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Territorial disparity index: a GIS-integrated data framework for territorial disparities measurement in rural Morocco

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ABSTRACT

Despite availability of numerous indicators for territorial evaluation and the measurement of their deprivation or advantage, the results remain confined to a coarse-grained spatial scale and cannot be applied at finer levels of territories like to Moroccan rural entities known as douars. This paper presents a bottom-up framework termed territorial disparity index (TDI) that quantitatively conceptualize territories as entities shaped through data-driven technological processes in order to better control and develop them and above all to reduce their multi-scale disparities. Through this study, we propose a geographic information system (GIS)-integrated data for composite index through two key dimensions: socio-economic and spatial-environmental aspects, quantified as scores based on 32 variables translated into indicators, then converted into decile ranks through a systematic data processing pipeline. The framework of TDI not only enhances spatial sensitivity often overlooked, but also provides a highly objective tool for mapping territorial disparity. Applied to actual data of a real Moroccan territory, in Berkane, this research introduces a novel methodology for territorial data collection, combining cross-sectional and spatial data analysis to digitally perceive these territories according to their levels of disadvantage. Principal component analysis (PCA) is then used to ensure robustness and objectivity of TDI index.

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1. INTRODUCTION

Nowadays, the concepts of 'smart city' and 'smart territories' tend to cover all forms of digital transformation that affect public policies. There is no doubt that the ambitions surrounding these two concepts are already becoming clearer and are being driven by data covering the issues of sustainability, inclusion, resilience, attractiveness and equity. However, the various government action plans and initiatives across the globe have shown that crafting public policy is a highly nuanced and delicate art, given the marked heterogeneity of territories and their maturity, not only at national level but also at local level [1].

Today, thanks to the latest technological developments, decision-makers fortunately have access to a large quantity of territorial data capable of reporting on the various opportunities, challenges and risks to achieving a territorial development that could-normally-reduce disparities, correct dysfunctions and combat the deterioration of living environments, with a view to meeting the evolving needs of populations.

Two main methods are used to measure disparities, including spatial analysis and statistical analysis. However, interpreting raw data can present significant challenges. This is why composite indexes are used. They consolidate data from different sources to more clearly capture the multidimensional nature of a given concept [2].

The construction of a composite indicator is fundamentally a data-driven process that goes far beyond the simple application of mathematical techniques. At every stage, data plays a pivotal role from the initial definition of the conceptual framework to the final robustness checks. The process begins with a clear and theoretically grounded measurement framework, which guides the selection of relevant and high-quality datasets capable of capturing the various dimensions of the concept under study. The chosen data then inform the aggregation method, which may include differential weighting to reflect the relative importance of each dimension. Ultimately, the reliability and validity of the composite indicator depend not only on methodological rigor but also on the quality, relevance, and interpretation of the underlying data [3]. Moreover, as data selection and processing often involve subjective decisions, it is essential that researchers make these choices and their implications fully transparent [4].

Our research adopts a composite index framework in form of territorial disparity index (TDI) to examine the degree of socio-spatial deterioration in rural areas, using the Berkane Province of Morocco as a case study. Without being exhaustive, next section endeavor to give a brief overview of the main indices, derivedn from both Moroccan and international contexts, applied in academic settings as well as in real-world practice. Section 3 discusses the conceptual justification and background for employing TDI as a methodological tool to quantify rural marginalization in the Moroccan context, then describes the methodology, design process and calculation process in Berkane Province. Section 4 displays the results generated by this context-specific design across the 206 rural entities (douars), with structured tabular summaries and cartographic representations. Principal component analysis (PCA) is then implemented in order to characterize the underlying structure of the data, evaluate the robustness of the index and potential dimensionality reduction, to simplify its adoption. It also explores a potentially predictive approach to improve score estimation and ranking classification. Section 5 concludes the paper.

2. MOTIVATION AND BACKGROUND

2.1. Background

Indicators, whether individual or composite, serve to represent underlying concepts or latent variable. Given the multidimensional nature of most territorial realities, relying on a single indicator is often insufficient to reflect their complexity. Consequently, a wide range of composite indices, developed within both Moroccan and global frameworks, have been adopted in academic sphere as well as by governmental institutions for practical implementation.

2.1.1. Social development index

It is an index developed by the Moroccan National Observatory for Human Development (ONDH) in the form of maps of social deficits at regional level, taking into account two dimensions: education and health. For health, the indicator used is the rate of medical care measured at provincial level. For education, the indicator used is the success rate at the end of the college cycle, measured at circle level [5]. The social development index (SDI) is therefore the arithmetic mean of the indices obtained for each of the two dimensions. The ranking is done at the regional level.

2.1.2. Human development index

The most commonly referenced illustration of a composite indicator. Developed by the United Nations Development Programme (UNDP), this is a composite index resulting from the weighted average of three indicators (life expectancy at birth, standard of living and level of education) [6]. It is typically calculated at the national level, but some organizations may also calculate it at the regional or communal level with communal human development index (CHDI) [6].

2.1.3. National human development index

In the same context, the ONDH has further developed this UNDP index with a view to providing a better context at national level. It‘s measured by reliable and coherent result indicators that combine the accessible indicators recommended by the UNDP with those required for monitoring and evaluating public policies at Moroccan national level [7]. The six dimensions of the national human development index (NHDI) are: ‘education’ dimension, ‘health’ dimension, ‘standard of living’ dimension, ‘Living environment’ dimension, ‘social cohesion and human security’ dimension, and ‘subjective well-being’ dimension.

2.1.4. French deprivation index

A social disadvantage index constructed using PCA on four socio-demographic variables: the unemployment rate, the proportion of workers in the active population, the proportion of adults with a secondary education diploma, median household income. However, only the first factor in the PCA is retained [8].

2.1.5. The Canadian index of multiple deprivation

A composite index, which combines several indicators to provide a comprehensive assessment of deprivation. It takes into account four dimensions: residential mobility, economic dependence, conditional vulnerability, and ethno-cultural composition [9]. Calculated from 17 socio-economic variables, the index is targeted at the neighbourhood level, allowing a detailed analysis of patterns of deprivation in Canadian cities and regions.

2.2. Problem statement

These approaches to index design highlight the need to use proxy variables to reflect the multidimensional aspect. However, these composite indicators present several significant shortcomings:

- The focus on the human aspect of development through the capacity of individuals to produce, while completely neglecting the spatial component, which affects these socio-economic indices.
- The absence of interpretable measurement scales: these scores are only used in their composite form and cannot be interpreted or compared mathematically by development sector.
- These scores are adapted to macroscopic contexts ranging from the commune to the region, and do not take account of specific rural features.
- These indexes cannot be used to zoom in on Morocco's rural ‘douars’ socio-spatial context. In fact, these disadvantaged areas, which are both extensive and fragile, need other sets of indicators capable of helping decision-makers to provide their populations with the basic amenities of life, namely access to drinking water, access to paved roads and proximity to vital services, headed by health and education establishments.

Hence, the interest in devising a new way of understanding this territorial inequality in rural areas from a cross-cutting perspective that takes into account the heterogeneous spatial aspect of Moroccan rural areas. Our case study will be the rural environment of the Province of Berkane with its 206 rural entities (douars).

3. METHOD

Our index of territorial disparity is based on two main components:

- The socio-economic component, referred as household resources (HR), given that it reflects the standard of living of the population and possible projections for action in terms of economic development and convergence.
- The spatial-environmental component, referred as territorial resources (TR), to make up for the absence or timid presence of the geographical dimension observed in the aforementioned indices and others. This component derives its legitimacy from the fact that the socio-economic profile is strongly influenced by the environment and the space occupied by the social group. In addition to its multidimensional advantage, this index is interesting in that it guarantees a high degree of objectivity with a score matrix derived from several parameters. What's more, this battery of indicators can be extended (there is no limit to the number).

3.1. Design process of the index

The index construction methodology comprises three major phases covering the process from the collection of raw data, which gave rise to indicators represented by variables, to finally generate the synthetic index that is the subject of our study, according to the pyramid known from Braat [10] Figure 1:

- Phase 1: collection, structuring and use of basic data.
- Phase 2: determination of indicators based on understanding needs and field observations.
- Phase 3: definition of the synthetic index reflecting the state of rural deprivation.

3.2. Collecting and preprocessing of data

The choice of the target data is mainly linked to our definition of the index by combining the two dimensions, spatial-environmental and socio-economic.

3.2.1. Data source

This study aims to evaluate the potential of geographic information system (GIS) tools in facilitating the implementation of sustainable development within rural areas [11], with a particular focus on rural Berkane.

The selection of this specific Moroccan area is primarily motivated by the availability of relevant and reliable data. Moreover, Berkane is considered, at the national level, as a pioneering territorial entity in terms of digital transformation and administrative innovation. It has multi-layer spatial data on its integrated geographic information system (IGIS), the main source of our study. This GIS fits in perfectly with the smart vision of territories, since it represents one of the crucial sources of data common to all smart territory frameworks [12]. During this study, it provided us with multidimensional information relating to each geographical point (douar), which we were able to exploit thanks to various geo-requests, namely spatial join, network analysis and spatial analysis in addition to data analysis. For these purposes, we use ArcGIS Pro 3.0 for geographic data and Python 3.12.11 for scripts of data analysis.

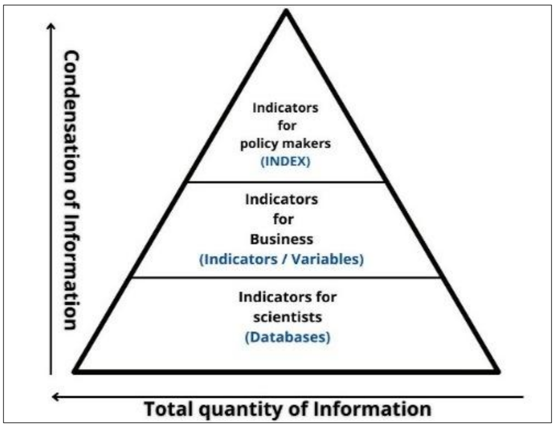

Figure 1. Relationships between indicators [10]

3.2.2. Geographical scope of the data

The data used concerns n=206 rural entities (douars) in the Province of Berkane, covering 10 rural communities: Aghbal, Madagh, Laatamna, Fezouane, Zegzel, Chouihia, Tafoughalt, Sidi Bouhria, Boughriba, and Rislane.

3.2.3. Datasets and indicators definition

The indicators and variables used in this paper are summarized in Table 1. For each variable, the table reports the variable, symbol, unit, weighting for certain ones, and the resulting indicator and scores. Table 1 presents an overview of the indicators and variables used in this conception. Each variable is subsequently described to explain its meaning, justification of use, contribution to the overall analysis and reference to calculation procedure.

As previously introduced in this section, spatial-environmental and socio-economic components are detailed below.

Considering spatial-environmental component, already referred as TR

The indicators selected for this dimension are as follows:

- Gross area (A_g) km²: a territory is more prosperous when it has a large surface area (and above all a useful surface area (agricultural land, forests, bodies of water, and habitat). This data is automatically derived from the Berkane provincial GIS [13] and given by (1):

$$\mathrm{A_g} = \sum_{i=1}^{n} \mathrm{A_i} \tag{1}$$

where A_i is the area of douar "i".

- Surface weighted by NDVI (A_{NDVI}): the normalized difference vegetation index (NDVI) [14] is an index measuring vegetation health based on normalized spectral differences. It is based on satellite image processing [13], reflecting the density and health of vegetation per pixel. NDVI classes (k) are defined according to the values obtained. The weighted area consists of multiplying the area of each class by a weight that reflects the importance of that class. A_{NDVI} is defined as (2):

$$\mathrm{A_{NDVI}} = \sum_{k} \mathrm{A_g}\,(k) * NDVI(k) \tag{2}$$

where k € {0; 0,1; 0,2; 0,3; 0,4; 0,6}.

– Gini index applied on neighborhood density (G_{ND}): this concept expresses the concentration/dispersion of a cloud of points in a given space. It involves a spatial analysis of the population's neighborhood distances over consecutive intervals of 100 m, 200 m, … up to 800 m. To achieve this, we first calculate the neighborhood aggregation, which measures the sum of household in same buffer zones.

Table 1. Summary table of variables and transformation into indicators

Component	Variable	Unit	Weight (w)	Indicator	Score
Spatial-environmental (TR)	Gross area (A_g)	km²		Ratio A_{NDVI}/A_g	Area score **(s1)**
	NDVI	-		Surface weighted by NDVI A_{NDVI}	Relief score **(s2)**
	Altitude (z)	m		Z-weighted area(Az_i)	
	Slope (s)	°		Slope-weighted area (Asw_i)	
	Surface population density (D_p)	H/km²		Contrasted and weighted altitude (Z_i) Ratio $A_{NDVI}/z/A_g$ Ratio $(\frac{A_{NDVI}}{A_g})/s$	
	Total length of paved roads L_{pr}	km		Ratio of paved road (km/km²)	Paved road area ratio score **(s3)**
	Distance from paved road	km			Distance to paved road score **(s4)**
	Distance from the municipal's seat	km			Average proximity from the municipal seat **(s5)**
	Distance from primary schools	km	0.8	Distance from schools after weighting	School proximity score **(s6)**
	Distance from middle schools	km	0.15		
	Distance from high schools	km	0.05		
	Distance from rural health centers (RHC)	km			Health center proximity score **(s7)**
	Gini Index applied on neighborhood density (G_{ND})	-		$(D_p) \times (G_{ND})$	Density score **(s8)**
Socio-economic (HR)	Total population (P)	Number			Total population score **(s9)**
	Male population ($male\ p_i$)	Number			Score w/m ratio **(s10)**
	Female population ($female\ p_i$)	Number		Women/men ratio ($R_{w/m}$)	
	Women between 15-45 years ($female\ p_{CB}[15-45]$)	Number			Women [15-45 y] score **(s11)**
	Children between 0-14 years ($P_{ch[0-15]}$)	Number		Dependency ratio ($R_{dependency}$)	Dependency score **(s12)**
	People over 60 years ($N_{P>60}$)	Number			
	Unemployed people ($N_{unemployed}$)	Number			
	Employed people	Number			Employed people score **(s13)**
	People with special needs (PSN)	Number			Person in special need score **(s14)**
	People with chronic illnesses	Number			Illness sore **(s15)**
	Users of buses	Number		Ratio of public mobility mean	Mobility score **(s16)**
	Users of mixed transport	Number			
	Users of big taxis	Number			
	Users of cars	Number	1	Ratio of private mobility mean (R_{mob})	
	Users of motos	Number	0.2		
	Users of bikes	Number	0.1		
	Household with water access	Number		R_{DWA}	Drinking water access score **(s17)**
	Household with electricity access	Number		R_{electr}	Electricity access score **(s18)**
	Household with sanitation connection	Number		$R_{sanitation\ connx}$	Sanitation connection score **(s19)**

Once generated, we apply the Gini index [15] also known as the "GINI coefficient" to these clusters (cells) according to (3) referred as (G_{ND}):

$$G_{\mathrm{ND}}=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|p_i-p_j\right|}{2\sum_{i=1}^{n}\sum_{j=1}^{n}p_j}=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|p_i-p_j\right|}{2n^{2\bar{p}}} \quad (3)$$

where $\sum_{i=1}^{n}\sum_{j=1}^{n}\left|p_i-p_j\right|$ is the absolute difference between the populations of two cells. $\sum_{j=1}^{n}p_j$ represents the sum of all populations in the cluster.

G_{ND} value falls between 0 and 1. A G_{ND} of 0 signifies complete equality in population distribution, meaning every area has the same population count. Conversely, a G_{ND} approaching 1 indicates extreme inequality, where the entire population is clustered in just one area.

This calculation shows how density alone cannot reflect the true degree of dispersion or concentration of an entity. A dispersed population in a small douar gives a high density. Alternatively, a well-concentrated population in a large douar gives a very low density, which in no way represents reality.

These aggregations of entities are then contrasted with the density coefficient in order to give greater weight to over-densified areas, hence the data relating to the surface density of the population.

– Surface population density H/km² (D_p): thanks to the geo-localized population layer (p_i) and the polygonal division of the study entity (douar), we get (4):

$$D_{\mathrm{p}} = \frac{\sum_{i=1}^{n} p_i}{\sum_{i=1}^{n} \mathrm{A_i}} \quad (4)$$

Land form: the topography is a determining factor for the development of territories [16]. It has been taken into consideration along with altitude (Z) and slope (S), which are generally the cause of isolation and the difficult climatic conditions they foster.

To consider these constraints, three parameters come into play in the spatial analysis, based on the digital elevation model (DEM) of the study area, which was integrated into [13]:

– Contrasted and weighted altitude (Z_i): this is the product of the mean altitude and the contrasted altitude of douar “i”, calculated as (5):

$$\mathrm{Z_i} = \mathrm{Z_{mean}} * (\mathrm{Z_{max}} - \mathrm{Z_{min}}) \quad (5)$$

– Z-weighted area(Az_i): using the GIS of [13], we calculate the mean altitude Z of each douar (i) and the corresponding area, which enables us to calculate the Z-weighted area according to (6):

$$Az_i = \sum \mathrm{A_{g\,(i)}} \times Z_i \quad (6)$$

where z_i € {min=100 m, 200 m, ..., 1400 m, max=1500 m) then the $\mathrm{A_g}$ /Az ratio.

– Slope-weighted area (Asw_i): using the same z-weighted area calculation method, we determine this information for each douar “i“ as (7):

$$Asw_i = \sum \mathrm{A_g}\,(\mathrm{i}) * s_i \quad (7)$$

where s_i € {10°, 20°, 30°, 40°, 50°, 60°, 70°} derived from spatial analysis.

– Paved road ratio (R_{pr}): the surface ratio of paved roads expressed in km/km² and the average distance (L_i) from the paved road, which can be computed for each douar “i“ obtained by (8):

$$\mathrm{R_{pr}} = \frac{\sum_{i=}^{n} L_{\mathrm{i}}}{\mathrm{A_g}} \quad (8)$$

– Proximity indicators (km): distance to basic social amenities. These include distance from the community's headquarters, from schools (weighted by school category: school 80%, secondary 15%, and high school 5%) and from RHC.

Considering socio-economic component, referred below as HR.

The indicators selected for this dimension are as follows:

– Population (p_i): the more populated a douar is, the more likely it is to develop, since man is a factor of production.

– Women/men ratio ($R_{w/m}$), defined for each douar “i” as showed by (9):

$$\mathrm{R_{w/m}} = \frac{Number\ of\ women}{Number\ of\ men} \quad (9)$$

where a ratio greater than 1 reveals a fragile territory especially in rural context.

– Percentage of women of childbearing age (15 to 45) ($P_{\mathrm{w,\,CB}}$): where this category of women demands more attention and is a source of development. It’s given by (10):

$$P_{\mathrm{w,\,CB[15\text{-}45]}} = \frac{female\ p_{CB}[15-45]}{female\ p_i} \times 100 \quad (10)$$

– Access to work (N_{employed}): equivalent to the existence of a household income. It equals to number of unemployed people.
– People in charge ($R_{dependency}$): these are mainly people over 60 (P_{60+}), the unemployed people ($P_{\text{Unemployed}}$) and children aged 0 to 15 ($P_{\text{ch[0-15]}}$). These categories contribute to a region's vulnerability and inertia. It's defined with the sum (11):

$$\text{Dependency ratio } (\text{R}_{\text{dependency}}) = P_{\text{ch}[0-15]} + P_{60+} + P_{\text{Unemployed}} = \left(\frac{N_{\text{ch[0-15]}}}{P} + \frac{N_{\text{P>60}}}{P} + \frac{N_{\text{unemployed}}}{P}\right) \times 100 \quad (11)$$

– PSN: a vulnerable group adding more burdens to the life constraints of the social group.
– People with chronic illnesses (N_{ill}): requiring lifelong treatment and ongoing care.
– Total public transport users (N_{PT}): corresponds to bus users, taxi users and mixed transport users.
– Mobility (R_{mob}): (12) reflects mobility rate that takes into account the best-known means of transport, i.e., cars (N_{cars}), motorbikes (N_{motos}), and bicycles (N_{bikes}), with weightings for each, according to its impact on mobility. This weighting; 1 for cars, 0.1 for motorbikes, and 0.2 for bicycles; takes into account the specific nature of the rural world, with its size and dispersal, and even the purpose of use.

$$\text{R}_{mob} = N_{cars} + \frac{N_{motos}}{5} + \frac{N_{bikes}}{10} \quad (12)$$

– Access to drinking water rate (R_{DWA}): representing the ratio in (13) between household with access to drinking water (H_{DW}) and total households (H_{Total}) for each douar "i":

$$\text{R}_{DWA} = \frac{H_{DW}}{H_{Total}} \quad (13)$$

– Electrification rate (R_{electr}): representing the ratio (14) between household with access to electricity (H_{electr}) and total household (H_{Total}) of each douar "i":

$$\text{R}_{electr} = \frac{H_{electr}}{H_{Total}} \quad (14)$$

– Sanitation connection rate ($R_{sanitation\ connx}$) reflecting the ratio (15) between household with access to sanitation ($H_{sanitation\ connx}$) and total household (H_{Total}) of each douar "i":

$$\text{R}_{sanitation\ connx} = \frac{H_{sanitation\ connx}}{H_{Total}} \quad (15)$$

3.3. Calculation process

The workflow of this work is depicted at two complementary levels: Figure 2 illustrates an overall conceptual overview of the calculation process, then detailed for each component in Figures 3 and 4. Algorithm 1 explicitly formalizes the mathematical process through the pseudocode.

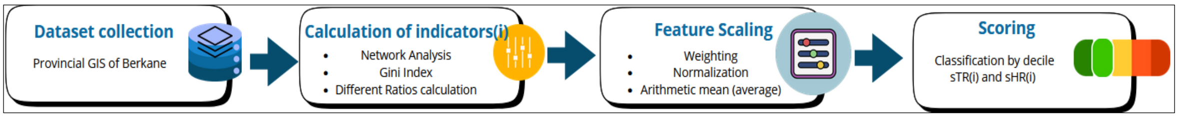

Figure 2. Conceptual overview of the process

The process of calculation is moving from the raw data collected from provincial GIS to the indicator detailed in Table 1 and using the previously defined equations. We calculate the average for each component after weighting and normalizing steps. Finally, we address the scoring procedure by generating scores classified by decile.

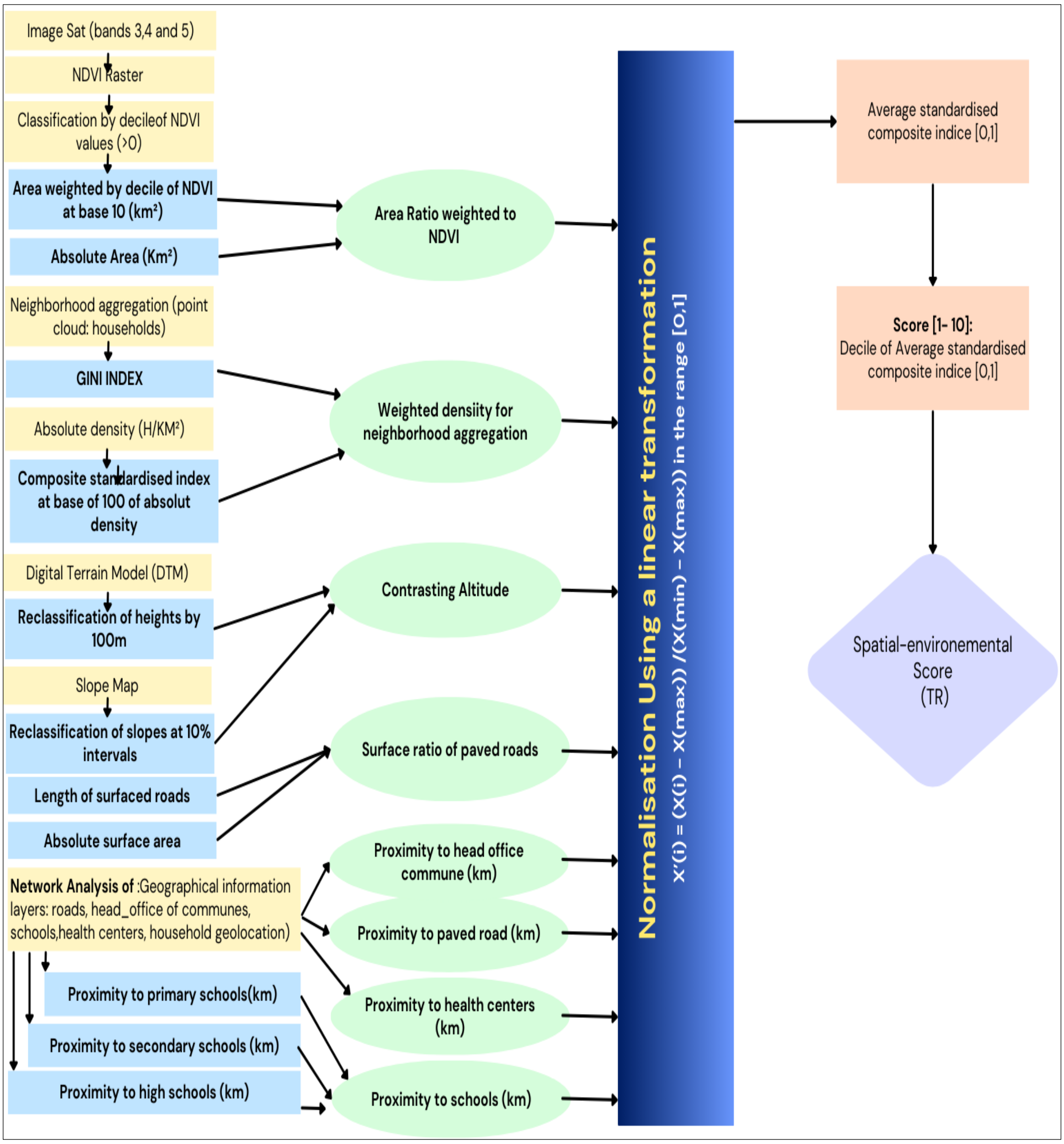

Figure 3. TR or spatial-environmental component workflow (TR)

Weighting and normalization with min-max scaling method [17] as recommended by [4], were chosen to manage the variability within the dataset, preventing any single feature from outweighing others due to scale differences, and to enhance the scoring accuracy for objectively classifying our geographic units (douar). Deciles are used due to their non-parametric robustness and multi-scale flexibility. In the same time, they ensure a sufficient level of granularity without being excessive. This avoids broad classifications (quantiles) or overly fine classifications (percentiles). In this study we estimate decile thresholds using linear interpolation (Type7) [18], a widely recommended method in quantitative data analysis. Figures 3 and 4 detail the process of each component TR(i) and HR(i), following the approach of Figure 2.

The scoring framework is based on deciles, and is implemented through five sub-steps. Algorithm 1 provides a clear and reproducible pseudocode of the proposed processing pipeline. Let the input of the algorithm be the data matrix X [n, k], where n douars and k variables, while the output consists of scores: S1 [n] for TR component, S2 [n] for HR component, and TDI [n] our composite index. The central step is the decile computation Di (p), performed after the transformation phase, during which variables are processed using functions f [k] reported in Table 1 and subsequently arranged in a normalized matrix *X'* [n, k].

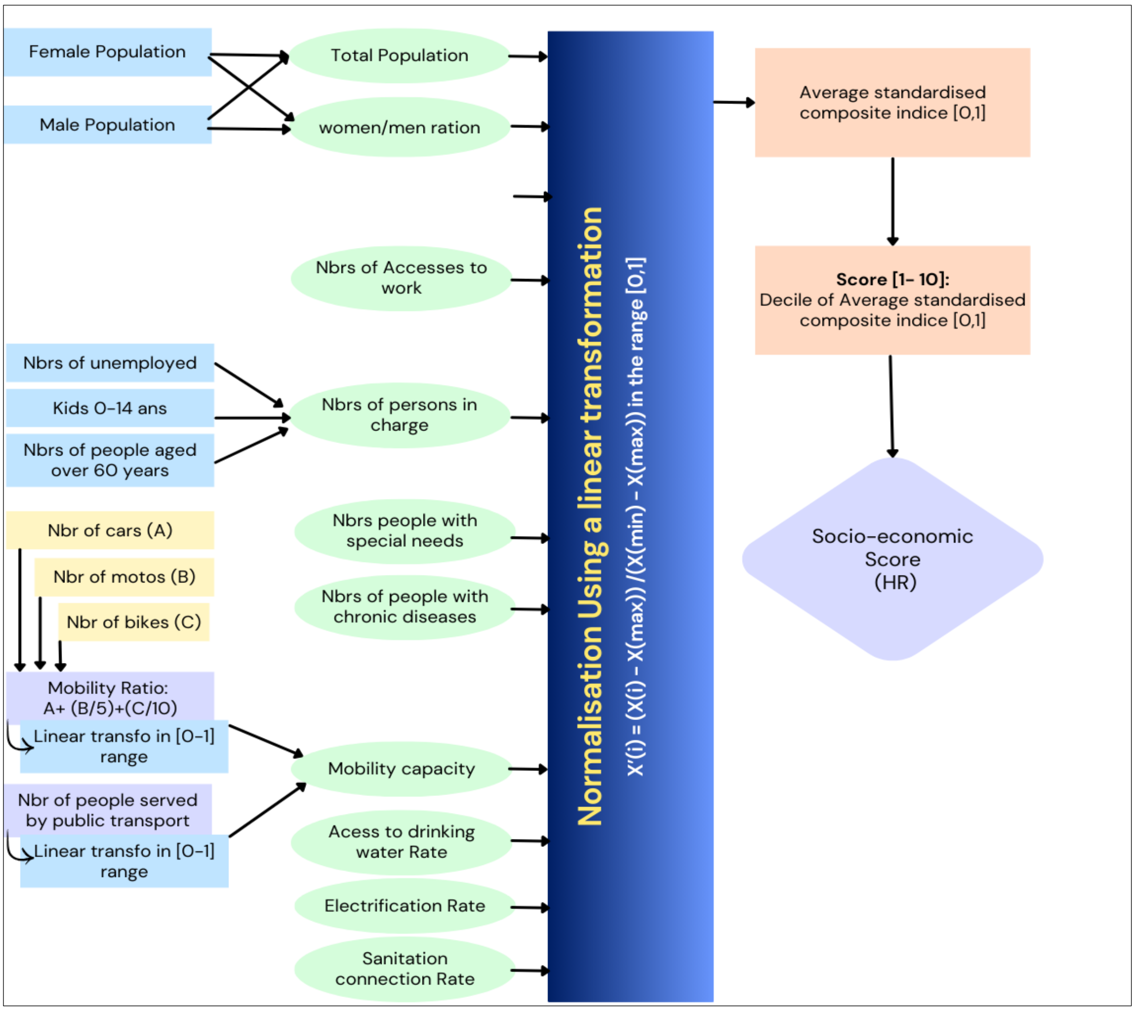

Figure 4. HR or socio-economic component workflow (HR)

Algorithm 1. Decile ranking and composite score construction algorithm

```
Inputs:
X [n, k] //Data matrix: n douars, k variables
f [1…k] // Transformation functions following Table1.
c1=8 variables related to spatial-environmental component
c2=11 variables related to socio-economic component
Outputs:
        S1[n]    // Spatial-environmental score for douar n.
        S2[n]    // Socio-economic score for douar n.
        TDI [n]  // TDI score for douar n.

Algorithm:
1- Initialize I [n, k] // Matrix to store indicators.
2- // step1: calculate indicators
        for i=1 to k do
                for j =1 to n do
                        I [j, i] = f[i] (X [j, i])
                end for
        end for
3- Initialize X'[n, k] // Normalized indicators
4- //step2: Min-Max normalization
        for i=1 to k do
                min_val_i = min (I [:, i])
                max_val_i = max (I [: , i])
                for j =1 to n do
                        X' [j, i] = (I[j, i] - min_val_i) / (max_val_i - min_val_i)
                end for
        end for
```

```
5- // step 3: Compute intermediate scores
 For j =1 to n do
 M1 [j] = mean (X’ [j, 1...c1] // average for variables related to component 1.
 M2 [j] = mean (X’ [j, c1+1...c1+c2] // average for variables related to component 2.
6- // step4: compute deciles and assign ranks
 // For M1 column
 Sort M1 in ascending order -> M’1
 For p= 1 to 9 do
 Pos = p*(n+1)/10 // theoretical position of the decile in the distribution
 Lower = floor (pos) //preceding observation, floor round down
 upper = ceil(pos) // following observation, ceil = round up

 If lower == upper then
 D1 [p] = M’ 1[pos]
 Else
               D1[p] = M’1 [lower]+(pos – lower) * (M1[upper] – M’1[lower]) //
              interpolation
          end if
       end for
 // For M2 column
 Sort M2 in ascending order -> M’2
 For p= 1 to 9 do
 Pos = p*(n+1)/10 // theoretical position of the decile in the distribution
 Lower = floor (pos) //preceding observation
 upper = ceil(pos) // following observation

 If lower == upper then
 D2 [p] = M’ 2[pos]
 Else
               D2[p] = M’2 [lower]+(pos – lower) * (M2[upper] – M’2[lower])// intrpolation
          end if
       end for
7-// Step5: Decile assignment
       for j=1 to n do
              S1[j] = decile_rank (M1[j], D1)
              S2[j] = decile_rank (M1[j], D1)
       end for
8- //Step 6: Final score computation: TDI score
 for j=1 to n do
       TDI [j] = S1[j] + S2[j]
 end for

 Return S1 , S2, TDI
```

4. RESULTS AND DISCUSSION

We remind that this battery of indicators was used and grouped according to the typology of TR(i) and HR(i). The two scores are combined by adding them together in an abacus of 10 deciles to produce a gradient matrix from 2 to 20 as showed in Algorithm 1, which forms the basis of the proposed ranking.

Table 2 provides an illustrative example of the calculation results for two indicators (s6) and (s9) as defined previously in Table 1, related respectively to spatial-environmental and socioeconomic components and considering ten 10 douars.

Table 2. Snippet of data matrix considering s6 and s9 for ten douars

DC	Dist_PS	Dist_MS	Dist_HS	Dist_S	I_Dist_S	score (s6)	Pop	I_Pop	score (s9)	TR score	HR score	TDI score
L11	2.34	7.45	5.86	3.28	0.89	6	142	0.03	8	6.00	5.77	11.77
L12	1.91	8.51	8.03	3.21	0.89	6	71	0.02	9	6.38	5.00	11.38
L13	1.17	6.45	5.71	2.19	0.93	3	397	0.09	5	4.75	4.05	8.80
L14	2.75	2.46	12.25	3.18	0.89	5	605	0.14	4	4.88	4.50	9.38
L15	1.01	3.17	2.14	1.39	0.97	2	1669	0.39	1	5.13	5.00	10.13
L16	1.10	0.54	2.02	1.07	0.98	1	1471	0.34	1	3.63	6.18	9.81
L17	1.85	0.95	9.72	2.11	0.94	3	158	0.04	8	6.25	5.77	12.02
L18	0.99	6.51	3.30	1.93	0.94	3	156	0.04	8	3.13	4.18	7.31
L19	1.97	13.12	2.47	3.67	0.88	6	1017	0.24	2	5.38	5.50	10.88
L20	1.78	6.83	4.76	2.68	0.91	4	435	0.10	5	4.50	4.68	9.18

DC: douar code; Dist_PS: distance to primary schools (km); Dist_MS: distance to middle schools (km); Dist_HS: distance to high school (km); Dist_S: distance to schools (km); I_Dist_S: normalized index of distance to schools ([0-1]); score (s6): school proximity; Pop: total population; I_Pop: normalized index of total population([0-1]); score (s9): total population score; TR score: spatial environemental score; and HR score: socio economic score.

The study's objective is to illustrate this disparity classification derived from Matrix of Figure 5 on a more representative mapping. Figure 6 shows the stratification results by TDI, while Figures 7 and 8 projects the outcomes considering respectively spatial-environmental and socio-economic dimensions.

Beyond this main scores, our multi-scale approach of TDI index enables mapping deprivation level across to each domain-specific score (s1, s2, ..., s19). Figure 9 reports the distribution of douars per score following a ceiling-based discretization of score values, as produced by the final stage of the processing pipeline. It can be observed that over 80% of douars are distributed across [13]-[18] score interval.

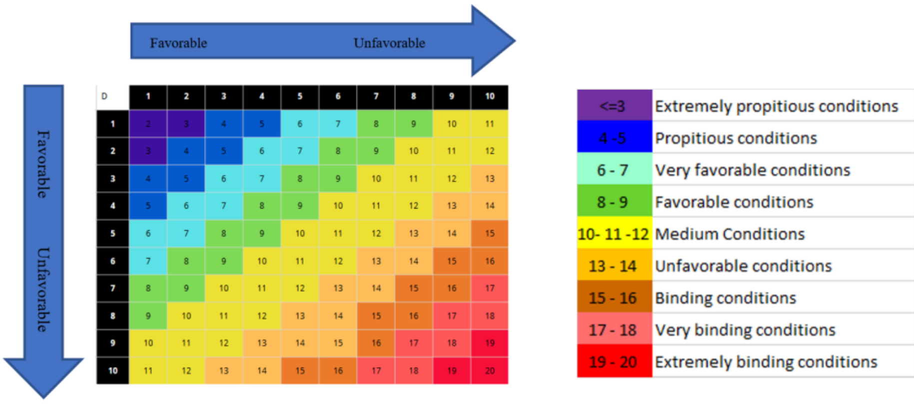

Figure 5. Matrix of scores

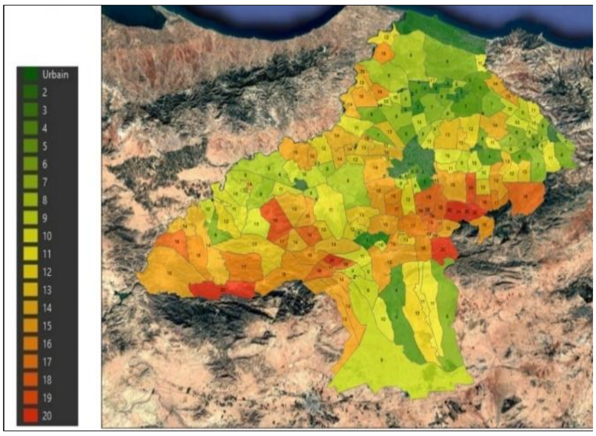

Figure 6. TDI applied to douars of Province of Berkane

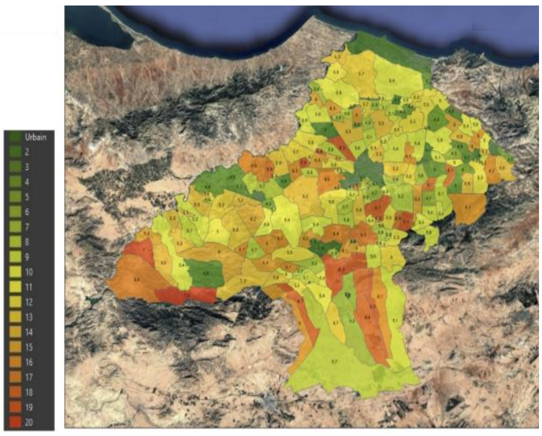

Figure 7. Spatial-environmental score applied to Province of Berkane

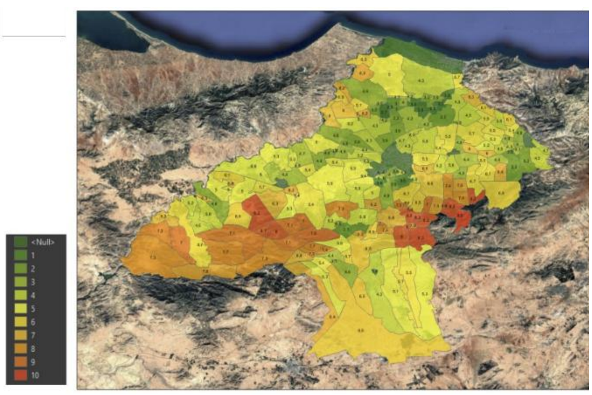

Figure 8. Socio-economic score applied to Province of Berkane

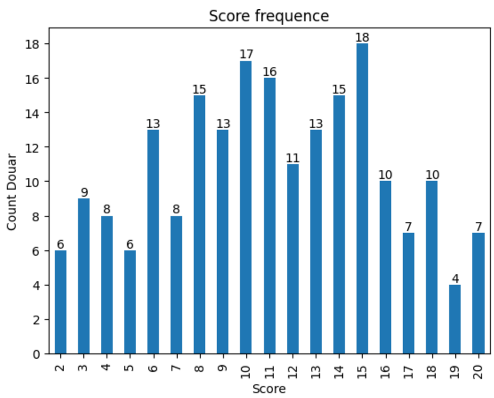

Figure 9. Total geographic entities (douars) by score

These results demonstrate a strong alignment with on-the-ground realities as recognized by relevant government bodies and local decision-makers in the Province of Berkane. The index proves to be a reliable tool for objectively prioritizing territorial development efforts. In practice, it has helped depoliticize project selection and ensure fair targeting of douars, reinforcing transparent and evidence-based decision-making.

This exercise encompasses various development projects, such as roads, health centers, schools, social centers, and water access infrastructure. As illustrated in Figure 10, once submitted by local actors, projects are evaluated through the TDI framework, which assigns two scores: a general deprivation score (TDI score) and a second score specific to the intervention axis (education, health, roads, water, and sanitation). Based on these two scores, the suggested projects are ranked according to their degree of importance. If this corresponds to reality, then it is accepted; otherwise, the project is directed towards a more needy area.

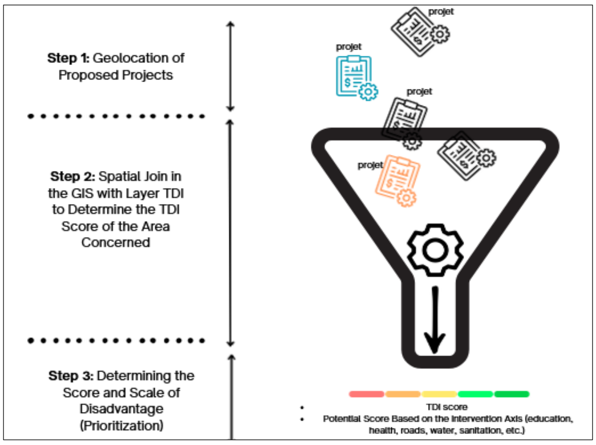

Figure 10. Process of TDI filter

Figures 11 and 12 give an example of concrete results of TDI application to prioritize projects related to borehole and rural roads according to the level of need (score and ranking). The proposed projects are shown in colors, indicating whether the target entity is really in need (red color gradient) or not.

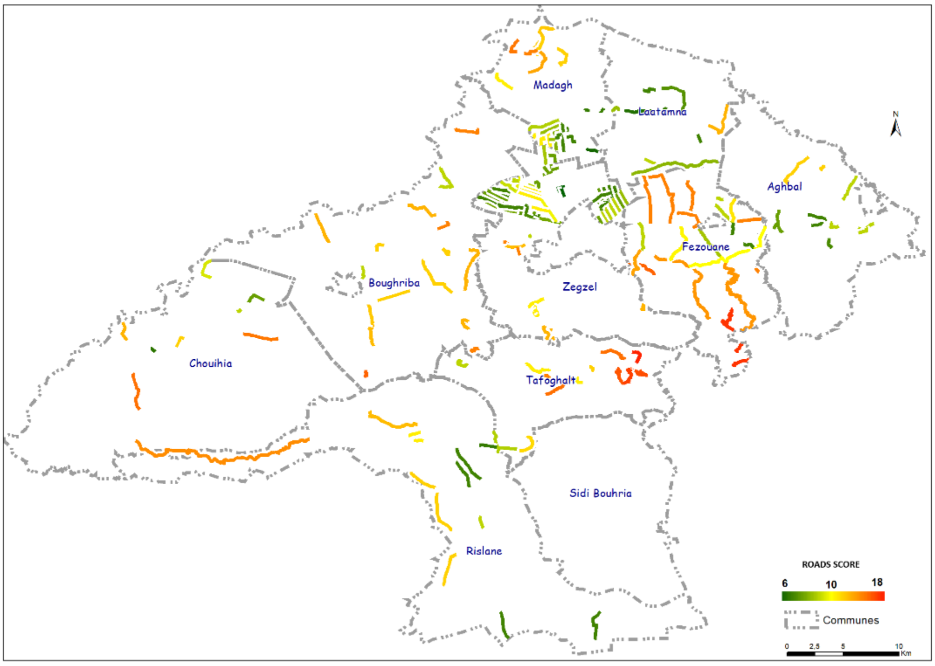

Figure 11. Example of rural road projects proposition submitted to TDI framework before definitive selection

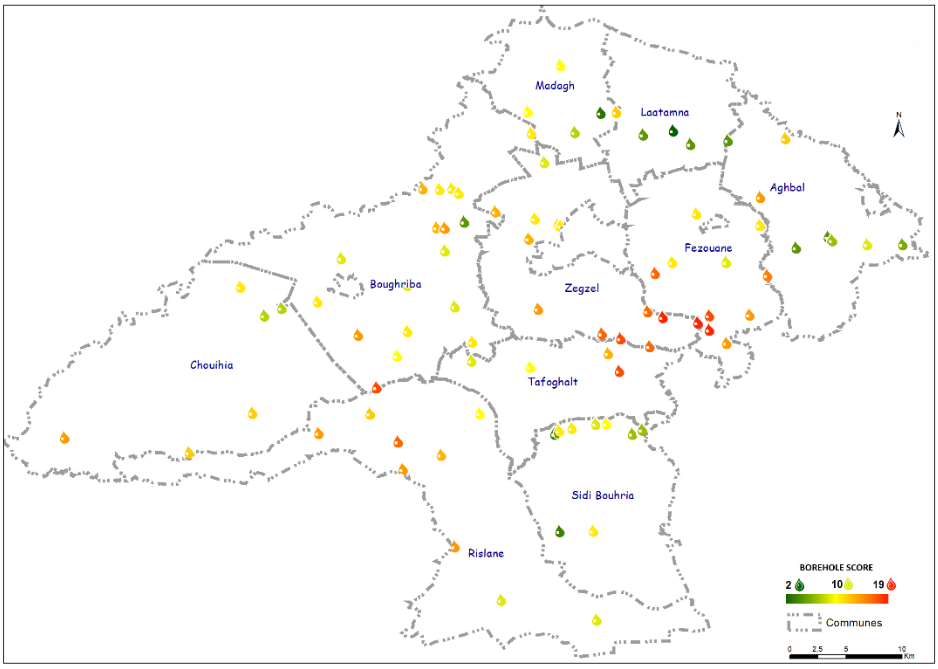

Figure 12. Example of borehole projects proposition submitted to TDI framework before definitive selection

However, we have seen that calculating this index requires a large amount of data. PCA was selected to look for possibility of reduce dimensionality [19] by capturing the maximum amount of variance in the data, regarding to multidimensional aspect of our index.

Before applying PCA, the adequacy was evaluated using the Kaiser-Meyer-Olkin (KMO) measure. The resulting value of global-KMO was 0.838, indicating good adequacy of the data for factor extraction. Table 3 displays measure of sampling adequacy (MSA) of each variable. Most variables showed very satisfactory measure around 0.8, but three variables are below 0.5 (s4), (s10), and (s12). Nevertheless, they will be retained regarding their theoretical relevance.

Table 3. MSA table of variables

Variables	MSA
Area score (s1)	0.598379
Relief score (s2)	0.877838
Paved road area ratio score (s3)	0.766000
Distance to paved road score (s4)	0.471441
Average proximity from the municipal seat (s5)	0.868440
School proximity score (s6)	0.896931
Health center proximity score (s7)	0.850431
Density score (s8)	0.850341
Total population score (s9)	0.785124
w/m ratio score (s10)	0.177867
Women [15-45 y] score (s11)	0.788514
Dependency score (s12)	0.438760
Employed people score (s13)	0.862073
Person in special need score (s14)	0.951334
Illness sore (s15)	0.916540
Mobility score (s16)	0.955366
Drinking water access score (s17)	0.882339
Electricity access score (s18)	0.829177
Sanitation connection score (s19)	0.946953

We apply PCA [4]-[20], with the 19 scores as input variables and 206 douars as samples, with the aim of assessing the relevance of the variables used and their impact on the calculation. Table 4 shows the initial output and presents the eigenvalues, the percentage of variance explained by each principal component, and the cumulative percentage. Figure 13 gives complementary representation of results in a scree plot. It shows the variance explained by each principal component and the cumulative explained variance. The green dotted line indicate the 70% threshold [21]. This threshold helps identify the minimum number of components to retain.

Table 4. Output 1 of PCA application

	Eigenvalue	Variability (%)	Cumulative (%)
F1	7.063	37.174	37.174
F2	2.402	12.645	**49.818**
F3	1.323	6.963	56.781
F4	1.244	6.550	63.331
F5	1.113	5.859	**69.190**
F6	1.040	5.471	74.661
F7	0.912	4.803	79.464
F8	0.733	3.856	83.319
F9	0.638	3.357	86.676
F10	0.558	2.936	89.613
F11	0.407	2.142	91.755
F12	0.352	1.851	93.606
F13	0.289	1.521	95.127
F14	0.263	1.385	96.512
F15	0.235	1.236	97.748
F16	0.202	1.061	98.809
F17	0.134	0.706	99.515
F18	0.083	0.439	99.954
F19	0.009	0.046	100.000

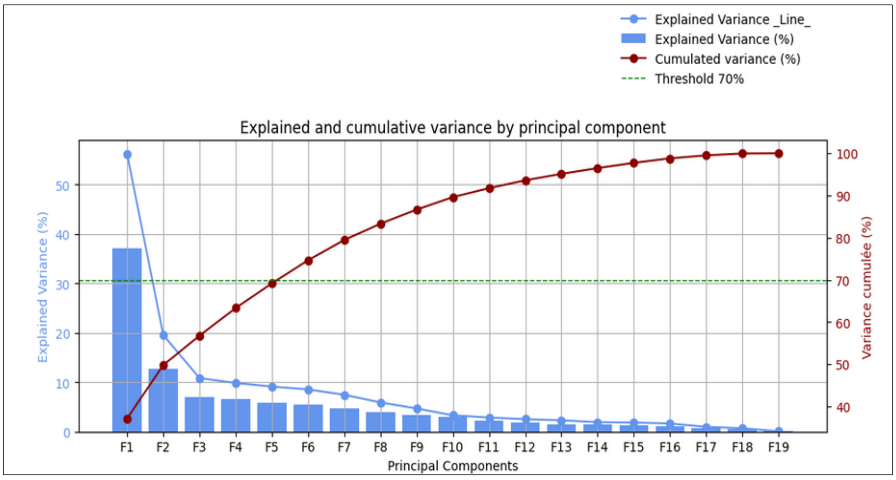

Figure 13. Scree plot

According to Table 4 and the scree plot in Figure 14, the first five components ensure a faithful representation of the initial data cloud with 69.19%. Additionally, the same explained variance was plotted in a linear format to detect the "elbow" point (k), which serves as a criterion for selecting the number of components to keep [22]. This approach produced a cumulative explained variance of 57.59% for k=3, which corresponds to component F3.

Considering F1, F2, and F3, we get Figure 15 with 3D representation thanks to Python scripts. It shows the contribution of each original variable to these first three principal components. For readability reasons, we focus on the first two components F1 and F2, where F1 (37.174%) and F2 (12.645%) account for approximately 49.82% of the total variance, supporting their selection as the primary axes for interpretation and graphical representation in Figure 16.

Table 5 complements the visualization of Figures 14 and 15 by providing exact variable loadings. It shows that the first principal component (F1) is mainly structured by the variables: total population score (11.218%), women of childbearing age [15-45 years] score (11.193%), transport and mobility score (11.385%), density score (9.883%), and disability score (8.382%), suggesting a common dimension underlying these indicators: the socio-economic component.

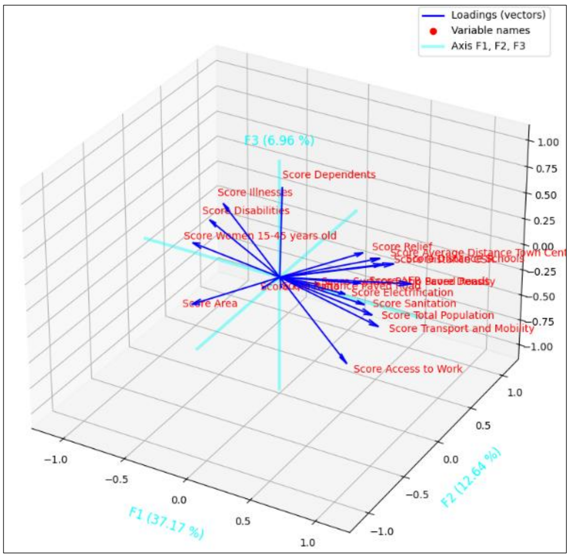

Figure 14. Scree plot of F1. F2. and F3

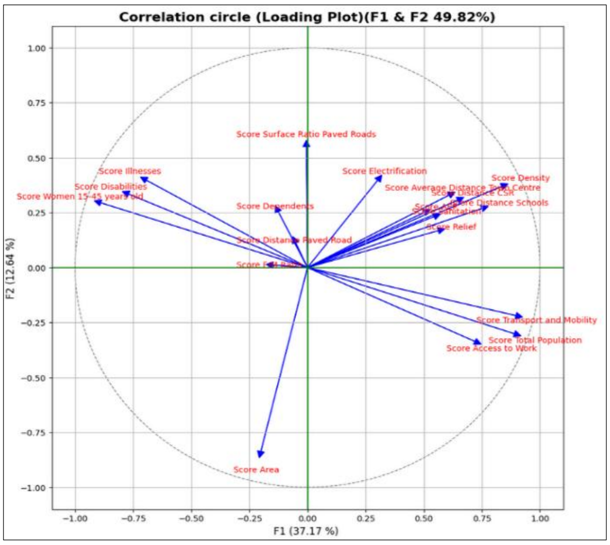

Figure 15. Loading plot

The second component (F2) is heavily impacted by: the surface area score, which alone accounts for nearly 30% of the total contribution and score surface ratio paved roads (12.6%), which represent the territory dimension and support our interest to integrate the spatial-environmental dimension in the conception of TDI.

These outcomes indicate a multidimensional structure in the data, where multiple axes contribute significantly to the overall variability. The dispersion of information suggests that the selected variables capture complementary and non-redundant aspects of the phenomenon under investigation, thereby supporting the relevance of interpreting them.

However, we take this analysis further by attempting to reduce dimensionality though the elimination of highly correlated variables. To this end, Figure 16 shows the Pearson matrix, which visualizes the linear correlation coefficients between all pairs of variables, enabling the detection of multicollinearity, redundancy, and underlying data structures. Correlated variables are shown in warm colors.
Thus, we observe a strong correlation between:
- Score women 15-45 and score total population: -0.99
- Score handicaps and score total population: -0.77
- Score handicaps and score women 15-45: 0.77
- Score transport and mobility and score total population: 0.87

– Score transport and mobility and score women 15-45: -0.87

So, by setting a threshold >=0.75, variables to be removed to avoid redundancy are:

– Score handicaps
– Score transport and mobility
– Score women 15-45

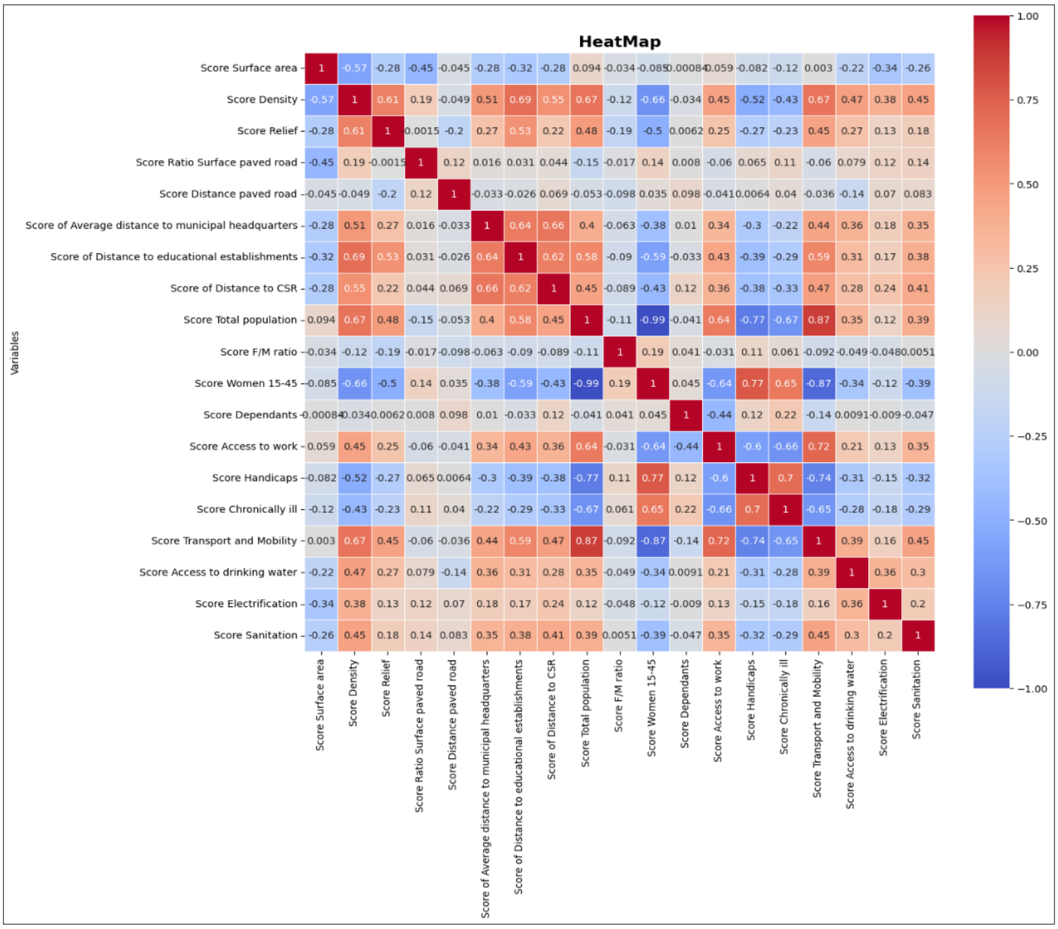

Figure 16. Heat map of correlation matrix (Pearson)

On the basis of this finding, the composite index was recalculated after removing variables of: score handicaps, score transport and mobility, and score women 15-45. Subsequently, a correlation analysis between the initial index "TDI (initial)" and the reduced index "TDI (reduced)" is conducted to assess the robustness of the index using Pearson correlation coefficient which measure linear relationships for normally distributed data. Besides, the ranking of observations is re-examined using Spearman method, a complementary tool to measure monotonic associations for non-normal, ordinal data, or data with outliers, in order to evaluate the stability of the classification [23]. Table 5 and the corresponding figure in Figure 17 present the results.

Table 5. Validation metrics measuring correlation between TDI (initial) and TDI (reduced)

Method	Coefficient of correlation	p-value
Pearson	0.982506	7.004592e-151
Spearman	0.980131	2.697595e-145

The scatterplot exhibits a strong linear correlation (r=0.98 and p<0.001) confirming that eliminating correlated variables preserves information and that multicollinearity has been effectively managed, thereby improving the stability and interpretability of the composite model of TDI. The reduced index is then a reliable proxy for the initial index with less inputs for subsequent deep analysis, such as clustering or predictive methods [24].

The results obtained with this study are a first step and will be subject to further analysis in future work. The primary objective of this study was to verify the relevance of taking the spatial dimension into account in the construction of the index. The results confirm that this dimension provides substantial additional information and then directly contributes to SDG 10 ("reduce inequalities") and SDG 11("sustainable and inclusive urban regional development") [25]. In fact, beyond the direct correspondence of target 10.2 with observation of pronounced disparities in rural areas, target 10.3 highlights the importance of eliminating structural barriers that impede the development of such territories, especially those related to infrastructure, and then spatial dimension. Moreover, target 10.4 emphasizes the critical role of well-targeted public interventions, which aligns closely with the objective of our TDI framework.

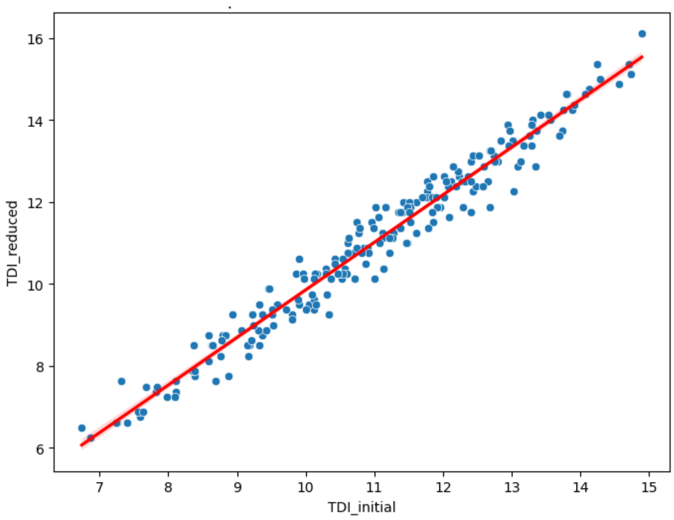

Figure 17. Scatter plot between TDI (initial) and TDI (reduced) after dimensional reduction

Thus, the proposed index helps to reduce the gap observed in the indices already available, in particular those used in Moroccan context (NHDI, human development index (HDI)), which focus mainly on socio-economic indicators, without explicitly integrating spatial scale.

This results is consistent with many other studies like those made in India [26], and Central Java [27] on HDI. Many spatial models were applied (panel. Morgan I) to show that not only traditional socio-economic indicators matter, but also the spatial configuration and locality. However, these studies discuss how neighbor territories can affect socio-economic development and do not use spatial data to calculate geographic disparities.

In the same setting, other recent researches identify how French deprivation index (FDepI) is operationalized at a small census geography, named IRIS, in France [28]. Nevertheless, this spatial application is mostly confined to public health and epidemiology, and is less suited for broader spatial development studies or policies.

5. CONCLUSION

The present study uses a combination of primary and secondary data sources, including different row data to provide a deep knowledge of geographic entities (douar) of Berkane Province, Morroco. The classification results obtained for our study area reaffirm the importance of considering multiple dimensions when characterizing territories and using mapping as a tool for interpretation if this approach is supported by a clear and reliable methodology demonstrating the relevance of the chosen dimensions. This is especially true for small and medium-sized provinces.

The results obtained show an excellent match with the reality observed by specialist government departments (Province of Berkane). This index seems to reflect a real state of affairs, which makes it an excellent tool for any approach aimed at developing a given territory by objectively prioritizing the proposed geographical entity.

The TDI, as conceived, can significantly contribute to development planning in provinces by acting as a filter that categorizes territories based on their level of disadvantage and prioritizes development actions according to the overall score of each geographic unit as well as scores related to specific development axis.

Admittedly, having such a comprehensive set of data is not easy to achieve across various Moroccan provinces at present. as it requires a robust and rich informational foundation for collecting and sharing. However, this study opens the way for future works toward smarter AI-based models that can effectively train predictive systems to improve the design of this index, keep it updated, and facilitate the classification of territories with minimum of inputs and then anticipate their needs.

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AUTHOR CONTRIBUTIONS STATEMENT

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El Houcine Addou					✓					✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The dataset analyzed during the current study is the exclusive property of Province of Berkane and was accessed under a non-disclosure agreement.

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