NEW MACHINES AND EQUIPMENT

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Temporal Similarity of the Mechanization Level and Crop Yield in Eritrea

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ABSTRACT

BACKGROUND**:** The dynamics of agricultural production have gradually moved toward mechanization and maximizing efficiency. Understanding the relationship between mechanization and crop yield is crucial to improve productivity.

AIM**:** This study assesses the temporal pattern similarity between crop yield and the level of mechanization (LOM) and examines how LOM influences crop productivity over time.

MATERIALS AND METHODS**:** The study used ordinary least squares (OLS) regression with interaction terms for trend analysis and dynamic time warping (DTW) for pattern similarity. Descriptive statistics (standard deviation, mean, minimum, and maximum) and error metrics (MAE and RMSE) were used to assess the DTW distance performance between sequences.

RESULTS**:** The OLS analysis showed almost parallel trend lines (0.038% and 0.053%). The DTW analysis showed significant temporal alignment, with a 44.4% perfect match and a similarity score of 34 (34 optimal paths across 28 dataset pairs). Performance evaluation metrics—standard deviation, mean, minimum, and maximum—were 7.56×10^{-3}, 1.08×10^{-2}, 1.42×10^{-5}, and 3.22×10^{-2}, respectively. MAE and RMSE values were 6.33×10^{-3} and 7.56×10^{-3}, respectively. Based on these values, average similarity, consistency, alignment quality, and error metrics were used to assess the level of similarity. These values indicate high similarity and consistency (based on the low mean DTW distances, standard deviation, and error metrics), despite occasional poor alignment.

CONCLUSION**:** The temporal similarity between LOM and crop yield showed that variations in LOM significantly impacted cereal crop yields. Agricultural productivity could benefit from mechanization through the use of contemporary technologies, improved supportive policies, and the integration of sustainable practices.

Keywords: data alignment; dynamic time warping; ordinary least square; optimal path.

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НОВЫЕ МАШИНЫ И ОБОРУДОВАНИЕ

Оригинальное исследование

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Временное сходство уровня механизации и урожайности в Эритрее

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АННОТАЦИЯ

Обоснование. Динамика сельскохозяйственного производства направлена на прогрессивное повышение уровня механизации и максимизацию эффективности. Понимание взаимосвязи между механизацией и урожайностью сельскохозяйственных культур имеет важное значение для повышения производительности.

Цель исследования — оценка временного сходства между урожайностью сельскохозяйственных культур и уровнем механизации (УМ), с упором на то, как УМ влияет на урожайность сельскохозяйственных культур с течением времени.

Методы. В исследовании использовалась метод наименьших квадратов (МНК) с условиями взаимодействия для анализа тренда и динамическое выравнивание временных последовательностей (ДВВ), для анализа сходства паттернов. Для оценки эффективности определения расстояния ДВВ между последовательностями использовались описательная статистика — стандартное отклонение, среднее, минимальное и максимальное значения — наряду с показателями ошибок, в частности, абсолютной средней ошибки (MAE) и среднеквадратичной ошибки (RMSE).

Результаты. Анализ МНК выявил почти параллельные наклоны линий тренда (0,038 и 0,053 процента). Анализ ДВВ показал значительное временное выравнивание, с 44,4% идеального совпадения и оценкой сходства 34 (34 оптимальных пути в 28 парах наборов данных). Соответствующие значения метрик оценки производительности — стандартное отклонение, среднее, минимум и максимум были рассчитаны как $7{,}56\text{x}10^{-3}$, $1{,}08\text{x}10^{-2}$, $1{,}42\text{x}10^{-5}$ и $3{,}22\text{x}10^{-2}$; значения MAE и RMSE были вычислены как $6{,}33\text{x}10^{-3}$ и $7{,}56\text{x}10^{-3}$ соответственно. На основе этих значений были использованы среднее сходство, согласованность, качество выравнивания и ошибки для оценки уровня сходства. Наборы данных продемонстрировали высокий уровень сходства и согласованного выравнивания (на основе низких средних расстояний ДВВ, стандартного отклонения и ошибок), несмотря на некоторые случаи плохого выравнивания.

Заключение. Временное сходство в ДВВ и урожайности показало, что урожайность зерновых культур значительно зависит от колебаний в ДВВ. Сельскохозяйственная продуктивность может выиграть от механизации за счёт внедрения современных технологий, улучшения поддерживающих политик и интеграции устойчивых практик.

Ключевые слова: выравнивание данных, динамическое искажение времени, метод наименьших квадратов, оптимальный путь.

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BACKGROUND

Agriculture relies on a diverse range of input resources for successful and efficient production, in addition to essential cultivation environment, including power sources (humans, animals, and/or machines) [1]. Agricultural production has progressively advanced toward a highly mechanized state, striving to maximize output with fewer resources [2–6].The level of mechanization (LOM) can be measured by the extent to which mechanical power is used in the agricultural sector. One common LOM indicator is the horse power (hp) per thousand hectares of cultivated land [3,4].

This metric varies over time, particularly in low-income countries, reflecting the influence of prevailing socioeconomic, governmental, and other factors. Although technological advancements offer cost-effective and efficient machines, agricultural sectors can be sensitive to investments in mechanization during economic fluctuations (growth or recession) [5–8]. This progression of LOM could exhibit periodic trends, influenced by a complex interaction of socioeconomic, environmental, and policy factors that may fluctuate over time [9], leading to corresponding variations in the agricultural production and productivity. This can be treated as a time series problem, and the similarities in the pattern of the fluctuations between the two sequences can be assessed using the ordinary least square (OLS) and the dynamic time warping (DTW) methods.

OLS is a versatile, widely used technique for establishing statistical relations between parameters. Sharma et al. (2011), Larrabee et al. (2014), and Sharma et al. (2013) have used the OLS to analyze the relationships between crop yields and influencing factors such as average precipitation [10], soil properties, management practices [11], and product quality and influencing factors [11]. OLS is useful for analyzing economic factor effect [12], quantifying the effect of farm machinery on crop yield, identifying the determinants of farm machinery adoption, examining the relationship between the use of machinery and input resources, and assessing farm machinery investment feasibility and profitability. It also enhances input management tactics and assesses the combined impact of equipment adoption and off-farm employment on farm performance [13]. However, it lacks precision in analyzing the temporal patterns of time series datasets.

The DTW is particularly effective in comparing sequences of similar patterns but differing in timing, alignment, or length, and finding their optimal alignment [14–17]. In 1978, Sakoe applied the DTW optimization algorithm to recognize spoken words [16]. The DTW algorithm can also be used for automatic speech-to-lip alignment [18,19], fingerprint matching validation [20], and facial and eye detection. It can be used for comparing, aligning, and combining time series sequences across comparable [17,19] or incomparable spaces in multivariate time series classification [21]. DTW also facilitates similarity analysis between two sequences of datasets with temporal variability—whether shifted, scaled, or globally invariant [15]—and supports data mining for determining averages and indexing [22].

In agriculture, DTW is useful for measuring similarities between two temporal sequences for land use and land cover classification and mapping [23], for weighted derivative modification of DTW in crop mapping [24–26], for determining the temporospatial characteristics of agricultural non-point source pollution loads, and for identifying dominant processes and influencing factors.

The LOM is a significant determinant of production and productivity [8]. In Eritrean agriculture, particularly in cereal production, the LOM's modest growth and volatility may contribute to the insignificant growth trend over the years. To examine the LOM's effect on production, similarity analysis can be conducted using time series records of the LOM and yield. However, few studies have examined the similarity between cereal production and LOM time series datasets, both globally and in Eritrea, particularly through DTW. Eritrean cereal production varies over the years with mild growth, similar to the LOM. However, no scientific evidence establishes this relationship, effect, dependence, or similarity in pattern between these datasets.

Study Aim: This study analyzes the similarity between cereal production (yield) and the level of mechanization (LOM) in Eritrean agriculture to examine LOMs impact on crop yield using ordinary least squares (OLS) regression method for trend analysis and DTW for pattern similarity evaluation. By analyzing the temporal pattern similarity between yearly crop yields and LOM fluctuations, this study evaluates the influence of LOM on agricultural productivity.

MATERIALS AND METHODS

Assessment of the LOM

Power availability per unit area serves as a fundamental parameter in evaluating the extent of mechanization in agricultural systems. Accordingly, the LOM in kW/ha (hp/ha), as a function of mechanical power available in a farm, is given by equation 1 [4].

$$LOM = \sum_{i=0}^{n} \frac{P_i}{L_i} \qquad [1]$$

where P_i is the machinery power (kW or hp) and L_i is the total cultivated area (ha).
According to the United States department of agriculture (USDA), the LOM data for countries worldwide from 1961 to 2020 is available online in an interactive format [27], allowing users to inspect the LOM for each year within that range. A freely available CSV file containing diverse, extensive data, part of which is the total horsepower (in multiples of 1000 hp) of farm machinery in each country for specific years, is provided. These data were used to determine the LOM in this study, with the corresponding year's cultivated area (in multiples of 1000 ha) obtained from the Eritrean Ministry of Agriculture.

Similarity analysis

A comprehensive multistep analysis was conducted to examine the similarity between the LOM and yield. First, we used OLS regression with an interaction term for preliminary time series trend similarity analysis and, second, we used a comprehensive analysis using DTW with robust similarity metrics. This approach clarifies the temporal relationship between the LOM and yield. The analysis was conducted in Python using appropriate libraries and packages. To address the different scales of datasets, the yield dataset was standardized and scaled simultaneously to match the LOM using equation 2 [28]:

$$Y_s = \frac{Y - \overline{Y}}{\sigma_Y} \times \sigma_x + \bar{x} \qquad [2]$$

where Y_s is the standardized yield; $\overline{Y}$ is the mean of the yield; σ_Y is the yield standard deviation; σ_x is the LOM standard deviation; and $\bar{x}$ is the LOM mean.

Ordinary Least Squares (OLS) Regression

The dependent and independent variables were modeled using OLS regression with an interaction term: Interaction = Year_Centered × (Standardized Yield not NA). "LOM" and "Standardized Yield" using first combined before configuring the regression model as [29]:

$$y = \beta_0 + \beta_1 \times Year\_Centered + \beta_2 \times Interaction + \varepsilon \qquad [3]$$

Dynamic Time Warping Distance Similarity Analysis

DTW aligns two datasets using dynamic programming to estimate local costs. For two multivariate time series sequences, the standard DTW formulation (equation 4) analyzes the time series $x \in \mathrm{R}^{T_x \times p}$ and $y \in \mathrm{R}^{T_y \times p}$, where T_x and T_y represent the sequential duration of the respective time series. Both sequences must have the same dimension p [15].

$$DTW = \min \sum_{\pi \in A(i,j)(i,j)\in\pi}^{n} d(x_i - y_i) \qquad [4]$$

where A (i, j) is the set of all permissible alignments between *x* and *y*. For most instances, the ground metric *d* is defined as $d(x_i, y_j) = \|x_i - y_j\|^2$. To efficiently estimated similarity, we use dynamic programming based on the formulation in (equation 4) [14,15,21,30]:

$$DTW(x_{\to t_1}, y_{\to t_2}) = d(x_{t_1}, y_{t_2}) + \min \begin{cases} DTW(x_{\to t_1}, y_{\to t_2 - 1}) \\ DTW(x_{\to t_1 - 1}, y_{\to t_2}) \\ DTW(x_{\to t_1 - 1}, y_{\to t_2 - 1}) \end{cases} \qquad [5]$$

where $x_{\to t}$ represents the time series x observed up to time *t*.

The distance matrix of datasets $X = \{x_1, x_2, \dots x_n\}$ and $X = \{y_1, y_2, \dots y_m\}$ with lengths *n* and *m*, aligned using DTW, is derived from the information contained in the *n*×*m* matrix as

$$distMatrix = \begin{pmatrix} \mathrm{d}(x_1,y_1) & \mathrm{d}(x_1,y_2) & \dots & d(x_1, y_m) \\ \vdots & & \ddots & \vdots \\ \mathrm{d}(x_n,y_1) & \mathrm{d}(x_n,y_2) & \cdots & d(x_n, y_m) \end{pmatrix} \qquad [6]$$

where *distMatrix* (*i*, *j*) is the distance of point *i* on X and point *j* on Y, and $1 \le i \le n$ and $1 \le j \le m$. The DTW aims to discover the warping path $\pi = \{\pi_1, \pi_2, \dots, \pi_K\}$ of the adjoining elements that minimizes the cost function.

DT W Algorithm

Input: Two sequences to be aligned: $X = \{x_1, x_2, \dots x_n\}$ and $X = \{y_1, y_2, \dots y_m\}$ and num_iterations (default is 1) and *Output:* optimal_path => similarity_score.

Algorithm Steps:

1. *Data Alignment:*
   > No preprocessing is required as sequences are assumed to be aligned.
2. *Dynamic Programming:* Initialize a cumulative cost matrix A with size (m + 1) x (n + 1) where m and n are the lengths of x and y, respectively, and initialize all cells of the matrix with infinity values except for the top-left cell, A [0,0].
   > For each cell A[i, j] in the matrix: local cost = |X[i] – Y[j]| => Update X[i] and Y[j] as A[i, j] = $local_{cost}$ + minA[i – 1, j], A[i, j – 1] A[i – 1, j – 1]
3. *Optimal Path Extraction:* Initialize an empty list optimal path => start from A [m − 1, n − 1] (bottom-right corner) =>trace back to the top-left corner A [0, 0].
4. *Similarity Measurement => similarity score => plot for visualization*.

Evaluation of DTW distance similarity performance:

To measure the similarity between yield and LOM, we used the following DTW distance parameters: mean, minimum, maximum, standard deviation, mean absolute error (MAE) and root mean square error (RMSE). A combination of these metrics was used to measure the level of similarity between the time series datasets, with lower values reflective of a better degree of similarity, and vice versa.

RESULT

The LOM of the country for a specific year is determined by dividing the total available horsepower in that year by the yearly cultivated area. The crop yield and the LOM over the years are shown in Fig. 1. The yield followed a pattern similar to the LOM, although decreases and increases varied, except in certain years where the yield response was affected by rainfall and other factors. The yield response lagged by one year, as LOM introduced at the start of the production season affected the yields later. Therefore, the LOM values were shifted forward by one year for better alignment (Fig. 1).

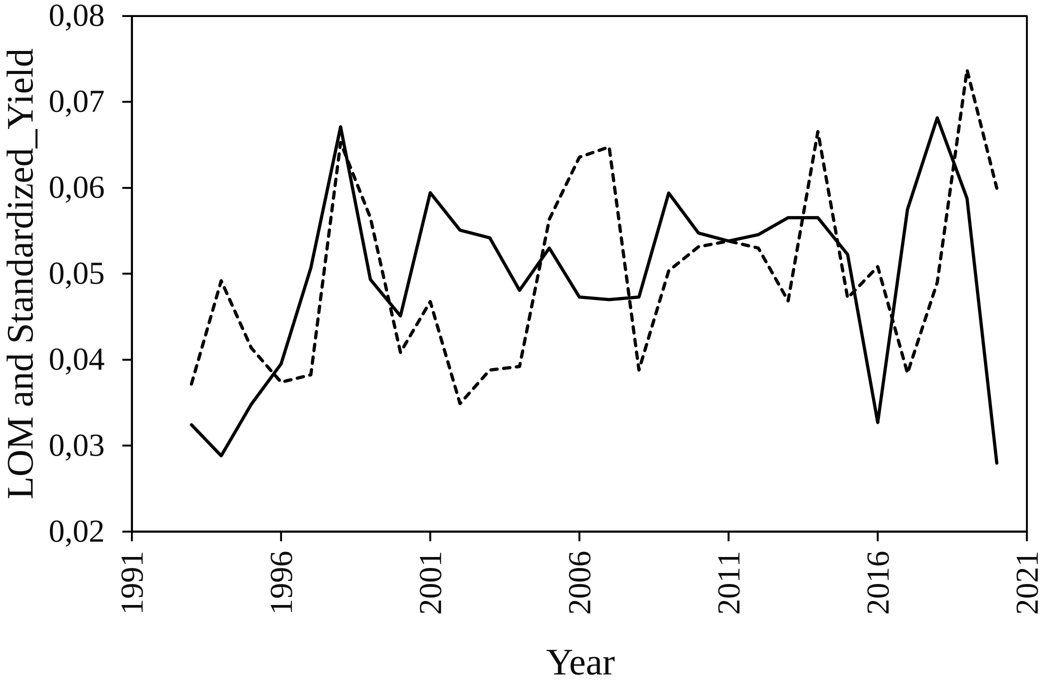

Fig. 1. LOM was horizontally shifted by one year for better analysis, with yield plotted over the years 1993–2020. The broken line represents standardized yield, while the solid line represents LOM.
Рис. 1. Уровень механизации (LOM) сдвинут на один год вперед для лучшего анализа, а урожай нанесен на график за 1993-2020 годы; пунктирная линия представляет стандартизированный урожай, а сплошная линия — LOM.

Trend similarity and statistical analysis

The analysis aimed to determine whether the two datasets had similar trends. The slope (%) of the LOM and yield trendlines (see Fig. 2) were 0.038 and 0.053, respectively (with a small slope difference of 0.015%). The interaction term's *p*-value was 0.123, exceeding the critical *p*-value of 0.05, indicating no significant difference between the trends. Overall, the rising slope indicated that over the past 28 years, an increase in LOM has been associated with an increase in the yield.

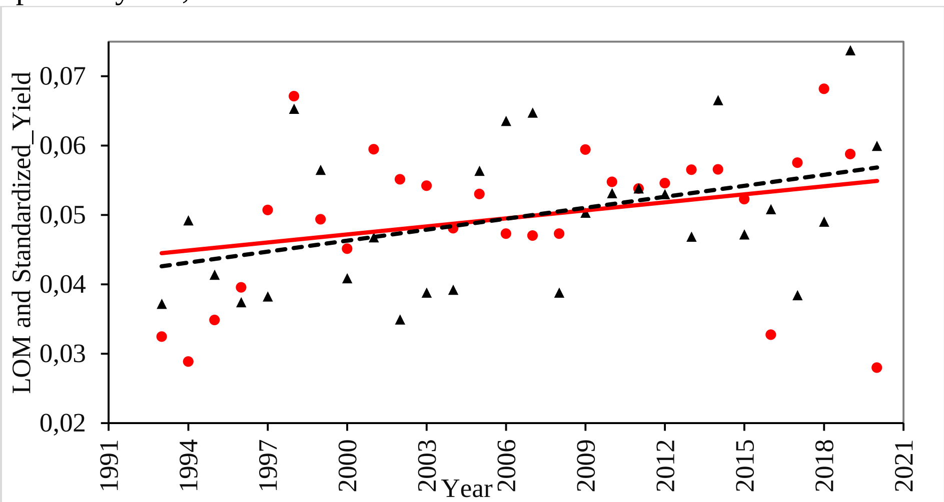

Fig. 2. Trend Similarity between the LOM (red solid line) and crop yield (dark broken line) over the years 1993–2020.
Рис. 2. Сходство тенденций между уровнем механизации (LOM) (красная сплошная линия) и урожайностью сельскохозяйственных культур (темная ломаная линия) за 1993-2020 годы.

DTW similarity analysis

The initial segment of the optimal path (Fig. 4), from (1995, 1995) to (2001, 2001), shows a diagonal alignment between yield and LOM, indicating their close temporal proximity (Fig. 3), before diverging from (2002, 2001) to (2005, 2001). A deviation from the diagonal indicates compression and expansion of the time axis, as one element matches many (Fig. 3), reflecting the temporal variance between yield and LOM.

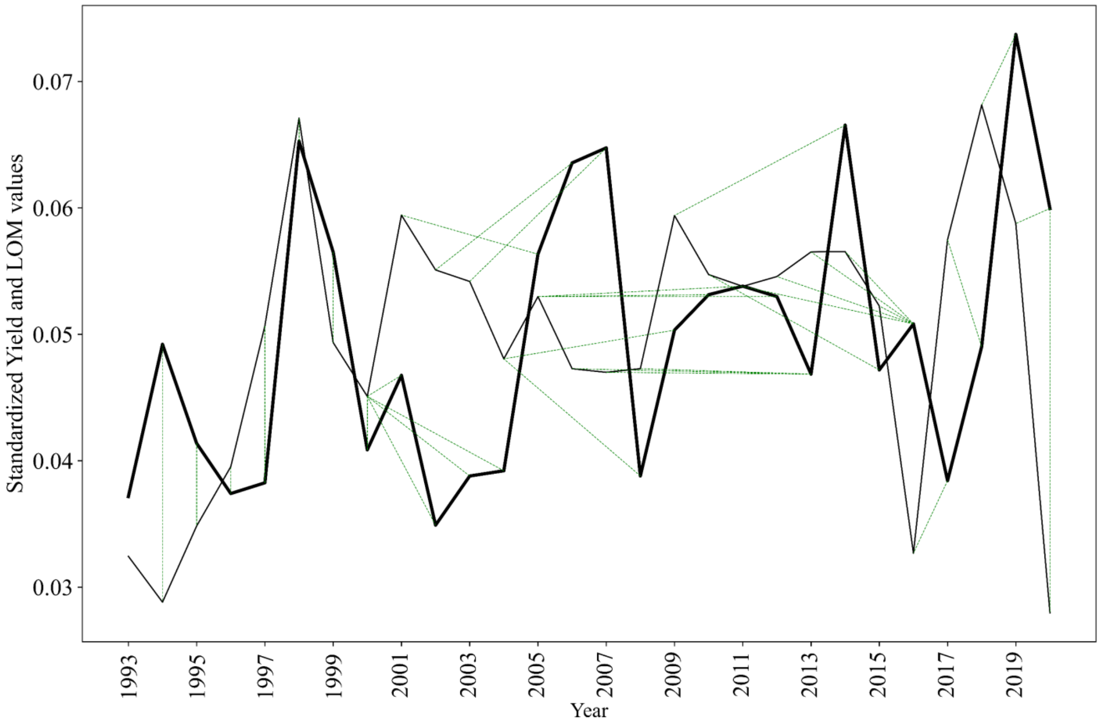

Fig. 3. DTW distance matching involves repeating or compressing points to minimize the distance between them. The thick line represents the standardized yield, the thin line indicates the LOM, and the green broken lines show the optimal path finder.

Рис. 3. Сопоставление дистанции DTW путем повторения или сжатия точек таким образом, чтобы минимизировать расстояние между ними; толстая линия представляет стандартизированный урожай, тонкая линия — LOM, а зелёные пунктирные линии обозначают путь оптимального поиска.

The optimal cumulative cost path navigated the cost matrix by addressing the length differences. Finally, the path followed the matrix's diagonal from (2017, 2016) to (2021, 2020), representing the temporal invariance between the datasets (Fig. 4).

Evaluation of the DTW distance similarity performance:

The DTW distance performance evaluation metrics were as follows: standard deviation (7.56×10^{-3}), mean (1.08×10^{-2}), minimum (1.42×10^{-5}), and maximum (3.220×10^{-2}). The MAE and RMSE were calculated as 6.33×10^{-3} and 7.56×10^{-3}, respectively. Based on these evaluation metrics, further interpretation is provided in the discussion section.

DISCUSSION

Overall, 44.4% of the elements in the two sequences showed perfect temporal matching, indicating that the timing of the yield and LOM was aligned (see Fig. 4) and, that the yield was responding to fluctuations in the LOM for 44.4% of the years. In the remaining years, other factors, such as rainfall, had a greater influence on the yield. However, there was some similarity in the other sections of the pair of sequences, possibly suppressed by additional factors. The similarity score was 34, indicating 34 pairs of aligned elements between the two sequences, which reflects a comparatively higher degree of similarity.

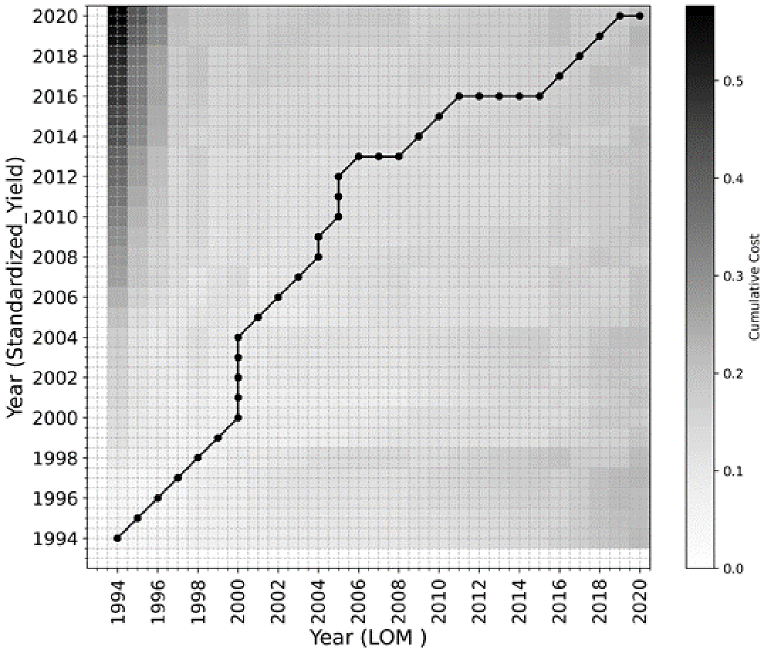

Fig. 4. Optimal similarity path between the LOM and crop yield from 1993 to 2020.
Рис. 4. Оптимальный путь схожести между LOM и урожайностью за годы 1993-2020.

The level of similarity was assessed using average similarity, consistency, alignment quality, and error metrics. The mean DTW distances were relatively low, suggesting a fairly similar time series sequences, on average. The standard deviation of the DTW distances is relatively low, indicating consistent similarity across the dataset. The minimum DTW distance is small, indicating good alignment between sequences, although some instances show larger DTW distances, suggesting occasional poor alignment. The small MAE and RMSE values indicate close observed DTW distances.

CONCLUSION:

The OLS regression and DTW analysis show a steady increase in LOM and crop yields in Eritrea over the past 28 years with no significant trend differences, despite low growth rates. Furthermore, the DTW analysis reveals that 44.4% of the yield variations correlate with fluctuations in the LOM. This implies that mechanizing agricultural operations in Eritrea significant impacts crop yield, highlighting the need for enhancing LOM in the country. The mean distances, standard deviation, minimum value, and error metrics show similar patterns in both datasets over the years. However, the analysis showed minor disparities in cereal yields with respect to LOM. While the LOM significantly enhances agricultural productivity, as seen in the upward trend and optimal alignment of the DTW method, variations in alignment in certain years suggest that other factors, such as climatic conditions, also significantly impact yield. To augment LOM's role in crop yield, recommendations include aligning agricultural mechanization with sustainable practices, developing adaptable climate policies, investing in new technologies, and reinforcing environmentally friendly policies for mechanization for sustained development of Eritrea's agricultural sector.

ADDITIONAL INFORMATION

Author contributions: T.A. Medhn: conceptualization, study design, data collection, methodology, formal analysis, writing — original draft; A.G. Levshin: technical advice and guidance throughout the research process; S.G. Teklay: writing — review and editing, enhancing clarity. Thereby, all authors made a substantial contribution to the conception of the work, acquisition, analysis, interpretation of data for the work, drafting and revising the work, final approval of the version to be published and agree to be accountable for all aspects of the work.

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ДОПОЛНИТЕЛЬНАЯ ИНФОРМАЦИЯ

Вклад авторов. Т.А. Медхн — обзор литературы, концептуализация, разработка исследования, сбор данных, методология, анализ и написание рукописи; А.Г. Левшин — технические советы и руководство в течение всего процесса исследования; С.Г. Теклай — рецензирование и редактирование рукописи для повышения ясности. Все авторы одобрили рукопись (версию для публикации), а также согласились нести ответственность за все аспекты работы, гарантируя надлежащее рассмотрение и решение вопросов, связанных с точностью и добросовестностью любой её части.

Этическая экспертиза. Неприменимо.

Источники финансирования. Отсутствуют.

Раскрытие интересов. Авторы заявляют об отсутствии отношений, деятельности и интересов за последние три года, связанных с третьими лицами (коммерческими и некоммерческими), интересы которых могут быть затронуты содержанием статьи.

Оригинальность. При создании настоящей работы авторы не использовали ранее опубликованные сведения (текст, иллюстрации, данные).

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Рассмотрение и рецензирование. Настоящая работа подана в журнал в инициативном порядке и рассмотрена по обычной процедуре. В рецензировании участвовали один внешний рецензент, член редакционной коллегии и научный редактор издания.

REFERENCES | СПИСОК ЛИТЕРАТУРЫ

1. Srivastava A, Goering C, Rohrbach R, Buckmaster D. Engineering principles of agricultural machines. second. Peg McCann, editor. American Society of Agricultural and Biological Engineers; 2006.
2. Andrew W. Handbook of FARM, DAIRY AND FOOD MACHINERY ENGINEERING SECOND EDITION. second. Kutz M, editor. New York: Elsevier; 2013.
3. Medhn TA, Teklay SG, Mengstu MT. Analysis of the Level of Agricultural Mechanization in Eritrea Based on USDA Data Sources. European Journal of Agriculture and Food Sciences. 2023 Nov 14;5(6):39–46. doi: 10.24018/ejfood.2023.5.6.664
4. Абдуллатиф ААД, Майстренко НА, Балабанов ВИ. Результаты оптимизации уборочно-транспортного комплекса по уборке хлопка в условиях Сирийской Арабской Республики. Агроинженерия. 2018;(1 (83)):48–51. doi 10.26897/1728-7936-2018-1-48-51.
5. Майстренко НА, Уваров ВП, Левшин АГ, и др. Унификация расчетов производительности транспортных и транспортно-технологических средств. Инженерные технологии и системы. 2020;30(4):637–58. doi 10.15507/2658-4123.030.202004.637-658.
6. Сысоев АМ, Ерохин МН, Измайлов АЮ, и др. Предложения о внесении изменений в федеральный регистр технологий производства продукции растениеводства (систему

технологий) с учетом функциональных возможностей семейства новых грузовых автомобилей сельскохозяйственного назначения. 2011;
7. Bello SR. Agricultural Machinery & Mechanization: Basic Concepts. DPS Dominion publishing services Nigeria; 2012. 1–344 p.
8. Hanayem A, Almohamed S, Alassaf A, Majdalawi M. Socioeconomic Analysis of Soil-Less Farming System -An Comparative Evidence from Jordan, The Middle East. Int J Food Agric Econ. 2022 Jul 1;10: 205–23.
9. Eritrea Overview: Development news, research, data | World Bank [Internet]. [cited 2023 Feb 9]. Available from: https://www.worldbank.org/en/country/eritrea/overview
10. Amongo RMC, Onal MKS, Larona MVL, et al. Level of Agricultural Mechanization in Oriental Mindoro, Laguna and Quezon, Philippines Using the Modified Agricultural Mechanization Index for Lowland Rice. Philippine Journal of Agricultural and Biosystems Engineering. 2018; XIV:55–71.
11. Kiru OK. The agricultural mechanization in Africa: micro-level analysis of state, drivers and effects. In: 6th African Conference of Agricultural Economists. Abuja, Nigeria Copyright: Research in agricultural & applied economics; 2019. p. 1–30.
12. Li W, Wei X, Zhu R, Guo K. Study on factors affecting the agricultural mechanization level in China based on structural equation modeling. Sustainability (Switzerland). 2019 Jan 1;11(1).
13. Sharma V, Irmak A, Kabenge I, Irmak S. Application of GIS and geographically weighted regression to evaluate the spatial non-stationarity relationships between precipitation vs. Irrigated and rainfed maize and soybean yields. Trans ASABE. 2011;54(3):953–72.
14. Larrabee B, Scott HM, Bello NM. Ordinary Least Squares Regression of Ordered Categorical Data: Inferential Implications for Practice. 2014. doi: 10.1007/s13253-014-0176-z
15. John K. M. Kuwornu. Irrigation access and per capita consumption expenditure in farm households: Evidence from Ghana. J Dev Agric Econ. 2012 Feb 12;4(3). doi: 10.5897/JDAE11.105
16. Ma W, Renwick A, Grafton Q. Farm machinery use, off-farm employment and farm performance in China. Australian Journal of Agricultural and Resource Economics. 2018 Apr 1;62(2):279–98. doi: 10.1111/1467-8489.12249
17. Tsinaslanidis PE. Subsequence dynamic time warping for charting: Bullish and bearish class predictions for NYSE stocks. Expert Syst Appl. 2018 Mar 15;94: 193–204. doi: 10.1016/j.eswa.2017.10.055
18. Vayer T, Tavenard R, Chapel L, et al. Time Series Alignment with Global Invariances. 2020 Feb 10;
19. Sakoe H. Dynamic Programming Algorithm Optimization for Spoken Word Recognition. IEEE Trans Acoust. 1978;(1):43.
20. Cohen S, Luise G, Terenin A, et al. Aligning Time Series on Incomparable Spaces. 2021;
21. Halperin T, Ephrat A, Peleg S. Dynamic Temporal Alignment of Speech to Lips. 2018 Aug 19;
22. Shokoohi Y. M, Hu B, Jin H, et al. Generalizing DTW to the multi-dimensional case requires an adaptive approach. Data Min Knowl Discov. 2017 Jan 1;31(1):1–31. doi: 10.1007/S10618-016-0455-0/FIGURES/20
23. Kovâcs-Vajna ZM. A fingerprint verification system based on triangular matching and dynamic time warping. IEEE Trans Pattern Anal Mach Intell. 2000 Nov;22(11):1266. doi: 10.1109/34.888711
24. Ruiz AP, Flynn M, Large J, et al. The great multivariate time series classification bake off: a review and experimental evaluation of recent algorithmic advances. Data Min Knowl Discov. 2021 Mar 1;35(2):401–49. doi.org/10.1007/s10618-020-00727-3
25. Cassisi C, Montalto P, Aliotta M, et al. Similarity Measures and Dimensionality Reduction Techniques for Time Series Data Mining. In: Advances in Data Mining Knowledge Discovery and Applications. InTech; 2012.
26. Maus V, Câmara G, Cartaxo R, et al. A Time-Weighted Dynamic Time Warping method for land use and land cover mapping. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 2016;9(8):3729-3739. doi: 10.1109/JSTARS.2016.2517118
27. Belgiu M, Zhou Y, Marshall M, Stein A. Dynamic time warping for crops mapping. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives. 2020 Aug 6;43(B3):947–51. doi: 10.5194/ISPRS-ARCHIVES-XLIII-B3-2020-947-2020
28. Mohamedi D. M. Assessing the transferability of random forest and time-weighted dynamic time warping for agriculture mapping. 2019.
29. Rafif R, Kusuma SS, Saringatin S, et al. Crop intensity mapping using dynamic time warping and machine learning from multi-temporal planetscope data. Land (Basel). 2021 Dec 1;10(12).
30. USDA ERS - International Agricultural Productivity [Internet]. 2023 [cited 2023 Mar 6]. Available from: https://www.ers.usda.gov/data-products/international-agricultural-productivity

31. Sebastian R. About Feature Scaling and Normalization [Internet]. 2014 [cited 2024 Sep 26]. Available from: https://sebastianraschka.com/Articles/2014_about_feature_scaling.html
32. Keane M, Neal T. Climate change and U.S. agriculture: Accounting for multidimensional slope heterogeneity in panel data. Quant Econom [Internet]. 2020 Nov 1 [cited 2024 Jun 25];11(4):1391–429. Available from: https://onlinelibrary.wiley.com/doi/full/10.3982/QE1319
33. Miao X, Zhao D, Lin B, et al. A Differential Protection Scheme Based on Improved DTW Algorithm for Distribution Networks with Highly-Penetrated Distributed Generation. IEEE Access. 2023; 11:40399–411. doi: 10.1109/ACCESS.2023.3269298

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