Kenya Food Security & Agriculture II

Utilizing NASA Earth Observations to Enhance Drought Warning Systems and Develop Capacity to Use the RHEAS Model in Kenya

**Technical Report**

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# 1. Abstract

Twenty-three counties in Kenya experience frequent drought, which damages agricultural productivity and threatens the health and wellbeing of millions. NASA DEVELOP partnered with NASA SERVIR, the Regional Centre for Mapping of Resources for Development (RCMRD) and Kenya’s National Drought Management Authority (NDMA) to enhance drought-detection capacity using NASA Earth observations. Currently, the NDMA publishes monthly Early Warning Bulletins with drought conditions for each arid or semi-arid county in Kenya. These bulletins utilize the Vegetation Condition Index (VCI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) as well as a variety of biophysical, social and economic drought indicators, but do not allow for advanced forecasting. To improve drought-monitoring capabilities, the team created a Combined Drought Indicator (CDI) using the Regional Hydrologic Extremes Assessment System (RHEAS) model and data from Aqua and Terra MODIS and the National Centers for Environmental Prediction.  The CDI combined precipitation anomalies, soil moisture anomalies, evaporative stress, and VCI according to weights determined by principal component analysis. To evaluate the performance of the CDI across Kenya, the team compiled a dataset of drought events from historical reports and the NDMA’s records. Results suggested that the CDI detected drought earlier than VCI alone. However, more validation is needed to ensure that the CDI accurately and consistently detects drought earlier than current warning systems. In order to better understand the behavior of individual indices and the potential for earlier drought detection, the team also conducted a time-lag analysis. The team found that VCI responds to drought, on average, one month later than most other indices included in the CDI, suggesting that incorporating additional indices could improve early drought warning systems in Kenya.

**Keywords**

RHEAS, remote sensing, drought, Aqua, Terra, MODIS, SERVIR

# 2. Introduction

***2.1 Background Information***

Drought is a widespread climate hazard that affects millions of people and causes severe economic damage (WMO, 2016; Sepulcre-Canto et al., 2012). Definitions of drought vary, but the three main types of drought recognized by the scientific community are meteorological, agricultural, and hydrological drought (Balint et al., 2013). Droughts can lead to reduced agricultural production (Sepulcre-Canto et al., 2012; Balint et al., 2013; Narasimhan et al., 2005), large scale food insecurity, outbreaks of diseases, and severe land degradation (Masih et al., 2014). Consequently, decision-makers are currently interested in predicting drought to mitigate impacts on economic production and human wellbeing. Despite the complicated drivers and effects of drought, its relatively slow onset makes it better suited for monitoring than other natural hazards (WMO, 2016). Drought can be monitored through meteorological indicators, such as precipitation anomalies, and agricultural indicators, like crop yield and vegetation stress (Balint et al., 2013). Since drought has such severe economic and social consequences and may often occur in areas with insufficient *in situ* data (Andreadis et al., 2017; Bayissa et al., 2019), there is a need to develop more accurate drought prediction tools based on remotely sensed data.

One effective tool for monitoring drought is a combined drought indicator (CDI). A CDI facilitates visualization of drought progression and decision making because multiple drought indices are combined into a single indicator. An additional value of utilizing a CDI is the ability to predict agricultural drought progression based on the cause-effect relationship between precipitation deficit and vegetation stress, as demonstrated in Sepculcre-Canto et al. (2012). A CDI predicts these stages of drought based on the timing when each index demonstrates an anomaly, improving its robustness.

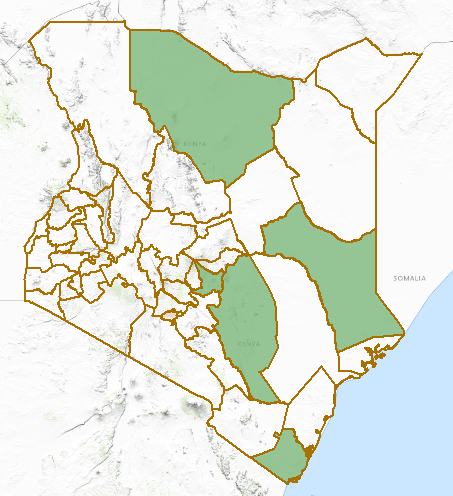
Roughly 80% of Kenya is classified as arid or semi-arid lands (ASALs), where arid lands receive less than 550mm of rain a year and semi-arid lands receive less than 850mm a year (Uhe et al., 2018). Thirty percent of Kenya’s population lives in ASALs, and rain-fed subsistence agriculture is one of the primary economic activities across the country (Uhe et al., 2018). This economic dependence on agriculture means that severe droughts can be debilitating for the country, both economically and socially (Barrett et al., 2019), due to the fact that many of Kenya’s crops are not drought resistant. During 2016 and 2017, for example, roughly 3 million people in Kenya required food aid as a result of severe drought (Uhe et al., 2018).

The first term of this project utilized the Regional Hydrologic Extremes Assessment System (RHEAS) to create a drought time series at the county-level in Kenya and analyzed various drought indices to determine which would best complement current drought management in Kenya. RHEAS utilizes the Variable Infiltration Capacity (VIC) model and allows for the assimilation of multiple datasets at varying resolutions. The first team ingested data from Global Precipitation Measurement (GPM) Dual-frequency Precipitation Radar (DPR), Soil Moisture Active Passive (SMAP) L-band Radiometer, Aqua Moderate Resolution Imaging Spectroradiometer (MODIS), Terra MODIS, and ancillary datasets, including National Centers for Environmental Prediction (NCEP) climatological data and Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS). Results showed that drought indices calculated over a longer time period performed best, but the coarse spatial resolution (25km) and limited validation made the results difficult to implement. This term continued to use outputs from the RHEAS model to study drought in Kenya (Figure 1), but at a finer 5km spatial resolution.

Km

N

0 60 120 240



Garissa

Marsabit

Embu

Kitui

Kwale



*Figure 1.* The study area for this project is the country of Kenya. Five case study counties (highlighted in green) were chosen for further analysis.

***2.2 Project Partners***

The National Drought Management Authority (NDMA) is a government agency in Kenya mandated to mitigate drought risk to avoid a widespread crisis. The NDMA coordinates drought risk management between the government and stakeholders, implements programs to provide aid to affected areas, and communicates drought warnings to the public through monthly drought Early Warning Bulletins (NDMA, 2020). These bulletins are published on the NDMA’s website for each arid and semi-arid county. The drought classification system currently in place uses five drought classes: Normal, Alert, Alarm, Emergency, and Recovery. The NDMA uses this classification system to direct its programs to avoid widespread social and economic damage in counties experiencing drought. Drought is classified by evaluating a series of biophysical, social, and economic indicators (rainfall, livestock production, crop production, access to water, terms of trade and health and nutrition) as well as VCI calculated from MODIS derived indices. The NDMA has the capacity to use Earth observation models at the county and national scale. However, the NDMA’s current analysis focuses on the use of VCI, which means that drought can only be detected after it has begun to affect vegetation. Currently, the NDMA works closely with the Regional Centre for Mapping of Resources for Development (RCMRD) and NASA SERVIR for technical support and guidance. For this project, the team collaborated with the RCMRD and NASA SERVIR to better understand and meet the NDMA’s needs.

***2.3 Project Objectives***

This project used the RHEAS model outputs and NASA Earth observations to calculate drought indices and create a CDI that accurately detects drought up to one month earlier than current systems. A combination of drought indices was used to create a CDI that functions across arid and semi-arid counties in Kenya and detects drought more rapidly than current drought warning systems that are based only on VCI calculated from MODIS-derived Normalized Difference Vegetation Index (NDVI). Understanding the indices that function best within a CDI will inform future approaches to monitor drought in the region and provide the NDMA with enhanced information for their monthly bulletins. The team clearly documented the creation and operation of this CDI to facilitate implementation by our partners and collaborators. Specifically, project results will complement the NDMA’s current approach to monitoring drought, while improving their ability to predict drought within their Early Warning System.

# 3. Methodology

***3.1 Data Acquisition***

The team collected data necessary to construct a CDI as well as data to evaluate the performance of the CDI. To create a CDI, the team utilized drought indices related to precipitation, soil moisture, and vegetation. NASA SERVIR provided daily RHEAS model outputs at 5km resolution from 1990 to 2018. The RHEAS output is based on CHIRPS precipitation data and NCEP climate data (Table 1). These outputs are in the form of daily tiff files and were used to calculate drought indices based on precipitation and soil moisture. The CDI also included drought indices related to vegetation (VCI and Evaporative Stress Index [ESI]), which are further described in Table 1. To evaluate the performance of the CDI, the team compiled a dataset of drought early warning phases from NDMA’s Early Warning Bulletins from January 2016 to December 2019 for five case study counties. The case study counties considered for this project (Garissa, Marsabit, Embu, Kitui, and Kwale) were chosen because they include both arid and semi-arid counties and cover different geographic regions in Kenya. Further definition of data used to evaluate CDI performance is in Table 2.

Table 1

*Data used to develop a CDI*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Data** | **Source** | **Sensor** | **Dates** | **Area** |
| NDVI | AppEEARS | MODIS | March 2001 –  April 2019 | Kenya |
| ESI | Climate SERV | MODIS, Suomi NPP VIIRS | January 1, 2016 –  May 5, 2019 | Kenya |
| RHEAS Precipitation | NASA SERVIR | N/A | January 1, 1990 – December 31, 2018 | Kenya |
| RHEAS Soil Moisture | NASA SERVIR | N/A | January 1, 1990 – December 31, 2018 | Kenya |

Table 2

*Ancillary data used to assess CDI robustness*

|  |  |  |  |
| --- | --- | --- | --- |
| **Data** | **Source** | **Dates** | **Area** |
| Early Warning Bulletins | NDMA | January 2016 – December 2019 | Embu, Garissa, Kitui, Kwale, Marsabit counties |

***3.2 Data Processing***

To prepare the data that was incorporated into a CDI, the team processed the raw RHEAS outputs, NDVI, and ESI data and calculated drought indices. The team used the Rasterio package within Python to calculate each drought index (Table 3). The team based index selection on the indices used by Sepulcre-Canto et al. (2012). RHEAS precipitation outputs were used to calculate the Standardized Precipitation Indices at a 1-month timescale. Soil Moisture Anomalies (SMA) for each of three layers of soil were calculated using RHEAS outputs for soil moisture. VCI was calculated from NDVI. The first step in calculating the drought indices was to average (in the case of RHEAS soil moisture, NDVI, and ESI) or sum (in the case of RHEAS precipitation) daily or weekly files into monthly tiff files. Next, the team calculated long term (30 year) monthly means and standard deviations for each pixel to calculate SPI and SMA, and long term (20 year) monthly minimum and maximums for each pixel to calculate NDVI. The equations used to calculate each drought index are described in Table 3. Before combining all indices into a CDI, RHEAS outputs and VCI data were resampled and re-gridded using Python scripts to match ESI data. The team did not incorporate the ESI data into the final CDI but did include ESI in the time lag analysis.

Table 3

*Indices used in CDI*

|  |  |  |  |
| --- | --- | --- | --- |
| **Index** | **Category** | **Data Used** | **Equation\*** |
| SPI | Precipitation | RHEAS precipitation |  |
| SMA1, 2, 3 | Soil | RHEAS soil moisture (Layers 1, 2, and 3) |  |
| VCI-1 | Vegetation | MODIS derived NDVI |  |
| VCI-1 Anomalies | Vegetation | MODIS derived NDVI |  |

\* Where Xi is the observed value at a given month, is the long-term mean, is the long-term standard deviation, and min and max are the long-term minimums and maximums, respectively.

***3.3 Data Analysis***

To better understand the relationships between the selected drought indices, the team conducted a time lag analysis using Pearson’s Correlation in Excel. Calculating time lag for variables used in CDI is important because it shows how indices are temporally related. All variables used in computing the CDI, as well as ESI, were considered within the time lag analysis. The correlation was tested by offsetting data by months and then evaluating with linear regression. The team also compared the regression results at the county level to account for index spatial variation. Results from the time lag analysis are found in Table 4.

Table 4

*Results from Time Lag Analysis*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Comparison | Time Lag | Average Pearson’s Correlation Coefficient | | |
| Arid | Semi-Arid | Non-ASAL |
| SPI vs SMA-1 | SMA-1 +0 months | 0.9 | 0.81 | 0.82 |
| SPI vs SMA-2 | SMA-2 +1 months | 0.18 | 0.52 | 0.62 |
| SPI vs SMA-3 | SMA-3 +2 months | 0.37 | 0.46 | 0.48 |
| SPI vs ESI | ESI +1 month | 0.63 | 0.62 | 0.61 |
| SPI vs VCI | VCI +1 month | 0.58 | 0.52 | 0.56 |
| SMA-1 vs VCI | VCI +2 months | 0.61 | 0.49 | 0.59 |
| SMA-2 vs VCI | VCI +0 months | 0.58 | 0.63 | 0.6 |
| SMA-3 vs VCI | VCI -1 month | 0.6 | 0.61 | 0.49 |
| ESI vs VCI | VCI +0 months | 0.78 | 0.77 | 0.7 |

Next, the team performed multiple Principal Component Analyses (PCA) in Python in order to determine how to combine the indices into a CDI. PCA is useful for CDI development because it determines appropriate weights for indices based on the amount of variance they contribute. The team carried out PCA within Python using the indices given in Table 3. The first CDI (CDI-1) was created by conducting PCA at the county level for five case study counties. Uniform weights were then applied across the country of Kenya. Subsequent versions of the CDI (i.e. CDI-2) utilized PCA calculated across all counties, only arid counties, only semi-arid counties, and for different seasons. Results from this PCA analysis are included in Table 5 and are further explained in Section 4.1.

Table 5

*Variable weights resulting from PCA*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **PCA** | **CDI** | **SPI** | **SMA1** | **SMA2** | **SMA3** | **VCI** |
| Five-County | CDI-1 | 0.202 | 0.209 | 0.233 | 0.154 | 0.201 |
| All Counties | CDI-2\* | 0.322 | 0.281 | 0.186 | 0.136 | 0.074 |
| Arid Counties | CDI-2 | 0.412 | 0.372 | 0.032 | 0.064 | 0.120 |
| Arid – Long Rains | CDI-2 | 0.398 | 0.344 | 0.038 | 0.083 | 0.137 |
| Arid – Non-Rain | CDI-2 | 0.413 | 0.367 | 0.033 | 0.070 | 0.115 |
| Arid – Short Rains | CDI-2 | 0.424 | 0.403 | 0.025 | 0.038 | 0.110 |
| Semi-Arid Counties | CDI-2 Semi-Arid\* | 0.329 | 0.262 | 0.173 | 0.143 | 0.092 |
| Semi-Arid Long Rains | CDI-2 | 0.338 | 0.282 | 0.161 | 0.125 | 0.095 |
| Semi-Arid – Non-Rain | CDI-2 | 0.318 | 0.254 | 0.180 | 0.153 | 0.094 |
| Semi-Arid – Short Rains | CDI-2 | 0.341 | 0.260 | 0.174 | 0.142 | 0.085 |

\*Graphs including CDI-2 Arid and CDI-2 Semi-Arid are located in the Appendix as Figures 10 and 11.

# 4. Results & Discussion

***4.1 Data Analysis***

The team conducted a time lag analysis of drought indices and created several versions of CDIs that may detect drought earlier than current warning systems. Sepulcre-Canto et al. (2012) conducted a time-lag assessment prior to developing a CDI for Europe and found that the drought indices showed a cause-effect relationship, with precipitation indices detecting drought first, followed by soil moisture indices, and vegetation indices. To determine whether incorporating additional drought indices would improve the NDMA’s drought detection abilities, the team conducted a time lag assessment with SPI, SMA-1, SMA-2, SMA-3, ESI, and VCI (Table 4).

As expected, the time lag analysis found that SPI responds, on average, one month ahead of VCI, suggesting that including SPI in addition to VCI would improve current warning systems. However, the results also demonstrated that SMA-1 (surface layer of soil) responds two months ahead of VCI, while SMA-2 and SMA-3 respond in the same month as VCI, and one month later than VCI, respectively. Finally, ESI and VCI showed the strongest correlation in the same month. These results match up with the time lag analysis found in Sepulcre Canto et al. (2012), concluding that the time lag trend would be similar in Kenya.

These results indicate that incorporating either SPI or SMA-1 would improve drought detection by up to one month. The time lag analysis would help to improve the NDMA’s warning system by taking into account the understanding of the timing that indications of drought would appear after precipitation. This analysis could be used in future work and could potentially be very useful for the NDMA when considering implementing a combined drought indicator rather than just using VCI since using multiple drought indices gives the opportunity to take advantage of known time lags and can lead to more advanced drought forecasting.

While the results from this time lag assessment offer valuable information about the response times of different drought indices relative to each other, this analysis was calculated monthly. Future work could include calculating time lags twice or three times per month, to determine more precise differences in lag time. An accurate assessment of time lag would be particularly important in developing a CDI that uses thresholds for individual indices to take advantage of the cause-effect relationship demonstrated between precipitation, soil, and vegetation.

***4.2 CDI Development***

The first CDI that the team created was based on the results from the five-county PCA, which considered SPI, SMA-1, SMA-2, SMA-3, and VCI-1.  Subsequent versions of the CDI incorporated PCA results from only arid counties, only semi-arid counties, as well as different seasons (as described in Table 5) and replaced VCI-1 with VCI-1 anomalies. The resulting CDI’s were produced monthly. Each version of the CDI resulting from subsequent PCA analyses was plotted as a time-series and visually assessed to determine which factors (arid, semi-arid, or seasonal) affected the output. The team found that conducting PCA seasonally (and creating season-specific CDI’s) did not greatly impact the performance of the CDI. Given that current drought warning systems based on VCI are known to struggle to detect drought in arid regions, the team anticipated that the arid CDI and semi-arid CDI would differ significantly from each other and the overall CDI. However, the team found that the semi-arid CDI was almost identical to the overall CDI, and the arid CDI showed only subtle differences.

A time-series chart of the first CDI (CDI-1), second overall CDI (CDI-2 Overall), and second CDI based on arid regions (CDI-2 Arid) are included in Figure 2. Figure 2 highlights the fact that replacing VCI-1 with VCI-1 anomalies and conducting a more targeted PCA analysis improved the range and sensitivity of the CDI to drought and flood events. Furthermore, Figure 2 demonstrates that while CDI-2 based on exclusively arid counties appears to show more extreme drought and flood events than CDI-2 Overall, it captures all of the same drought and flood events.

CDI-1 and CDI-2 Comparison with Rainy Seasons

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*Figure 2*. This graph shows the first version of our CDI (CDI-1) compared to the second version of our CDI for Arid counties (CDI-2 Arid), and the second version of our CDI over all the counties (CDI-2 Overall). The three CDI versions are plotted on top of bars representing rainy seasons in Kenya. High values for the CDI represent wetter periods, and lower values for the CDI represent drier periods.

Because current drought warning systems are known to struggle to detect drought in arid regions, the team anticipated that conducting PCA over exclusively arid counties would function to create a CDI that performs better in arid counties. Given that the resulting arid CDI functions so similarly to the overall CDI, a more rigorous validation should be conducted to determine whether the CDI performs well across all counties. If the CDI is found to perform worse over arid counties, then additional CDI methods could be explored, including utilizing different indices in different counties or setting county-specific drought thresholds for each index in the CDI.

*4.2.1 CDI Evaluation*

While the comparison of CDI-1 and CDI-2 demonstrates that CDI-2 often detects additional variation that CDI-1 does not, the comparison alone does not indicate which CDI is better suited to detecting drought in Kenya. To evaluate the performance of each CDI, the team compiled a dataset of historical drought events between 2000 and 2018. Due to the lack of county-specific historical drought data, the team evaluated the CDIs at the country-level. While there have been several major recorded drought events during this time period, there are no precise details as to when each drought event began and ended in Kenya, which makes it difficult to confirm whether the CDIs are successfully detecting drought events before they become severe. Figure 3 depicts CDI-1 from January 2003 to December 2018 in red, and CDI-2 in blue from January 2016 to December 2018. The figure below demonstrates that most of the very low values recorded for CDI-1 corresponded to recorded drought events, but historical records often provide no month-to-month details about the progression of drought throughout the country, which limited the level of historical validation the team could achieve. CDI-2 appears to detect the 2016-2017 drought in Kenya earlier than CDI-1, but further validation was limited because only one drought event fell within CDI-2’s time range (2016-2018).

A close up of text on a white background

Description automatically generatedCDI-1 and CDI-2 Comparison with Historic Drought Events

*Figure 3.* This graph shows CDI-1 and CDI-2 compared to recorded historic drought events. This graph demonstrates several instances that CDI-1 showed low values matching known drought events in Kenya. Likewise, CDI-2 (which was produced from January 2016 to December 2018) was able to detect the significant drought that took place from 2016 to 2017.

Due to the lack of historic drought records available for Kenya, the team was not able to perform extensive historic validation to ensure that our CDI was able to accurately detect all historic droughts that took place in Kenya during the time period of our research. Furthermore, the lack of county-specific historical records limited the team to country-level evaluation. Even during months that appear to have experienced extreme drought in Figure 3, such as December 2016, the maps of the CDI indicate that there is a high degree of variability across the country (Figure 4). Therefore, a more thorough historic validation dataset would consist of county-specific and temporally specific drought and flood events across the study period. Future work could consist of validating the CDIs against this extensive database to give a more accurate depiction of the overall accuracy of our CDI.

A close up of a map

Description automatically generatedCDI-2 Drought Intensity Map for December 2016

*Figure 4.* CDI-2 map depicting drought intensity for December 2016. December 2016 appears to be a severe drought on the time-series graph (Figure 3), but the map highlights the variation across the country, particularly in the northeast region.

Due to the relative lack of recorded drought and flood events at the county-level for Kenya, the team decided to conduct a more thorough validation of the CDI outputs utilizing the NDMA Early Warning Bulletins. While the NDMA’s records are county-specific and published monthly, complete records begin in 2016. The team evaluated CDI-1, CDI-2, and VCI using the Early Warning Phases from NDMA’s Early Warning Bulletins for our five case study counties between January 2016 and December 2018. Figure 5 below, and Figures 6-9 in the Appendix show this comparison for each of the five counties. CDI-1 often was unable to detect drought consistent with the early warning phase in arid counties; however, CDI-2 improved consistency with the warning phase. In Figure 5 below, CDI-1 detects “Normal” conditions in February 2018 significantly before CD1-2 and VCI but then fails to match the warning phase from March through September. Using VCI anomalies in CDI-2 drastically improved drought detection during this period. CDI-2 appeared to perform better in arid counties (such as Marsabit and Garissa) than CDI-1. In semi-arid counties, CDI-1 was more consistent with NDMA records but less accurate than CDI-2. For all five counties, CDI-1 and 2 seemed to detect drought before VCI.

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Description automatically generatedCDI-1, CDI-2, VCI and NDMA Early Warning Phase for Marsabit  
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*Figure 5*. This figure represents CDI-1, CDI-2, and VCI performance at Marsabit county compared with NDMA Early Warning Phase records from January 2016 to December 2018. CDI-1 was computed using SPI, SMA-1, SMA-2, SMA-3, and VCI-1. CDI-2 was computed by changing VCI-1 to VCI-1 anomaly. The VCI shown in the figure is a 1-month VCI product.

The evaluation with the NDMA warning phases indicates that, overall, CDI-2 performs better in arid counties than CDI-1, which suggests that VCI-anomalies may be better suited to arid regions than VCI alone. It is also important to note that NDMA’s early warning phases are based on VCI, meaning that VCI should be most strongly correlated with the drought phases in Figures 5-9. In cases where the CDI appears to function ahead of the NDMA’s warning phase, drought conditions may have already begun at that time, but vegetation had not yet begun to show signs of stress detectable from VCI.

***4.3 Limitations***

The team encountered delays when receiving outputs from the RHEAS model, due to issues with ingesting the climate data from CHIRPS and NCEP when run at a higher resolution. Additionally, due to initial technical issues calculating drought indices within RHEAS, the team calculated drought indices from general RHEAS outputs but was only able to include SPI at a 1-month timescale, rather than SPI calculated over longer timescales. Finally, the sparse drought records at the county-level for Kenya made it difficult to conduct a thorough historical validation over a long time period. While NDMA Early Warning Bulletins allowed for a more complete evaluation of the CDI, we were only able to utilize the early warning phases during the three years the bulletin data coincided with our CDI (2016-2018).

***4.4 Future Work***

Future work could include utilizing drought indices calculated within RHEAS, rather than using separate scripts to calculate indices based on raw outputs. Specifically, the team was unable to utilize SPI calculated at longer timescales, which other research has shown to be useful in drought detection. Furthermore, consolidating all the calculation of drought indices to RHEAS and streamlining the process to eliminate additional external calculations would facilitate the adoption of RHEAS by the NDMA for their drought detection.

Additional work may also seek to conduct a more thorough validation of the developed CDI by compiling an extensive historical drought database on the county and monthly level with a detailed description of the time period and areas affected, potentially based heavily on in-country contact knowledge. Researchers could also process and compile a quantitative database using NASA Earth observations or *in situ* data that can be used to compare and validate the CDI. Additionally, developing a threshold-based CDI that utilizes the results of our time lag analysis could be used to compare how well our CDI performs compared to another method of drought indication. A threshold-based CDI would set drought thresholds for each index, either based on expert knowledge or machine learning algorithms using a training database, and would allow the cause-effect relationship between precipitation, soil moisture, and vegetation to improve the speed of drought detection.

# 5. Conclusions

The goal of this research was to create a CDI that could be implemented by the NDMA that would be able to pick up drought events better than VCI alone. While further validation and analysis is required, the team found that there is room to improve current drought warning systems and that the CDI did detect drought earlier than VCI in some instances. Additionally, the CDI performance suggests that some drought indices function better in semi-arid counties than arid counties since the CDIs picked up drought events differently in arid and semi-arid counties. Also, after analyzing the timing between drought indices, the team found that the time lag assessment suggests the potential to detect drought much earlier than current systems based on VCI alone. Accounting for the differences in time between different indicators of drought can lead to better prediction and management of drought in the future. Although our CDI did seem to detect certain drought events earlier than VCI, more extensive validation would be required to ensure that our CDI performs better than VCI. This would include a detailed historic drought event database that could validate the accuracy of our CDI. Our research and analysis show that the implications of a combined drought indicator that utilizes a variety of drought indices has the potential to more accurately detect drought and that with more validation, our CDI could outperform VCI.

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# 7. Glossary

**ASAL** – Arid and Semi-Arid Lands - Areas receiving less than 550 mm (arid) or between 550 and 850 mm (semi-arid) lands of rainfall annually

**CDI** – Combined Drought Indicator - A categorical drought index that takes precipitation, soil moisture, and vegetation stress into account

**CHIRPS** – Climate Hazards Center InfraRed Precipitation with Station

**DPR** – Dual-frequency Precipitation Radar

**Earth observations** – Satellites and sensors that collect information about the Earth’s physical, chemical, and biological systems over space and time

**ESI** – Evaporative Stress Index

**MODIS** – MODerate Resolution Imaging Spectroradiometer

**NCEP** –National Centers for Environmental Prediction

**NDMA** – National Drought Management Agency

**NDVI** – Normalized Difference Vegetation Index

**RCMRD** – Regional Centre for Mapping of Resources for Development

**RHEAS** – Regional Hydrologic Extremes Assessment System

**SMA-1** – Soil Moisture Anomaly layer 1

**SMA-2** – Soil Moisture Anomaly layer 2

**SMA-3** – Soil Moisture Anomaly layer 3

**SMAP** – Soil Moisture Active Passive

**SPI** – Standardized Precipitation Index calculated from monthly averages (also SPI-1)

**VCI** – Vegetation Condition Index calculated from monthly averages (also VCI-1)

**VIC** – Variable Infiltration Capacity

# 8. References

Andreadis K.M., Das N., Stampoulis D., Ines A., Fisher J.B., Granger S., Kawata J., ... & Behrangi, A.(2017). - The regional hydrologic extremes assessment system: A software framework for hydrologic modeling and data assimilation. *PLoS ONE, 12*(5), art. no. e0176506. DOI: 10.1371/journal.pone.0176506

Balint, Z., Mutua, F., Muchiri, P., & Omuto, C. (2013). Monitoring Drought with the Combined Drought Index in Kenya. *Developments in Earth Surface Processes, 16,* 341-356. DOI: 10.1016/B978-0-444-59559-1.00023-2.

Bayissa, Y. A., Tadesse, T., Svoboda, M., Wardlow, B., Poulsen, C., Swigart, J., & Andel, S. J. V. (2019). Developing a satellite-based combined drought indicator to monitor agricultural drought: A case study for Ethiopia. *GIScience & Remote Sensing, 56*(5), 718–748. DOI: doi.org/10.1080/15481603.2018.1552508

Didan, K. (2015). *MOD13A3 MODIS/Terra vegetation Indices Monthly L3 Global 1km SIN Grid V006* [Data set]. NASA EOSDIS Land Processes DAAC. Accessed 2020-04-02 from https://doi.org/10.5067/MODIS/MOD13A3.006

Masih, I., Maskey, S., Mussá, F & Trambauer, P. (2014). A review of droughts on the African continent: A geospatial and long-term perspective. *Hydrology and Earth System Sciences, 18*, 3635-3649. DOI: 10.5194/hess-18-3635-2014.

Myneni, R., Knyazkhin, Y. (2018). VIIRS/NPP Leaf Area Index/FPAR 8-Day L4 Global 500m SIN Grid V001 [Data set]. NASA EOSDIS Land Processes DAAC. Accessed 2020-04-02 from https://doi.org/10.5067/VIIRS/VNP15A2H.001

NDMA National Drought Management Authority. (2020). Retrieved from https://www.ndma.go.ke/

Sepulcre-Canto, G., Horion, S., Singleton, A., Carrao, H., & Vogt, J. (2012). Development of a Combined Drought Indicator to detect agricultural drought in Europe. *Natural Hazards and Earth Systems Sciences, 12,* 3519–3531. https://doi.org/10.5194/nhess-12-3519-2012.

Uhe, P., Philip, S., Kew, S., Shah, K., Kimutai, J., Mwangi, E., …& Otto, F. (2018). Attributing drivers of the 2016 Kenyan drought. *International Journal of Climatology, 38*(S1), e554-e568. https://doi.org/10.1002/joc.5389

# 9. Appendix

A picture containing table

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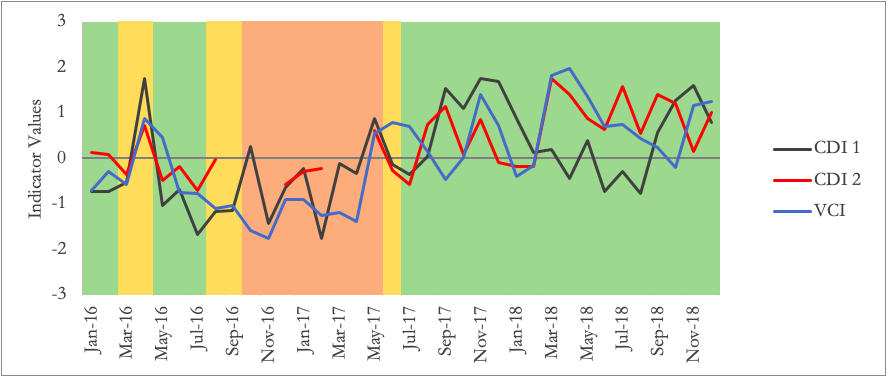
Description automatically generated*Figure 6.* This figure represents CDI 1, CDI 2, and VCI performance at **Garissa** (arid) county compared with NDMA Early Warning Phase records from January 2016 to December 2018.

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Description automatically generated*Figure 7*. This figure represents CDI 1, CDI 2, and VCI performance at **Embu** (semi-arid) county compared with NDMA Early Warning Phase records from January 2016 to December 2018.

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Description automatically generated*Figure 8.* This figure represents CDI 1, CDI 2, and VCI performance at **Kitui** (semi-arid) county compared with NDMA Early Warning Phase records from January 2016 to December 2018.

*Figure 9*. This figure represents CDI 1, CDI 2, and VCI performance at **Kwale** (semi-arid) county compared with NDMA Early Warning Phase records from January 2016 to December 2018.

*Figure 10*. Arid seasonal CDI-2 showed higher sensitivity in the arid county of Garissa. Still, there is little variation between the two.

*Figure 11*. For Kitui, the Semi-Arid Seasonal CDI-2 functioned so similarly to the all-county CDI-2 that there is little visual difference.