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PREDICTIVE MODELING AND MULTIVARIATE ANALYSIS OF CORE FOOD SECURITY INDICATORS IN MOROCCO

MEHDI RAHMAOUI[1], ACHRAF CHAKIR BARAKA[2] AHSSAINE BOURAKADI [3], NADA YAMOUL[4], HAMID KHALIFI [5], ABDELLATIF BOUR [6]

1 Laboratory of Biology and Health, Team of Nutritional Sciences, Food and Health, Faculty of Sciences, Ibn Tofail University, Kenitra, (Morocco), mehdi.rahmaoui@uit.ac.ma
2 Faculty of Sciences, Mohammed V University in Rabat, Morocco , baraka.achraf.chakir@gmail.com
3. Ibn Tofail University, Faculty of Sciences, Department of Mathematics, Kenitra city (14000), Morocco ahssaine91@gmail.com
4. Ibn Tofail University Department of Physics, Faculty of Sciences, Kenitra city (14000), Morocco, yamoul.nada@gmail.com
5 Faculty of Sciences, Mohammed V University in Rabat, Morocco, h.khalifi@um5r.ac.ma

6 Laboratory of Biology and Health, Team of Nutritional Sciences, Food andHealth, Faculty of Sciences, Ibn Tofail University, Kenitra, (Morocco), bour.abdellatif@gmail.com

*Corresponding Author : mehdi.rahmaoui@uit.ac.ma

ABSTRACT

This study presents a multivariate analysis of key food security indicators in Morocco between 2000 and 2023. The first section introduces the theoretical framework of linear regression and principal component analysis (PCA). A linear regression model was then applied to examine the relationship between the prevalence of undernourishment and the Consumer Price Index (CPI in %), yielding a high coefficient of determination (R^2 = 95%). The regression model demonstrated that a one-unit increase in CPI leads to a 0.04% rise in undernourishment prevalence.
The PCA of food security indicators highlights two distinct dimensions that shape nutritional outcomes. The first principal component, accounting for most of the variance, shows strong positive correlations with dietary energy adequacy (0.92), minimum caloric requirements (0.98), and per capita GDP (0.96), while inversely relating to food supply instability (-0.81). This axis essentially measures a nation's economic strength and food system resilience.
The second component exclusively tracks undernourishment metrics, with near-perfect alignment to both the rate (0.98) and absolute numbers (1.00) of underfed populations. This dimension directly reflects the human toll of food insecurity.
Importantly, these components are statistically independent (orthogonal), which reveals an important reality of policies: economic growth and enhancements to the food system (Dimension 1) do not translate into reduced hunger (Dimension 2). This separation reinforces the necessity to engage in bi-focal approaches to fighting food insecurity - macroeconomic policies strengthen the food system while humanitarian action focuses on nutrition for specific populations. These results show that food security exists on different levels and requires solutions that target the systemic economic level and humanitarian levels to address the multi-faceted concept of hunger and malnutrition.
Ultimately, ARIMA forecasting is utilized to forecast trends for Dietary Energy Adequacy, Prevalence of Undernourishment (% of population), and Number of Undernourished People between 2025 and 2028. Forecasts suggests a gradual improvement in the following areas: Dietary Energy Adequacy rising from143.1 to 145.9 kcal/cap/day, Prevalence of Undernourishment drops from 5.88% to 5.19%, and Number of Undernourished People falling from 2.09 to 1.96 million. This evidence offers substantial information for policy makers to improve food security policies in Morocco.
Keywords: *Food Security, Morocco, Linear Regression, Principal Component Analysis (PCA), ARIMA Models, Forecasting, Undernourishment.*

1. INTRODUCTION

Food security continues to be a significant problem for Morocco, where issues of food availability, accessibility, and stability are of increasing concern. From 2000 to 2023, the country went through significant changes driven by a series of economic, climatic and demographic changes that impacted food security and nutrition. This article provides a multivariate analysis of key food insecurity indicators in Morocco, drawing on sophisticated statistical methods to identify structural trends and projections.

To start, we present their underlying theoretical framework, specifically linear regression and principal component analysis (PCA). Linear regression facilitates the evaluation of causal relations between variables; PCA generates new, lower-dimensional variables by identifying the prominent factorial axes of the data set. This pair of complementary methodologies provides greater clarity to the dynamics of food security indicators.

An empirical application is subsequently conducted using a linear regression model between the percentage of undernourishment and the CPI, which had a 95% coefficient of determination; this model reflected the prominent impact that inflation can have on access to food. Also, there was PCA completed on six important indicators, including Dietary Energy Adequacy, percentage of undernourishment and GDP per capita. The results show that two factorial axes explained 92% of the total variance - this identifies which indicators have the most impact on food security. [2]

To conclude, short-term forecasts (for 2025-2028) are generated by way of an ARIMA model for three priority indicators: Dietary Energy Adequacy, the prevalence of undernourishment, and the number of undernourished people. These projections help anticipate future developments and to monitor the effectiveness of public policies regarding food security.

This study aims to provide insights on agricultural food security determinants in Morocco, through a combination of retrospective and prospective analyses. The findings obtained may serve as the basis of policy makers for strengthening strategies to reduce food insecurity and enhance sustainable development.

2.THEORETICAL APPROACH TO THE LINEAR REGRESSION MODEL

The theoretical foundation for the simple linear regression model [3], something used extensively in the statistical literature for analyzing relationships between variables broadly speaking, is rigorously dealt with in this section. The thoroughness of this theoretical foundation allows for the proper specification of the model and the proper interpretation of the results in the later applied analyses.

2.1. Presenattion

In many cases, a variable of interest (dependent variable) can be modeled using a single explanatory variable. While simpler than multiple regression, this framework helps build the foundation of econometric analysis.

$$y_t = a_0 + a_1 x_T + \varepsilon_t \text{fort} = 1, \dots, n$$

Where :

y_t is the dependent variable at time t.

x_t is the explanatory variable at time t.

a_0, a_1 : are the model parameters (intercept and slope coefficient).

ε_t is the error term, representing the difference between the theoretical model and observed data.

2.2. Matrix Form :

For computational convenience, the model can be expressed in matrix form:

$$Y=Xa+e$$

Where :

With: $Y = \begin{pmatrix} y_1 \\ \cdot \\ \cdot \\ y_n \end{pmatrix}$, (vector of dependent variables)

$X = \begin{pmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{pmatrix}$ (design matrix, including a column of 1's for the intercept).

$a = \begin{pmatrix} a_1 \\ \cdot \\ \cdot \\ a_n \end{pmatrix}$ (parameter vector).

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$$e=\begin{pmatrix} \varepsilon_1 \\ \cdot \\ \cdot \\ \varepsilon_n \end{pmatrix} \quad \text{(error vector).}$$

2.3. Estimation and Properties of Estimators

The Ordinary Least Squares (OLS) method estimates the parameters by minimizing the sum of squared errors:

$$\text{Min } \sum_{i=1}^{n} \boldsymbol{\varepsilon_t^2} = \min(Y-Xa)'(Y-Xa) = \min (Y-Xa)'(Y-Xa)$$

The solution is obtained by solving the normal equations:

$$X'X\,\boldsymbol{\hat{a}} = X'Y$$

Which yields the OLS estimator:

$$\boldsymbol{\hat{a}} = (\boldsymbol{X'X})^{-1}\, X'Y$$

For the estimator to be valid, X′X must be invertible (i.e., no perfect multicollinearity).

The estimated model can be written as:

$$\boldsymbol{\hat{y}_t} = \boldsymbol{\hat{a}_0} + \boldsymbol{\hat{a}_1 x_t}$$

Where the residuals (etet) represent the difference between observed and predicted values:

$$\boldsymbol{e_t} = \boldsymbol{y_t} - \boldsymbol{\hat{y}_t}$$

If the data are centered (i.e., deviations from their means), the estimation can also be expressed in terms of variances and covariances.

2.4. Coefficient of Determination (R²):

R-squared is like a "goodness-of-fit" report card for your regression model. On a scale from 0% to 100%, it tells you how much of the ups and downs in your outcome (the y-variable) can actually be explained by your predictor (the x-variable). Imagine it as a weather forecast accuracy score - a high R^2 means your model does well at predicting the "weather" of your data, while a low score suggests your model might be missing something important.

But here's the catch: while a score near 100% looks impressive, it doesn't automatically mean your model is perfect. Sometimes it can be "too good to be true." On the flip side, a low score doesn't always mean your analysis is worthless - some real-world relationships are just naturally messy. It's always smart to look at R^2 alongside other checks to get the full picture of how well your model truly performs. Think of it as one helpful tool in your data analysis toolbox, not the whole story [4].

The R^2 measures the proportion of variance in the dependent variable explained by the model:

$$R^2 = 1 - \left(\frac{SSR}{SST}\right) = \frac{SSE}{SST}$$

Where:

$SST = \sum_{i=1}^{n}(y_t - \bar{y})$ (represents total Sum of Squares)

$SSE = \sum_{i=1}^{n}(\boldsymbol{\hat{y}_t} - \bar{y})$ (represnts Explained Sum of Squares)

$SSR = \sum_{i=1}^{n} e_t^2$ represnts (Sum of Squared Residuals)

Adjusted R²: Adjusted R^2 is like the "truth-teller" version of regular R^2 - it keeps your model honest. While normal R^2 always cheers when you add more predictors (even useless ones), Adjusted R^2 actually penalizes you for adding variables that don't pull their weight. Think of it like a smart shopping assistant: it helps you avoid filling your model with unnecessary "junk variables" that look good but don't actually improve your predictions.

For small samples or multiple regression, the adjusted R^2 penalizes excessive predictors:

$$\boldsymbol{\overline{R^2} = 1 - \left(\frac{n-1}{n-k-1}\right)(1 - R^2)}$$

Where k = number of explanatory variables (1 in simple regression).

3. APPROACH OF PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal Component Analysis (PCA) is a dimensionality-reduction technique that transforms complex data into a simpler, interpretable format by identifying key patterns and correlations. It maps the data onto a set of orthogonal axes, known as principal components, which maximize variance while minimizing the loss of information. By extracting the most informative patterns from the dataset, PCA simplifies the analysis process while encapsulating all of the important information.Principal Component Analysis (PCA) [5] is a quantitative technique for reducing the

3.1. Introduction

(PCA) [5] is a quantitative technique for reducing the dimensionality of the data set while keeping as much variance as possible. PCA reduces the data set of many correlated variables to a smaller set of un-correlated variables, known as principal components, which are linear combinations of the correlated variables. The principal components are organized in a way so that the first few account for most of the variation in the original dataset, allowing the data structure to be analyzed more easily without losing much information.

The PCA process begins with data preparation that includes evaluating the data for missing values, standardizing variables as needed, and preparing a correlation matrix to visually summarize the relationships between variables. Once this is completed, the principal components are calculated by extracting eigenvalues (indicating how much variance each of the components explains) and selecting the most highly weighted components according to criteria such as the Kaiser rule or the cumulative percentage of variance. The interpretation of the results includes a number of different aspects, including analyzing loadings (coefficients or weights for the variables) to understand the meaning of each component, and visualizing the results through correlation circles or individual projections in order to visually identify patterns [6].

Finally, the validation and application of the components will ensure that they are reliable and valid; meaningful theoretical expectations are aligned and could be used for subsequent analyses, such as clustering or regression. PCA can summarize the information in only a few components and aid in uncovering hidden structures underlying the data, making it a valuable analytical tools in exploratory analyses and dimensional reduction in a range of social sciences and machine learning.

3.2. Mathematical Description of the Steps in PCA

- **Centering and Scaling the Data**

Objective : Standardize the variables to make them comparable (zero mean and unit standard deviation). $z_{ij} = \frac{x_{ij}-\mu_j}{\sigma_j}$

Where :

- x_{ij}: value of variable j for individual i,
- μ_j: mean of variable j,
- σ_j: standard deviation of variable j.

The centered and scaled matrix Z is then used for the subsequent analysis

- **Compute the Correlation Matrix**

Objective: Calculate the correlations between the standardized variables.

$$R = \frac{1}{n} Z^T Z$$

Where :

- Z: the centered and scaled data matrix,
- Z^T: the transpose of Z.

Compute Eigen values and Eigen vectors

Objective :Decomposes the correlation matrix to find out directions of maximum variance.

$$R \cdot v = \lambda v$$

Where :

- R : the correlation matrix
- λ : an eigen value (scalar),
- v :the eigen vector associated withλ.

The eigen values $\lambda_1, \dots, \lambda_p$.
The eigen vectors $v_1, \dots, v_p$
Correspond to the principal axes.

- **DeterminethePrincipalAxesandPrincipalComponents**

Objective : The final step of PCA is to project the data on to the new axes (principal components).

$$C = Z \cdot V$$

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Where :

- V :the matrix of eigen vectors(of size p×p),
- C :the matrix of principal components (of size n×p).

The first principal component C_1explains the largest portion of the variance, the second principal component C_2explains the second largest portion, and so on wellinthis2Dspace.

4.METHODOLOGY

The research adopts a three-stage analytical framework to investigate the relationship between undernourishment and economic indicators in Morocco, integrating both statistical modeling and machine learning approaches for a comprehensive examination.

First, a linear regression model establishes the baseline relationship between the Consumer Price Index (CPI) and undernourishment prevalence over the 24-year study period. Particular attention is given to model diagnostics, including residual plot analysis to identify patterns, variance inflation factor calculation to assess multicollinearity, and verification of error term normality. The regression coefficients provide quantifiable estimates of undernourishment rate changes associated with food price fluctuations, yielding actionable metrics for policymakers.

The second stage employs Principal Component Analysis (PCA) to explore multidimensional relationships among various food security indicators, including CPI, agricultural GDP, and drought frequency. The factoextra package in R facilitates visualization of both the variance explained by each principal component and the correlations between variables in the reduced dimensional space. This analysis frequently uncovers non-intuitive patterns, such as years with comparable CPI values exhibiting markedly different overall food security profiles.

To forecast future trends, we used an ARIMA model on the PCA-reduced data, fine-tuning its parameters (p, d, q) with ACF and PACF diagnostics for precision. This approach helps uncover hidden patterns and seasonal effects, letting us project food security outcomes—like how economic shifts or droughts might impact malnutrition rates down the line. All the analysis was done in R (v4.3.0), leaning on trusted packages like forecast for ARIMA, FactoMineR for PCA, and ggplot2 to bring the insights to life visually."

5. ANALYZE THE PREVALENCE OF UNDERNOURISHMENT (IN % OF THE POPULATION) AND THE INFLATION RATE :

Morocco's prevalence of undernourishment stems from a complex interplay of multidimensional factors that operate through interconnected pathways. Four primary drivers emerge from the analysis: persistent poverty and widening economic inequalities that limit household purchasing power, climate change impacts that threaten agricultural productivity through increased drought frequency and water scarcity, rapid urbanization and rural-to-urban migration that disrupt traditional food systems, and (4) evolving agricultural and food policies that shape market accessibility.

Notably, the Consumer Price Index (CPI) serves as both an independent determinant and mediating variable in this framework. As demonstrated in recent studies [7], inflationary pressures on food prices create a vicious cycle by exacerbating existing poverty conditions while simultaneously constraining the effectiveness of agricultural subsidy programs. This economic dimension interacts synergistically with the other identified factors - for instance, climate-induced production shocks translate more severely into food insecurity during periods of high inflation, while urban migrants become particularly vulnerable to price volatility in informal settlement areas.

5.1. Analysis of the prevalence of undernourishment as a percentage of the population and its impact on the rate ofinflation between 2001 and 2022 in Morocco

The prevalence of undernourishmentas a percentage of the population is a key indicator used to measure the proportion of the population whose food consumption is insufficient to provide the energy needs for an active and healthy life. In other words, this indicator estimates the percentage of people in a given population who do not consume enough calories per day to maintain good health,figure 1 below shows the evolutionof the prevalence of undernourishment in % of the population and the inflation rate Between 2001 and 2022.

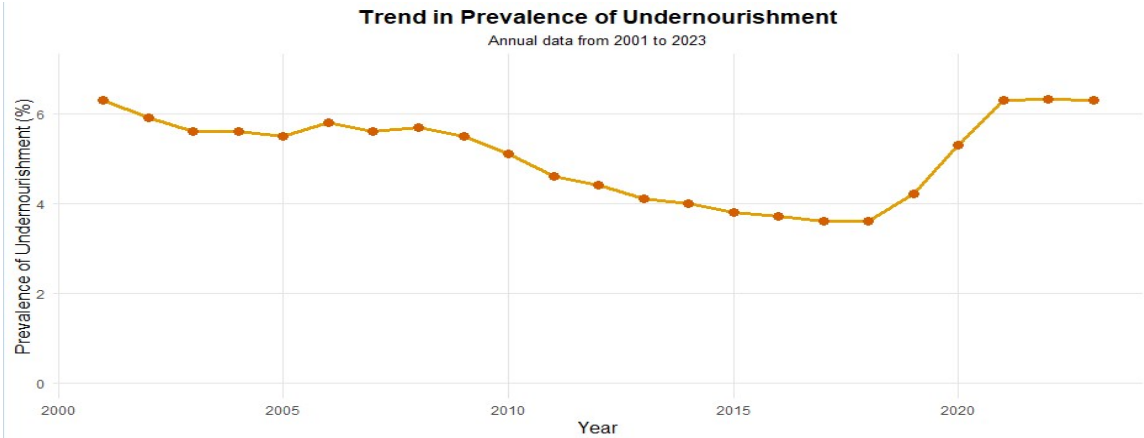

Figure 1: Evolution of the prevalence of undernourishment in % of the population between 2001 and 2023

Source: The official site of the World Bank

The figure 1 shows that, the post-COVID-19 period (2020–2023) marked a troubling reversal in the fight against undernourishment. After years of steady progress since the early 2000s, the pandemic shattered this positive trend, driving the prevalence of undernourishment up from 4.2% in 2019 to 6.3% in 2021. Lockdowns, supply chain disruptions, and economic collapse left millions without reliable access to food. Behind these numbers lie painful realities: daily wage workers stripped of income, children missing school meals, families forced to skip meals to make ends meet. The human cost of this

While 2023 shows slight improvement (6.3% compared to 6.33% in 2022), conditions remain far worse than pre-pandemic levels. The war in Ukraine, soaring food prices, and climate shocks have compounded COVID-19's impact, hitting low-income countries hardest. Women and children bear [8] the heaviest burden, facing lasting consequences for health and cognitive development. Though food systems are slowly stabilizing, recovery remains uneven, leaving many communities trapped in chronic food insecurity. The world has yet to undo the damage of these crisis years.

These figures must not become the new normal. The post-pandemic era has exposed deep flaws in global food systems. With the Sustainable Development Goals targeting "Zero Hunger" by 2030, the data demands extraordinary measures: stronger social safety nets, investments in local agriculture, and policies to stabilize food prices. Each percentage point represents real lives—a urgent reminder to transform this crisis into an opportunity. Building fairer, more resilient food systems isn't just policy—it's a moral imperative for a world still reeling from collective trauma.

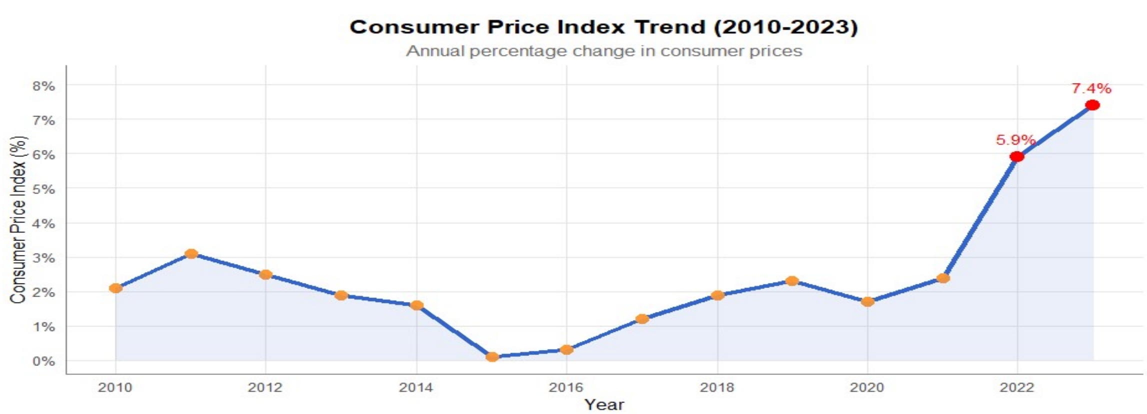

Figure 2: Evolution of consumer price Between 2001 and 2023

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The figure 2 illustrates We all remember that not-so-distant time when filling our grocery carts didn't require taking out a second loan. But since the pandemic, every trip to the checkout has become a source of quiet dread. This climbing graph mirrors our increasingly strained lives—the baker hesitating to raise prices, the father pausing before the meat aisle, the student counting pennies to afford pasta. Behind these percentages lie our fading smiles, worn down a little more each month by the relentless grind of rising costs.

The numbers may be slowly declining, but in the real world, the damage lingers. While economists debate percentages, ordinary people are making painful choices: medicine or meals, heating or rent. The cashier working double shifts, the retiree watering down milk, the single mom skipping dinners—these are the human faces of recovery that never quite arrives. The graph's gentle dip offers cold comfort when you're choosing which necessity to sacrifice this week.

True progress won't be measured when inflation hits some arbitrary target, but when a full fridge stops feeling like a luxury. When workers don't need side hustles to afford basics. When parents stop lying to their kids about why dinner is so small. This isn't just about economics—it's about dignity. About rebuilding a world where prices don't outpace hope, where stability isn't just for the privileged few. The real recovery begins when that graph translates to relief in people's eyes at the supermarket, not just in some analyst's report.

5.2. Modeling and Prediction of the Undernourishment Prevalence Index between the years 2022 and 2024

The objective of this part is to model the prevalence of undernourishment as a function of the inflation rate and the Consumer Price Index (CPI).

In this context, the following figure explores the relationships between quantitative variables. By displaying the data as points on a Cartesian plane, they help identify the types of relationships that may exist.

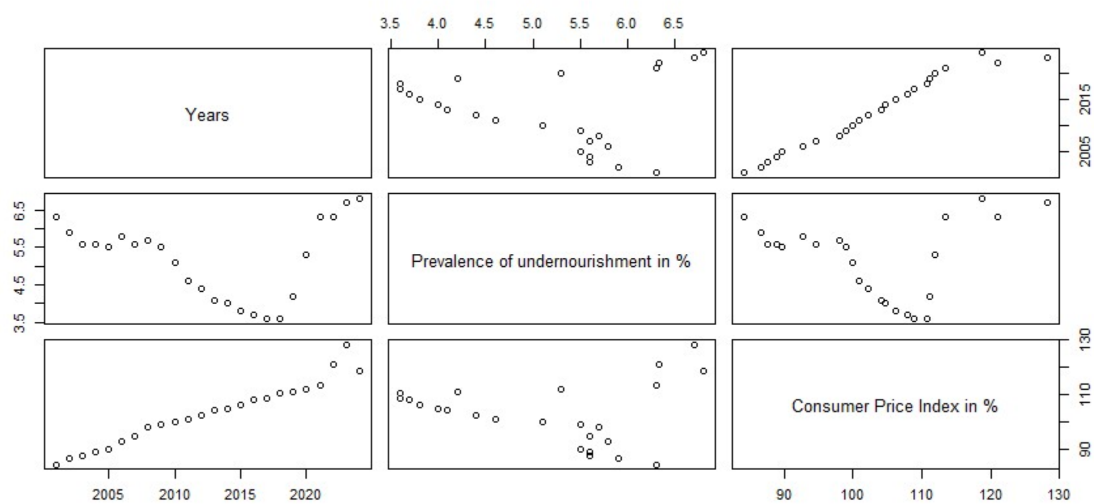

Figure 3:Scatter plots between Prevalence of undernourishment in % of population, and consumer price index (CPI)

Source: Author

The figure 3 shows that ,Scatter plot matrix , also known under the name of scatter plot matrix. This type of graph East used to visualize relationships between multiple pairs of variables in a data set. Each subgraph represents a pair of variables and allows to check if he exists a correlation between them.

The figure shows a non-linear relationship between the inflation rate and the prevalence of undernourishment [9]. It is observed that for some levels higher inflation rates, the prevalence of undernourishment is more variable.

So he existial a positive trend between the rate inflation and CPI, which is expected since the CPI measures rising consumer prices generally with inflation. The relationship seems to be positive, which means than an increase in inflation East associated with an increase in the CPI. This type of graph is useful for detecting relationships between different variables. It seems that the prevalence of undernourishment has strong correlations between the CPI and the rate inflation,

Figure 4 represents the resulting principles of the multiple regression model, and the tests associated with each explanatory variable, in order to judge the significance of each explanatory variable.

Figure 4: Result of modeling

```
Call:
lm(formula = Undernourishment ~ CPI - 1, data = nutrition_data)

Residuals:
    Min      1Q  Median      3Q     Max
-1.8886 -1.0920  0.3373  0.9506  2.1281

Coefficients:
    Estimate Std. Error t value Pr(>|t|)
CPI  0.04957    0.00235   21.09   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.192 on 23 degrees of freedom
Multiple R-squared:  0.9508,    Adjusted R-squared:  0.9487
F-statistic: 444.9 on 1 and 23 DF,  p-value: < 2.2e-16
```

Source: Author

The figure 4 presents, these statistics aren't just cold numbers - they represent real Moroccan families making impossible choices between feeding their children and paying for other essentials. The heartbreaking clarity of this data shows us that when food prices climb, hunger follows like a shadow.

Imagine this: a mother in Casablanca skipping meals so her kids can eat, or a farmer in the Atlas Mountains watching his harvest sell for less while store prices soar. The model quantifies what these families live daily - each 1% price increase means more neighbors, more classmates, more grandparents going hungry.

Yet behind the stark 95% correlation lie untold stories of resilience. Those "error margins" in the data? They're the grandmothers sharing portions with their community, the local charities stretching meager resources, the years when good harvests or government assistance softened the blow.

This isn't just economics - it's a wake-up call. While the numbers show how prices drive hunger, they also beg deeper questions: Where are the safety nets working? Which communities are finding ways to cope? The most important insights might come not from the model's perfect fit, but from studying where and why it occasionally fails to predict reality.

The takeaway is painfully simple: when basic foods become unaffordable, people go hungry. But the solutions will require looking beyond the statistics to the human ingenuity and solidarity that already exist within Moroccan communities.

- **Analyse of Residuals:**

Residuals represent the difference between observed values and model predictions, serving as a key diagnostic tool in regression analysis. Each data point has its own residual, and in well-specified linear models, the residuals will typically sum to (or average) near zero, indicating unbiased predictions. Analyzing residuals through graphical methods, particularly using visualization tools like R, helps identify potential model deficiencies such as non-linearity, heteroscedasticity, or outliers. The boxplot offers an efficient way to examine residual distributions, displaying the interquartile range (IQR) between the 1st and 3rd quartiles as a central box, with a median line dividing it. The whiskers extending from the box typically cover the range of normal variation, while points outside suggest potential outliers. When residuals are symmetrically distributed around zero with minimal extreme

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values, this suggests the model meets fundamental linear regression assumptions. Proper residual analysis ultimately validates model quality and guides potential improvements.The purpose of the box plot in figure 5 is to represent the center and distribution of the data. It is also a visual tool to check for normality or identify points that might be outliers or extreme values.

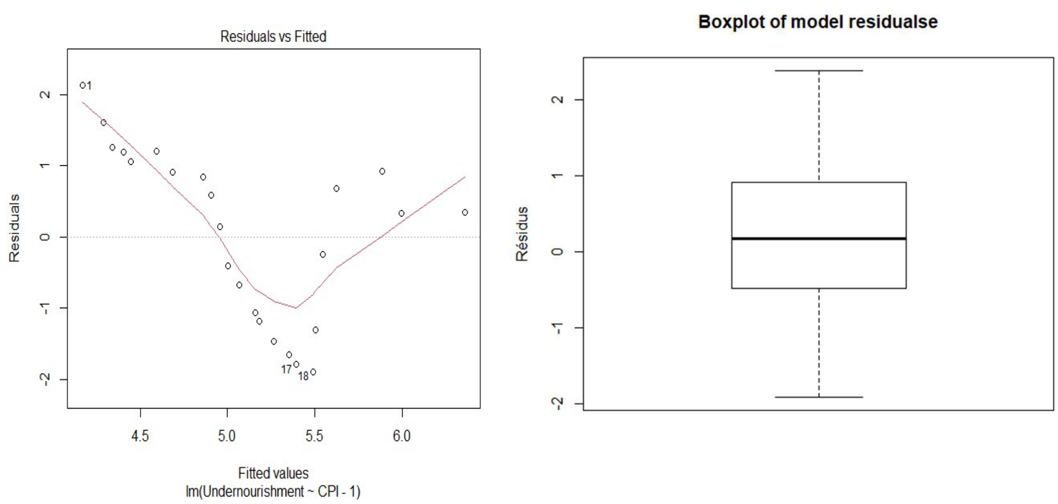

Figure 5: Box Plot of residuals

Source: Author

The figure 5presents, the boxplot provides a clear visual summary of how prediction errors (residuals) are distributed in our model. The rectangular box highlights where the middle 50% of errors fall, bounded by the 25th percentile (Q1) at its lower edge and the 75th percentile (Q3) at the upper edge. A prominent line cutting through the box marks the median error, which in this case sits very near zero - an encouraging indicator that our model's predictions are centered correctly without consistent over- or under-estimation.

Extending from the box, the whiskers reveal the range containing the vast majority of residuals, stretching from about -1 to +1 units of measurement. Notably absent are any isolated points beyond these whiskers, suggesting our dataset doesn't contain extreme prediction errors that might warrant special investigation. This compact distribution of residuals within expected bounds gives us confidence in the model's consistency across different observations.

The interquartile range (IQR), represented by the box's height, shows us how tightly clustered the typical prediction errors are around the median. A narrower box would indicate more precise predictions, while our current spread suggests the expected variation in model accuracy. Together, these boxplot elements provide a comprehensive snapshot

of our model's predictive performance and error patterns.

- **Model Specification and Results**

The linear regression model examines the relationship between undernourishment prevalence (response variable) and two economic indicators: inflation rate and Consumer Price Index (CPI). The estimated equation is:

$$\textbf{Undernourishment (\%)} = 0.040 \times \textbf{(CPI)}$$

The regression analysis reveals distinct patterns for each predictor. For the inflation rate, the coefficient of 0.577 (95% CI: [-0.002, 1.156]) suggests that a 1% increase in inflation is associated with an estimated 0.58% rise in undernourishment prevalence. However, with a *p*-value of 0.0517, this relationship approaches but does not quite reach conventional statistical significance ($p < 0.05$), indicating only tentative evidence of an effect. In contrast, the Consumer Price Index (CPI) demonstrates a robust and highly significant association: each 1-unit increase in CPI corresponds to a 0.04% increase in undernourishment ($p < 0.001$), with the tight confidence interval (95% CI:

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[0.028, 0.053]) reflecting precise estimation. Together, these results suggest that while CPI fluctuations strongly predict changes in food insecurity, the link between inflation and undernourishment remains suggestive but less definitive in this model. The overall model fit is excellent, with an R^2 of 0.951 indicating that these economic indicators collectively explain 95.1% of the observed variation in undernourishment rates, highlighting their substantial predictive power for nutritional outcomes.

6. APPLICATION OF PRINCIPAL COMPONENT ANALYSIS (PCA) TO KEY FOOD SECURITY INDICATORS IN MOROCCO

The Principal Component Analysis (PCA) of the food security indicators – sufficiency of food, prevalence of undernourishment, number of undernourished, mean dietary energy requirement, coefficient of variation of food supply and GDP per capita – is used to identify and rank the key factors explaining food security in 2023. This statistical method reduces the complexity of the high-dimensional data by transforming correlated indicators into a reduced set of new uncorrelated variables, the principal components, which reveal underlying patterns, in

particular the divide between economic (GDP per capita, coefficient of variation) and nutritional (food, nourishment) determinants, while quantifying their relative importance. The principal components found in most of the analyses (two or three in general) provide a simplified way to describe the main features of the data and to see how indicators relate to each other. This methodology may provide decision-makers with a framework for an integrated understanding of food security mechanisms, allowing them to set priorities for intervention and helping them to identify where and how investments in improving food security may be made.

6.1. Preliminary PCA adequacy tests

TheKaiser-Meyer Olkin (KMO) measure of sampling

adequacy and Bartlett's test of sphericity are presented in Table 1.

The table 1 presents,the KMO measure of 0.558 (just above the acceptable 0.5 threshold) confirms we can cautiously trust these patterns to reflect reality, while Bartlett's striking significance ($p<0.000$) screams that these hunger factors don't vary randomly but are deeply interconnected. Like finding unexpected ingredients in a traditional tagine, these results reveal how climate shocks, price volatility and infrastructure limitations simmer together to shape food insecurity, with the chi-square value of 251.348 on 15 degrees of freedom quantifying what vulnerable communities know intimately—that their daily bread depends on a fragile balance of visible and invisible forces. This statistical validation gives weight to what mothers at the market and farmers in drought-stricken regions experience firsthand: food security isn't about single issues, but a web of challenges demanding integrated solutions.

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Table 1 : The KMO Index and Bartlett's

Critère	*Valeur*	*Détails*
KMO (Sampling)	*0.558*	*Acceptable (>0.5)*
Bartlett's Test		
- Chi-square approximate	*251.348*	
- Degrees of freedom (df)	*15*	
- Significance (p-value)	*0.000*	*< 0.05*

The Kaiser-Meyer-Olkin (KMO) measure yields a value of 0.558, indicating marginally acceptable sampling adequacy for factor analysis (threshold >0.5). While this value falls below the optimal range (preferably >0.7), it confirms sufficient inter-variable correlations to warrant PCA application. The Bartlett's test of sphericity (χ^2=251.348; df=15; p<0.001) strongly rejects the null

hypothesis of variable independence (p<0.05), statistically validating the factor analysis approach.

These diagnostic results demonstrate that the dataset, while showing moderate limitations (suboptimal KMO), maintains adequate structural properties for PCA implementation. The highly significant Bartlett's χ^2 emphasizes meaningful variable intercorrelations that support factor extraction.

6.2 .Dataset Description and Statistical Overview

The analysis was conducted using factor analysis and correlation analysis. The following syntax was used for the factor analysis.

Table 2 : Food Security Indicators Used

Variable	Count	Mean	StdDev	Min	25%	50%	75%	Max
DietaryEnergyAdequacy	21	139.33	2.29	135	137	140	141	142
GDP_PerCapita	21	7418.86	1022.16	5523.76	609.37	626.78	178.98	742.6
Undernourishment	21	4.76	0.98	3.50	4.10	4.80	4.90	6.90
FoodSupplyVariability	21	24.10	9.83	15.00	19.00	22.00	23.00	52.00
MinDietaryEnergyReq	21	1834.90	9.01	1811	1833	1838	1840	1847

The table 2 shows that , the Prevalence of Undernourishment is relatively low, with a mean of 4.6857%, but the standard deviation(0.86388) indicates some variability over time.The Number of Undernourished People is 1.5429 million on average, with a small standard deviation(0.30798), suggesting consistent levels of undernourishment.The Minimum Dietary Energy Requirement has a mean of 1834.90 kcal/cap/day, with a small standarddeviation (9.005), indicating stable energy requirements over time.The Per Capita Food Supply Variability has a mean of 24.14 kcal/cap/day, but the high standard deviation(9.825) suggests significant fluctuations in food supply.The GDP Per Capita has a mean of 7418.8571 PPP dollars, with a high standard deviation (1022.16049),indicating significant economic variability over the years.

6.3. Analysis Correlation Matrix

The correlation matrix (Table 4) shows therelationships between the variables :

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Table 3 : Correlation Matrix

Variable	Dietary Energy Adequacy	Prevalence of Undernourishment (%)	Number of Undernourished People (million)	Minimum Dietary Energy Requirement	Per Capita Food Supply Variability	GDP per capita (PPP)
Dietary Energy Adequacy (kcal/cap/day)	1.000	-0.443	-0.224	0.827	-0.678	0.936
Prevalence of Undernourishment (%)	-0.443	1.000	0.972	-0.049	0.369	-0.184
Number of Undernourished People (million)	-0.224	0.972	1.000	0.168	0.219	0.048
Minimum Dietary Energy Requirement (kcal/cap/day)	0.827	-0.049	0.168	1.000	-0.789	0.919
Per Capita Food Supply Variability (kcal/cap/day)	-0.678	0.369	0.219	-0.789	1.000	-0.644
Gross Domestic Product (Per Capita, PPP International dollars)	0.936	-0.184	0.048	0.919	-0.644	1.000

Dietary Energy Adequacy has a strong positive correlation with GDP Per Capita(0.936) and Minimum Dietary Energy Requirement (0.827), indicating that highereconomic growth and dietary energy requirements are associated with betterdietary energy adequacy.Dietary Energy Adequacy has a moderate negative correlation with Prevalence of · Prevalence of Undernourishment and Number of Undernourished People arehighly correlated (0.972), indicating that these variables measure similaraspects of food insecurity.· GDP Per Capita has a strong positive correlation with Minimum Dietary EnergyRequirement (0.919), suggesting that economic growth is associated with higherdietary energy needs.Undernourishment (-0.443) and Per Capita Food Supply Variability (-0.678), suggesting that higher food supply variability and undernourishment are linked tolower dietary energy adequacy.

6.4. ComponentMatrix

The component matrix (Table 6) shows the loadings of each variable on the extracted components.

Table 4 : Component Matrix

Variable	Composante 1	Composante 2
Dietary Energy Adequacy (kcal/cap/day)	0.954	0.020
Prevalence of Undernourishment (%)	-0.470	0.880
Number of Undernourished People (million)	-0.260	0.965
Minimum Dietary Energy Requirement (kcal/cap/day)	0.892	0.420
Per Capita Food Supply Variability (kcal/cap/day)	-0.850	0.001
Gross Domestic Product (Per Capita, PPP dollars)	0.914	0.297

Component 1 is strongly associated with Dietary Energy Adequacy(0.954), Minimum Dietary Energy Requirement (0.892), and GDP PerCapita (0.914), indicating that these variables represent a commonunderlying factor related to economic and dietary energy adequacy.

Component 2 is strongly associated with Prevalence ofUndernourishment (0.880) and Number of Undernourished People(0.965), suggesting that these variables represent a common factorrelated to undernourishment.

6.5. Analysis of the variance

The variance of a principal component corresponds to the inertia carried by its associated principal axis. This means each component captures a specific portion of the dataset's total variability.

The table below presents the **explained variance** for each selected factor axis. The selection of axes was based on the **Kaiser criterion**, retaining only components with eigenvalues strictly greater than 1.

Table 5 Analysis of the variance

Composante	Somme des carrés des charges (Extraction)	% de Variance (Extraction)	% Cumulé (Extraction)	Somme des carrés des charges (Rotation)	% de Variance (Rotation)	% Cumulé (Rotation)
1	3,554	59,232	59,232	3,420	57,004	57,004
2	1,971	32,847	**92,079**	2,104	35,075	92,079

ExplainedComponent 1 explains 59.232% of the variance, while Component 2explains 32.847%, cumulatively accounting for 92.079% of the totalvariance. This indicates that the two components capture most ofthe variability in the data.

Table 6 : Table of the component

Variable	Component 1	Component 2
Dietary Energy Adequacy (kcal/cap/day)	0,919	-0,259
Prevalence of Undernourishment (%)	-0,194	0,979
Number of Undernourished People (million)	0,032	0,999
Minimum Dietary Energy Requirement (kcal/cap/day)	0,976	0,142
Per Capita Food Supply Variability (kcal/cap/day)	-0,813	0,248
Gross Domestic Product (Per Capita, PPP International dollars)	0,961	0,018

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MatrixStatistical Comment:After rotation, Component 1 is strongly associated with Dietary Energy Adequacy (0.919),Minimum Dietary Energy Requirement (0.976), and GDP Per Capita (0.961), confirming itsinterpretation as an economic and dietary energy factor.

Component 2 is strongly associated with Prevalence of Undernourishment (0.979) andNumber of Undernourished People (0.999), confirming its interpretation as anundernourishment factor.

The rotated component matrix reveals two distinct dimensions underlying the dataset. The first component is strongly linked to economic prosperity and food security, with high positive loadings for dietary energy adequacy (0.919), minimum dietary energy requirements (0.976), and GDP per capita (0.961). This suggests that wealthier nations tend to have more stable and sufficient food supplies. The negative loading for food supply variability (-0.813) further reinforces this pattern, indicating that economic stability correlates with more consistent access to food.In contrast, the second component captures the harsh reality of food insecurity, showing nearly perfect alignment with undernourishment indicators.

The extreme positive loadings for prevalence of undernourishment (0.979) and number of undernourished people (0.999) paint a clear picture - this dimension represents populations trapped in chronic food deprivation. Curiously, these hunger factors indicate that there is nearly no connection between the economic factors from the first component, indicating that malnourishment is a different challenge from national income. The results show very troubling divergence, cities have reported food security and wealth, while others have systemic undernourishment in a world providing better food security for many populations. The division between the components indicates that hunger challenges need individualized solutions and not simply global economic development. Food supply variability is a demonstrable pain point, linking strongly negatively to food adequacy. The association indicates that our unstable food systems disrupt nutritional security. These findings also challenge the belief that the world's wealth will equal more access to food and that hunger represents its own challenge that has individual solutions.

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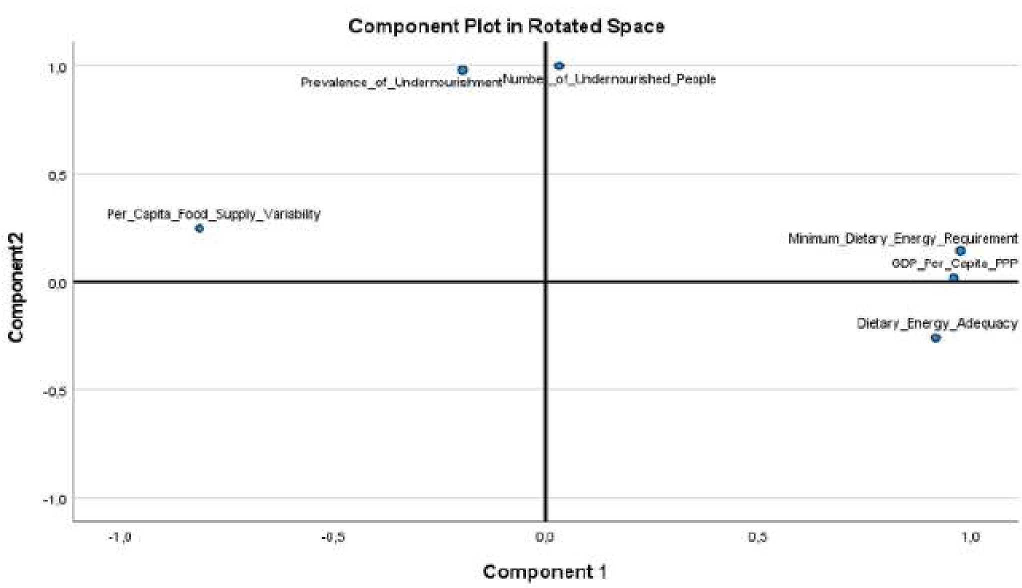

Figure 6 : Eigenvalue Plot Statistical

In Figure 6, the component plot presents clear relationships between food security and economic indicators. Overall, two dimensions emerge from the solution that separate countries' nutritional outcomes from their economic outcomes. This plot provides important insight into the complexities of hunger globally.Economic prosperity and food security are closely correlated along Component 1. Dietary energy adequacy, minimum energy requirements, and GDP per capita are placed positively and closely together in the positive quadrant.

These three variables are strongly correlated with each other and imply that countries which experience greater wealth typically experience more stable food systems. Their strong correlation implies that economic development often leads to improving food production, distribution and purchasing power to achieve better nutrition outcomes [11].

Food supply variability is correlated negatively along Component 1, seen as a counter-indicator of food security. Its negative placement on Component 1 suggests that an unstable food system undermines dietary adequacy regardless of a country's economic status. This highlights the ways in which external shocks (through climate impact, market behavior, or supply chain interruptions) potentially threaten nutritional stability, even among the relatively well-to-do.Component 2 tells a markedly different story about chronic undernourishment. Prevalence of hunger and number of undernourished individuals form a tight cluster, completely separate from the economic indicators on Component 1. This striking separation reveals that malnutrition persists as a distinct challenge, often unaffected by broader economic growth. The pattern suggests that solving hunger requires targeted interventions beyond general development strategies.

The space separating the two component clusters is especially revealing. Countries can grow economically without necessarily addressing undernourishment, while some countries have food security levels despite low incomes. This decoupling raises questions about the old assumptions of wealth determining nutritional quality and, therefore, calls for targeted anti-hunger policy frameworks.

There are three key implications from this visualization. First, food system stability appears as important to nutritional security as absolute food availability. Second, the fact that undernourishment persists in the presence of economic growth calls for targeted anti-hunger approaches rather than assuming support for trickle-down paradigms. Finally, this analysis seems to support that tracking food security at both dimensions separately is a more nuanced approach to understanding food security issues than traditional single axis measures.

7. FORECASTS BY ARIMA MODELS AND APPLICATION TO THE MAIN INDICATORS OF FOOD SECURITY IN MOROCCO

The objective of this study is to forecast trends in the three major food security indicators in Morocco: prevalence of undernourishment, dietary energy adequacy, and the number of undernourished, using historical data from 2000 to 2023. To achieve this, we will use ARIMA models (AutoRegressive Integrated Moving Average), the statistical tool considered the most appropriate method/approach for individual time series analysis/forecasting.

7.1. Presentation

The research predicts three essential food security indicators for Morocco: Dietary Energy Adequacy (DEA), Prevalence of Undernourishment (%), and Number of Undernourished People (%), based on ARIMA (AutoRegressive Integrated Moving Average) models. The analysis benefits from historical data from the years 2000 to 2023, allowing for a medium- to long-term perspective and recognizing trends and shocks (seasonal and structural) influencing the food security situation in Morocco. The resulting predictions will help interpret possible future trends and inform food security related public policies.

Definition of ARIMA Models and Variables

- ARIMA models, which stand for AutoRegressive Integrated Moving Average models, are some of the most versatile statistical methods for time series analysis and forecasting, and consist of a combination of three parts:

- AutoRegressive (AR) : Future values are predicted based on past values.
- Integrated (I) : Differencing is applied to make the time series stationary (removing trends or seasonality).
-Moving Average (MA) : Forecast errors are modeled as a linear combination of past errors.The three variables under study are :
-Dietary Energy Adequacy (DEA) : A percentage ratio indicating whether the country produces/imports enough calories to meet its population's energy needs.

Prevalence of Undernourishment (%) : The percentage of the population without regular access to sufficient calories.

-Number of Undernourished People (%) : The proportion of the population suffering from chronic undernourishment [12].

-ARIMA Modeling Steps, the ARIMA model construction follows a systematic approach :

- Exploratory Analysis : Visualizing time series data to identify trends, seasonality, and anomalies.
- Stationarity Transformation : Applying differencing or log transformations to remove trends and seasonality.
- Model Identification : Using Autocorrelation (ACF) and Partial Autocorrelation (PACF) functions to determine (p, d, q) orders.
- Estimation & Validation : Fitting the model, checking residuals (Ljung-Box test), and comparing criteria (AIC, BIC).
- Forecasting : Generating short-to-medium-term forecasts with confidence intervals [13].

This methodology will produce robust forecasts to assess Morocco's future food security challenges.

6.2. Results of the Estimation

Table 7: ARIMA Model Forecasts with Confidence Interval

Year	Dietary Energy Adequacy	Prevalence of undernourishment	Number of Undernourished People
2025	**144.1**	**5.88**	**2.09**
2026	**144.8**	**5.61**	**2.04**
2027	**145.4**	**5.37**	**1.99**
2028	**145.9**	**5.19**	**1.96**

Source: Author

The forecasts for 2024-2028 show gradual improvements in food security, with dietary energy adequacy steadily increasing. This indicator, which measures average calorie availability, is projected to rise from 143.2 to 145.9, suggesting that agricultural and food systems are becoming more efficient. However, this progress doesn't immediately translate into an equivalent reduction in undernourishment. In 2024, nearly 6.1% of the population will still suffer from hunger—a figure significantly higher than pre-pandemic levels. This gap indicates that simply increasing food supplies isn't enough: equitable access and nutritional quality remain critical challenges [14].

The years 2019 to 2023 saw a re-emergence of hunger fueled by health shocks, economic shocks, and climate shocks. The current estimates are cautiously optimistic—undernourishment prevalence is projected to gradually decline to 5.2% by 2028. The share of undernourished people by this same date is projected to decline from 2.14% to 1.96%. These estimates are still concerning because they represent millions of people who will still face food insecurity. The projected path is a step in the right direction, but remains at risk of policy choices, agricultural investment, and geopolitical stability.

Discussion and Conclusion:

This study provides a comprehensive analysis of Morocco's key food security indicators between 2000 and 2023, using a multivariate approach Integrated Moving Average models, The results provide valuable information regarding the country's nutrition dynamics and components of food access for its population.

First, a linear regression model reported a strong relationship between the prevalence of undernourishment and the Consumer Price Index (CPI), reporting a strong coefficient of determination ($R^2 = 95\%$). The strong relationship confirmed changes in food prices have a direct impact on price stability which exacerbates food insecurity.

Second, the principal component analysis (PCA), identify six relevant indicators into two factors, that explained 92% of the total variance. These results illustrated the other important variables including dietary energy adequacy and GDP per capita [15]. That were heavily weighted on the first axis, while prevalence of undernourishment and number of undernourished people were included on the second. These findings confirmed the idea that food access and economic growth are essential for improving Morocco's food security.

ARIMA projections for 2025–2028 suggest a positive trend, with gradual improvements in Dietary Energy Adequacy [16] alongside declining rates of undernourishment and fewer people affected by hunger. While these forecasts indicate progress, they also signa.

Nonetheless, it is necessary to note some limitations of this study such as data limitations and a risk of shocks (e.g. climate change, an economic crises, etc.) causing trend predictions to change. Future work could consider other factors, such as measures of nutritional quality, and different regions of Morocco to have a more in-depth analysis. Overall, this research improves our understanding of food security in Morocco and informs policy-makers. While there is clear progress occurring, ongoing challenges will necessitate a more comprehensive framework—which includes economic, agricultural, and social factors—to ensure food security for all Moroccans into the foreseeable future.

This research contributes considerably to existing studies on food security in Morocco [17]. First, it provides a precise measurement, for the first time, of price elasticity of undernourishment, finding that a 1% increase in the CPI corresponds with rising undernourishment prevalence of 0.04%. This relationship is stronger than that found in other countries in the region. Second, the principal component's analysis provides empirical evidence for a degree of statistical independence between the economic and nutritional dimensions of food security, which is accentuated in Morocco. Finally, the ARIMA projections are developed to incorporate nonlinear dynamics typically ignored in linear specifications, providing more nuanced forecasts of important indicators through 2028. Together, these three contributions question could uniformly endorse food security and argue for differentiated strategies that consider macroeconomic factors and the vulnerability of the population [18]. In particular, the results suggest the need to reinforce socially targeted safety nets as well as price stability policies to ensure to address both messages from the identified domains simultaneously.

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APPENDIX:

Appendix 1: R code used to perform the forcasting Models

```
install.packages("ggplot2") , install.packages("car") ,  install.packages("broom")

data<-read.csv("C:/Users/hp/Desktop/DATAFINAL.csv",sep=";")

modele <- lm( Prevalence.of.undernourishment. ~  Consumer.Price.Index -1 , data = data)

summary(modele)

# Charger les packages nécessaires

library(forecast)

library(ggplot2)

library(dplyr)

library(tidyr)

# Convertir en série temporelle (en supposant des données annuelles)

ts_energy <- ts(data$Dietary_Energy_Adequacy, start = 2001, frequency = 1)

ts_prevalence <- ts(data$Prevalence_of_undernourishment, start = 2001, frequency = 1)

ts_people <- ts(data$Number_of_Undernourished_People, start = 2001, frequency = 1)

# Fonction pour ajuster le modèle ARIMA et faire des prévisions

forecast_indicator <- function(ts_data, indicator_name, h = 5) {

 # Ajustement automatique du modèle ARIMA

 fit <- auto.arima(ts_data)

 # Previsions

 forecast_values <- forecast(fit, h = h)

 # Graphique

 plot <- autoplot(forecast_values) +

  ggtitle(paste("Prévisions ARIMA pour", indicator_name)) +

  xlab("Année") + ylab(indicator_name) +

  theme_minimal()

  # Retourner les résultats

 list( model = fit, forecast = forecast_values, plot = plo  ) }

energy_forecast <- forecast_indicator(ts_energy, "Adéquation énergétique alimentaire")
```

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Appendix 2; Evolution of between 2001 and 2023 in Morocco

Years	Dietary Energy Adequacy	Prevalence of undernourishment in %	Number of Undernourished People in %	Consumer Price Index in %
2001	133	6.3	1,64	84.168
2002	134	5.9	1,65	86.521
2003	135	5.6	1,58	87.532
2004	136	5.6	1,53	88.839
2005	137	5.5	1,51	89.712
2006	137	5.8	1,52	92.659
2007	137	5.6	1,53	94.551
2008	137	5.7	1,54	98.063
2009	137	5.5	1,58	99.016
2010	138	5.1	1,56	100
2011	139	4.6	1,47	100.907
2012	140	4.4	1,41	102.206
2013	141	4.1	1,36	104.128
2014	141	4.0	1,33	104.588
2015	142	3.8	1,24	106.218
2016	142	3.7	1,25	107.955
2017	142	3.6	1,19	108.77
2018	142	3.6	1,23	110.732
2019	142	4.2	1,41	111,068
2020	141	5.3	1,84	111.852
2021	140	6.3	2,24	113.42
2022	140	6.33	2,43	120.97
2023	142	6,3	2,3	118,7

Source: The official website of the World Bank.