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Floods risk determination through a fuzzy logic system in developing countries. Case study Magdalena River, Colombia

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Abstract

Natural disasters around the world, and specifically floods, can generate great economic, environmental, and human life losses in short periods of time. Early warning systems have been developed as a tool to mitigate the impact of these floods, nevertheless, most of this information is dispersed. In the particular case of the Colombian context, the Institute of Hydrology, Meteorology and Environmental Studies of Colombia (IDEAM) has developed a platform called Famine Early Warning Systems Network (FEWS), which presents data of interest for the different stations in the basins of the territory, such as: level, flow, and rainfall. From the height level of water table data of each station, the platform presents three possible alerts: yellow, orange, and red, which are obtained by comparing with reference or threshold levels associated with each station. However, the method currently used to determine the alerts does not consider the variation of the water table level as a function of time, nor the degree of danger represented by a value close to or tending to flood threshold levels. This work proposed a contribution to determine the flood risk level, based on the development of a fuzzy system, taking as inputs the water table level and the level variation as a function of time, to obtain as output the flood risk level in numerical and linguistic terms. For the determination of the risk level, the system applies inference logic rules, involving operations between fuzzy sets represented through mathematical membership functions. Finally, the operation of the fuzzy system was validated using data from the FEWS platform for the hydrological stations of the Bajo Magdalena basin. This project aims to serve as a reference to improve early warning systems of developing countries.

Keywords: early warning systems, floods disaster prevention,early warning in Latin America, fuzzy logic systems.

1 Introduction

Extreme hydrogeological events can produce massive floods and landslides, generating direct effects such as the destruction of homes, health centers and infrastructure, loss of material goods and crops, among others, causing loss of human life and incalculable damage to the economy in the short, medium and long term [1, 2, 3, 4]. Specifically, floods are a natural phenomenon that occurs due to heavy rains and overflow of water bodies [5]. Floods are also generated by anthropic causes since human settlements can produce alterations in river and coastal systems.

These events are often accompanied by indirect or secondary effects such as devastating economic crises with consequent loss of employment and the formation of social wounds and increased inequality. These are increasingly recurrent and violent, especially in the tropical areas of the world [6, 7, 8]. About three fifths of cities worldwide with at least 500,000 inhabitants are at high risk of a natural disaster (cyclones, floods, droughts, earthquakes, landslides or volcanic eruptions, or a combination), according to the Department of United Nations Economic and Social Affairs. Together, these cities are home to about a third of the world's urban population. On the other hand, a recent report by the United Nations Office for Disaster Risk Reduction (UNISDR) found that natural disasters have killed 1.3 million people in the last 20 years and left another 4.4 billion injured, homeless or in need of emergency assistance [9].

1.1 Early Warning Systems (EWS)

Due to the development of intensive agriculture and the lack of planning in urban development in the last century, the risk of flooding has become one of the priorities of the various engineering disciplines [10, 11, 12, 13, 14, 15]. According to different international authors [16, 17] risk management incorporates five main components: 1) risk identification and assessment; 2) risk reduction; 3) financial protection; 4) disaster preparedness and response; and 5) disaster recovery.

The fourth component includes early warning systems (EWS), the subject of this work. An EWS can be defined as the set of tools, control devices, management capacities and technological instruments that the competent institutions identify to disseminate information in an appropriate timeline to the communities exposed to a risk. Its results are mitigation measures, aimed at reducing the effects of natural disasters and the economic and life losses, [18, 19, 20]. In the specific case of floods, for the establishment of an EWS it is essential to study and understand the temporal and spatial functioning of the hydrological system associated with flood risks, through the systematic and permanent control of the hydrological, hydrodynamic and water level conditions in the area of interest. In this regard, some local flood phenomena can be understood and mitigated only with a broad view of the territory and its geomorphology, [21, 22, 23, 24, 25, 26].

In the development of the EWS, Basher et al., (2006) and Domínguez & Lozano, (2014), among others, [19, 20, 27] identify four stages: 1) pre-scientific systems, which are based on the first observations of simple phenomena such as the shape of clouds, the state of the ocean or the visibility of stars; 2) Ad hoc EWS, which are specific systems developed at the initiative of scientists or people interested in the subject of risk; 3) EWS developed by meteorological services, which involve an organized, linear and unidirectional delivery of alert products to users by experts; and 4) the comprehensive EWS, which links all the necessary elements for early warning and effective response, and includes the role of the human element of the system and risk management.

Different EWS are found in the literature, specifically using variable monitoring methods but not predictive response to changes in said variables (see Table 1). These applications in most cases use descriptive statistics for the analysis of the results (analysis after the measurement in real time) and in some cases classic logic (using only criteria of change in the water level, water flow or of precipitation) without considering anticipatory criteria in real time for evaluating the risk of flooding due to the speed of rapid increase in the level in the basins or high risk of flooding areas.

Table 1: Some of the most relevant EWS worldwide

Level	EWS	Location	Type of risk	Predicts the risk of flooding in advance	Fuzzy Logic	Ref
International	Global Flood Alert System (GFAS - JAXA)	Global	Flooding	No	No	[28]
	DFO Flood Observatory	Global	Flooding	No	No	[29]
	European Flood Awareness System	Europa	Flooding	No	No	[30]
	HYDRATE	Europa	Flooding	No	No	[31]
	A NOAA-USGS demonstration flash-flood and debris-flow early-warning system	USA	Flooding	Yes	No	[32]
	Early Warning System for Central America (SATCA, for its initials in Spanish)	Central America	Flooding	Yes	No	[33]
Colombia	Famine Early Warning Systems Network (FEWS)	Colombia	Flooding	No	No	[34]
	Early warning system of the Capital District of Bogotá, Colombia	Bogotá,Colombia	Seismic - Flood	No	No	[35]
	Environmental Early Warning System (SIATA, for its initials in Spanish)	Medellín, Colombia	Flooding	No	No	[36]
	Early Agroclimatic Warning System (SAAT, for its initials in Spanish)	Upper basin of the Cauca River, Colombia	Flooding	No	No	[37]
	Early Warning System for the Combeima River Basin	Center-west of the department of Tolima, Colombia	Flooding	No	No	[38]
	Early warning systems in the Combeima and Coello Cocora Canyon	Ibagué,Colombia	Flooding	No	No	[39]
	Bucaramanga Early Warning System	Bucaramanga,Colombia	Flooding	No	No	[40]
	Guajira early warning system	Guajira,Colombia	Flooding	No	No	[41]
	Early Warning Systems (S.A.T, for its initials in Spanish) for the Reduction of the Risk of Flash Floods and Atmospheric Phenomena in the Metropolitan Area of Barranquilla	Barranquilla,Colombia	Flooding	No	No	[42]
	Norte de Santander Early Warning System	North of Santander, Colombia	Flooding	No	No	[43]

1.2 Famine Early Warning Systems (FEWS)

At the national level, the entity in charge of risk monitoring and prevention is the Institute of Hydrology, Meteorology and Environmental Studies of Colombia (IDEAM), which, through the FEWS platform, monitors the different risk basins in the country [34]. This system does not have prediction capacity and is limited to monitoring and analysis of the water level, flow, and rainfall during the last 6 months. Likewise, the monitoring frequency of these variables for some stations is twelve hours and for others it is one hour. Based on historical data, the platform shows the water level variable, its variation over time, as well as its relationship with predetermined values of yellow alert, orange alert and red alert for each season. As an example, Figure 1 graphically presents the consolidated flow levels for the Banco - Magdalena station between May and December 2021. According to Figure 1, for each station it is possible to graphically identify the time periods where the monitored levels exceed or not certain reference values of the three alerts. Despite the above, the use of classical logic punctually comparing the levels captured with the previously defined reference levels instead of using predictive models to determine early warnings, prevents values close to and below the levels of reference to be considered as potential risk. In the case of floods this is a key factor since there are events that can be triggered in a short period of time. Likewise, not considering the variation of the level as a function of time prevents it from being possible to determine the risk level of the alert more precisely. In this way, since IDEAM's FEWS platform does not allow the generation of early warnings, it can be considered more of a visualization platform for the level and flow variables, which are not updated in real time. In this sense, the previous problem can be approached through fuzzy logic. In fact, fuzzy logic allows to determine the risk value in mathematical and linguistic terms, taking into account the degree of belonging or membership from the input value to the reference alert values and considering the variation of the water sheet level as a function of time.

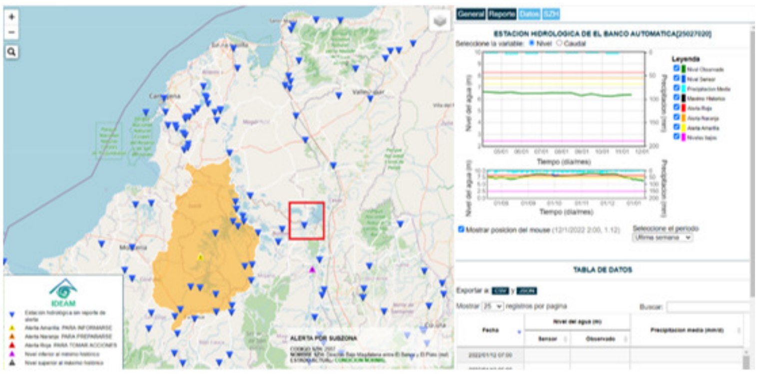


Figure 1: Level values for the Bank station during a 6-month window (Source [34])

A system based on fuzzy logic could receive as input the values of the water table level and the variation of the level as a function of time and deliver the level of flood risk as output. This could contribute to the efficient generation of early warnings at each station, considering that the computational cost of fuzzy systems is lower than the use of other predictive methods. Therefore, the objective of this work is to determine the level of risk in the face of flooding on the data provided by IDEAM for the hydrological stations of the Lower Magdalena basin as a case study, through the development of a diffuse system. For this, a system based on fuzzy logic is implemented, which, based on input variables such as the level of the water and the variation of the level of the water as a function of time, determines an exit alert risk level, through a set of inference rules. The proposed system is implemented and validated in one of the largest and mightiest rivers in Latin America. The foregoing considering that by the end of 2021 these stations showed changes in their alert levels from the winter wave. Based on the results obtained by the diffuse system, it is possible to make decisions with greater anticipation in the face of flood events.

2 Methodology

For the development of this research, the four phases of the iterative research pattern proposed by Pratt were used [44] (see Figure 2). The first step to apply this pattern is to observe the target application, these observations are then used to help identify the research problem. A solution to the selected problem is then developed and tested on the original domain where the problem was identified. These tests are then observed and the next iteration begins [44]. In the first phase of the methodology, corresponding to the problem observation, it is involved the characterization of the shortcomings of the IDEAM-FEWS platform, in order to identify the variables and methods used by this platform to determine the yellow, orange and red alerts. For this, a diagnosis of the platform was made based on the reports provided regarding the hydrological stations of different basins. The second phase, corresponding to the Problem Identification, included the definition of the input variables and the output variable, as well as the specification of their membership functions and the inference rules that defined their relationship. The input variables (IV) (water table level and level variation as a function of time) and output variables (AV) (flood risk alert level) of the diffuse system and the mathematical equations of the IV and AV were identified, as well as their associated fuzzy sets. Subsequently, the inference rules were designed and formalized in fuzzy control language (FCL).

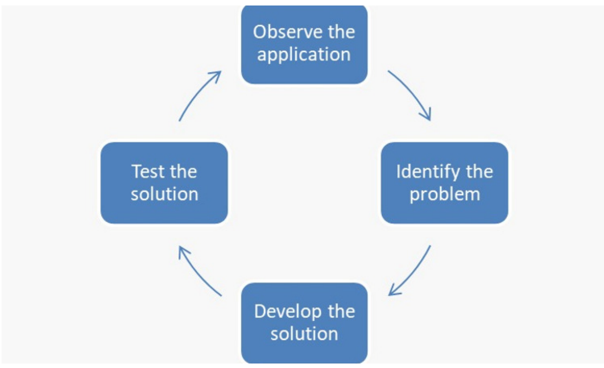


Figure 2: Adopted methodology (Source [44])

The third phase included the Solution Development, in the way functional modules of the system and their implementation were designed. The identification and selection of tools and/or technologies was made for the implementation of fuzzy logic and inference to determine the level of risk in floods. Then the architecture of the fuzzy system was defined, and the functional modules defined in the architecture of the system were implemented. The fourth phase involved the Test Solution and validation of the fuzzy system implemented with the case study datasets. A dataset corresponding to the data from the hydrological stations of the Lower Magdalena was selected and the implemented fuzzy system was applied to the extracted input variables. Finally, the level risk obtained with the fuzzy system and the levels of alerts provided by the FEWS tool were compared, critically analyzing the results obtained.

3 Results and Discussion

This section presents the development of phases 2, 3 and 4 of the methodology, which corresponds to the definition of inputs and outputs membership functions, as well as the inference rules specification, and the design and implementation of the modules of the system. Then, the case study developed from a test dataset extracted from the IDEAM platform is presented.

3.1 Problem Identification: Membership Functions and Inference Rules

For the diffuse system, the level and the variation of the level as a function of time were defined as input variables to the system, while the flood alert level was defined as the output variable. shows the description of the input and output variables defined for the system. Regarding the definition of the

Table 2: Input and output variables considered by the system

Variable Type	Name	Description
Input	Level	Corresponds to the value read by the IDEAM stations and which refers to the water table level in meters. For this variable, 3 levels or fuzzy sets were defined: emergency, high and normal. The ranges for the definition of these sets are determined considering the reference values associated with the levels of each station of the FEWS platform.
Input	Level Variation	It corresponds to the water level variation speed as a function of time and is calculated considering the previous reading of the level. Three levels or fuzzy sets are defined for this variable: negative, zero and positive. The ranges considered in this variable depend on the proportional values of each of the level measurements at the different stations of the FEWS platform.
Output	Flood alert level	It corresponds to the variable that indicates the level of flood risk, which is obtained from the input variables and the inference rules that relate the inputs to the output. Four levels or fuzzy sets associated with the alerts are defined for this variable: green, yellow, orange and red. The ranges of this variable are expressed on a percentage scale.

fuzzy sets for the flood alert level variable, both the predefined levels for each yellow (y), orange (o) and red (r) alert station were taken into consideration. As well as half of the distance between these levels (m), in such a way that these values were used to define the limits of the membership functions to structure the equations. It is worth mentioning that in all stations these levels are equidistant, that is, the distance between the yellow and orange alerts is the same as the distance between the orange and red alerts. Table 2 shows the description of the input and output variables defined for the system. Regarding the definition of the fuzzy sets for the flood alert level variable, both the predefined levels for each yellow (y), orange (o) and red (r) alert station were taken into consideration. As well as half of the distance between these levels (m), in such a way that these values were used to define the limits of the membership functions to structure the equations. It is worth mentioning that in all stations these levels are equidistant, that is, the distance between the yellow and orange alerts is the same as the distance between the orange and red alerts.

Figure 3 shows the membership functions for the normal, high and emergency fuzzy sets, in which the values in meters of the alert levels are y=7 m, o=9 m and r=11 m. Although this graph is for a particular example of a station, the structure of the membership functions is the same for all stations preserving the proportions between the distances of the alert levels (y, o, and r). These membership functions were defined taking into account the recommendations given in [45].

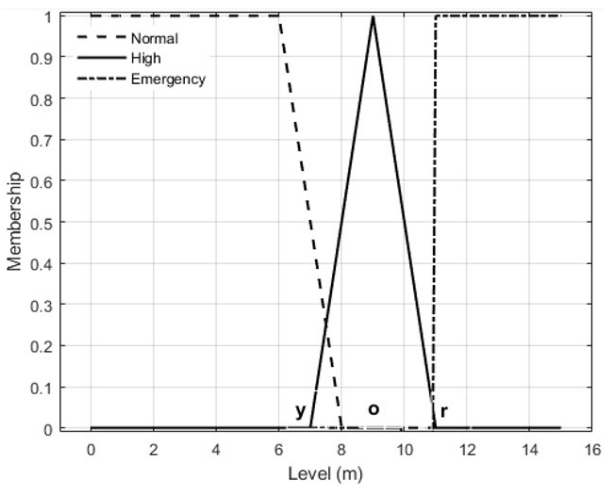


Figure 3: Level Variable Membership Functions (Source own)

From the definition of the generic membership functions for the level variable, the 3 equations associated with the normal, high, and emergency fuzzy sets were specified. Equation 1 presents the mathematical function associated with the normal fuzzy set that depends on the value of the yellow alert level (y). Within the equations, the variable "m" was used, which corresponds to half the distance between the yellow (y) and orange (o) levels or also between the orange (o) and red (r) levels.

$$\mu_{\text{normal}} = \begin{cases} 1, & x < y - m \\ \frac{y-m-x}{(y+m)-(a-m)}, & y - m \leq x \leq y + m \\ 0, & x > y + m \end{cases} \tag{1}$$

Similarly, in Equation 2 the general function for the high fuzzy set is presented, which depends on the value of the yellow (y), orange (o) and red (r) alert level.

$$\mu_{\text{high}} = \begin{cases} 0, & x < y \\ \frac{x-y}{o-y}, & y \leq x \leq o \\ \frac{r-x}{r-o}, & o \leq x \leq r \\ 0, & x > r \end{cases} \tag{2}$$

Finally, Equation 3 presents the general function for the emergency fuzzy set, which depends on the value of the red alert level (r) and the mean distance (m) between the red alert (r) and the orange alert (o) for each station.

$$\mu_{\text{emergency}} = \begin{cases} 0, & x < r - m \\ \frac{x-(r-m)}{r-(r-m)}, & r - m \leq x \leq r \\ 1, & x > r \end{cases} \tag{3}$$

On the other hand, regarding the fuzzy sets of the level variation variable, half of the distance "m" between the reference levels associated with the yellow, orange, and red alerts was considered. This value was used both for the structuring of the membership functions and for the specification of the equations associated with said functions. 4 show the membership functions associated with the negative, zero and positive fuzzy sets. The value of the variable "m" is assumed to be 1 meter, however, said value depends on each station and its value does not alter the shape of the membership functions, for which Figure 4 can be considered generic.

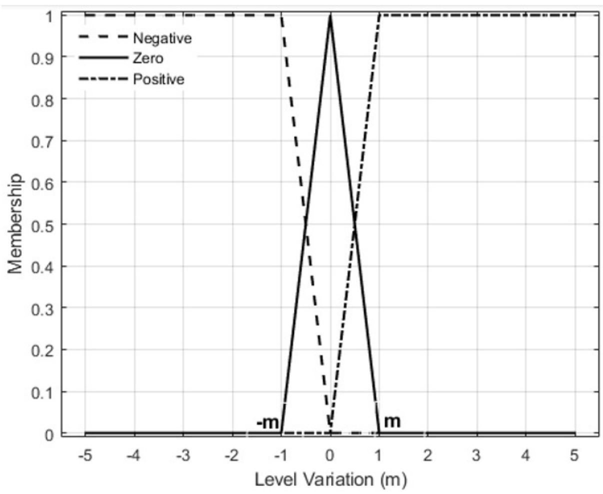


Figure 4: Membership functions of the level variation variable (Source own)

The definition of the membership functions for the variable “level variation” are associated with the negative, zero and positive fuzzy sets. Thus, in Equation 4 the left saturation mathematical function is presented, which represents the negative fuzzy set, said function depends on half the distance between the reference levels (m).

$$\mu_{\text{negative}} = \begin{cases} 1, & x < -m \\ \frac{-x}{m}, & m \leq x \leq 0 \\ 0, & x > 0 \end{cases} \tag{4}$$

Similarly, in Equation 5 the triangular mathematical function for the zero fuzzy set is presented, this function depends on half the distance between the reference levels (m).

$$\mu_{\text{zero}} = \begin{cases} 0, & x < -m \\ \frac{x+m}{m}, & -m \leq x \leq 0 \\ \frac{m-x}{m}, & 0 \leq x \leq m \\ 0, & x > m \end{cases} \tag{5}$$

Continuing with the fuzzy set equations, Equation 6 presents the right saturation mathematical function that describes the positive fuzzy set, this function depends on half the distance between the reference levels (m), (see Figure 4).

$$\mu_{\text{positive}} = \begin{cases} 0, & x < 0 \\ \frac{x-m}{m}, & 0 \leq x \leq m \\ 1, & x > m \end{cases} \tag{6}$$

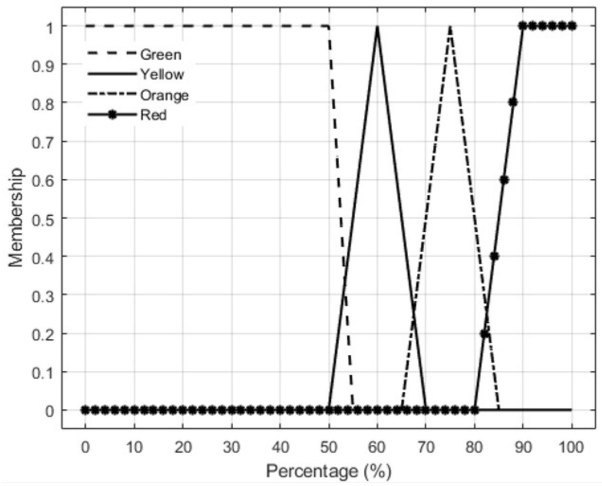


Figure 5: Membership functions for the flood alert level variable (Source own)

Once the membership functions of the fuzzy system inputs were defined, was specified the mathematical equations of the fuzzy sets of the flood alert level (output variable of the fuzzy algorithm). It is worth mentioning that for the output of the fuzzy system to be intelligible, the universe of discourse is in percentage terms. Figure 5 shows the membership functions corresponding to the green, yellow, orange and red alert fuzzy sets. In this way, from the definition of the membership functions for the alert level variable (see Figure 5), the 4 mathematical equations associated with the green, yellow, orange and red fuzzy sets were specified. In this way, Equation 7 presents the membership function for the green flood alert level.

$$\mu_{\text{green}} = \begin{cases} 0, & x < 50 \\ \frac{55-x}{5}, & 50 \leq x \leq 60 \\ 0, & x > 55 \end{cases} \tag{7}$$

Similarly, Equation 8, shows the membership function that represents the yellow flood alert level.

Table 3: Fuzzy system inference rules

id	Rule
1	IF level IS normal AND level_variation IS negative THEN alert_level IS green
2	IF level IS normal AND level_variation IS zero THEN alert_level IS green
3	IF level IS normal AND level_variation IS positive THEN alert_level IS yellow
4	IF level IS high AND level_variation IS negative THEN alert_level IS yellow
5	IF level IS high AND level_variation IS zero THEN alert_level IS orange
6	IF level IS high AND level_variation IS positive THEN alert_level IS red
7	IF level IS emergency AND level_variation IS negative THEN alert_level IS red
8	IF level IS emergency AND level_variation IS zero THEN alert_level IS red
9	IF level IS emergency AND level_variation IS positive THEN alert_level IS red

$$\mu_{\text{yellow}} = \begin{cases} 0, & x < 50 \\ \frac{x-50}{10}, & 50 \leq x \leq 60 \\ \frac{70-x}{10}, & 60 \leq x \leq 70 \\ 0, & x > 70 \end{cases} \tag{8}$$

Likewise, Equation 9 presents the membership function that describes the orange flood alert level.

$$\mu_{\text{orange}} = \begin{cases} 0, & x < 80 \\ \frac{x-65}{10}, & 65 \leq x \leq 75 \\ \frac{70-x}{10}, & 75 \leq x \leq 85 \\ 0, & x > 85 \end{cases} \tag{9}$$

Finally, Equation 10 shows the membership function that represents the red flood alert level.

$$\mu_{\text{red}} = \begin{cases} 0, & x < 80 \\ \frac{x-80}{10}, & 80 \leq x \leq 90 \\ 1, & x > 90 \end{cases} \tag{10}$$

After defining the membership functions for the inputs (level, level variation) and for the system output (flood alert level), the fuzzy inference rules were defined so that the system, through of operations based on fuzzy sets, get the output from the input values. An inference rule can be defined as a set of propositions combined with each other, which are made up of antecedents (input variables) and consequent (output variables), [46]. Table 3 shows 9 inference rules in terms of the FCL language syntax.

Thus, by multiplying the number of fuzzy sets of the inputs (3x3), 9 possible outputs were obtained, which are mapped to the 4 fuzzy sets of the output variable. From Table 3 and the use of the FCL language, a configuration file was defined including the ranges and the universe of discourse of the different sets of inputs and output, as well as the inference rules that relate said fuzzy sets, in addition to the methods used for the inference. Based on the above and considering that the configuration file must include numerical values, the reference values for the alert levels of the Banco Magdalena station were used (see Figure 6).

According to Figure 6 , the levels of the yellow (y), orange (o) and red (r) alerts for the Banco station are y=7.3 m, o=7.8 m and r=8.3 m. Similarly, half the distance between the stations is m=0.25 m. From these values and considering the membership functions for the input variables presented in equations 1 to 6, which are a function of y, o, r and m, the ranges of the fuzzy sets are defined considered in the configuration file by means of the FCL language.

3.2 Solution Development: Fuzzy System

For the construction of the fuzzy system, the jFuzzyLogic library was selected from the literature. It corresponds to an API compatible with the Java language and from the open-source domain, which allows the implementation of systems based on fuzzy logic through the definition of the membership functions associated with the inputs and outputs of the system, as well as the specification of inference

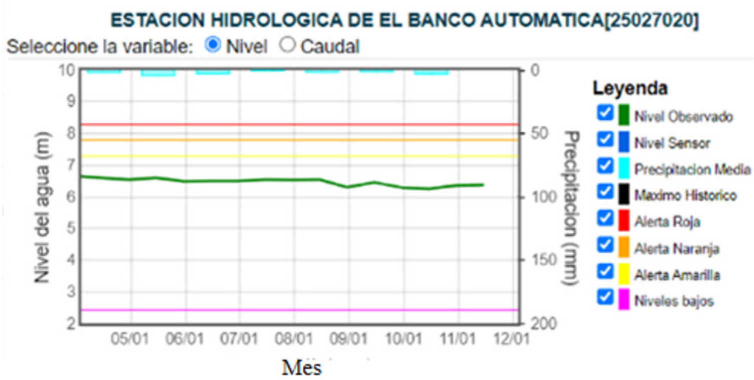


Figure 6: Reference levels for the Banco Magdalena station (Source [34])

rules that relate inputs to outputs. Both the membership functions and the inference rules are specified in the FCL language and interpreted by the library. Additionally, the library allows generating the graphs of the membership functions of the inputs and outputs of the system, through its own graphical component [48]. Given the compatibility of the jFuzzyLogic library with the Java language, for the development of the fuzzy system, the standard packages of said language were also used together with the Swing library for the management of the system's graphical interfaces. Figure 7 shows the architecture of the proposed fuzzy system, which was implemented using the jFuzzyLogic Java library. The fuzzy system is made up of three main modules, a fuzzification module, a central inference module and a defuzzification module. The fuzzification module is in charge of receiving the water table level and water level variation variables as input in order to determine the fuzzy sets to which said variables may belong according to the membership functions as well as the degree of belonging or membership to said sets, (see Figure 3 and Figure 4), which is in the interval from 0 to 1. From this, the inference module uses a set of defined rules to estimate the variable "flood alert level", the degree of belonging to one or more fuzzy sets. Finally, the defuzzification module of the system estimates a numerical output value (gravity center method) from the result of the inference, which in this case corresponds to a percentage value that determines the flood alert level, which can also be expressed in linguistic terms.

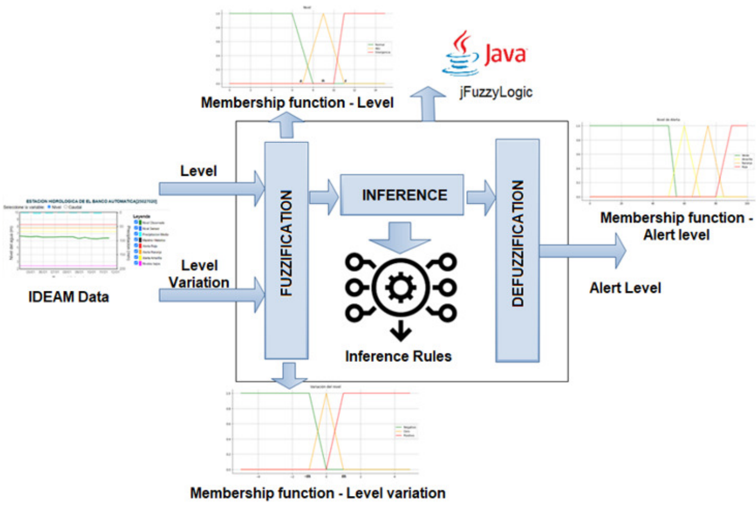


Figure 7: Fuzzy system architecture (Source own)

Considering the architecture of the implemented fuzzy system, Figure 8 shows a block diagram representing the functional modules that make up the fuzzy system implemented. The GUI module oversees generating and managing the graphical interface that makes up the fuzzy system, as well as handling the events associated with the interface controls. The file processing module, for its part, is in charge of reading and processing the .csv file that contains the data obtained from the IDEAM's

FEWS platform with the aim of extracting the information corresponding to the date and the level obtained by the target station at different times. The fuzzy logic module is the brain of the system and is in charge of implementing the three main blocks described in the architecture of the fuzzy system (fuzzification, inference and defuzzification), in such a way that it receives the level and level variation variables to obtain the fuzzy set to which these variables belong together with their degree of belonging, from which the output flood alert level is determined in numerical and linguistic terms by means of the inference rules. This module is also closely linked to the membership graph generation module, which is responsible for enabling the creation of membership functions for the input variables and for the output variable, highlighting in these functions the fuzzy sets in which the variables were classified. In this sense, for which it makes use of the jFuzzyLogic library. To finish this stage, the reports module allows the generation of a .csv file with the results of the fuzzy analysis on the input data and its comparison with the data estimated by the FEWS platform.

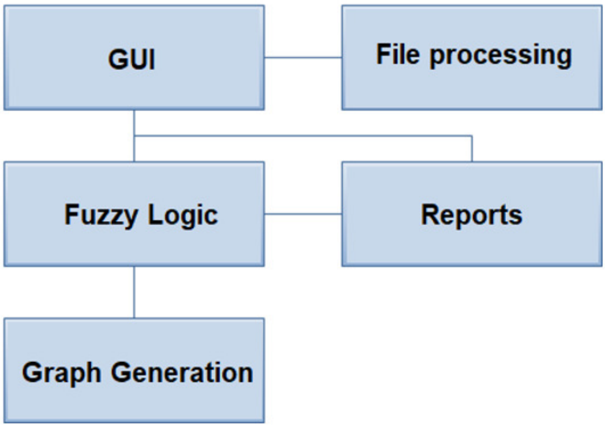


Figure 8: Fuzzy system block diagram (Source own)

The constructed fuzzy system is made up of a total of four tabs: "Station Data", "Fuzzy Analysis", "Membership Graphs" and "Comparison (see Figure 9). In the "Station Data" tab, it is possible to load the data of a given IDEAM station by pressing the "Read CSV" button, then said data is presented in a table within the interface, which has the columns "Id", "Date", "Level" and "Level Variation". The "Level Variation" column is calculated by the system from the records in the "Level" column by subtracting the current level from the previous level. As an example, for the description of the system interfaces presented in this section, data from the Banco-Magdalena station were loaded, which has reference levels: y=7.3, o=7.8, r=8.3,m=0.25.

On the other hand, Figure 10 shows the graphical interface associated with the "Fuzzy Analysis" tab, in which the fuzzy system obtains the output alert level in numerical and linguistic terms from the inputs (level and level variation) of each of the records of the .csv file loaded in the "Station Data" tab.

In this way, for the inputs level and level variation of each record, the system performs a fuzzification process taking into account the previously defined membership functions. From the degrees of membership obtained and considering the rules of inference presented in Table 3, using the Mandami method, the value of the flood alert level was defuzzified (Gravity Center Method), obtaining from the rules that are activated of the 9 defined. The estimated output value is presented and marked in the membership function presented in Figure 10. To complement, in Figure 10 shows the results obtained for record 4 of the test data loaded in the "Station Data" tab. For the variable "level" of said record (6.3), a degree of membership of 1 is obtained to the set diffuse "Normal". While for the variable "level variation" of said record (0.099), a membership degree of 0.6 is obtained to the "Zero" fuzzy set and a membership degree of 0.399 to the "Positive" fuzzy set. According to these results and considering the rules of inference, it is obtained that rule 2 and rule 3 are activated, with respective membership degrees of 0.6 and 0.399, which ultimately means that for the variable "alert level" a value of 58.53 with a degree of belonging to the "Yellow" fuzzy set of 0.853 is obtained as an output. This is clearly seen in the system-generated membership function at the top right of the interface. Although the

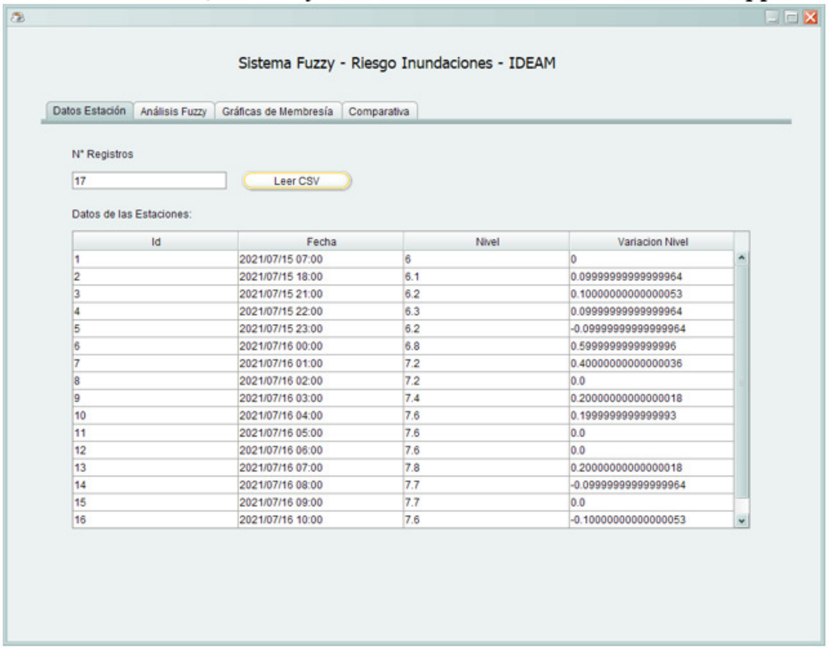


Figure 9: Fuzzy system main interface (Source own)

output fuzzy set is the one associated with the yellow alert, the API's predefined colors do not allow customizing the presentation of the fuzzy sets in the membership function. However, the results are intuitive due to the order of presentation from left to right. Thus, the "Green" fuzzy set is presented first in the membership function and in yellow color, the "Yellow" fuzzy set is presented second in the function and with purple color, the green fuzzy set is presented third and with green color, while in the case of the red fuzzy set it is presented last with the same color. Finally, the output value estimated by the fuzzy system (58.53) is marked with a black line on the membership function (Figure 11). Continuing with the tabs of the implemented fuzzy system, in Figure 11 the graphical interface associated with the "Membership Graphs" tab is presented.

In this tab, the fuzzy system allows obtaining from the fuzzification and defuzzification processes the fuzzy set in which the inputs were classified within the membership functions, as well as the value of the output alert level and the fuzzy set at that belongs within the membership function of said variable. This is done by choosing the record or reading on which is needed to view the graphs in the list of options and pressing the "Consult" button. For the level and level variation values of record 4 of the data loaded in the "Station Data" tab Figure 11 shows the two membership functions of the inputs and the membership function of the output. Regarding the variable "level" (6.3), its classification in the fuzzy set "Normal" can be seen, while regarding the variable "variation of level" (0.1) its classification in two fuzzy sets " Zero" and "Positive", the degree of participation being greater than the "Zero" set. Finally, regarding the membership function of the output variable " flood alert level ", it is observed that the estimated value (58.53) was classified in the fuzzy set of the "Yellow" alert. In Figure 12 the graphical interface of the "Comparative" tab is shown, in which the fuzzy system presents for each of the data records loaded in the "Station Data" tab the estimated level of the output variable in numerical or percentage terms and linguistic (Alert Level and Linguistic Level columns), together with the values estimated by the IDEAM's FEWS platform, taking into account the classical logic and the reference levels considered for the analyzed station.

Thus, in Figure 12 it is observed the comparison between the results obtained by the system for the test data used in this section and the results obtained by the FEWS platform when comparing the value of the level with the reference levels of the Banco Magdalena station (y=7.3, o=7.8, r=8.3, m=0.25). It can be seen that in the case of registers 10, 11 and 12, the FEWS platform classifies these values with a yellow alert level, while the fuzzy system classifies these values in the "orange" and "red" alerts, taking into account the positive or negative rate of change that the level has in each consecutive record. Finally, in the "Comparison" tab, the option to generate a table report was

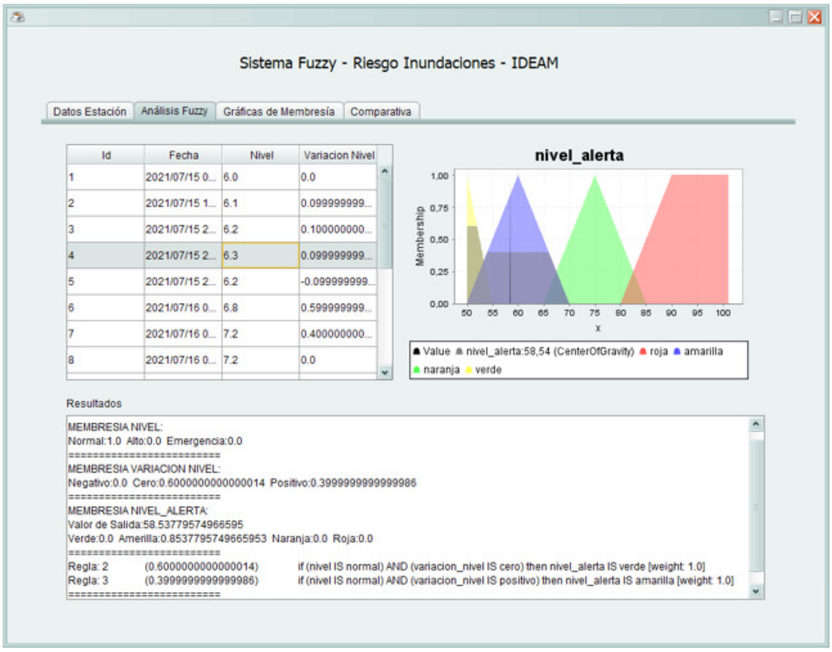


Figure 10: “Fuzzy Analysis” tab of the fuzzy system (Source own)

Table 4: Columns of the report generated by the fuzzy system

Columns	Description
Id	Corresponds to the identifier of the analyzed record. It is represented by a consecutive number starting at 1.
Date	Corresponds to the date and/or time stamp on which the level variable was read.
Level	It represents the value read in meters within the station under study.
Variation	It refers to the difference between the current level and the previous level.
Risk	It corresponds to the value estimated by the fuzzy system in numerical terms from the inputs and the inference rules, using the Mandami method.
Alert	It corresponds to the estimate of the variable level of risk or alert level, but in linguistic terms.
Green	It represents the membership degree of the output value estimated by the system for the “Green” fuzzy set.
Yellow	It represents the degree of belonging of the output value estimated by the system to the "Yellow" fuzzy set.
Orange	It represents the degree of belonging of the output value estimated by the system to the “Orange” fuzzy set.
Red	It represents the degree of belonging of the output value estimated by the system to the "Red" fuzzy set.
State	It corresponds to the type of alert estimated by IDEAM in its FEWS platform for the input level, taking into account the reference levels (yellow, green and red) for the station under study.

programmed; pressing the "General Report" button generates a file in .csv format compatible with Excel and includes the columns described in Table 4.

3.3 Solution Test: Application to the Case Study

The basin under study is that of Banco-Magdalena, Colombia, with the data corresponding to the year 2020 between June and December, with a reading frequency of 1 per hour. A sample of 744 records corresponding to the month of September was taken (see Figure 13). In that month, the levels recorded exceeded the yellow alert level defined for this station (y=7.3 meters, o=7.8 meters, r=8.3 meters). It was observed that in the selected data there were no null values, for which the application of imputation techniques was not necessary, [48, 49].

Once the work dataset had been selected and considering the ranges of the fuzzy sets in the FCL file, the .csv file of the study case was loaded into the “Station Data” tab of the system. In the "Fuzzy Analysis" tab it is possible to view the output alert level from the fuzzification of the level and level variation variables corresponding to the different records of the case study (see Figure 14). It can be observed, for example, that for record 161, whose value of the level variable is 6.85 meters and

Figure 11: Tab “Membership Graphs” of the fuzzy system (Source own)

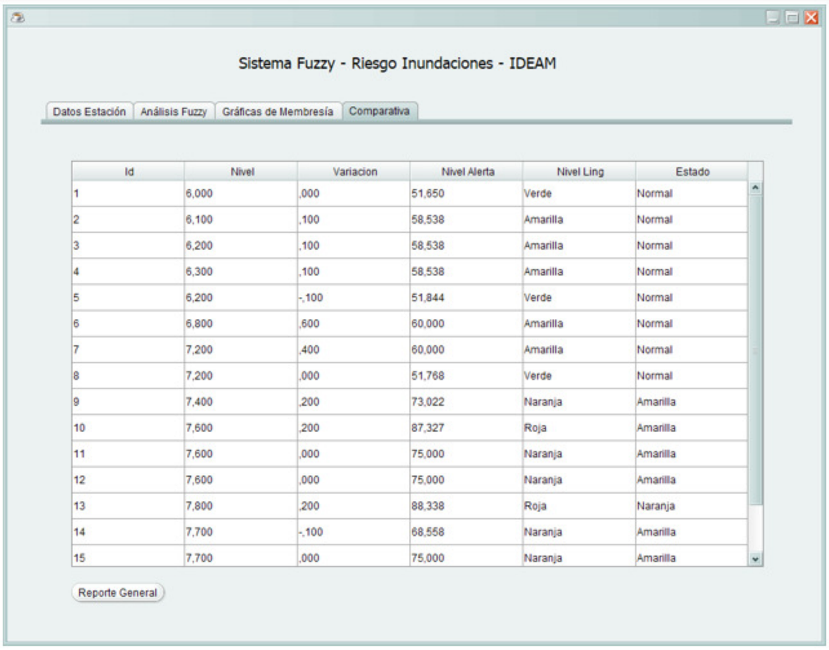
Table 5: Membership of input and output variables for register 161

Variable	Membership
Input: Level = 6.86 m	Membership Normal = 1.0 Membership High = 0.0 Membership Emergency = 0.0
Input: Level variation = 0.03 m	Membership Emergency = 1.0 Membership Negative = 0.0 Membership Zero = 0.879
Output: Flood alert level = 55.98	Membership Green = 0.0 Membership Yellow = 0.598 Membership Orange = 0.0 Membership Red = 0.0

Rules activated:
 	
Rule 2 (0.8799999999999999)
if (Level is normal) AND (Level_Variation is zero) then Alert_Level IS green [weight: 1.0]
 	
Rule: 3 (0.120000000000001)
if (Level IS normal) AND (Level_Variation IS positive) then Alert_Level IS yellow [weight: 1.0]	

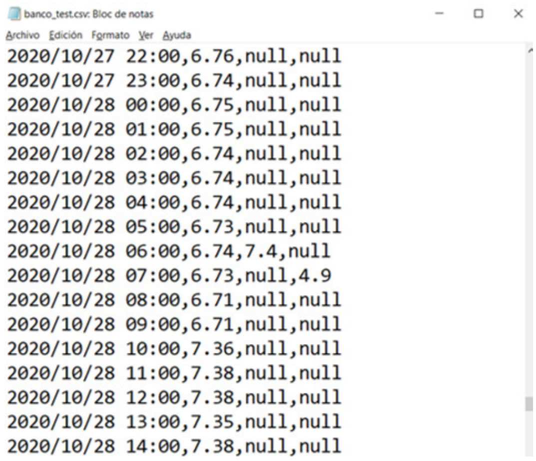
its increase with respect to the previous level is 0.03 meters, the exit flood alert level is yellow alert with 55.98% of level of risk, something that for the FEWS platform would be recorded as a normal level. By better specifying the results obtained by the system for the validation record, in Table 5 the membership values of the inputs and output are presented in addition to the estimated flood alert risk level.

According to Table 5, the input level of register 161 was assigned to the normal fuzzy set with a membership level of 1, that is, if only this variable were considered, the output level would be normal. However, the variation of the level causes the output to be a yellow alert (positive increase of the water level every 60 minutes). In this sense, for the input variation value of 0.03 m/min, the system assigns two zero and positive fuzzy sets, with respective membership values of 0.879 and 0.12. Taking into account the fuzzy sets determined for the system inputs, in the inference module are activated rule 2 (relates the normal fuzzy set of the level variable and the zero fuzzy set of the level variation variable) and rule 3 (relates the normal fuzzy set of the level variable and the positive fuzzy set of the level variation variable), with respective degrees of membership. From the activated rules, Mandami's method determined that the output level is 55.98, which corresponds to the yellow alert according to the membership function of the output level variable. The above explanation can be seen in Figure15 where the membership functions associated with the inputs and outputs for register 161 in particular



Id	Nivel	Variacion	Nivel Alerta	Nivel Ling	Estado
1	6,000	,000	51,650	Verde	Normal
2	6,100	,100	58,538	Amarilla	Normal
3	6,200	,100	58,538	Amarilla	Normal
4	6,300	,100	58,538	Amarilla	Normal
5	6,200	-,100	51,844	Verde	Normal
6	6,800	,600	60,000	Amarilla	Normal
7	7,200	,400	60,000	Amarilla	Normal
8	7,200	,000	51,768	Verde	Normal
9	7,400	,200	73,022	Naranja	Amarilla
10	7,600	,200	87,327	Roja	Amarilla
11	7,600	,000	75,000	Naranja	Amarilla
12	7,600	,000	75,000	Naranja	Amarilla
13	7,800	,200	88,338	Roja	Naranja
14	7,700	-,100	68,558	Naranja	Amarilla
15	7,700	,000	75,000	Naranja	Amarilla

Figure 12: "Comparative" tab of the fuzzy system (Source own)




```
2020/10/27 22:00,6.76,null,null
2020/10/27 23:00,6.74,null,null
2020/10/28 00:00,6.75,null,null
2020/10/28 01:00,6.75,null,null
2020/10/28 02:00,6.74,null,null
2020/10/28 03:00,6.74,null,null
2020/10/28 04:00,6.74,null,null
2020/10/28 05:00,6.73,null,null
2020/10/28 06:00,6.74,7.4,null
2020/10/28 07:00,6.73,null,4.9
2020/10/28 08:00,6.71,null,null
2020/10/28 09:00,6.71,null,null
2020/10/28 10:00,7.36,null,null
2020/10/28 11:00,7.38,null,null
2020/10/28 12:00,7.38,null,null
2020/10/28 13:00,7.35,null,null
2020/10/28 14:00,7.38,null,null
```

Figure 13: Dataset considered for the study case (Source own)

are shown.

In Figure 15 the two upper graphs correspond respectively to the membership functions of the level and level variation variables, in which the fuzzy sets selected for each variable after the fuzzification process can be seen by means of a black line. Similarly, the lower graph shows the membership function associated with the alert level variable with a black line that determines the fuzzy set and the value estimated by the system for said entries (55.98% - yellow alert).

In Figure 16, the proposed fuzzy system has the ability to compare the output level estimated by the system with the value assigned by the FEWS platform through classical logic. Thus, it is observed how, although the level captured by the station (column 2 of the table shown in Figure 16) is approaching the reference level for yellow alert (7.3 meters), the FEWS platform estimates said level as normal or green ("Status" column of the Figure 16), while the fuzzy system estimates yellow alert when the level variation increases (Linguistic Level column of the Figure 16), something that is essential in early warning systems. Likewise, the estimation results are quickly presented for the 744 records of the case study, turning the expert system into a real-time predictive method, different from other artificial intelligence approaches, where the training process and estimate is not immediate.

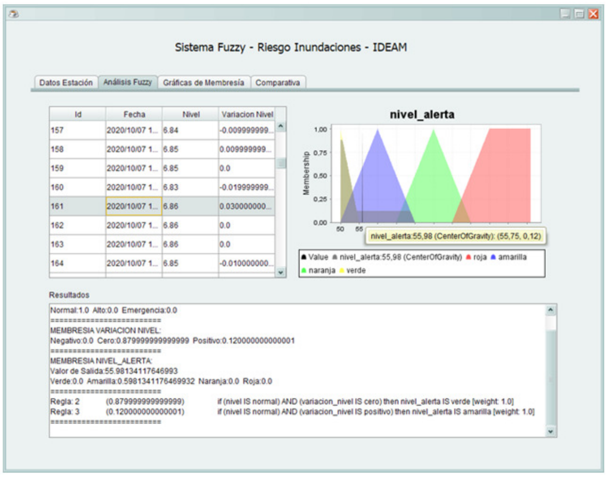
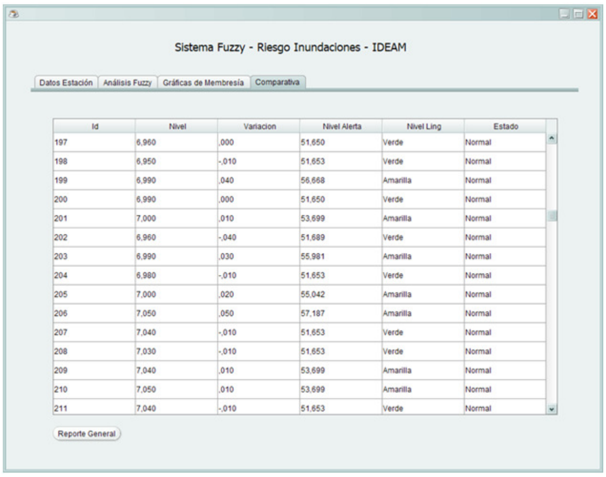


Figure 14: Fuzzy analysis of the case study data (Source own)

Figure 15: Membership functions of the case study (Source own)

4 Conclusions

In this work, the development of a fuzzy system was proposed to allow the estimation of the level of alert or risk from the input variables of water level and variation of the water level over time. From the evaluation, it was observed that, during the 100 executions carried out, the minimum time used to process a record of the 744 of the study case was 0.08 milliseconds and a maximum time of 0.15 milliseconds. The above within a computer with a core i7 processor (2.60GHz) and 8 GB RAM. These calculations were made from the characteristics of the Java System class, which allows computations of execution times. The results obtained consolidate the idea that the proposed system can be used adequately for real-time estimation of alert levels, making it an excellent alternative to enrich the FEWS platform under the considerations and assumptions mentioned. One of the main contributions of the implemented fuzzy system was the consideration of the water level variation variable, which determines the rate of increase of the level variable from one reading to another. Thus, if the value of the level is close to the yellow alert level and the variation is positive, the system will be able to estimate an early warning, while with the method used in the FEWS platform, until the yellow alert level is exceeded, the alarm is not triggered. This makes the platform unsuitable for generating timely forecasts, given the particularities of flood events and the speed with which they develop. The equations and/or membership functions were proposed in a generic way and taking into account the reference levels for yellow (y), orange (o) and red (r) alerts of the stations, as well as half the distance between them. In this way, the system can be customized in the FCL configuration file, considering the specific values or ranges of each station according to the generic membership functions, with-


Sistema Fuzzy - Riesgo Inundaciones - IDEAM

Datos Estación | Análisis Fuzzy | Gráficas de Membresía | Comparativa

Id	Nivel	Variacion	Nivel Alerta	Nivel Ling	Estado
197	6,960	,000	51,650	Verde	Normal
198	6,950	-,010	51,653	Verde	Normal
199	6,990	,040	56,668	Amarilla	Normal
200	6,990	,000	51,650	Verde	Normal
201	7,000	,010	53,699	Amarilla	Normal
202	6,960	-,040	51,689	Verde	Normal
203	6,990	,030	55,981	Amarilla	Normal
204	6,980	-,010	51,653	Verde	Normal
205	7,000	,020	55,042	Amarilla	Normal
206	7,050	,050	57,187	Amarilla	Normal
207	7,040	-,010	51,653	Verde	Normal
208	7,030	-,010	51,653	Verde	Normal
209	7,040	,010	53,699	Amarilla	Normal
210	7,050	,010	53,699	Amarilla	Normal
211	7,040	-,010	51,653	Verde	Normal

Reporte General

Figure 16: Comparative analysis of the results (Source own)

out affecting the structure of the system and its ability to estimate the alert level. Considering the characteristics of early warning systems, specifically in what corresponds to real-time operation, these systems require an artificial intelligence component that allows estimating alert levels efficiently or at low computational cost. This is how the proposed fuzzy system, based on a finite set of inference rules that relate the inputs to the output, proved to be an alternative both at a methodological and computational level for estimating alert levels in a real-time context. Thus, the runtime measurement results showed that the maximum time the system takes to estimate a response in a weather station application domain is 0.15 milliseconds, which is a competitive advantage over other artificial intelligence methods. Given that the IDEAM platform provides extra-temporary monitoring of the hydro-meteorological stations of the different basins, it is essential, before articulating this type of predictive methods, to guarantee that the data from the stations can be captured and displayed in real time, with a view to the progressive constitution of an early warning system. In other words, it is necessary to update the IDEAM capture infrastructure in such a way that it is articulated within the current trend of the Internet of Things (IoT). The case study developed with the 744 records of the Banco-Magdalena station, made it possible to determine that the diffuse system responds adequately to changes in the level, without being subject only to the level captured exceeding the limits defined for each alert. Likewise, the fuzzy system determines the level of risk associated with each alert in numerical and linguistic terms, which may be more understandable for the end users of the fuzzy system. When performing the validation and operation with the existing records (744), it was observed that in 260 cases (corresponding to 35% of the records) the IDEAM FEWS platform did not generate an early warning. Similarly, in 484 of the cases (corresponding to 65% of the records or readings made) the alert was generated correctly. In this way, the proposed diffuse system represents a representative improvement in terms of generating flood alerts in advance. Finally, in future research, input variables such as rainfall should be added, as well as implementing data pre-processing with regression methods and developing a real-time simulator, among others.

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6 Author contributions

The authors contributed equally to this work.

7 Conflict of interest

The authors declare no conflict of interest.

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