Right to the City and Urban Neural Networks

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Abstract

In a recent paper titled ENTHROPY AND URBAN ENTHALPY (EUE), (1) the relationship between the Right to the City and the Urban System is analyzed. The Urban Dynamics_Entropy_Enthalpy mathematical analysis applies the New European Bauhaus principles to TUS Territorial and Urban Dynamic System, calculating the probability of its sustainability in addition to predicting the moment in which the city shows signs of degradation, abandonment and death (2), filling a scientific gap in urban planning matter through the integration of syntax and spatial semantics. This analysis explores the comprehensive relationship between economic, social, environmental, and spatial urban variables that explain the functioning of the Urban System. The equations relating the different urban variables are derived from various theoretical and practical studies across the different disciplines that analyze these four fields.

Complementarily now to the aforementioned heuristic methods that relate urban variables through equations, predictions of target variables can be obtained from input variables using Urban Neural Networks within the framework of Artificial Intelligence, without prior knowledge of the equations relating the urban variables. The processing power of modern processors, combined with the metaheuristic capabilities of neural networks, allows for the incorporation of a significantly larger number of input and output variables than the previous structured method. This enables the identification of hidden patterns among the various variables of the Complex Urban System, predicting outcomes that contribute to addressing the urban vulnerability of the Right to the City.

Keywords: *Right to the City; Neural Network; Urban Science; Artificial Intelligence*

1. INTRODUCTION

Experience in Urban Ecosystem Analysis (UEA) allows for the identification of the variables that constitute the main components of each Urban Field, forming an Urban Matrix that relates the economic, social, environmental, and spatial urban variables of the urban system.

To develop the Urban Neural Networks (UNNs), which allow for decision-making based on the predictions obtained, a database has been created with selected variables obtained from a large number of similar cities analyzed. The values of each variable, obtained from the hidden patterns

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identified by the UNNs, allow for a comparison of the difference between the existing reality and the prediction. This difference will vary depending on the input values included in the UNN.
Three UNNs were built in Visual Studio Code and Colab. were built with 1 input neuron and 1 output neuron to prediction and two hidden layers with 64 and 32 neurons in order to calculate Artificial soil surface area, Population% of main dwellings , % of industrial use, storage, and parking
The predictions allow for an analysis of the urban or territorial reality in order to identify discrepancies or imbalances that contribute to correcting the aforementioned variable and/or directly or indirectly addressing the affected urban rights.

2. METHODOLOGY

2.1. Urban Mechanics and Urban Thermodynamics

Urban Mechanics (UM) and Urban Thermodynamics (UT) analysis reduces the Complex City to a mathematical model that allows calculating the probability of its sustainability and predicting the moment when the city shows degradation signs, abandonment, and demise (2).

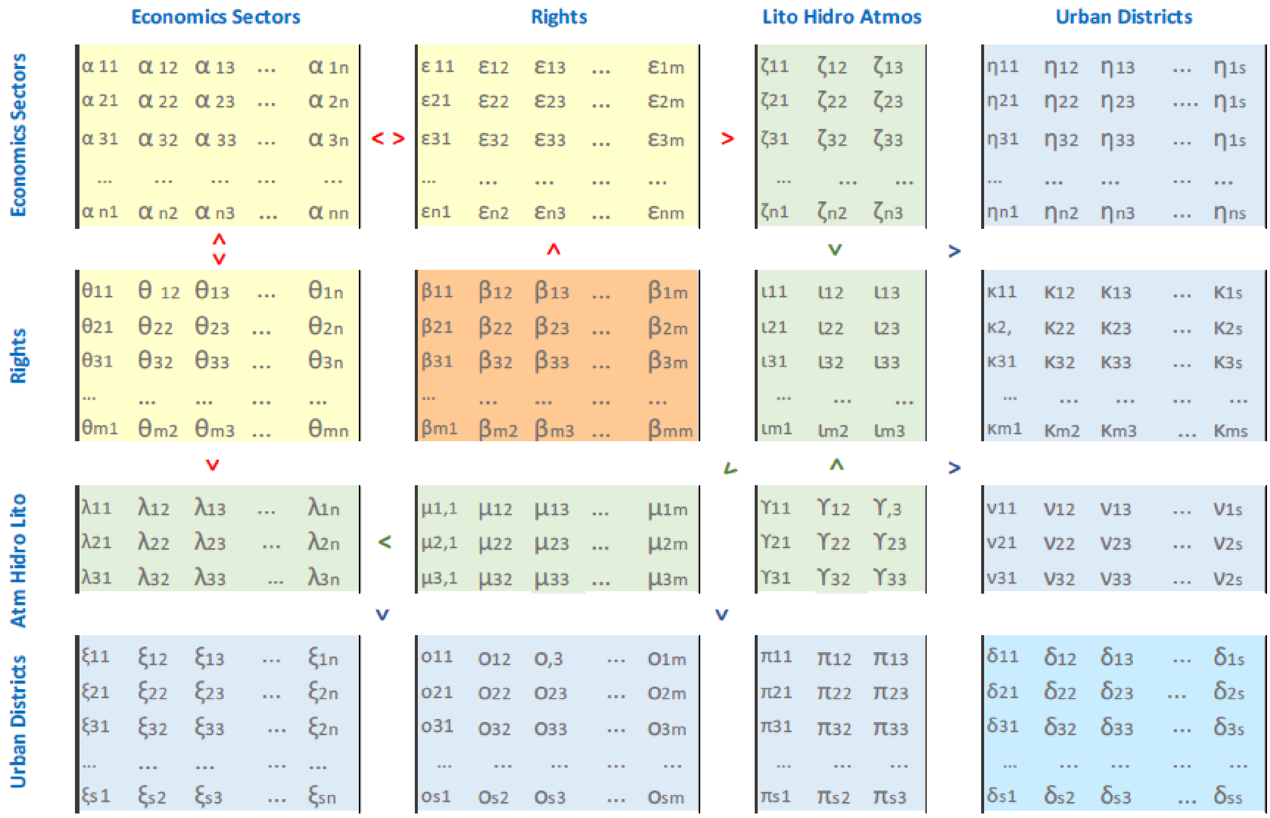

Figure 1. Urban Matrix: Urban Mechanics
Source: Own elaboration

Urban Mechanics (UM) models the Complex City using an urban matrix consisting of four diagonal submatrices α, β, γ, and δ that represent internal flows of each Urban Vector—

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economic, social, environmental and spatial—and 12 submatrices that represent flows between the four vectors, integrating urban semantics and spatial syntax.

Urban Thermodynamics (UT) analyzes the Urban Growth Potential and the Urban Carrying Capacity, predicting the state of urban vitality and the probability of city death based on population values of non_dependence n1 and dependence n0

n0/n1=1/e

Matriz Alpha (1,1)	Actividades Económicas. Medida: Miles de euros			
Sectores	Agricultura	Industria	Construcción	Servicios
Agricultura	57,02	135,12	0,04	3,45
Industria	262,17	766,32	328,82	118,02
Construcción	3,71	7,43	184,90	15,12
Servicios	672,81	1.257,38	1.488,21	2.179,97
	995,71	**2.166,24**	**2.001,98**	**2.316,56**

Matriz Epsilon (1,2)	Provisión de Derechos Sociales. Medida: miles de euros				
	Vivienda	Salud	Educación	Seguridad	Servicios
Agricultura	1,39	0,02	0,01	0,02	0,00
Industria	4,94	0,06	0,05	0,07	0,00
Construcción	4,68	0,03	0,03	0,07	0,00
Servicios	2,12	0,15	0,09	0,04	0,00
	13,13	**0,26**	**0,18**	**0,20**	**0,01**

Matriz Zeta (1,3)	Impacto Ambiental Sectores Economicos			
	Ha	m³	CO_2 tn	Mwh
	Litosfera	Hidrosfera	Atmosfera	Energia
Agricultura	38,5	0,1	70,6	15,8
Industria	403.306,9	0,2	302,5	73,9
Construcción	218,4	0,2	11.127,9	121,6
Servicios	17.427,0	0,4	425,3	5,7
	420.990,9	**0,9**	**11.926,3**	**217,1**

Matriz eta (1,4)	Origen Económico-Espacial. Medida: PIB sectorial por Hectáreas		
Seccion/Sector	1190201001	1190201002	1190201003
Agricultura	4,49	0,03	1,02
Construcción	665,50	0,54	79.651,73
Industria	324,32	14,15	44,55
Servicios	760,80	542,79	880,12
	1.755,11	**557,50**	**80.577,41**

Matriz tetha (2,1)	Derecho al Empleo. Medida: cantidad empleos estimados			
Sectores	Agricultura	Industria	Construcción	Servicios
Vivienda	18,21	64,49	61,14	27,72
Salud	5,42	18,56	11,58	34,55
Educación	3,67	12,40	6,10	30,32
Seguridad	4,65	16,47	15,39	8,04
Servicios	0,54	1,88	1,36	2,71
	32,49	**113,80**	**95,56**	**103,34**

Matriz Beta (2,2)	Entropia. Unidades de Peso Estructural				
Derechos	Vivienda	Salud	Educación	Seguridad	Servicios
Vivienda	2.166,000	0,001	0,002	0,001	0,004
Salud	0,407	3,000	1,333	0,667	3,000
Educación	0,838	-	4,000	0,500	2,250
Seguridad	0,000	-	-	2,000	4,500
Servicios	-	-	-	-	9,000
	2.167,24	**3,00**	**5,34**	**3,17**	**18,75**

Matriz iota (2,3)	Impacto Ambiental Derechos sociales			
	Ha	m³	CO_2 tn	Mwh
	Litosfera	Hidrosfera	Atmosfera	Energia
Vivienda	79,69	219.099.438,31	1.470,81	5.678,80
Salud	20,81	4.981.636,33	244,12	942,54
Educación	0,67	7.253.023,49	355,42	1.372,29
Seguridad	11,56	5.696.868,57	279,17	54,75
Servicios	13,21	289.364,73	14,18	3.447,45
	126	**237.320.331**	**2.364**	**11.496**

Matriz Kappa (2,4)	Distribución Espacial de Derechos. Unidades de Dotaciónes y viviendas		
	1190201001	1190201002	1190201003
Vivienda	846,0	861,0	459,0
Salud	2,0	1,0	0,0
Educación	3,0	1,0	0,0
Seguridad	2,0	0,0	0,0
Servicios	4,0	3,0	2,0
Indice de Shannon	**1,840**	**1,946**	**0,637**

Matriz Lamda (3,1)	Fiscalidad ambiental. Medida: Recaudación en euros			
Sectores	Agricultura	Industria	Construcción	Servicios
Litosfera	33,9	354.677,5	192,1	15.325,7
Hidrosfera	1.259,0	2.012,6	2.012,6	3.900,5
Atmosfera	23,7	101,4	3.728,9	142,5
Energia	45.753,4	213.663,4	351.460,3	16.543,4
	47.069,9	**570.454,9**	**357.394,0**	**35.912,2**

Matriz μ (mu) (3,2)	Contribución de los DD a la s. ambiental. Unidades fisicas				
	Vivienda	Salud	Educación	Seguridad	Servicios
Litosfera	-	-	-	-	-
Hidrosfera	-	-	-	-	-
Atmosfera	-	-	-	-	-
Energia	-	-	-	-	-
	-	-	-	-	-

Matriz Gamma (3,3)	Entalpia			
	Ha	m³	CO_2 tn	Mwh
	Litosfera	Hidrosfera	Atmosfera	Energia
Litosfera	- 419.512,09	-	-	-
Hidrosfera	-	-210846569,4	-	-
Atmosfera	-	-	- 7.877,767	-
Energia	-	-	-	6399
	- 419.512,1	**- 210.846.569,4**	**- 7.877,8**	**6.398,7**

Matriz Nu (3,4)	Recurso de cobertura Ha superficie. Medida: Ha		
	1190201001	1190201002	1190201003
Litosfera	-	5.995,61	-
Hidrosfera	18,07	7.653,91	28,93
Atmosfera	-	11.299,57	-
Energia	-	538,33	-
	18,1	**25.487,4**	**28,9**

Matriz Xi (4,1)	Vulnerabilidad Económica. Medida: P. poblacional por seccion censal			
	Agricultura	Industria	Construcción	Servicios
1190201001	2,65	0,01	0,03	0,06
1190201002	2,38	0,13	0,00	0,00
1190201003	4,06	0,00	0,12	0,02
	9,1	**0,1**	**0,1**	**0,1**

Matriz Omicron (4,2)	Vulnerabilidad de Derecho. Medida: P. poblacional por seccion censal				
	Vivienda	Salud	Educación	Seguridad	Servicios
1190201001	2,7165	0,0064	0,0096	0,0064	0,0128
1190201002	2,4976	0,0029	0,0029	0,0000	0,0087
1190201003	4,1741	0,0000	0,0000	0,0000	0,0182
	9,3882	**0,0093**	**0,0125**	**0,0064**	**0,0397**

Matriz Phi (3,4)	Capacidad de Restauración Neta			
	Ha	m³	CO_2 tn	Mwh
	Litosfera	Hidrosfera	Atmosfera	Energia
1190201001	-	62.106,37	0	-
1190201002	1.604,72	26.312.219,62	6412,223372	18.111,65
1190201003	-	99.436,88	0	-
	1.604,7	**26.473.762,9**	**6.412,2**	**18.111,6**

MatrizDelta (4,4)	Estructura Poblacional. Medida: Numero de hanitantes		
ORIGEN	1190201001	1190201002	1190201003
1190201001	**1624**	202	132
1190201002	182	**1779**	221
1190201003	119	199	**1066**
	1.924,7	**2.179,6**	**1.419,3**

(blue)	Matrices Inputs
(pink)	Matrices Ouputs

Figure 2. San José del Valle Urban Matrix 2026: Urban Mechanics

Source: Own elaboration

2.2 Characteristics of Multilayer Neural Networks (MLPRegressor)

For the interactive widget, we trained two regression models using the MLPRegressor class from sklearn.neural_network. Both models share a similar architecture and configuration, optimized for the specific task of predicting urban features from a single input.

1. Common Configuration for Both Models:

a. Hidden Layer Architecture (hidden_layer_sizes = (64, 32)):

Both models use two hidden layers. The first layer has 64 neurons, and the second layer has 32 neurons. This configuration strikes a balance between capturing nonlinear relationships in the data and being overly complex for the task.

b. Activation Function (activation = 'relu'):

The Rectified Linear Unit (ReLU) activation function is used. ReLU is a popular choice due to its computational efficiency and its ability to mitigate the vanishing gradient problem, helping the network learn more quickly.

c. Optimizer (solver = 'adam'):

The Adam optimization algorithm is used to adjust the network weights during training. Adam is an efficient and robust optimizer that adapts the learning rate for each weight individually.

d. Initial Learning Rate (learning_rate_init = 0.001):

The initial learning rate is set to 0.001, a common value that allows for stable learning.

e. Maximum Iterations (max_iter = 2000):

The network is trained for a maximum of 2000 epochs (complete iterations on the training set).

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ISBN:

f. Early Stopping (early_stopping = True):
This technique prevents overfitting. Training will stop if the model's performance on a validation set (10% of the training data) does not improve significantly over a predefined number of epochs.
g. Validation Fraction (validation_fraction = 0.1):
10% of the training data is reserved for validation during early_stopping.
No Change Tolerance (n_iter_no_change = 30):
Training will stop if validation performance does not improve for 30 consecutive epochs.
Random State (random_state = 42):
A seed is set for the random number generator, ensuring reproducible training results.
2. Differences in Prediction Tasks: Although the architecture and base configuration are identical, each model is trained on a specific dataset:
a. model1: Trained to predict 'Artificial Floor Area ' using 'Population' as the only input feature.
b. model2: Trained to predict '% Main Dwellings' using. The number of homes per 1,000 inhabitants is the sole input characteristic.
c. model 3: Trained to predict '% of industrial use, storage, and parking % of residential use
Three models are designed to be lightweight and efficient in their predictions, which is essential for a smooth user experience in the interactive widget.

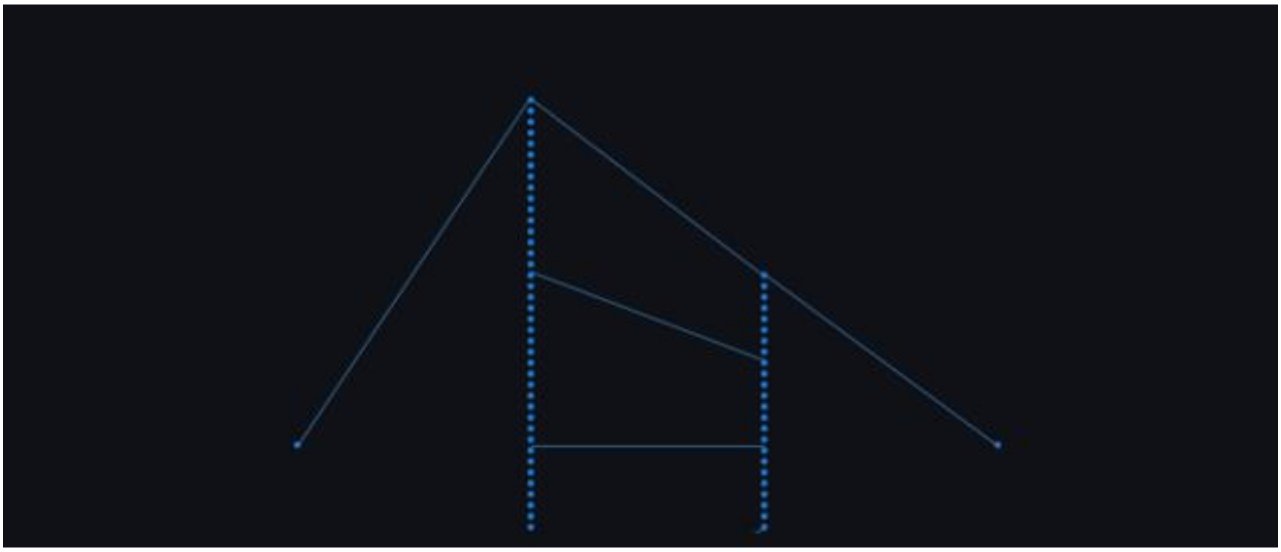

Figure 3.: Urban Neural Networks
Input Layer: 1 neuron (as they each take a single input feature).
Hidden Layers: 2 hidden layers.
The first hidden layer has 64 neurons.
The second hidden layer has 32 neurons.
Output Layer: 1 neuron (as they each predict a single output target).
Source: Own elaboration

3. URBAN NEURAL NETWORKS UNN

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UM identifies the main variables of each urban vector related to each other using proven functions, ensuring predictions of target variables are obtained from input variables through UNN analysis.
Three UNNs were built (Visual Studio Code and Colab).
An interactive tool has been developed to explore urban indicators. Our goal was to simplify the analysis of complex data and allow users to visualize the impact of different variables.

1. Data Loading and Preparation
It all starts with the data. We loaded an Excel file with urban indicators containing more than 350 social, economic, environmental, and spatial indicators from 8,132 municipalities in Spain.
A calculation of the correlation coefficient (R^2) was performed between selected indicators related to urban planning: population, land use (of different categories), economy, housing, and others for Spain and Andalusia.

ESPAÑA	% Uso industrial, almacenamiento y estacionamiento 2024	% Uso residencial 2024	% Uso terciario 2024	% Otros usos 2024	Superficie de suelo artificial 2016	% Viviendas principales 2021	% Viviendas no principales 2021	D.29. Número de viviendas por cada 1.000 habitantes	Población 2024	% Población parada 2022	% Parados menores de 25 años 2022	% Parados de 25 y 44 años 2022	% Parados mayores de 45 años 2022	% Salarios s/rentas totales	Renta neta media por persona 2023	Población potencialmente activa 2024	parados 2022_2024	ocupados 2022_2024	Vitalidad urbana= 0,3678-(parados/ ocupados)
% Uso industrial, almacenamiento y estacionamiento 2024	1	0,299602	0,001794	0,005455	0,00442	0,018856	0,019192	0,026385	0,003873	0,024043	0,001323	0,008405	0,028552	0,076015	0,014735	0,003746	0,00477	0,003635	0,020344
% Uso residencial 2024	0,299602	1	0,020105	0,058391	0,004781	0,084321	0,084933	0,064198	0,001185	0,059921	0,011462	0,046855	0,043519	0,139775	0,059631	0,00119	0,002151	0,001114	0,052885
% Uso terciario 2024	0,001794	0,020105	1	0,004267	0,080002	0,141705	0,141226	0,086795	0,028319	3,56E-05	0,012815	0,074988	0,024854	0,047475	0,002988	0,028216	0,039655	0,027119	0,000145
% Otros usos 2024	0,005455	0,058391	0,004267	1	0,008571	0,060572	0,061308	0,048445	0,00278	0,0289	0,002917	0,031991	0,018158	0,086451	0,026466	0,002701	0,004007	0,002582	0,023304
Superficie de suelo artificial 2016	0,00442	0,004781	0,080002	0,008571	1	0,061661	0,06163	0,026134	0,767728	0,005402	0,007837	0,042003	0,019948	0,029589	0,000743	0,764142	0,800686	0,754523	0,004467
% Viviendas principales 2021	0,018856	0,084321	0,141705	0,060572	0,061661	1	0,997316	0,657739	0,026221	0,002489	0,040883	0,215538	0,086152	0,361102	0,00034	0,025829	0,034518	0,024946	0,000777
% Viviendas no principales 2021	0,019192	0,084933	0,141226	0,061308	0,06163	0,997316	1	0,658133	0,026203	0,002469	0,041024	0,215328	0,086374	0,361759	0,000355	0,025811	0,034496	0,024929	0,000763
D.29. Número de viviendas por cada 1.000 habitantes	0,026385	0,064198	0,086795	0,048445	0,026134	0,657739	0,658133	1	0,008321	0,003963	0,029091	0,158909	0,07742	0,359121	0,005743	0,008185	0,011295	0,007881	0,001246
Población 2024	0,003873	0,001185	0,028319	0,00278	0,767728	0,026221	0,026203	0,008321	1	0,001193	0,001991	0,01116	0,004967	0,007365	0,001993	0,999585	0,907961	0,998597	0,000972
% Población parada 2022	0,024043	0,059921	3,56E-05	0,0289	0,005402	0,002489	0,002469	0,003963	0,001193	1	0,002551	0,008032	0,038056	0,034902	0,261609	0,001151	0,006928	0,000883	0,992288
% Parados menores de 25 años 2022	0,001323	0,011462	0,012815	0,002917	0,007837	0,040883	0,041024	0,029091	0,001991	0,002551	1	0,04004	0,003747	0,011537	0,014497	0,001971	0,003503	0,001848	0,00224
% Parados de 25 y 44 años 2022	0,008405	0,046855	0,074988	0,031991	0,042003	0,215538	0,215328	0,158909	0,01116	0,008032	0,04004	1	0,135344	0,099454	0,023734	0,010904	0,015884	0,010442	0,005963
% Parados mayores de 45 años 2022	0,028552	0,043519	0,024854	0,018158	0,019948	0,086152	0,086374	0,07742	0,004967	0,038056	0,003747	0,135344	1	0,05729	0,022754	0,004822	0,006606	0,004646	0,032897
% Salarios s/rentas totales	0,076015	0,139775	0,047475	0,086451	0,029589	0,361102	0,361759	0,359121	0,007365	0,034902	0,011537	0,099454	0,05729	1	0,004416	0,007373	0,009354	0,007157	0,021252
Renta neta media por persona 2023	0,014735	0,059631	0,002988	0,026466	0,000743	0,00034	0,000355	0,005743	0,001993	0,261609	0,014497	0,023734	0,022754	0,004416	1	0,00192	0,000242	0,002112	0,247119
Población potencialmente activa 2024	0,003746	0,00119	0,028216	0,002701	0,764142	0,025829	0,025811	0,008185	0,999585	0,001151	0,001971	0,010904	0,004822	0,007373	0,00192	1	0,904424	0,99935	0,000939
parados 2022_2024	0,00477	0,002151	0,039655	0,004007	0,800686	0,034518	0,034496	0,011295	0,907961	0,006928	0,003503	0,015884	0,006606	0,009354	0,000242	0,904424	1	0,888912	0,006372
ocupados 2022_2024	0,003635	0,001114	0,027119	0,002582	0,754523	0,024946	0,024929	0,007881	0,998597	0,000883	0,001848	0,010442	0,004646	0,007157	0,002112	0,99935	0,888912	1	0,0007
Vitalidad urbana= 0,3678-(parados/ocupados)	0,020344	0,052885	0,000145	0,023304	0,004467	0,000777	0,000763	0,001246	0,000972	0,992288	0,00224	0,005963	0,032897	0,021252	0,247119	0,000939	0,006372	0,0007	1

Figure 3. Spain Urban Data 2026: Urban Neural Networks
Source: Own elaboration

ANDALUCIA	% Uso industrial, almacenamiento y estacionamiento 2024	% Uso residencial 2024	% Uso terciario 2024	% Otros usos 2024	Superficie de suelo artificial 2016	% Viviendas principales 2021	% Viviendas no principales 2021	Número de viviendas por cada 1.000 habitantes	Población 2024	% Población parada 2022	% Parados menores de 25 años 2022	% Parados de 25 y 44 años 2022	% Parados mayores de 45 años 2022	% Salarios s/rentas totales	Renta neta media por persona 2023	Población potencialmente activa 2024	parados 2022_2024	ocupados 2022_2024	Vitalidad urbana= 0,3678-(parados/ ocupados)
% Uso industrial, almacenamiento y estacionamiento 2024	1	0,459668	0,080929	0,009198	0,082241	0,01082	0,010778	0,008284	0,067102	0,005075	0,007352	0,007405	0,002715	0,028543	0,015522	0,067947	0,055575	0,069885	0,005314
% Uso residencial 2024	0,459668	1	0,006673	0,006056	0,015042	0,008029	0,008067	0,00486	0,012153	0,043721	0,005972	0,001343	0,006146	0,006391	0,015859	0,012311	0,007819	0,013104	0,044609
% Uso terciario 2024	0,080929	0,006673	1	0,00886	0,223153	0,146152	0,146594	0,145227	0,169535	0,040635	0,028405	0,059005	0,010181	0,175631	0,037994	0,171547	0,159661	0,173028	0,038356
% Otros usos 2024	0,009198	0,006056	0,00886	1	0,004638	0,022374	0,022402	0,025591	0,003348	0,002414	0,006524	0,024835	0,002725	0,008373	0,003599	0,003386	0,003269	0,003395	0,002238
Superficie de suelo artificial 2016	0,082241	0,015042	0,223153	0,004638	1	0,062556	0,062488	0,055846	0,750119	0,032846	0,003671	0,021632	0,00928	0,088214	0,065121	0,756668	0,741758	0,756919	0,031576
% Viviendas principales 2021	0,01082	0,008029	0,146152	0,022374	0,062556	1	0,999522	0,853766	0,052575	0,001413	0,133821	0,181628	0,001526	0,245178	0,004506	0,053614	0,052847	0,053584	0,00128
% Viviendas no principales 2021	0,010778	0,008067	0,146594	0,022402	0,062488	0,999522	1	0,853541	0,052564	0,001273	0,133775	0,180761	0,001457	0,244714	0,004421	0,053603	0,052842	0,053572	0,001147
D.29. Número de viviendas por cada 1.000 habitantes	0,008284	0,00486	0,145227	0,025591	0,055846	0,853766	0,853541	1	0,036528	0,000406	0,154598	0,23447	0,005048	0,254273	0,020997	0,037474	0,034337	0,037889	0,000323
Población 2024	0,067102	0,012153	0,169535	0,003348	0,750119	0,052575	0,052564	0,036528	1	0,020487	0,001904	0,010015	0,004537	0,041681	0,060006	0,999601	0,986021	0,998925	0,019553
% Población parada 2022	0,005075	0,043721	0,040635	0,002414	0,032846	0,001413	0,001273	0,000406	0,020487	1	0,000114	0,0018	0,050451	0,051866	0,015289	0,020615	0,03279	0,018836	0,996395
% Parados menores de 25 años 2022	0,007352	0,005972	0,028405	0,006524	0,003671	0,133821	0,133775	0,154598	0,001904	0,000114	1	0,147261	0,014794	0,008499	0,069121	0,001948	0,001465	0,002028	0,000158
% Parados de 25 y 44 años 2022	0,007405	0,001343	0,059005	0,024835	0,021632	0,181628	0,180761	0,23447	0,010015	0,0018	0,147261	1	0,009723	0,054164	0,057506	0,010217	0,008078	0,010559	0,00116
% Parados mayores de 45 años 2022	0,002715	0,006146	0,010181	0,002725	0,00928	0,001526	0,001457	0,005048	0,004537	0,050451	0,014794	0,009723	1	0,031112	0,0099	0,004614	0,004346	0,004645	0,046427
% Salarios s/rentas totales	0,028543	0,006391	0,175631	0,008373	0,088214	0,245178	0,244714	0,254273	0,041681	0,051866	0,008499	0,054164	0,031112	1	0,143462	0,043778	0,039222	0,044417	0,04451
Renta neta media por persona 2023	0,015522	0,015859	0,037994	0,003599	0,065121	0,004506	0,004421	0,020997	0,060006	0,015289	0,069121	0,057506	0,0099	0,143462	1	0,059832	0,057542	0,060036	0,012678
Población potencialmente activa 2024	0,067947	0,012311	0,171547	0,003386	0,756668	0,053614	0,053603	0,037474	0,999601	0,020615	0,001948	0,010217	0,004614	0,043778	0,059832	1	0,984774	0,999594	0,019664
parados 2022_2024	0,055575	0,007819	0,159661	0,003269	0,741758	0,052847	0,052842	0,034337	0,986021	0,03279	0,001465	0,008078	0,004346	0,039222	0,057542	0,984774	1	0,979447	0,031994
ocupados 2022_2024	0,069885	0,013104	0,173028	0,003395	0,756919	0,053584	0,053572	0,037889	0,998925	0,018836	0,002028	0,010559	0,004645	0,044417	0,060036	0,999594	0,979447	1	0,017879
Vitalidad urbana= 0,3678-(parados/ocupados)	0,005314	0,044609	0,038356	0,002238	0,031576	0,00128	0,001147	0,000323	0,019553	0,996395	0,000158	0,00116	0,046427	0,04451	0,012678	0,019664	0,031994	0,017879	1

Figure 4. Andalucia Urban Data 2026: Urban Neural Networks
Source: Own elaboration

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Some differences are observed, but the correlation between the following variables is significant:

Population	Artificial soil surface area
Number of dwellings/1,000 inhabitants	Population% of main dwellings
% of residential use	% of industrial use, storage, and parking

Urban Neural Networks (UNNs) are being prepared.
The relationship between Population and artificial soil surface area is evident, although the degree of compaction can cause dispersions in the indicator.
The other two relationships have varying degrees of reciprocal influence.
It has been found that soil surface area explains very little of the municipality's economic vitality.

2. Training of Interactive Models
Three Multilayer Neural Network models, specialized in predicting the impact of certain variables, have been trained:
Model 1: Predicts 'Artificial soil surface area' based on 'Population'. This allows us to understand how population growth could influence infrastructure development.
Model 2: Predicts the 'Percentage of Primary Residences' based on the 'Number of dwellings per 1,000 inhabitants'. This helps us analyze housing density and quality of life in cities.
Model 3: Predicts the percentage of industrial use, storage, and parking based on the variation in residential use.
These models learn patterns from the data to offer fast and relevant predictions.

3. Interactive Widget
The interactive widget allows any user to enter data via sliders to formulate forecasts of the behavior of correlated variables.
4. Model Evaluation
Finally, the predictive strength is evaluated using standard metrics: MAE (Mean Absolute Error) and RMSE (Root Mean Square Error) indicate how closely the predictions match the actual values.
R^2 (R-squared) indicates the percentage of the variation in the dependent variable that we want to predict that is explained by the independent variables. The interpretation varies depending on the field of study:
0.9 to 1.0 Excellent and very reliable for making predictions.
0.7 to 0.9 Good fit; the model captures most of the trend.
0.35 to 0.7 Acceptable fit, but the prediction will have a margin of error,
<0.35 Poor fit; the model fails to accurately explain the data, and other variables should be considered.
The results are also visualized with scatter plots that compare the predictions with the actual values.

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Mean Absolute Error (MAE) : 228.2587
Root Mean Squared Error (RMSE): 419.1929
R-squared (R2) : 0.3445

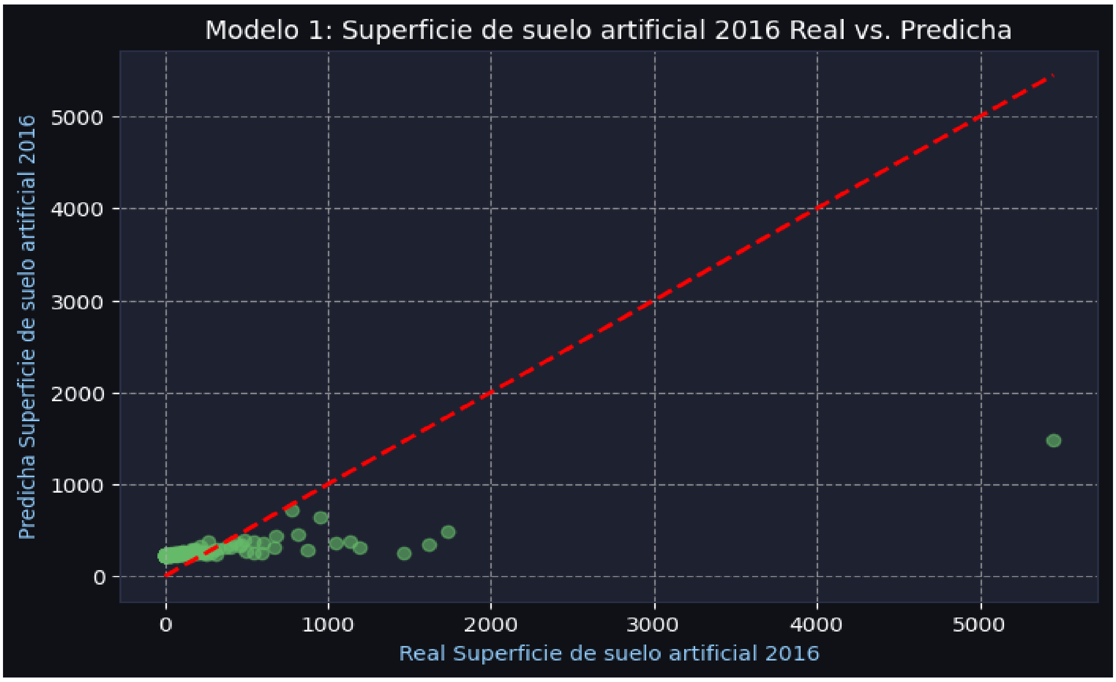

Figure 5. UNN1 Artificial soil surface area
Source: Own elaboration

Mean Absolute Error (MAE) : 2.3874
Root Mean Squared Error (RMSE): 3.0401
R-squared (R2) : 0.9509

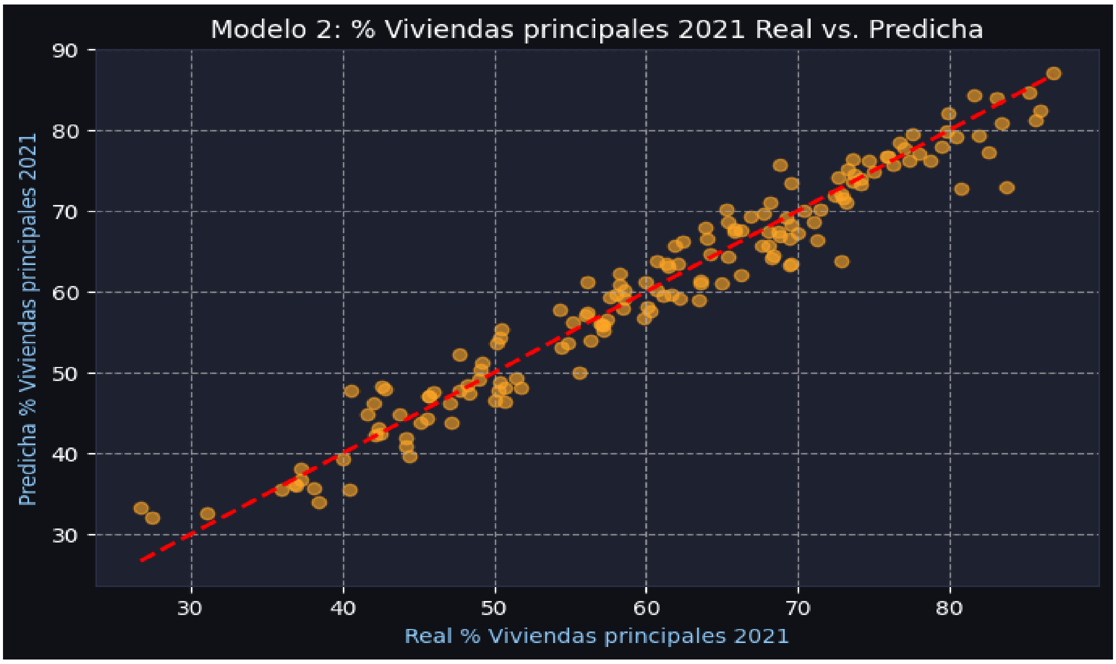

Figure 6. UNN2 Population% of main dwellings
Source: Own elaboration

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Mean Absolute Error (MAE)   : 4.2196
Root Mean Squared Error (RMSE): 5.5986
R-squared (R2)   : 0.2623

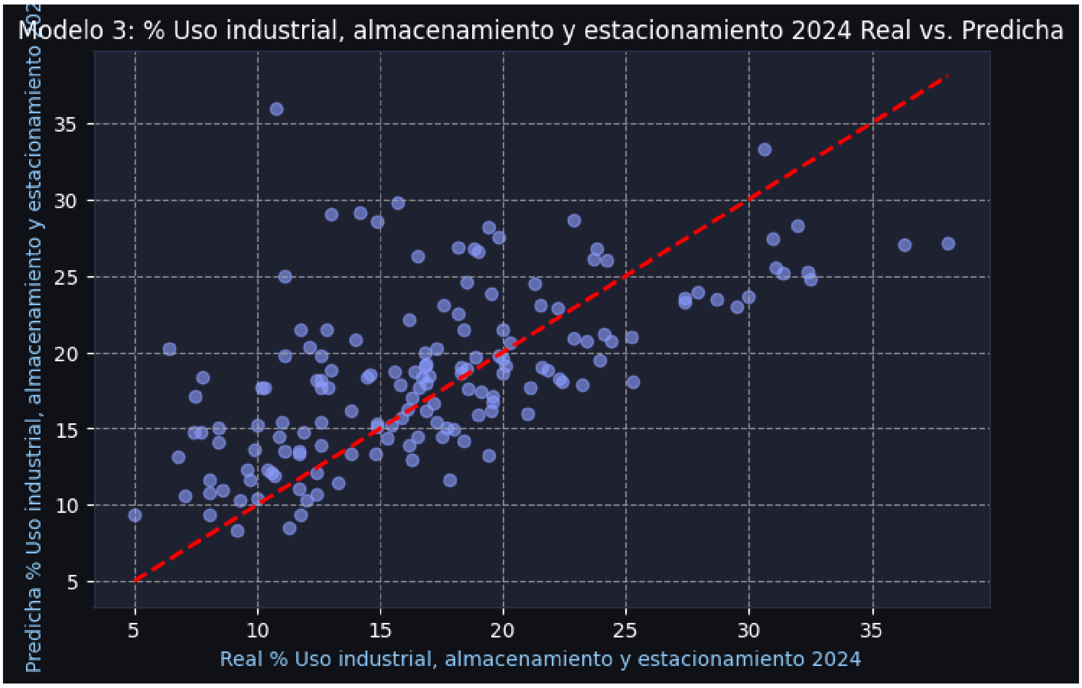

Figure 7. UNN3 Population% of main dwellings
Source: Own elaboration

4. CONCLUSIONS

Results confirm the hypothesis raised about UNN as valid tools for modeling and predicting integrated urban dynamics. Unlike traditional planning, RNU allows us to address territorial complexity from a systemic perspective, anticipating emerging behaviors and facilitating evidence-based decision-making.

The forecast value can be used in two different ways. First, as the target value for the non-existent indicator whose result is desired obtain. Second, as a benchmark value for the indicator within the research context, to assess the difference from the existing actual value.

UNN use brings methodological innovation to current urban planning and opens new lines of research in articulation between quantitative urban modeling, governance, and the Right to the City. Its ability to reflect urban complexity allows for the construction of adaptive models, useful in current contexts of territorial uncertainty.

The complexity of algebraic calculations through Urban Mechanics and Thermodynamics is substantially reduced through AI.

Application of these models has great social potential. Predictions improve the technical understanding of urban space and enable the implementation of policies that strengthen urban equity and the Right to the City through the early detection of territorial imbalances (deficits in investment, infrastructure, or housing).

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Urban planning will be multidisciplinary (network sociology, psychology, economics, mathematics, computer science, geography and the environment, engineering and architecture, among others), and citizen participation will be expanded.
The interactive nature of the developed models facilitates their transfer to public administrations, planning entities, and citizen groups. This opens the door to designing more inclusive and transparent urban strategies focused on urban planning, or indirectly addressing the affected urban rights

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