SDS WARNING ADVISORY SYSTEM EVALUATION

BDRC-2023-004

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22 May 2023

Series: Barcelona Dust Forecast Center (BDFC) Technical Report

TECHNICAL REPORT

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Summary

This report outlines the methodology employed for the evaluation of the Warning Advisory System, which has been developed by the Barcelona Dust Regional Center and is currently operational in several African countries. The evaluation is based on visibility reduction data due to dust, extracted from SYNOP and METAR reports. A comparison with the Persistence model and potential improvements to the system are also discussed.

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1. Introduction: WAS Background and Goal of the Evaluation

The development of Early Warning Systems (EWS) and Warning Advisory Systems (WAS) is one of the goals of the SDS-WAS RC. The first WAS pilot project was carried out by the SDS-WAS NAMEE RC in 2018 for Burkina Faso (Terradellas et al, 2018) in the framework of the CREWS (Climate Research and Early Warning Systems) WMO initiative.

The core of this WAS is a universally understood system based on color-coded maps. Every day, the Barcelona Dust Regional Center (BDRC) produces three maps with the warning levels for each of the provinces of the corresponding countries (first administrative division) for the current day (D, run day) and the next two days (D+1 and D+2). This clear, concise information is expected to help planning any activity vulnerable to airborne dust or activate services and procedures aimed at the mitigation of damages caused in agriculture, public health or any other vulnerable sector. The final goal is to offer a clear, easy-to-understand and time-saver tool for assessing dust events.

The warning level for each region is set accordingly to the highest concentration value expected for the day at any model grid-point within the region. It is important to point out that province thresholds will differ based on geographic location and distance to dust sources, and therefore WAS will provide qualitative warnings.

In this part of the project, we have extended the WAS for Niger, Chad and Mali and we have tried to build an objective evaluation system to assess the performance of the WAS and easily test the improvements and changes that are implemented regularly in the warning system. For this first attempt of evaluation, we have used visibility reduction observations provided in the SYNOP reports, along with other sources of data to complement them.

In the next sections are depicted the results of the evaluation of the WAS carried out for each SYNOP station with enough data available, from November 2022 to April of 2023, using observational and model data from the same months from 2017 to 2022. The models included in the multimedian forecast can be found in Table 5. 5 (Annex 5.6).

1.1. Warning thresholds calculation methodology

In this section is described how the WAS how the thresholds are set and the warning colors calculated.

The warning advisory thresholds have been set based on a percentile-based approach, so that they are higher for the regions prone to high dust concentrations, than for the regions where strong dust events are not so common. Therefore, this WAS assess qualitatively the dust surface concentration forecasted by the multimodel median.

The first step consists in the calculation of the daily dust surface concentration maximum values, predicted by the multi-model median (Annex 5.6), for the period 2017 to 2022 (6 years). Afterwards the daily maximum value for each region is selected among all the grid points in the region. Finally, with these values, the time series of daily maximum values are built and the percentiles calculated.

To define the dust surface concentration warning thresholds, the following percentiles have been chosen: 80th percentile for high concentration, 90th percentile for very high concentration and 97.5th percentile extremely high concentration. In the last step, we compare the current multi-median daily maximum forecast with the thresholds to assign a color warning to each region. Forecasted values below the 80th percentile are classified as normal dust surface concentration.

As a result, a color-coded map is provided with four levels of warning advisory:

- red to indicate extremely high concentration of airborne dust.
- orange to indicate very high concentration.
- yellow to indicate high concentration.
- green to indicate normal dust surface concentration.

2. WAS evaluation methodology

The purpose of this section is to describe the WAS evaluation method and the observation data used. The goal is to use observational data to define color-coded maps similar to the ones offered in the WAS and then compare both sets of warning maps to evaluate the WAS.

2.1 Observation data filtering

Due to the lack of in-situ particulate matter (PM) measurements of dust surface concentration in the region, visibility reduction data provided every three or six hours by the SYNOP reports have been used for the evaluation. Visibility reduction could be considered as a good proxy for a dust event (Camino et al., 2015, Annex 5.4). Other observational data, namely wind, humidity or aerosol optical depth, have also been used to complete the analysis.

In order to better assess dust events, visibility data are filtered by the following three conditions:

- Visibility reduction is considered only when dust, sand or haze are observed
- Relative Humidity (RH) has to be less than 70%
- Visibility daily mean less than 8 km to avoid dust resuspension

The second condition is applied because high RH values can increase the capabilities of aerosols of reducing visibility (Zhang et al., 2010).

The last condition allows us to avoid dust resuspension in towns, especially during rush hours and after a strong dust event, when visibility is reduced significantly both early in the morning and late in the afternoon affecting 6 and 18 UTC SYNOP reports. An example for a day with dust resuspension at rush hours classified as Green (non dust event day) would be:

UTC	00	03	**06**	**09**	12	15	**18**	**21**	
VIS (km)	8	10	**8**	**6**	10	10	**6**	**8**	mean = 8.25 km classified as Green

Table 2. 18 km daily mean filter for resuspension. 06,09,18,21 UTC hours affected by traffic

Furthermore, SYNOP visibilities greater than 10 km have been replaced by 10 km in the calculation of the daily mean visibility to include dust events which don't affect the whole day. An example would be:

UTC	00	03	06	09	12	15	18	21	
VIS (km) reported	**15**	**15**	10	10	8 DU	6 DU	4 DU	2 DU	mean = 8.75 km not included without filter
VIS (km) corrected	**10***	**10***	10	10	8 DU	6 DU	4 DU	2 DU	mean = 7.5 km included with filter

Table 2. 2 VIS>10 km at 00 and 03 have been replace by 10 km (corrected visibility)*

2.2 Visibility thresholds calculation method

After filtering the data, a time series of the daily minimum visibility is calculated. Similarly to the WAS, color thresholds of each SYNOP station are calculated based on the percentiles of this time series. We have assigned to each color the same percentiles that we used for the definition of the WAS with some modifications (Table 2. 3 and Table 2. 4).

2.2.1 Color threshold modifications

SYNOP visibility is not a continuous variable with many reports with exactly the same value. For example, daily values during a month could be: 20 days with 10 km, 5 days with 8 km, 3 days with 2 km, and 2 with 1 km. This distribution of the visibility into a few bins makes the threshold calculation difficult because different percentiles will have the same value. To deal with issue, we have replaced the equal percentiles values for different ones following the next rules:

Condition	Red	Orange	Yellow
Initial percentiles	97.5th	90th	80th
when 97.5th = 90th	99th	90th	80th
when 90th = 80th = 8km	97.5th	90th-90th-97th2	80th
when 80th = 90th < 8km	97.5th	90th	70th

Table 2. 3 Color-Percentile for each condition.

An example is shown in Table 2.4.

Condition	99th	97.5th	90th	80th	70th	Red	Orange	Yellow
Initial percentiles	0.5	1	2	3	4	1	2	3
when 97.5th = 90th	0.5	2	2	3	4	0.5	2	3
when 90th = 80th = 8km	3	4	8	8	10	4	6	8
when 80th = 90th < 8km	0.5	1	3	3	4	1	3	4

Table 2. 4 Example of the threshold modification applying the different conditions. (Percentile values are in km)

2.3 Statistical methods used: Bootstrapping and Chi-squared tests and Contingency tables

We have used three methods to evaluate and compare the warnings based on visibility and the WAS:

- Bootstrapping test
- Chi-squared test
- Contingency tables

Our bootstrapping test consists in generating random samples (5000) in order to reject the null-hypothesis of no relationship between the warnings based on visibility and the WAS. In addition, we have obtained a confidence interval and a mean square error. Furthermore, we have compared the WAS with the Persistence model. (Figure 2. 2)

The chi-squared test consists in the analysis of the contingency table and it is used to examine whether two categorical variables are independent or dependent. In our case, our variables are the warning colors from observation and model. (Figure 2. 1)

A contingency table is a matrix that shows the frequency distribution of the observations and the model warning colors. These contingency tables display Hits and False Alarm ration for each SYNOP station. (Figure 2. 3)

Furthermore, in the next figures and statistics where we show the results at country level, only days when a dust event was observed or forecasted are considered. In other words, days with no significant events observed or forecasted (green-green days) are removed from the study. The number of green-green days are around 70-80% of the total days and therefore their statistical weight is very significant. So, by removing them we obtain clearer and easier to interpret statistics. To show the effect of the green-green days in the statistics, an example of a station where the green-green days are included is shown in Figure 2. 5

In addition, some SYNOP stations have also been removed (Figure 2. 1) from the calculation because of the discontinuity of the observation data series and also stations with no significant dust events days where visibility is always above 8 km despite dust concentration conditions.

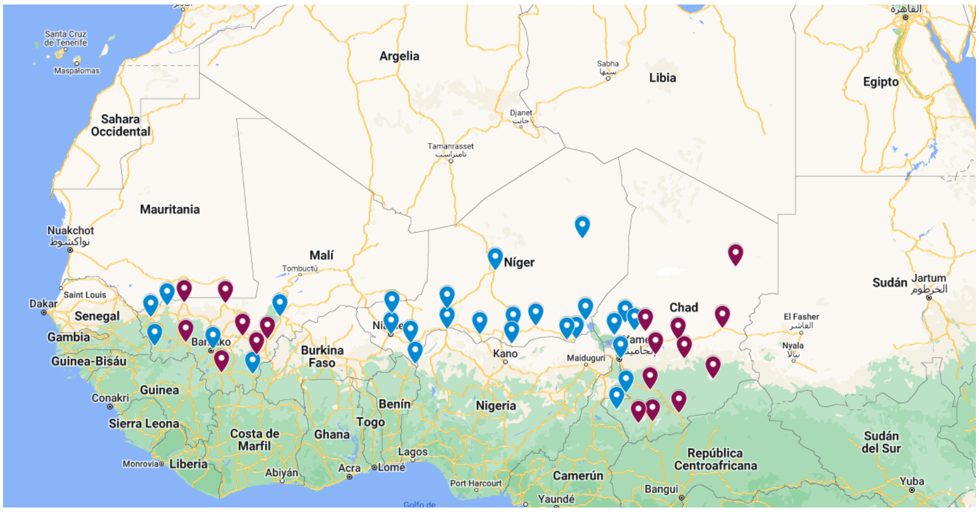
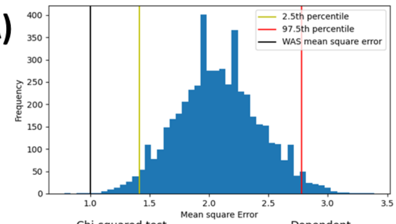


Figure 2. 1 Station location map, in red the dismissed stations and in blue the stations not included.

The graphs showing the statistical tests and graphs are explained below:

Bootstrapping Ndjamena Chad

(A)



(B)

OB\WAS	green	yellow	orange	red
green	0.0	24.39	4.88	0.0
yellow	19.51	19.51	12.2	0.0
orange	2.44	2.44	2.44	12.2
red	0.0	0.0	0.0	0.0

(C)

Chi-squared test	Dependent
Days :	180
Days OBS without green:	29
WAS MOD without green:	32
Days without green-green :	41
WAS mean square error:	1.0
Bootstrap mean square error:	2.08
The confidence interval 95%:	[1.41 2.78]
p-Value =	0.08 %
Thresholds Visibility(m) :	837 2000 5000
Thresholds Models(ug/m3) :	1313 974 732

(D)

Hits :	21.95 %
Total-Hits :	48.78 %
Misses :	21.95 %
Underforecasting :	24.39 %
False Alarms :	29.27 %
Overforecasting :	53.66 %

Figure 2. 2 Example of bootstrapping and contingency table with percentage data. We have removed the green-green cases.

(A)Probability distribution function graph built from the bootstrapping random samples.

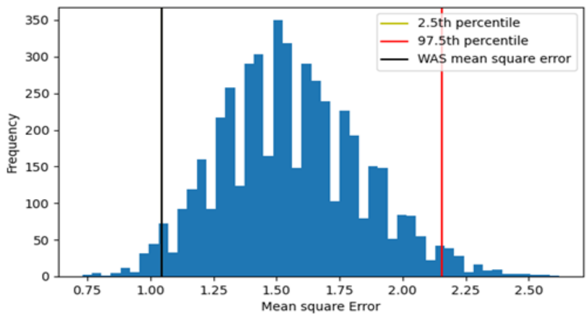


Figure 2. 3 Example of probability distribution of the random values and the empirical value.

(B) Contingency Table

OB\MO	green	yellow	orange	red
green	0.0	28.89	0.0	0.0
yellow	6.67	24.44	4.44	0.0
orange	6.67	13.33	2.22	0.0
red	0.0	4.44	6.67	2.22

OB\MO	green	gold	orange	red
green	0.0	28.89	0.0	0.0
gold	6.67	24.44	4.44	0.0
orange	6.67	13.33	2.22	0.0
red	0.0	4.44	6.67	2.22

Figure 2. 4 Example of contingency table with percentage data. Green-green values have been removed.

(C) Data information:

- Chi-squared test is the result of the test (dependent or independent)
- Days is the number of days with valid data.
- Days OBS without green is the number of observed days with a color other than green.
- WAS MOD without green is the number of forecast days with a color other than green.
- Days without green-green is the number of days that the observation and forecast have a color other than green.

- WAS mean square error is the mean of the subtraction between the color observation and the color model for each day.

$$\frac{1}{N}\sum(ColorModel - ColorObservation)^2$$

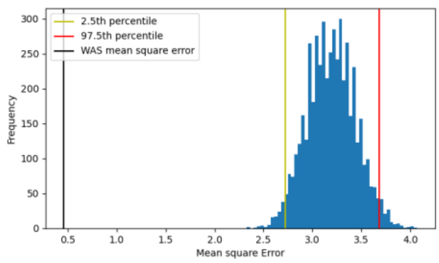
where N is the number of days without green-green, ColorModel and ColorObservation are the values associated with each color i.e green: 1, yellow: 2, orange: 3 and red: 4.

- Bootstrap mean square error is the mean square error of the random values.
- The confidence interval 95% is the value of the confidence interval 95%
- p-Value is the probability of obtaining test results under the assumption that the Null-Hypothesis is correct.
- Thresholds of visibility and model for each station are included.

(D) Data Contingency Table

- Hits is the sum of the diagonal values.
- Total-Hits is all values less Misses and False Alarms.
- Misses are the dust events observed but not forecasted, first column.
- False Alarms are the dust events not observed but forecasted, first row.
- Over-forecasting is the sum of the values under diagonal.
- Under-forecasting is the sum of the values below the diagonal.

Bootstrapping Bilma Niger



OB\WAS	green	yellow	orange	red
green	76.11	5.0	2.22	0.56
yellow	3.33	2.22	1.11	0.56
orange	2.22	0.56	1.67	3.33
red	0.56	0.56	0.0	0.0

Chi-squared test	Dependent
Days :	180
Days OBS without green:	29
WAS MOD without green:	32
WAS mean square error:	0.46
Bootstrap mean square error:	3.19
The confidence interval 95%:	[2.72 3.68]
p-Value =	0.0 %
Thresholds Visibility(m) :	1702 3500 6000
Thresholds Models(ug/m3) :	1475 971 764

Hits :	80.0 %
Total-Hits :	86.11 %
Misses :	6.11 %
Underforecasting :	7.22 %
False Alarms :	7.78 %
Overforecasting :	12.78 %

Figure 2. 5 Example for Bilma (Niger) where the green-green cases have been included.

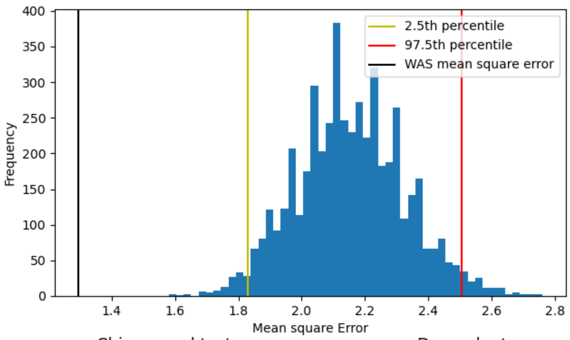
3. WAS and Persistence comparison results

One of the simplest ways of producing a forecast is the persistence method. It assumes that the conditions at the time of the forecast will not change. For example, if today we have observed a dust event with a certain intensity, the forecast for tomorrow will be exactly the same dust event. On the contrary, if today is a non-dust day, tomorrow it will be forecasted as a non-dust day.

The persistence method works well when weather patterns change very little. However, if weather conditions change significantly from day to day, the persistence method usually breaks down and is not the best forecasting method to use. In our particular case, where dust events can last several days in a row, persistence is performing quite well getting high rate scores. This makes persistence a "hard to beat" method, even when removing the green-green days. On the other hand, persistence performs well on long events but always fails to predict when a dust event starts or ends. In comparison, we have calculated that the WAS is able to forecast when an event begins or ends with an accuracy rate of around 60%, which represents a significant added value to the forecast.

Bootstrapping test shows that both WAS and Persistence are not random forecast systems, even when the green-green days are not included, and therefore the Null-Hypothesis can be rejected. Graphical evaluation at country level for Mali, Niger and Chad are shown in the next page. Graphs for each station, with and without green-green days, can be found on the same website where you get this document.

Bootstrapping Chad Chad

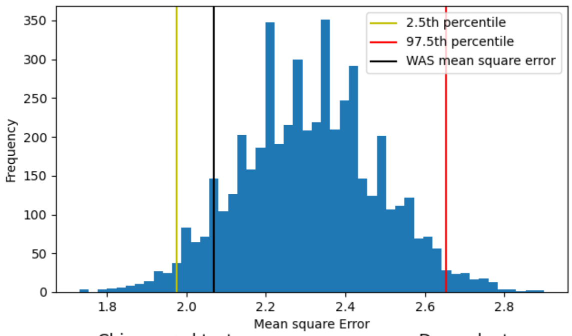


OB\WAS	green	yellow	orange	red
green	0.0	17.01	6.7	0.52
yellow	14.43	10.31	6.19	0.0
orange	9.28	9.28	10.82	7.22
red	0.52	0.0	2.06	5.67

Chi-squared test	Dependent
Days :	951
Days OBS without green:	147
WAS MOD without green:	147
Days without green-green :	194
WAS mean square error:	1.29
Bootstrap mean square error:	2.15
The confidence interval 95%:	[1.83 2.51]
p-Value =	0.0 %
Thresholds Visibility(m) :	Each station threshold
Thresholds Models(ug/m3) :	Each station threshold

Hits :	26.8 %
Total-Hits :	51.55 %
Misses :	24.23 %
Underforecasting :	35.57 %
False Alarms :	24.23 %
Overforecasting :	37.63 %

PERSISTENCE Bootstrapping Chad Chad



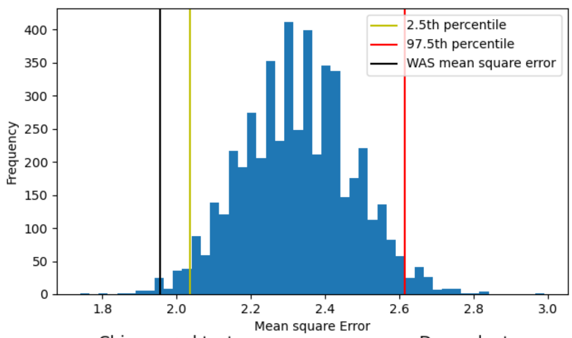
OB\WAS	green	yellow	orange	red
green	0.0	16.1	14.15	2.44
yellow	14.15	7.32	4.39	1.95
orange	13.17	3.41	13.17	1.95
red	1.95	1.95	2.44	1.46

Chi-squared test	Dependent
Days :	915
Days OBS without green:	138
WAS MOD without green:	145
Days without green-green :	205
WAS mean square error:	2.07
Bootstrap mean square error:	2.31
The confidence interval 95%:	[1.98 2.65]
p-Value =	8.2 %
Thresholds Visibility(m) :	Each station threshold
Thresholds Models(ug/m3) :	Each station threshold

Hits :	21.95 %
Total-Hits :	38.05 %
Misses :	29.27 %
Underforecasting :	37.07 %
False Alarms :	32.68 %
Overforecasting :	40.98 %

Figure 3. 1. Results from Chad. (Green-green days have been removed)

Bootstrapping Mali Mali

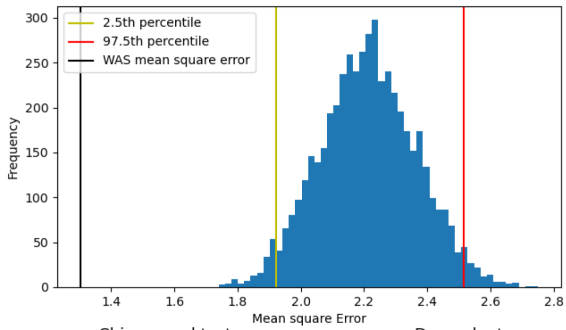


OB\WAS	green	yellow	orange	red
green	0.0	22.02	9.03	0.72
yellow	24.55	5.42	3.25	1.08
orange	14.08	3.97	3.97	2.53
red	3.61	0.36	2.17	3.25

Chi-squared test	Dependent
Days :	1074
Days OBS without green:	189
WAS MOD without green:	160
Days without green-green :	277
WAS mean square error:	1.96
Bootstrap mean square error:	2.32
The confidence interval 95%:	[2.04 2.61]
p-Value =	0.67 %
Thresholds Visibility(m) :	Each station threshold
Thresholds Models(ug/m3) :	Each station threshold

Hits :	12.64 %
Total-Hits :	25.99 %
Misses :	42.24 %
Underforecasting :	48.74 %
False Alarms :	31.77 %
Overforecasting :	38.63 %

PERSISTENCE Bootstrapping Mali Mali



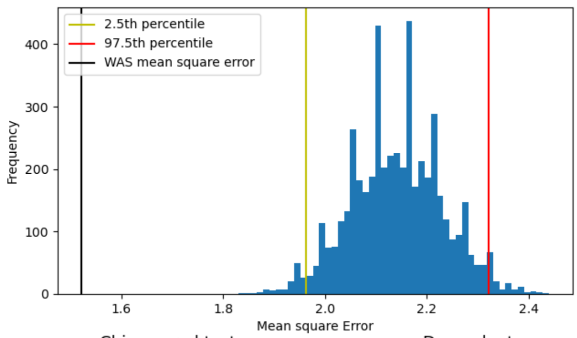
OB\WAS	green	yellow	orange	red
green	0.0	17.86	6.75	0.79
yellow	16.27	15.08	5.16	0.79
orange	8.73	2.78	12.3	3.17
red	0.4	1.59	2.78	5.56

Chi-squared test	Dependent
Days :	1056
Days OBS without green:	188
WAS MOD without green:	188
Days without green-green :	252
WAS mean square error:	1.3
Bootstrap mean square error:	2.21
The confidence interval 95%:	[1.92 2.52]
p-Value =	0.0 %
Thresholds Visibility(m) :	Each station threshold
Thresholds Models(ug/m3) :	Each station threshold

Hits :	32.94 %
Total-Hits :	49.21 %
Misses :	25.4 %
Underforecasting :	32.54 %
False Alarms :	25.4 %
Overforecasting :	34.52 %

Figure 3. 2 Results from Mali. (Green-green days have been removed)

Bootstrapping Niger Niger

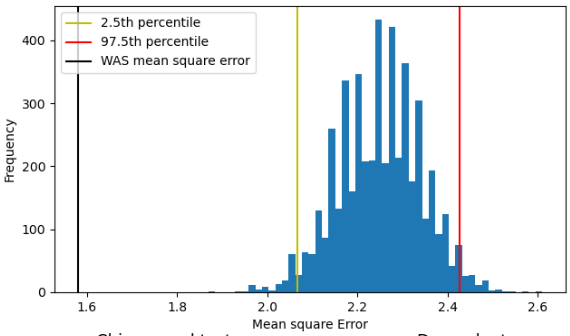


OB\WAS	green	yellow	orange	red
green	0.0	15.97	6.57	0.9
yellow	21.64	11.79	7.61	1.49
orange	8.06	6.72	7.31	3.28
red	1.94	1.34	1.49	3.88

Chi-squared test	Dependent
Days :	2697
Days OBS without green:	513
WAS MOD without green:	458
Days without green-green :	670
WAS mean square error:	1.52
Bootstrap mean square error:	2.14
The confidence interval 95%:	[1.96 2.32]
p-Value =	0.0 %
Thresholds Visibility(m) :	Each station threshold
Thresholds Models(ug/m3) :	Each station threshold

Hits :	22.99 %
Total-Hits :	44.93 %
Misses :	31.64 %
Underforecasting :	41.19 %
False Alarms :	23.43 %
Overforecasting :	35.82 %

PERSISTENCE Bootstrapping Niger Niger



OB\WAS	green	yellow	orange	red
green	0.0	21.16	6.77	1.55
yellow	18.9	11.0	8.46	0.99
orange	8.18	5.5	7.19	2.26
red	1.83	1.55	1.27	3.39

Chi-squared test	Dependent
Days :	2664
Days OBS without green:	500
WAS MOD without green:	504
Days without green-green :	709
WAS mean square error:	1.58
Bootstrap mean square error:	2.25
The confidence interval 95%:	[2.07 2.43]
p-Value =	0.0 %
Thresholds Visibility(m) :	Each station threshold
Thresholds Models(ug/m3) :	Each station threshold

Hits :	21.58 %
Total-Hits :	41.61 %
Misses :	28.91 %
Underforecasting :	37.24 %
False Alarms :	29.48 %
Overforecasting :	41.18 %

Figure 3. 3 Results from Niger. (Green-green days have been removed)

4. Conclusions of the Evaluation (Nov 2022 - Apr 2023)

We have different WAS performance rates depending on the country. For Chad the WAS performance was better than the persistence, with similar results for Niger and worse for Mali.

In general, WAS False Alarm rate is between 20 and 30%. The yellow-green Miss rate is quite high, between 16 and 23%, essentially due to the difficulty of setting the yellow threshold for the observed warning. We have realized that many dust events are not able to reduce the daily mean visibility below 8 km and despite the relatively high dust concentration, no warning is issued increasing the false alarm rate.

Finally, the WAS have a 60% accuracy rate in forecasting when an event starts or ends for all countries.

From these results, we can conclude that one of the next steps in order to improve the WAS performance significantly would be to define dust homogeneous regions, based on a reanalysis model or other kind of data.

5. ANNEX:

5.1 Python Scripts

We have created a sqlite database to store the Synop bulletins from **January 2017 to July 2023** from the AEMET database. This database contains the following metadata and meteorological parameters of the SYNOP stations:

Name and ID of the station
Visibility
Present weather
Country
Latitude and longitude
Station altitude
Wind speed and direction
Relative humidity

Table 5. 1 Database fields

All the scripts developed for this project have been written in the Python programming language.

Main_Synop_BBDD.py	**Create and load SYNOP reports in a sqlite database**
Classes and methods	
Download.py	Download reports from AEMET database
Process.py	Read the reports and process their information
DataFrame.py	Creates a two-dimensional, size-mutable, potentially heterogeneous tabular data from the processed reports

Main_Models.py	**Take the information from multi-model median**
Classes and methods	
Thresholds.py	Create multi-model median thresholds
Data.py	Create time series colored to assess

Main_OBS.py	**Take the information from sqlite database and filter data**
Classes and methods	
Thresholds.py	Create observations thresholds
Data.py	Create time series colored to assess

BootstrappingPoint.py	**Create bootstrapping test and contingency table based on time series colored of visibility and multi-model median.**

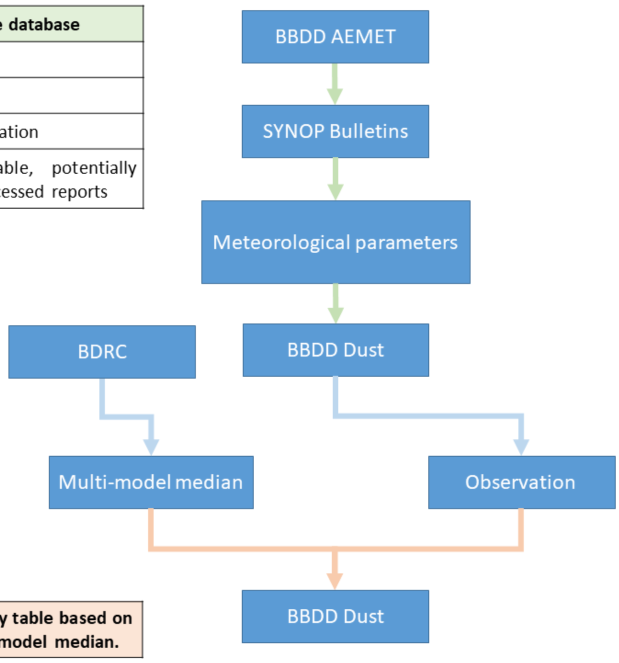


Figure 5. 1 Diagram of the Python scripts.

5.2 Warning Charts based on Visibility Reduction

As we have mentioned before, due to the lack of in-situ measurements of dust surface concentration in the study area, we have used METAR and SYNOP reports for the WAS evaluation. Apart from the evaluation carried out for each SYNOP station, a first administrative division warning level evaluation has also been calculated, applying two different sets of thresholds: one based on a fixed visibility range (Table 5. 2 and Figure 5. 3) and the second based on the percentiles of the visibility time series of the dry seasons from 2017 to 2022. Furthermore, charts of Aerosol Optical Depth (Figure 5. 4) and daily minimum visibility (Figure 5. 2) have been plotted to help monitor the SDS events.

These observations are filtered with the same conditions from the section WAS evaluation methodology-Observation data filtering.

5.2.1 First method: Fixed visibility range

These are the thresholds to assign a color to each province based on the visibility observations:

Visibility (m)	Warning Color
(5000, 8000]	Yellow
(1000, 5000]	Orange
[0, 1000]	Red

Table 5. 2 Visibility ranges and its color.

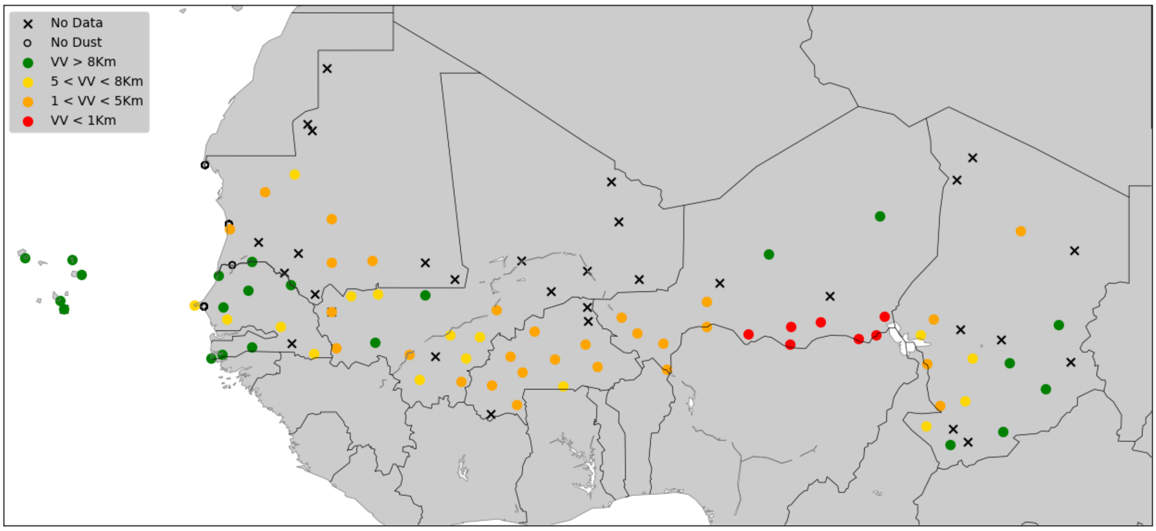


Figure 5. 2Daily Minimum visibility from METAR and SYNOP bulletins for the date 20 February 2023. The colored dots indicate the visibility reduced by dust or sand for different ranges. The empty dot indicates visibility reduced by other phenomena like fog, rain, etc. The cross indicates a station without data

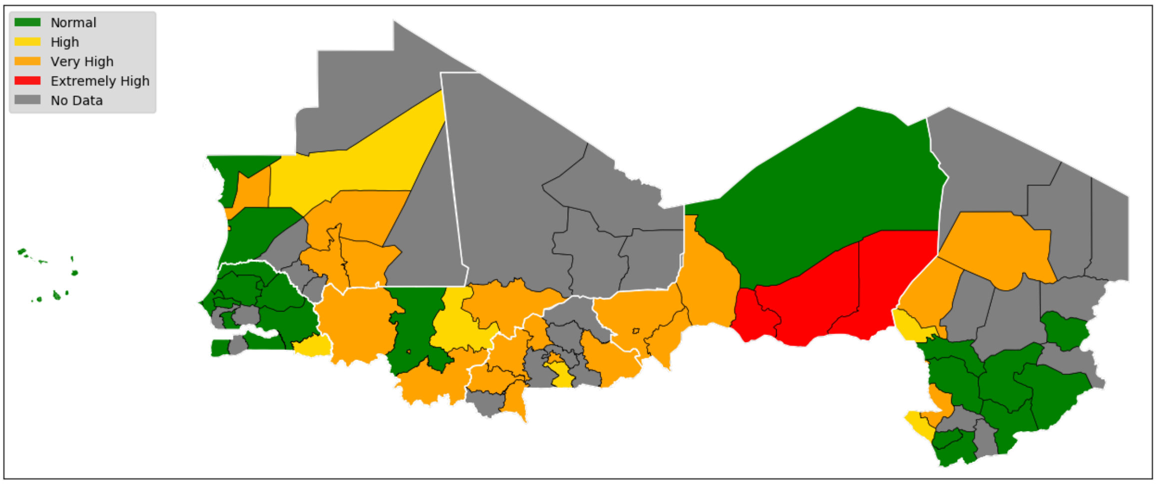


Figure 5. 3 Warning Advisory System for the 20 February 2023 for Cape Verde, Senegal, Mauritania, Mali, Burkina Faso, Niger and Chad. The thresholds used are calculated with the fixed visibility range.

5.2.2 Second method: Visibility time series

This second method is described in Section 2.2

In this graph the color for each province corresponds to the SYNOP stations located in the region.

5.3 Aerosol Optical Depth Charts

Direct-sun photometric measurements are a powerful tool that provides retrieval of column-integrated aerosol properties. In particular, AERONET is a comprehensive set of continental and coastal sites complemented with several sparsely distributed oceanic stations that provides large and refined data sets in near real-time (Holben et al., 1998; Dubovik and King, 2000). Retrievals from around 11 stations in Northern Africa are used here (Figure 5. 4). In particular, level 1.5 of version 3 inversion products have been used. Level 1.5 data are cloud-screened, but no other algorithm or correction has been applied.

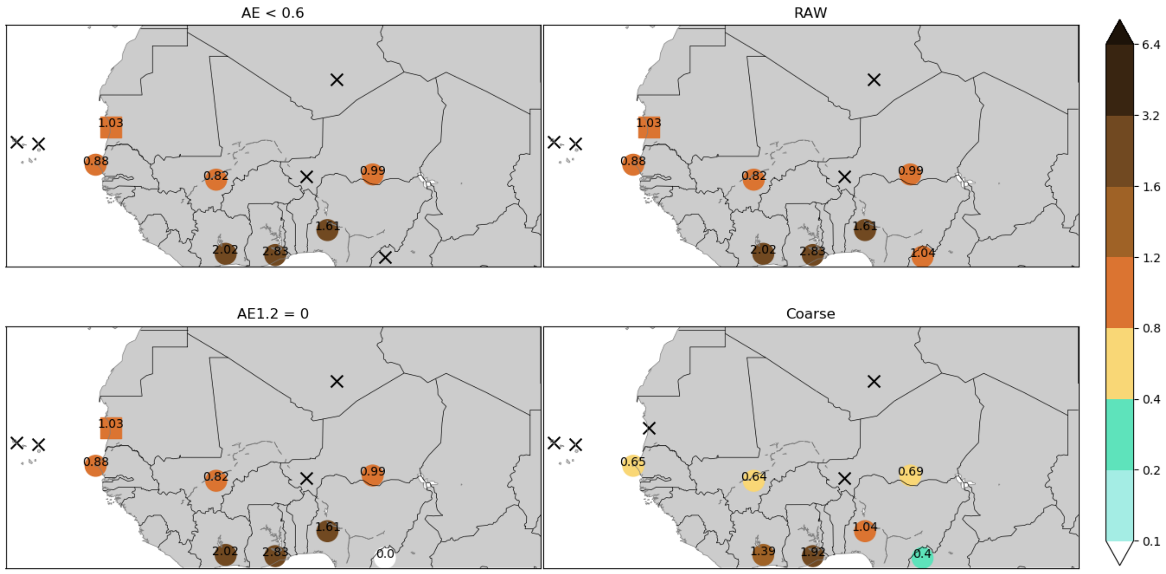


Figure 5. 4 Daily mean AOD from AERONET (550nm) and Calitoo (540nm) data from 20 February 2023. There are four different filters: AE<0.6 (Angstrom Exponent (AE) less than 0.6), RAW (no filters), AE1.2=0 (replace with 0 the value with an AE greater than 1.2 and AE less than 0.6) and the Coarse section. The AERONET data are represented by circles while Calitoo data are represented by squares.

To estimate the contribution of mineral dust from the total AOD, we have considered the following filtering methods:

- *AE<0.6*, data with an Angstrom Exponent (AE) less than 0.6 are removed (Basart et al., 2009)
- *AE1.2=0*, like the previous case but when AE is greater than the 1.2 the AOD value is replaced by 0. We do it because the contribution of dust with AE greater than 1.2 is practically null.
- *Coarse*, AOD yields by the spectral deconvolution algorithm (SDA) O'Neill et al. (2003). This algorithm is part of the AERONET routine calculations and provides fine (sub-micron) and coarse (super-micron) AOD values at a standard wavelength of 500 nm.

Date	Time (UTC)	AOT_465	AOT_540	AOT_619	Alpha
2023-02-20	11:59	1.1084	1.0781	1.0799	0.09
2023-02-20	11:03	1.0227	0.9891	0.9776	0.16

Table 5. 3Calitoo data from Mauritania. AOT_465, AOT_540 and AOT_619 indicate aerosol optical depth for the different frequencies and Alpha is Angstrom Exponent.

To complement AERONET network measurements in the region, hand-held sun photometers can be used. In this project, Calitoo hand-held sun photometers have been used to increase the number of data in the region. These devices can determine the rate of aerosols in the atmosphere and to characterize their size distribution (smoke, polluting gasses, ice crystals, dust). Calitoo measures the optical thickness of the atmosphere at different wavelengths: blue (465 nm), green (540 nm) and red (615 nm) and calculates Angstrom exponent. Calitoo is equipped with a GPS, pressure and temperature sensor (https://www.calitoo.fr).

In the framework of the MAC-CLIMA Interreg initiative, Calitoo AOD measurements have been carried out in Nouakchott (Mauritania) during the last year. Three times a day AOD is measured Table 5. 3 and Figure 5. 4) to help monitor SDS events. In this project, it is intended to send one Calitoo sunphotometer to each country involved, namely Mali, Niger and Chad to improve the geographical coverage of AOD data.

5.4 Empirical equations PM10-Visibility

We have included a table with reference values (Table 5. 4) for the relationship between visibility and dust concentration. Empirical equations provide us with local relationships between these parameters that can be used to roughly estimate dust concentration from visibility measurements. Below a graphical output of these empirical equations

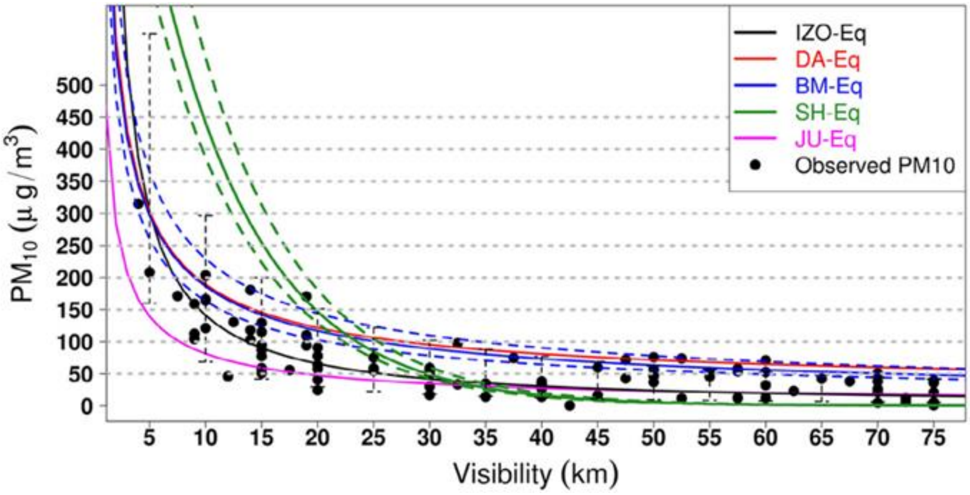


Figure 5. 5 Daily mean PM10 (lg/m3) versus daily mean visibility (km) recorded at IZO (black dots). Best fit found at IZO (IZO-Eq), and estimated PM10 from DA-Eq, BM-Eq, SH-Eq and JU-Eq. The error bars represent ±r of estimated PM10 using the IZO-Eq. Since BM-Eq and SH-Eq provide TSP, the estimated values are converted to PM10 using an averaged TSP/PM10 ratio of 0.65 obtained at IZO station. These lines are confined within the dashed lines computed with the minimum (0.57) and maximum (0.80) PM10/TSP values, respectively. (Camino et al., 2015)

VIS (m)	DA-Eq (µg/m3)	IZO-Eq (µg/m3)
10000	189	141
8000	**219**	**180**
5000	301	302
3000	**429**	**529**
1500	699	1135
1000	933	1772
500	1535	3800

Table 5. 4 DA-Eq and IZO-Eq VIS/PM10 concentration.

5.5 Bilma (Niger) SYNOP station

Bilma (Lat 18.69, Lon 12.92) (Figure 5. 6a) is an oasis town and commune in north east Niger with, as of the 2012 census, a total population of 4,016 people. It lies protected from the desert dunes under the Kaouar Cliffs and is the largest town along the Kaouar escarpment.

Bilma dust concentration thresholds are very high but thresholds (Figure 5. 8) calculated with visibility reduction by dust are relatively low due to the location of Bilma sheltered by orography (Figure 5. 6b) and vegetation (Figure 5. 7). The models don't have enough resolution to distinguish the particular location of Bilma that is situated near the Bodélé depression and it was expected to have more days with impaired visibility. The WAS performance is affected by this as it can be seen in the high value of the false alarms.

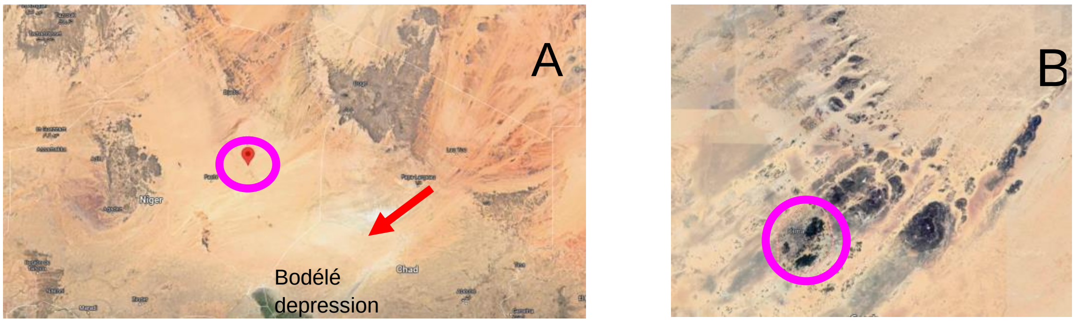
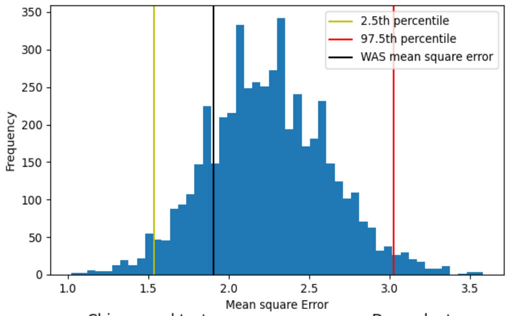


Figure 5. 6 a. Bilma (Niger). b. Zoom Bilma oasis and orography. Source: Google Maps

Figure 5. 7 Bilma Oasis (Niger) Source: Holger Reineccius

Bootstrapping Bilma Niger



OB\WAS	green	yellow	orange	red
green	0.0	20.93	9.3	2.33
yellow	13.95	9.3	4.65	2.33
orange	9.3	2.33	6.98	13.95
red	2.33	2.33	0.0	0.0

Chi-squared test	Dependent
Days :	180
Days OBS without green:	29
WAS MOD without green:	32
Days without green-green :	43
WAS mean square error:	1.91
Bootstrap mean square error:	2.24
The confidence interval 95%:	[1.53 3.02]
p-Value =	18.53 %
Thresholds Visibility(m) :	1702 3500 6000
Thresholds Models(ug/m3) :	1475 971 764

Hits :	16.28 %
Total-Hits :	41.86 %
Misses :	25.58 %
Underforecasting :	30.23 %
False Alarms :	32.56 %
Overforecasting :	53.49 %

Figure 5. 8 . Results of Bilma (Niger)

5.6 Seasonal 1st Administrative Division Thresholds

In this section, we have included the tables with the 1st administrative division seasonal thresholds for each country. These new seasonal thresholds will be implemented in the next revision of the WAS and are yearly updated with the values of the previous year.

The models that have been used in the calculation of the multimodel are listed in Table 5. 5. These thresholds are complemented with the median which is provided as a reference.

Model	Institution
MONARCH	BSC-CNS
CAMS	ECMWF
GEOS-5	NASA
DREAM8-NMME-CAMS	SEEVCCC
SILAM	FMI
LOTOS-EUROS	TNO
WRF-CHEM	NOA
MetUM	MetOffice

Table 5. 5 Models used in the calculation of the thresholds

5.6.1 1st Administrative Division thresholds: Mali

CODE	ML01	ML02	ML03	ML04	ML05	ML06	ML07	ML08
Region	Kayes	Koulikoro	Sikasso	Ségou	Mopti	Tombouctou	Gao	Kidal

Mali: 1st Administrative Division thresholds Spring (2017/03/01-2022/05/31)

percentiles	ML01	ML02	ML03	ML04	ML05	ML06	ML07	ML08
50th	266	213	146	230	279	679	560	607
80th	388	352	254	383	454	1070	877	981
90th	476	428	354	483	605	1365	1166	1391
97.5th	615	615	510	661	823	1983	1831	2156

Mali: 1st Administrative Division thresholds Summer (2017/06/01-2022/08/31)

percentiles	ML01	ML02	ML03	ML04	ML05	ML06	ML07	ML08
50th	165	114	49	123	146	623	510	618
80th	288	196	83	203	214	908	736	894
90th	380	244	119	254	267	1142	876	1068
97.5th	482	371	161	331	366	1536	1084	1475

Mali: 1st Administrative Division thresholds Fall (20170901-20221130)

percentiles	ML01	ML02	ML03	ML04	ML05	ML06	ML07	ML08
50th	191	175	113	188	225	589	479	512
80th	299	290	188	310	353	859	706	765
90th	366	356	241	370	430	1033	823	933
97.5th	472	440	331	478	591	1415	1126	1243

Mali: 1st Administrative Division thresholds Winter (2017/12/01-2022/02/28)

percentiles	ML01	ML02	ML03	ML04	ML05	ML06	ML07	ML08
50th	321	305	245	332	393	742	700	696
80th	474	470	370	499	593	1172	1086	1156
90th	591	580	444	596	717	1404	1290	1482
97.5th	768	768	603	795	942	1786	1770	2126

5.6.2 1st Administrative Division thresholds: Niger

CODE	NER001	NER002	NER003	NER004	NER005	NER006	NER007	NER008
Region	Agadez	Diffa	Dosso	Maradi	Tahoua	Tillaberi	Zinder	Niamey

For Niamey we are using the same thresholds as Tillaberi because there is no gridpoint in Niamey province.

Niger: 1st Administrative Division thresholds Spring (2017/03/01-2022/05/31)

percentiles	NER001	NER002	NER003	NER004	NER005	NER006	NER007
50th	904	830	251	308	490	331	575
80th	1437	1559	457	590	745	524	1041
90th	1864	2020	607	790	963	699	1263
97.5th	2465	2724	1009	1169	1598	1001	1773

Niger: 1st Administrative Division thresholds Summer (2017/06/01-2022/08/31)

percentiles	NER001	NER002	NER003	NER004	NER005	NER006	NER007
50th	780	448	91	119	476	190	344
80th	1060	692	159	196	657	281	486
90th	1269	893	204	243	783	329	617
97.5th	1573	1475	258	338	1046	395	933

Niger: 1st Administrative Division thresholds Fall (20170901-20221130)

percentiles	NER001	NER002	NER003	NER004	NER005	NER006	NER007
50th	757	736	184	292	405	244	527
80th	1126	1275	347	462	602	390	813
90th	1336	1645	447	559	726	488	967
97.5th	1737	2029	597	811	972	613	1344

Niger 1st Administrative Division thresholds Winter (2017/12/01-2022/02/28)

percentiles	NER001	NER002	NER003	NER004	NER005	NER006	NER007
50th	1115	1273	482	551	679	513	871
80th	1614	1957	673	839	1040	725	1286
90th	1845	2313	806	973	1269	838	1594
97.5th	2352	2755	992	1248	1974	1024	1880

5.6.3 1st Administrative Division thresholds: Chad

CODE	TD01	TD02	TD03	TD04	TD05	TD06	TD07	TD08
Region	Batha	Borkou	Chari-Baguirmi	Guera	Hadjer-Lamis	Kanem	Lac	Logone Occidental

CODE	TD09	TD10	TD11	TD12	TD13	TD14	TD15
Region	Logone Oriental	Mandoul	Mayo-Kebbi Est	Mayo-Kebbi Ouest	Moyen-Chari	Ouaddai	Salamat

CODE	TD16	TD17	TD18	TD19	TD20	TD21	TD22	TD23
Region	Tandjile	Wadi Fira	N'Djamena	Bahr el Gazel	Ennedi-Est	Sila	Tibesti	Ennedi-Ouest

Chad: 1st Administrative Division thresholds (Spring 2017/03/01-2022/05/31)

percentiles	TD01	TD02	TD03	TD04	TD05	TD06	TD07	TD08	TD09	TD10	TD11	TD12
50th	604	1257	203	180	314	856	435	91	75	72	152	130
80th	1075	2304	457	314	664	1638	846	220	182	152	340	322
90th	1595	2685	728	491	950	2072	1109	370	305	249	587	493
97.5th	2528	3717	1264	856	1644	2995	1827	589	542	385	982	918

percentiles	TD13	TD14	TD15	TD16	TD17	TD19	TD20	TD21	TD22	TD23
50th	86	264	144	103	400	660	419	173	928	794
80th	164	409	254	232	622	1220	696	275	1646	1466
90th	242	526	340	400	830	1758	948	348	1970	1885
97.5th	445	831	558	653	1249	2724	1295	650	2689	2578

Chad: 1st Administrative Division thresholds (Summer 2017/06/01-2022/08/31)

percentiles	TD01	TD02	TD03	TD04	TD05	TD06	TD07	TD08	TD09	TD10	TD11	TD12
50th	330	718	59	71	94	440	141	19	17	20	39	25
80th	468	1201	107	125	166	659	225	46	41	44	70	58
90th	580	1635	136	152	198	836	282	61	60	61	94	76
97.5th	961	2220	174	189	258	1353	410	89	81	82	134	108

percentiles	TD13	TD14	TD15	TD16	TD17	TD19	TD20	TD21	TD22	TD23
50th	27	137	56	24	244	311	286	84	595	577
80th	54	208	100	55	347	442	422	140	935	834
90th	67	254	122	72	404	572	569	179	1159	1045
97.5th	92	330	161	105	514	954	849	212	1671	1443

Chad: 1st Administrative Division thresholds (Fall 2017/09/01-2022/11/30)

percentiles	TD01	TD02	TD03	TD04	TD05	TD06	TD07	TD08	TD09	TD10	TD11	TD12
50th	477	1381	175	129	270	762	356	63	59	56	112	93
80th	920	2006	345	210	481	1419	626	138	114	101	251	227
90th	1188	2280	450	267	636	1670	836	184	152	129	342	318
97.5th	1650	2791	768	402	1030	2178	1289	339	267	173	565	553

percentiles	TD13	TD14	TD15	TD16	TD17	TD19	TD20	TD21	TD22	TD23
50th	62	192	99	70	303	538	304	121	811	743
80th	111	270	155	150	451	1095	470	176	1258	1063
90th	136	329	191	201	551	1371	567	201	1482	1272
97.5th	180	440	267	363	751	1846	911	309	1790	1612

Chad: 1st Administrative Division thresholds (Winter 2017/12/01-2022/02/28)

percentiles	TD01	TD02	TD03	TD04	TD05	TD06	TD07	TD08	TD09	TD10	TD11	TD12
50th	1031	1967	507	313	698	1383	828	242	193	139	404	366
80th	1631	2558	858	500	1090	2127	1326	424	336	243	702	627
90th	1969	2856	1041	685	1347	2536	1536	545	435	357	810	739
97.5th	2424	3351	1247	863	1642	2967	1994	693	637	590	1037	920

percentiles	TD13	TD14	TD15	TD16	TD17	TD19	TD20	TD21	TD22	TD23
50th	138	305	198	246	488	1086	443	190	1117	1064
80th	235	434	305	443	722	1820	685	298	1686	1499
90th	322	534	412	553	869	2145	823	363	1916	1777
97.5th	510	695	568	787	1133	2608	1122	545	2422	2361

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