EUROPEAN SPACE AGENCY CONTRACT REPORT

The work described in this document was done under ESA Contract. Responsibility for the contents resides in the author or organisation that prepared it.

WASCIA – WATER STRESS AND CLIMATE INDICES FOR AFRICA

State-of-the-art Review Report - relevant EO-based methods and solutions

Reference	WaSCIA.TN.008	**Iss./Rev.**	1.1
		Date	07/03/2023

Prepared By	**Approved By**
Guy Schumann (RSS-Hydro)	E. Biescas – Project Manager (TPZ-UK)
Mohamad Nobakht (TPZ-UK)	S. Kaur – QA Manager (TPZ-UK)

CHANGE LOG

Reason for change	Issue	Revision	Date	Page(s) and Paragraph(s) affected
Initial version	1	0	15/02/2023	All
Consideration of the use of Sentinel-2 data	1	1	07/03/2023	Pages 14-15

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

1.1 *PURPOSE OF DOCUMENT*

This document is part of the D3 deliverable for the ESA Water Stress and Climate Indices for Africa (WaSCIA) project. It contains a comprehensive review of the state-of-the-art of EO-based methods and information technology with direct relevance to the proposed specific issue being addressed.

It also includes the science and applications underlying the climate indicators being proposed.

1.2 *CONTENTS OF DOCUMENT*

Following this introductory section, the document layout is as follows:

Section 2 presents the review of the soil moisture and water stress.

Section 3 presents the review of climate data and services.

This is partitioned as:

Section 3.1 contains the climate data review.

Section 3.2 contains the climate indices review.

Section 3.3 contains the review of climate services.

Section 4 presents the Conclusions.

1.3 REFERENCES

1.3.1 Applicable Documents

The following applicable documents are those referenced in the Contract or approved by the Agency. They are referenced in this document in the form [AD n.]:

AD	Title	Version / Date
AD 1.	Statement of Work - ESA Express Procurement [Plus] - [EXPRO+] - EO AFRICA - NATIONAL INCUBATORS EXPRO+	1.0 26/10/2021
AD 2.	KPT91865-AO11039-Proposal-EOAFRICA-R1r0.pdf	1.0 18/02/2022
AD 3.	WASCIA-KO-Minutes_1.0.pdf	1.0 07/10/2022

1.3.2 Reference Documents

The following reference documents are those referenced within this document. They are referenced in this document in the form [RD n.]. They are not applicable documents.

RD	Title / source	Version / Date
RD 1.	Gerhards, M.; Schlerf, M.; Mallick, K.; Udelhoven, T. Challenges and Future Perspectives of Multi-/Hyperspectral Thermal Infrared Remote Sensing for Crop Water-Stress Detection: A Review. *Remote Sens.* **2019**, *11*, 1240. https://doi.org/10.3390/rs11101240	2019
RD 2.	Rodríguez-Fernández, Nemesio, Ahmad Al Bitar, Andreas Colliander, and Tianjie Zhao. 2019. "Soil Moisture Remote Sensing across Scales" Remote Sensing 11, no. 2: 190. https://doi.org/10.3390/rs11020190	2019
RD 3.	Peng, Jian, and Alexander Loew. 2017. "Recent Advances in Soil Moisture Estimation from Remote Sensing" Water 9, no. 7: 530. https://doi.org/10.3390/w9070530	2017
RD 4.	Toby N. Carlson & George P Petropoulos (2019): A new method for estimating of evapotranspiration and surface soil moisture from optical and thermal infrared measurements: the simplified triangle, International Journal of Remote Sensing, DOI: 10.1080/01431161.2019.1601288	2019
RD 5.	Petropoulos, George P., Ionut Sandric, Dionissios Hristopulos, and Toby Nahum Carlson. 2020. "Evaporative Fluxes and Surface Soil Moisture Retrievals in a Mediterranean Setting from Sentinel-3 and the "Simplified Triangle"" Remote Sensing 12, no. 19: 3192. https://doi.org/10.3390/rs12193192	2020

RD	Title / source	Version / Date
RD 6.	Ke, Yinghai, Jungho Im, Seonyoung Park, and Huili Gong. 2016. "Downscaling of MODIS One Kilometer Evapotranspiration Using Landsat-8 Data and Machine Learning Approaches" Remote Sensing 8, no. 3: 215. https://doi.org/10.3390/rs8030215	2016
RD 7.	DeGaetano, A.T., 2006. Attributes of several methods for detecting discontinuities in mean temperature series. Journal of Climate, 19(5), pp.838-853.	2006
RD 8.	Begert, M., Zenklusen, E., Haberli, C.H.R.I.S.T.I.A.N., Appenzeller, C. and Klok, L., 2008. An automated procedure to detect discontinuities; performance assessment and application to a large European climate data set. Meteorologische Zeitschrift, 17(5), p.663.	2008
RD 9.	Yang, W., John, V.O., Zhao, X., Lu, H. and Knapp, K.R., 2016. Satellite climate data records: Development, applications, and societal benefits. Remote Sensing, 8(4), p.331.	2016
RD 10	Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D. and Simmons, A., 2020. The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society, 146(730), pp.1999-2049.	2020
RD 11	Ssenyunzi, R.C., Oruru, B., D'ujanga, F.M., Realini, E., Barindelli, S., Tagliaferro, G., von Engeln, A. and van de Giesen, N., 2020. Performance of ERA5 data in retrieving Precipitable Water Vapour over East African tropical region. Advances in Space Research, 65(8), pp.1877-1893.	2020
RD 12	Sterl, S., Liersch, S., Koch, H., Lipzig, N.P.V. and Thiery, W., 2018. A new approach for assessing synergies of solar and wind power: implications for West Africa. Environmental Research Letters, 13(9), p.094009.	2018
RD 13	Sadoti, G., Albright, T.P. and Johnson, K., 2017. Applying dynamic species distribution modelling to lek-mating species. Journal of Biogeography, 44(1), pp.75-87.	2017
RD 14	Patara, L., Vichi, M. and Masina, S., 2012. Impacts of natural and anthropogenic climate variations on North Pacific plankton in an Earth System Model. Ecological modelling, 244, pp.132-147	2012
RD 15	Martinez, C.J., Baigorria, G.A. and Jones, J.W., 2009. Use of climate indices to predict corn yields in southeast USA. International Journal of Climatology: A Journal of the Royal Meteorological Society, 29(11), pp.1680-1691.	2009

RD	Title / source	Version / Date
RD 16	Y. Liu, J. Qian and H. Yue, "Comprehensive Evaluation of Sentinel-2 Red Edge and Shortwave-Infrared Bands to Estimate Soil Moisture," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 7448-7465, 2021, doi: 10.1109/JSTARS.2021.3098513.	2021
RD 17	Gao, B.-C. 1996. NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment 58: 257-266. Link to Article	1996

1.4 ACRONYMS AND TERMS

The following acronyms and terms are used in the document and have the identified meaning.

Acronym / Term	Definition
C3S	Copernicus Climate Change Services
CCKP	Climate Change Knowledge Portal
CDS	Climate Data Store
ECMWF	European Centre for Medium-Range Weather Forecasts
ECV	Essential Climate Variable
EF	Evaporation Fraction
EO	Earth Observation
ET	Evapotranspiration
ETCCDI	Expert Team on Climate Change Detection and Indices
GCOS	Global Climate Observing System
GPM	Global Precipitation Measurement
GUI	Graphical User Interface
IOC	Intergovernmental Oceanographic Commission
ISC	International Council for Science
JAXA	Japan Aerospace Exploration Agency
MARS	Meteorological Archival and Retrieval System
NASA	National Aeronautics and Space Administration
NCEP	National Center for Environmental Prediction

Acronym / Term	Definition
NDVI	Normalized Difference Vegetation Index
RF	Random Forest
UNESCO	United Nations Educational, Scientific and Cultural Organization
WaSCIA	Water Stress and Climate Indices for Africa
WMO	World Meteorological Organization

2 SOIL MOISTURE AND WATER STRESS

Soil moisture plays an important role in the water, carbon and energy cycles. The amount of moisture in the soil is an important variable for understanding surface-atmosphere coupling. As an Essential Climate Variable (ECV), soil moisture is a key component in improving weather forecasting and climate models as well as improving precipitation estimates, monitoring droughts, and forecasting natural hazards such as landslides and floods. Thanks to a series of sensors with different characteristics, it is possible to study soil moisture content at different spatial scales, from a few tens of kilometres to tens/hundreds of metres.

[RD 1] provides a detailed review of challenges and future perspectives of multi-/hyperspectral thermal infrared remote sensing for crop water-stress detection. Many methods exist to derive water stress indicators from remote sensing, and generally speaking, performances can vary greatly and there is not one best method. Rather, a well-informed decision should be made based on data availability and user needs and requirements.

Combining data from different instruments with sensors across the electromagnetic spectrum (different microwave, visible, infrared, active and passive sensors) can improve the quality of soil moisture data obtained from a single instrument [RD 2]. Extensive validation studies, either by direct comparison with in situ measurements or comparison between different remote sensing products, have been conducted to quantify the accuracy of these soil moisture products. In addition, the applications of these products have been extensively researched in many fields such as agriculture, hydrology, and climate science. However, there are still potentials to improve the interrogation algorithms and open scientific questions on the validation and application of the remote sensing products. In addition, there is a strong need to develop soil moisture products with high spatial and temporal resolution and reduced latency [RD 3].

[RD 4] proposes a very simple method to implement, yet reliable to calculate Evapotranspiration Fraction (EF) and surface Moisture availability (Mo) from remotely sensed imagery of Normalized Difference Vegetation Index (NDVI) and surface radiometric temperature (Tir). According to their study, the method is unique in that it derives all of its information solely from these two images. As such, it does not depend on knowing ancillary surface or atmospheric parameters, nor does it require the use of a land surface model. This of course has many advantages, it is straightforward to implement, and easy to upscale. Also, it does not require the introduction of a complex energy balance model, nor resource-intensive field data collection.

Moreover, as the scheme is not tied to any particular sensor, it can also be implemented with technologically advanced EO (Earth Observation) sensors launched recently or planned to be launched such as Landsat 9+ and Sentinel-3 next generation. It is worth noting here that the use of these two satellite missions offers a number of key advantages in terms of future implementation of the method and wider use for research and practical applications alike.

Water stress monitoring in this project will be based on Sentinel-3 data as described in [RD 5]. For calculating evaporative losses and soil wetness dynamics, the "**Simplified Triangle**" technique will be used. It is a new Ts/VI (surface temperature & vegetation) technique proposed by [RD 4], and makes it possible to derive spatial estimates of the surface wetness (Mo, which refers to the first few millimetres of a surface covered by bare soil) and of the evaporative fraction (EF, being the ratio of evapotranspiration to net radiation (Rn)). The principle on which the method is based is illustrated in Figure 2-1.

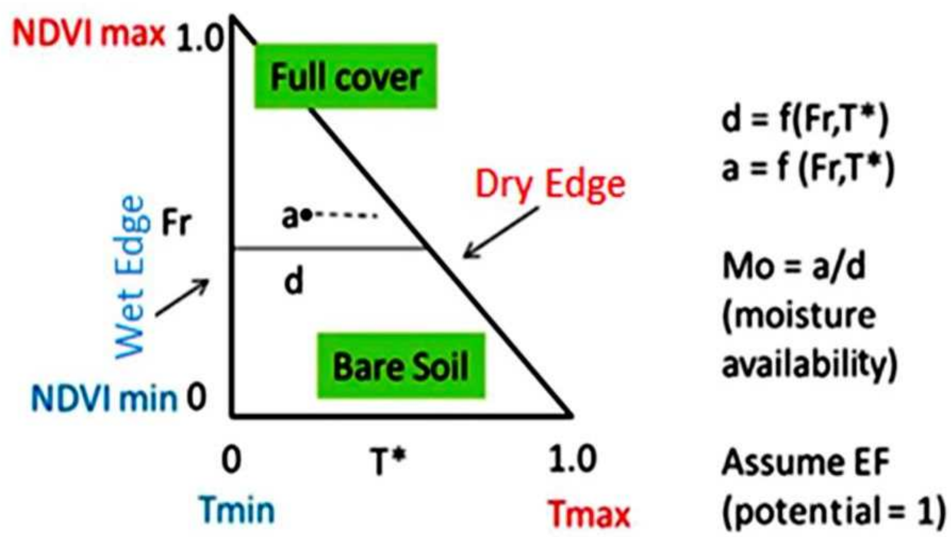

Figure 2-1: Illustration of the concept of the simplified triangle technique [RD 5]

In order to minimize measurement errors, the two images, those of Tir and NDVI, must represent a reasonably uniform terrain height (not varying by more than about 10%) and should not contain a large fraction of standing water or cloud. Although different vegetation types may be present in the image without great loss of accuracy, highly inhomogeneous vegetation such as a forest situated aside a field of corn or grass might introduce some error (including edge effects) in the derived surface parameters [RD 4].

The WaSCIA service will primarily use Sentinel-3 data for water stress monitoring, given the suitability of its sensors and the correct temporal resolution. In order to achieve a better spatial resolution, the application will fuse Sentinel-3 with Landsat 8 or 9. The Sentinel-3 derived indicators will be downscaled to 30 m resolution using the Random Forest (RF) model that demonstrates the relationship between the Landsat channels and the Sentinel-3 channels, which are at a lower spatial resolution but much higher temporal resolution.

As illustrated by Figure 2-2, the RF model is then used to predict 30 m water stress indicators based on Landsat 8 or 9. Such models have already successfully applied to downscale MODIS 1 km daily Evapotranspiration (ET) with Landsat 8 [RD 6].

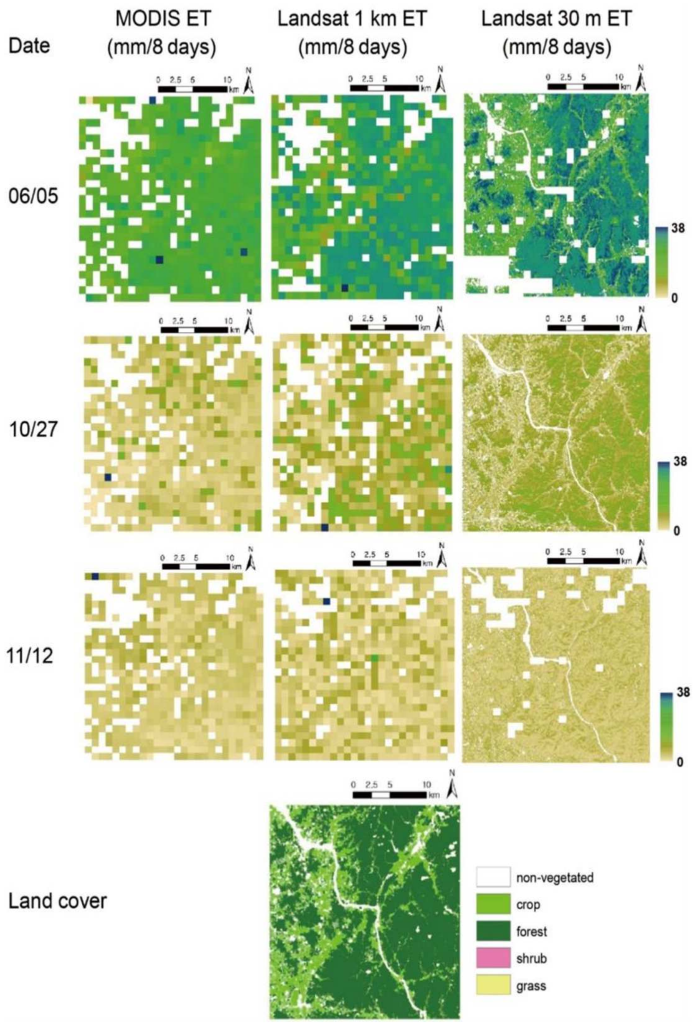

Figure 2-2: MODIS 8-day ET, Landsat 1 km ET and downscaled Landsat (for a study site used in [RD 6])

Other than using Landsat to downscale the water stress index from Sentinel-3, the WaSCIA project will also explore the use of Sentinel-2 red edge (R) and near-infrared (NIR) bands as demonstrated by [RD 16] to estimate soil moisture. This paper states that this SMMI (Soil Moisture Monitoring Index) correlates well with soil moisture measured at a depth of up to 0.5 m. The SMMI is given by the following equation:

$$\mathrm{SMMI} = \frac{OB}{OD} = \frac{\sqrt{{R_{\mathrm{red}}}^2 + {R_{\mathrm{NIR}}}^2}}{\sqrt{2}}$$

Another relevant index based on Sentinel-2 that could be used to correlate to the Sentinel-3 derived water stress index and thereby allowing a downscaling to even 10 m (as opposed to the Landsat 30 m resolution), is the NDMI (Normalized Difference Moisture Index) as inspired by [RD 17]. The NDMI uses NIR and SWIR bands (Sentinel-2 NDMI = {B08 - B11} / {B08 + B11}) to estimate moisture content in vegetation. The SWIR band reflects changes in both the vegetation water content and the spongy mesophyll structure in vegetation canopies, while the NIR reflectance is affected by leaf internal structure and leaf dry matter content but not by water content. The amount of water available in the internal leaf structure largely controls the spectral reflectance in the SWIR interval of the electromagnetic spectrum. SWIR reflectance is therefore negatively related to leaf water content. In short, NDMI is used to monitor changes in water content of leaves.

The script for Sentinel-2 based NDMI is freely available on GitHub from here: https://github.com/sentinel-hub/custom-scripts/tree/master/sentinel-2.

3 REVIEW OF CLIMATE DATA AND SERVICES

Reliable and decision-relevant climate information at a local and national level and on all weather and climate time scales are needed for monitoring drought and water stress. For instance, timely information on precipitation and air temperature during the growing season, particularly at late vegetative and early reproductive stages of crop development, is of crucial importance for in-season monitoring of crop performance. Temperature also plays a key role in modulating surface hydrology and the severity of droughts. For many end-users in the agriculture sector, assessments of crop development for the current cropping seasons are particularly important. This is especially true for agro-policy in Africa, as early indications of production anomalies are of paramount importance for food security and early warning systems that operate at local and national scale.

We have reviewed the relevant literature on climate data and services, with a focus on the agriculture sector, using a three-step approach as presented in the following sections.

3.1 *CLIMATE DATA*

There is a high demand for accurate climate data with high spatial and temporal resolution, at both near-real time (for monitoring) and historical timescales (for trend analysis). However, the end-users and mostly agricultural researchers still face critical limitations for accessing basic sources of climate data due to a number of factors, including data availability, data accessibility and maintenance and data quality checks [RD 7].

There has been a global effort in recent decades to improve access to standardized climate records for users across different sectors. For instance, the Global Climate Observing System (GCOS) was established in 1992 as an internationally coordinated network of observing systems and programme of activities, to ensure sustained provision of reliable observations and data records needed to address climate-related issues. GCOS is co-sponsored by the World Meteorological Organization (WMO), Intergovernmental Oceanographic Commission (IOC) of United Nations Educational, Scientific and Cultural Organization (UNESCO), United Nations Environment Programme (UN Environment), and International Council for Science (ISC). Despite their great successes, global climate observations are not yet complete. The 2021 GCOS Status Report on the Global Climate Observing System identified several areas of concern. For example, in-situ observations for almost all the Essential Climate Variables (ECV) are consistently deficient over certain regions, most notably parts of Africa, South America and Southeast Asia.

When it comes to the agriculture sector, the in-situ weather data at local level are often scarce because either (1) weather stations are sparse or not available; (2) weather stations are poorly maintained so data are either only available for a short period or contain gaps; (3) collected data are not properly stored; (4) data do not pass basic quality checks; and/or (5) access to data is restricted by holding institutions. Apart from the constraints related to access and weather station locations, data quality was highlighted by several studies as probably the most important issue regarding weather data ([RD 8], [RD 7]).

Over the past half-century the climate observations have been transitioning from in-situ, regional, and short-term observations to multiple, global, and long-term observations, due to rapid advances satellite observations from geostationary and polar-orbiting satellites, equipped with both passive and active sensors [RD 9]. Today, long-term consistent Earth Observation (EO) are becoming indispensable for providing information for improved detection, attribution, and prediction of global climate and environmental changes.

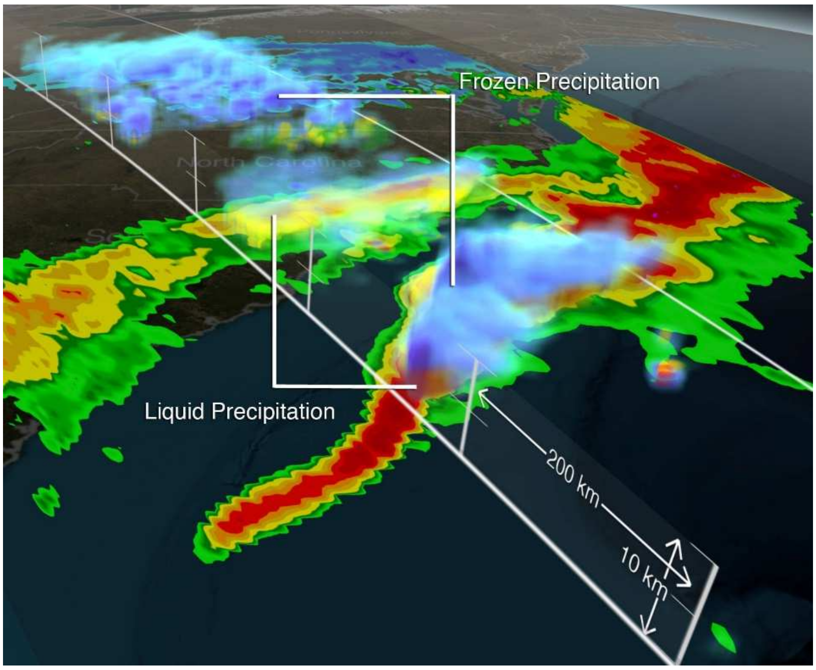

Figure 3-1: Full range of precipitation, from rain to snow, observed by the Global Precipitation Measurement (GPM) Core Observatory, a joint mission of NASA and the Japan Aerospace Exploration Agency (JAXA), on March 17 2014, eastern United States (credit https://gpm.nasa.gov)

Despite the great advantages of satellite EO data such as extended spatial coverage and enhanced temporal coverage, near surface atmospheric variables driven from satellite EO cannot entirely replace the in-situ observations. Some of the main limitations of satellite EO solutions identified in literature are as follows:

- Large uncertainties in assessment of atmospheric variables from space
- Poor temporal resolution compared to weather stations
- Problems with aerosols and clouds in optical imagery

- Vertical distribution of atmospheric variables is very complex and cannot be resolved from EO imagery
- Problems in many retrieval mechanisms, especially over land
- Satellite EO data records are not long enough for long term climate reconstruction

To understand climate change and current weather extremes, it is crucial to have observations of the ECVs going back as far as possible in time. However, observations have always been unevenly distributed and even in the satellite era, observations alone cannot provide all the weather and climate information needed by the end-users across different sectors.

Atmospheric reanalyses fills this gaps in the observational record, and they do so in a way that is consistent in time, thus minimising any spurious signals of change. Reanalysis products are often considered as an alternative solution to observational weather and climate data due to availability and accessibility problems, particularly in data-sparse regions such as Africa.

Reanalysis products combine observations, advanced modelling and data assimilation systems to provide a comprehensive description of how the climate has evolved during recent decades over three-dimensional grids at sub-daily time intervals.

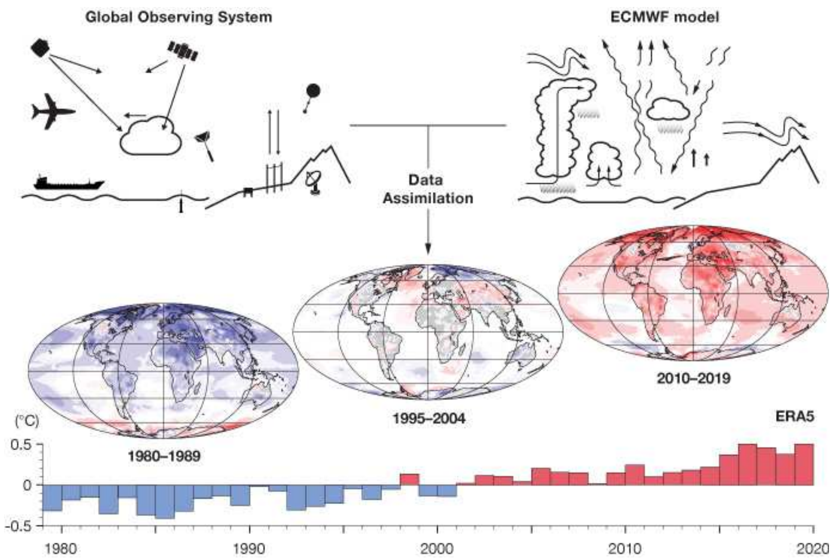

Figure 3-2: A schematic of the reanalysis process (https://www.ecmwf.int)

There are a handful of global reanalysis datasets available from international meteorological data providers such as the European Centre for Medium-Range Weather

Forecasts (ECMWF)[1] and National Center for Environmental Prediction (NCEP)[2]. ERA5 is one of the latest released atmospheric reanalysis datasets, developed by the ECMWF [RD 10]. It contains hourly estimates of atmospheric parameters such as precipitation and air temperature for the period 1950 to present at 0.25° (~31 km). It has been used in numerous studies for climate change impact assessments and shown to be suitable for a range of applications, in particular over regions with limited in-situ data availability such as Africa ([RD 11], [RD 12]). ERA5-Land is the newest reanalysis dataset which is a re-run of the land component derived from the ERA5 reanalysis. The land component has improvements that benefits applications in areas such as agriculture, water resources management and drought prediction, particularly with its enhanced resolution 9 km versus 31 km for ERA5.

3.2 *CLIMATE INDICES*

Climate indices are standardised metrics for assessing climate variability based on various meteorological variables, often using daily meteorological data. They are useful in conveying long-term climate variability and characterising the climate anomalies. Some climate indices are used to detect extremes in temperature and precipitation, such as the 27 core indices developed by the Expert Team on Climate Change Detection and Indices (ETCCDI). However, many more indices are used for socio-economic sectors such as agriculture, tourism, health and energy. For instance, Agro-climatic indices are often used in species distribution modelling [RD 13], ecological modelling [RD 14] and in studying phenological developments of plants under varying climate conditions [RD 15].

There are a substantial overlap between different sets of climate indices recommended in the literature. Through the WaSCIA service we will provide a set of climate indices by processing ERA5-Land hourly temperature and precipitation data from 1950 to five days behind real-time. Delivered through a highly flexible and interactive interface, WaSCIA climate indices enable end-users to quickly assess the climate condition in their region of interest and analyse both the long-term trends in climate variability and the current season anomalies up to 5 days behind real time. The end-users will also be able to take advantage of the advanced interfaces to interrogate the data and produce customised metrics useful for their operations.

[1] https://www.ecmwf.int/
[2] https://www.ncep.noaa.gov/

Table 3-1 presents a list of initial climate indices that will be provided by WaSCIA service. This list will be refined during the agile development cycles to reflect African end-user's requirements.

Table 3-1: Climate indices provided by WaSCIA

Indicator	Description
GSL	Growing Season Length
SPEI	Standardised Precipitation Evapotranspiration Index
CDD	Maximum number of consecutive dry days (Drought spell)
CFD	Maximum number of consecutive frost days (Cold spell)
CSDI	Cold-spell duration index
WSDI	Warm-spell duration index
CSU	Maximum number of consecutive summer days (Hot spell)
CWD	Maximum number of consecutive wet days (Wet spell)
WW	Warm and wet days
DTR	Mean of diurnal temperature range
GDD	Growing Degree Days
R10mm	Heavy precipitation days
R20mm	Very heavy precipitation days
RR	Precipitation sum
RR1	Wet Days
SDII	Simple daily intensity index

3.3 *CLIMATE SERVICES*

Recent advances in cloud computing and geospatial visualization has opened the door for delivering the data and information through full featured interfaces which allows data interrogation and visualisation as well as performing complex analytical processes. In the context of the EO and climate services, these solutions can be categorised into four generations of EO and climate data delivery systems:

1. Data archives for climate data and pre-calculated climate indices, which allows data retrieval as granular data files in common formats e.g. NetCDF, HDF, GRIB, TIFF, etc. An example of this generation is ECMWF's Meteorological Archival and Retrieval System (MARS)[3] which allow users select the required climate variables and download the data over API, HTTP or FTP protocols.

[3] https://confluence.ecmwf.int/display/UDOC/MARS+user+documentation

2. Data catalogues which allow exploration of archives and visualising raw and pre-processed data. An example of this generation is Copernicus Open Access Hub[4] which allows user to explore the archive through a Graphical User Interface (GUI) and download the data for the area of interest defined by the user.

3. Data catalogues with analytical capabilities that enable performing data analytics such as temporal and spatial aggregation, averaging, etc. on the fly via an interactive GUI. An example of this generation is the World Bank Climate Change Knowledge Portal (CCKP)[5], where users are able to select the data, perform data analytics and generate country level information in the form of interactive plots etc.

4. Advanced data catalogues with programming interfaces to allow direct interaction with the underlying EO and climate data. The programming environment links the raw and pre-processed data products to online computing power. An example of this generation of services is Copernicus Climate Change Services Climate Data Store (C3S CDS)[6] which is powered by a toolbox that enables creating applications in Python programming language and running them on the CDS computers. Users are able to retrieve the data, run the calculations and processes they require and display/store the results in the format that suits their needs (e.g. graphs and maps) without downloading any data on the local machines.

[4] https://scihub.copernicus.eu/
[5] https://climateknowledgeportal.worldbank.org/
[6] https://cds.climate.copernicus.eu/

4 CONCLUSIONS

This document reviewed two main parts of the WaSCIA project: soil moisture and water stress as well as the climate indices.

Many different approaches exist to derive soil moisture and water stress information from remote sensing. The aim of the WaSCIA project is to upscale a mapping algorithm all over Senegal, and potentially other countries in Africa, using an online cloud computing platform. Therefore, the review of soil moisture and water stress focuses on the simple “triangle” method that uses only the NDVI and the thermal images from satellites to derive information on soil moisture.

The review of the relevant literature on climate data and services focuses on the agriculture sector and describes the climate indices offered that are based on reanalysis data and focus on drought-related parameters.

It should be noted that the EO-based method selected for deriving information about soil moisture and water stress is very complementary to the climate indices being proposed in this project.

[End of Document]