

Article

Assessing Trends and Interactions of Essential Climate Variables in the Historic Urban Landscape of Sfax (Tunisia) from 1985 to 2021 Using the Digital Earth Africa Data Cube

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Highlights

What are the main findings?

- The performance of the six urban spectral indices varies according to their spectral band combinations, with ENDISI and ASI showing higher sensitivity to annual urbanisation dynamics, while ENDISI, NBI, and BUI better capture spatial heterogeneity within the study area.
- Overall, the tested urban spectral indices demonstrate comparable accuracy in delineating built-up areas when validated against the Global Human Settlement Layer.
- Urban spectral indices based on SWIR and NIR bands (NDBI, BUI, NBI) exhibit stronger statistical associations with temperature-related variables, with temporal variations more strongly associated with air temperature at 2 m than with land surface temperature.

What are the implications of the main findings?

- Integrating vegetation indices and land-use/land cover information enhances interpretation of USI trends, supporting urban planning and monitoring of urban heat islands and microclimatic effects.
- The methodology using DEA data cube and automated Python workflows provides an effective framework for the long-term monitoring of Essential Climate Variables trends, offering insights for climate change adaptation, urban expansion management, and preservation of Historic Urban Landscapes.

Abstract

Cloud-based Earth observation platforms, such as data cubes, enable reproducible analyses of long-term satellite time series for climate and urban studies. In parallel, Essential Climate Variables (ECVs) provide a standardised framework for monitoring climate dynamics, with urban land cover and temperature being particularly relevant in historic urban contexts. This study analyses long-term trends and statistical associations between satellite-based ECVs and urbanisation indicators within the Historic Urban Landscape (HUL) of Sfax (Tunisia) from 1985 to 2021. Using the Digital Earth Africa (DEA) data cube, we derived six urban spectral indices (USIs), land surface temperature, air temperature at 2 m, wind characteristics, and precipitation from Landsat and ERA5 reanalysis data. An automated and reproducible Python-based workflow was implemented to assess USI behaviour, evaluate their performance against the Global Human Settlement Layer (GHSL),



Academic Editor: Donglian Sun

Received: 4 December 2025

Revised: 10 January 2026

Accepted: 13 January 2026

Published: 21 January 2026

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and explore spatio-temporal co-variations between urbanisation and climate variables. Results reveal a consistent increase in air and surface temperatures alongside a decreasing precipitation trend over the study period. The USIs demonstrate comparable accuracy levels ($\approx 88\text{--}90\%$) in delineating urban areas, with indices based on SWIR and NIR bands (NDBI, BUI, NBI) showing the strongest statistical associations with temperature variables. Correlation and multivariate regression analyses indicate that temporal variations in USIs are more strongly associated with air temperature than with land surface temperature; however, these relationships reflect statistical co-variation rather than causality. By integrating satellite-based ECVs within a data cube framework, this study provides an operational methodology for long-term monitoring of urban-climate interactions in historic Mediterranean cities, supporting both climate adaptation strategies and the objectives of the UNESCO HUL approach.

Keywords: temperature; spectral indices; satellite-based ECVs; data cube; python; HUL; digital earth Africa

1. Introduction

The United Nations recognises climate change and urban expansion as the two most critical global challenges. These interconnected phenomena significantly contribute to extreme events and natural hazards [1–4] and impact cultural assets [5,6]. In 2011, UNESCO published the recommendations on the Historic Urban Landscape (HUL) as a conservation approach, considering that historic urban areas represent some of the most abundant and diverse expressions of cultural heritage and recognising urbanisation and climate change as challenges (2011: II.17; II.19), as well as encouraging research to target them (V.26). As a result, the HUL approach was integrated into urbanisation and climate change research [7–10].

In 2003, the Global Climate Observing System (GCOS) defined 55 variables from the different earth system components to help characterise Earth's climate and its trends and support the work of the United Nations Framework Convention on Climate Change (UNFCCC), which are known as the Essential Climate Variables (ECVs). The land cover properties and temperature at different levels of the atmosphere are commonly used ECVs for understanding the dynamics of urban expansion and climate change [11,12]. The main source of these variables is remote sensing [13,14]. Satellite-based ECVs are widely used in research since they provide long-term records with higher spatial coverage [15].

Thermal and meteorological satellites deliver temperature and other climatic parameters that are instrumental in studying various climate change-related phenomena [16], such as wildfires [17] and floods [18], and those contributing to it, such as air pollution [19] and urbanisation [20]. The global reanalysis product ERA5 provides multiple open climate data in a gridded format from the European Centre for Medium-Range Weather Forecasts (ECMWF), provides accurate ECVs, and is commonly used by researchers [21,22]. Additionally, urban spectral indices (USI) derived from satellite surface reflectance data, such as Landsat's and Sentinel's, play a critical role in extracting valuable information for quantification of urban land cover changes [23], which is a crucial aspect of ECVs. They also provide insights into the interactions between urbanisation and climate change [24]. However, the extraction of urban land cover information from USI remains challenging, considering that urban areas have complex spectral properties. Therefore, a wide range of comparative studies for assessing the performance of different USIs and the threshold methods are present in the literature [25–27].

Detecting trends of urban landscapes and climate variables requires time-series analysis with optimal temporal resolution. This presents challenges in data acquisition, processing, and analysis [28,29]. Recent advancements in cloud computing and parallel processing have provided solutions to address these challenges. Cloud computing platforms, such as Google Earth Engine [30], have been widely used in research to study urbanisation [31,32] and climate change [33,34]. In recent years, earth observation data cube technologies have emerged as cloud-based computational platforms, offering the advantage of supporting decision-ready products and simplifying access to big Earth Observation data and their processing [35,36]. On the national scale, initiatives like the Australian Data Cube [37], the Swiss Data Cube [38,39], and the Colombian Data Cube [40] have emerged to enable faster and more accessible analyses of satellite data for monitoring land use, climate, and environmental changes.

Africa's version is Digital Earth Africa (DEA), which covers the entire continent and provides free and open access to a sandbox environment with Python 3.0 packages in Jupyter Lab and a data cube of ARD from multiple satellites, in addition to Real World Examples (RWE) as notebooks ready to execute targeting international-scale challenges such as urbanisation and climate change [41]. Despite the use of DEA in multiple African studies targeting land cover information [42], vegetation properties [43–45], water bodies [46], and elevation [47], it was barely applied in climate change and urbanisation research, though it provides two RWEs for that purpose.

In this context, many African cities are affected by these global phenomena [48], particularly northern African cities on the Mediterranean shore, given that the Mediterranean is experiencing increasing heat waves [49] and is considered as a “climate change hotspot” [50]. Moreover, these cities have a historic and heritage value [51,52], which makes them more vulnerable. Despite the growing body of literature on urban spectral indices and urban-climate interactions, several limitations persist. Many studies focus on short temporal windows, single indices, or isolated climatic variables, limiting the understanding of long-term urban-climate co-evolution, particularly in Historic Urban Landscapes. Moreover, the performance of different USIs and their sensitivity to both spatial heterogeneity and temporal urban growth remain insufficiently assessed in Mediterranean and North African cities, where arid and semi-arid conditions increase spectral complexity. Finally, few studies implement fully reproducible, cloud-based workflows that integrate multi-decadal satellite and reanalysis datasets within a unified ECV framework.

Accordingly, this study addresses the following research questions: (1) How do different urban spectral indices respond to long-term urbanisation dynamics within the Historic Urban Landscape of Sfax? (2) How do trends in satellite-based ECVs (urban land cover, temperature, wind, and precipitation) co-vary over the 1985–2021 period? (3) To what extent are temporal variations in USIs statistically associated with air and land surface temperature, and what are the limitations of these associations?

To answer these questions, we employ the Digital Earth Africa data cube to develop an automated and reproducible workflow for long-term ECV analysis, with a specific focus on Sfax city centre as an African Mediterranean case study.

2. Materials and Methods

2.1. Area of Interest

Sfax is a Tunisian governorate and a North African city (Figure 1). The urbanisation has led to increasing LST and an urban heat island (UHI) that reached 5 degrees [53]. Characterised by non-homogenous time series, increasing trends of temperature were notably observed starting from 1984 [54]. The city centre is the historic urban structure with the medina, which was registered on the indicative list of the UNESCO in 2012, and the European

city constructed in the French colonial era. This ensemble is considered for a world heritage registration proposal following the recommendations on the HUL of UNESCO since 2013. Urban and architectural studies highlighted the historic value of urban features [55] and spatial-temporal dynamics in Sfax city centre [56]. More recent environmental studies provide insights about management issues [57], urban discharges [58], air quality [59], and thermal comfort [60]. Thus, updated information on urban dynamics and their relation with climate change is missing in the literature, as well as an USI-based approach.

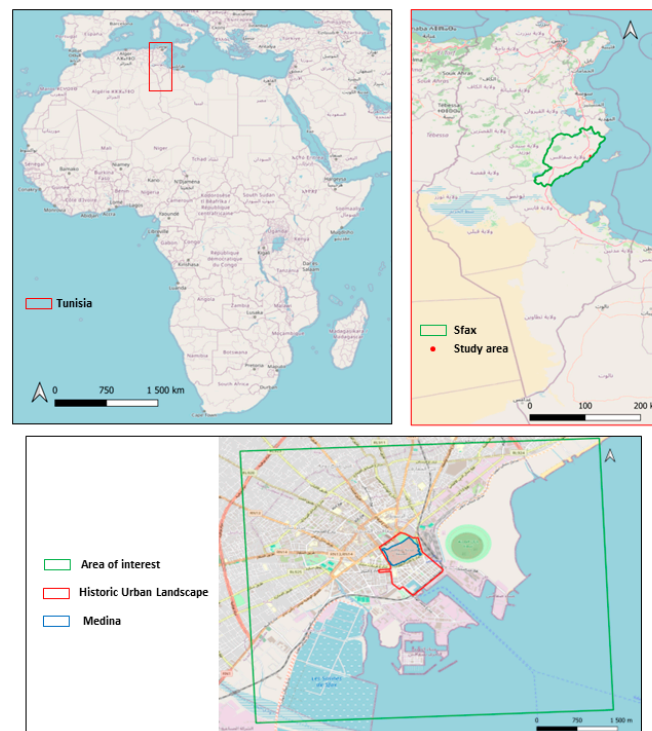


Figure 1. Location of the study area in Africa and Tunisia with the Historic Urban Landscape boundaries.

2.2. Satellite-Based ECV's Acquisition and Preparation

In this study, we used ECVs from diverse earth system components. Surface atmosphere ECVs included precipitation (PP), wind speed (Ws) and direction (Wd), and air temperature at 2 m (Ta). From the land level, we incorporated land cover information, derived from USI, and land surface temperature (LST). The remote sensing datasets used in this study were loaded from the DEA data cube and processed within its sandbox environment using a temporal coverage spanning 1985 to 2021. We loaded the Landsat Collection to derive land variables, while ERA5 Reanalysis product data provided atmospheric ECVs (Table 1).

Table 1. Satellite-based ECV's used in this study and their characteristics.

ECV	Dataset	Provider	Source	Temporal Resolution	Spatial Resolution	Unit	Data Loaded	Data Processed
USI	Landsat Collection	USGS	DEA	16 days	30 m	-	1898	37
LST						°C	1898	
Ta	ERA5	ECMWF	AWS S3	Hourly	13 km	°C	2322	
U						m/s	2322	
V						m/s	2322	
PP				Daily		Mm	2322	

For Landsat datasets, we used the function that loads ARD (load_ard), which provides the collection 2, level 2 at 30 m spatial resolution calibrated in the range of [0–1] and converts thermal data to Kelvin. We generated annual geomedian composites for surface reflectance with the function geomedian_with_mads to calculate six urban spectral indices

with `calculate_spectral_indices`, which is a DEA function that has predefined formulas of different common spectral indices (Table 2) that use the corresponding band combination for each Landsat sensor (Table 3). Water was masked using the Water Observations from Space (WOFs) DEA product that provides water masks covering Africa. In fact, masking water in USI-based studies is recommended by the literature to avoid bias caused by water surface reflectance [61,62]. LST datasets were grouped by year and converted from Kelvin to degrees by subtracting 273.15.

Table 2. Urban spectral indices used in this study from DEA's function.

Index	Author	Predefined Formula	Description
NDBI	[63]	$\frac{swir1-NIR}{swir1+PIR}$	Normalised Difference Built-up Index
BUI	[64]	$\frac{swir1-NIR}{swir1+NIR} - \frac{NIR-Red}{NIR+Red}$	Built-up index
ENDISI ¹	[65]	$\frac{Blue-\alpha \times (swir_{diff} + mndwi^2)}{Blue+\alpha \times (swir_{diff} + mndwi^2)}$	Enhanced Normalised Difference Impervious Surface Index
BAEI	[66]	$\frac{Red+0.3}{Green+swir1}$	Built-up Area Extraction Index
NBI	[67]	$\frac{Red-swir1}{NIR}$	New Built-up index

$$^1 \alpha = \frac{2 \times \text{mean}(\text{blue})}{\text{mean}(swir_{diff}) + \text{mean}(mndwi^2)} \text{ and } mndwi = \frac{green-swir1}{green+swir1}.$$

Table 3. Landsat 5, 7, and 8 spectral bands properties used in USIs calculations.

Spectral Channel	Corresponding Band and Wavelength	
	Landsat 5 and 7	Landsat 8
Red	Band 3: 0.63–0.69 μm	Band 04: 0.64–0.67 μm
Green	Band 02: 0.52–0.60 μm	Band 03: 0.53–0.59 μm
Blue	Band 01: 0.45–0.52 μm	Band 02: 0.450–0.51 μm
NIR	Band 04: 0.76–0.90 μm	Band 05: 0.85–0.88 μm
SWIR1	Band 05: 1.57–1.65 μm	Band 06: 1.55–1.75 μm

We loaded PP, Ta, and eastward (U) and northward (V) wind components from the ERA5 Reanalysis product available in the Amazon Web Services (AWS) S3 bucket. The `load_era5` function in DEA enabled access to these datasets. Ws and Wd were calculated from U and V wind components using the Formulas (1) and (2), respectively. All loaded datasets were grouped by year; air temperature was converted from Kelvin to degrees.

$$Ws = \sqrt{(U^2) + V^2}, \quad (1)$$

$$Wd = \arctan2(-U, -V) \times \pi 180 + 180, \quad (2)$$

The data and products used in this study have a coordinate reference system (CRS) EPSG: 6933-WGS84 NSIDC EASE-Grid 2.0 Global, which is the CRS adopted by DEA.

2.3. Computational Framework

We created a Jupyter Lab notebook in the DEA sandbox for loading and processing data in the cloud using Python libraries and predefined DEA functions. Since we are loading big earth observation data, we launched a local Dask cluster for parallel processing to gain time and reduce CPU consumption. The proposed methodology is presented in Figure 2.

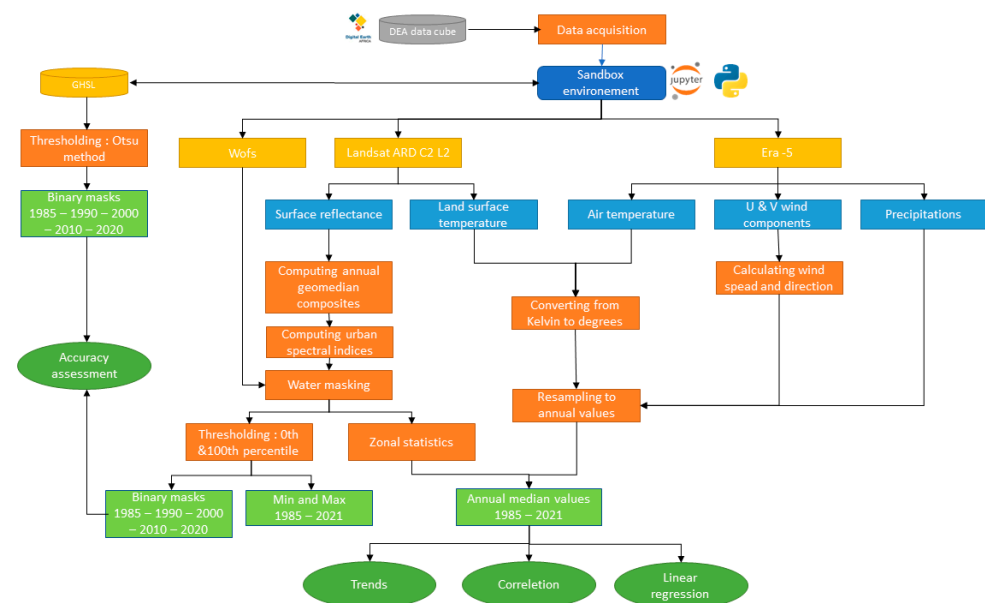


Figure 2. Flowchart of the followed methodology.

2.3.1. USI Threshold

Six urban spectral indices were calculated in DEA from annual geomedian composites of Landsat’s surface reflectance with masked water surfaces. To define urban areas, minimum and maximum thresholds were defined based on percentiles derived from histograms [68]. The minimum threshold value was set to the 1st percentile to reduce the influence of extreme negative values, while the maximum threshold value corresponded to the 100th percentile to ensure that the complete spectral response range of the indices was captured. This choice was motivated by the need for a fully automated and temporally consistent thresholding method applicable to long-term time series and multiple indices, avoiding manual tuning for individual years. Percentile-based thresholds have been widely used in urban remote sensing to accommodate inter-annual spectral variability and sensor differences. However, the use of the 100th percentile may include extreme values potentially associated with sensor noise or mixed pixels. To mitigate this limitation, water bodies were masked prior to index computation. These percentiles were automatically extracted [69] with a Python function that fetches all the time series in the dataset. Zonal statistics were also performed automatically to derive annual median values of the spectral indices. The metrics were generated as a Pandas data frame.

2.3.2. USI Accuracy Assessment

The related urban area binary maps from automatic threshold were compared with the corresponding Global Human Settlement Layer (GHSL) product from Copernicus, which we downloaded (Link: <https://human-settlement.emergency.copernicus.eu/download.php>, accessed on 12 January 2026) and imported to the DEA sandbox. We selected five time steps, 1985, 1990, 2000, 2010, and 2020, for accuracy assessment and comparison (Table 4). The workflow was Inspired by the existing RWE of “urban index comparison”, which includes the Otsu threshold method for GHSL and a predefined function to calculate global precision and F1 score with Formulas (3)–(6) for one specific year. We automated these two Python scripts to run for 5 years and generate binary GHSL maps and a table with accuracy metrics.

$$\text{Global precision} = (\text{True positive} + \text{True negative}) / (\text{True positive} + \text{True negative} + \text{False positive} + \text{False negative}), \quad (3)$$

$$\text{F1 score} = (2 \times (\text{PPV} + \text{TPR})) / (\text{PPV} + \text{TPR}), \quad (4)$$

$$PPV = \text{True positive} / (\text{True positive} + \text{False positive}), \quad (5)$$

$$TPR = \text{True positive} / (\text{True positive} + \text{False negative}), \quad (6)$$

where PPV is positive predictive value and TPR is the true positive rate.

Table 4. GHSL products used for comparison with the calculated USIs.

Year	GHSL Product Name
2020	GHS_BUILT_S_E2020_GLOBE_R2023A_54009_100_V1_0_R5_C19
2010	GHS_BUILT_S_E2010_GLOBE_R2023A_54009_100_V1_0_R5_C19
2000	GHS_BUILT_S_E2000_GLOBE_R2023A_54009_100_V1_0_R5_C19
1990	GHS_BUILT_S_E1990_GLOBE_R2023A_54009_100_V1_0_R5_C19
1985	GHS_BUILT_S_E1985_GLOBE_R2023A_54009_100_V1_0_R5_C19

2.3.3. ECVs Trends and Interrelation

For the other ECVs related to temperature, wind, and precipitation, we calculated the annual median from 1985 to 2021 and generated a data frame. In this study, we chose the median to yearly group the ECVs rather than the mean to avoid the influence of extreme values, which are common in environmental datasets [70], and ensure robust temporal trends. To calculate interrelations between ECVs, we concatenated the data frames of annual median values. We predicted trends with linear regression and assessed the distribution with the Shapiro–Wilk test using the `scipy_stats` library from Python. We then performed Spearman’s and Kendall’s correlation coefficient calculations using the `pandas`’ correlation function. We also performed multivariate linear regression with the `sklearn.linear_model` library, choosing T_a and LST as dependent variables and SUIs and PP as independent variables to better understand the interactions between urbanisation and the two-level temperature trends.

3. Results

3.1. Urbanisation in the HUL of Sfax City

3.1.1. The HUL Spectral Behaviour

The histogram shapes and the distribution of pixel values are a fundamental tool in the assessment of the spectral indices performance and are critical in the threshold process. The resulting overall intensity distributions in Figure 3 reveal that all the plots show unimodal distribution. ENDISI and ASI show right-skewed distributions in 1985, reflecting the dominance of non-urban surfaces at that time. Over the period 1985–2021, the histograms progressively become more symmetric, indicating a substantial increase in high-index values associated with urbanisation. In parallel, the NBI distribution is relatively symmetric. However, BAEI, NDBI, and BUI show a consistent skewness across all years.

A total of 30 index-based maps were constructed as a result of the computation process of USIs using the DEA data cube and functions (Figure 4). At first glance, the contrast between land covers is more pronounced in ENDISI, NBI, and BUI, and more confusion between land covers is noticed with ASI and BAEI. ENDISI and ASI highlight the most difference between 1985 and 2021, whose histograms showed variations in skewness.

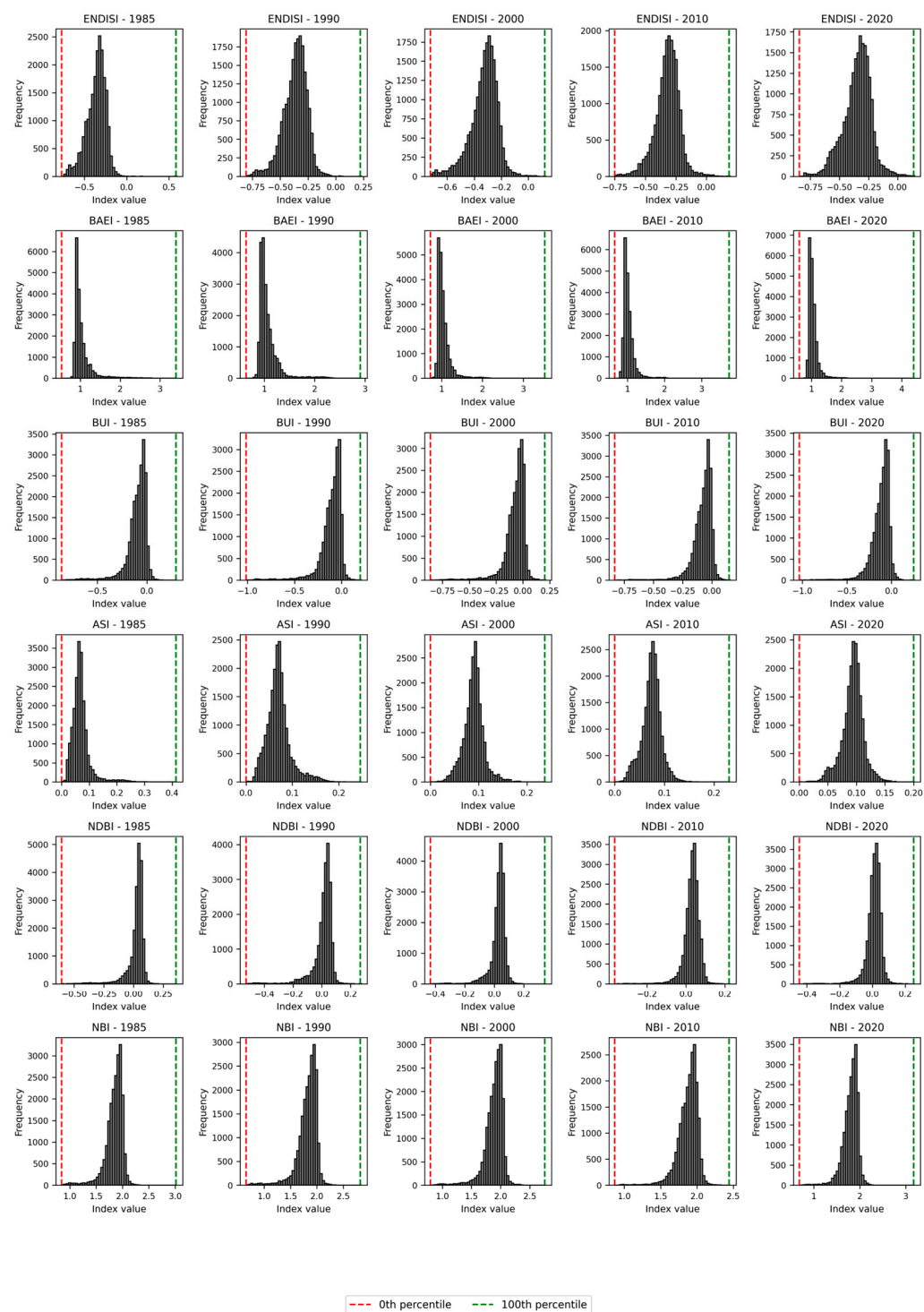


Figure 3. Histograms of USI pixel values in 1985, 1990, 2000, 2010, and 2020.

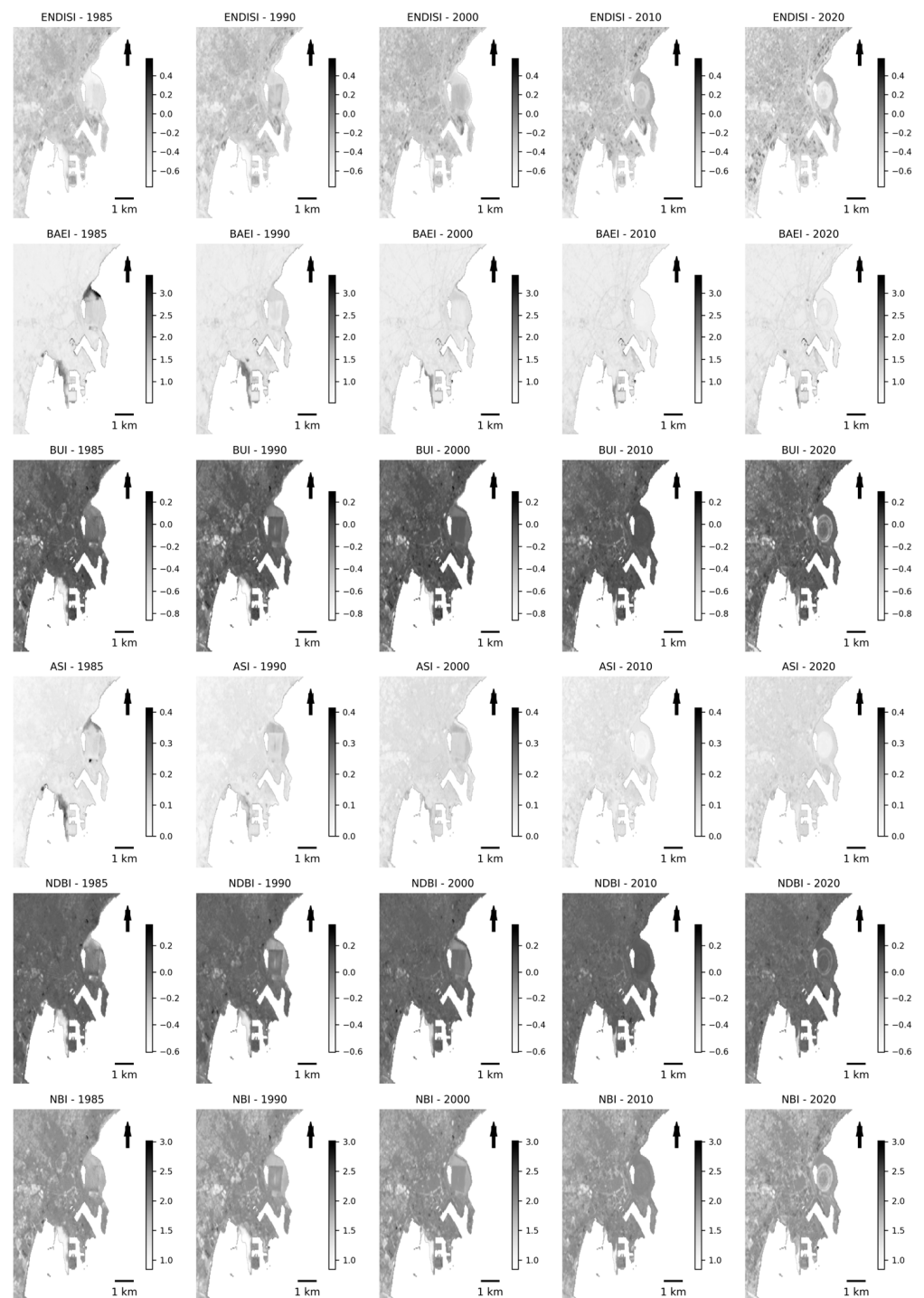


Figure 4. Index-based maps plotted with threshold values as min and max in 1985, 1991, 2001, 2011, and 2021.

3.1.2. USI Comparison with GHSL

USI was extracted for the study area from the Landsat collection annual geomedian composite. Consequent to the automatic threshold with percentiles, USI maps in 1985, 1990, 2000, 2010, and 2020 were compared to the corresponding GHSLs by calculating their global precision and F1 score. Table 5 contains a detailed summary of threshold performance metrics. The results show that the USIs have comparable accuracy levels ranging between 89% and 90%, indicating their effectiveness in capturing land cover information and the robustness of the automatic threshold using histogram-derived 1st and

100th percentiles. The accuracy of USI shows a consistent upward trend from 1985 to 2021, as assessed through comparison with the GHSL, which can be explained by improvements in satellite data quality, which is, in our case, the Landsat surface reflectance collection, as well as processing techniques of the GHSL product over time. The highest accuracy values observed in 2021 are with NBI, reaching 90.118%, while in 1985, ASI achieved the highest accuracy of 88.594%.

Table 5. Threshold, accuracy values, and F1 score representing the performance of USI binary masks from percentile threshold method in comparison with GHSL.

Index	Year	Threshold Interval	Global Precision	F1 Score
ENDISI	2021	[−0.768, 0.580]	90.11353	0.891791
	2011	[−0.745, 0.119]	89.95169	0.889743
	2001	[−0.744, 0.081]	89.64976	0.885785
	1991	[−0.772, 0.165]	88.92995	0.876765
	1985	[−0.779, 0.112]	88.58937	0.872386
BUI	2021	[0.530, 3.397]	90.11594	0.891815
	2011	[0.688, 2.935]	89.94203	0.889637
	2001	[0.745, 3.441]	89.63768	0.885649
	1991	[0.650, 4.701]	88.92512	0.876704
	1985	[0.654, 3.502]	88.58696	0.872363
ASI	2021	[−0.860, 0.293]	90.11594	0.891809
	2011	[−0.861, 0.185]	89.94928	0.889719
	2001	[−0.881, 0.236]	89.64976	0.885785
	1991	[−0.890, 0.131]	88.92995	0.876758
	1985	[−0.967, 0.168]	88.5942	0.872434
NBI	2021	[0.000, 0.414]	90.11836	0.891838
	2011	[0.000, 0.317]	89.94686	0.889696
	2001	[0.000, 0.301]	89.6401	0.885678
	1991	[0.000, 0.207]	88.93237	0.876788
	1985	[0.000, 0.211]	88.58696	0.872363
NDBI	2021	[−0.606, 0.356]	90.11353	0.891791
	2011	[−0.475, 0.257]	89.94686	0.889696
	2001	[−0.403, 0.370]	89.6401	0.885678
	1991	[−0.402, 0.197]	88.92995	0.876765
	1985	[−0.456, 0.228]	88.58696	0.872363
BAEI	2021	[0.845, 3.017]	90.11353	0.891785
	2011	[0.697, 2.690]	89.94928	0.889719
	2001	[0.816, 2.949]	89.64976	0.885785
	1991	[0.771, 2.354]	88.93237	0.876788
	1985	[0.797, 2.614]	88.58937	0.872386

3.2. ECVs Contribution to Climate Change

3.2.1. Trends of Temperature, Precipitation, and Wind

Temperature variables and PP show heterogeneous variations, with increasing trends observed for Ta and LST by 0.035 degrees per year and 0.127 degrees per year, respectively, and a slightly decreasing trend for PP by 0.002 mm per year (Figure 5). The dominant wind direction is southwest, representing more than 50% of occurrences with moderate to high-speed winds with a dominance of winds at the speed of 0.7–1.1 m/s (Figure 6).

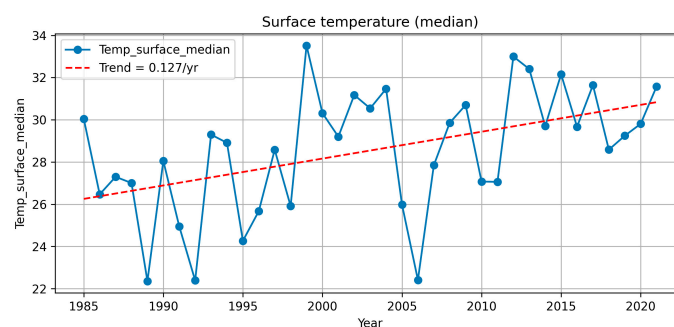


Figure 5. Cont.

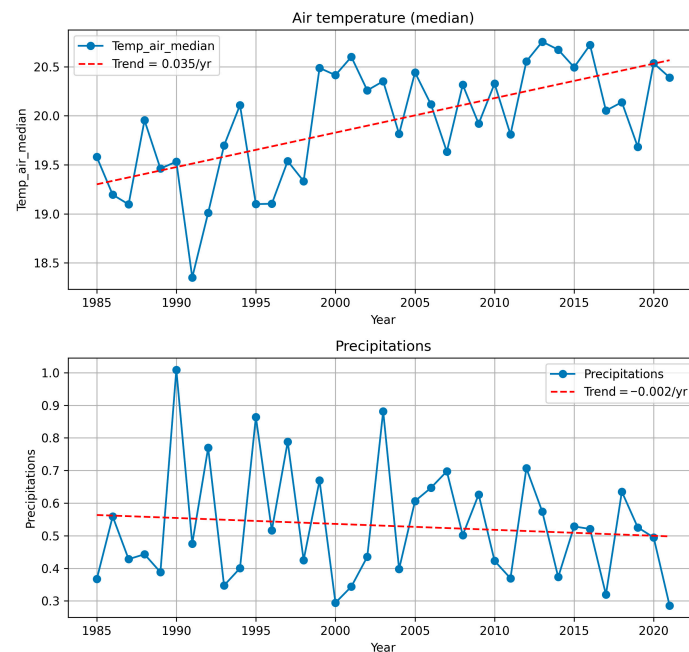


Figure 5. Annual variations and trends of median values of LST, Ta, and PP.

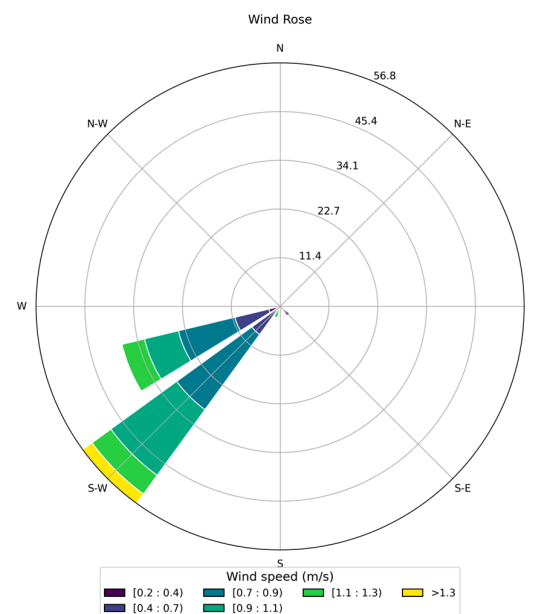


Figure 6. Wind rose of Sfax city centre.

3.2.2. Correlations Between the ECV's

The ShaNIRO normality test showed non-homogeneous distribution of ECVs; thus, we used the non-parametric Spearman and Kendall correlation coefficients (Figure 7). The matrices show that LST and Ta show positive correlations (0.65 in Spearman, 0.47 in Kendall). The USIs that show the strongest Spearman correlations with LST are NDBI, BUI, and NBI; the same indices have higher correlation coefficients with the Ta. For example, NDBI has a correlation coefficient with LST equal to 0.68 and to 0.70 with Ta. NDBI and BUI also show the strongest correlations between temperature values, with the Kendall method showing a higher correlation with the Ta. NBI also showed a notable positive correlation with Ta. Between USIs, NDBI, BUI, and NBI have the strongest positive correlation; this might be related to the fact they highlight the same spectral behaviour, as their formulas are based on the same channels: SWIR 1, NIR, and Red (Table 2). The PP has a non-significant

correlation with the other ECVs; this might be explained by the fact that there are other atmospheric variables that impact PP other than temperature and land cover.

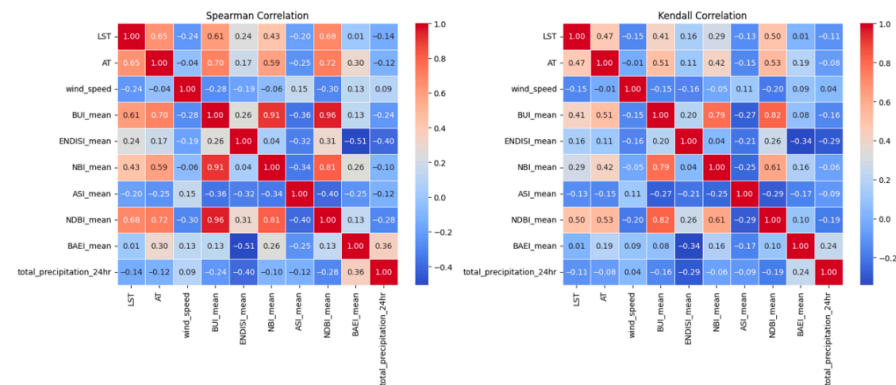


Figure 7. Kendall and Spearman correlation matrices.

3.2.3. Urbanisation and Temperature Trends

The linear regression analysis shows that the model performs better for predicting Ta, as the points are more tightly clustered around the perfect prediction line. Some deviations are visible for LST, where the spread of points away from the red line is more pronounced (Figure 8). The coefficient of determination (R^2) is 0.564 and the p -value is 0.000514 when using LST as a dependent variable, and $R^2 = 0.638$ and the p -value = 4.61×10^{-5} when using Ta as a dependent variable. The regression results indicate stronger statistical associations between USIs and Ta than with LST, but they do not demonstrate a direct causal influence of USIs on temperature. These findings should be interpreted as evidence of temporal co-variation rather than causal relationships and be considered exploratory and interpreted within the broader context of urban-climate complexity.

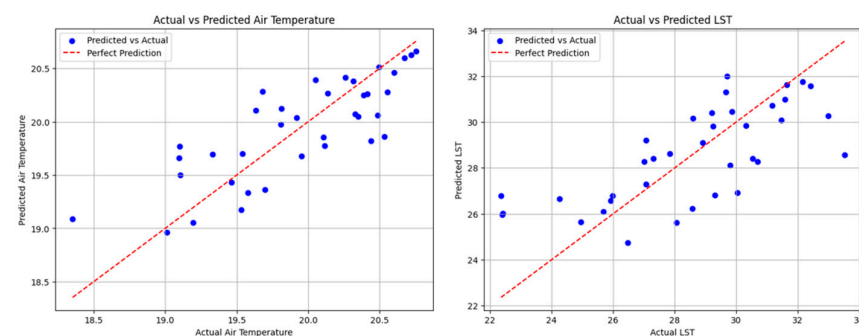


Figure 8. Scatter plots showing the relationship between estimated LST (right) and Ta (left) and the other ECV's.

4. Discussion

This paper suggests a methodology to study ECV's trends and their interrelation with the urbanisation process, with particular focus on the evaluation of the performance of six USIs (ENDISI, BUI, NDBI, NBI, ASI, BAEI) in Sfax city centre. It also offers insights on the application of the DEA data cube and develops new scripts and workflows based on its data and processing ecosystem applicable to similar regions.

The visual analysis of histogram distribution and USI-based maps reveals that USIs have different spectral responses to urban land cover and its spatial-temporal variations. The skewness interpretation showed that ENDISI and ASI are the most affected by annual variations, highlighting urbanisation, while ENDISI, NBI, and BUI are most affected by spatial variations. Previous studies have shown that ENDISI can substantially reduce confusion between impervious surfaces and bare soil or arid land [71]; other studies also

confirmed that BUI is good at extracting built-up areas [72], and BAEI is the worst at capturing different built-up surfaces' reflectance [25].

Accuracy assessment using the GHSL dataset indicates that the tested USIs achieve comparable performance levels in delineating built-up areas. While overall accuracy values are relatively high, these results should be interpreted with caution. The GHSL product has above 90% overall accuracy from the adopted validation process (Pesaresi et al., 2013) [73]. Melchiorri et al. (2019) [74] have tested the GHSL and identified it as an essential variable for Sustainable Development Goal 11: sustainable cities and communities. However, it is important to mention that the automatic thresholding method using the 1st and the 100th percentile is operationally efficient for large-scale and long-term analyses but does not necessarily represent an optimal urban extraction strategy for individual years or highly heterogeneous urban fabrics.

The trend prediction showed that ECVs related to temperature are increasing, which agrees with global trends, accompanied by a tendency to drought with decreasing precipitation, which is common in semi-arid Mediterranean regions. It is further proved by this study that the indices based on SWIR and NIR band combinations have a significant correlation with temperature variables (NDBI, BUI and NBI). Alexander, 2020, has proved that spectral indices using NIR and SWIR Landsat bands are strongly correlated with LST [75]. Furthermore, temporal variations in the USIs are more strongly associated with T_a than with LST, which reflects microclimatic conditions, as indicated by the multivariate linear regression results. While the classical state of the art has largely focused on relationships between USIs and LST, recent large-scale studies have highlighted the complexity and spatial instability of urban–climate relationships when air temperature is considered. For example, Li et al. (2020) [76] demonstrated that correlations between surface urban heat island (SUHI) intensity and T_a vary substantially across climatic regions and are strongly influenced by urban–rural vegetation differences. Such findings suggest that the stronger associations observed in our study between USIs and T_a reflect context-dependent microclimatic co-variations rather than direct causal effects. This reinforces the need for further research on the UHI and SUHI effects and their predictors to better understand the implications of USIs and T_a for urban climate analysis.

5. Conclusions

This study applied a satellite-based ECV framework to analyse long-term urbanisation and climate trends within the Historic Urban Landscape of Sfax using the Digital Earth Africa data cube. Results highlight consistent warming trends and decreasing precipitation, reflecting global phenomena of climate change and urbanisation, as well as heating and drought in the Mediterranean. The comparative assessment of six urban spectral indices demonstrates that their performance and sensitivity vary according to spectral band combinations, with SWIR–NIR-based indices showing stronger statistical associations with temperature variables.

Importantly, the observed relationships between urban spectral indices and temperature reflect temporal co-variation with T_a . The proposed cloud-based and reproducible workflow provides an operational tool for long-term urban-climate monitoring in historic cities, while acknowledging limitations related to thresholding methods and reference datasets. Future work should integrate vegetation indices, land-use information, and comparisons between different urban landscapes to further validate and generalise the findings.

Author Contributions: Conceptualization, P.P. and S.S.; methodology, P.P., S.S., and M.C.; software, S.S.; validation, M.C.; formal analysis, S.S. and M.C.; writing—original draft preparation, S.S.; writing—review and editing, M.C.; visualisation, S.S.; supervision, P.P., M.C., and F.A.K.; project

administration, M.C. and F.A.K.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study. Requests to access the datasets should be directed to marianne.cohen@sorbonne-universite.fr.

Acknowledgments: This work was conducted in Géotèca platform under the mobility grant programme of the Partnership Hubert-Curien Utique (PHC Utique) n° 48857SG.

Conflicts of Interest: The authors declare no conflicts of interest.

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