Published in final edited form as:

Ann N Y Acad Sci. 2016 October ; 1382(1): 31–43. doi:10.1111/nyas.13090.

Meteorological variability and infectious disease in Central Africa: a review of meteorological data quality

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Abstract

Central African countries may bear high climate change–related infectious disease burdens because of preexisting high rates of disease, poor healthcare infrastructure, land use changes, and high environmental change vulnerabilities. However, making connections between climate and infectious diseases in this region is hampered by the paucity of high-quality meteorological data. This review analyzes the sources and quality of meteorological data used to study the interactions between weather and infectious diseases in Central African countries. Results show that 23% of studies used meteorological data that mismatched with the disease spatial scale of interest. Use of inappropriate weather data was most frequently identified in analyses using meteorological station data or gridded data products. These findings have implications for the interpretation of existing analyses and provide guidance for the use of climate data in future analyses of the connections between meteorology and infectious diseases in Central Africa.

Keywords

climate; infectious disease; Central Africa; data quality

Introduction

African countries currently contribute little to the total global emissions of greenhouse gasses; however, they bear high climate change–related health burdens,[1] including the direct physiological effects of increasing temperatures, reduced agricultural productivity, water insecurity, and changing patterns of vector-borne diseases. In Africa, infectious diseases remain a leading cause of mortality. Half of all years of life lost are due to infectious diseases,[2] such as HIV, tuberculosis, malaria, and waterborne diarrheal diseases.[2–5]

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Supporting Information
Additional supporting information may be found in the online version of this article.
Table S1. Papers categorized by country.
Figure S1. The number of papers published over time on climate and infectious diseases in Central Africa.

Conflicts of interest
Jeffrey Shaman discloses partial ownership of SK Analytics.

Within the African continent, Central Africa—defined as Angola, Burundi, Cameroon, Central African Republic, Chad, Equatorial Guinea, Gabon, South Sudan, Republic of Congo, Rwanda, and Uganda—has a high burden of infectious disease and has been subject to recurrent outbreaks of emergent infectious diseases, such as Ebola.[6] This region remains predominantly forested with high biodiversity because of a historical reliance on oil and mining, rather than forestry and agriculture; however, recent population growth has motivated an increase in logging and the number of road networks penetrating uninhabited areas.[7] With this increasing infiltration into previously undisturbed forest ecosystems, humans, livestock, and wildlife are mixing in new ways, and the risk of emerging infectious diseases is considered to be high.[8–10]

Environmental change vulnerability, which is a combined measure of a community's exposure to climatic change, its sensitivity to these changes, and its ability to adapt,[11,12] is particularly high in Central African countries. Underlying vulnerabilities include existing heat, food, and water stress, disease transmission, and poor healthcare infrastructure. Given these susceptibilities, Central African countries may experience a greater impact of climate change on human infectious diseases. Despite awareness of Central Africa's vulnerability to climate change,[13] there remains limited empirical evidence on the influence of climate change on infectious diseases for this region, as well as Africa overall.[14,15]

In light of climate change, it is important to understand the influence of meteorological conditions on infectious diseases. Such research is particularly important in areas where climate change is expected to have a greater impact. However, in areas such as Central Africa, the data to make these connections are often lacking. In this paper, we aim to review the literature on meteorology and infectious diseases in Central Africa, to assess the types and quality of the meteorological data being used to study weather and infectious diseases in Central Africa, and to use these findings to provide suggestions related to meteorological data use in future analyses of weather and infectious diseases in this region. We begin with a review of the types of meteorological data available and description of our review methods.

Meteorological data

Studies of climate and infectious disease, disease monitoring, surveillance, and early warning systems depend on the availability of reliable meteorological information. Existing meteorological data, including variables such as temperature and precipitation, are derived from ground-based measurements, satellite measurements, or interpolated gridded datasets. This section summarizes the quality and availability of such datasets in Central Africa; see Table 1 for specific data sources.

Ground-based measurements

Ground-based measurements are the most direct measure of temperature and precipitation at the surface. However, ground-based observation networks report inadequate coverage in Africa both spatially (i.e., the density of gauges) and temporally (i.e., intermittent, erratic recordings).[16–18] Additionally, there has been an observed decline in gauge observations across Africa in the past decade(s),[19] and existing stations tend to be biased toward higher elevations.[20] Ground-based measurements are particularly sparse and intermittent in Central

Africa (Fig. 1, Table 2). Very few meteorological stations provide data within each Central African country, and the existing observations have poor temporal coverage.

Satellite measurements

Precipitation and, to a lesser degree, temperature are variable in space and time and require high-gauge density for accurate measurement. Given the low density of ground-based observations in Central Africa, satellite-based estimates are an attractive alternate source for meteorological data. While there is controversy surrounding the relative accuracy of satellite-derived precipitation and temperature observations, many researchers have concluded that the observations are of acceptable quality in Africa.[21–24] These satellite-derived measurements benefit from more regular, even continuous, observation in time and space; however, the spatial resolution of most remotely sensed data is low compared with the localized measurements provided by ground-based observations.

Satellite-based precipitation is measured by thermal infrared (TIR) sensors, microwave sensors, or a combination of both. TIR sensor estimates are best used for estimating precipitation in convective clouds[25] and have been shown to do well in Africa because of the predominance of rainfall from deep convective systems.[24] Microwave sensors are more accurate than TIR estimates but are more limited because of low temporal resolution.

TIR wavelengths are also used for measuring land surface temperature. However, processing is necessary to convert the TIR readings to accurate land surface temperatures. A variety of satellite platforms (e.g., ASTER, Landsat, AVHRR, and MODIS) can provide these estimates of land surface temperature with high temporal and spatial resolution.[26]

Gridded products

Gridded products employ spatial interpolation to provide continuous estimates of meteorological conditions in both space and time. These datasets are typically constructed from gauge data, satellite data, or both. Gridded datasets do not sufficiently resolve local conditions to allow local analyses and are intended only for global or regional scale analyses.[27] Further, gridded gauge–satellite precipitation products have been found to poorly characterize rainfall in Central Africa.[28] For both satellite-based measurements and gridded climate products, more validation is needed; however, the scarcity of ground-based measurements remains an impediment to such assessments.[29]

Methods

Search strategy and inclusion criteria

We searched Web of Science for articles on meteorology and infectious diseases in Central Africa, published in English between January 1, 1970 and June 30, 2015. Search key terms were split into three categories: infectious disease, meteorology, and country. We defined Central Africa as the following 12 countries: Angola, Burundi, Cameroon, Central African Republic, Chad, Equatorial Guinea, Gabon, South Sudan, Republic of Congo, Rwanda, and Uganda. These countries make up an area of 7.5 million km^2, with a total population of about 206 million.[30] Each search session contained one key term from each category, and searches were carried out using all possible combinations of key terms (Table 3). Studies were included if they pertained to human infectious diseases; included temperature, humidity, and/or precipitation variables in the analyses; and carried out analyses in a Central African country. In order to focus on local and regional scale analyses, all continental and global scale studies were excluded.

Data source extraction

A data extraction table was created to summarize the meteorological and disease data used in the included papers. The table contains sources, variables included, and spatial scales/resolutions for every dataset used in each paper. Ultimately, sources for meteorological and disease data were aggregated into larger categories.

The meteorological data sources were coded as local meteorological station data, directly measured data (i.e., primary data collection), satellite data, large gridded datasets, hydrological data, seasonal, and unknown. Papers with seasonal meteorological data did not use quantitative data, but instead categorized time periods as hotter/colder or wetter/drier. When the source of meteorological data was not stated in a manuscript, the data source was categorized as unknown.

Disease data sources were classified into five categories: existing human disease datasets, primary collection of human disease data, animal host or vector sampling data, water samples, and species occurrence datasets. Human disease datasets are obtained from any source that aggregates human data, such as the World Health Organization (WHO) or local hospitals. Primary collection of human disease data, as well as animal host or vector sampling, implies active collection of disease information from participants or animals.

Spatial mismatch analysis

The spatial mismatch analysis aimed to determine whether the meteorological data used in each paper were measured at an appropriate spatial scale, given the disease data. First, using maps, information provided in the papers, and online sources, we estimated the geographical region represented by the disease data. Areas were estimated in km^2 and then categorized as local (subnational or national) or regional (multinational) spatial scales. Methods for determining spatial mismatch differed on the basis of whether the meteorological data were point estimates or gridded products. Two investigators conducted all analyses separately and compared their results in order to strengthen validity. If disagreements occurred, the investigators reviewed the relevant information together and reached a consensus.

Point estimates—Meteorological point estimates came from meteorological station data and direct measurements by researchers. Papers that used this type of meteorological data either had disease point estimates or disease data covering a prescribed locality. For papers that used disease point estimates, we determined the distance between the disease and the meteorological point estimates (if possible). If this distance was greater than 100 km, we classified a spatial mismatch, as the meteorological data are likely too far away to accurately represent conditions at the site of disease data.

Alternatively, for studies that contained a larger proscribed area of disease data (i.e., data points spanning a geographical region), we estimated the density and placement of meteorological stations within that area (if possible). Spatial mismatch was assigned when the density was less than one station per 100 km^2 or the station(s) was further than 100 km from the disease region.

Gridded data—Many gridded meteorological data products exist. We first determined the types of observations used to create each gridded dataset: satellite, gauge (i.e., meteorological stations), or both. Owing to the sparse and discontinuous nature of gauge data in Central Africa, gauge-only interpolated datasets provide insufficient information for local scale analyses. Hence, we assigned spatial mismatch to any local analysis using gauge-only gridded data. To determine spatial mismatch of gridded data derived entirely or partially from satellite data, we calculated the number of grid cells within the geographical area of the disease data using the gridded-product spatial resolution. If the ratio of grid cells to the disease data area was less than one grid cell per 100 km^2, we assigned spatial mismatch.

Spatial threshold—Our justification for choosing a spatial threshold of 100 km was based on prior estimates of the decorrelation length scale for precipitation. Moron *et al.*[31] estimated the spatial scale, defined as the distance at which spatial correlation falls below r = 0.37, for daily rainfall intensity in tropical regions with diverse topography. They found that spatial correlation decayed exponentially with increasing distance and became much lower than r = 0.37 for distances greater than 100 km.[31] Other papers using satellite data have found similar spatial scales (95–150 km) for tropical rainfall.[32,33] Although temperature has a larger spatial scale than rainfall in the tropics, almost every paper included in this review that used temperature estimates also used rainfall estimates in their analyses (96%). Since all variables need to be spatially matched, we defined 100kmas the distance demarcation of mismatch. Of the two papers that used temperature estimates only, the spatial resolution of the meteorological data was very high and spatial mismatch was not a problem. Additionally, because Moron *et al.*[31] conducted their analyses in topographically diverse regions, the estimated length scale of 100 km can be used for all topographic contexts.

Results

We screened 167 papers obtained from online searches and ultimately included 66 papers written between 1970 and 2015 in this review. The papers investigated a number of infectious diseases, but the majority studied vector-borne disease (61%), specifically malaria (44%) (Table 4). Studies were most frequently carried out in Uganda (44%), Cameroon (22%), Rwanda (9%), and Burundi (9%) (Table S1 in Supporting Information), and only a few pertained to other Central African countries. The number of published papers on meteorology and infectious diseases has increased since 1970. Two-thirds of the papers included in this review were published after 2005 (Fig. S1 in Supporting Information).

Climate data

The papers used climate data from many different sources (Table 5). For example, one-third (33%) of the studies used climate data directly from meteorological stations, and 16 papers (24%) used data from gridded datasets. Fewer studies used satellite data ($n = 10$, 15%) and directly measured data ($n = 8$, 12%). None of the papers used hydrological data or modeling. Notably, four papers (6%) did not provide a source for the climate data used, and 12 papers (18%) compared disease metrics across defined seasons instead of using climate data.

Disease data

Many types of infectious disease data were used (Table 6). Of the papers using human disease data, 36 papers (55%) retrieved the data from local healthcare centers or large existing datasets (e.g., WHO, U.S. Centers for Disease Control and Prevention, local Ministry of Health), whereas 15 papers (23%) collected primary data, such as blood samples or questionnaires. Many papers used data pertaining to animal hosts or vectors, obtained from either primary data collection using trapping or sampling ($n = 19$, 29%) or from existing species occurrence data ($n = 2$, 3%). Last, five papers (8%) collected water samples to measure the presence of infective fecal matter or bacteria.

Spatial mismatch analysis

Results from the spatial mismatch analysis revealed patterns of mismatch on the basis of the type of climate data used. Findings for each climate data category are discussed below. Table 7 summarizes the distribution of papers with spatial mismatch and papers that did not provide adequate information about their data (referred to as unknown). Overall, the results showed 23% of papers having spatial mismatch, and mismatch could not be determined in 25% of papers.

Directly measured—No spatial mismatch was observed between directly measured meteorological variables and health data. Researchers placed the monitoring devices in the locations where health data were collected or available. Although this method often limits the temporal length of data collection, it provides the placement precision needed to avoid spatial mismatch. All papers using directly measured climate data provided sufficient information about their data collection to assess spatial mismatch.

Local meteorological stations—All papers reviewed using meteorological station data directly accessed these data from local government meteorology departments. Of the 22 papers using meteorological station data, 10 (45%) did not provide enough information to assess spatial mismatch of the data. These papers provided locations for the health data collected, but did not provide locations for the meteorological stations, making it impossible to determine whether the locations of the meteorological stations accurately represent temperature and rainfall in the health area of interest.

We identified spatial mismatch in six (27%) of the papers that provided adequate spatial information. In these papers, a limited number of meteorological stations was used to represent climatic conditions of a large disease catchment area. Many of these papers used rainfall data, which vary on much shorter spatial scales, as well as temperature data from meteorological stations.

Satellite data—No spatial mismatch was identified in the studies using satellite data. Although there was no spatial mismatch, few papers addressed the issue of data autocorrelation or provided an explanation of how gridded data with different resolutions were aggregated.

Large gridded datasets—Spatial mismatch occurred in almost half (44%) of the papers using large gridded datasets. The papers with this spatial mismatch used interpolated datasets based on very sparse meteorological station records. Despite the paucity of observations in these datasets, seven papers used them for fine spatial scale analyses. Four papers (25%) did not provide enough information about the climate data for evaluation of spatial mismatch. In these papers, datasets that are not publically available were referenced, preventing determination of spatial mismatch. As a sensitivity analysis, the threshold was increased to one grid cell per 200 km^2. All results remained the same, except for one paper that was no longer classified as a spatial mismatch.

Discussion

This review included 66 papers looking at meteorology and infectious diseases across Central Africa. Eleven of these papers compared disease outcomes across different seasons, and four papers did not source their meteorological data. Of the papers that did use meteorological datasets, nearly one-fourth (23%) used data mismatched with the disease spatial scale of interest. One-fourth of the studies (25%) did not provide enough information about their meteorological datasets to assess spatial mismatch. Spatial mismatch was most commonly identified in analyses using gridded datasets and/or local meteorological station data.

Development of improved gauge-based datasets

The primary reason for spatial mismatch is the use of datasets based on sparse and intermittent ground-based observations. Gauge-only interpolated datasets in Central Africa do not contain adequate information for local-scale analyses, yet researchers are continuing to use them. Conclusions from these studies must be interpreted cautiously due to the poor quality of the underlying meteorological data. Spatial mismatch occurs when estimates of temperature, rainfall, or humidity are obtained from locations farther than the defined decorrelation length from the area of disease data collection. If the meteorological estimates used in the analyses do not truly represent the meteorological conditions at this area of interest, the results will not be reliable or accurate. This could produce spurious relationships or hide true relationships between meteorological variables and diseases.

The recognition of sparse ground-based observational data in Africa may lead to improved coverage in the future (e.g., initiatives of the World Meteorological Organization and Trans-African HydroMeteorological Observatory). Many countries in Africa have station networks that are not publicly available,[34] but gaining access to these station networks would greatly improve the breadth and precision of ground-based observations. The International Research

Institute for Climate and Society has gained access to national station networks in several East African countries and, using these data streams, has created gridded data products with much greater resolution at local scales. Similar initiatives in Central Africa could improve the coverage of gauge-based datasets.

Is using satellite data a good alternative?

In the absence of adequate ground-based observations, satellite data could be a good alternative data source. Remotely sensed data have the benefit of continuity in time and space, and have spatial resolutions appropriate for local analyses. However, the accuracy of satellite-derived estimates of precipitation and temperature remains unclear. Indeed, the accuracy of satellite rainfall estimates is noted to vary by location, topography, and rainfall type.[35] Despite this, some scientists have concluded that satellite-based precipitation retrieval algorithms have acceptable accuracy across Africa.[21–24] For temperature, some researchers conclude that the relationship between satellite-and ground-measured air temperature has not been adequately quantified in Africa,[36] whereas others maintain that satellite-based estimates of temperature in Africa are an accurate representation of ground-based measurements.[37] For now, researchers might rely on the recommendations by Hay and Lennon,[38] who suggest that interpolated temperature data more accurately depict temperatures, while satellite-based estimates better represent precipitation. However, researchers must continue to evaluate the reliability and accuracy of satellite data for estimating ground meteorological conditions in Central Africa.

Lack of information about climate data

Many papers in this review did not provide adequate information about the meteorological data used in the analysis (27%). Notably, four of these papers did not even provide a source for their data. Without information on the underlying data source and quality, it is impossible to assess the quality of the findings. In order to move forward in understanding the links between weather and infectious diseases, it will be important for researchers to describe and address their meteorological data sources and quality.

Temporal mismatch

The meta-analysis presented in this paper focuses on spatial mismatch of data, but there may also be temporal mismatch, which occurs when the meteorological and disease data are recorded during different time periods. The time scales over which data were collected and analyzed differ greatly in the papers included in this review. Many analyses looked at variability during 1–2 years, while others have data that span over 20 years. Temporal mismatch was observed: for example, one paper used satellite-derived meteorological data from 2002 and disease incidence rates from 2006; another paper used meteorological data spanning 1950–1960 and daily disease data from one month in 1991. Such temporal mismatch between meteorological and disease data can also cause bias and inaccuracy of results. Further research should investigate the true prevalence and impact of temporal mismatch in papers studying meteorology and infectious diseases.

Conclusion

Results linking weather and infectious diseases must be supported by high-quality, spatially matched underlying data. In Central Africa, meteorological data are limited by sparse ground-based data and satellite data that have not been sufficiently validated. The scientific community must remain apprised of the limitations of the datasets available in this region and work to improve the collection, abundance, and availability of both meteorological and infectious disease data for credible analyses of interactions at the intersection of climate and infectious disease.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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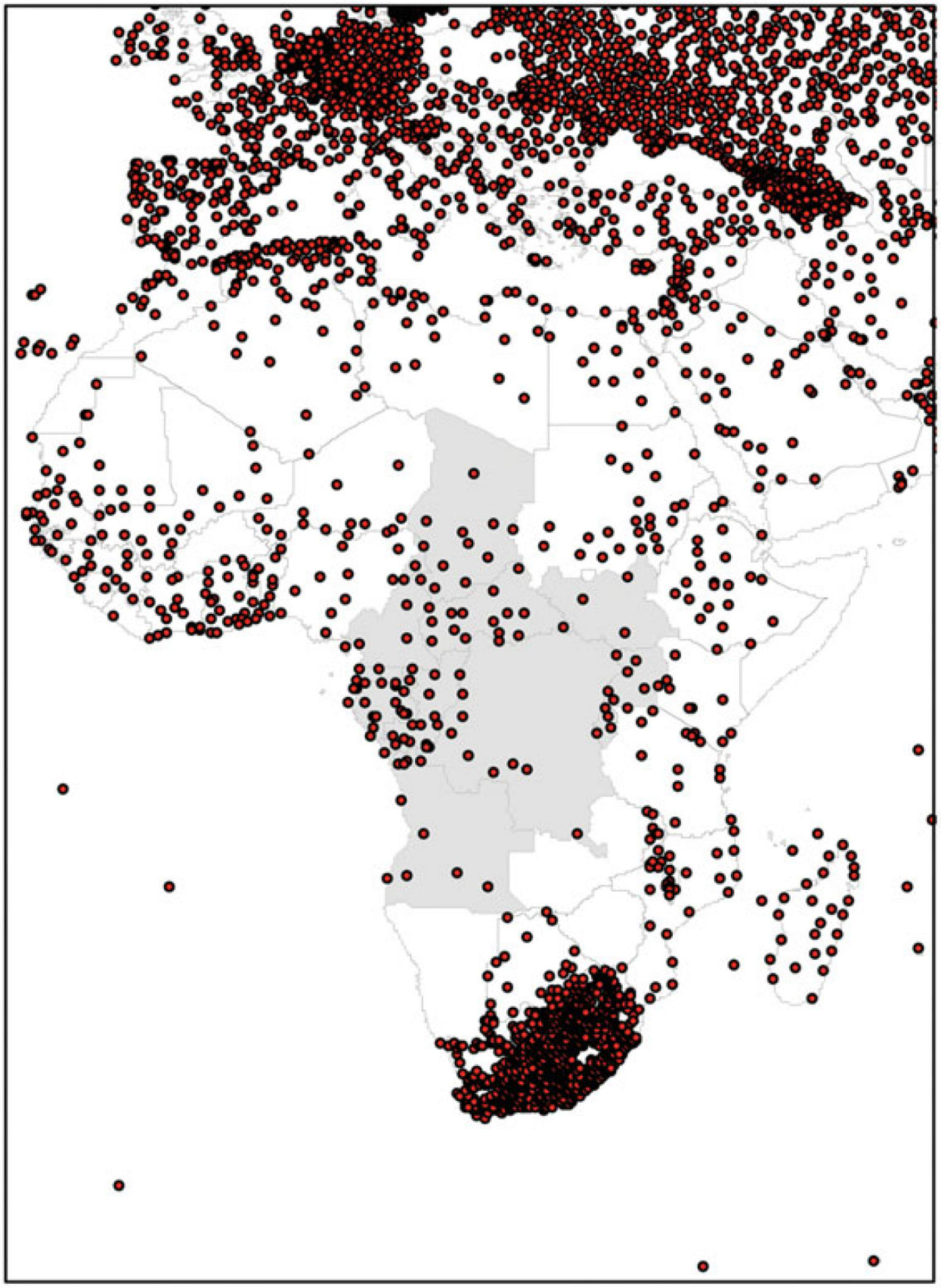

Figure 1.

Spatial distribution of gauge (GHCN) meteorological stations in Africa. Central African countries are indicated in gray.

Table 1

Climate data sources, including satellite sensors and gridded datasets

Sensor/ dataset	Satellite/ source	Spatial resolution	Temporal resolution	Dates	Metrics	Acronym	Notes
High-resolution sensors							
TM	Landsat 5 (USGS, NASA)	120 m (TIRS)—LST 30 m (VNIR)—NDVI	16 days	1984–2013	Temperature NDVI	TM: Thematic Mapper USGS: United States Geologic Survey NASA: National Aeronautics and Space Administration OLI: Operational Land Imager TIRS: Thermal Infrared Sensor VNIR: visible near-infrared LST: land surface temperature NDVI: normalized difference vegetation index	
ETM+	Landsat 7 (USGS, NASA)	60 m (TIRS)—LST 30 m (VNIR)—NDVI	16 days	1999–present	Temperature NDVI	ETM+: Enhanced Thematic Mapper Plus	
OLI	Landsat 8 (USGS, NASA)	100 m (TIRS)—LST 30 m (VNIR)—NDVI	16 days	2013–present	Temperature NDVI	OLI: Operational Land Imager	
ASTER	Terra (NASA, METI)	90 m (TIRS)—LST 15 m (VNIR)—NDVI	16 days	1999–	Temperature NDVI	ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer METI: Japanese Ministry of Economy Trade and Industry	
Moderate-resolution sensors							
AVHRR	NOAA (multiple)	1.1 km	12 h	1979–present	Temperature	AVHRR: Advanced Very High–Resolution Radiometer	LST: Split-window approach
MODIS	Terra, Aqua (NASA)	1 km—LST 250 m–1 km—NDVI	12 h	2000–present	Temperature NDVI	MODIS: Moderate-Resolution Imaging Spectroradiometer	LST: Split-window approach PPT: IR—multispectral methods, cloud properties

Sensor/ dataset	Satellite/ source	Spatial resolution	Temporal resolution	Dates	Metrics	Acronym	Notes
MVIRI	Meteosat (EUMETSAT)	5 km	Sub-daily Daily Monthly	1983–2005	Temperature	MVIRI: Meteosat Visible and Infrared Imager Meteosat: Meteorological Satellite EUMETSAT: European Organisation for the Exploitation of Meteorological Satellites	PPT:IR—cloud index methods, multispectral methods, life cycle methods, cloud model methods
SEVIRI	MSG, Meteosat-8	3 km	24 h	2005–	Temperature	SEVIRI: Spinning Enhanced Visible and InfraRed Imager MSG: Meteosat Second Generation	LST: Split-window approach, four-channel approach (3.9, 8.7, 10.8, 12.0 μm) PPT: IR—multispectral methods, cloud properties
AMSU	NOAA, Aqua, MetOp	15 km	2 h	1998–2013	Precipitation	AMSU: Advanced Microwave Sound Unit	MW
AMSR	NOAA, Aqua	15 km	Daily	1998–2011	Precipitation	AMSR: Advanced Microwave Scanning Radiometer	MW
SSM/IS	NASA, DMSP	0.25 DD	Daily	1987–2015	Precipitation	SSM/IS: Special Sensor Microwave/Imager and Sounder DMSP: Defense Meteorological Satellite Program	MW
TMI and PR	TRMM (NASA, JAXA)	0.25 DD	Sub-daily Daily Monthly	1997–2015	Precipitation	TMI: TRMM Microwave Imager PR: Precipitation Radar TRMM: Tropical Rainfall Measuring Mission JAXA: Japan Aerospace Exploration Agency	MW, IR
GMI and DPR	GPM (NASA, JAXA)	0.1 DD	2–3 h	2014–present	Precipitation	GMI: Multichannel GPM Microwave Imager DPR: Dual-Frequency Precipitation Radar GPM: Global Precipitation Measuring Mission	MW, IR
STRM	NGA, NASA	1 arcsecond (30 m)		2000	Elevation	STRM: Shuttle Radar Topography Mission NGA: National Geospatial Intelligence Agency	
Gridded data—gauge only							
LocClim	FAO	Unknown	Daily	1880–present	Temperature	LocClim: Local Climate Estimator	Gauge (FAOCLIM 2.0), interpolated

Sensor/ dataset	Satellite/ source	Spatial resolution	Temporal resolution	Dates	Metrics	Acronym	Notes
CRU TS v2.1	Tyndall Centre (UEA)	0.5 DD	Monthly	1901–2002	Temperature Precipitation	CRU TS: Climatic Research Unit Time Series UEA: University of East Anglia	Gauge, interpolated
CRU TS v3.23	CRU (UEA)	0.5 DD	Monthly	1901–2014	Temperature Precipitation		Gauge, interpolated
CPC-unified gauge	CPC (NOAA)	0.5 DD	Daily	1979–2005	Precipitation	Climate Prediction Center	Gauge (GHCN & others), interpolated
GPCC	DWD (WMO)	0.5 DD 1.0 DD 2.5 DD	Daily Monthly	1900–present	Precipitation	GPCC: Global Precipitation Climatology Centre WMO:World Meteorological Organization DWD: Deutsche Wetterdienst (German Weather Service)	Gauge (lists number of gauges in each grid), interpolated
WorldClim	WorldClim	30 arcseconds (1 km)	Climatology		Temperature Precipitation		Gauge (GHCN and others)
CRU CL 1.0	Tyndall Centre (UEA)	0.5 DD	Climatology	1961–1990	Temperature Precipitation	CRU CL: Climatic Research Unit Climatology	Gauge
PREC/L	NOAA	0.5 DD	Monthly	1948–2013	Precipitation	PREC/L: Precipitation Reconstruction over Land	Gauge (GHCN), interpolated
GISTEMP	NASA GISS	2 DD	Monthly	1880–2013	Temperature	GISTEMP: GISS Temperature Analysis GISS: Goddard Institute for Space Studies Surface	Gauge (GHCN), interpolated
CRUTEM4	CRU UEA	5 DD	Monthly	1850–2013	Temperature	CRUTEM4: Climate Research Unit Temperature 4 CRU: Climate Research Unit	Gauge (GHCN and others), interpolated
MLOST	NOAA NCDC	5 DD	Monthly	1880–2013	Temperature	MLOST: NOAA Merged Land–Ocean Surface Temperature Analysis	Gauge (GHCN), interpolated
BEST	UC Berkeley	5 DD	Daily	1701–2013	Temperature	BEST: Berkeley Earth Surface Temperatures	Gauge (GHCN & others), interpolated
Willmott and Matsuura	University of Delaware	0.5 DD	Monthly	1900–2014	Temperature		Gauge (GHCN & others), interpolated
Gridded data—satellite only							

Sensor/ dataset	Satellite/ source	Spatial resolution	Temporal resolution	Dates	Metrics	Acronym	Notes
CHOMPS	CICS	0.25 DD	Daily	1998–2007	Precipitation	CHOMPS: CICS High-Resolution Optimally Interpolated Microwave Precipitation from Satellites CICS: Cooperative Institute for Climate and Satellites	MW (SSM/I, AMSU, AMSR-E, and TRMM)
CMORPH	CPC	0.25 DD	Daily	2002–2015	Precipitation	CMORPH: CPC Morphing Technique CPC: Climate Prediction Center	MW
eMODIS	MODIS FEWS (USGS/EROS)	250 m	10 days	2000–present	NDVI	eMODIS: EROS Moderate-Resolution Imaging Spectroradiometer FEWS: Famine Early Warning System EROS: Earth Resources Observation and Science USGS: United States Geological Survey	IR
GIMMS	AVHRR (NOAA)	8 km	Bimonthly	1981–2006	NDVI	GIMMS: Global Inventory Modeling and Mapping Studies	
GlobCover	MERIS, ENVISAT (ESA)	300 m		2004–2006	Land cover map	ESA: European Space Agency	
				2006–2009		ENVISAT: Environment Satellite	
GLC2000	SPOT 4	20 m		2000	Land cover map	GLC2000: Global Land Cover 2000	
						SPOT: Satellite pour l'Observation de la Terre	
IGAD/NILE MMbd	AVHRR	1.1 km	12 h	1979–present	NDVI	IGAD: Intergovernmental Authority on Development	LST: Split-window approach
					Temperature	AVHRR: Advanced Very High–Resolution Radiometer	PPT: IR—multispectral methods
Gridded data—satellite gauge							
RFE 2.0	CPC	0.1 DD	Daily	2001–present	Precipitation	RFE: African Rainfall Estimation Algorithm	Gauge (GHCN), IR, PMW
ARC 2.0	CPC	0.1 DD	Daily Monthly	1983–present	Precipitation	ARC2: African Rainfall Climatology, version 2	Gauge (GHCN), IR

Sensor/ dataset	Satellite/ source	Spatial resolution	Temporal resolution	Dates	Metrics	Acronym	Notes
CMAP	NOAA CPC	2.5 DD	Monthly	1979–2011	Precipitation	CMAP: Climate Prediction Center Merged Analysis of Precipitation	Gauge, PMW, IR
GPCP	GSFC (NASA)	1 DD	Daily	1996–2015	Precipitation		Station gauge data, satellite data
GPCP	GSFC (NASA)	2.5 DD	Monthly	1979–2015	Precipitation		Gauge satellite soundings
PERSIANN-CDR	CHRS	0.25 DD	Daily	1983–2015	Precipitation		Gauge, PMW, IR
TMPA	NASA and JAXA	0.25 DD	Sub-daily Daily Monthly	1998–2014	Precipitation	TMPA: TRMM Multisatellite Precipitation Analysis	PMW, AMW, IR, gauge (for calibration)
IMERG	NASA	0.1 DD			Precipitation	IMERG: Integrated MultiSatellite Retrievals for GPM	Gauge, PMW, IR
EPSAT-SG		4 km	Sub-daily	2004–	Precipitation	EPSAT-SG: Estimation of Precipitation by Satellite—Second Generation	Gauge, PMW, IR
MPE	EUMETSAT	4 km	Sub-daily	2007–	Precipitation		Gauge, IR, PMW, AMW
KNMI PPP		4 km	Sub-daily	2004–	Precipitation		IR
TARCAT TAMSAT	Meteosat	4 km	Daily	1983–present	Precipitation	TAMSAT: Tropical Applications of Meteorology using Satellite data and ground-based observations	IR, gauge (for calibration)
			Monthly			TARCAT: TAMSAT African Rainfall Climatology And Time Series	
NCEP/ NCAR R1		2.5 DD	Sub-daily Daily Monthly	1948–2015	Temperature	R1: First-generation reanalysis (Vintage: 1995) NCEP: National Centers for Environmental Prediction NCAR: National Center for Atmospheric Research	Gauge, satellite
AgMIP	MERRA	0.5 DD 0.25 DD	Climatology	1980–2010	Temperature Precipitation	AgMIP: Agricultural Model Intercomparison and Improvement Project MERRA: Modern Era Retrospective Analysis for Research and	Gauge, TRMM, CMORPH,PERSIAN

Sensor/ dataset	Satellite/ source	Spatial resolution	Temporal resolution	Dates	Metrics	Acronym	Notes
						Applications CFSR: Climate Forecast System Reanalysis	
OISST	AVHRR, AMSRE (NOAA)				SST	OISST: Optimum Interpolation Sea Surface Temperature	Ships, buoys, AVHRR, AMSRE
Other							
The Spatial Charac- terization			Monthly		Precipitation	The Spatial Characterization Tool—Africa v. 1.0	
Tool					Temperature	Texas Agricultural Experimental Station, Texas A&M University	
DARLAM	CSIRO	125 km				CSIRO: Commonwealth Scientific and Industrial Research Organisation	Regional Climate Model For Australia—outdated; now they are using ACCESS
The climate of Africa					Precipitation		BW Thompson, Oxford University Press, 1965
African Remote Sensing	ASECNA					ASECNA: Agency for Air Navigation Safety in Africa and Madagascar	
Data Bank							

Note: 1 DD= 111.32 km at equator; 30 arcseconds = 0.86 km^2 (1 km^2).

Table 2

Summary of data from 104 global historical climate network (GHCN) stations for Central African countries

Country	Station	Start date	End date	Days	Area (km^2)	Density (per 100,000 km^2)	Recordings with data	Coverage (%)
Angola	7	1/28/53	10/20/15	22,179	1,246,700	0.56	15,703	10.11
Burundi	2	1/1/50	12/31/89	14,609	27,834	7.19	27,941	95.63
Central African Republic	17	1/1/50	10/20/15	24,033	622,984	2.73	160,597	39.31
Cameroon	5	1/1/48	10/20/15	24,764	475,442	1.05	16,702	13.49
Chad	11	1/1/50	10/20/15	24,033	1,284,000	0.86	109,779	41.53
Democratic Republic of Congo	13	2/18/73	10/20/15	15,584	2,344,858	0.55	4278	2.11
Equatorial Guinea	2	5/1/96	10/20/15	7111	28,051	7.13	568	3.99
Gabon	19	1/1/50	10/20/15	24,033	267,668	7.10	15,5103	33.97
Republic of Congo	15	3/1/47	10/20/15	25,070	342,000	4.39	151,355	40.25
Rwanda	1	6/29/73	10/20/15	15,453	26,338	3.80	3513	22.73
South Sudan	4	1/1/50	10/20/15	24,033	619,745	0.65	34,871	36.27
Uganda	8	1/1/26	12/31/86	22,279	241,550	3.31	123,329	69.20

Note: Coverage is the number of days of temperature and precipitation observations divided by the total number of days of recording possible, calculated as the number of days between the first and last recording dates (days) multiplied by the total number of stations for each country (station). Area estimates are from the United Nations Statistics Division (unstats.un.org/unsd/demographic).

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Table 3

The key terms used forWeb of Science searches

Infectious disease	**Meteorology**	**Country**
Tuberculosis	Climate	Chad
Malaria	Meteorology	Central African Republic
Respiratory infection	Hydrology	South Sudan
Pneumonia	Humidity	Democratic Republic of Congo
Mosquito[a]	Water	Rwanda
Meningitis	Precipitation	Congo
Diarrhea[a]	Rainfall	Gabon
Diarrhoea[a]	Temperature	Equatorial Guinea
Cholera	Dew point	Cameroon
Influenza		Uganda
Infection[a]		Burundi
Zoono[a]		Angola
Vector-borne		
Water-borne		
Virus		
Bacteria		
Helminth		
Protozoa		
Fever		
Worm		
Parasite[a]		

Note: The key terms used for Web of Science searches were separated into three categories: infectious disease, meteorology, and country. Every search contained one key term from each category.

[a]The search was conducted with all completions of the indicated word.

Table 4

Papers categorized by disease topic

Mode of transmission	Disease	Number of papers (%)
Vector-borne		40 (60.6)
	Malaria	29 (43.9)
	African trypanosomiasis	4 (6.0)
	Plague	1 (1.5)
	Dengue fever	1 (1.5)
	Avian malaria	1 (1.5)
	Onchocerciasis	1 (1.5)
	Yellow fever	1 (1.5)
Water-borne		15 (22.7)
	Schistosomiasis	6 (9.0)
	Cholera	6 (9.0)
	Guinea worm	1 (1.5)
	Coliform bacterial infection	1 (1.5)
	Hepatitis E	1 (1.5)
Respiratory		7 (10.6)
	Meningitis	1 (1.5)
	Tuberculosis	1 (1.5)
	Acute respiratory infections	1 (1.5)
	Influenza	1 (1.5)
Direct contact		6 (9.0)
	Monkeypox	3 (4.5)
	Ebola	1 (1.5)
	Mycetoma	1 (1.5)
	Hookworm	1 (1.5)
Fecal oral		2 (3.0)
	Ascariasis	1 (1.5)
	Trichuriasis	1 (1.5)

Note: Several papers studied multiple diseases and were placed in all relevant disease categories.

Table 5

Summary of meteorological data used in papers

Meteorological data sources	Number of papers (%)
Local meteorological stations	22 (33.3)
Large gridded datasets	16 (24.2)
Seasons	12 (18.2)
Satellite data	10 (15.2)
Directly measured	8 (12.1)
Unknown	4 (6.0)

Note: Several papers used multiple types of data and are included in all relevant data categories.

Table 6

Summary of disease data types used in papers

Disease data type	Papers (%)
Human disease records	36 (54.4)
Animal host or vector sampling/collection/trapping	19 (28.7)
Primary human data collection	15 (22.7)
Water samples	5 (7.5)
Species occurrence data	2 (3.0)

Note: Several papers used multiple types of data and are included in all relevant data categories.

Table 7

Occurrence of spatial mismatch stratified by the type of climate data used

Data type	Unknown	Mismatched	Not mismatched	Total
Directly measured	0	0	8	8
Local meteorological station	10	6	6	22
Satellite	0	0	10	10
Large gridded dataset	4	7	5	16
Total	14	13	29	56

Note: “Unknown” indicates that insufficient information was provided to determine spatial mismatch. Each cell contains the total number of papers in that category.