



Development and validation of an AI-based predictive Global Sustainability Index (IGD) for community infrastructure: a methodological protocol for proactive management of public assets

Ahonankpon Hubert Frédéric GBAGUIDI 

Research Unit for the Sustainability of Urban Infrastructure and Services, Laboratory of Geosciences, Environment and Applications (LaGEA), National Higher School of Public Works (ENSTP), National University of Sciences, Technologies, Engineering and Mathematics (UNSTIM), Benin.

*Corresponding Author

Ahonankpon Hubert
Frédéric GBAGUIDI

Abstract: Community infrastructure management remains largely based on current-condition assessment and corrective or preventive interventions. This approach has a major limitation: it provides insufficient information about the likely deterioration trajectory of assets and the time at which their sustainability may cross a critical threshold. Research on the Global Sustainability Index (IGD) has introduced a multidimensional infrastructure assessment integrating physical, functional, environmental, economic, social and institutional dimensions. However, when calculated at a single point in time, the IGD remains essentially a state indicator.

This paper proposes a methodological protocol for developing and validating an Artificial Intelligence-based Predictive Global Durability Index (IGD_p). The approach relates to a longitudinal database combining repeated IGD assessments with technical characteristics, usage intensity, environmental exposure, maintenance history, spatial information, and economic, social and institutional variables. Several model families are proposed for comparison, including statistical baselines, Random Forest, Gradient Boosting, XGBoost and, where justified by data availability, neural and temporal models.

The validation framework combines five dimensions: predictive performance, temporal validation, robustness and generalization, explainability, and decision usefulness. Proposed performance metrics include mean absolute error, root mean square error and coefficient of determination. Explainability is integrated through feature-contribution approaches, including SHAP. Procedures for uncertainty quantification, sensitivity analysis of IGD weights and external validation are also proposed.

The methodological architecture predicts the future values of individual durability dimensions before aggregating them into the IGD_p. This strategy preserves the multidimensional interpretability of the index while adding a prognostic capability. The proposed protocol therefore constitutes an intermediate step between static sustainability assessment and prescriptive community infrastructure management.

Keywords: Global Sustainability Index; predictive IGD; artificial intelligence; community infrastructure; predictive maintenance; asset management.

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Introduction

Community infrastructure plays a vital role in the functioning of territories. Roads, sanitation and drainage works, public buildings, water supply facilities, markets, schools, health centers, public lighting systems and other collective facilities provide the physical support for services essential to economic and social development.

However, the progressive deterioration of these infrastructures poses a major challenge for local authorities. Budgetary constraints, inadequate maintenance programs, fragmented asset information, the effects of aging, increased usage, and exposure to environmental hazards frequently lead managers to intervene only after visible damage or malfunctions have appeared.

Such a logic remains essentially reactive. Sustainable asset management, on the other hand, requires answering the following questions successively: What is the current state of the infrastructure? How is this state evolving? What will its future state likely be? When and how should intervention take place? The first two questions mainly concern diagnosis and monitoring. The last two introduce forecasting and proactive decision-making.

The work dedicated to the Global Sustainability Index has made it possible to move beyond a purely physical assessment of the state of infrastructure. The framework tested in the municipality of Nikki is based on several complementary dimensions of sustainability, including physical, functional, environmental, economic, social, and institutional (Gbaguidi et al., 2025). Its subsequent application to the road network of Porto-Novo strengthened its decision-support function by linking sustainability assessment with intervention prioritization (Gbaguidi, 2026).

This work allows us to answer the question: what is the level of sustainability of the infrastructure at the time of the assessment? However, it does not yet allow us to answer with empirical precision the question: what will its level of sustainability be at a given future horizon? This limitation justifies the introduction of a predictive approach.

Recent developments in artificial intelligence now make it possible to leverage historical, technical, environmental, and behavioral data to predict the future evolution of assets. Applications include damage detection, anomaly recognition, condition prediction, remaining useful life estimation, and predictive maintenance. However, most research remains heavily focused on technical or structural performance. It less frequently incorporates functional, economic, social, or institutional dimensions within a single predictive architecture.

This article therefore starts from the hypothesis that a multidimensional sustainability index can constitute not only a diagnostic tool, but also a structured basis for learning future trajectories.

1. Methodological approach

The general problem is formulated as follows: How to develop and validate an artificial intelligence model capable of predicting the multidimensional evolution of the sustainability of community infrastructures from longitudinal measurements of the IGD and technical, environmental, economic, social and institutional variables?

The overall objective is to develop a validation protocol for a predictive Global Sustainability Index based on artificial intelligence.

The specific objectives are to:

1. to structure the variables necessary for the establishment of a longitudinal sustainability basis;
2. compare several statistical and artificial intelligence models for the prediction of IGD;
3. evaluate the performance, robustness and generalizability of models;
4. explain the factors contributing to the predicted trajectories;
5. validate the decision-making utility of predictive IGD for maintenance scheduling.

The research is organized around five questions:

1. Do the historical values of the constituent dimensions of the IGD allow us to predict their future evolution?
2. Does adding variables related to age, use, maintenance, climate, and institutional management improve the accuracy of predictions?
3. Which models offer the best compromise between predictive accuracy, robustness, ease of interpretation, and simplicity of deployment?
4. Does predictive IGD allow for earlier identification of infrastructures likely to reach a critical level?
5. Does the integration of the IGD_p improve the scheduling of interventions compared to prioritization based solely on the current state?

In order to answer these questions, the following hypotheses are formulated:

Successive measurements of the dimensions of the IGD contain sufficient information to allow prediction of their evolution in the short and medium term.

The integration of technical, environmental, usage and maintenance variables significantly reduces the prediction error compared to a model using only the previous IGD.

Nonlinear machine learning models exhibit better predictive performance than linear statistical models when the relationships between degradation factors are complex.

Explainable artificial intelligence methods make it possible to identify the dominant determinants of the sustainability trajectory and to improve the operational utility of the model.

The combination of current IGD, predictive IGD and criticality improves the prioritization of interventions compared to a decision based solely on the observed state.

2. Results and discussion

a. Conceptual foundations, definition of the predictive Global Sustainability Index and conceptual research model

At this moment t , the observed IGD of an infrastructure j is written as:

$$IGD_j(t) = \sum_{i=1}^n w_i D_{ij}(t)$$

with :

$$\sum_{i=1}^n w_i = 1$$

Repeated evaluation produces a series:

$$IGD_j(t_1), IGD_j(t_2), IGD_j(t_3), \dots, IGD_j(t_n)$$

This series transforms a one-time indicator into a sustainability trajectory.

Instead of using only the aggregate score, the search retains the vector:

$$X_j(t) = [D_{ph,j}(t), D_{fon,j}(t), D_{env,j}(t), D_{eco,j}(t), D_{soc,j}(t), D_{inst,j}(t)]$$

where D_{ph} , D_{fon} , D_{env} , D_{eco} , D_{soc} and D_{inst} respectively denote the physical, functional, environmental, economic, social and institutional dimensions.

A second vector encompasses the factors likely to influence the evolution:

$$Z_j(t) = [A_j, U_j, M_j, Cl_j, T_j, Sp_j, \dots]$$

Or A_j refers to age, U_j level of use, M_j maintenance history, Cl_j climatic exposure, T_j technical characteristics and Sp_j spatial characteristics.

The predictive IGD, noted $IGD_{p,j}$, represents the probable sustainability of the infrastructure j over the horizon $t + \Delta t$.

The preferred approach is to predict each dimension separately:

$$\widehat{D}_{ij}(t + \Delta t) = f_i[X_j(t), Z_j(t)]$$

then to reconstruct the index:

$$IGD_{p,j}(t + \Delta t) = \sum_{i=1}^n w_i \widehat{D}_{ij}(t + \Delta t)$$

This architecture is preferred to a direct prediction of the IGD alone, because it retains the possibility of identifying the dimension responsible for an unfavorable development.

The predicted variation is:

$$\Delta IGD_j = IGD_{p,j}(t + \Delta t) - IGD_j(t)$$

The average rate of change is:

$$V_{IGD,j} = \frac{IGD_{p,j}(t + \Delta t) - IGD_j(t)}{\Delta t}$$

The selected experimental setup is:

Observation $T_0 \rightarrow$ **IGD**(T_0) $\rightarrow$ **Observation** $T_1 \rightarrow$ **IGD**(T_1) $\rightarrow$ **Observation** $T_2 \rightarrow$ **IGD**(T_2) $\rightarrow$ **learning** $\rightarrow$ **prediction** $\rightarrow$ **subsequent real observation** $\rightarrow$ **comparison** $\rightarrow$ **recalibration**.

It can be summarized as follows:

"Historical data" $\rightarrow$ **"Training"** $\rightarrow$ **IGD_p** $\rightarrow$ **"Future observation"**

The model becomes truly scientific when the predicted value can be compared with a later, actually observed value.

b. Study population

The initial validation should not immediately mix all infrastructure categories. The mechanisms of degradation for a road, a building, a sewage system, or a public lighting system are different. Therefore, the first experiment should focus on a relatively homogeneous group. The municipal road network is a particularly relevant candidate due to the importance of the service, the existence of observable defects, the simultaneous influence of traffic, drainage, and climate, the frequency of maintenance needs, and the possibility of segmenting the network into homogeneous units. A second validation could then be conducted on the built heritage.

For a road network, the unit of observation can be a homogeneous road segment. Each segment must have a unique identifier. For built heritage, the unit can be the building or a homogeneous functional unit within the building. This distinction must be established before data collection.

The final sample size will need to be determined based on the number of available assets, the heterogeneity of the network, the number of variables, the frequency of

measurements, the expected rate of missing data, and the complexity of the models being tested. For an initial study, it is preferable to have a large number of relatively homogeneous units rather than a small number of very different assets.

Representativeness must take into account location, age, level of service, construction type, intensity of use, initial condition, and level of exposure. The predictive nature of the data necessitates multiple campaigns. The minimum protocol may include:

$$T_0, T_1, T_2, T_3$$

with :

$$IGD_j(T_0), IGD_j(T_1), IGD_j(T_2), IGD_j(T_3)$$

The frequency depends on the type of infrastructure. For heavily used road infrastructure, a campaign every six or twelve months could be tested. Additional observations will need to be carried out after any work, a major flood, a major weather event, or a substantial change in usage levels.

c. Database architecture and data quality

Table 1. Proposed structure of the longitudinal base

Band	Indicative variables	Nature
Identification	ID, coordinates, type	Stable
Time	date, campaign, interval	Temporal
Physical	condition, pathologies, materials	Dynamic
Functional	availability, capacity, service	Dynamic
Environmental	drainage, flooding, erosion, heat	Dynamic
Economic	costs, maintenance expenses	Dynamic
Social	population served, accessibility	Dynamic
Institutional	inspections, budget, responsibility	Dynamic
Use	traffic, visitor numbers, demand	Dynamic
Maintenance	date, type, cost, intensity	Events
Space	network, land use, hazards	Spatiotemporal
Target variable	IGD or future dimension	Predictive

Before any learning, the data must be audited for completeness, consistency, outliers, duplicates, spatial accuracy, temporal consistency, stability of definitions and the rate of missing data.

A data dictionary must accompany the database. Each variable must be associated with a definition, a unit, a measurement method, a source, a frequency, a scale, and a rule for handling missing values. The planned steps include cleaning, imputation, normalization, encoding, and the construction of derived variables. These derived variables may include time since last maintenance, frequency of interventions, age since rehabilitation, cumulative flood events, average usage intensity, and the historical slope of the IGD (Intensity of Gap).

d. Models to compare and validation strategy

The goal is not to demonstrate that a sophisticated model is automatically better. It is to identify the best compromise for real-world management.

- **Model M0 (Persistence)**

The simplest model assumes:

$$IGD(t + \Delta t) = IGD(t)$$

It constitutes a minimum standard.

- **Model M1 (Regression)**

A linear or regularized model allows for the establishment of an interpretable benchmark.

- **Model M2 (Random Forest)**

Random Forest is well -suited to non-linear relationships and interactions between variables.

- **Model M3 (Gradient Boosting)**

Boosting methods often allow for good performance on structured tabular data.

- **Model M4 (XGBoost)**

XGBoost can be tested for its ability to handle complex relationships while remaining compatible with explanation methods like SHAP.

- **M5 Model (Neural Network)**

It will only be retained if the size of the database justifies it.

- **Model M6 (Time Model)**

An LSTM or related time model will only be considered when the time depth is sufficient.

Table 2. Planned experimental comparison

Model	Main advantage	Main limit
Persistence	Very simple reference	No learning
Regression	Interpretability	Limited complex relationships
Random Forest	Robustness on tabular data	Limited extrapolation
Gradient Boosting	Good predictive ability	Setting
XGBoost	Performance and flexibility	Increased complexity
Neural network	Very complex relationships	Data requirements
Time model	Longitudinal dynamics	Need for long series

- **Fundamental principle**

A common mistake is to randomly mix past and future observations. For a predictive system, validation must be time-sensitive. The principle will therefore be:

passé → apprentissage

Then :

futur → test

- **Time validation**

Example: T_0 and $T_1 \rightarrow$ **learning**; $T_2 \rightarrow$ **validation**; $T_3 \rightarrow$ **independent test**.

This approach simulates the manager's real-life situation.

- **External validation**

When possible, the model developed for one municipality should be applied to another area within the same municipality, then to another municipality, or to a population of infrastructure not used during the training phase. This step measures territorial generalization.

e. Performance metrics, dimensional validation, and uncertainty analysis

For continuous scores, three main metrics are retained.

- **Mean absolute error**

$$MAE = \frac{1}{N} \sum_{j=1}^N |y_j - \hat{y}_j|$$

- **Root of the mean squared error**

$$RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^N (y_j - \hat{y}_j)^2}$$

- **Coefficient of determination**

$$R^2 = 1 - \frac{\sum_j (y_j - \hat{y}_j)^2}{\sum_j (y_j - \bar{y})^2}$$

No metric should be interpreted in isolation. A significant innovation is to measure errors at two levels.

In terms of dimensions:

MAE_{ph} , MAE_{fon} , MAE_{env} , MAE_{eco} , MAE_{soc} , MAE_{inst}

At the global level:

MAE_{IGD}

This double validation will make it possible to identify a situation in which the overall score would be correctly predicted despite significant errors on certain dimensions. A single prediction is insufficient for public decision-making. The system must provide:

$\widehat{IGD}_{p,j}$

accompanied by a prediction interval:

$$IP_{95\%} = [L_j, U_j]$$

The width of the gap itself constitutes information. Infrastructure exhibiting high uncertainty may be referred for further inspection.

Accuracy alone is not enough. The manager must be able to understand why the model predicts deterioration. SHAP methods can be used to measure the contribution of variables to the predictions. For a given infrastructure, the system could, for example, identify the time since the last maintenance, repeated exposure to flooding, age, overloading, poor drainage, or budget constraints. These results should be interpreted as predictive contributions and not automatically as causal relationships.

Two levels will be distinguished. The overall explanation answers the question: what factors most influence the model for the entire asset class? The local explanation answers: why does this particular infrastructure receive this prediction? This distinction is essential for territorial management.

- **IGD Sensitivity Analysis**

Since :

$$IGD = \sum_i w_i D_i$$

The result depends on the weightings. Therefore, the sensitivity analysis must test several configurations:

$$W^{(1)}, W^{(2)}, \dots, W^{(s)}$$

and recalculate:

$$IGD_p^{(1)}, IGD_p^{(2)}, \dots, IGD_p^{(s)}$$

The objective is to measure the stability of predictions and rankings.

- **Risk of information leakage and class imbalance**

The protocol must prevent data leakage . A variable should not be used to predict an event if it would not have been available at the actual time of the decision. For example, information recorded after an intervention cannot be used to predict the decision that led to that same intervention.

If the goal is to predict when a critical threshold will be crossed, failures may be rare. Particular attention must then be paid to recall, precision, the F1 score, the AUC, and the confusion matrix. Overall accuracy alone can be misleading.

f. IGD scientific validation criteria_p

The predictive IGD will be considered sufficiently validated only if it simultaneously satisfies several conditions.

Table 3. Proposed validation framework

Dimension	Question
Exactness	Is the future value correctly predicted?
Calibration	Does the announced uncertainty correspond to the observed errors?
Robustness	Does the model hold up to noise and missing data?
Temporality	Does it work based on future observations?
Generalization	Does it work on unseen assets?
Explainability	Can the determinants be interpreted?
Sensitivity	Do the results hold up to weight fluctuations?
Utility	Does prediction improve decision-making?
Feasibility	Can it be used with the available resources?

- **Validation of decision utility**

The final step is no longer just about statistics. It will be necessary to compare two strategies.

The strategy S_0 is based on:

$$IGD(t)$$

The strategy S_1 is based on:

$$IGD(t) + IGD_p(t + \Delta t) + ICR$$

The two strategies can be compared based on the number of failures avoided, maintenance costs, unplanned emergencies, service level maintenance, and the number of assets serviced before reaching a critical threshold. This comparison constitutes the true utility test of the model.

- **Integration of criticality**

Infrastructure that is susceptible to rapid degradation is not automatically a priority. Criticality can be represented by:

$$ICR_j = \alpha P_{f,j} + \beta S_j + \gamma E_j + \delta C_j + \varepsilon A_j$$

with :

$$\alpha + \beta + \gamma + \delta + \varepsilon = 1$$

The decision will then involve $IGD_j(t)$, $IGD_{p,j}(t + \Delta t)$ and ICR_j .

- **System maturity model**

Development can be organized into four levels.

Level 1: IGD descriptive

$$IGD(t)$$

Level 2: Longitudinal IGD

$$IGD(t_1), IGD(t_2), \dots, IGD(t_n)$$

Level 3: Predictive IGD

$$IGD_p(t + \Delta t)$$

Level 4: Prescriptive IGD

$$IGD_p(A_q, t + \Delta t)$$

This progression helps to avoid premature technological sophistication.

g. Expected results, interpretation criteria and discussion

This article does not report any fabricated empirical results. It defines the results that must be produced during the experimental phase.

The first expected outcome is a normalized longitudinal baseline of the studied infrastructure. The second is the identification of the model offering the best compromise between accuracy, robustness, explainability, and implementation cost. The third is the quantification of the ability to predict the crossing of critical thresholds. The fourth is the identification of the dominant factors influencing sustainability trajectories. The fifth is the evaluation of the added value of the IGD_p for maintenance planning.

The main methodological proposition of this research is to avoid directly asking the algorithm to predict a synthetic score without intermediate information. The preferred architecture involves predicting the six dimensions, either separately or using a multi-output model, and then aggregating them. IGD_p This approach allows for the preservation of a substantive interpretation of the result.

The goal is not to build the most complex model. The goal is to build a model that is efficient enough to be understood, fed, updated, audited, and used locally. A properly validated Random Forest or boosting model can therefore be preferable to a deep architecture that is difficult to maintain.

Community infrastructure typically lacks data comparable to that of heavily instrumented industrial databases. Therefore, the model must be designed to work with periodic inspections, administrative data, a GIS, georeferenced photographs, maintenance histories, and IGD indicators. This approach aligns with a frugal artificial intelligence logic.

A model that performs well in a single municipality can learn from very local characteristics. Its transferability should therefore never be assumed; it must be tested. The model with the best statistical error is not necessarily the best decision-making model. A slightly less precise but highly explainable model can be more useful to a community than an opaque one.

The protocol has several limitations.

- i. First, it assumes the possibility of carrying out repeated evaluations of the IGD.
- ii. Secondly, certain dimensions, particularly institutional and social ones, may evolve more slowly than physical dimensions.
- iii. Thirdly, maintenance interventions alter the natural trajectory of degradation.
- iv. Fourth, extreme events can produce disruptions that are difficult to predict based solely on historical trends.
- v. Fifth, the rarity of failure events may limit certain models. Sixth, the IGD weights must be explicitly integrated into the sensitivity analysis.

3. Scientific perspectives

The extensions of the IGD_p concern, in particular:

- **IGD-IA-SIG** for the spatialization of sustainability trajectories;
- **IGD-IA-LCA** for prediction integrating environmental impacts over the life cycle;
- **IGD-IA-BIM** for predictive monitoring of built heritage;
- **IGD-IA-digital twin** for dynamic discounting on highly instrumented assets;
- **IGD-IA-GNN** for taking into account dependencies between infrastructures;

- **IGD-IA-optimization** for selecting a portfolio of interventions under budgetary constraints.

After validation of the IGD_p , the next step will be to compare several interventions. For an infrastructure j :

$$IGD_{pj}^{A_q}(t + \Delta t) = f[X_j(t), Z_j(t), A_q]$$

The benefit associated with an intervention will be:

$$G_{j,q} = IGD_{pj}^{A_q}(t + \Delta t) - IGD_{pj}^{A_0}(t + \Delta t)$$

The management problem will then become:

$$A_j^* = \underset{A_q}{\operatorname{argmax}} U_j(A_q)$$

under budgetary constraints.

Conclusion

The shift from the Global Sustainability Index (IDG) to a predictive Global Sustainability Index (IGD_p) represents an important methodological development for the management of community infrastructure.

Conventional infrastructure planning (IP) answers the question: "Where is the infrastructure today?" Longitudinal IP adds: "In which direction is it evolving?" Predictive IP aims to answer: "Where is it likely to be tomorrow?" Finally, prescriptive IP should answer: "What intervention can favorably alter this trajectory?"

The proposed approach can be summarized as follows:

$$IGD(t) \rightarrow \text{Historique} \rightarrow \text{Apprentissage} \rightarrow IGD_p(t + \Delta t) \\ \rightarrow \text{Validation} \rightarrow \text{ICR} \rightarrow \text{Décision}$$

The protocol's major contribution lies in its choice to predict not only a technical state, but also the various components of sustainability before they are aggregated. This strategy preserves the multidimensional identity of the IGD and prevents opaque artificial intelligence from replacing an interpretable index. The guiding principle thus becomes: measure the present, learn from the past, anticipate the future, and prepare for decision-making.

The empirical validation of this architecture now constitutes the decisive step to transforming the IGD into a true instrument of territorial predictive intelligence applied to the sustainable management of community infrastructures.

References

1. Almulhim, AI (2025). Integrating artificial intelligence into smart infrastructure management for sustainable urban planning. *Technologies*, 13 (11), Article 481. <https://doi.org/10.3390/technologies13110481>

2. Gbaguidi, AHF (2026). An integrated methodological framework for sustainable urban road infrastructure management: The Global Sustainability Index (IGD) and prioritization matrix applied to Porto-Novu (Benin). *Engineering and Technology Journal*, 11 (3), 9216–9219. <https://doi.org/10.47191/etj/v11i03.12>
3. Gbaguidi, AHF, Ahanhanzo, LS, Daouda, L., & Arouna, O. (2025). Proposal for an analytical framework for evaluating the sustainability of infrastructure and equipment in the municipality of Nikki (Benin). *International Journal of Advanced Multidisciplinary Research and Studies*, 5 (4), 55–58. <https://doi.org/10.62225/2583049X.2025.5.4.4545>
4. Holling, C.S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, 4, 1–23. <https://doi.org/10.1146/annurev.es.04.110173.000245>
5. Ogunkan, D.V., & Ogunkan, S.K. (2025). Exploring big data applications in sustainable urban infrastructure: A review. *Urban Governance*, 5 (1), 54–68. <https://doi.org/10.1016/j.ugj.2025.02.003>
6. Saaty, T. L. (1980). *The analytic hierarchy process*. McGraw-Hill.
7. Shahrivar, F., Mahmoodian, M., Sidiq, A., Jayasinghe, S., Sun, Z., Alavi, A., & Setunge, S. (2026). AI-based remaining useful life prediction for civil infrastructure: Methods, challenges, and future research directions. *Artificial Intelligence Review*, 59, Article 138. <https://doi.org/10.1007/s10462-026-11547-0>
8. Shahrivar, F., Sidiq, A., Mahmoodian, M., Jayasinghe, S., Sun, Z., & Setunge, S. (2025). AI-based bridge maintenance management: A comprehensive review. *Artificial Intelligence Review*, 58, Article 135. <https://doi.org/10.1007/s10462-025-11144-7>
9. Spencer, B.F., Sim, S.-H., Kim, RE, & Yoon, H. (2025). Advances in artificial intelligence for structural health monitoring: A comprehensive review. *KSCE Journal of Civil Engineering*, 29 (3), Article 100203. <https://doi.org/10.1016/j.kscej.2025.100203>
10. Wettewa, S., Hou, L., & Zhang, G. (2024). Graph Neural Networks for building and civil infrastructure operation and maintenance enhancement. *Advanced Engineering Informatics*, 62, Article 102868. <https://doi.org/10.1016/j.aei.2024.102868>