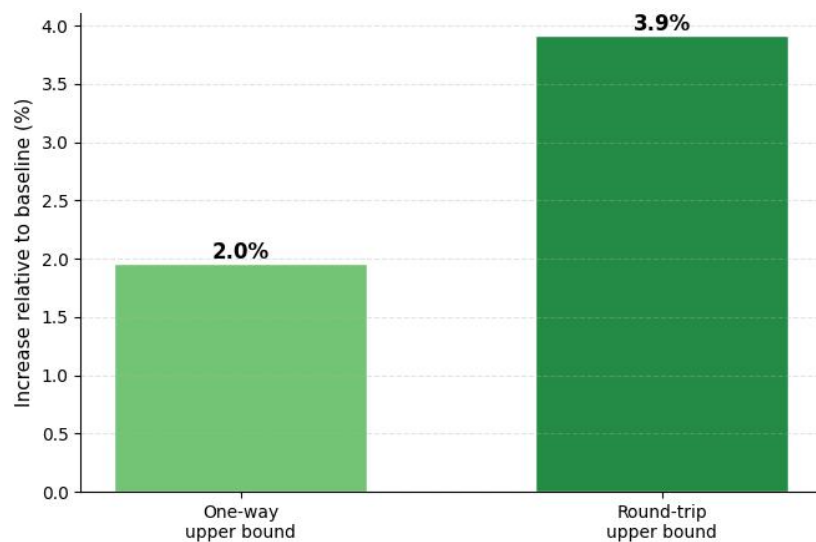
Supplementary methods S4: Upper-bound sensitivity analysis for home-to-park walking

The main analysis attributes health benefit to activity inferred from time spent within parks. To assess the possible contribution of walking to parks, we performed an upper-bound sensitivity analysis based on pedestrian network distance. This analysis was not intended to recover realized access-trip walking exactly, because the true trip origin and travel mode of each park visit were not observed. Instead, it was designed to evaluate the likely magnitude of the omitted component under a conservative scenario.

We restricted the analysis to routed user–park pairs with pedestrian network distance below 1.5 km. For this subset, we assumed that each visit originated from the inferred home location and that travel to the park was made entirely on foot. Let B_{up} denote the annual monetized health benefit originally assigned to user u and park p , and let ΔB_{up}^{acc} denote the additional hypothetical benefit from home-to-park walking. The sensitivity analysis therefore considered

$$B_{up}^* = B_{up} + \Delta B_{up}^{acc},$$

Population expansion was implemented using visit-level weights derived from 2019 census mesh population. Aggregating across all eligible user–park pairs, we found that including home-to-park walking increased the total monetized health benefit by 2.0% under a one-way assumption and 3.9% under a round-trip assumption. Thus, even under a conservative upper-bound specification, the contribution of access-trip walking remained modest relative to the baseline estimate.



Supplementary Fig. 2. Upper-bound sensitivity of population-scaled monetized health benefit to hypothetical home-to-park walking. Bars show the percentage increase relative to the baseline estimate under one-way and round-trip walking assumptions for routed user–park pairs within 1.5 km.

Supplementary methods S5: Sensitivity of results to the step-conversion coefficient

Because step counts were inferred from in-park dwell time rather than directly measured, we evaluated sensitivity to the step-conversion coefficient used to translate dwell time into steps. In the main analysis, inferred steps were calculated as dwell time multiplied by an assumed cadence and by the assumed fraction of in-park dwell time spent walking or being physically active. For sensitivity analysis, these two terms were treated jointly as a single effective conversion coefficient, rather than varied separately. We then applied global multipliers of 0.8, 0.9, 1.0, 1.1 and 1.2 to the baseline coefficient for all park visits, while keeping all cost inputs unchanged. These scenarios represent -20%, -10%, baseline, +10% and +20% perturbations around the main assumption.

For each scenario, we recomputed park-level annual monetized health benefit, annual net benefit and payback time. As expected, total monetized health benefit scaled proportionally across scenarios, whereas park-level benefit ranking remained unchanged in all cases. At the aggregate level, the share of parks recouping investment within 50 years ranged from 30.5% to 51.3%, compared with 41.1% in the baseline scenario, and the median finite payback time ranged from 86.6 to 56.5 years. Relative to baseline, 6.5–13.3% of parks changed payback category across alternative scenarios, indicating that the effect was concentrated mainly among parks near decision thresholds rather than producing a wholesale reordering of outcomes (Supplementary Table S1). Park-type differences were also robust: city block parks consistently showed the highest recoup potential, followed by neighborhood, district and comprehensive parks, whereas regional parks did not recoup within 50 years in any tested scenario (Supplementary Table S2). Together, these results indicate that uncertainty in inferred step counts affects the absolute magnitude of benefit and payback estimates more than the structural conclusions of the analysis.

Supplementary Table S1. Sensitivity of aggregate monetized benefit and payback outcomes to alternative step-conversion assumptions

Scenario	Step-conversion multiplier	Total annual monetized health benefit (JPY)	Parks recouping investment within 50 years (%)	Parks with non-estimable payback (%)	Median finite payback time (years)	Parks changing payback category vs. baseline (%)
Low (20%)	0.8	2.53×10^{11}	30.5	1.7	86.6	13.3
Low (10%)	0.9	2.84×10^{11}	35.9	1.4	76.6	6.5
Baseline	1.0	3.16×10^{11}	41.1	1.2	68.5	0.0
High (10%)	1.1	3.47×10^{11}	46.3	1.0	62.1	6.8
High (20%)	1.2	3.79×10^{11}	51.3	0.9	56.5	12.9

Supplementary Table S2. Robustness of park-type differences in recoup potential under alternative step-conversion assumptions

Park type	Number of parks	Parks recouping investment within 50 years under Low_20pct (%)	Parks recouping investment within 50 years under Baseline (%)	Parks recouping investment within 50 years under High_20pct (%)
City block park	1702	33.4	43.5	53.0
Neighborhood Park	1859	25.3	34.8	43.7
District Park	415	12.4	18.5	24.8
Comprehensive	144	4.7	10.1	16.9

Park type	Number of parks	Parks recouping investment within 50 years under Low_20pct (%)	Parks recouping investment within 50 years under Baseline (%)	Parks recouping investment within 50 years under High_20pct (%)
Park				
Regional Park	19	0.0	0.0	0.0

Supplementary methods S6: Construction of spatial representation weights for population scaling

To scale visit-derived benefits from the observed mobility sample to the population, we used spatial representation weights defined on inferred residential areas. Let r index residential areas, P_r^{cens} denote the census population assigned to area r , and let P_r^{obs} denote the number of unique observed users whose inferred primary residence was assigned to the same unit. For units with at least one observed user, the representation weight was defined as

$$\omega_r = \frac{P_r^{\text{cens}}}{P_r^{\text{obs}}}, \quad P_r^{\text{obs}} > 1$$

Each visit inherited the weight of the visitor's inferred residential area. Let $r(v)$ denote the inferred residential area associated with visit v , and let S_v denote the inferred step count for that visit. Population-scaled annual monetized health benefit for park k was then computed as

$$B_k^{\text{pop}} = \nu \sum_{v \in V_k} \omega_{r(v)} S_v$$

where V_k denotes the set of qualifying visits to park k .

This formulation corrects for spatial under- or over-representation of the observed sample relative to the census population distribution, while leaving within-sample visit behaviour unchanged. Under spatially uniform sample coverage, ω_r reduces to a constant across residential units, in which case the method collapses to the original single-factor upscaling approach. Because the weights are defined from the number of observed residential users rather than from visit counts, the adjustment targets sample coverage rather than behavioural intensity itself. To reduce instability from sparsely sampled residential units, we additionally tested robustness using a minimum threshold of 10 observed users per residential unit and winsorization of representation weights at the 1st and 99th percentiles.

Supplementary methods S7: Construction and O&M unit costs.

Because park-specific capital and operating budgets are not consistently available at scale, we adopted standardized unit-cost schedules to enable system-wide comparability under a unified accounting basis. For non-land construction cost, an industry assessment for newly opened, barrier-free metropolitan parks in Tokyo reports an overall development cost of approximately 14,000 JPY m⁻² and notes that planning, design and supervision are typically budgeted at 10–20% of construction expenditure¹. To align this benchmark with our accounting scope—which models non-land construction cost as a single area-based schedule and excludes soft-cost items that are not consistently reported at scale—we used *construction cost*

=12,000 JPY m⁻², which falls within the implied range when the benchmark development cost is adjusted for typical soft-cost shares.

Annual operation and maintenance (O&M) costs were calculated on an area basis using unit-cost statistics reported in the Tokyo Metropolitan Government Audit Office tables for park maintenance management costs: Table 2–7 (outsourcing-fee budget unit cost) and Table 2–8 (works-contract budget unit cost). We constructed an all-in O&M unit rate for each official maintenance category c as $k_{om,c} = u_c^{out} + u_c^{work}$, taking u_c^{out} from Table 2–7 and u_c^{work} from Table 2–8 for the same category and year. Guided by the latest-year magnitudes and the expected ordering of maintenance intensity across categories, we applied a conservative, harmonized five-level O&M schedule across the study to support system-wide accounting: block parks 225, conservation green spaces 67, district parks 270, regional parks 315, and special parks 385 (JPY m⁻²year⁻¹). Importantly, this O&M categorization is distinct from the area-based A–E grouping used for stratified analyses and reporting; A–E types are used only for analysis/presentation, whereas the official five-category scheme is used only to assign O&M unit rates. We used the latest-year values in Tables 2–7 and 2–8 as anchors and applied a conservative harmonized schedule across categories to support system-wide comparability. Because the step-value parameter and O&M unit rates were drawn from different source years, these monetary inputs were converted to constant 2019 JPY using official Japanese Consumer Price Index series. Specifically, the 2017 step-value parameter and the O&M unit rates derived from the 2003 source were restated on a 2019 price basis.

Supplementary methods S8: Land price

We performed land-price assignment using standard GIS workflows. Each park polygon was represented by its centroid. We generated a 500 m buffer around each centroid and performed a spatial join to retrieve all L01 land-price points intersecting the buffer. The park-level land price was computed as the mean of the unit prices (JPY m⁻²) of the matched points. If a centroid buffer contained no L01 points, we assigned the unit price of the nearest L01 point (nearest-neighbor join) to ensure complete coverage. These park-level land-price estimates were used in subsequent cost accounting. All distance-based GIS operations (buffers and nearest-neighbor joins) were performed in a projected coordinate reference system to ensure metric consistency.

Supplementary methods S9: Discount-rate sensitivity analysis

S9.1 Discount-rate sensitivity analysis

Here, 1%, 2% and 4% are used to represent lower, central and upper real discounting cases rather than interchangeable alternatives. In Japanese public-project appraisal, 4% remains a conventional benchmark largely for continuity with past practice, whereas recent MLIT materials also identify 1% and 2% as standard reference values under changed macro-financial conditions. Because the benefit stream evaluated here represents preventive-health returns generated by realised in-park walking rather than a conventional commercial project cash flow, we treat 2% as the central discounting case, consistent with Japanese health-economic evaluation guidance and broader international practice of applying lower discounting to health and life effects than to standard public investments. To isolate the effect of discounting, we repeated the

evaluation using real discount rates of 1%, 2% and 4%, while holding all other assumptions constant, including the 50-year evaluation horizon, the constant-2019-JPY accounting basis, and the base-case annual real growth assumptions for annual monetized health benefit and annual O&M cost ($g_B = 2\%$, $g_{OM} = 2\%$).

Estimated recoverability declined monotonically as the real discount rate increased. At 1%, 51.5% of parks recouped investment within 50 years and 51.5% had positive 50-year NPV, while 1.2% never fully recouped. At 2%, the corresponding values were 41.1%, 41.1% and 4.8%. At 4%, they declined to 22.9%, 22.9% and 57.8%, respectively. Lower discount rates therefore yield less restrictive recovery estimates, whereas the 4% case provides the most conservative benchmark among the tested discounting scenarios. Although absolute recovery levels vary, the overall structure of the results remains stable: smaller park types consistently retain a greater prospect of recouping investment, whereas larger parks remain concentrated in long-horizon or non-recoverable cases.

Supplementary Table S3. Sensitivity of discounted economic feasibility estimates to the discount rate

Discount rate	50-year present-value factor	Parks recouping within 50 years (%)	Parks never fully recouping (%)	Median payback among parks recouping within 50 years (years)	Mean payback among parks recouping within 50 years (years)
1%	39.196	51.5	1.2	30	29.3
2%	31.424	41.1	4.8	30	29.3
4%	21.482	22.9	57.8	26	26.5

S9.2 Growth-rate sensitivity analysis

The main analysis assumes annual real growth rates of 2% for both annual monetized health benefit and annual O&M cost. Because long-run growth in these recurring annual flows is uncertain, we additionally examined annual real growth assumptions over the 0% – 3% range while holding all other assumptions constant. In this analysis, the real discount rate was fixed at 2%.

Recovery outcomes changed in the expected direction. Higher annual real benefit growth increased the share of parks recouping within 50 years and reduced the share never fully recouping, whereas higher annual real O&M growth had the opposite effect. Across the tested grid, the share recouping within 50 years ranged from 22.1% to 52.6%, while the share never fully recouping ranged from 2.6% to 69.7% under finite-precision reporting. The base-case scenario ($r=2\%$, $g_B=2\%$, $g_{OM}=2\%$) lay near the middle of this range, with 41.1% of parks recouping within 50 years and 4.8% never fully recouping. These results indicate that economic-feasibility estimates are materially affected by assumptions about long-run growth in annual health-related benefit and maintenance burden, although the overall ranking by park type remains stable.

Supplementary Table S4. Sensitivity of discounted economic-feasibility estimates to annual real growth assumptions under the central discount-rate case (Discount rate fixed at $r=2\%$).

Benefit growth (g_B)	O&M growth (g_{OM})	Parks recouping within 50 years (%)	Parks with positive 50-year NPV (%)	Parks never fully recouping (%)	Median payback among parks recouping within 50 years (years)	Mean payback among parks recouping within 50 years (years)
0%	0%	23.2	23.2	57.8	26	26.4
0%	1%	23.0	23.0	60.5	26	26.4
0%	2%	22.5	22.5	65.3	25	26.0
0%	3%	22.1	22.1	69.7	25	25.9
1%	0%	31.3	31.3	29.5	28	28.0
1%	1%	31.1	31.1	31.5	28	28.0
1%	2%	30.6	30.6	39.8	28	27.9
1%	3%	29.9	29.9	49.6	28	27.7
2%	0%	42.3	42.3	2.6	30	29.6
2%	1%	41.7	41.7	2.7	30	29.4
2%	2%	41.1	41.1	4.8	30	29.3
2%	3%	40.2	40.2	20.9	30	29.1
3%	0%	52.6	52.6	0.0*	30	29.6
3%	1%	52.1	52.1	0.0*	30	29.5
3%	2%	51.6	51.6	0.1	30	29.5
3%	3%	51.0	51.0	1.2	30	29.4

Supplementary methods S10: Effective served population (Epop).

We computed an effective served population for each park, $E_{pop(p)}$, by allocating population from population units i to nearby parks under distance decay and competition normalization. Units were DID polygons from MLIT KSJ A16 (2019), with Pop_i and unit locations represented by polygon centroids. Equations used:

$$P(i) = p | dip \leq R, R = 6 km$$

$$w_{ip} = \sigma_{t(p)} \cdot d_{ip}^{\beta_{t(p)}}$$

$$share_{ip} = \frac{w_{ip}}{\sum_{q \in P(i)} w_{iq}}$$

$$E_{pop}(p) = \sum_i Pop_i \cdot share_{ip}$$

Candidate-site E_{pop} was computed by adding the candidate as an additional competitor within R . Distances were computed in a projected metric CRS.

Supplementary methods S11: Elasticity interpretation and local sensitivity of discounted payback performance

For park type $t \in \{A, B\}$, predicted annual health benefit was modeled as

$$\widehat{B}_{s,t} = \kappa_t \cdot land_price_s^{b_{1,t}} \cdot area_s^{b_{2,t}} \cdot E_{pop,s}^{b_{3,t}} \cdot maint_s^{b_{4,t}}.$$

The fitted parameter values for Types A and B are reported in Supplementary Table S11. Taking logs gives

$$\ln \widehat{B}_t = \ln \kappa_t + b_{1,t} \ln (land_price) + b_{2,t} \ln (area) + b_{3,t} \ln (E_{pop}) + b_{4,t} \ln (maint).$$

so $b_{1,t}$, $b_{2,t}$, $b_{3,t}$, and $b_{4,t}$ are benefit elasticities with respect to land price, area, effective served population, and maintenance intensity, respectively.

One-off planning cost was defined as

$$C_0 = \text{area} \cdot (\text{land_price} + k_{\text{con}}).$$

where k_{con} is the construction unit cost. Annual operation and maintenance cost in the base year was defined as

$$OM_0 = \text{area} \cdot \text{maint.}$$

Baseline annual net benefit was then defined as

$$N_0 = \widehat{B}_t - OM_0.$$

Predicted discounted payback time T_t was defined as the earliest year satisfying

$$\sum_{y=1}^{T_t} \frac{\widehat{B}_t(1+g_B)^{y-1} - OM_0(1+g_{OM})^{y-1}}{(1+r)^y} \geq C_0.$$

with the main specification set to

$$r=0.02, \quad g_B=0.02, \quad g_{OM}=0.02.$$

Under this specification, because the annual benefit growth rate, annual O&M growth rate, and discount rate are equal, discounted annual net benefit is proportional to the base-year net benefit. For local sensitivity analysis, discounted payback was therefore approximated by the continuous expression

$$T_t^* = \frac{(1+r) C_0}{N_0}$$

which provides a smooth local analogue of discounted payback time and avoids the stepwise behaviour of integer-valued payback years.

Local sensitivity was quantified as the elasticity of discounted payback with respect to each planning variable X :

$$\varepsilon_X = \frac{\partial \ln T_t^*}{\partial \ln X}$$

A positive elasticity indicates that increasing X lengthens discounted payback, whereas a negative elasticity indicates that increasing X shortens discounted payback. The effect of a 10% increase in X was summarized as

$$\% \Delta T_t^* = (1.1^{\varepsilon_X} - 1) \times 100\%$$

Representative baseline inputs were defined using the median observed land price, effective served population, and maintenance intensity within each park type, together with fixed representative candidate areas of 0.18 ha for Type A and 1.10 ha for Type B. These values are used as representative baselines for the local elasticity analysis; the spatial siting scenario in Fig. 4b uses 0.18 ha for Type A and 0.90 ha for Type B. Construction unit cost was inferred from the park-level accounting table and fixed at the median within each type.

For E_{pop} , which enters only the benefit function, the elasticity is

$$\frac{\partial \ln T_t^*}{\partial \ln E_{pop}} = -\frac{b_{3,t}\widehat{B}_t}{N_0}$$

For maintenance intensity, which enters both the benefit function and annual O&M cost, the net elasticity is

$$\frac{\partial \ln T_t^*}{\partial \ln maint} = \frac{OM_0 - b_{4,t}\widehat{B}_t}{N_0}$$

For park area, which enters one-off cost, annual O&M, and annual benefit, the net elasticity is

$$\frac{\partial \ln T_t^*}{\partial \ln area} = 1 - \frac{b_{2,t}\widehat{B}_t - OM_0}{N_0}$$

For land price, defining the land-cost share in one-off investment as

$$s_{land} = \frac{land_price}{land_price + k_{con}}$$

the net elasticity is

$$\frac{\partial \ln T_t^*}{\partial \ln land_price} = s_{land} - \frac{b_{1,t}\widehat{B}_t}{N_0}$$

These expressions show that the effects of area, land price, and maintenance intensity are net effects on discounted payback rather than pure benefit elasticities, because each variable affects both the cost side and the benefit side of the predictor.

Using the representative baseline values, the local elasticities for Type A were +0.095 for land price, +0.036 for area, -0.111 for E_{pop} , and -0.215 for maintenance intensity. These correspond to changes in discounted payback of +0.91%, +0.34%, -1.05%, and -2.03%, respectively, for a 10% increase in each variable. Thus, for Type A, maintenance intensity was the strongest variable shortening discounted payback, followed by effective served population, whereas land price and area weakly lengthened discounted payback.

For Type B, the corresponding local elasticities were +0.126 for land price, +0.297 for area, -0.101 for E_{pop} , and -0.25 for maintenance intensity. These correspond to changes in discounted payback of +1.20%, +2.87%, -0.96%, and -2.33%, respectively, for a 10% increase in each variable. Thus, for Type B, park area was the strongest variable lengthening discounted payback, whereas maintenance intensity was the strongest variable shortening discounted payback.

Overall, the local sensitivity analysis indicates that discounted payback performance in small parks is most responsive to maintenance intensity and effective served population in Type A, and to area and maintenance intensity in Type B. By contrast, land price exerts a positive but only moderate effect on discounted payback in both types under the representative baseline conditions.

Supplementary Table S11. Parameter estimates and local discounted-payback sensitivity for Types A and B parks.

Type	κ_t	$b_{1,t}$	$b_{2,t}$	$b_{3,t}$	$b_{4,t}$	Effect of +10% (land_price)	Effect of +10% (area)	Effect of +10% (E_pop)	Effect of +10% (maint)
A	0.035	0.813	0.966	0.106	0.251	+0.91%	+0.34%	-1.05%	-2.03%
B	0.337	0.772	0.722	0.095	0.294	+1.20%	+2.87%	-0.96%	-2.33%

Supplementary Note N1

Payback-period classes. The payback period is not a sufficient condition for whether a project “makes money”; rather, it is a capital tie-up and risk-exposure metric under financing constraints. It captures how long capital is locked in a project and the time window during which the project remains exposed to uncertainty before the initial outlay is recovered. Treating the government as a rational capital allocator, a longer payback period implies: (i) longer capital lock-in and higher opportunity costs, reducing fiscal flexibility for alternative investments; (ii) a longer exposure window to uncertainty and structural change (e.g., demand, maintenance regimes, and policy environments), increasing forecasting error risk; and (iii) under discounting, a markedly lower present-value weight on distant benefits, making very long recoveries intrinsically disadvantaged in economic ranking. Motivated by these considerations, we grouped payback periods into 0–5 years, 5–20 years, and 20–50 years, representing short-, medium-, and long-cycle projects in terms of recovery speed and risk profile. This binning provides a consistent scale for prioritization in an investment-oriented comparison, in line with guidance commonly used in large-park cost–benefit appraisal practice².

References

1. Tokuda, Hidenobu. *Ots series 4: effects of promoting “barrier-free” improvements in public transportation and other facilities*. (2014).
2. Ministry of Land, Infrastructure, Transport and Tourism (Japan), Urban Bureau, Parks and Landscape Division. *Daikibo Koen Hiyou Taikouka Bunseki Shuho Manual (Kaitei 4-han) [Large-scale Park Cost–Benefit Analysis Manual (4th rev. ed.)]*. <https://www.mlit.go.jp/common/001187812.pdf> (2017).