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Developing the Smart Farming Index Across Countries

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Abstract: As the current agricultural challenges, including climate change, population growth, and water availability, become more pronounced, regions that are highly dependent on agriculture are seeking new ways to track productivity in an effort to boost agricultural output. Hence, an emerging concept of data-driven agriculture, or "Smart Farming," is becoming increasingly relevant in these regions. However, due to variations in available resources and technology across countries, it is difficult to objectify the effectiveness of these methodologies. Therefore, this paper aims to evaluate the potential effectiveness of Smart Farming in countries across different regions of the world to determine which nations have the strongest potential for driving gain through the use of such technology. The potential effectiveness of Smart Farming is assessed by 1) creating and using an index from a selection of datasets that represents every nation's agricultural environment, economic status, and resources available for the application; and 2) running Principal Component Analysis (PCA) on the dataset to weigh each nation's relations to the application and determine their rankings. The top 5 nations for the applicability of Smart Farming are Iceland, New Zealand, Australia, Norway, and Finland. These countries present a viable model for other nations to follow in order to achieve sustainable growth through the adoption of data-driven farming techniques.

Keywords: Smart Farming, Agriculture, Cross-Country Analysis

1. Introduction

With data science improving, Artificial Intelligence (AI) and the Internet of Things (IoT) are providing realistic solutions to the challenges in many fields of study [10]. Agriculture is among those fields, and the new concept of “smart farming” emerged. The application of this concept is anticipated to help handle current challenges in agriculture, such as climate change and water availability. With the increasing demand for such technology, smart farming is advancing through the use of improved sensors, more-accurate computer vision systems, and powerful AI [8]. Smart farming will help farmers to precisely select the input and improve their knowledge of factors that affect agriculture by (1) managing planting; (2) measuring productivity effects and management measures; (3) tracing and controlling farm produce security; and (4) monitoring plant growth [9]. However, agriculture differs a lot depending on the site of farming, as most of the impactful resources and factors are related to the environment. Also, there could be limitations to apply smart farming in regions where internet infrastructure is not sufficient. Moreover, regions that are dependent on agriculture and are willing to invest more in the industry will more effectively adapt to the change. Due to these reasons, the effectiveness of smart farming will be divergent among all nations. In this context, this paper will evaluate the potential effectiveness of smart farming in each nation by creating an index that regards the country's resources, dependence on agriculture, internet infrastructure, and economic status.

Our paper is related to several others in the existing literature. In one such study, titled Digital Transformation for a Sustainable Agriculture in the US: Opportunities and Challenges Khanna et al. (2021), analyzes the emerging technologies that address the challenges of agriculture, such as herbicide resistance, waste of nitrogen and irrigation water, and cover crop planting [3]. The authors discuss the factors which might affect the application of these technologies and the methodologies for adopting them. They examine these technologies in enhancing economic and environmental sustainability. The analysis of emerging technologies provides a reason to research how it will affect each nation, but it does not address this.

In another paper, a review by Wolfert et al. (2017), the authors investigate how big data can be applied in agriculture, and how the future of the industry will be shaped [4]. The paper predicts the future of smart farming in two extreme scenarios, which are a closed system where the farmer is integrated into the food supply chain, and an open system in which farmers and stakeholders can flexibly choose business partners and technologies. According to these scenarios, the paper suggests business models which can be successful in each scenario. This review consists of a more general estimation of the impact of smart farming, but it does not show which region will be successful.

Maru et al. (2018) address the challenges that smallholders in agriculture go through, and how those challenges can be overcome via data-driven agriculture [5]. The challenges include gaining access to relevant data and services and risking themselves when opening their own data. Data-driven agriculture can help overcome them by helping farmers to find balance and mitigate many situations, such as climate change. This paper analyzes the impacts of data-driven agriculture on individual farmers, while it does not view the macroeconomic impacts.

Jouanjean (2019) evaluates the impact of digital transformation on the food system [6]. It discusses how the agriculture and food sector is changing due to the new technologies and opportunities to share information, and how this change impacts cross-border trade processes. It also emphasizes the current constraints regarding trade and new opportunities for agriculture in the digital economy. This paper's analysis is limited to the general application of smart farming in the digital economy, which can be improved by focusing on regions.

Finally, the UN (2017) looks at the establishment and development of a national e-agriculture plan [7]. It monitors and evaluates some of the implementations of e-agriculture, and it encourages nations to develop such plans. It puts emphasis on the fact that these strategies can develop and revitalize a country's approach in using ICT to achieve and widen its agriculture goals and priorities. This paper analyzes how each nation can utilize e-agriculture, but it does not provide information specific to a nation.

The reviewed literatures discuss the general impact and the future of smart farming. Building upon the existing literature, the current paper agrees on the positive impacts discussed in the literatures that smart farming can potentially bring. Our goal is to evaluate which nation is the most suitable to adapt and accommodate the current smart farming trend in agriculture.

The rest of the paper is organized as follows: In the next section, we discuss the conceptual framework. In section III, we present my data and the empirical method we use. In section IV, we present my results. Finally, in the last section, we provide some concluding remarks.

2. Conceptual Framework

To create an index that successfully represents the potential effectiveness, I select datasets that will be used as a basis of the index. The selected datasets can be classified into three categories: a nation's agricultural environment, economic status, and resources and infrastructure available.

The datasets which are included in the agricultural environment are Plant Species Threatened, Land for Cereal Production per capita, Water Productivity, and Emissions per capita. Plant Species Threatened shows the numbers of endangered species, and this value demonstrates if the nation is an environment where plants can thrive in. If this value is high, then it indicates that the environment is not very suitable. Land for Cereal Production per capita is important as agriculture requires some land for the crops to grow, and therefore, it is an important aspect when determining the potential output. Water Productivity shows the output of crops when a certain amount of water is put in, and therefore high values suggest it is a suitable environment for agriculture. Emissions per Capita is important, as researchers have found a remarkably consistent negative association between nitrogen dioxide and crop growth in major cropping regions [14]. High values suggest that the environment is not suitable for agriculture.

The datasets which are included in the economic status are GDP per capita, Agricultural Output per capita, and Agricultural Employment. GDP per capita shows how much wealth each person possesses, and this is important as investment is needed to apply this new concept to the agriculture industry. Agricultural Output per capita is selected because it shows how productive the nation is in agriculture, which suggests the ability in the industry. Agricultural Employment is also directly linked to the application of Smart Farming, as it shows the available workforces in the industry which can be used to adopt this concept.

The datasets which are included in resources and infrastructure available are Internet Users, Secure Internet Servers, R&D Spending, Energy Use per capita, Renewable Resources per capita, and Human Capital. Internet Users and Secure Internet Servers demonstrate the internet infrastructure of the nation, and for the interaction of data, the internet is needed. Thus, these values show if it is plausible to adopt Smart Farming. R&D Spending is important as it shows the available capital which might be used as an investment in this field. Energy Use per capita demonstrates the electricity infrastructure, and this is crucial in the same context as the internet infrastructure. Renewable Resources per capita is important as the persistent population growth requires ever-increasing energy consumption and other natural resources [11]. As the energy sources are currently being depleted, expecting a critical depletion within 50 years at current use levels [12, 13], the application of renewable resources is necessary as energy sources in the future, where Smart Farming will be active. Human Capital demonstrates the workforce available, but not limited to this industry. This overall workforce shows how other infrastructures can be improved, so that the potential output of Smart Farming can increase.

The created index will be useful for nations to determine how actively they should adopt this new concept of Smart

Farming. If a nation has a high value in this index, it will experience a high output compared to the investment it put in to adopt this concept, and vice versa for a low value. Also, it can show what each nation should improve to increase the output of Smart Farming.

3. Data and Methods

To construct the overall index, we use 13 variables. All these variables, as well as their descriptive summary statistics, are presented in Table 1. These variables are as follows: GDP per capita, Internet Users, Agricultural Output per capita, Secure Internet Servers, R&D Spending, Energy Use per capita, plant species threatened, renewable resources per capita, Agriculture Employment, Land for Cereal Production per capita, Emissions per capita, Human Capital, and Water Productivity. The datasets for all these variables were collected from World Development Indicators, which is part of the databank which the World Bank provides.

Following standard PCA procedure, the tails of all variables are reduced[i] by 1% up and down to eliminate the influence of extreme values. According to Table 1, all variables exhibit significant standard deviations, indicating that they can be subject to PCA. In order to be as comprehensive as possible, our index includes 13 variables. Previous studies have used various methods for index creation with multiple variables, of which one of the commonest is PCA. We, therefore, applied PCA to the 16 variables following the standard methodology of Baxter (1995) and Joliffe (2002) [1, 2].

Table 1. *Descriptive Summary Statistics.*

Variable	Mean	Median	Std. Dev.	Min.	Max.	# of Countries
GDP per capita	18747.90	7233.39	27570.22	236.80	173688.20	213
Internet Users	61.21	69.79	28.12	0.00	100.00	209
Agricultural Output per Capita	486.91	351.69	903.36	5.84	9436.63	196
Secure Internet Servers	16911.43	514.09	59242.33	0.08	741078.8	215
R&D Spending	0.92	0.46	1.06	0.01	5.44	124
Energy Use per capita	2243.41	1233.32	2876.32	9.56	17922.70	172
Plant Species Threatened	79.19	18.00	186.26	0.00	1859	215
Renewable Resources per Capita	15071.01	2516.03	46300.01	0.00	481967.3	183
Agriculture employment	23.32	17.37	21.59	0.03	86.21	187
Land for Cereal Production Per cap	0.09	0.06	0.11	0.00	0.78	180
Emissions per cap	0.0005	0.0003	0.0005	0.00	0.004	189
Human Capital	0.56	0.56	0.14	0.29	0.88	174
Water Productivity	83.29	21.48	184.69	5.44	1348.11	176

After first comparing all inter-variable correlations, we check the normality of all variables and transform any that require it.[ii] Normalization and trimming outliers (1 percent) from the data is required because PCA is not scale-invariant. We then adjust all variables to the same scale and index them within a range of 0-100. To do this, we calculate the ratio of the difference between the actual value of a variable and its minimum value to the difference between the maximum and the minimum value and multiply this ratio by 100.

We then run the PCA using all 13 transformed variables. The PCA produces the same number of components as the number of variables used in the analysis, which is 13 in this study. These components are basically linear combinations of the variables. The number of components chosen for the final index should be such that the associated eigenvalue does not go beyond 1. For all statistical analyses, we use STATA version 17.

Table 2 presents the eigenvalues and proportions of the explained variance in the dataset for each component. The table notes present various test results for PCA. The value of the Kaiser-Meyer-Olkin (KMO) index, which compares the correlations between the variables and the partial correlations, resulted in 0.84, where a value for the KMO test above 0.8 is considered to be ‘good’ and ‘adequate’ [15], thereby indicating the efficiency of the PCA and adequate sampling. Similarly, Bartlett’s test of sphericity is also satisfactory, rejecting the null hypothesis that the observed correlation matrix does not deviate significantly from the identity matrix. Finally, the scale variability is also acceptable, with a Cronbach’s alpha value of 0.77. The principal components (eigenvectors) are presented in full in Table A1 in the appendix.

As Table 2 shows, the analysis indicates using six components since component 6 has an eigenvalue below 1. With five components, the analysis can account for about 81% of the variance in the overall data.

Table 2. *Eigenvalues in the Principal Component Analysis.*

Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	5.25	3.41	0.40	0.40
Component 2	1.84	0.41	0.14	0.54
Component 3	1.43	0.40	0.11	0.65
Component 4	1.03	0.03	0.08	0.73
Component 5	1.01	0.30	0.08	0.81
Component 6	0.71	0.17	0.05	0.87

KMO test=0.84, Bartlett’s test of sphericity: approx., Chi-Square= 420.12 Significance=0.001, Cronbach’s alpha=0.77.

The final index is calculated using the following formula, where PCAx for x = 1, 2, 3, 4, 5, refers to each principal component:

$$\text{Index} = \left(\frac{0.40}{0.81}\right)\text{PCA1} + \left(\frac{0.14}{0.81}\right)\text{PCA2} + \left(\frac{0.11}{0.81}\right)\text{PCA3} + \left(\frac{0.08}{0.81}\right)\text{PCA4} + \left(\frac{0.08}{0.81}\right)\text{PCA5}$$

Notice that the coefficient of each principal component is equal to the proportion of variation explained individually by each principal component divided by the total cumulative proportion of variation in the whole data explained by all six principal components.

As an alternative to the PCA-based index measure, we also create an alternative index using the unweighted arithmetic average of all 13 (0-100) transformed variables and finally transforming it to a 0-100 range. Since the correlation between the two indices is 0.81, we only continue with the PCA-based index in the subsequent analysis. Table A1. in the appendix presents both series by country.

Table 3. *Descriptive Summary Statistics of the Indices.*

	Mean	Median	Std. Dev	Min.	Max.
PCA Index	17.79	13.27	14.76	0.00	100.00
Unweighted Average	33.52	31.46	19.63	0.00	100.00

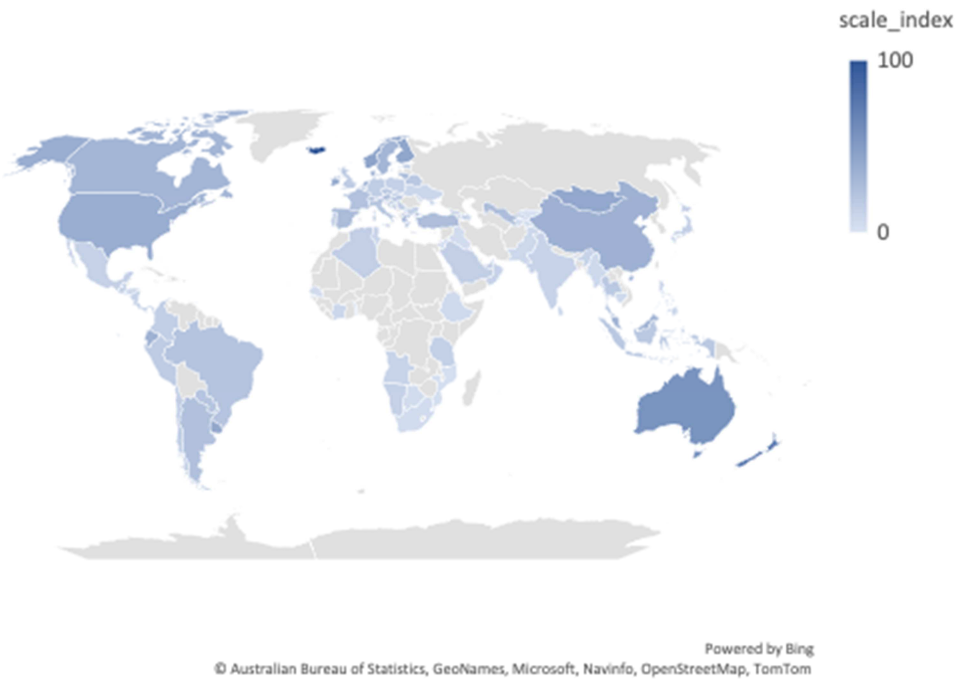

Figure 1. *Global heat map of the PCA Index.*

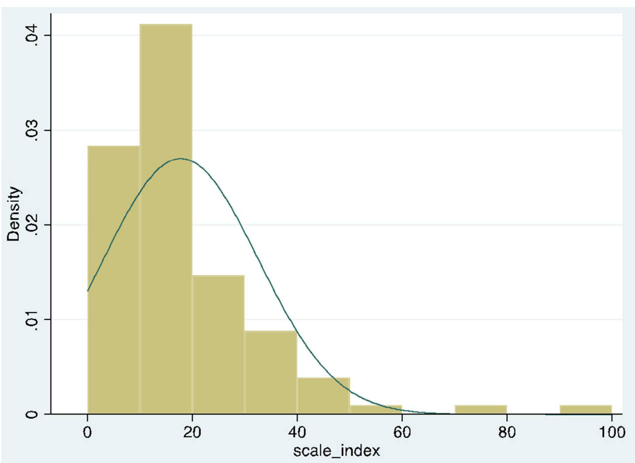

Figure 2. *Histogram and the Associated Normal Distribution of the Smart Farming Index.*

Figure 1 is a global heat map of the PCA index, which shows which part of the world is ranked high for the potential effectiveness of smart farming. The top five nations that are ranked high in the index are Iceland (100), New Zealand (70.05063), Australia (55.90287), Norway (44.22781), and Finland (42.50343).

Next, in Figure 2 is the histogram and associated normal distribution of the index. The density of the index in the range of 0 to 20 is very high, and the density decreases as the value of the index increases.

Finally, Figure 3 shows the percentage improvement in the index after a 10-percent improvement in each component, ordered from lowest to highest. Thus, the top five improvers in terms of the policy are increasing human capital (13.22 percent), R&D spending (12.32 percent), internet users (11.10 percent), water productivity (11.10 percent), and secure internet servers (9.98 percent).

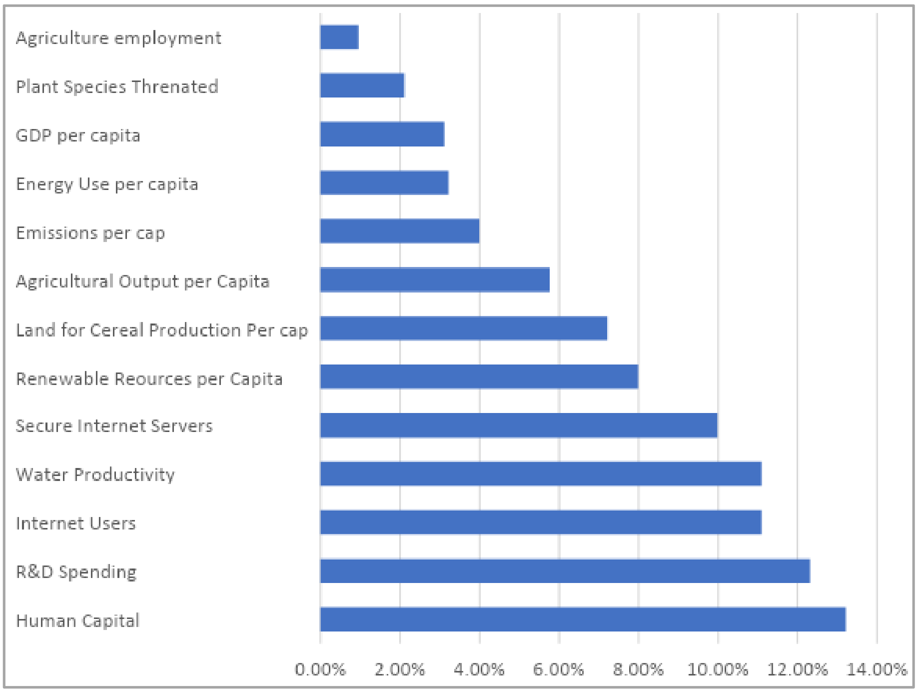

Figure 3. *Potential Improvements of the Overall Index.*

4. Conclusion

For the evaluation of the potential effectiveness of smart farming in each nation, we constructed an index. The data collected and used for the construction of my index represented the nation's agricultural environment, economic status, and resources and infrastructure available. With those datasets, we used the Principal Component Analysis to weigh each dataset differently based on their relation and contribution to the application of smart farming. The top five nations rated by this index are Iceland, New Zealand, Australia, Norway, and Finland.

With the index constructed and the general evaluation provided in this paper, further research in this broad emerging field of smart farming is possible. Some suggestions include case studies about smart farming application specific to a single or limited number of nations, or the exploration of the socioeconomic effects which a successful adaptation of smart farming can bring. Also, nations can use this index for their objectification of problems existing to adopt smart farming, and can potentially improve their environment for a more effective application.

Appendix

Table A1. *Index Values by Country.*

Country	Benchmark Index	Alternative Index
Algeria	13.88574	12.21216
Angola	10.67195	11.88784
Argentina	23.94448	18.84329
Armenia	13.19273	14.64959
Australia	55.90287	34.27734
Austria	23.7311	24.76957
Azerbaijan	11.16593	16.95602
Belarus	18.81532	20.5539
Belgium	13.30251	24.58793
Bosnia and Herzegovina	9.48016	14.98654
Botswana	5.282246	12.07302
Brazil	21.61626	18.93529
Brunei Darussalam	13.91322	20.11406
Bulgaria	12.04702	17.5962
Cambodia	6.559508	11.49371
Canada	31.58702	30.64041
Chile	14.96192	16.90711
China	34.69871	22.00089
Colombia	13.94525	15.10345
Congo, Dem. Rep.	1.410195	10.40566
Costa Rica	19.07543	15.50217
Cote d'Ivoire	8.315577	9.775088
Croatia	16.5219	18.59873
Cyprus	11.29265	18.44352
Czech Republic	19.35826	22.20513
Denmark	33.62543	31.92797
Ecuador	34.26243	22.37587
Egypt, Arab Rep.	12.01647	13.00261
El Salvador	3.129885	10.93008
Estonia	15.89082	24.911
Eswatini	7.48402	6.844073
Ethiopia	6.6447	11.74874
Finland	42.50343	28.64306
France	23.02323	23.71976
Gambia, The	0	8.580935
Georgia	10.70267	16.07079
Germany	14.98742	25.04656
Greece	22.73216	18.7761
Guatemala	11.51037	11.57403
Honduras	7.102434	10.75909
Hungary	17.52092	20.75447
Iceland	100	40.96629
India	10.99523	13.99463
Indonesia	18.03086	14.75162

Country	Benchmark Index	Alternative Index
Iran, Islamic Rep.	18.02903	17.04939
Iraq	4.733222	9.565526
Ireland	38.98674	29.60965
Israel	24.94854	26.63718
Italy	20.07475	18.73087
Japan	13.10561	23.24453
Jordan	2.704244	10.20928
Korea, Rep.	24.53427	26.67118
Kuwait	3.30238	17.96603
Kyrgyz Republic	1.245996	11.72748
Lebanon	7.378401	11.96226
Lithuania	25.44544	24.86341
Luxembourg	33.53133	33.07529
Malaysia	32.1326	20.44571
Malta	5.813711	17.56125
Mauritius	8.322129	12.42916
Mexico	12.53246	16.08146
Moldova	11.80777	17.3808
Mongolia	41.77635	22.02386
Mozambique	3.0103	11.15691
Myanmar	7.365685	12.85668
Namibia	12.85871	11.60839
Netherlands	29.31794	24.93286
New Zealand	70.05063	28.37308
Nicaragua	11.13061	11.98786
North Macedonia	10.89179	14.04227
Norway	44.22781	28.62652
Oman	11.35493	16.65384
Pakistan	7.474359	8.701845
Panama	12.76728	13.16162
Paraguay	21.06693	16.99236
Peru	15.9318	15.98449
Philippines	8.575476	11.87173
Poland	12.33843	21.02604
Portugal	14.41162	18.93844
Saudi Arabia	13.78871	17.28726
Senegal	4.922134	10.3014
Serbia	13.23857	18.96556
Slovak Republic	12.62857	19.18706
Slovenia	16.29754	21.53259
South Africa	4.705297	11.99981
Spain	26.90811	21.77836
Sri Lanka	8.108745	11.7282
Sweden	31.80776	28.17735
Switzerland	25.6003	28.18319
Tajikistan	4.549869	9.862195
Tanzania	13.0019	14.56131
Thailand	17.86778	19.13346
Togo	1.274165	9.208184
Trinidad and Tobago	3.422761	18.01272
Tunisia	9.875833	13.53151
Turkiye	25.91071	18.22976
Ukraine	8.653941	17.9555
United Arab Emirates	12.00403	21.20257
United Kingdom	15.97016	23.56787
United States	37.42968	30.98636
Uruguay	40.85581	20.8212
Uzbekistan	25.85125	15.43904

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[i] We also replicated our analysis without dropping the 1-percent tail of the distribution. The results did not change significantly. This additional analysis is available upon request from the corresponding author.

[ii] None of the variables satisfy the normality assumption. Therefore, all are transformed.