From skepticism to conviction: The emerging statistical methodologies in integrating satellite and reanalysis data with station data.

[1]Bashiru Imoro Ibn Saeed*, [1]Caleb Nurideen Nambyn, [1]Ebenezer Tawiah Arhin, [1]Amidu Abdul Hamid.

[1]Tamale Technical University, Laboratory for Interdisciplinary Statistical Analysis, (LISA), Tamale, Ghana.

*Email: sirbash156@gmail.com

Abstract

Africa has just one-eighth the minimum density of weather stations recommended by the World Meteorological Organization, which means there is a problematic lack of data about dozens of countries that are among the most vulnerable to climate change. Historically, meteorological and climate research predominantly relied on ground-based station data, but inherent limitations, such as sparse coverage and potential biases, have prompted a paradigm shift towards the integration of satellite and reanalysis data. This shift, from skepticism to conviction, reflects the growing recognition of the value and potential inherent in merging satellite and reanalysis data with traditional station data. This transformation, while promising, introduces challenges in data harmonization, validation, and the development of robust statistical methodologies. The growing body of research into the validation and evaluation of satellite products at various regions is increasingly building confidence in the use of satellite based products for various applications. This study highlighted emerging statistical methodologies in integrating satellite and reanalysis data with station data and also compared the daily temperature records from 2001 to 2015 from the CHIRTS satellite and station-based temperature network with temperature data records of at least 15 years' duration from three locations in Ghana. To evaluate CHIRTS performance, the station data were also contrasted with ERA5 temperatures. On the daily and monthly basis, the CHIRTS estimates showed good agreement with the station data than on the annual levels.

The CHIRTS dataset generally exhibited better correlations, lower errors, and more favorable Nash-Sutcliffe Efficiency values compared to ERA5, indicating its better performance in estimating and predicting meteorological parameters at these stations. As we move forward in this era of climate uncertainty, harnessing the full potential of integrated data sources is paramount. The evolving landscape of statistical methodologies plays a pivotal role in this endeavor, facilitating a more comprehensive understanding of our changing climate. By bridging the gap between skepticism and conviction, we are better equipped to address the pressing issues of climate change and its far-reaching impacts.

Keywords: Satellite data, Validation, CHIRTS, ERA5, Integration, Reanalysis, Skepticism

Introduction

In an era where climate change and its far-reaching impacts dominate global discussions, accurate and reliable climate data has never been more critical. Monitoring and understanding climate patterns, weather events, and long-term trends require a comprehensive approach that integrates various sources of data. Historically, meteorological and climate research have primarily relied on ground-based station data. However, the limitations of station data, such as sparse coverage and potential biases, have spurred a paradigm shift towards the integration of satellite and reanalysis data. This shift from skepticism to conviction reflects the growing recognition of the value and potential of merging satellite and reanalysis data with traditional station data. The integration of these diverse data sources not only enhances the spatial and temporal coverage but also improves data accuracy and reliability. Nevertheless, this transformation presents significant challenges in terms of data harmonization, validation, and statistical methodologies.

Traditional air temperature data has historically relied on ground station measurements, but in Africa, there exists a significant shortage of these stations, with the lowest density network globally (WMO, 2019). Access to high-quality, long-term temperature records is crucial for various applications affecting people's lives, livelihoods, and ecosystem services. Moreover, station networks are unevenly distributed, mainly catering to densely populated areas (Dinku, 2019), leaving numerous rural regions without pertinent local climate data. Consequently, understanding temperature trends and extreme heat events becomes challenging, hindering the implementation of effective adaptation strategies and local-level early warning systems. The recently introduced Climate Hazards Center Infrared Temperature with Stations (CHIRTS-daily) dataset, as detailed by Verdin et al. in 2020, marks a significant advancement in temperature data products. This dataset provides daily estimates of both minimum and maximum air temperatures on a nearly global scale, spanning from 1983 to 2016. CHIRTS-daily achieves this by integrating satellite infrared data with an extensive network of ground-based weather stations, as well as incorporating air temperature estimates derived from the European Centre for Medium-Range Weather Forecasts Re-Analysis (ECMWF), specifically the ERA5 reanalysis dataset, as highlighted by Hersbach et al. in 2020. What distinguishes CHIRTS-daily as a particularly promising data product is its remarkable spatial resolution, providing temperature estimates at 5-kilometer intervals (0.05° resolution). This resolution surpasses that of several other prominent temperature datasets, including the Japanese 55-year reanalysis (0.5°) as described by Ebita et al. in 2011, the ERA5 reanalysis (0.25°), and the ERA5-Land reanalysis (0.1°) as outlined by Muñoz-Sabater et al. in 2021. This heightened spatial resolution significantly enhances CHIRTS-daily's capacity to offer localized temperature information.

In this study, we delve into the evolving landscape of statistical methodologies that play a pivotal role in reconciling the disparities between different data sources, thereby bolstering confidence in the integrated datasets. We explore the background and rationale behind this shift, examining how skepticism has gradually transformed into conviction regarding the usefulness of integrated data for climate and meteorological research.

The study also aims to compare the performance of CHIRTS-daily maximum temperature records in Ghana to station data records from a selection of three Synoptic stations using a variety of metrics. To compare the performance of CHIRTS-daily to the station data records, another high-resolution temperature product, ERA5 is used. Temperature estimates are evaluated daily, with some daily analysis split by month to account for seasonal variation and by year, where the annual maximum mean temperatures are compared. We focus on a limited set of stations dispersed over Ghana with excellent temperature data going back at least 15 years. The results will give an indication of performance in various climates across Ghana and allow for evaluation of performance aspects that require long-term records, especially climate extremes, despite the fact that the lack of station locations in this study limits the confidence with which claims about specific locations can be made.

Related works

The integration of satellite and reanalysis data with ground-based station data is a topic that has evolved over the years, with researchers gradually transitioning from skepticism to conviction regarding the usefulness of integrated datasets. Early satellite data were subject to criticism for their accuracy and reliability. Skeptics questioned whether satellite sensors could provide data of sufficient quality for scientific research. Calibration and validation were recurring concerns (Huffman et al., 1997). Another skepticism involved the limited spatial and temporal resolution of early satellite data. Some researchers argued that the coarser resolutions made it difficult to use satellite data for local or fine-scale studies (Holben et al., 1983). The frequency of cloud cover and atmospheric interference obstructed clear observations, leading to concerns about data availability (Gutman and Ignatov, 1998). Cloud cover was a significant impediment to consistent data collection. Integrating data from satellites and ground-based stations posed technical and methodological challenges. Calibration, validation, and data compatibility were essential but complex tasks (Huffman et al., 1997). Also, the sustainability of satellite programs and the continuity of data records over time were questioned as consistent, long-term data records are critical for climate research (Bodas-Salcedo et al., 2011). Rigorous scientific validation was called for to ensure the accuracy and reliability of satellite-derived data. Skeptics questioned whether satellite data could replace or supplement station-based measurements (Wielicki et al., 1996).

Numerous initiatives have been undertaken to assess the accuracy of satellite-derived rainfall products when compared to measurements obtained from rain gauges (Ali et al., 2005; Gosset et al., 2013; Jobard et al., 2011; Lamptey, 2008; Laurent, Jobard, & Toma, 1998; Nicholson et al., 2003a, 2003b; Roca et al., 2010). Nevertheless, these evaluations have predominantly been conducted on a regional scale, considering multiple countries with varying geographical and climatic characteristics. As indicated by Toté et al. (2015), the outcomes of such investigations reveal notable discrepancies in algorithm performance contingent upon factors such as location, topography, local climate, and season (Maidment et al., 2013). While relatively limited in number, certain studies have undertaken assessments of satellite rainfall products at the country level within Africa, according to the work of Moctar Dembélé and Sander J. Zwart (2016). These include evaluations in Angola (Pombo, de Oliveira, & Mendes, 2015), Ethiopia and Zimbabwe (Dinku et al., 2007; Diro et al., 2009; Hirpa, Gebre Michael, & Hopson, 2010), Kenya (Tucker & Sear, 2001), Mozambique (Toté et al., 2015), and Uganda (Asadullah, McIntyre, & Kigobe, 2008; Maidment et al., 2013). According to Moctar Dembélé and Sander J. Zwart (2016), the majority of satellite-based rainfall products have exhibited favorable agreement with rain gauge data at both monthly and annual temporal scales. However, it is noteworthy that while extensive evaluations have been carried out on satellite-based rainfall products, there has been relatively limited research focused on the assessment of satellite-based temperature products. In a study by Parsons et al. (2022), satellite-derived air temperature estimates were scrutinized at eight diverse sites across Africa, covering a range of climate zones and geographical conditions. The findings of this study highlight the promise of CHIRTS-daily, which demonstrates superior performance compared to ERA5 and ERA5-Land in many regions. CHIRTS-daily consistently delivers commendable results across a diverse set of African sites, indicating its potential for accurate temperature estimation in the region.

These findings underscore the importance of expanding research efforts in the evaluation of satellite-based temperature products, as accurate temperature data are fundamental for a wide range of applications, including agriculture, public health, and climate change assessments. The inclusion of more sites and a broader geographic scope in such evaluations will further enhance our understanding of the strengths and limitations of satellite-derived temperature datasets and their potential benefits for various sectors across Africa.

Methodology

Validation of air temperature records

Study area

Three sites across Ghana are used in this study. Although the choice of locations was ultimately restricted by the availability of long-term, high-quality daily temperature records, the sites represent diverse regions and climates across Ghana.

Station Data

The three sites contained daily minimum and maximum temperature station records. Table 1 displays station details and temperature record specifications. The station data was obtained from the Ghana Meteorological Services. Many of the station records predate 1983 and some extend beyond 2016, but only data from this time period were used to correspond with the time period of CHIRTS-daily. Prior to analysis, the station records were quality controlled using a variety of the World Meteorological Organization's consistency and statistical tests (WMO, 2021). The employed the graphical and statistical tests used by (Parsons et.al 2022) as follows: maximum and minimum temperature consistency (maximum > minimum), out-of-range check based on monthly climatological ranges, rapid change check of more than 10 C difference from the previous value, and spike test with the same 10 C difference threshold. The few values that failed these quality-control checks were corrected with the assistance of the data provider.

Table 1 Details of the three station sites and properties of the data records

Station	Longitude	latitude	Data Range Used
Accra-Kiamo	-0168	5.6098	1st Jan 2001-31st Dec 2015
Navrongo	-1.0832	10.878	
Kumasi	-1.5916	6.7169	

Gridded data

To investigate the added value of CHIRTS-daily, temperature records from individual pixels of three gridded data products are compared to station data records. Table 2 provides an overview of the key features of these products.

CHIRTS-daily (Verdin et al 2020) is produced by combining satellite infrared temperatures with a large collection of station temperature records from around the world to produce gridded monthly mean maximum temperatures, which are then combined with ERA5 temperature values to produce disaggregated daily maximum and minimum temperature values on a 0.05 quasi-global scale from 1983 to 2016. The performance of CHIRTS is compared to the performance of ECMWF's 2m temperature records from ERA5 reanalysis. The ERA5 reanalysis uses data assimilation systems to produce hourly estimates of a variety of variables for the entire globe by combining global climate models with ground, ocean, and satellite observations from a variety of sources. From 1979 to the present, ERA5 2 m temperature records are available as hourly instantaneous values with a spatial resolution of 0.25◦ (Hersbach et.al 2020). The daily minimum and maximum temperature values were calculated from ERA5 by calculating the maximum and minimum of the 24 hourly values over each 24-hour period beginning at 6 AM UTC.

Table 2 Overview of gridded temperature based products

Product	Spatial Resolution	Temporal Resolution	Data availability	Coverage	Method
CHIRTS-daily	0.05◦ (~5 km)	Daily	1983–2016	Quasi-Global	Merged Station, Satellite & Reanalysis
ERA5	0.25◦ (~30 km)	Hourly	1979–Present	Global	Reanalysis

Validation process

Validation was performed for the overlapping timeframe of the various data sources, spanning from 2001 to 2015. Our validation approach was primarily focused on point-to-pixel analysis, drawing upon established methodologies (Parsons et al., 2022; Moctar Dembélé & Sander J. Zwart, 2016; Cohen Liechti et al., 2012; Thiemig et al., 2012). Instead of interpolating gauge measurements into a gridded product, we adopted a method wherein we directly extracted satellite estimates for the specific point-based station locations. It's worth noting that utilizing point data, as highlighted by Toté et al. (2015), inherently introduces complexities into the validation process. This arises from the inherent differences between point-based station measurements and satellite pixel estimates. Satellite estimates represent spatial averages over grid cells, resulting in a fundamentally smoother spatial and temporal variance. Consequently, some systematic disparities between point observations and pixel-based estimates are to be anticipated.

To comprehensively assess the accuracy and reliability of the integrated datasets, we conducted a comparison of satellite estimate data and station data at three distinct temporal scales: daily, monthly, and annual. This multi-temporal analysis provided a comprehensive evaluation of the performance and suitability of the integrated datasets for a wide range of applications.

Validation statistics

The methodology employed in this study was guided by the outcomes of the GPCP's 3rd Algorithm Intercomparison Project, as documented by Ebert in 1996. This method relies on both pairwise comparison statistics and categorical statistics to comprehensively assess the performance of satellite products in estimating rainfall amounts and rain detection capabilities.

Table 3 succinctly presents the five key statistical indicators computed for the pairwise comparison statistics: Pearson Correlation Coefficient (r): As noted by Moctar Dembélé & Sander J. Zwart (2016), this metric evaluates the degree of correspondence between the estimates and observed values. A higher r value signifies a stronger correlation, indicating better alignment between estimated and observed data. Mean Error (ME): ME serves as an indicator of the average estimate error. A positive ME suggests a tendency to overestimate the maximum temperature, while a negative ME indicates underestimation. Bias: The Bias metric quantifies the extent to which the measured value differs from the estimate, shedding light on whether the estimates are consistently biased toward overestimation or underestimation. Root Mean Square Error (RMSE): RMSE is a widely employed measure to assess differences between two variables. It calculates the average magnitude of estimate errors, with lower RMSE values indicating stronger central tendencies and smaller extreme errors in general. Nash-Sutcliffe Efficiency Coefficient (E): The Nash-Sutcliffe Efficiency coefficient, as detailed by Toté et al. (2015), ranges from negative infinity to one and is particularly effective in predicting observed time series. Negative values suggest that the gauge mean outperforms the satellite-based estimate, while zero indicates equivalence, and a score of 1 signifies a perfect match between gauge measurements and satellite-based estimates. For general purposes, products featuring high r and E values and low RMSE and ME values are deemed preferable, indicating superior performance in estimation and prediction accuracy.

Table 3 Summary of statistical indicators

Statistical Indicator	Formula	Value Range	Perfect score
Bias	$\text{Bias} = \frac{\sum_{i=1}^{n} s_i}{\sum_{i=1}^{n} G_i}$	0 to ∞	1
Correlation(r)	$\text{Correlation } (r) = \frac{\sum_{i=1}^{n}(G_i-\bar{G})(s_i-\bar{s})}{\sqrt{\sum_{i=1}^{n}(G-\bar{G})^2}\sqrt{\sum_{i=1}^{n}(s_i-\bar{s})^2}}$	-1 to 1	1
Root Mean Square Error	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i-G_i)^2}$	0 to ∞	0
Nash–Sutcliffe Efficiency coefficient(E)	$E = 1 - \frac{\sum_{i=1}^{n}(S_i-G_i)^2}{\sum_{i=1}^{n}(G_i-\bar{G})^2}$	$-\infty$ to 1	1
Mean Error	$ME = \frac{1}{n}\sum_{i=1}^{n}(S_i-G_i)$	$-\infty$ to ∞	0

($where\ G_i$, represents station measurement; $\bar{G}$, average station measurement; S_i satellite estimate; $\bar{S}$, average satellite estimate; and$n$, number of data pairs)

Statistical Methodologies and Techniques for Integrating Satellite and Station Data

The integration of satellite data with station data, often referred to as data fusion or data integration, is an important area in environmental science, climate monitoring, and remote sensing (Hengl et al., 2017). This integration involves combining data from different sources to provide more accurate and comprehensive information for various applications. Researchers and scientists employ various statistical methodologies and techniques in this field to enhance the quality and usability of the integrated data.

One emerging approach is the application of machine learning and deep learning techniques (McR. Convolutional Neural Networks (CNNs), for instance, can be used to process remote sensing images and extract features and patterns that are relevant to the variables of interest, such as temperature or precipitation. Recurrent Neural Networks (RNNs) are effective for modeling temporal patterns in time-series data, making them suitable for integrating time-series station data with satellite data (Hengl et al., 2017). Another crucial aspect is spatial interpolation, which can help fill in gaps in data. Geostatistical techniques like kriging are often employed to interpolate values between sparse station data points, providing estimates at unobserved locations (Cressie & Wikle, 2015). Additionally, spatial regression techniques, such as spatial autoregressive models and spatial error models, can incorporate spatial relationships between stations and satellite pixels (Hengl et al., 2017). Data assimilation systems (DAS), including advanced techniques like the Ensemble Kalman Filter (EnKF) and the Particle Filter, are used to integrate observations from various sources, including satellite and station data, into numerical models for weather and climate forecasting (Liu & Gupta, 2007). These systems help create a coherent and accurate representation of the environmental conditions. Bayesian methods are also gaining traction in the integration of satellite and station data (Campozano et al., 2019). Bayesian hierarchical models allow for the incorporation of prior information, such as knowledge about the spatial and temporal relationships between variables, into the integration process. These models enable researchers to capture complex interactions and dependencies within the data (Cressie & Wikle, 2015). Furthermore, remote sensing data fusion, involving the combination of data from multiple sensors on satellites, provides a more comprehensive understanding of land, atmosphere, and ocean conditions. Multisensory data fusion can enhance the quality and diversity of information available for analysis.

In this ever-evolving field, the application of these statistical methodologies and techniques is central to harnessing the full potential of integrated satellite and station data. These approaches continue to advance our understanding of the environment, drive improvements in weather and climate forecasting, and support critical decision-making across various domains.

Results and Findings

Daily comparison

The point-based station locations scale was used to compare all daily maximum temperature satellite estimates and station data. On a daily basis, the overall correlations (not shown here) between CHIRTS and station data are high ($r \geq 0.80$) for all stations and higher than or comparable to those for ERA5. When there is seasonality in the data, however, the overall correlation can be misleading because high correlation values can be achieved by values that model the seasonality well without necessarily strong correlation of values within seasons as discussed in Parsons et.al (2022).

Monthly and Annual Comparisons

The CHIRTS monthly mean maximum temperatures estimates are strongly positively correlated ($r \geq 0.97$) for all stations. The highest correlation is recorded in Accra ($r = 0.9969$). ERA 5 estimates have lower positive correlations in Kumasi and Accra. In Kumasi, ERA 5 shows a negative correlation ($r = -0.4411$). The highest mean errors and mean square errors are associated the ERA 5 estimates. Generally, the CHIRTS estimates outperformed the ERA 5 estimates as shown in Table 4 and also the scatter matrices illustrated in Figure 2 and Figure 3.

Table 4 Monthly Statistical Indicators

Station	Product	r	me	rmse	% bias	E
Navrongo	CHIRTS	0.9725	0.7132	0.983	2.1	0.8791
	ERA 5	0.9877	1.505	1.572	4.4	0.7034
Kumasi	CHIRTS	0.9898	-0.0392	0.2732	-0.1	0.9746
	ERA 5	-0.4411	5.252	5.594	20	-570.8
Accra	CHIRTS	0.9969	0.1008	0.5233	0.3	0.9684
	ERA5	0.9889	2.474	2.478	8.6	-1.305

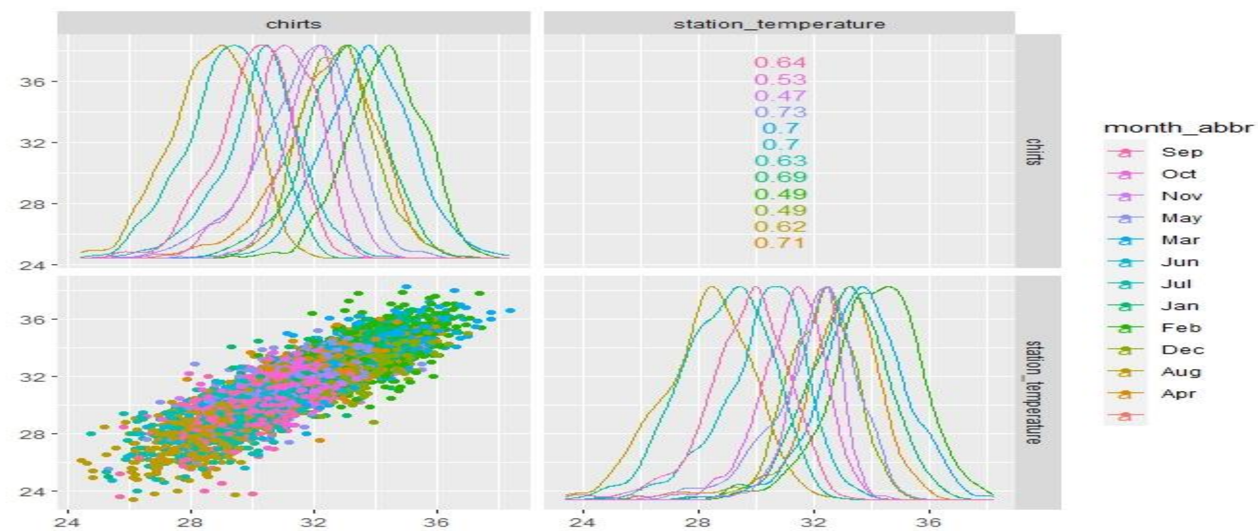

Figure 1 Scatter matrix of station data and CHIRTS (Kumasi)

The statistical indicators at the annual level are provided in Table 5. CHIRTS relatively showed higher correlations at all stations compared to ERA 5. It also outperformed the ERA 5 overall at the annual levels from the annual statistical indicators. However, the performance of the products at the annual levels were significantly lower compared to daily and monthly measurements

Table 5 Annual Statistical Indicators

Station	Product	r	me	rmse	% bias	E
Navrongo	CHIRTS	0.6348	0.6817	0.7525	2	-0.25

	ERA 5	0.172	1.473	1.58	4.3	-9.428
Kumasi	CHIRTS	0.538	-0.0472	0.2751	-0.1	-1.07
	ERA 5	-0.2764	5.22	5.51	19.9	-10.41
Accra	CHIRTS	0.66	0.1759	0.4776	0.6	-7.567
	ERA5	0.373	2.548	2.578	8.9	-195.2

Discussion and Conclusion

The evolution and availability of high spatial and temporal resolution continental and global satellite-based products are increasingly facilitating and stimulating the implementation of climatic early warning activities in data-scarce regions. However, before using these satellite products for any specific application, their accuracy, strengths, and weaknesses must be evaluated.

The growing body of research into the validation and evaluation of these satellite products at various regions is increasingly building confidence in the use of satellite based products for various applications. Most researchers have shown that most of these products have greater potential in diverse applications. However, there is limited research in the validation of temperature based satellite products as many studies have focused on satellite-based rainfall products.

The integration of satellite and ground-based station data, known as data fusion, is a vital discipline within environmental science, climate monitoring, and remote sensing. It involves the amalgamation of data from diverse sources to enhance accuracy and comprehensiveness for various applications. Researchers have employed several key statistical methodologies and techniques to optimize this integrated data. Machine learning methods, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), process remote sensing images and model temporal patterns in time-series data, facilitating the integration of station and satellite data. Spatial interpolation techniques, like kriging, fill gaps between sparse station data points, providing estimates at unobserved locations. Spatial regression models, such as spatial autoregressive and spatial error models, incorporate spatial relationships, bolstering data quality. Advanced Data Assimilation Systems (DAS) like the Ensemble Kalman Filter (EnKF) and the Particle Filter integrate observations from multiple sources, including satellites and ground stations, into numerical models for weather and climate forecasting. Bayesian hierarchical models incorporate prior information regarding spatial and temporal variables, capturing complex data interactions. Lastly, remote sensing data fusion, which combines data from various satellite sensors, offers a comprehensive understanding of land, atmosphere, and ocean conditions, augmenting information diversity and quality for analysis.

The study compared the daily temperature records from 2001 to 2015 from the CHIRTS satellite and station-based temperature network with temperature data records of at least 15 years' duration from three locations in Ghana. To evaluate CHIRTS performance, the station data were also contrasted with ERA5 temperatures. On the daily and monthly basis, the CHIRTS estimates showed good agreement with the station data than on the annual levels. The CHIRTS estimates also outperformed the ERA 5 estimates at all levels of comparisons.

The CHIRTS dataset, according to the study's findings, is a promising addition to the group of gridded data sets that offer estimates of the near-global, long-term, high-resolution air temperature. When combined with current reanalysis temperature data products or used independently, CHIRTS data are based on satellite data and integrate station data records, thus they complement and may provide extra information. In comparison to data from the stations, CHIRTS fared similarly to or better than ERA5 records on many metrics.

It is suggested that, further studies concentrating on certain geographic regions or topographies should be studied. Additionally, it is important to include more ground stations in future research so that spatial patterns of temperature utilizing satellite products may be examined and a pixel-to-pixel analysis can be used to carry out in-depth analysis.

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