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Intelligent System for Managing and Forecasting Urban Population Growth Using Artificial Intelligence

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Abstract—*Urban demographic growth represents one of the major challenges of contemporary territorial planning, particularly in cities where the dynamic of spatial extension, pressure on facilities and social needs manifest themselves more quickly than ordinary management mechanisms. This article proposes an intelligent system for managing and forecasting urban population growth produced by artificial intelligence. The latter combines demographic, socioeconomic, geographic, environmental and infrastructural data to model population dynamics, identify areas subject to strong urban pressure and anticipate future needs in housing, public services, mobility, collective facilities and urban resources. Machine learning approaches make it possible to take advantage of historical data, identify correlations between factors explaining growth and produce forecast scenarios adapted to strategic analysis for decision-making. The dashboard, spatial indicators and predictive models of this management system contribute to the emergence of more responsive, factual and sustainable urban governance. The projected results indicate that such a system could provide definite assistance to municipal authorities in assessing investment opportunities, helping to reduce territorial imbalances, and improving the allocation of resources. The study calls for attention, however, to the quality of data, the transparency of models, the protection of personal data and the taking into account of institutional reality in the development of artificial intelligence tools*.

Keywords— *Urban growth, artificial intelligence, forecasting, planning, machine learning, governance*.

I. INTRODUCTION

Urbanization constitutes one of the major transformations of the 21st century. According to United Nations projections, nearly seven in ten people will live in urban areas around 2050, while cities already concentrate a major share of global economic production (United Nations, 2019; World Bank, 2026). This dynamic creates a direct tension between population growth, land availability, infrastructure, social services and environmental resilience.

Classic demographic projection tools, often constructed from aggregated annual series, remain useful but insufficient when cities are rapidly transforming. Intra-urban migrations, spatial sprawl, variations in land prices, climate crises and economic changes produce ruptures that linear models have difficulty capturing. Artificial intelligence therefore offers a promising framework for integrating heterogeneous data and learning non-linear relationships between population, urban form, accessibility and service offering.

II. PROBLEMATIC

Faced with rapid urbanization and the complexity of demographic dynamics, how can artificial intelligence enable predictive, reliable and ethical management of urban growth to improve city planning and reduce socio-spatial imbalances?

This problem raises several secondary questions:

- How can we use demographic, geographic, economic and social data to predict changes in the urban population?
- Which artificial intelligence models are best suited to forecasting population growth?
- How can we guarantee the reliability, transparency and ethics of the forecasts produced?
- How can we transform these forecasts into concrete decisions for urban planning?

III. METHODS

A. General system design

The proposed system follows a decision-making platform logic. The data is collected in an urban data lake, standardized by statistical area, and then transformed into spatial and temporal variables. The AI engine combines time series models, tabular supervised models, and recurrent or temporal networks when the data is long enough. An exploitability layer restores the dominant factors of the forecast, so that the decision remains auditable.

B. Data and variables

Urban growth's demographic, spatial, financial, and infrastructural elements should be considered in the input variables. Recommended sources include censuses, administrative records, household surveys, construction data,

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Sentinel or Landsat images, building maps, aggregated mobility data and utility indicators. Sensitive data is aggregated, pseudonymized and subjected to an impact analysis.

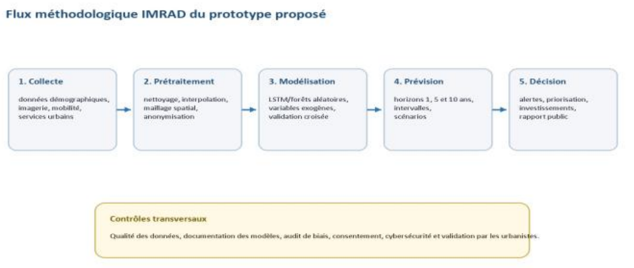

Figure 1: Methodological flow of the proposed prototype

TABLE 1: Methodological flow of the proposed prototype

Family	Examples of variables	Analytical role
Demographics	Population, age, households, net migration	Measure the initial state and calibrate trends.
Urban morphology	Built-up area, density, peripheral expansion	Detect urban sprawl and land pressure.
Économie	Employment, land prices, income, attractiveness	Explain settlement and mobility hubs.
Services	Schools, health, water, transport, energy	Link growth and absorption capacity.
Environment	Flood risk, heat, pollution	Identify sustainability constraints.

Input variables are the data used by the AI system to understand and predict urban population growth. They can be grouped as follows:

TABLE 2: Grouping of input variables

Category	Possible input variables
Demographic	Current population, birth rate, mortality rate, age, sex, household size, internal migration, external migration
Geographic and spatial	Urban area, population density, land use, neighborhood expansion, buildable areas, satellite imagery
Economic	Employment rate, income level, housing prices, land costs, commercial activity, industrial zones
Social	Education level, healthcare access, poverty level, sécurité, living conditions
Infrastructure	Road networks, public transport, écoles, hôpitaux, drinking water, electricity, sanitation, available housing
Environmental	Flood risks, pollution, temperature, protected areas, availability of natural resources
Urban mobility	Travel flows, travel time, transport use, aggregated GPS data, daily migration
Policy and administrative	Urban plans, construction projects, public investments, housing policies, administrative boundaries

The main variable to predict is generally the future population of a given city, neighborhood or urban area.

C. Modeling and validation

The target variable is the urban population by grid, neighborhood or municipality at horizon h. Three families of models are compared:

- A simple statistical reference, for example ARIMA or exponential smoothing;
- A robust supervised model, for example random forest or gradient boosting;
- And a deep temporal model, for example LSTM, when the available sequences are sufficient. The performance is evaluated by sliding temporal validation in order to avoid information leakage.

The primary metrics are mean absolute error, mean squared error, mean absolute percentage error, and forecast interval coverage. Outputs are produced with uncertainty to indicate not only an expected value, but also a plausible range useful for planning.

IV. Application of Artificial Intelligence Algorithms in an Intelligent System for Managing and Forecasting Demographic Growth in the City of Kinshasa

A. Context of the example

Kinshasa is experiencing strong demographic pressure, with growing needs for housing, transport, schools, water, electricity and health services. An intelligent system based on artificial intelligence can help the city anticipate this growth by analyzing urban data by municipality or district.

In this demonstration, the available Excel dataset contains 500 rows, including 18 observations associated with Kinshasa. The data is used as a teaching aid to show how families of algorithms can be integrated into an intelligent system.

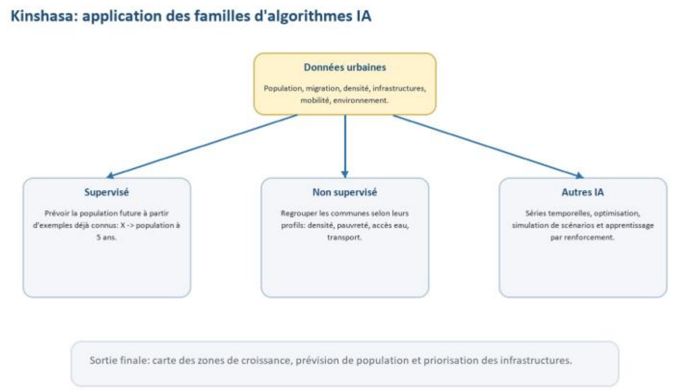

Figure 2: Overview of AI algorithm families applied in Kinshasa

B. System Input Data

TABLE 3: Input variables used by the intelligent system

Data family	Examples pour Kinshasa	Use for AI
Demographic	Current population, birth rate, mortality, migration nette	Forecast the future population.
Geographic and spatial	Density, area, distance from the center, built-up area	Identify densification areas.
Economic	Median income, employment, housing prices	Explain the attractiveness of municipalities.

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Social	Poverty, education, access to healthcare	Identify vulnerable areas.
Infrastructure	Roads, schools, hospitals, water, electricity	Measure carrying capacity.
Mobility and administration	Travel flows, permits, public investments	Plan public interventions.

C. *Learning: Predicting future population*

1) *Supervised Learning*

Supervised learning uses examples where the target variable is already known. In the case of Kinshasa, inputs can be current population, net migration, building permits, density, access to water and transport. The expected output is the expected population in five years.

Example of possible algorithms: linear regression, random forest, gradient boosting or neural network. The model learns the relationship between the characteristics of a municipality and its future growth.

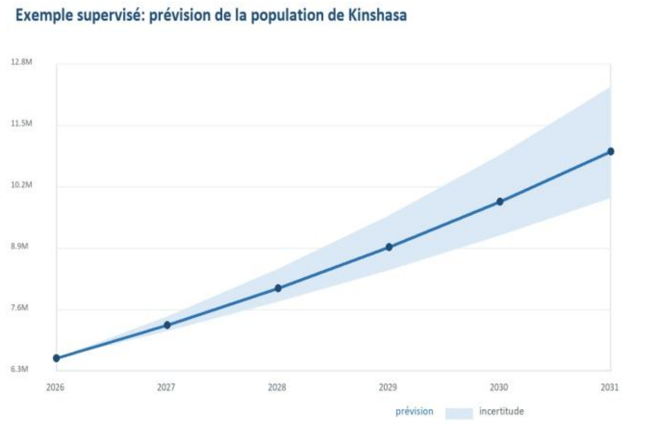

Figure 3: Example of supervised forecast of the population of Kinshasa with uncertainty interval

TABLE 4: How supervised learning works in the system

Model inputs	Algorithm	Output
Current population, migration, density, permits, access to water, transport	Regression / random forest / neural network	Population forecast at 5 years
History by year and municipality	LSTM or time model	Future growth curve

2) *Unsupervised learning: bringing together municipalities*

Unsupervised learning is used when the system does not necessarily have a target response. It is used to discover natural groups in the data.

For Kinshasa, we can group municipalities according to density, access to services, poverty, level of mobility and environmental risk.

Example of possible algorithms: K-means, hierarchical classification or DBSCAN. The result helps distinguish central municipalities, rapid growth areas and vulnerable areas requiring priority investments.

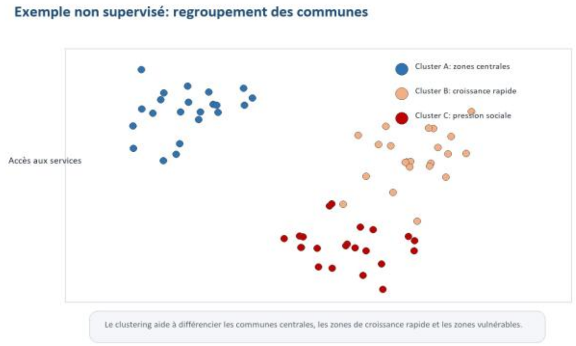

Figure 1 : Example of clustering the municipalities of Kinshasa according to their urban profiles.

3) *Application of K-means, hierarchical classification and DBSCAN*

a) OBJECTIF

Let's show how K-means, hierarchical classification and DBSCAN algorithms can be applied in an intelligent system for managing and forecasting population growth in the city of Kinshasa. The objective is not only to present the results, but also the calculations carried out: normalization of variables, distances, centroids, assignments to groups and detection of atypical areas.

The data used comes from the available urban dataset. To obtain a complete example, 24 communes or zones of Kinshasa are used. The variables retained are: population density, access to water, poverty index and expected growth.

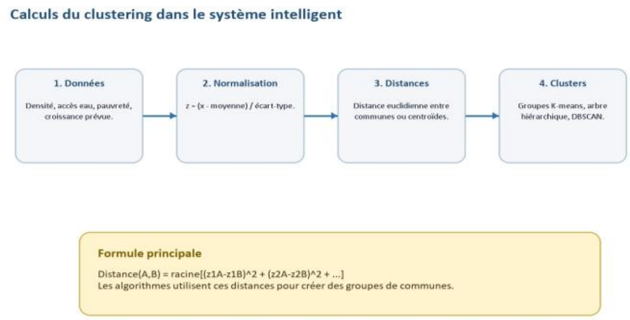

Figure 5: Clustering calculation chain in the intelligent system.

b) DATA AND STANDARDIZATION

The variables do not have the same units: density is in inhabitants/km2, access to water in percentage, poverty in percentage and expected growth in percentage. To compare them correctly, the system applies z-score type normalization. Formula used: z = (x - mean) / standard deviation. After standardization, each variable is expressed on a comparable scale.

c) K-MEANS: CALCULATING CENTROIDS AND DISTANCES

- Choix du nombre de groupes

The number of clusters is not fixed arbitrarily: it is determined by comparing, for K varying from 2 to 6, the intra-class inertia (elbow method) and the silhouette coefficient.

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The silhouette reaches its maximum for K = 3 (0.36), which justifies the choice of three groups for the K-means algorithm.

TABLE 5: Normalization parameters calculated for the municipalities of Kinshasa

Variable	Mean	Standard deviation	Calculation
Densite_hab_km2	15687.88	10547.76	z = (x - moyenne) / écart-type
Acces_eau_pct	88.00	9.29	z = (x - moyenne) / écart-type
Indice_pauvrete_pct	57.07	12.38	z = (x - moyenne) / écart-type
Croissance_prevue_pct	10.77	2.20	z = (x - moyenne) / écart-type

TABLE 6: Extract of standardized calculations. The paper uses these z scores for distances

Municipality	Density	z dens.	Eau	z water	Poverty	z pauv.	Growth	z croiss.
Gombe	17546	0.18	99.0	1.18	35.0	-1.78	10.39	-0.17
Lingwala	5672	-0.95	97.8	1.06	43.4	-1.10	12.80	0.92
Barumbu	21821	0.58	68.0	-2.15	61.5	0.36	10.30	-0.21
Kasa-Vubu	6739	-0.85	86.8	-0.13	60.3	0.26	12.80	0.92
Bandalungwa	14481	-0.11	85.2	-0.30	50.9	-0.50	12.37	0.73
Kalamu	17844	0.20	67.9	-2.16	62.6	0.45	6.64	-1.88
Ngiri-Ngiri	8546	-0.68	96.2	0.88	43.7	-1.08	10.81	0.02
Bumbu	31032	1.45	93.0	0.54	57.0	-0.01	8.67	-0.95
Makala	4612	-1.05	88.1	0.01	54.1	-0.24	12.68	0.87
Lemba	21194	0.52	97.6	1.03	62.3	0.42	11.46	0.31

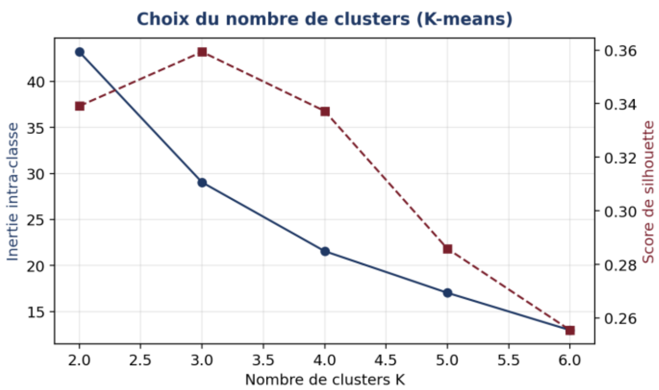

Figure 6: Choice of number of clusters (elbow and silhouette method)

K-means seeks to form K groups. Here, K = 3. The calculation starts with three initial centroids, then each municipality is assigned to the closest centroid according to the Euclidean distance. Then, the centroids are recalculated as the average of the municipalities in each group.

Formule de distance :

d(A,C) = root[(z1A-z1C)^2 + (z2A-z2C)^2 + (z3A-z3C)^2 + (z4A-z4C)^2].

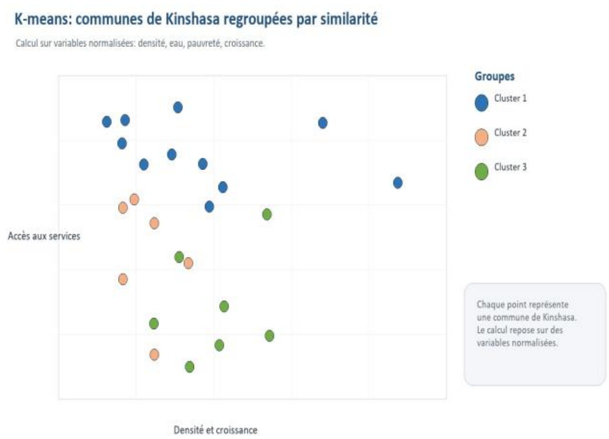

Figure 2 : Illustration des groupes K-means obtenus

With K = 3, the algorithm identifies three contrasting urban profiles: a first group bringing together municipalities marked by high poverty and limited access to services; a second group, the most numerous, corresponding to better-endowed municipalities of intermediate density; a third group bringing together municipalities with very high density. The projection by principal component analysis confirms the separation of these groups.

TABLE 7: Final centroids calculated by K-means

Centroid	z density	z water	z poverty	z growth	No. of municipalities
C1	0.14	0.74	-0.86	0.38	11
C2	-0.94	-0.33	0.80	0.78	6
C3	0.58	-0.87	0.66	-1.26	7

TABLE 8: All K-means assignment calculations: each municipality goes to the nearest centroid

Municipality	Distance C1	Distance C2	Distance C3	Assignment
Gombe	1.17	3.34	3.40	Cluster 1
Lingwala	1.28	2.36	3.74	Cluster 1
Barumbu	3.22	2.61	1.68	Cluster 3
Kasa-Vubu	1.81	0.60	2.75	Cluster 2
Bandalungwa	1.18	1.54	2.48	Cluster 1
Kalamu	3.90	3.44	1.49	Cluster 3
Ngiri-Ngiri	0.93	2.38	3.06	Cluster 1
Bumbu	2.07	3.19	1.82	Cluster 3
Makala	1.60	1.10	2.97	Cluster 2
Lemba	1.37	2.09	2.49	Cluster 1
Limete	3.73	3.59	1.04	Cluster 3
Matete	2.68	2.27	0.47	Cluster 3
Ndjili	0.91	1.79	3.15	Cluster 1

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Masina	1.95	1.92	1.05	Cluster 3
Kimbanseke	2.34	4.36	3.47	Cluster 1
Nsele	3.97	1.80	3.20	Cluster 2
Maluku	1.56	2.51	3.87	Cluster 1
Mont-Ngafula	2.34	3.62	3.16	Cluster 1
Selembao	1.22	1.70	3.23	Cluster 1
Ngaliema	3.08	0.90	3.09	Cluster 2
Kintambo	3.58	3.16	1.45	Cluster 3
Ngaba	2.36	0.55	2.51	Cluster 2
Kisenso	1.50	1.23	2.41	Cluster 2
Kinshasa	1.18	2.87	2.40	Cluster 1

d) HIERARCHICAL CLASSIFICATION: DISTANCES AND MERGERS

Hierarchical classification does not immediately fix the number of groups. It calculates the distances between municipalities, merges the closest ones, then repeats the operation. An average connection and Euclidean distance are used in the example: The mean distance between two groups' municipalities is the difference between them.

Applied to the same data with a Ward link, the hierarchical classification produces a dendrogram consistent with the division into groups, while revealing the municipalities which aggregate later, that is to say the most singular.

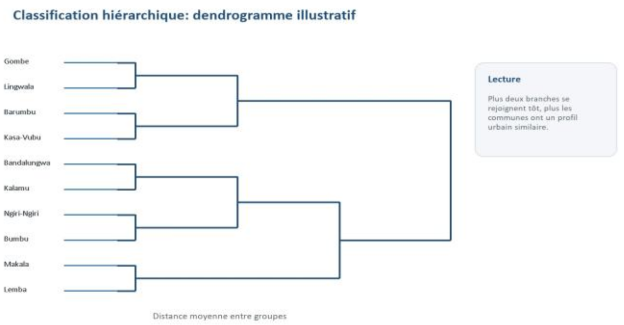

Figure 8: Illustrative dendrogram of hierarchical classification

TABLE 9: Extract from the matrix of Euclidean distances used by hierarchical classification

Municipality	Gombe	Lingwala	Barumbu	Kasa-Vubu	Bandalungwa	Kalamu
Gombe	-	1.72	3.99	2.85	2.18	4.37
Lingwala	1.72	-	4.01	1.81	1.72	4.68
Barumbu	3.99	4.01	-	2.73	2.35	1.71
Kasa-Vubu	2.85	1.81	2.73	-	1.09	3.62
Bandalungwa	2.18	1.72	2.35	1.09	-	3.35
Kalamu	4.37	4.68	1.71	3.62	3.35	-

a) DBSCAN : VOISINAGE, POINTS NOYAUX ET ANOMALIES

DBSCAN brings together municipalities that have enough neighbors within a given radius. The parameters used here are eps = 1.35 and minPts = 3. A municipality is a core point if it has at least 3 neighbors, it is a border if it belongs to the neighborhood of a core, and it is atypical if it does not join any dense group.

TABLE 10: Main calculated hierarchical merge steps

Step	Group A	Group B	Average distance	Size of new group
1	Lingwala	Maluku	0.51	2
2	Kasa-Vubu	Makala	0.56	2
3	Ndjili	Selembao	0.80	2
4	Matete	Masina	0.94	2
5	Lingwala, Maluku	Ndjili, Selembao	0.99	4
6	Ngaliema	Ngaba	0.99	2
7	Bandalungwa	Kasa-Vubu, Makala	1.06	3
8	Ngiri-Ngiri	Lingwala, Maluku, Ndjili...	1.09	5
9	Bumbu	Kinshasa	1.18	2
10	Kisenso	Bandalungwa, Kasa-Vubu, Makala	1.20	4
11	Kalamu	Limete	1.24	2
12	Ngiri-Ngiri, Lingwala, Maluku...	Kisenso, Bandalungwa, Kasa-Vubu...	1.45	9

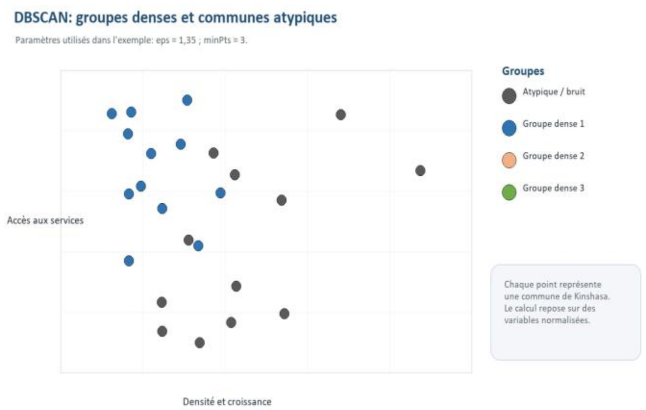

Figure 3 : Illustration DBSCAN: groupes denses et communes atypiques

TABLE 1 : Tous les calculs DBSCAN : nombre de voisins, statut et cluster

Municipality	No. of eps neighbors	Status	DBSCAN cluster	Nearby neighbors
Gombe	2	Border	Groupe 1	Gombe, Ngiri-Ngiri
Lingwala	5	Core	Groupe 1	Lingwala, Ngiri-Ngiri, Ndjili, Maluku...
Barumbu	1	Outlier	Noise	Barumbu
Kasa-Vubu	7	Core	Groupe 1	Kasa-Vubu, Bandalungwa,

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International Journal of Multidisciplinary Research and Publications
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				Makala, Ndjili...
Bandalungwa	5	Core	Groupe 1	Kasa-Vubu, Bandalungwa, Makala, Ndjili...
Kalamu	2	Outlier	Noise	Kalamu, Limete
Ngiri-Ngiri	6	Core	Groupe 1	Gombe, Lingwala, Ngiri-Ngiri, Ndjili...
Bumbu	2	Outlier	Noise	Bumbu, Kinshasa
Makala	6	Core	Groupe 1	Kasa-Vubu, Bandalungwa, Makala, Ndjili...
Lemba	1	Outlier	Noise	Lemba
Limete	2	Outlier	Noise	Kalamu, Limete
Matete	2	Outlier	Noise	Matete, Masina
Ndjili	9	Core	Groupe 1	Lingwala, Kasa-Vubu, Bandalungwa, Ngiri-Ngiri...
Masina	2	Outlier	Noise	Matete, Masina
Kimbanseke	1	Outlier	Noise	Kimbanseke
Nsele	1	Outlier	Noise	Nsele
Maluku	5	Core	Groupe 1	Lingwala, Ngiri-Ngiri, Ndjili, Maluku...
Mont-Ngafula	1	Outlier	Noise	Mont-Ngafula
Selembao	9	Core	Groupe 1	Lingwala, Kasa-Vubu, Bandalungwa, Ngiri-Ngiri...
Ngaliema	2	Border	Groupe 1	Ngaliema, Ngaba
Kintambo	1	Outlier	Noise	Kintambo
Ngaba	3	Core	Groupe 1	Kasa-Vubu, Ngaliema, Ngaba
Kisenso	5	Core	Groupe 1	Kasa-Vubu, Makala, Ndjili, Selembao...
Kinshasa	2	Outlier	Noise	Bumbu, Kinshasa

b) Comparison and use in intelligent system

Table 2 : Comparison of calculations and their use in planning

Method	Main calculation	Output	Use for Kinshasa
K-means	Distance to 3 centroids followed by recalculation of means.	3 groups of municipalities.	Classify areas as low-, medium-, or high-pressure.
Classification hiérarchique	Distances between municipalities followed by successive merges.	Dendrogram.	Understand which municipalities are similar.
DBSCAN	eps neighborhood and minimum number of neighbors.	Dense groups and anomalies.	Detect atypical municipalities requiring investigation.

In the intelligent system, these results feed into a dashboard. Municipalities classified as under high pressure may receive priority for schools, transport, housing, water and health. Atypical municipalities reported by DBSCAN merit additional investigation, as they may represent a break in trend or a particular social situation.

V. Illustrative case: LSTM model anticipating the future population of an urban neighborhood

A. Chosen artificial intelligence tool: LSTM

The example uses an LSTM type recurrent neural network, that is to say an artificial intelligence model adapted to time series. In an urban demographic management system, this tool learns the past evolution of the population and relates it to urban factors such as housing construction, migration, mobility, employment, public facilities and the extension of buildings visible by satellite.

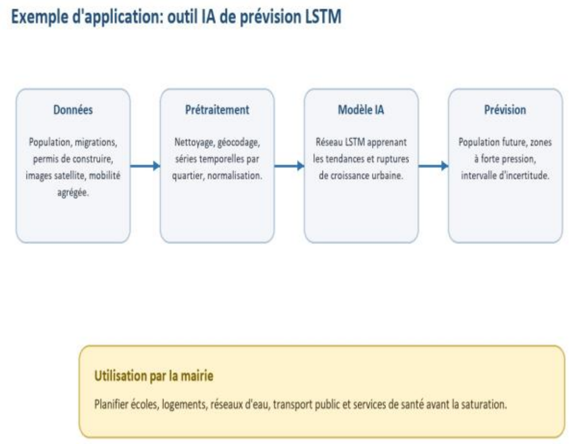

Figure 10: Application of an LSTM model in the intelligent urban forecasting system.

B. Input data used

The model does not predict growth from population alone. It receives several families of data which describe the real dynamics of the city.

TABLE 13: Data feeding the AI forecasting tool

Input data	Examples	Use for AI
Demographic	Current population, birth rate, mortality, migrations.	Understand the baseline trend.
Satellites	Built-up area, new neighborhoods, densification.	Detect urban expansion.
Economic	Employment, housing prices, commercial activities	Explain area attractiveness.
Infrastructure	Roads, schools, water, health, transport	Measure carrying capacity.
Mobility	Travel flows et travel time agrégés	Identify settlement hubs.

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C. *Example of concrete application*

Suppose that the town hall of the N'Sele commune in Kinshasa wants to forecast the population of the Q24 district for the next five years. The system gathers historical data from the neighborhood, extracts the evolution of the building from satellite images, adds building permits and mobility flows, then trains the LSTM model. The model produces an annual forecast and a level of uncertainty.

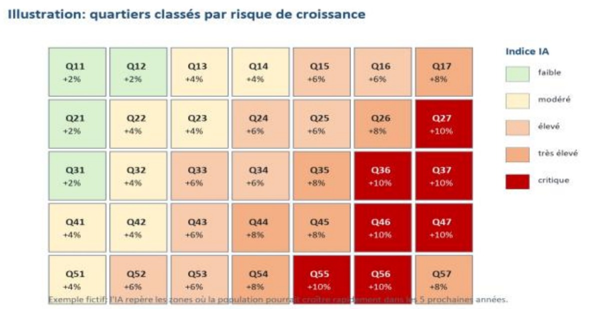

Figure 11: Fictional map of neighborhoods classified according to population growth risk

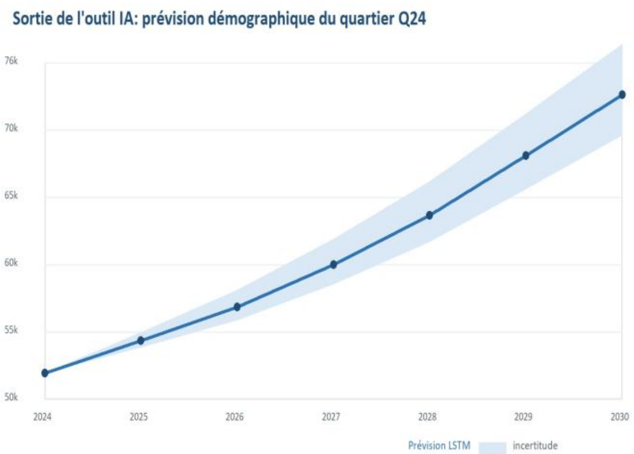

Figure 12: Fictitious population forecast produced by the LSTM model

D. *Result provided to decision-makers*

The system transforms the model output into actionable information: high-growth neighborhoods, estimated number of additional residents, level of pressure on services and planning recommendations.

TABLE 14: Transformation of AI forecasting into urban decision-making

AI output	Interpretation	Possible decision
Forecast population	The Q24 neighborhood grows strongly.	Revise the urban development plan.
Critical index	Public services are at risk of saturation.	Prioritize investments.
High uncertainty	The data are unstable or incomplete.	Request an additional survey.

For example, if the Q24 district increases from 52,000 inhabitants in 2024 to around 73,500 in 2030, the town hall can schedule schools, water points, transport, social housing and health centers earlier.

This example shows that artificial intelligence does not replace urban planners: it provides them with an anticipated, rapid and visual reading of population growth. The LSTM tool helps identify areas that are growing quickly, estimate future needs and better allocate public resources.

VI. SECURITY, DATA GOVERNANCE AND SYSTEM ETHICS

A decision support system such as the one proposed is only valuable if it is trustworthy. However, it aggregates particularly sensitive data – censuses, household surveys, traces of mobility, socio-economic and health indicators – relating to identifiable populations. Security, data governance and ethics are therefore not additional considerations, but conditions for the validity of the system. This section specifies the guarantees that must accompany the architecture described above.

6.1. Data governance and quality

The creation of an urban data warehouse (data lake) requires explicit governance. Each source must be documented (origin, date, collection method) and classified according to its degree of sensitivity, in order to modulate the protections applied. Two principles structure this governance: limitation of purposes, which prohibits the reuse of data collected for a given objective for other purposes without a legitimate basis, and minimization, which restricts collection to only the variables necessary for demographic forecasting. The quality of the data — completeness, freshness, representativeness — directly conditions the reliability of the models: a poorly governed warehouse propagates its biases and errors all the way to planning decisions. Governance finally covers the complete life cycle of the data, from ingestion to archiving or deletion, in accordance with the retention periods justified by the purpose.

6.2. System, data and learning pipeline security

The security of the device is based on the three classic properties of confidentiality, integrity and availability, taken up by the Congolese Digital Code (Ordinance-Law No. 23/010, 2023). Concretely, access to data and models must obey the principle of least privilege, exchanges and storage must be encrypted, and all sensitive operations must be logged in order to guarantee the traceability and auditability of the system. Alignment with a security management framework such as ISO/IEC 27001 provides a proven framework for these controls.

Added to these measures is a dimension specific to artificial intelligence systems: the security of the learning pipeline itself. A training dataset can be deliberately altered to skew predictions (data poisoning); a deployed model can be manipulated by adversarial inputs or have its parameters exfiltrated. Model governance — versioning, integrity control, validation before production — must therefore be treated at the same level of requirements as data security. The NIST AI

NTEME MALAMA Jean-René, BONTE KASSONGO Merveille, and MANIEKA NGUMBU Roger, "Intelligent System for Managing and Forecasting Urban Population Growth Using Artificial Intelligence," *International Journal of Multidisciplinary Research and Publications (IJMRAP)*, Volume 9, Issue 1, pp. 1063-1071, 2026.

Risk Management Framework (2023) provides a framework suited to this analysis.

6.3. Privacy protection and risk analysis

Privacy protection must be integrated by design rather than added as an afterthought. Directly identifying data is pseudonymized or aggregated, and analyzes favor the area level rather than the individual level. Above all, a system of this magnitude justifies a formal risk analysis, carried out for example according to the EBIOS Risk Manager (ANSSI) method or in the form of an impact analysis relating to data protection: identification of threat scenarios, assessment of their seriousness and likelihood, and definition of risk reduction measures. This approach transforms the protection intentions into a verifiable system, and anticipates the requirement for a supervisory authority such as the Data Protection Authority provided for by the Digital Code.

6.4. Ethics, fairness and explainability

Beyond security, a system that guides public planning decisions raises issues of equity. Learning models reproduce and amplify the biases present in their data: a municipality under-represented in the sources – typically an informal neighborhood – risks being systematically underestimated, and therefore disadvantaged in the allocation of resources (Mehrabi et al., 2021). An audit of biases by area, comparing the performance of the model according to municipal profiles, is therefore essential. Explainability constitutes the second pillar: decision-makers must understand why the system makes a certain prediction. Interpretation methods such as SHAP (Lundberg & Lee, 2017) allow each variable to be assigned its contribution to the prediction, making the model auditable. Finally, the system must remain a decision-making tool: human supervision and final responsibility for development choices remain the responsibility of the authorities, never delegated to the algorithm.

6.5. Compliance with the Congolese and African legal framework

The system is part of a legal framework now established in the Democratic Republic of Congo. The right to respect for private life is guaranteed by Article 31 of the Constitution, and the processing of personal data is governed by Book III of the Digital Code (Ordinance-Law No. 23/010 of March 13, 2023), which notably enshrines the principles of purpose, consent and the rights of the persons concerned, as well as the obligation to appoint a data protection delegate. The African Union Convention on Cybersecurity and Personal Data Protection (Malabo Convention, 2014) was ratified by the DRC at the continental level in 2025. Any operational deployment of the system must therefore align with these requirements, under the control of the Data Protection Authority.

VII. RESULTS

The conceptual prototype results in four operational outcomes.

- First: it consolidates previously dispersed sources into a common spatial repository.
- Second: It produces multi-horizon forecasts per urban area.
- Third: it ranks neighborhoods according to an index of demographic pressure and service vulnerability.
- Fourth: It makes visible the factors that drive growth. There is accessibility, land availability, jobs, prices, environmental risks and existing infrastructure.

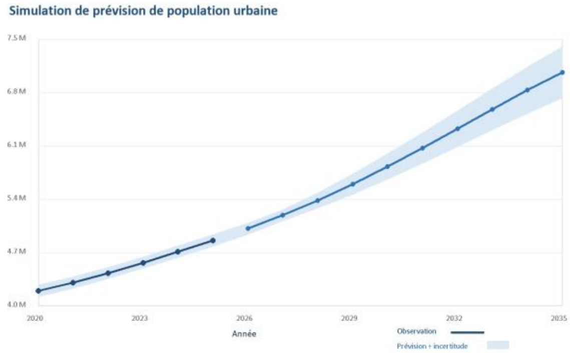

Figure 13: Simulated example of forecast with uncertainty interval

TABLE 15: Expected decision results from the intelligent system

System output	Use by the local authority	Decision indicator
Growth map	Locate rapid densification areas.	Forecast annual rate by neighborhood.
Scenarios	Compare transport, housing, or zoning policies.	Expected population by horizon.
Alerts	Report service-capacity exceedances.	Population/capacity ratio.
Explainability	Justify choices to decision-makers and citizens.	Variable contribution.

VIII. DISCUSSION

The scientific interest of the device lies in the integration between demography, remote sensing, data science and urban planning. Work on urban analytics shows that cities must be understood as complex and dynamic systems; AI approaches make it possible to observe these dynamics at finer scales than traditional administrative statistics (Batty, 2013; Boeing et al., 2021).

However, using AI does not automatically guarantee a better decision. Models can reproduce data biases, underestimate informal settlements, confuse correlation with causation, or hide uncertainty behind visually compelling maps. System governance must therefore include data documentation, performance audit by area, validation by local experts, appeal mechanisms and publication of limits.

Another limitation concerns transferability. A model trained in a metropolis with rich data may lose accuracy in a secondary city where records are incomplete. The recommended solution is hybrid: combining global models, local calibration, context variables and field knowledge.

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IX. CONCLUSION

An intelligent system for managing and forecasting urban population growth can become a strategic instrument for anticipating collective needs and reducing reactive decisions. The article proposed an integrated architecture, a modeling method and directly usable decision-making outputs. The approach to grouping urban areas (K-means, hierarchical classification and DBSCAN) was illustrated in a reproducible manner on a demonstrative dataset, the choice of the number of groups being justified by internal validation criteria. Beyond the predictive aspects, the article underlined that the value of such a system rests on its reliability: security, data governance and ethical supervision - including the protection of privacy, bias auditing and compliance with the Congolese Digital Code - constitute conditions of validity and not simple complements.

The expected benefits concern infrastructure planning, budgetary prioritization, urban resilience and the transparency of public policies. Future research should test the system on real, sourced data, compare models by city type, and deepen the governance, security and equity standards applicable to urban artificial intelligence, under the control of the competent authorities.

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