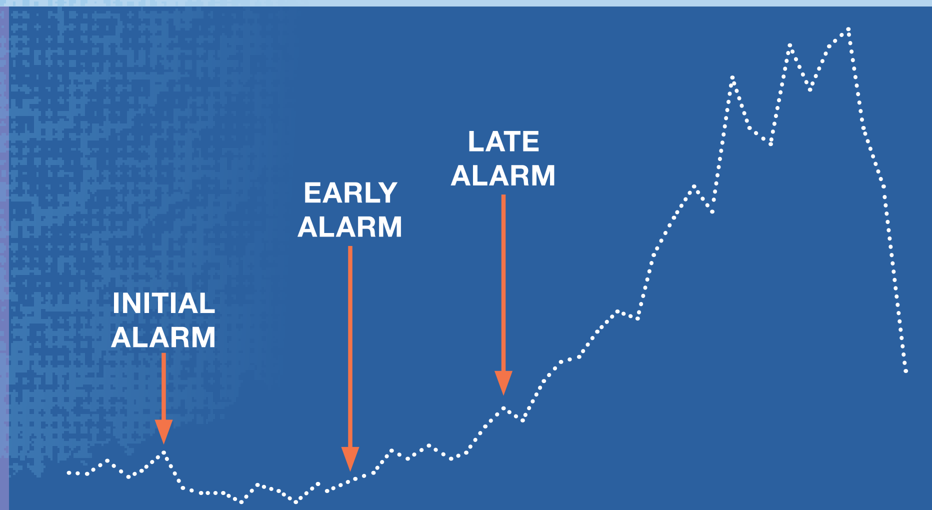
OPERATIONAL GUIDE
using the web-based dashboard



Early Warning and Response System (EWARS) for dengue outbreaks

SECOND EDITION

World Health Organization

TDR For research on diseases of poverty
UNICEF • UNDP • World Bank • WHO

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FOREWORD

Currently, dengue fever is the fastest-spreading mosquito-borne viral disease worldwide with epidemics overburdening stretched health systems and threatening the stability of societies. Although the transmission of dengue and recently also of chikungunya and Zika can be controlled with a combination of effective vector control interventions and an efficient vaccine, late detection and inadequate response mechanisms are compounding the effects of rapid transmission. Furthermore, despite the existence of outbreak alert indicators, the means of deploying them in early warning systems is often lacking.

With this in view, a programme led by TDR, the Special Programme for Research and Training in Tropical Diseases, conducted multi-country research into alarm signals for outbreaks and their use within early warning systems. In line with the prevailing literature,[1,2,3] alarm variables, such as hospitalized confirmed or probable dengue, chikungunya and Zika cases, as well as a set of epidemiological, entomological and environmental variables evidenced predictive abilities.[4] However, it was clear that countries are in need of a standardized and compatible approach to deploy these alarm signals in a predictive and operational way. It was on this basis that an accessible, adaptable and user-friendly early warning system was developed.[5]

This guide is an update to the previous version. This revised edition of *Operational guide using the web-based dashboard: Early Warning and Response System (EWARS) for dengue outbreaks, second edition* aims to provide programme managers with a user-friendly tool that can: (i) analyse and draw conclusions from historic dengue, chikungunya and Zika datasets; (ii) identify appropriate alarm indicators that can sensitively and specifically predict forthcoming outbreaks at smaller spatial scales; and (iii) use these results and analyses to build an early warning system to detect dengue outbreaks in real-time and respond accordingly. Together, these three components will build technical capacity and provide a standardized methodology for predicting dengue outbreaks in countries with great need. Furthermore, this web-based EWARS tool can ensure enhanced, fast and secured communication, between national and subnational levels, and standardized utilization of surveillance data.

The original guide was produced by TDR together with WHO's Neglected Tropical Diseases (WHO/ NTD) and WHO regional offices in the context of a European Union-financed research programme, the International Research Consortium on Dengue Risk Assessment, Management and Surveillance (IDAMS), to develop an evidence-based, early warning system for outbreak detection and management of dengue fever, chikungunya and Zika outbreaks.

[1] Hii YL, Zhu H, Ng N, Ng LC, Rocklöv J (2012). Forecast of dengue incidence using temperature and rainfall. *PLoS Negl Trop Dis.* 6:e1908.

[2] Halide H, Ridd P (2008). A predictive model for dengue hemorrhagic fever epidemics. Int J Environ Health Res. 18:253–265.

[3] Hii YL, Rocklöv J, Wall S, Ng LC, Tang CS, Ng N (2012). Optimal lead time for dengue forecast. *PLoS Negl Trop Dis.* 6:e1848.

[4] Bowman LR, Tejeda GS, Coelho GE, Sulaiman LH, Gil BS, McCall PJ et al. (2016). Alarm variables for dengue outbreaks: a multi-centre study in Asia and Latin America. PLoS One. 11:e0157971.

[5] Hussain-Alkhateeb L, Kroeger A, Olliaro P, Rocklöv J, Sewe MO, Tejeda G et al. (2018). Early warning and response system (EWARS) for dengue outbreaks: recent advancements towards widespread applications in critical settings. PLoS One 13:e0196811.

PREFACE

Welcome to *Operational guide using the web-based dashboard: Early Warning and Response System (EWARS) for dengue outbreaks, second edition*. This guide will provide you with the information and tools necessary to use and analyse surveillance data to predict dengue outbreaks. Below are step-by-step instructions to help you organize your raw data, enter it into the web-based dashboard, run the analysis and interpret your results. At the end of this guide there is an annex providing technical information on the processes and statistics you will be using. However, you do not need to use it to build your early warning system.

The computerized statistical program that the EWARS will be using is called 'R', version 3.4.3. Before running analyses, it is important that the data you have collected are in the correct format; otherwise, the analytical software will not recognize your data and will not work properly.

ACKNOWLEDGEMENTS

The original version of *Operational guide using the web-based dashboard: Early Warning and Response System (EWARS) for dengue outbreaks, second edition* was written by Laith Hussain-Alkhateeb. It was coordinated and supported by Axel Kroeger and Piero Olliaro of TDR, the Special Programme for Research and Training in Tropical Diseases. Special thanks goes to Joacim Rocklöv and his team; Maquins Odhiambo Sewe for the development of the analytical programming during the transfer process from the STATA-to-R statistical package; and, to Aditya L. Ramadona for providing insight and key developmental contributions to the web-based dashboard. We also acknowledge David Benitez (Mexico) and Balvinder Gill (Malaysia) for beta testing the materials, as well as the following colleagues for contributing valuable country data to enable the development of EWARS: Roberta Carvalho (Brazil); Giovanini Coelho (Brazil); Lokman Hakim (Malaysia); Luong Quang (Viet Nam); Ronald Skewes Ramm (Dominican Republic); and Gustavo Sanchez Tejeda (Mexico).

The original version of the guide was developed in the context of a dengue research programme supported by a grant from the European Commission (Grant Number m281803) to the International Research Consortium on Dengue Risk Assessment, Management and Surveillance (IDAMS) within the 7th Framework Programme of the European Commission (FP7), and by TDR.

This version is a revision, to include reference to other arbovirus diseases for which the tool can be used, and to include an additional chapter on the automatized EWARS tool.

GLOSSARY

Term	Definition
R-package	Specialized software used to process and analyse your data and to generate meaningful results.
Endemic channel	This represents the number of cases within the expected normal seasonal range of specific area; anything above this moving threshold would be considered representative of an unprecedented number of cases, i.e. an outbreak.
Outbreak indicator	The dependent variable(s) used to define outbreaks. Usually probable or hospitalized dengue cases.
Alarm indicator	The independent variable(s) used to predict outbreaks. This could be one of a number of meteorological variables, e.g. rainfall, temperature, or other entomological/epidemiological variables.
Spline	A function to capture both positive and non-linear associations between the same alarm indicator(s) and outbreak indicator(s).
Sensitivity	The proportion of outbreaks correctly predicted by alarms. A higher number indicates higher true positive alarms.
Positive predictive value (PPV)	The proportion of alarms that successfully predicted outbreaks. A higher number indicates lower false positive alarms.
Standard deviation (SD)	This is the standard deviation, which is a measure that is used to quantify the amount of variation or dispersion of a set of data values. A low standard deviation indicates that the data points scatter close to the mean (average).

Chapter 1
Preparing your dataset

1.1 Surveillance data, contents and format

Before running the analysis, your dataset should contain the list of variables described below. Variables “year”, “week” and “district” need to be written in lower-case letters, as presented in figure 1. At least one alarm indicator is required (e.g. mean temperature) but additional alarm indicators can also be included. A minimum of three years’ data records is needed to run this program.

Figure 1. Summary list of variables

A	B	C	D	E	F	G	H	I	J	K	L	M
year	district	week	population_annual_number	weekly_hospitalized_cases	weekly_humidity_mean	weekly_rainfall_sum	weekly_temperature_mean					
2015	1	39	200000	3	62,0	0,0	0,0					
2015	1	40	200000	0	65,1	11,7	23,9					
2015	1	41	200000	1	72,3	0,0	26,9					
2015	1	42	200000	1	66,0	2,8	23,8					
2015	1	43	200000	2	71,1	1,3	26,8					
2015	1	44	200000	3	71,0	0,0	27,0					
2015	1	45	200000	1	72,7	23,5	28,1					
2015	1	46	200000	4	70,0	30,4	29,4					
2015	1	47	200000	5	68,7	25,0	29,9					
2015	1	48	200000	3	66,7	15,0	30,1					
2015	1	49	200000	2	70,0	50,5	30,9					
2015	1	50	200000	1	71,4	90,2	31,0					
2015	1	51	200000	0	74,1	139,4	31,0					
2015	1	52	200000	0	84,0	369,7	30,9					
2015	2	1	3450000	2	62,0	0,0	0,0					
2015	2	2	3450000	2	65,1	11,7	23,9					
2015	2	3	3450000	4	72,3	0,0	26,9					
2015	2	4	3450000	3	66,0	2,8	23,8					
2015	2	5	3450000	5	71,1	1,3	24,8					
2015	2	6	3450000	4	71,0	0,0	27,0					
2015	2	7	3450000	3	72,7	0,0	28,1					
2015	2	8	3450000	2	70,0	0,5	29,4					
2015	2	9	3450000	1	68,7	1,3	29,9					
2015	2	10	3450000	1	66,7	0,0	30,1					
2015	2	11	3450000	3	70,0	1,8	30,9					
2015	2	12	3450000	2	71,4	0,3	31,0					
2015	2	13	3450000	0	74,1	139,4	31,0					
2015	2	14	3450000	1	84,0	369,7	30,9					

The user can add more "alarm" indicators here!

1.1.1 General variables

- “year”: the year when the data were collected. The year must be entered in full using “four” numbers (e.g. 2015, 2016, etc.);
- “week”: the number of the epidemiological week (Sunday to Saturday) when data were collected/obtained. The week number must be entered in full (e.g. 1, 2, 3, etc.);
- “district”: a number (code) that represents the district, locality or municipality where data were captured (e.g. 1, 2, 15, 22, etc.);
- “population_annual_number”: the annual population size of a district is reported in absolute numbers in the surveillance data. See column G in figure 1, above.

1.1.2 Outbreak indicator

- "weekly_hospitalized_cases": this is the number of hospitalized cases in a given district per epidemiological week, based on the date of hospital admission. Unless rigorous analysis using statistical imputation and validation methodologies have been performed on other outbreak indicators beforehand, we recommend using hospitalized cases as the most appropriate records. You could substitute probable case data where hospitalized data are missing, but this must be distinguished and consistent across all datasets. You cannot mix hospitalized and probable case data.

1.1.3 Alarm indicator(s)

You need a minimum of one alarm indicator, but there is no maximum limit. Please ensure that you enter the exact variable name of the alarm indicator in the Dashboard I interface but avoid alarm indicators with substantial missing records. Some examples of alarm indicators are listed below:

- "weekly_humidity_mean": the weekly mean humidity (as a percentage), for a corresponding district and year;
- "weekly rainfall_sum": the total weekly rainfall (in mm) for a corresponding district and year;
- "weekly_temperature_mean": the weekly mean temperature in either Celsius or Fahrenheit (do not use Celsius and Fahrenheit data in the same spreadsheet: choose one or the other), for a corresponding district and year;
- "ovitrap index", measured as the proportion of positive ovitraps per block or other indicators (i.e. infested with *Aedes* eggs).

Please note, it is important that the corresponding variable names are entered correctly where specified in the Dashboard I interface, i.e. they should have the exact spelling and format as in the original surveillance dataset (column).

Chapter 2
Dashboard I: Data calibration (for user at central level)

In this web-based interface (Dashboard I), you are going to make necessary settings and calibrations and, eventually generate the algorithm and parameter coefficients that users at district levels will be using for their prospective analyses (in Dashboard II). This process can take place once a year. In addition, and prior to doing any calibration, you will need to assign local users at districts level an 8-digit password to access their corresponding district account and run their prospective analysis.

The instructions below relate to these steps before linking to the prospective analysis (Dashboard II).

2.1 Accessing the EWARS dashboard

Countries can contact **ewars@post.com** to request their own EWARS accounts for free access and applications. The use of a country's own dashboard account increases the usage capacity and ensures privacy and data protection.

Once requested, each country will be provided with usernames and passwords to access their own dashboard accounts as well as a Google drive account to link both dashboards. Users at central (national) level will need to use Dashboard I for the setting and calibration process and, users at local (district/provincial) level will need Dashboard II for declaring alarm signals (if any) and responding to alarms accordingly (prospective phase). Users at the central level will need to log into their corresponding Google drive accounts and install into their local PC, where they can view all files generated from dashboard I. You can access your account by simply clicking on the link provided in the EWARS COUNTRY PACKAGE then use the given user name and password to run.

Along with the EWARS package, the R-program script and additional instructions are also provided (under the "HELP" tab in Dashboard I) to assist countries with interest in building their own national hub or integrating this EWARS tool into their existing national surveillance program. This is recommended as it can facilitate a more feasible and sustainable application.

For the purpose of demonstration and training, *demo Dashboard* accounts and a *demo dataset* are provided in the box below:

Dashboard I & II:
https://alramadona.shinyapps.io/Demo_Automated_Ewars/

Once you access Dashboard I, you can download the "Demo Dataset" from the "HELP" tab for further practical understanding of the tool.

2.2 Setting the country, password and the surveillance dataset

2.2.1 Country code and password settings (to allow access for local users)

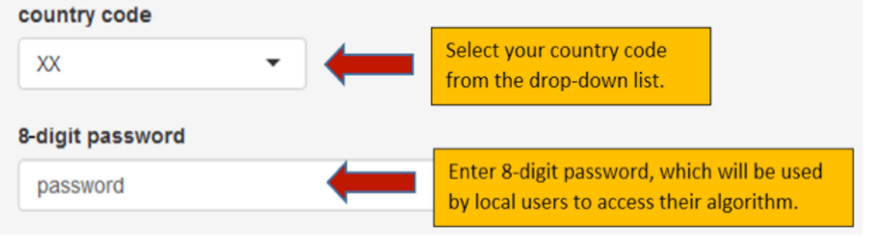
Before running Dashboard I, you can choose your country code from the list (for the demo account only!).

Users at central level need to assign secured 8-digit passwords for local users at district-level (Dashboard II) to use when accessing their corresponding district information (algorithm and coefficients) they require on a weekly basis for the prospective analysis.

Figure 2 shows where you can find and change these settings. More settings follow after the figure and are illustrated in the section below.

This option is only available for country-specific Dashboards

Figure 2. Language setting and assigning password for local users to access their corresponding algorithms

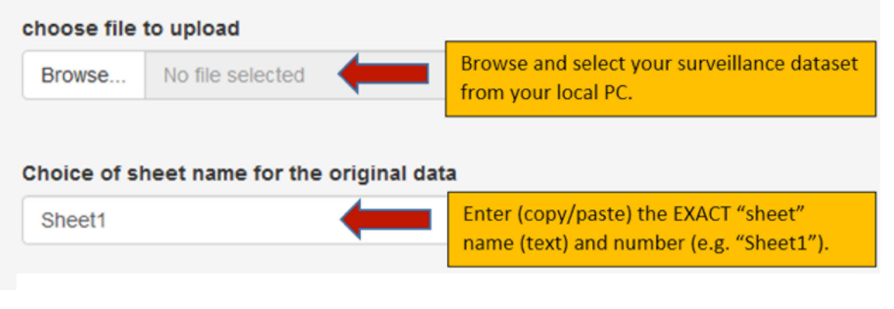


2.2.2 Uploading your surveillance dataset

Browse and select your dataset in order to upload it and run the calibration process. In Excel, a spreadsheet is divided into “sheets”. These sheets can be given a name, but unless you do, the usual name is “Sheet1”. Enter (copy/paste) the EXACT sheet name (text) and number (e.g. “Sheet1”) into the corresponding box in your dashboard interface so the analytical tool can allocate your dataset.

This option is found under ‘Data’ tab in Dashboard !

Figure 3. Uploading your dataset and entering the corresponding sheet name and number



2.3 Calibrating your instrument

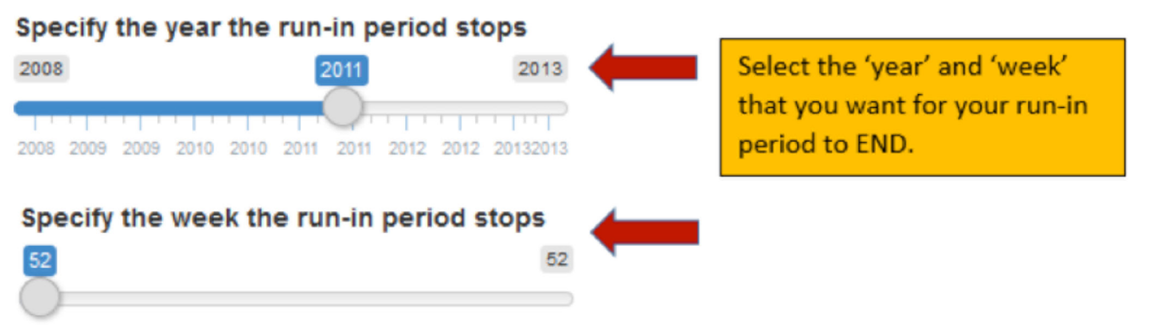
2.3.1 Dividing your dataset into run-in and evaluation data

Before running Dashboard I, you must change the model settings in accordance with your data and the analysis you want to run (changing values, alarm/outbreak thresholds, etc.). This will define and improve the prediction of outbreaks.

The figures in this section show you where to find these settings so that you can change them.

This option is found under 'Variables & Run-in' tab in Dashboard I

Figure 4. Dividing your dataset

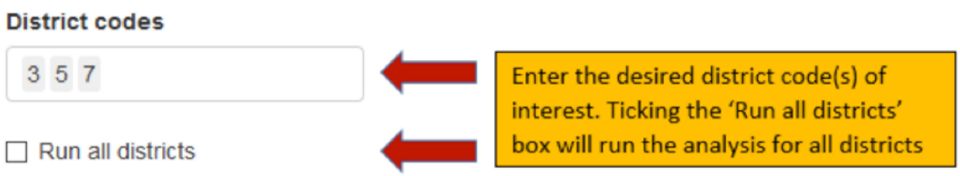


- To detect alarm indicators that can help you predict outbreaks, you need to first run a retrospective analysis of your data. For this step, the model requires that you divide your dataset into two time periods. Now you must choose the dates of your historic/run-in period and the evaluation period.
- See sections 2.1.1 and 2.1.2 in Annex 1 for more details on the "run-in period" and "evaluation period"!
- To do so, enter the year and week that you want your "run-in period" to END. The analytical tool will automatically use all data after this date as the "evaluation period". For example, enter 201326 with no space between the year and week digits for year "2013" and week "26".
- *This corresponds to* **steps 1** *and* **10** *in the annex.*

2.3.2 Defining the districts to be analysed

This option is found under 'Data' tab in Dashboard I

Figure 5. Choosing your districts

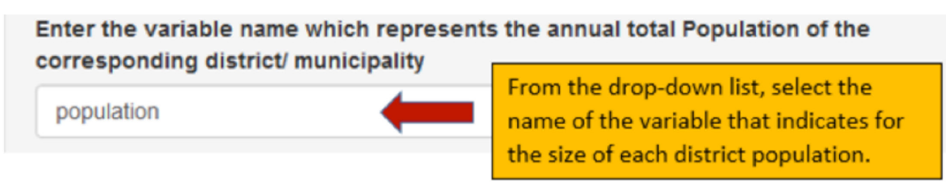


- Here you can choose to analyse specific districts or all districts.
- Enter the desired district code(s) of interest.
- The user can enter more than one district code by using 'comma' between each district code.
- *This precedes* **step 1** *in the annex.*

2.3.3 Defining the district population

This option is found under 'Variables & Run-in' tab in Dashboard I

Figure 6. Defining the annual number of people in your districts

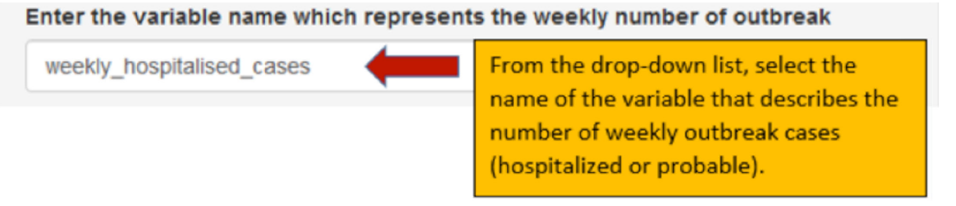


- In each district you will have a different human population.
- Here, you must type the name of the variable that tells the analytical program the size of each district population, e.g. if your spreadsheet column is labelled population, please type "population" into the box.
- It is important to type the EXACT text of the variable names (i.e. the title of the column) as it appears in the surveillance data.
- *This corresponds to* **step 3a** *in the annex.*

2.3.4 Defining your outbreak indicator

This option is found under 'Variables & Run-in' tab in Dashboard I

Figure 7. Labelling the number of outbreak cases



- Here you must consider what incident case data have been captured. For example, it might be the number of "weekly_hospitalised_cases" (recommended) or weekly probable clinical cases or other possible case indicators.
- Please type in the indicated box, the column name that describes these data – it must be the same as in your surveillance dataset.
- *This corresponds to* **step 3a** *in the annex*.

2.3.5 Defining your outbreak period

This option is found under 'Variables & Run-in' tab in Dashboard I

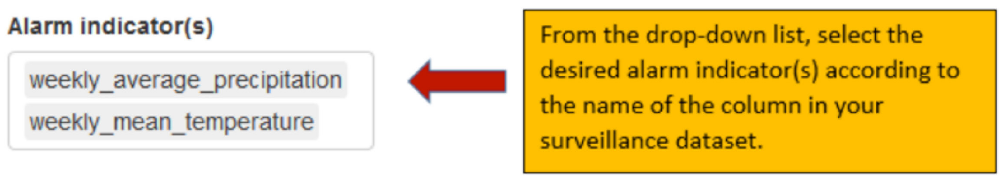
Figure 8. Defining the outbreak period

- A collection of consecutive "outbreak weeks" defines an outbreak. It is up to you how to define an outbreak, but we recommend 2 or 3 weeks.
- Enter the desired choice of the minimum number of outbreak weeks needed to define the outbreak period. For example, if you enter 3 in this box then a minimum of "3" consecutive outbreak weeks is required to define an outbreak (outbreak period), and a minimum of "3" consecutive NON-outbreak weeks is required to declare a no-outbreak period.
- *This corresponds to* **step 3b** *in the annex*.

2.3.6 Defining your alarm indicator(s)

This option is found under 'Variables & Run-in' tab in Dashboard I

Figure 9. Defining the alarm indicator

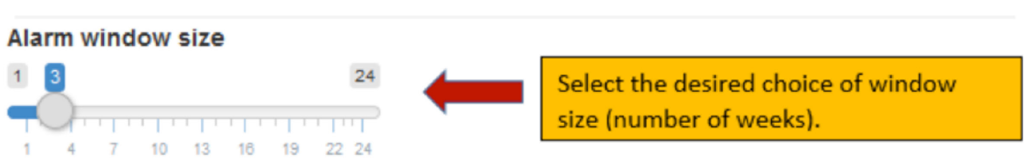


- Alarm indicators are defined as an alarm that can predict a forthcoming outbreak.
- Here you can choose which "alarm indicator"(s) you want to test for predictive capacity.
- Enter the desired alarm indicator(s) according to the name of the column in your surveillance dataset; you may include an unlimited number of alarm indicators in this command.
- Missing data will negatively affect the results so be sure that you have a complete dataset before running any or multiple alarm indicators.
- Do not alter the alarm indicator(s) text.
- It is important that the name of the alarm indicator you enter in this option is EXACTLY the same as the variable name in the surveillance data (i.e. the same text you find in the column title in your surveillance data).
- *This corresponds to* **step 4** *in the annex.*

2.3.7 Defining your window size for the alarm indicators

This option is found under 'Calib1' tab in Dashboard I

Figure 10. Defining window size for the alarm indicators



- The values of each "alarm indicator" will be recalculated by the program to produce an average over a given time period. Here you can alter this time period.
- Enter the desired choice of window size (number of weeks) from which the mean value of the alarm indicator can be calculated.
- For example, entering a value of "3" for this option suggests that you are calculating the mean value (average) of the alarm indicator (e.g. temperature) of the current week and two previous weeks, consecutively. A minimum value of

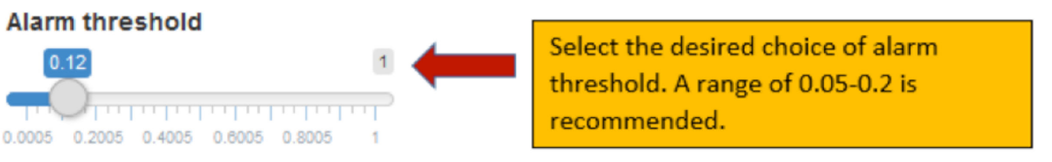
"1" means you are measuring the alarm indicator unit of the current week!

- *This corresponds to* **step 4** *in the annex.*

2.3.8 Defining your alarm threshold

This option is found under 'Calib1' tab in Dashboard I

Figure 11. Defining the alarm threshold

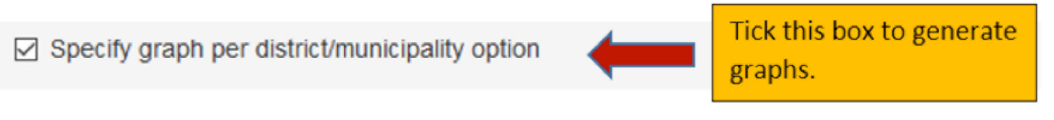


- Here you decide what "alarm threshold" is used to signal an alarm.
- At this stage, a probability of an outbreak is calculated based on the user's input. The alarm threshold is, therefore, a value you need to enter to define a possible alarm signal (an alarm signal is declared when the calculated outbreak probability > the alarm threshold you entered).
- If the threshold you entered is too high, you may not have any alarms and, therefore, no alarm outbreaks will be predicted. If the threshold is too low, you may have many alarms that detect all outbreaks but you will also have many false alarms. You need to experiment with the appropriate value by changing the threshold to get a good balance between a low number of false alarms (positive predictive value or PPV) and high outbreak prediction rate (sensitivity).
- The optimal threshold value has often been shown to be in the range of 0.05–0.2.
- *This corresponds to* **step 13** *in the annex.*

2.3.9 Defining the graphical outputs

This option is found under 'Calib1' tab in Dashboard I

Figure 12. Selecting your graphical output

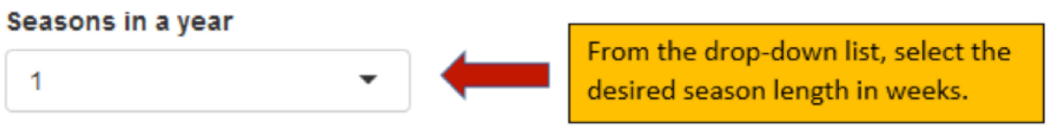


- Here you can generate a graph for a specific district, many districts or all districts.
- Tick the indicated box for the graph presentation of the outcome.
- Leaving this option blank will not generate the basic "run-in" analysis graph.
- *This corresponds to* **step 14** *in the annex.*

2.3.10 Defining your seasonal variation

This option is found under 'Calib1' tab in Dashboard I

Figure 13. Choice of the seasonal variation

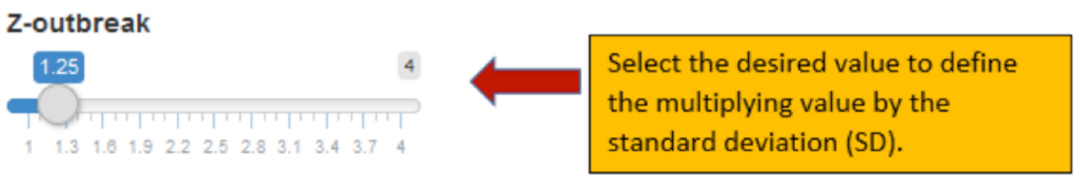


- If you believe that some alarm indicators are better predictors at different times of the year, you can allow for this by dividing the year into different periods.
- For example, "season length"=4 means that the first alarm indicator analysis is based on the first 4 weeks of the year, the second is based on week 5–8, the third is week 9–12, etc.
- A maximum season length value of 52 is acceptable. Your minimum season length value should be > the value you entered for the window size (e.g. 2) for measuring the mean alarm indicator including the current week.
- *This corresponds to* **step 8** *in the annex.*

2.3.11 Defining your endemic channel

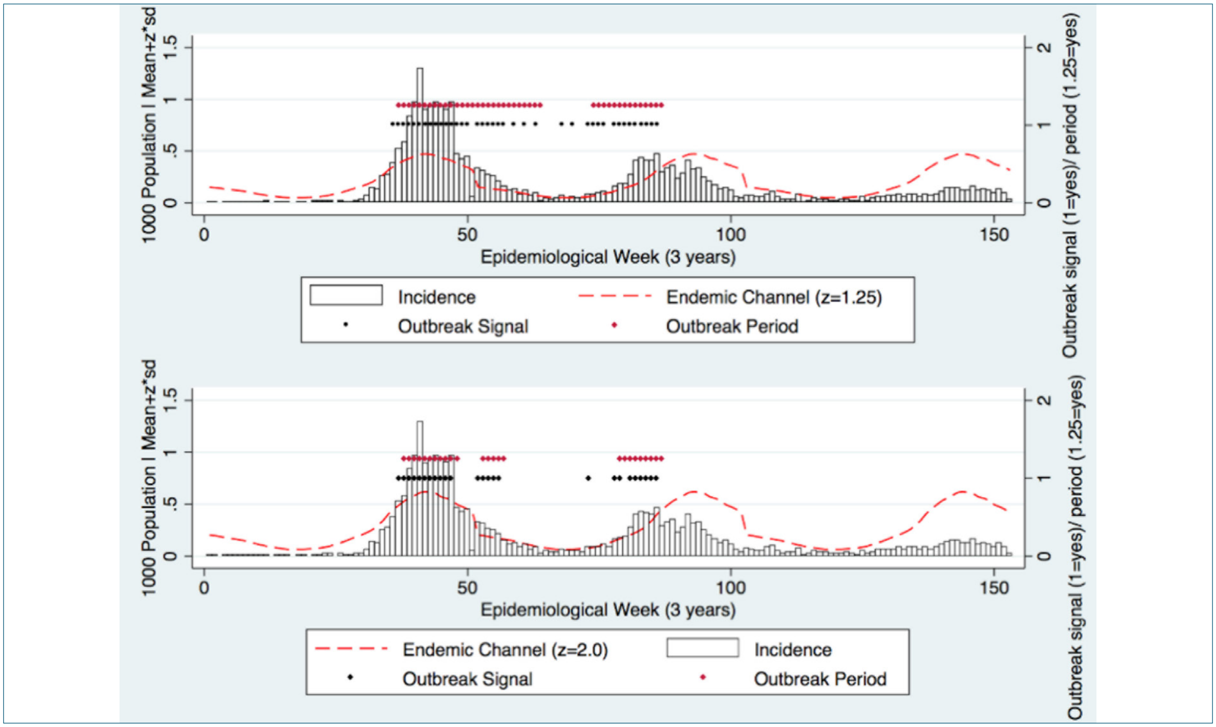
This option is found under 'Calib2' tab in Dashboard I

Figure 14. Changing the endemic channel (the outbreak threshold)



- Here you can change the number of cases required to form an outbreak week and therefore an outbreak. By increasing this threshold you will define fewer outbreaks, and by decreasing this you will increase the number of recorded outbreaks (figure 15).
- Enter the desired value to define the "multiplying value" by the "standard deviation (SD)", for example, z=1 is the same SD, z=1.5 is one and half times the SD, z=2 is two times the SD, etc. See figure 15 below.
- *This corresponds to* **step 2** *in the annex.*

Figure 15. Modelling the endemic channel[a]

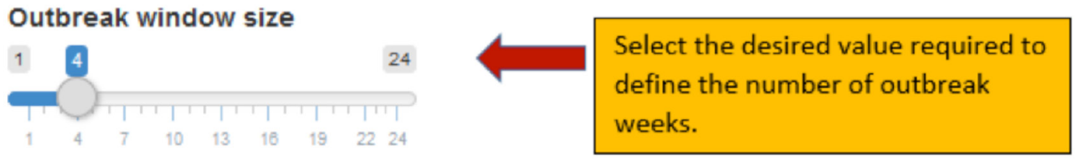


[a] The modelling illustrates two z-values (top: z=1.25 and bottom: z=2.0) to form the endemic channel – outbreak signals are fewer when z-value is increased.

2.3.12 Defining your window size for the outbreak indicator

This option is found under 'Calib2' tab in Dashboard I

Figure 16. Defining the number of outbreak weeks (window size)

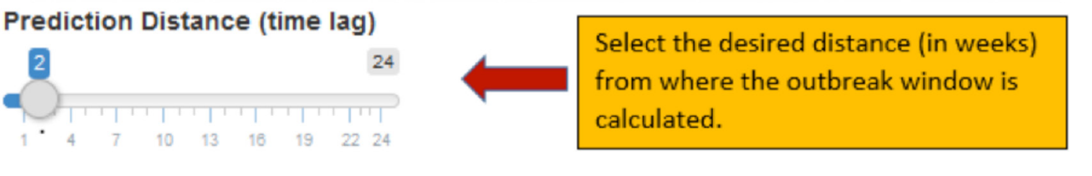


- In section 2.3.5, you defined the outbreak period. In this section, you can choose a suitable window size (or denominator) for calculating the proportion from these outbreak periods. For example, if you choose a window size of "4", the program will take the "sum of values" of 4 consecutive outbreak periods and divide it by 4 to generate a proportion – this proportion is then needed in the next steps to formulate the outbreak signal.
- Decreasing this window size can increase the sensitivity of predicting an outbreak. At the same time, you may have to choose to increase this window size when you have some missing records in your data.
- The choice of your window size depends on the evaluation criteria that give the best outbreak predictions, see step 14 in the annex.
- *This corresponds to* **step 5** *in the annex.*

2.3.13 Defining your prediction distance

This option is found under 'Calib2' tab in Dashboard I

Figure 17. Defining the prediction distance (in weeks)

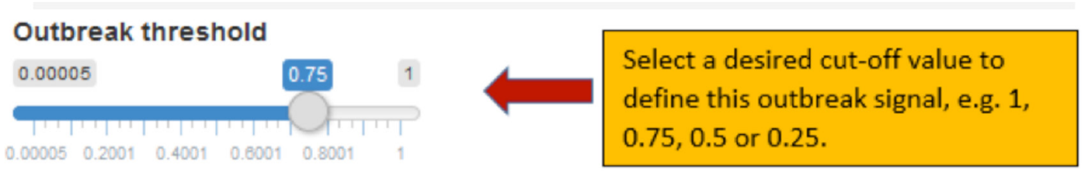


- Enter the desired "choice of distance between current week and target week to predict an outbreak signal".
- For example, at week 10, if prediction distance=2 and outbreak window=4 (previous option), this will mean that you start counting from week 12 up to week 15 (4 weeks) to predict an outbreak signal.
- *This corresponds to* **step 5** *in the annex.*

2.3.14 Defining your outbreak signal

This option is found under 'Calib2' tab in Dashboard I

Figure 18. Defining the cut-off point of the outbreak signal



- In a previous step (2.3.12), you computed the "proportions" from the outbreak periods. The proportion is a value between zero and one and in order to process this value to generate an outbreak signal, it needs to be converted into either zero (which means no outbreak) or one (which means an outbreak).
- Here, in this step, you can choose a "cut-off value" to define this outbreak signal. For example, if you choose a cut-off value of 0.5, then every proportion value above this cut-off value (e.g. 0.7> 0.5) will be given the code one (indicating that there is an outbreak), and any proportion value less than this cut-off (e.g. 0.3< 0.5) will be given the code zero (indicating no outbreak). This way you have defined your outbreak outcome (a binary variable 0,1), which is the dependent variable needed for the logistic regression.
- The choice of a relevant value depends on the evaluation criteria that give the best prediction of outcome, see step 14 in the annex.
- *This corresponds to* **step 7** *in the annex.*

2.3.15 Activating the process for monotonic relationship (spline)

This option is found under 'Data' tab in Dashboard I

Figure 19. Choice of the spline application

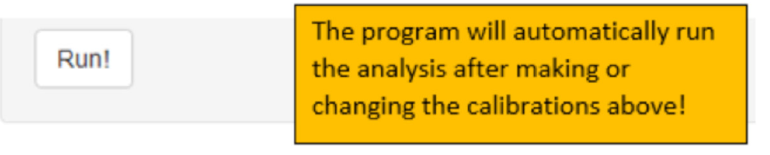
- "Spline" is a function that allows the program to treat a certain type of relationship between alarm indicators and dengue cases.
- Without spline, the program will assume linear (non-monotonic) relationships, i.e. as the temperature increases, dengue cases increase.
- With spline, the program will assume monotonic relationships, e.g. as the temperature increases, dengue cases go down. (This is due to decreased vector activity because of excessive temperatures. Another example is increased rainfall where the risk of outbreak increases with increased rainfall, which provides more water for breeding. However,

too much rain, e.g. flooding, can flush out larvae and pupae, hence, temporarily reducing the outbreak risk.) Here you can choose between two options.

- Enter the desired spline option, i.e. code 0=No (non-monotonic relation) or 1=Yes (monotonic relation).
- You can see how spline affects your (sensitivity and PPV) results by first running without spline and then with spline.
- *This corresponds to* **step 6** *in the annex.*

2.3.16 Running the program

Figure 20. Running the surveillance workbook

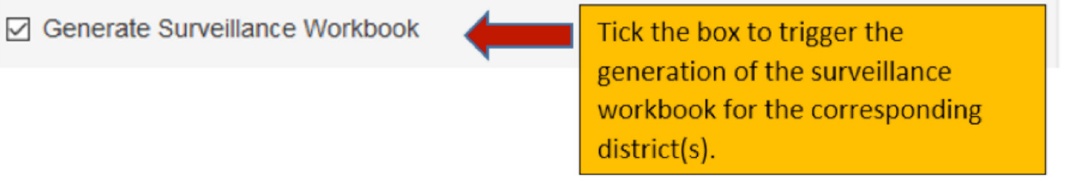


- Once you have completed the changes, the program automatically start the analytical process and generate results..

2.3.17 Generating the surveillance workbook

This option is only available for country-specific Dashboards!

Figure 21. Generating the surveillance workbook



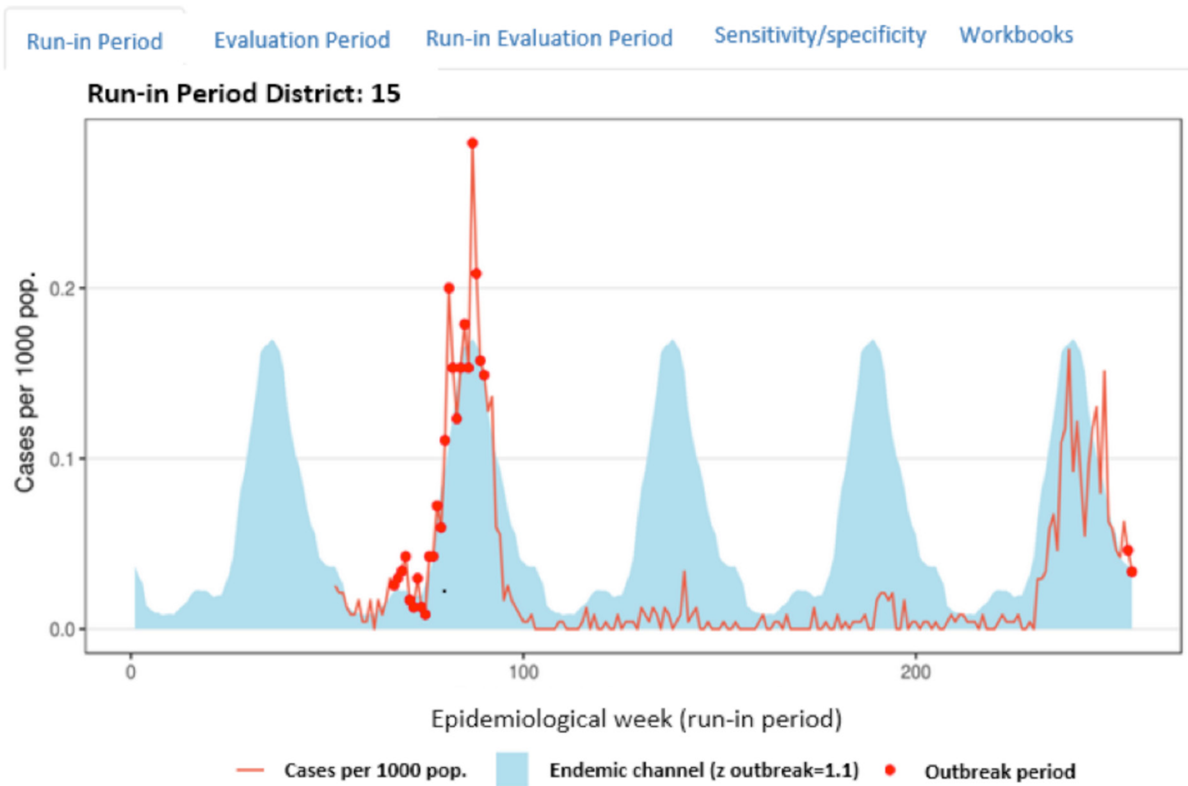
- Leaving the "Generate Surveillance Workbook" box empty (e.g. un-ticked) runs a retrospective analysis of your dataset that allows you to find your alarm indicators. You should do this first (leaving an empty box) every time you make a change to the settings (calibration stage).
- Ticking this box generates the prospective early warning system in Excel and automatically links it to the prospective analysis of the local district (Dashboard II). Only choose this if you have already run the retrospective analysis, made all necessary calibrations, already identified your alarm indicators, and are satisfied with the resulting sensitivity and PPV.
- *This corresponds to* **step 16** *in the annex.*

2.4 Understanding your calibration outputs

Each time you run the program after making or changing your settings, one table of results will be displayed on the dashboard screen, from which you will need to verify your calibration. Graphs will also be generated to help you understand the current process and whether or not there are any errors or gaps in your data.

2.4.1 Graph: run-in period

Figure 22. Graph of the run-in data showing the endemic channel, number of cases and outbreak period



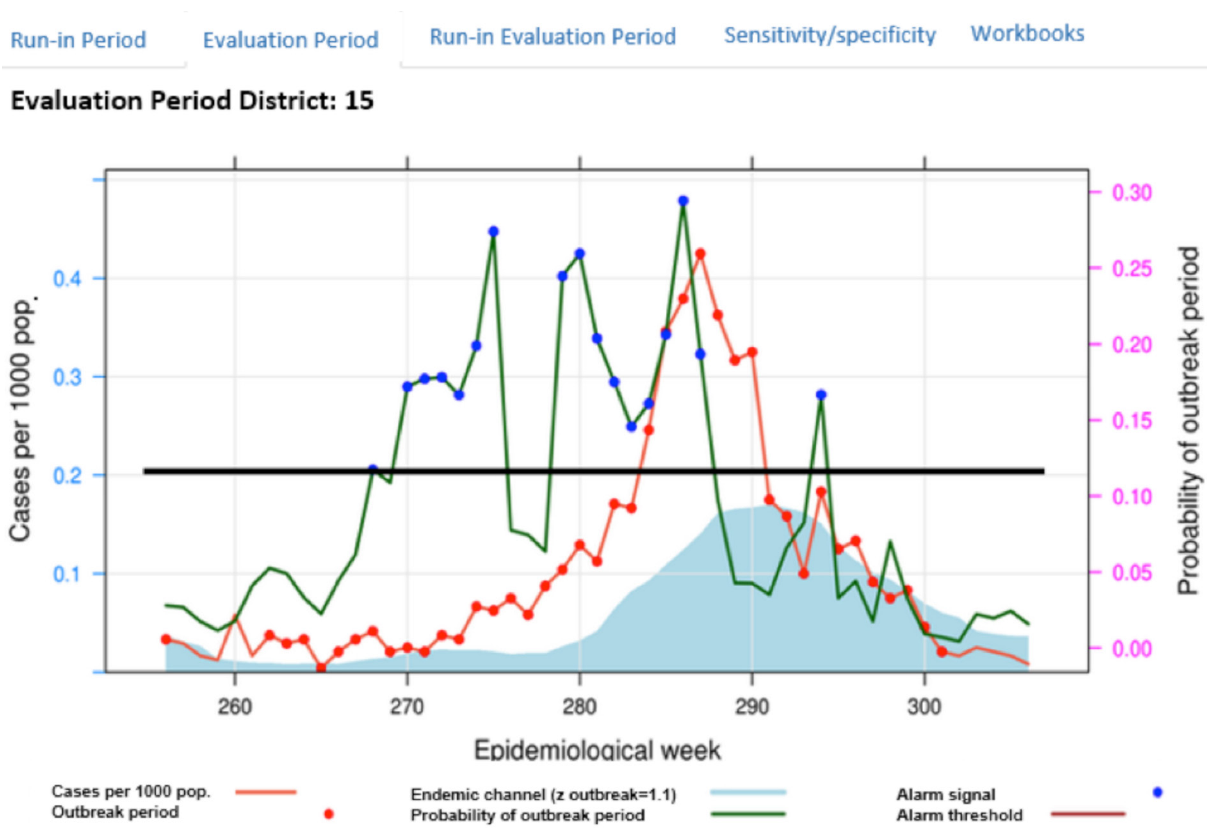
This graph summarizes the first half of your data, which is the "Run-in Period" data.

- Here you can learn about the duration of the data (from the X-axis; every 51 epidemiological week is one year), the average number of cases/1000 throughout the "Run-in Period" and the size of your "Endemic channel" defined by the given "z" value.

- Cases that exceed the endemic channel and trigger an "Outbreak period" are also presented.
- This graph can also indicate the quality of your data, for example a gap in the endemic channel indicates that there are missing data. At this point, you may need to change your configuration to take into account these missing records by increasing the outbreak and alarm window size!

2.4.2 Graph: evaluation period

Figure 23. Graph of the evaluation data showing the general parameters including the probability of outbreak period

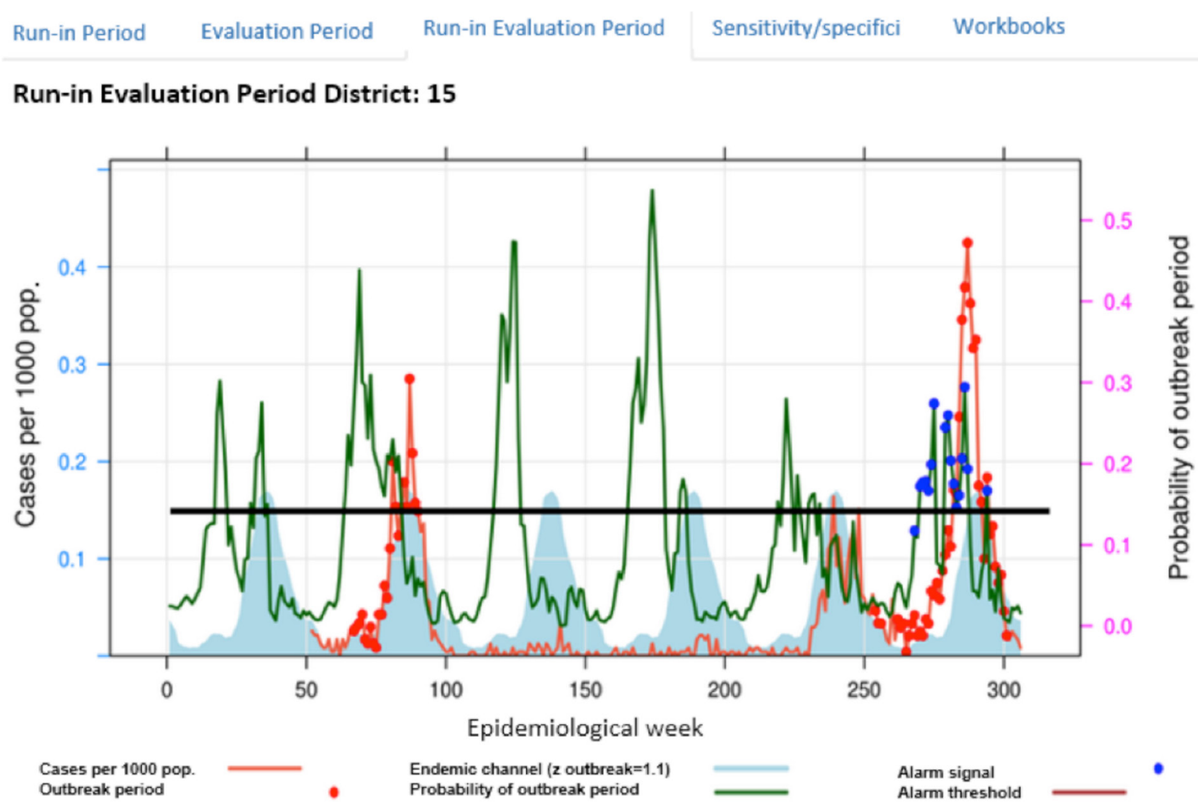


- This graph summarizes the second half of your data, which is the "Evaluation Period" data. It simply tells how your model performs according to the given settings/calibrations in the run-in data.
- Here you can view the continuation of analysis duration (from the X-axis; every 51 "Epidemiological week" is one year, now continuing from the first half of the run-in data).

- More information is provided here. In addition to the information presented in the run-in data, you also find details on "Alarm signal", "'Alarm threshold" and the "Probability of outbreak period".
- When the probability of outbreak exceeds the given alarm threshold during a particular epidemiological week, the alarm signal (blue dots) is triggered, indicating an upcoming outbreak.

2.4.3 Graph: run-in and evaluation period

Figure 24. Graph of the combined run-in and evaluation data showing all information



- This graph summarizes both the run-in and evaluation data and their corresponding information.
- It provides you with a comprehensive picture of the duration of the analysis and an overview of how well the model is performing.

2.4.4 Summary of calibration results, and sensitivity and PPV

For the purpose of providing detailed illustration of the derived terms and values to guide you through this process, we split this table into two parts; the first table (figure 25), demonstrates the absolute numbers of the results from the retrospective phase and the success/failure of the parameters (alarm threshold, z value, etc.) that were used to analyse the dataset (this table also summarizes “all cases” and “cases below threshold”, which are not displayed in this figure). The second table (figure 26) describes the proportion of successfully detected outbreaks (sensitivity) and the proportion of false alarms (PPV). The sensitivity and PPV can directly guide you to make appropriate choices for the calibration inputs.

Figure 25. Absolute values in the output table, example showing total number of outbreaks, missed outbreaks, alarms, correct alarms and false alarms

District	Weeks	Outbreak Weeks	Outbreak Periods	Alarms	Correct Alarms	False Alarms	Missed Outbreaks	No Alarms, No Outbreaks
12	51	32	34	12	10	2	25	14
15	51	34	35	17	16	1	18	16
Total	**102**	**66**	**69**	**29**	**26**	**3**	**43**	**30**

The definitions of each of the column headings are presented below.

1. “Weeks”: indicates the size of your evaluation data presented by the total number of weeks, e.g. 51=almost one year, 102=two years of data records were used in the evaluation data after you have initially split your surveillance data into run-in and evaluation datasets.
2. “Outbreak Weeks”: a week where the number of cases is above the endemic channel (z*SD + moving average).
3. “Outbreak Periods”: consecutive outbreak weeks (for our definition, this is an outbreak).
4. “Alarms”: total number of alarm signals.
5. “Correct Alarms”: alarm that correctly predicted the outbreak.
6. “False Alarms”: alarms that falsely predicted the outbreak (false positive).
7. “Missed Outbreaks”: alarms that could predict the outbreak if the alarm threshold was lower.
8. “No Alarms, No Outbreaks” (negative correct alarms): no alarms when there is no outbreak.

Figure 26. Sensitivity and PPV (screenshot of the output table – success of predicting outbreaks is shown in sensitivity/PPV)

Sensitivity/specificity | Workbooks

Sensitivity	PPV
0.77	0.97
0.80	0.47

Definitions (tests of validity)

- "Sensitivity": the percentage of outbreaks correctly predicted by alarms. This should be as close to 100% as possible. Minimum value of 50% is acceptable.
- "PPV": the percentage of alarms that correctly predicted outbreaks. This should be as close to 100% as possible. Minimum of 50% is acceptable.
- To increase the number of correct alarms and decrease the number of false alarms, we suggest that you alter the z value and alarm threshold, then, if necessary, alter the remaining parameters as desired. Then re-run the program.

Operational perspective

- If sensitivity is, for example 60%, then for every 10 outbreaks, the early warning system will detect 6 outbreaks correctly. It will miss 4 outbreaks.
- If PPV is, for example 70%, then 7 out of 10 alarms will be correct, 3 out of 10 alarms will be false. That means that 3 times out of 10, resources will be incorrectly mobilized, i.e. wasted.
- Consider this: in Dashboard II below, you will build the early warning system using your retrospective data. The results above are based on the presence of 1 alarm signal before an outbreak. The early warning system below uses a total of 3 alarm signals to better warn of outbreaks. Therefore, in the presence of 2 or 3 (or more) alarms, the chances of detecting an outbreak increases and the chances of wasting resources decreases with each alarm.

Chapter 3
Dashboard II: Harvesting the Results (for users at local level)

3.1 Prospective early warning system

This section summarizes the parameters and settings that were found to be most relevant and provided the best prediction model (highest sensitivity and PPV).

We discuss how to build your prospective early warning system using results from your retrospective analyses in Dashboard I (users at central level).

At this stage, you know which alarm indicators are the best predictors of outbreaks in your district/country. Now we need to apply the derived results within an early warning system that will allow you to detect outbreaks in real-time.

By the end of this chapter, you will be familiar with the analysis outputs, data entry and interpretation of alarms.

PLEASE NOTE, THIS PROSPECTIVE PROCESS NEEDS TO BE PERFORMED ON A WEEKLY BASIS!

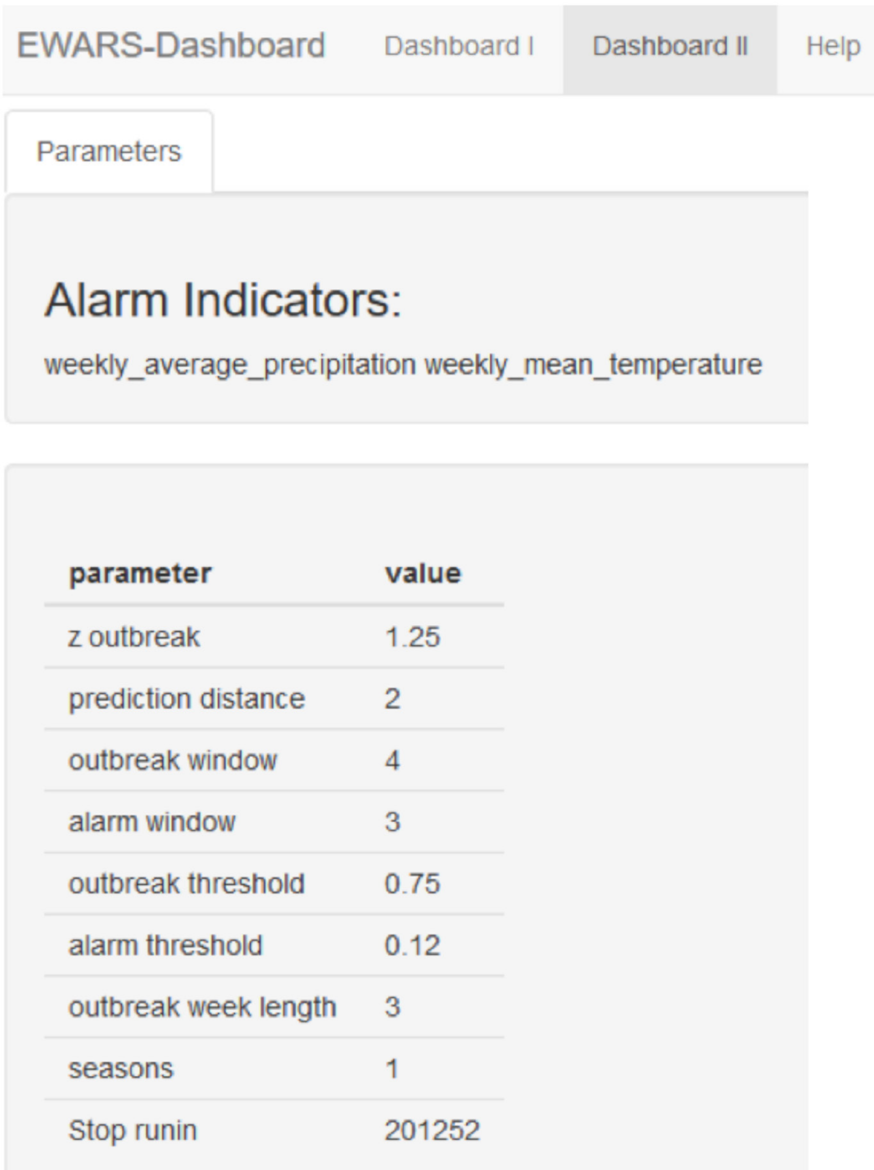
3.1.1 Access to and summary of parameters: where to find them in Dashboard II and their usefulness

Dashboard II (provided for users in the EWARS PACKAGE, see section 2.1 above).

- This section under "## parameters", provides a useful summary of all parameters and settings used in the retrospective analysis (Dashboard I) that were found to be the most relevant and generated the best prediction model (highest sensitivity and PPV) (figure 27).
- Under "## parameters", the "alarm indicator" headings display the actual alarm indicator(s) that were used in the retrospective analysis and need to be used again in the prospective process for the outbreak prediction. For instance, here the user from Dashboard I used "meantemperature" and "rainfallsum". Therefore, for the outbreak prediction in the prospective analysis, weekly records from both of these parameters need to be used in Dashboard II.
- Other parameters are also presented. The "prediction distance" is another useful factor in informing the time lag for when to expect an outbreak, in case the alarm signal is triggered (i.e. we have a forthcoming outbreak). For instance, if an alarm signal were triggered at the current week (say week 7 when you enter the prospective information) and the chosen "prediction distance"=2, then you would expect an outbreak to occur during week 9.

This option is found under 'Parameters' tab in Dashboard II

Figure 27. Summary of parameters from the retrospective analysis (Dashboard I)



parameter	value
z outbreak	1.25
prediction distance	2
outbreak window	4
alarm window	3
outbreak threshold	0.75
alarm threshold	0.12
outbreak week length	3
seasons	1
Stop runin	201252

3.1.2 The three sub-links in Dashboard II: “Retrospective”, “Dataset”’ and “Help”; their definitions and uses

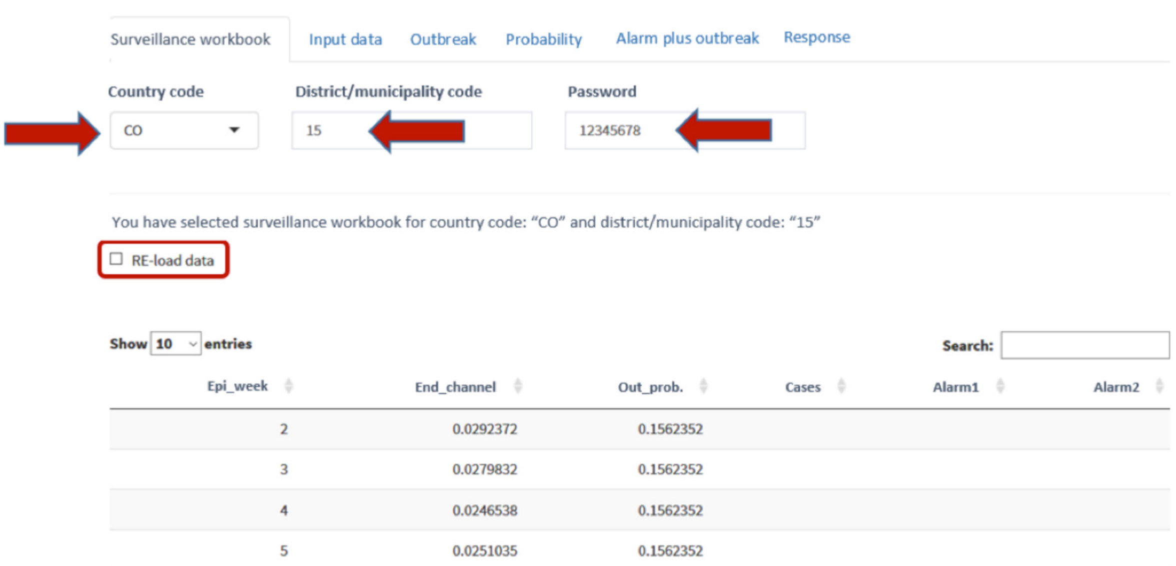
As outlined at the top left-hand corner in figure 27, there are three main sub-links to follow.

1. The “Retrospective” tab is the main location for running the prospective analysis and interpreting the findings.
2. The “Datasets” tab: this is where you can locate and access the nearest meteorological stations to retrieve the needed prospective alarm indicator information (e.g. weekly mean temperature, rainfall and humidity).
3. The “Help” tab enables you to access the user’s operation workbook and the short training video.

3.1.3 The surveillance workbook tab: all you need to know for this section

This option is only available for country-specific Dashboards!

Figure 28. Surveillance workbook tab: all you need to know for this section



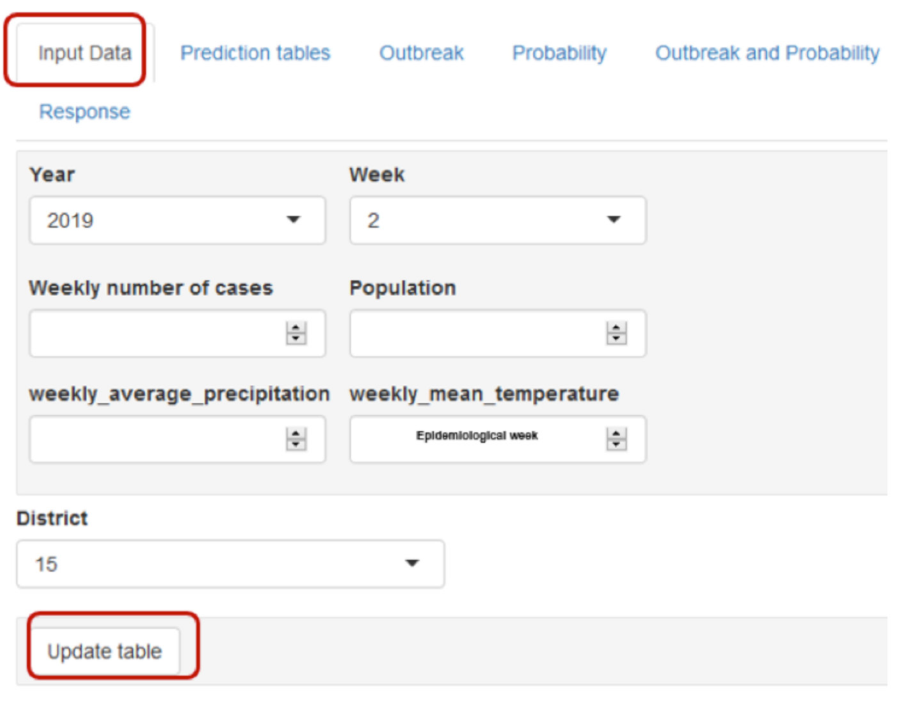
- Under the “surveillance workbook” tab, you can set the corresponding “Country code “and “District/municipality code”, enter the assigned password to access your district information and perform the prospective analysis (e.g. CO=Colombia, MX=Mexico, DO=Dominican Republic).
- To demonstrate how to use, view and apply the applications in Dashboard II, we include demonstration data that you can select from the drop-down “country code” menu with the code “XX”.

- The "District/municipality code": this follows the same district code given in the original surveillance dataset. You need to enter your corresponding district/municipality code to allow access to your account for doing the prospective analysis.
- Under "Password" enter the assigned password that was generated and sent to you during the retrospective stage. This is an 8-digit password usually unique to each district to allow access to this account.
- You need to tick the "RE-load data" button to upload the new prospective data when you enter new weekly information under the "Input data" tab. Every time you add more weekly information under this tab, you need to come here and un-tick then tick the "RE-load data" box to upload fresh information. You will need to repeat the process if you have entered incorrect weekly information. After you have entered the correct information, you need to come to this section to un-tick and tick the "RE-load data" box, to see the refreshed information appearing in the table.
- The table displays information on the epidemiological week ("epi_week"), endemic channel ("end_channel"), outbreak probability ("out_prob"), number of "cases", and average weekly alarm indicator ("alarm 1", "alarm 2", etc.). The numbering of the alarm follows that displayed under "##parameters".

3.1.4 The input data tab: all you need to know for this section

This option is found under 'Input Data' tab in Dashboard II

Figure 29. The input data tab: all you need to know for this section

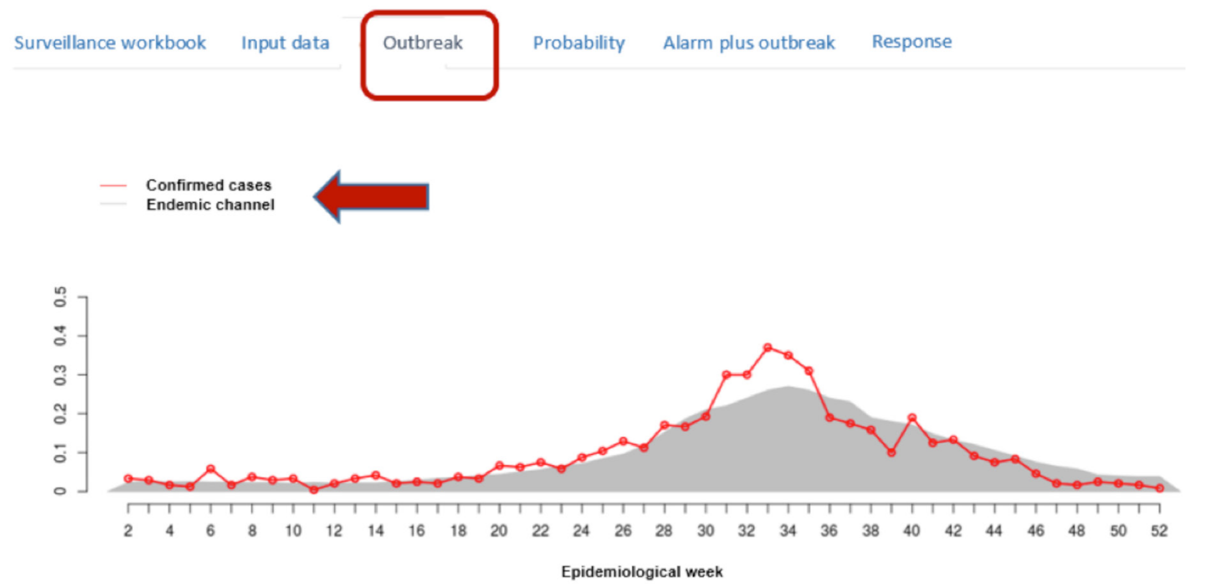


- Under the “Input data” tab, you can enter the corresponding information of “Year”, “Population”, “Epidemiological week”, number of “Hospitalized cases” and the average number of alarm indicators to run your prospective analysis of the current week.
- The “Send” button is pressed once you have entered all corresponding information under this tab. After you send this information to the prospective analysis, you need to go back to the previous “Surveillance workbook” tab and click on the “Re-load data” button so that the information is uploaded into the EWARS programming process. Once the “Re-load data” button is clicked, you can see the updated information displayed in the table under the “Surveillance workbook” tab.
- In case you discovered that you have entered incorrect weekly information, you can simply re-enter the corresponding weekly information, send it and then tick “Re-load” data, and you will see the new records in the table.

3.1.5 The outbreak tab: all you need to know for this section

This option is found under ‘Outbreak’ tab in Dashboard II

Figure 30. The outbreak tab: all you need to know for this section

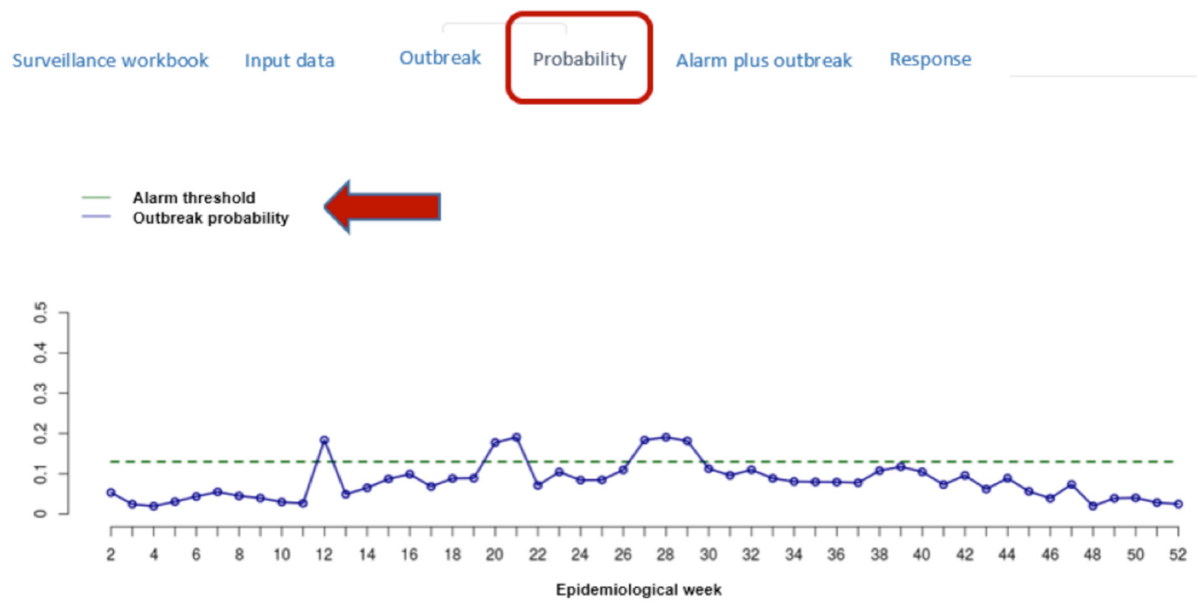


- Under the “Outbreak” tab, you can see a summary of previous history and the current week with respect to the “Endemic channel” and the rate of confirmed cases (or alternative choices of outbreak indicators such as probable cases).
- When “Confirmed cases” (RED LINE) exceed the “Endemic channel” (GREY SHADED AREA), we can say we have an outbreak week!

3.1.6 The probability tab: all you need to know for this section

This option is found under 'Probability' tab in Dashboard II

Figure 31. The probability tab: all you need to know for this section

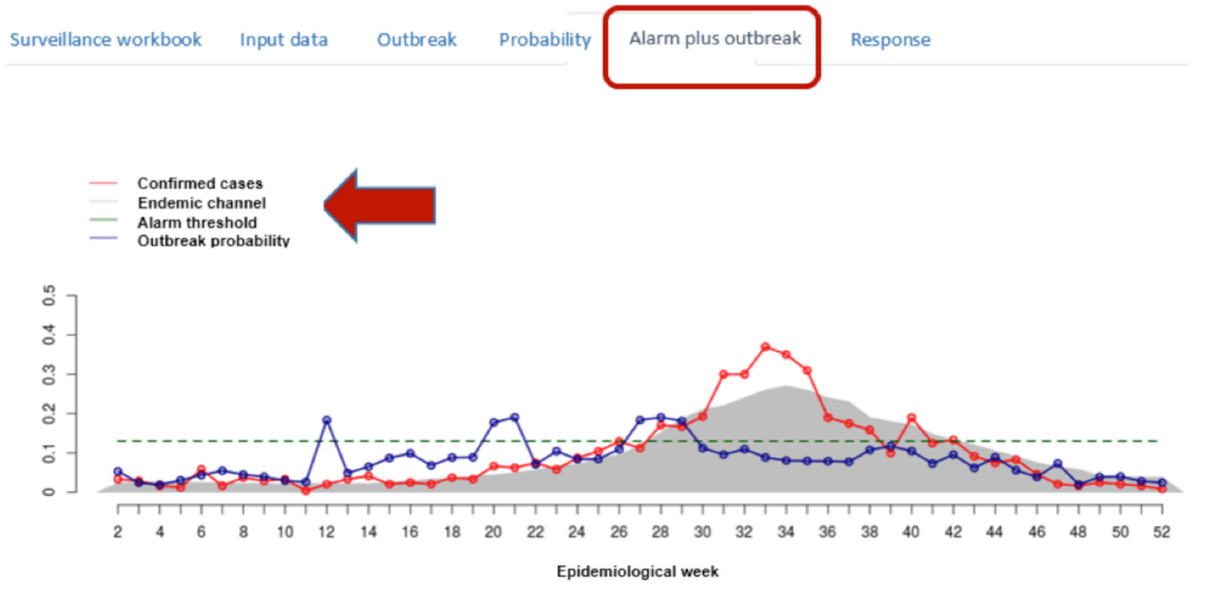


- Under the "Probability" tab, you can see a summary of previous history and the current week with respect to the "Alarm threshold" and the "Outbreak probability".
- When the "Outbreak probability" (BLUE LINE) crosses the "Alarm threshold" (GREEN LINE), then the outbreak prediction model is alerting you to an upcoming outbreak (alarm signal). By looking back at the "##parameters" summary to see what prediction distance was chosen, for example if prediction distance=2, we say there will be an outbreak happening in next two weeks!

3.1.7 The alarm plus outbreak tab: all you need to know for this section

This option is found under 'Outbreak and Probability' tab in Dashboard II

Figure 32. The alarm plus outbreak tab: all you need to know for this section

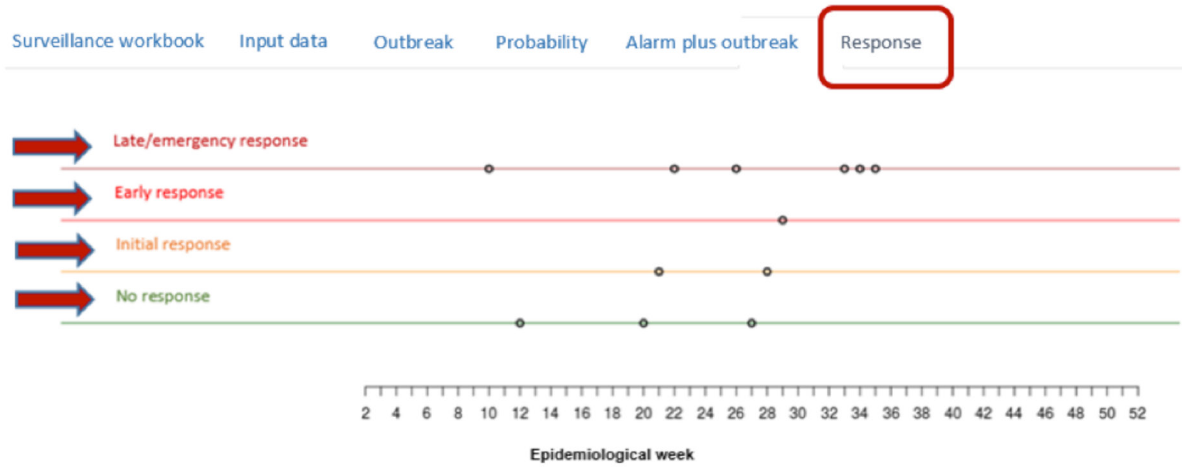


- Under the "Alarm plus outbreak" tab, you can see a summary of previous history and the current week with respect to all the "Confirmed cases", "Endemic channel", "Alarm threshold" and the "Outbreak probability".
- This tab is useful in putting together the relevant information on past outbreak trends and carrying out predictive modelling of the current week, and the probability of an outbreak (alarm signal).

3.1.8 The response tab: all you need to know for this section

This option is found under 'Response' tab in Dashboard II

Figure 33. The response tab: all you need to know for this section



- Under the "Response" tab, you can see a summary of previous history and the current week with respect to the type of response for an upcoming outbreak.
- This section follows the outbreak prediction as outlined in the previous tab ("Alarm plus outbreak"), mainly for the relationship between the outbreak probability and the alarm threshold and, following the national recommendation for outbreak responses at district/municipality level.
- According to national guidelines:
  1. "Late/emergency response" is technically declared when more than three consecutive ***outbreak weeks*** take place! Furthermore, the "Late/emergency response" is declared when four or more consecutive ***alarm signals*** occur. Figure 33 shows the "Late/emergency response" in week 10 occurred due to an alarm signal (outbreak probability exceeding the alarm threshold) happening at weeks 7, 8 and 9. Then, due to this consecutive occurrence of alarm signals, the program notified a "Late/emergency response" to be considered at week 10. In this scenario, the dashboard must have already declared "Initial response" at week 8 (since there had already been two consecutive alarm signals) and an "Early response" in week 9 (since there had already been three consecutive alarm signals)!
  2. "Early response" is declared when three consecutive alarm signals occur, to avoid "Late/emergency response". Another example from figure 33 shows that early response in week 29 occurred due to an alarm signal (outbreak probability exceeding the alarm threshold) at weeks 27, 28 and again in week 29. Then, due to this consecutive occurrence of alarm signals, the program notified that an early response should be considered at week 29. In this scenario, the dashboard must have already declared "Initial response" at week 28 since there had already been two consecutive alarm signals!

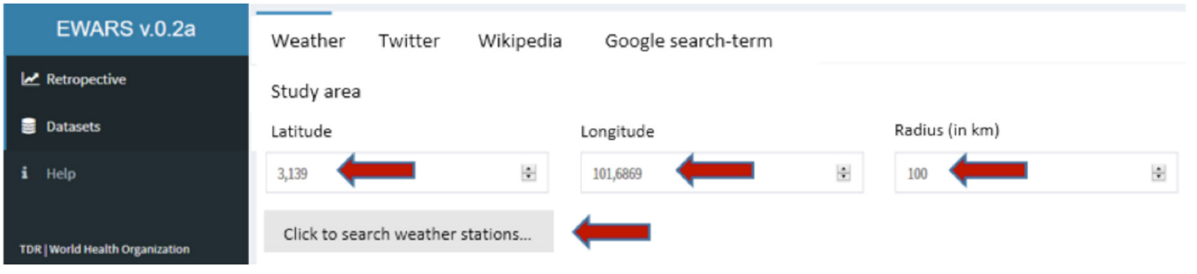
3. "Initial response" is declared when two consecutive alarm signals occur. Let's take an example from figure 33, the initial response in weeks 21 occurred due to an alarm signal (outbreak probability exceeding the alarm threshold) happening at weeks 20 and 21. Then, due to this consecutive occurrence of alarm signal, the program notified that an initial response should be considered at week 21.
4. "No response" is declared when are no alarm signals or only one alarm signal in the current week.

3.2 Retrieving online meteorological information on weekly alarms (datasets sub-link)

PLEASE NOTE, ONLY THE WEATHER APPLICATION IS CURRENTLY ACTIVE!

3.2.1 Setting your local district/municipality spatial information to detect nearest meteorological station

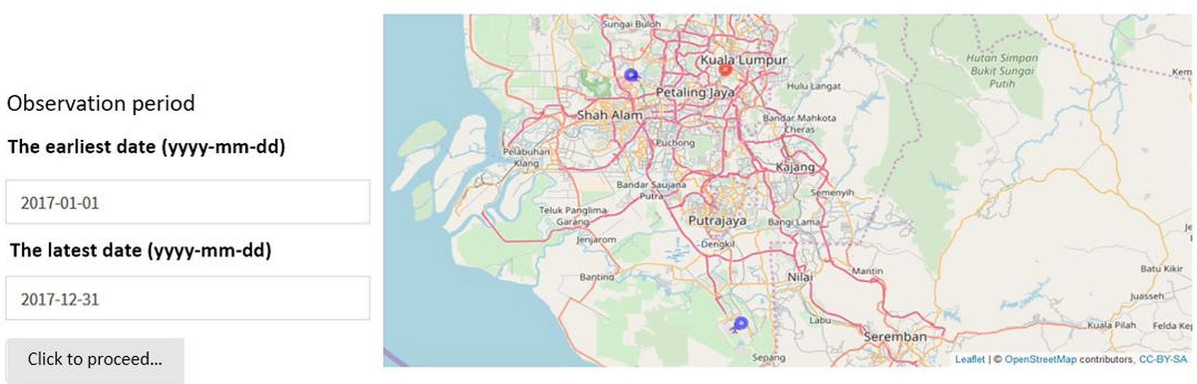
Figure 34. Retrieving online meteorological information: setting your district's spatial information



- Under the "meteorological" tab, you can set your spatial information of your district/municipality to detect your nearest meteorological station.
- In the "Latitude" box, enter the corresponding latitude value of your district/municipality.
- In the "Longitude" box, enter the corresponding longitude value of your district/municipality.
- Hint! You may use the Google search engine to obtain this information and enter it into this box.
- In the "Radius" box, enter the size of the area for your search. For example, entering a value of 100, the search for nearest meteorological station will cover an area of 100 sq km within your district/municipality.
- Once all the information is entered, "Click to search weather stations" button and a map will appear to show the locations of nearest meteorological stations.

3.2.2 Setting your period of interest for deriving the meteorological information

Figure 35. Retrieving online meteorological information: defining the period of interest



- This section defines the period for the meteorological information to be obtained.
- In this map, the blue circles are the meteorological stations and the red circle is your study site (district/municipality).
- Enter the date for the start of the meteorological information under "The earliest date" and the end date under "The latest date". For example, if you are interested in obtaining all records of meteorological information for last two weeks from your current week, say, 26 November 2017, then the start date will be 12 November 2017 ("2017-11-12") and the end date will be 26 November 2017 ("2017-11-26").
- Then, click on the "Click to proceed..." button.

3.2.3 Selecting a desired meteorological station from the obtained list

Figure 36. Retrieving online meteorological information: selecting a desired meteorological station

This section displays the list of all meteorological stations available to retrieve the alarm information. The list on the right-hand side refers to each one of these stations.

- The graph shows an overview of how each station presents its meteorological information and whether there is an agreement between them. As a user, you may select anyone that you find representative and relevant in terms of being in the nearest location to your district.
- Enter the corresponding station code (from the list presented at the right-hand side) in the “Weather station ID” box, then “Click to select...” button.
- Once this is done, you will see a list of the alarm indicators presented for the period you initially selected.

3.2.4 Using the derived information of the alarm indicators

Figure 37. Reading the retrieved online meteorological information for alarm indicators

Show 12 entries | Search:

	YM	tavg	prcp
1	Jan 2017	26.97	2448
2	Feb 2017	27.21	1688
3	Mar 2017	27.65	2423
4	Apr 2017	27.73	1171
5	May 2017	28.29	655
6	Jun 2017	28.19	389
7	Jul 2017	28.03	138
8	Aug 2017	27.51	358
9	Sep 2017	27.27	1168
10	Oct 2017	27.85	507
11	Nov 2017	27.43	1306

Showing 1 to 11 of 11 entries | Previous 1 Next

- This section displays the derived information of alarm indicators from the selected meteorological station. You can use the available information for your data input to run the prospective analysis.
- The column "YM" represents the period corresponding to when the alarm indicator information was collected.
- The column "tavg" represents the temperature average.
- The column "prcp" represents the precipitation or the rainfall in millimetres.
- Based on this information, you can calculate weekly alarm indicator averages.

Chapter 4
The automatization of EWARS

4.1 Background

Recent developments in machine learning and the use of big data applications enable complex analysis and enhanced predictions of early warning systems, which can fundamentally innovate response effectiveness, if structured and deployed strategically. Innovating the EWARS into a fast, reliable and harmonised tool, will aid users in endemic countries to apply more efficiently at wider-spread approach. The automatization development proposed here is one-step forward towards this vital goal.

The automatization phase was built on the same methodological and conceptual model of the original EWARS with further modifications to speed the calibration and evaluation process and expand the range of possible calibration scenarios for sufficiently testing best alarm predictors against outbreaks. i.e. optimal sensitivity and PPV.

Unlike the older version, the automatized EWARS version has both dashboard 1 (retrospective) and dashboard 2 (prospective) embedded under one link, which is now provided free of charge. The new platform maintains the same level of data accessibility and security across districts (i.e. allows access by central level only but not vice versa) but deliver immediate results, interpretations and guideline for staged-response of outbreaks. It is further innovated to facilitate easy, cheap and compatible integration of the tool (script) into existing national surveillance systems, which ensure countries' full ownership of their data.

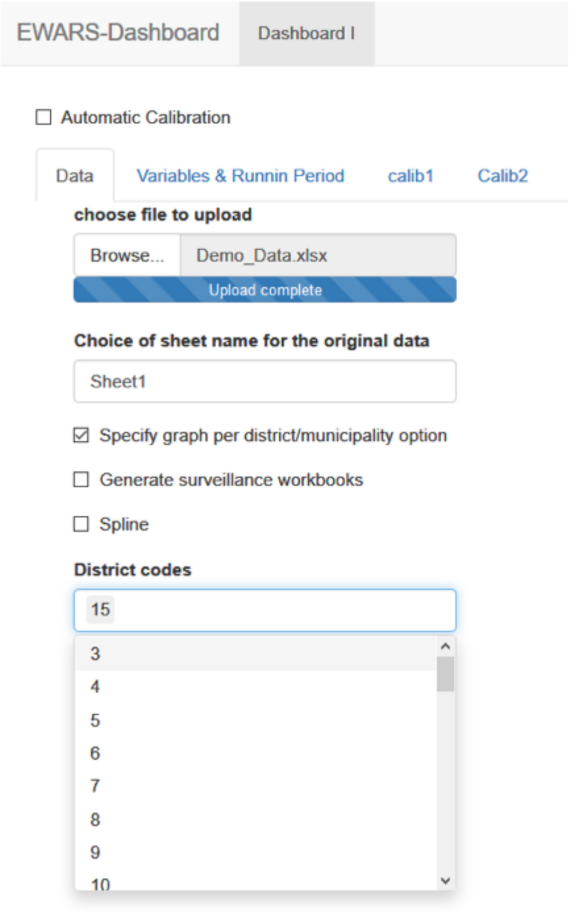
4.2 Accessing the EWARS dashboard

Countries can request their new free EWARS tool via the same source; ewars@post.com. Upon request, countries will be provided with their private account and password to access the generic EWARS. Countries have the option of either obtaining their own EWARS dashboard (by obtaining a private account and password to access their hub) or, to request the direct ownership by directly installing this tool in to their national surveillance program which grant users full and independent control of their data (thus, countries will receive the programming materials to install).

The shiny server used for this new version is an open source from the R package that provides an elegant and powerful web framework for building web applications using R. Shiny is more efficient in running and maintaining which has a basic annual cost of 990 USD and does not require IT maintenance (unlike the older server). It is also easy to install therefore, it facilitate a smoother process of transferring the EWARS into a national program (100% country ownership).

Users at central level can assign unique passwords for users to access district-level information (for running prospective data). With the new advancement, countries can also integrate this into their national surveillance program without significant IT running and maintenance cost. A package including information on the programming script, operational guide, mechanism for obtaining and instantly processing metreological data will be provided to aid the country ownership of the tool, and reduce the burden of limited accessibility to timely climate information.

Figure 38. Importing surveillance data into the EWARS.



4.3 Calibrating the instrument

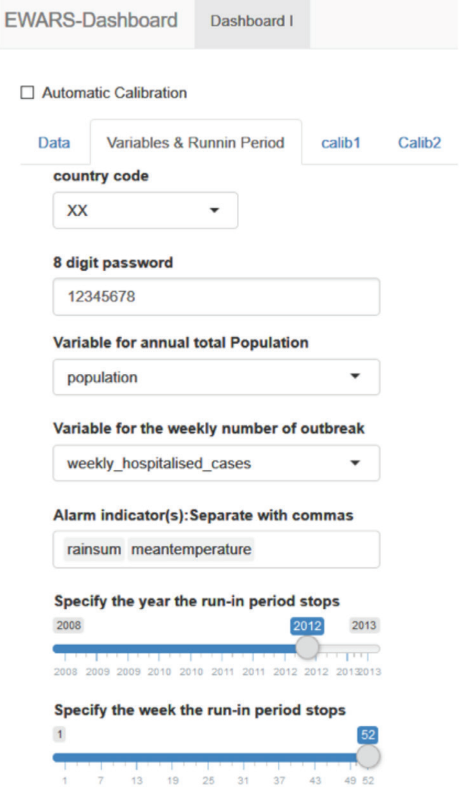
The new tool allows running both 'manual' and 'automatized' calibration, a step that typically occurs in the first dashboard; 1. Manual calibration: similar to the original design and instruction provided in chapter 2 of the user guide. 2. Automatized form: this is the simpler and fast approach introduced in this innovation stage of EWARS, which is outlined hereunder:

Surveillance dataset should follow the same format described in chapter 1 in the operational guide. Under the 'Data' tab, users can browse and import their surveillance data directly into the tool. The name of 'sheet' will appear under the second box exactly as named in the surveillance data, see figure 38. In order to display the graph of the results, users need to tick the first box, as outlined in figure 38. This version has modified the data entry by introducing a drop-down menu for selecting all information from the surveillance dataset. For choosing the district(s) of interest, drag down and select from the list under 'District codes'.

4.3.1 Manual Calibration

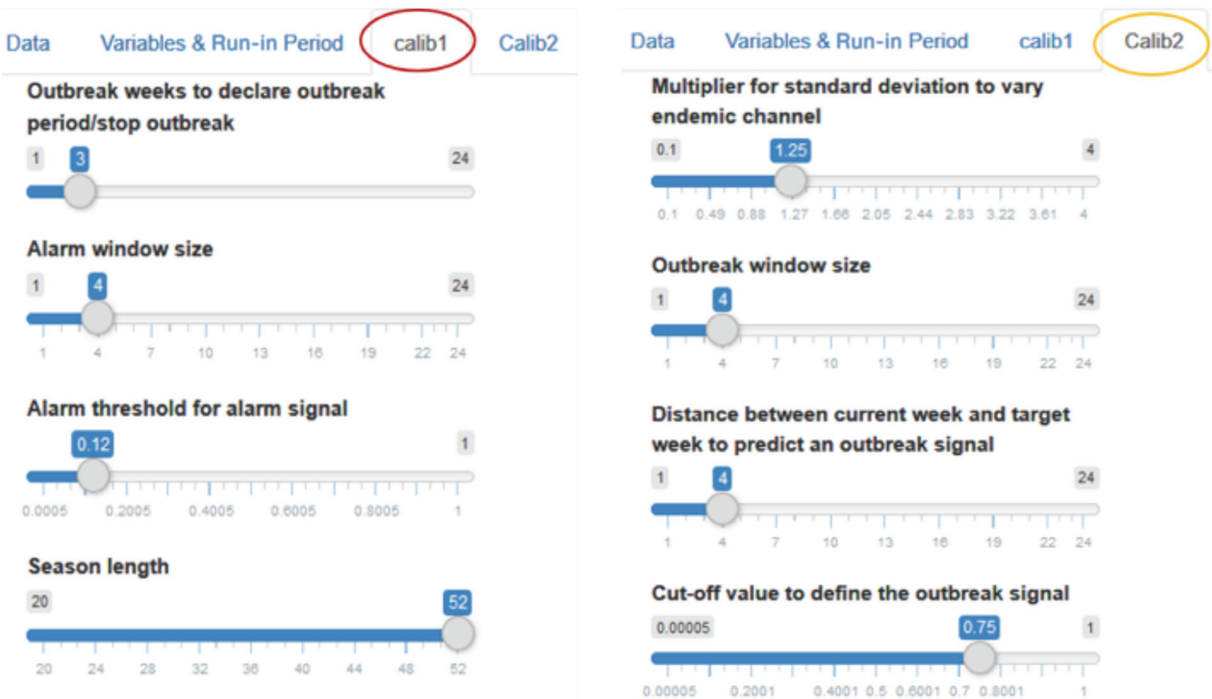
The manual calibration mode is active as far as the box 'Automatic Calibration' in figure 39 is kept unticked. Users at the central level can assign unique 8-digit password for corresponding districts, under the box '8 digit password' (figure 2). All variables 'population', 'outbreak cases' and 'Alarm indicators' can be selected through the drop-down menu list available under the boxes as outlined in figure 39. In order to define the 'run-in' period (which follows the same concept outlined in chapter 1 in the operational guide), users can chose a cut-off for the 'year' and 'week' from the scales shown in figure 39.

Figure 39. Selecting the list of variables and defining the running period



The descriptions of all variables used for the calibration are already provided in chapter 1. Under the manual calibration mode, users need to define values for 'outbreak period, 'alarm window size' 'alarm threshold' and season length' which are displayed under the tab 'Calib1'. The 'z-outbreak value', 'outbreak window size' and 'distance between outbreak and alarm signal' as well as the 'outbreak cut-off' will be provided under 'Calib2'. Each variable can be calibrated using the scale range as illustrated in figure 40.

Figure 40. Doing the calibration (manual mode)



Graphs as well as the calibration outputs displaying all parameters including the sensitivity and PPV of the analysis will be displayed on the same page, as shown in figures 41 and 42 below

Figure 41. Illustrating an example of graphical presentation from the calibration stage

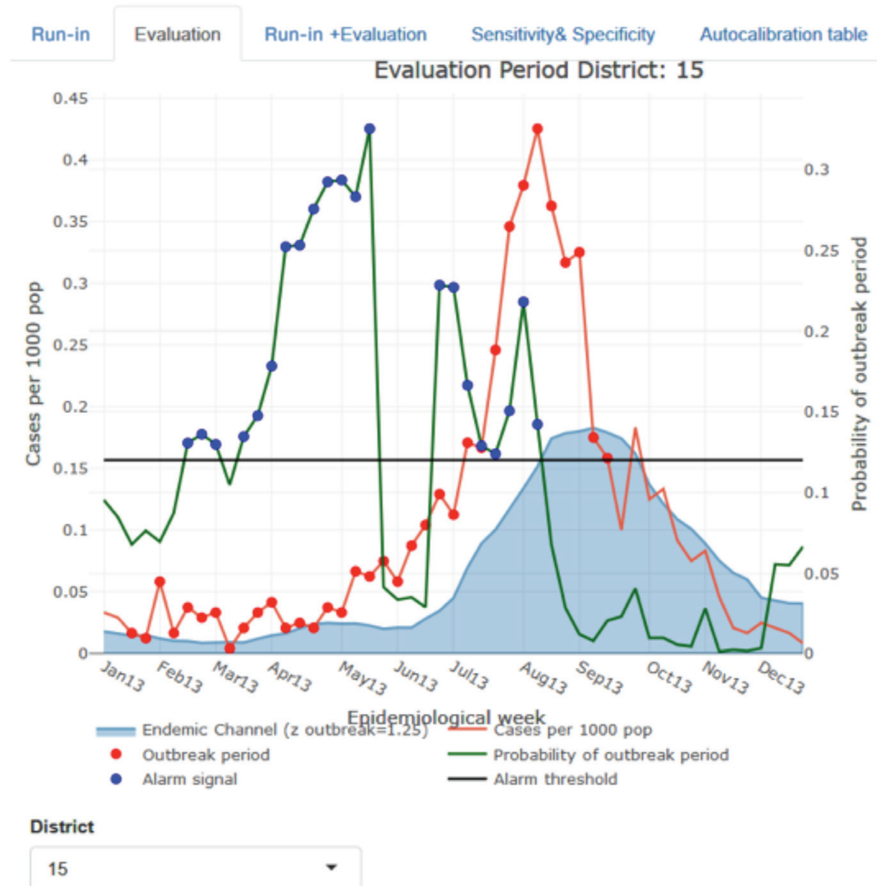
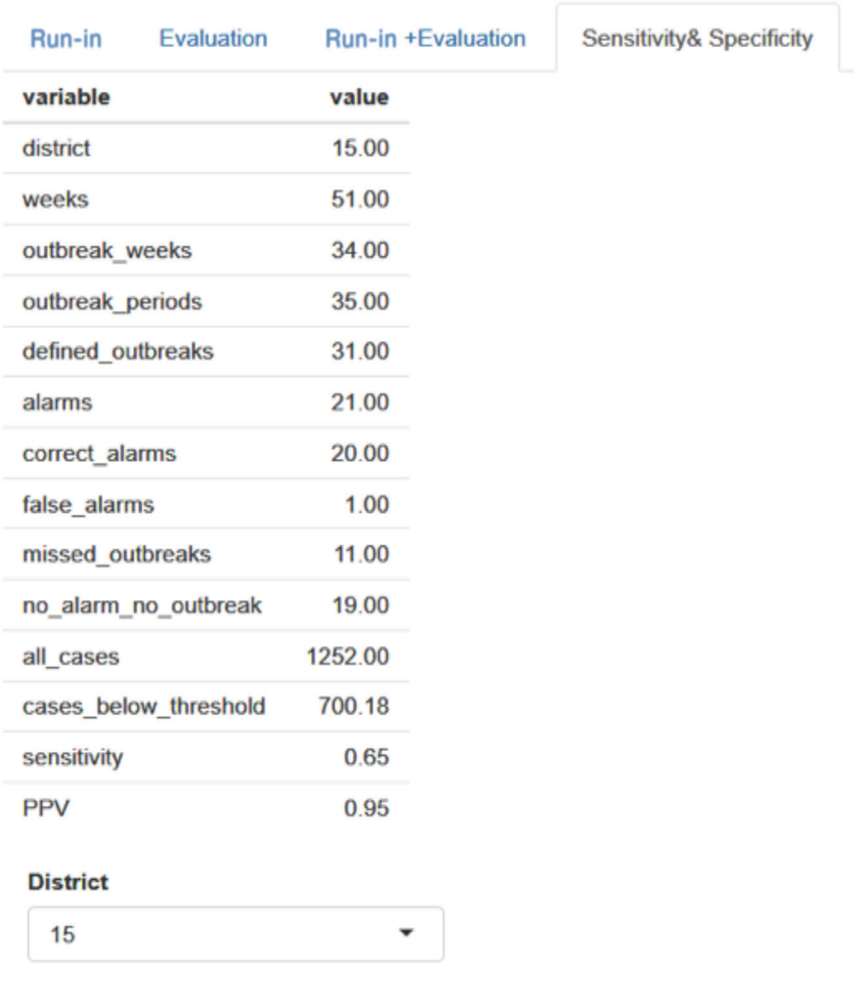


Figure 42. Illustrating an example of outputs for the calibration parameters including sensitivity and PPV.

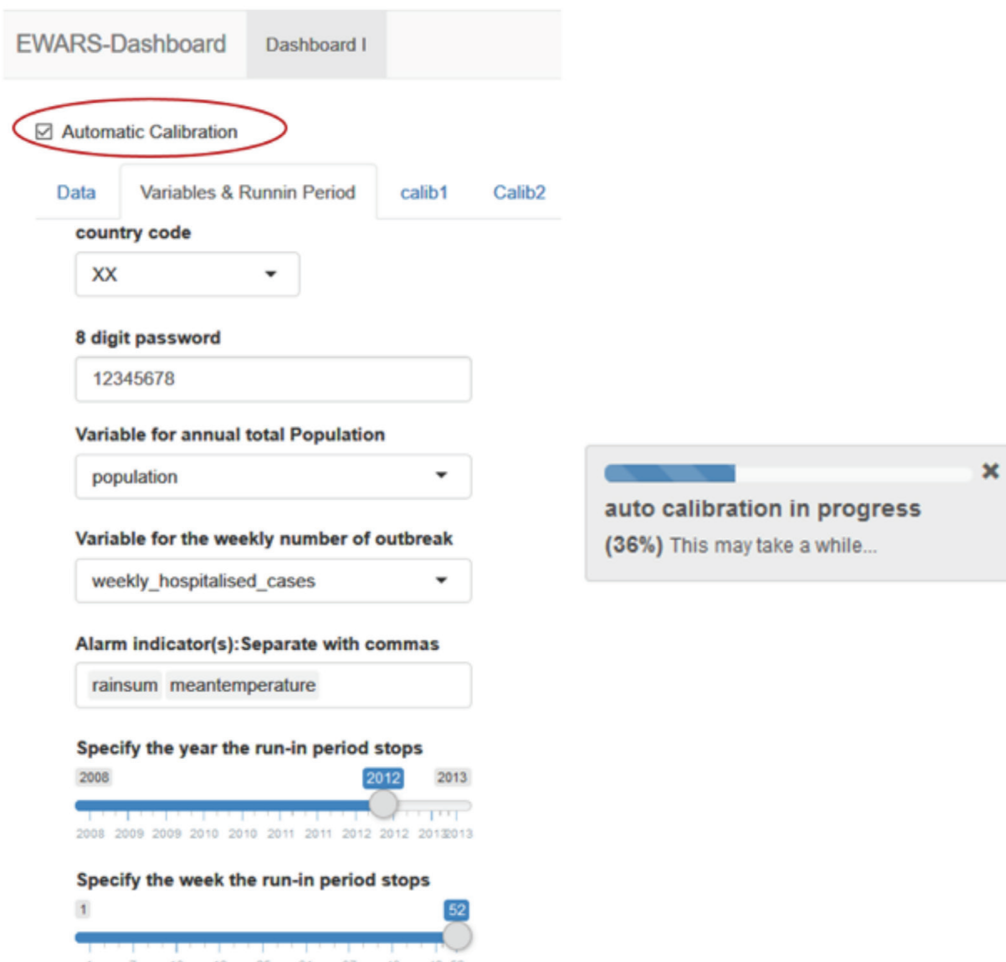


variable	value
district	15.00
weeks	51.00
outbreak_weeks	34.00
outbreak_periods	35.00
defined_outbreaks	31.00
alarms	21.00
correct_alarms	20.00
false_alarms	1.00
missed_outbreaks	11.00
no_alarm_no_outbreak	19.00
all_cases	1252.00
cases_below_threshold	700.18
sensitivity	0.65
PPV	0.95

4.3.2 Automatized Calibration

This is a more efficient approach of running the calibration attempt when defining best prediction algorithm. Under this form of calibration, both tabs 'Calib1' and 'Calib2' will no longer need to be filled (figure 3). Once the data is imported and variables are selected (for the population, district, outbreak and alarm variables), the user can tick the 'Automatic Calibration' box as illustrated in figure 6. Once the box is ticked, the tool starts processing the data, with a small box displaying the percentage of process.

Figure 43. Doing the automatized calibration.



At the end of the automatized process, users can view the tab 'Sensitivity & Specificity' to obtain the generated calibration outputs, as in the manual calibration. The displayed outputs are based on the most optimal calibration i.e. settings and alarm variables that generate the highest sensitivity and PPV values. An output of some scenarios is presented (in order from best to worst outcomes; higher Kappa indicates for a better calibration model) under the 'Auto calibration table' as shown in figure 44, below. These outputs have no direct use in the interpretations rather to give an overview of appropriate settings to assign for obtaining optimized calibration..

Figure 44. Example of output illustrations from the automatized calibration

Run-in | Evaluation | Run-in +Evaluation | Sensitivity& Specificity | Autocalibration table

variable	Run0001	Run0002	Run0003	Run0004	Run0005	Run0006	Run0007
district	15.00	15.00	15.00	15.00	15.00	15.00	15.00
outbreak_week_length1	5.00	5.00	2.00	4.00	6.00	3.00	6.00
alarm_window1	5.00	5.00	6.00	7.00	9.00	4.00	3.00
alarm_threshold1	0.03	0.11	0.14	0.21	0.26	0.19	0.27
z_outbreak1	1.16	1.33	1.09	1.07	1.20	1.58	1.25
outbreak_window1	1.00	3.00	3.00	1.00	2.00	3.00	1.00
prediction_distance1	2.00	2.00	2.00	0.00	4.00	5.00	4.00
outbreak_threshold1	0.70	0.64	0.58	0.74	0.57	0.56	0.73
Kappa	0.51	0.37	0.27	0.16	0.13	0.08	0.04

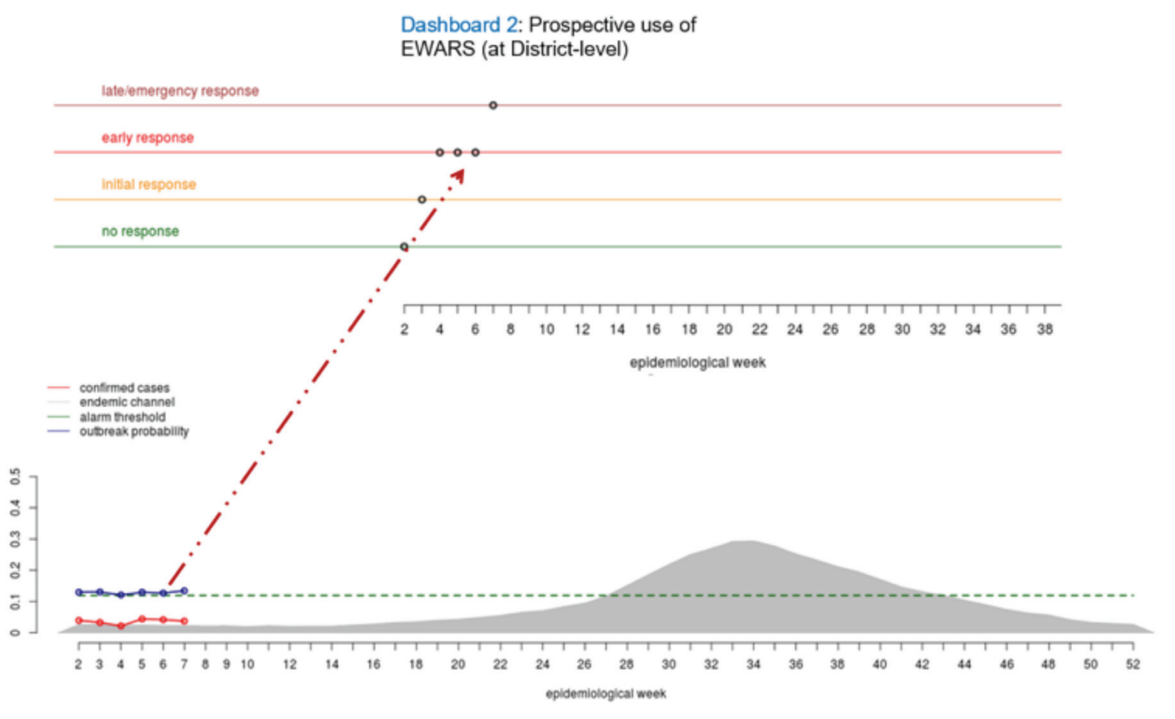
District

15

4.4 Dashboard 2: prospective application

The new EWARS tool integrates both dashboards under on link, whereas dashboard 2, used for prospective data entry and interpretations as in the previous version. Example illustration is displayed in figure 45 hereunder.

Figure 45. Example of prospective phase using the automatized calibration



Annex.
Technical guide

1. Introduction

This technical guide explains the scientific rationale behind *The Early Warning and Response System (EWARS) for Dengue Outbreaks: operational guide using the web-based dashboard*.

This project has focused on developing a validated R-based model that can enable the prediction of "out of control" dengue cases (outbreaks) as defined by dengue incidence (probable/hospitalized cases). The early warning system detects changes in the alarm indicators (entomological, meteorological and epidemiological) to predict dengue outbreaks. The purpose of this *Guide* is to provide an overview of the applied method and its rationale. Additionally, it presents block diagrams to describe the applied method with further details on each step. This will assist the user to follow the *Guide* and link to the corresponding step number. It also discusses general requirements for the R program and potential errors while using the available do-files.

2. Methodology

The general methodological concept of this analysis follows two major phases that are summarized below.

2.1 Retrospective phase

This phase uses retrospective surveillance data to create two datasets: (i) run-in data, used to develop the prediction model; and (ii) evaluation data, used to evaluate the derived parameters from the prediction model.

2.1.1 Run-in data

This dataset uses past records to estimate/calibrate the model parameters of the relationship between the outbreak indicator and alarm indicator(s). This parameterization is then tested during the evaluation process (step 2, below) and applied by the user to predict an outbreak. These data include information on the year, week and district, outbreak indicator (probable, confirmed cases, or other forms of outbreak indicators), and alarm indicator(s), such as the weekly mean temperature, sum of rainfall, mean humidity and probable cases.

2.1.2 Evaluation data

This dataset is used to: (a) evaluate the prediction model; and (b) provide summary statistics that are used to build the prospective early warning system.

2.2 Prospective early warning phase (i.e. Dashboard II)

The populated file of results (final parameters) in Dashboard II, allows the user to enter prospective information to estimate the probability of an outbreak in a foreseeable period. This is simply derived by inserting weekly data of outbreak and alarm indicator(s) for the district(s) of interest.

2.2.1 Rationale for the approach

The final model derived for estimating the probability of an outbreak is generated via systematic steps (creating/evaluating parameters) by assessing the association between the level in the alarm indicators (i.e. mean rainfall, mean temperature, mean of humidity, etc.) and dengue outbreaks. Logistic regression is used to assess this association. This regression model processes the computed proportions of the outcome (computed via a cut-off value given by the user), to predict the probability of dengue outbreaks for a forthcoming period. Throughout these steps, the user is able to define relevant measures such as the size of the endemic channel, the outbreak duration, the alarm threshold and the prediction distance. Descriptions of these measures can be found in the following chapter.

3. Structural design

The block diagram in figure 38 outlines 16 steps in the overall process distributed across two different phases. Phase I (retrospective) is divided into: (i) the "Run-in data"; and (ii) the "Evaluation data". Phase II (prospective) is the final analysis using summary statistics to populate an Excel-based early warning system that can be used in real-time to detect future dengue outbreaks. A summary of each step is presented below.

3.1 Phase I (retrospective: Dashboard I)

3.1.1 Using the run-in data to create the prediction model (part one)

Step 1

In this step, the original data are divided into "Run-in data" and "Evaluation data". The user determines this by entering the period (cut-off), in year-week, when the run-in data end and the evaluation data begin. A minimum of two years' data are required for the run-in data though more than two years' data are recommended.

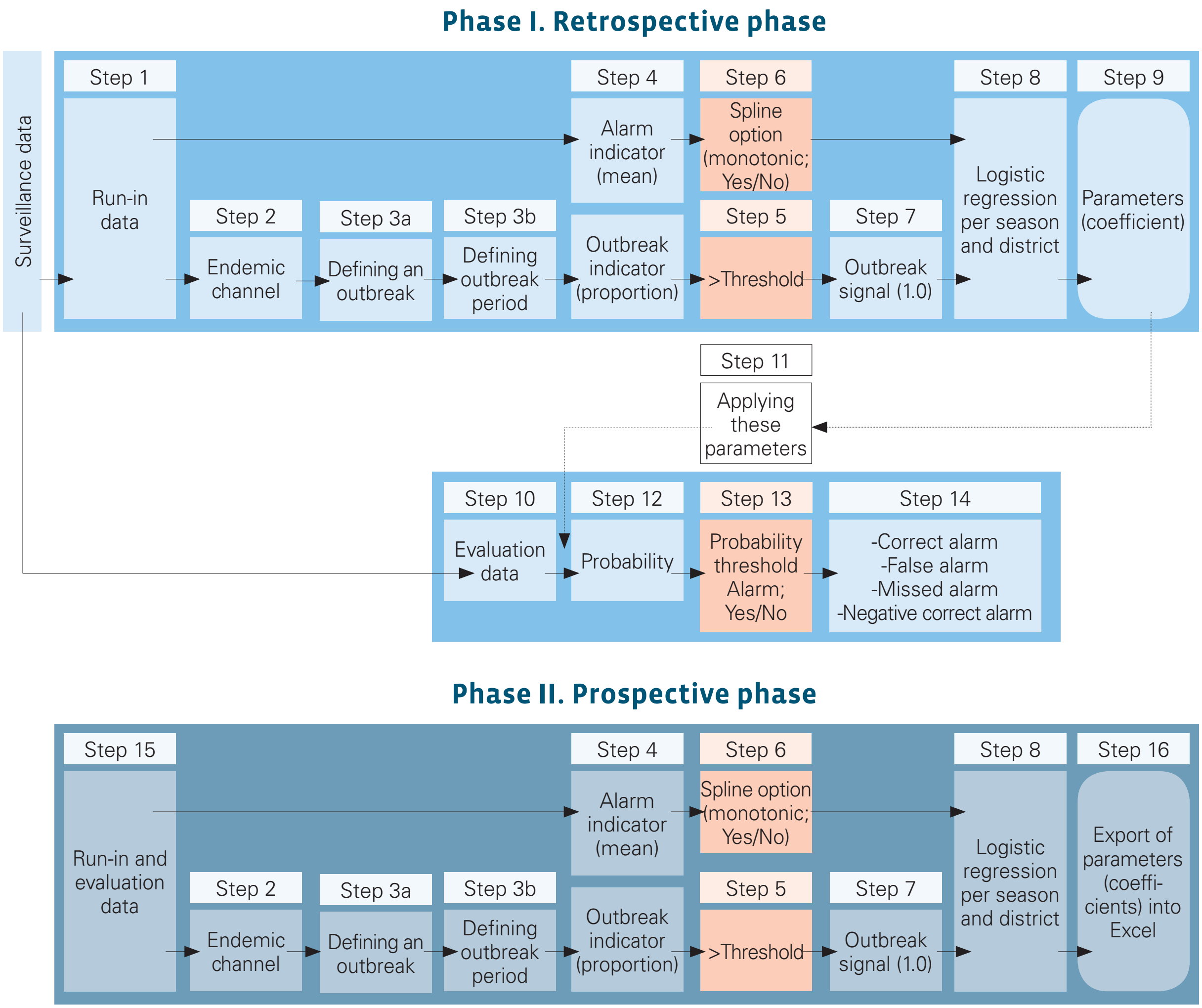
Step 2

This step refers to the "Endemic channel" and is represented by the following equation:

$$\text{Endemic channel} = (Z*SD) + \text{moving average}$$

"Z" is a multiplier value of the SD provided by the user to vary the breadth of the endemic channel. This part will assist in declaring the "out of control" status. For instance, a value of Z=1.5 would increase the breadth one and a half times the expected normal range of the number of dengue cases. The moving average is the mean number of dengue cases within the expected normal or seasonal range, calculated for a window size of three preceding and three succeeding weeks from the point (week) of measure.

Figure 46. Block diagram illustrating the process and steps of the retrospective and prospective phases (I, II)



Step 3a

In this step, an "outbreak" is defined by the proportion of number of incident cases in relation to the annual population for a corresponding district. The user is given the option to choose which outbreak indicator to use, for example, probable or hospitalized cases.

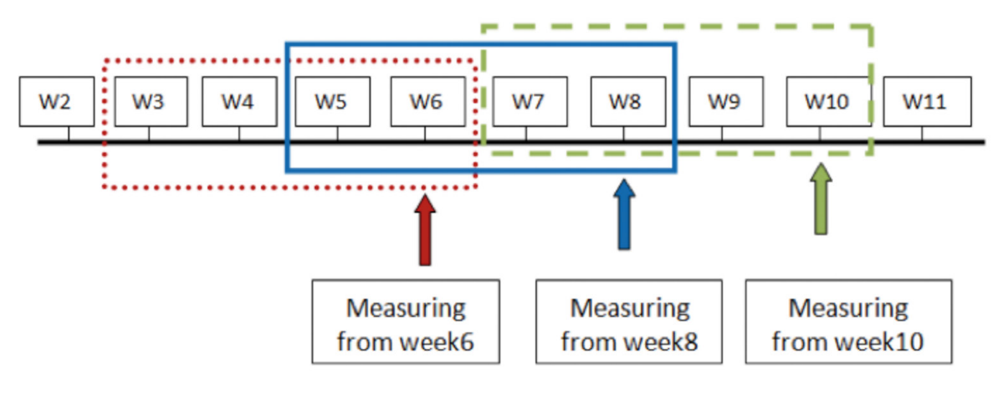
Step 3b

In this step, the user may choose the desired length of an "outbreak period". The user can define the length of the outbreak period by determining the number of consecutive weeks (1, 2, 3, etc.) that dengue cases must exceed the endemic channel. For example, for "outbreak_week_length=3", we can say that our outbreak period is defined when the dengue cases continue to exceed the endemic channel value for 3 consecutive weeks.

Step 4

This step illustrates how data from the "Alarm indicator" is used in relation to the alarm window (figure 39). We measure the mean of each alarm indicator (mean temperature, weekly rainfall, etc.) during the preceding pre-defined alarm window size (e.g. choosing alarm window size of 4, this step will measure the mean of each of these alarm indicators during the last four consecutive weeks including the week we are measuring from).

Figure 47. Illustrated process of measuring the alarm indicator(s) for a defined alarm window size



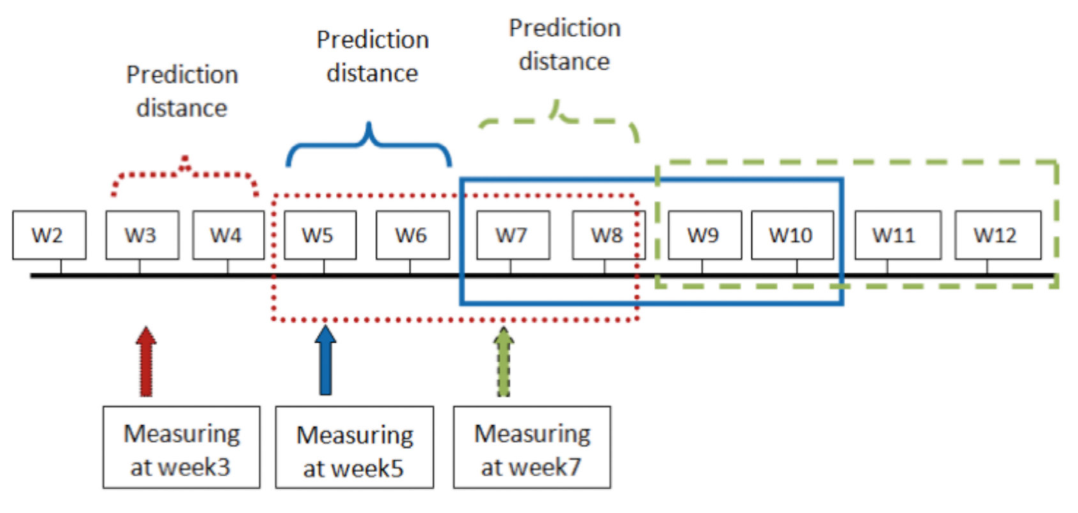
Step 5

This step illustrates how data from the outbreak period are used with the window size to define an outbreak (figure 40).

Here, the formulated outbreak period (from step 3b) is converted into proportions by dividing the "sum of values" from the outbreak periods by a given window size (or denominator) which generates values that lie between "0" and "1" (proportion). The user usually defines the window size during the calibration stage, which defines these proportions and which will, in later steps, be used to form the outbreak outcome (using the outbreak threshold).

For example, if the user chooses a window size of 4, then the analytical program will take the "sum of values" of 4 consecutive outbreak periods and divide it by 4 to generate a proportion. Figure 40 illustrates this process by also describing how other information (also defined by the user) can be used in this step. The prediction distance is another factor used in this process that defines the point where computing the proportion should begin in the data.

Figure 48. Illustration of the moving average process of measuring the outbreak indicator for a defined outbreak window size



Step 6

The "Spline option" handles a non-monotonic relationship between the alarm indicator(s) and the outbreak indicator(s). A non-monotonic relationship occurs when there is an increase in the mean alarm indicator during a particular period with a decreased number of dengue cases (outbreak) for the same period. Applying this option (yes=1 (non-monotonic)/ no=0 (monotonic)) is decided during the evaluation stage (section 2.3.15 Choice of the spline application; line 35 in the do-file).

The user can observe the performance (evaluation table) of the prediction model when the spline is selected or removed. The method of checking the performance of the prediction model is illustrated in step 14 below.

Step 7

In step 5, proportions from the outbreak periods were computed using a pre-defined window size and prediction distance. In this step, the outbreak signal is formulated by converting the derived proportions into a binary variable (0=no outbreak or 1=outbreak), which is necessary for running the logistic regression in the next step.

In this step (7), the user chooses a suitable cut-off point (threshold) which defines an "Outbreak signal" (i.e. code "1") or not (i.e. code "0"). For example, if you choose a threshold value of 0.5, then any proportion above this threshold (e.g. 0.7> 0.5) will be given the code one (an outbreak signal) and any proportion value less than this threshold (e.g. 0.3< 0.5) will be given the code zero (not an outbreak signal). This will result in a binary outbreak outcome variable that is ready to enter the logistic regression process.

Step 8

In this step, we assess the association between the binary outcome of the outbreak signal (0, 1) and the alarm indicators using logistic regression. This relationship will be influenced by the "season_length" input. For example, if season_length=4 weeks, the logistic regression model will generate a coefficient for this period length alone. Then the next coefficient will be specific to the following 4 consecutive weeks and so forth.

Step 9

The coefficients generated from this regression model will be stored/applied during the evaluation stage.

3.1.2 Using the evaluation data to assess how the derived parameters from the run-in data would predict an outbreak (part two)

Step 10

Refers to the second part after splitting the surveillance data, which we call the "Evaluation data" (the first part of the original data was used in step 1, i.e. the "Run-in data"). The user determines this by entering the period, in year-week (e.g. 201452) for when the run-in data ends and the evaluation data begins. A minimum of two years' data records is required for each dataset.

Step 11

In this step, we are evaluating the coefficients that were initially generated by the "Run-in data". This evaluation is performed by applying these coefficients to the "Evaluation data" to observe the performance of the prediction model in detecting outbreaks.

Step 12

The derived function from the logistic regression step 8 and its parameters are used to estimate the "Probability" of an outbreak occurrence.

Step 13

The generated probability from step 12 will require a threshold to determine an alarm signal. For instance, for a probability of 0.4, with a threshold of 0.3 (i.e. the probability ≥ threshold), this record is said to be an alarm signal. If, however, the probability were less than the threshold, then it is not an alarm signal.

Step 14

In order to ensure that the given threshold (in step 13) is reliable to predict an outbreak, the program will further present four evaluation criteria to assess the choice given in step 13. These criteria are:

1. correct alarm: probability ≥ threshold with a true outbreak (for a target period);
2. false alarm: probability ≥ threshold with no true outbreak (for a target period);
3. missed outbreak: probability ≤ threshold with a true outbreak (for a target period);
4. no alarm, no outbreak: probability ≤ threshold with no true outbreak (for a target period).

An optimal threshold (option in step 13) would lead to an increased number of correct alarms and negative correct alarms but a decreased number of false alarms and missed alarms. By observing these results (which will be displayed on the screen of the program – output), the user can alter the threshold in step 13, accordingly.

3.2 Phase II (prospective surveillance: Dashboard II)

Step 15

In this step, the program will run through the entire dataset (i.e. both run-in + evaluation) to populate the output file (Dashboard II) that includes information on the probability formula, model parameters and details on the applied settings from the evaluation period. Once the user has entered real-time prospective data into the empty columns, the file will automatically estimate and graph the probability of an outbreak to predict an outbreak.

Step 16

In this final step, the program will populate the surveillance workbook, which is directly linked and displayed in Dashboard II. The user will input data on year, week, outbreak indicator, and alarm indicator(s) for a corresponding district directly into Dashboard II, which can automatically calculate the probability of an outbreak and produce an instant graphical presentation and alarm signals/responses.

NB: Settings from steps 2–8 in phase II (the prospective surveillance) will be automatically fixed according to the performed settings during the evaluation stage, i.e. the tool applies the same settings that the user approved during the evaluation stage to provide best prediction.

NOTES

NOTES

TDR, the Special Programme for Research and Training in Tropical Diseases, is a global programme of scientific collaboration established in 1975. Its focus is to improve the health and well-being of people burdened by infectious diseases of poverty through research and innovation. TDR is co-sponsored by the following organizations:

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