NRCS-CN ESTIMATION FROM ON-SITE AND REMOTE SENSING DATA FOR THE MANAGEMENT OF A RESERVOIR IN THE EASTERN PYRENEES

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ABSTRACT

On-site and Earth observation (EO) data are used for the calibration of the Natural Resources Conservation Service-Curve Number (NRCS-CN) value in a hydrological simulation model. The model was developed for La Muga catchment (Eastern Pyrenees) highly vulnerable to flood and drought episodes. It is an integral part of a regional reservoir management tool, which aims at minimizing the flood risk, while maximizing the preservation of water storage. The CN values were optimized for five recorded events for the model to match the observed hydrographs at the reservoir, when supported with the measured rainfall intensities. This study also investigates the possibilities of using antecedent moisture conditions (AMC) retrieved from satellite data to inform the selection of the NRCS-CN losses parameter. A good correlation was found between the calibrated CN values and the AMC obtained from satellite data. This correlation highlights the interest in using EO data to update NRCS-CN estimates. This advances in hydrologic-hydraulic coupled modelling combined with new remote sensing datasets present valuable opportunities and potential benefits for flood risk management and water resources preservation.

Key words: NRCS-CN, remote sensing, flood risk, reservoir management, hydrological distributed modelling, antecedent moisture condition (AMC), Mediterranean region.

1. INTRODUCTION

Droughts and floods are recurrent situations in Mediterranean catchments. In this semi-arid region, streams are characterized by intermittent flows due to the irregularity of rainfall and to the seasonal temperature variability. In a large portion of the Mediterranean region, the highly-urbanized areas and the population seasonality due to tourism, increase the water demands and at the same time the flood risk. Periods of water scarcity alternate with periods of frequent flooding that are becoming more severe under the influence of climate change (Arnell 1999; IPCC 2014a; Lehner et al. 2006). The management of water resources in these water-stressed areas is therefore complex.

Floods are the most catastrophic natural hazard around the world (Fonseca et al. 2018; ISDR 2009; Kron 2005). In the Mediterranean region, according to the EM-DAT (2019) Disaster Database, floods are around 30 % of the natural disasters that occurred in the 20th century. On the other hand, droughts are a cyclic phenomenon in the Mediterranean region. Their management is a challenge for water administrations, especially during the summer season with its higher demand for water resources. The vulnerability of the Mediterranean area to droughts and floods is continually increasing due to the high economic dependency on water resources and to the possible consequences of climate change (GECCC 2016; IPCC 2014b).

In this context, dams and reservoirs are essential elements for providing protection against flooding and ensuring the water supply year-round. The complexity of water resources and dam management requires the integration of several disciplines (meteorology, hydrology, hydraulics, etc.) and a deep knowledge of the system characteristics (catchment), inputs (rainfall) and outputs (demands). The use of realistic modelling that considers all these factors can lead to more effective predictions and more effective hazard mitigation.

At present, several modelling tools integrate two-dimensional hydraulic modelling with distributed hydrological modelling (Anees et al. 2017; Caro 2016; Cea et al. 2010; Kim et al. 2012;

Roux et al. 2011; Viero et al. 2014; Yu and Duan 2017). Integrated or coupled modelling can better represent the real hydrologic and hydraulic processes than using these models independently. Nevertheless, models depend on a large number of parameters (e.g. soil and land characteristics, underground fluxes, etc.) as well as on expertise in their implementation for risk and water resources management applications. The calibration and use of these tools can be complex, as the number of the required parameters depends often on limited data or on data with inadequate quality, and are not always directly physically measurable.

In this context, this paper first presents the results of the implementation and calibration of a coupled hydrological and hydraulic model. This model was used as a tool to define and implement management strategies for the Boadella Dam, located in the upper part of La Muga catchment (NE of Spain). This model belongs to a series of methods developed under the PGRI-EPM project (*Forecasting and management of flood risk in the Pyrenees-Mediterranean Euroregion*) for the operational management of reservoirs in the region (Roux et al. 2020; Sanz-Ramos et al. 2018). The designed management method is mainly based on modelling in a cascade of the involved processes (short-term precipitation forecast and coupled hydrologic and hydraulic processes). The objective is to minimize the flood risk and, at the same time, to maximize the preservation of water resources during the management of extreme events.

The main factors that influence flood generation are related with the rainfall characteristics and the physical and hydrological characteristics of the catchment. The losses, mainly by infiltration and interception, are a determining factor in the rainfall-runoff transformation process. One of the most extended methods for losses estimation is the Soil Conservation Service Curve Number method (SCS-CN; NRCS 2004), also referred as the NRCS-CN method after the Agency was renamed as the Natural Resources Conservation Service. The fact that requires only one parameter for modelling losses has contributed to its success. In the NRCS-CN method, the Curve Number parameter (CN), although not physically-based, is a quantitative descriptor which embodies the complex physical characteristics of the soil type, antecedent soil moisture conditions (AMC), and land use and cover (LULC) in a catchment. Hence, a proper choice of the CN value is essential to achieve realistic rainfall-runoff simulations.

The determination of the AMC and thus of the CN value can be improved with the use of remote sensing techniques. These techniques provide spatially distributed retrievals for a wide variety of hydrological parameters (Estévez et al. 2014; Marti-Cardona et al. 2013; Martí-Cardona et al. 2010; Ramos-Fuertes et al. 2013; Torres-Batlló et al. 2019; Wu et al. 2018), including surface soil moisture (SM). Also, remote sensing is a powerful tool for the observation of the hydrological processes and a relevant source of information for the calibration of numerical models describing such processes (Li et al. 2019; Ramos-Fuertes et al. 2013). The hydrological modelling community is progressively benefiting from the incorporation of spatial soil moisture measurements, with a varied degree of success (Brocca et al. 2017). Remote sensing has been used for indirect estimation of the CN value by obtaining land use information from satellite images (Tirkey et al. 2014), but also for the adjustment of loss parameters (Silvestro et al. 2015). Rajib et al. (2016) explored the usage of spatially distributed remotely sensed soil moisture in the calibration of a hydrological model.

Against this background, this work aims at showing the relevance of remote sensed soil moisture data for the CN estimation within a coupled distributed hydrologic-hydraulic model procedure oriented at water reservoir management. This main objective is achieved through three secondary goals applied on a case study: (i) set up and calibration of the hydrological model; (ii) analysis of the variability of the CN within several registered events and (iii) identification of a relationship between the calibrated CN values and the estimated SM data from EO. The application of this technique in the study case is intended to provide better information for integrated flood risk and water resources management in continuous modelling.

2. STUDY AREA

2.1. SITE AND CATCHMENT CHARACTERISTICS

La Muga is a cross-border basin of 961 km^2 located at the northeast of Catalonia (northeast Spain) that drains from the south-east Pyrenees to the Mediterranean Sea (Fig. 1a). The basin is partially regulated by the Boadella Dam (182 km^2), at the upper-part of the catchment, with 62 hm^3 of storage and a regulating capacity of 15 hm^3. The basin, which includes some highly developed tourist areas at its lower part (Costa Brava), is highly vulnerable to drought due to excessive water demand (agriculture and human consumption) and to flooding (ACA 2007).

The topography of the study area ranges from mountains to lowlands (Fig. 1a) and the rainfall regime in the catchment is significantly influenced by the Mediterranean Sea. The average annual rainfall ranges from 550 mm near the coast to 1200 mm in the upper part. Heavy rainfall episodes tend to concentrate in late summer, autumn and spring, lasting from several hours up to a few days. The variable rainfall frequency and long dry periods cause the area to suffer from severe water scarcity (Llasat and Rodriguez 1992; Martín-Vide 1994).

This work focuses on the upper part of La Muga basin, upstream of the Boadella Dam, where there is a single rainfall gauge and one water level gauge (Fig. 1a). The study area has an extension of 181 km^2 and is mainly characterized by large-forest coverage (above 90 %, Fig. 1b), low permeability and low ground storage capacity (ACA 2007). The reservoir is included in the hydrological analysis and modelling, and it has been calibrated with the measures of water level and their variations during extreme rainfall events.

2.2. DATA SET

Rainfall and water level

A detailed analysis of extreme rainfall events was performed within the PGRI-EPM project (Sanz-Ramos et al. 2018) through which more than 60 significant rainfall episodes registered during the last 100 years were evaluated. From the results of that analysis, five extreme rainfall events were selected for calibration of the proposed model (Table 1). The selected events, occurred between March 2011 and March 2015, are labelled with the starting date and the duration in days. The selected episodes have all mean rainfall intensities above 20 mm/h in 5 minutes, and total precipitation volumes over 120 mm in periods between 2 and 4 days.

The data of precipitation and water level in the reservoir were provided by the Servei Meteorològic de Catalunya (SMC) and the Agència Catalana de l'Aigua (ACA) respectively. They consisted of 5-minute hyetographs recorded at the Boadella dam station; rasters of 1x1 km spatially distributed hourly rainfall derived from radar (Bech et al. 2005; Corral et al. 2009); and the evolution of the water level in the reservoir (5-minute resolution).

Digital terrain model (DTM) and land uses

Topographical data were derived from a high-resolution 2x2 m DTM provided by the Institut Cartogràfic i Geològic de Catalunya (ICGC). The DTM includes the bathymetry of the reservoir above 145.0 m.a.s.l. (below the minimum water level during the events).

Land use data, obtained from the CORINE project (EEA 2007), was used for the implementation of the surface roughness coefficient (*n* Manning coefficient). Additional details regarding these data can be found in Table 2.

Soil Moisture Data

Soil moisture data were obtained from the European Space Agency Climate Change Initiative for Soil Moisture (ESA CCI SM) (Liu et al. 2011, 2012; Wagner et al. 2012). The combined product version 4.2 (ESA et al. 2018) was obtained for the periods covering the selected rainfall events and for some days prior to their onset, with a maximum of 50 days. The product consists of daily rasters of volumetric soil moisture for the soil´s top 20 mm. The rasters are provided with a spatial resolution of 0.25º degrees, which for the study area corresponds to approximately 27.5 km.

La Muga catchment is encompassed by two resolution cells of the ESA CCI SM product. 85 % of the catchment area overlays a raster cell entirely located on the southern Pyrenees, while the remaining 15 % falls within a cell mainly covering the northern Pyrenean side. Moisture data from both cells exhibit a markedly distinctive behavior, as expected from the different precipitation regimes on either side of the mountain range. Since the study catchment belongs to the southern Pyrenees, only the ESA CCI SM moisture records from the southern cell were used, assuming that they would better represent the catchment moisture status than a weighted average of both cells.

3. METHODS

The cascade workflow presented herein is as follows: 1) building-up a coupled hydrological-hydraulic numerical model balancing the computational cost and the results accuracy; 2) calibrating the numerical model (CN and *n*) with on-site data, first with rain gauges and then fine-tuning with radar data; and 3) relating the CN values with EO data (SM) aiming to obtain the information needed to continuously support the numerical model for the reservoir management in future events.

3.1. NUMERICAL MODEL

The coupled distributed hydrological and hydraulic numerical tool Iber (Bladé et al. 2014b; Cea and Bladé 2015) was used for both rainfall-runoff transformation and flow characterization. Iber is based on the dynamic wave solution of the Shallow Water Equations (SWE) with the finite volume method (Cea et al. 2016; Toro 2009), and it includes a specific numerical scheme for overland flow named Decoupled Hydrologic Discretization, DHD (Cea and Bladé 2015). After it was released in 2010, Iber has undergone several improvements. These enhancements allow the model to consider precipitation and losses varying in time and space and improved mesh definition for very shallow flows (i.e. a *fill-sinks*-option) (Bladé et al. 2014a; Caro 2016; Cea et al. 2015; Cea and Bladé 2015; Juárez D. et al. 2014).

Additionally, Iber implements a specific drying method for hydrological computations, which handling the transition from wet to dry conditions, and vice versa. Briefly, a wet-dry limit (ε_{wd}) is used to define the water depth threshold below which a cell is considered to be dry. For drying cells, the scheme uses an adaptation to finite volume numerical schemes of the method used in LISFLOOD (Bates and De Roo 2000), in order to guarantee mass conservation. This method reduces numerical instabilities during simulation and ensures that all mesh cells have a zero or positive depth.

3.2. MODEL SETUP

The study area was spatially discretized using an irregular triangular mesh of approximately 50,000 elements of area from 150 m^2 (in rivers) up to 200,000 m^2 (in hillslopes) (Fig. 2). This discretization is a compromise between accuracy of the results and computational time. The DTM was treated using a *Fill sinks* algorithm, based on the algorithm proposed by Wang and Liu (2006) to ensure a good definition of the flow path removing unreal depressions (Fig. 2). The DHD scheme was used with a wet-dry limit threshold of 10^{-4} m.

The current set-up configuration allowed the simulation of events that last from 2 to 4 days with a computational time between 1 and 3 hours using 1 CPU core (i7 fourth generation to 3.5 GHz). It is worth mentioning that after the end of the project there have been substantial improvements in the computational time of Iber by using Graphics Processing Unit (GPU) computing techniques (García-Feal et al. 2018). With this novelty, the presented simulations would run in about 1 minute, achieving speed-up up to 100.

There is only one initial condition imposed to the model which is the water level in the reservoir at the beginning of the simulation events. The river was assumed to be dry at the beginning of the simulations, which is an acceptable assumption as normal discharges are negligible when compared with flood discharges. No boundary conditions were imposed as there are no streams flowing into the study area. Rainfall intensities were applied on the corresponding mesh element. Manning coefficients (*n*) were associated with each element, based on their land use according to the CORINE map (EEA 2007) (Fig. 1b).

The NRCS-CN method was used to evaluate the losses in the rainfall-runoff process. For its application, the initial abstraction (I_a) was linked to the soil potential retention (S) through a 0.2 factor ($I_a = 0.2 \cdot S$) as proposed by USDA (1986) and Ponce and Hawkins (1996). Due to the homogeneity of the land uses, soil type and AMC conditions in the study site, where over 90 % of the area corresponds to forest coverage (Fig. 1b), a single value of CN was used for the whole basin. The value of CN was later adjusted within the calibration process.

3.3. RELATING CN TO EARTH OBSERVATION SOIL MOISTURE DATA

ESA CCI SM data provide information of the soil moisture in the top 20 mm layer of the soil. These measurements are well-correlated with previous rainfall days but might not be representative of the AMC, which have a relevant influence on the CN value. In this study, it was assumed that the evolution of daily surface moisture over several days before the onset of the rainfall event could inform of the water content in deeper soil layers, and hence it could be used as a proxy of the AMC and CN. In order to explore this relationship, daily SM values were averaged for periods ranging from 2 to 40 days before the beginning of the analyzed rainfall event. Then, a correlation between the averaged SM and the calibrated CN values was established.

4. RESULTS AND DISCUSSION

4.1. HYDROLOGICAL MODELLING AND CALIBRATION STRATEGY

The purpose of the calibration process is the adjustment of the values of CN and the terrain roughness (*n*). The CN mainly influences on the mass balance of the whole event, while the *n* coefficient is expected to have an effect on the water front propagation and the water elevation evolution.

A sensitivity analysis of the Manning's roughness coefficient was carried out. The reference values for the *n* coefficients were determined following the recommendations from the USGS Guide (Arcement and Schneider 1989). A 0.11 value of *n* was assumed for the dense forest land use that represents around 75 % of the study area (Fig. 1b). As a result of the analysis, no significant influence on the model response in terms of water front and water elevation in the reservoir was observed under *n* variations in a range of ±20 %. Hence, it is assumed that CN is the main calibration parameter. Results obtained by using the dense forest land use data for the *n* sensitivity analysis are shown in Fig. 3.

The CN was adjusted during calibration process to properly represent the evolution of the water stored in the reservoir during the events. For events 20110313_4d and 20130304_3d, rain data were available only from the rain gauge source. For events 20131116_3d, 20141129_2d and 20150320_3d, both data from rain gauges and radar were available and used in the calibration process. For these last three events, the gauge data are used for a first estimation of the CN value and what we called CN_{rg}. This value of CN was later fine-tuned with the radar information calling it CN_{r}.

Table 3 shows the CN value that best fit for all five events taking into account each data source. A seasonal trend could be inferred from these values, with higher values of CN during spring and moderate during autumn, though the number of events is not large enough to take more quantitative conclusions of seasonal variations.

In the study area, there are two alternative sources of information for the CN values: CEDEX (2003) and ACA (2019). Both are georeferenced databases available online and provide values of the initial abstraction from which the value of CN can be derived. According to CEDEX the mean CN value for the study area is 64.9 ± 7.6 (standard deviation) while according to ACA it is 62.0 ± 12.8 under so-called normal catchment conditions (neither *wet* nor *dry*). If possible variations due to AMC are considered according to NRCS (2004), the CN values can be updated and varies in a range from 44.5 to 81.1 (initial CN from CEDEX database) and from 41.5 to 79.1 from ACA information. Thus, the CN values obtained from the calibration process for this study area and rainfall events are within the limits of values that would be obtained from these data provided by the public administration. However, it should be noted that the CN values provided by the mentioned public entities may be based on an outdated topographic base (Campón et al. 2015). Thus, the values that can be obtained by an ad-hoc calibration using hydrological models and real rainfall data should generally provide more representative values of CN.

Table 4 shows the total cumulated rainfall and the effective rainfall for each event from rain gauge data and radar data. For the events 20131116_3d, 20141129_2d and 20150320_3d, with radar dataset available, significant differences between the effective rainfall derived from gauge data and from radar were observed. The gauge station registered higher cumulative rainfall than values obtained from the radar source. Thus, in general, the estimated CN_{rg} is smaller than the CN_r in order to reach the same water level in the reservoir. For events 20131116_3d and 20141129_2d, the differences between this two CN values can be considered reasonable. However, for the event 20150320_3d, this difference is significant (Table 3). Regarding this, it can be hypothesized that there may have been a highly non-uniformly distributed rainfall. The gauge station probably registered high intensities locally concentrated around the gage's location, which were not representative of the global rain pattern in the catchment during the event. This situation can be corroborated from radar data which are analyzed below.

The total rainfall cumulated at the end of the events 20131116_3d, 20141129_2d and 20150320_3d is also represented in Fig. 4. The non-uniformity is easily observable in the rainfall spatial distribution recorded by the radar. For the event 20131116_3d, the maximum cumulated precipitation registered by the gage (123 mm) is close to the radar maximum (120 mm). However, this value is observed only locally at the south of the study area, and the average rain depth is lower for the radar source than from the gauge source. For this reason, the CN_r is higher than the CN_{rg}. For the event 20141129_2d, the distribution of radar rainfall shows high accumulations at the east part of the study area (205 mm). However, the average values from gauge and radar are very similar (slightly higher for the rain gauge). Thus, the CN_r for this event is also slightly higher than CN_{rg}. Finally, for the event 20150320_3d the differences are the largest. In this case, the cumulated rainfall from the raingauge source is 200 mm while the radar does not exceed 80 mm (average value). As mentioned before, a high local rainfall was registered by the rainfall station, which is not representative of the rainfall pattern in the basin, which in turn could explain the large differences between the CN_{rg} and the CN_r.

Based on what has been observed so far, the calibration process therefore focused on the adjustment of the CN value. The CNs finally selected by event showed in Table 3 were a combination of the calibration process according to the best statistical fitting (Table 5). Thus, the CNs value derived from the calibration process ($CN_{selected}$) range between 55 and 94 (Table 3).

For the assessment of the fitting between observed and simulated results (water level at the dam) several indicators were used: mean absolute error (MAE); root mean square error (RMSE); and Nash-Sutcliffe model efficiency coefficient (NSE) (Nash and Sutcliffe 1970). Table 5 summarizes the performance of the model for both rainfall data sources by event. In general, the simulations performed from radar (r) source data produce a better fit than those obtained with the gauge (rg) data in terms of water front evolution. This statement can be seen in Table 5 through the smallest mean differences (MAE and RMSE) and highest values of NSE.

Fig. 5 shows the performance of the model for both rain sources with the selected CN value. Events 20110313_4d and 20130304_3d, calibrated with rain gauge data, shown in general a good performance. The modelled water level rise in the reservoir is slightly delayed with respect to the observed data, and the water level at the end of the event was slightly higher than the observed one. A slightly overestimation of the water level was observed at the end of events 20131116_3d and 20141129_2d. For the event 20150320_3d instead, the water level obtained from the rain gauge data rapidly increase exceeding the capacity of the reservoir (160 m.a.s.l), far from the prediction made with radar data. Regarding the inconsistencies using gage data in this last analyzed event, we refer to the non-uniform spatial distribution of the rainfall that may explain this result as was previously explained.

It can be seen then that the availability of radar rainfall data can help to improve the hydrological model results since timely rainfall measurements, provided by a rainfall station, might be not enough representative of the complex spatial rainfall variation at the catchment scale. Moreover, rainfall data obtained from radar have a much higher spatial resolution (1 km^2 in this case) which allow a better spatial representation when modelling.

Table 6 shows the results of the mass balance in the reservoir through the differences between observed data and simulation results. The differences in water level (WL_{start} and WL_{end}) and stored volume (V_{start} and V_{end}) at the start and end of the simulation period are shown for all the events. In general, good agreement between both observed and simulated results for the simulations performed with either data from the station or radar sources are observed. However, a significant difference is predicted for the event 20150320_3d. For this last event a 252 % difference in stored volume can be observed from the simulations carried out using gauge data. As previously hypothesized, significant differences observed using raingauge data could be generated due to high localized rainfall near the gauge location.

For event 20110313_4d, the obtained CN value is close to the highest value of the parameter, which would imply that the losses are minimal. This unusually high value can be explained by two possible reasons: 1) the limitations of working with only one gauge and 2) possible errors in the water level records in the reservoir (the water evolution during the days before the event or the lack of data). With respect to the first cause suggested, from the Fig. 5 (Event 20110313_4d, dotted line) the water level in the reservoir increases during the first period while there is no rainfall registered by the gauge. This means that either it could have rained heavily during the previous days, or there was rain in some parts of the basin that was not registered by the gauge. Additionally, some errors (lack of data and sudden steps) were detected on the water level records registered in the reservoir. It should be noted that the initial water level was 151 m (constant value during the firsts 3 hours of the simulation period) while after 10 min it increased to 152 m. This difference means 2.67 hm^3 in terms of water volume in the reservoir, which is around 12 % of the volume stored during the event. These considerations are presented here as possible reasons that explain the high value for the CN calibrated for this episode.

On the other hand, the estimated CN for the event 20130304_3d is 81 also using rain gauge data. As shown in Fig. 5, the delay in the arrival time of the water front into the reservoir is approximately 10 h, but there is a good adjustment in terms of water levels after that. For the mentioned episode, the difference in water level in the reservoir at the end of the episode is lower than 0.03 m.

4.2. RELATIONSHIP BETWEEN EARTH OBSERVATION BASED SOIL MOISTURE DATA AND CURVE NUMBER

Fig. 6 illustrates the relationship between the five calibrated CNs and the daily EO surface moisture values averaged for different periods prior to the five rainfall events. For clarity, not all analyzed periods are represented in Fig. 6. As the number of averaged days approaches 16, the relationship between CN and the averaged SM converges to a clear linear trend.

Fig. 7 depicts the squared linear correlation coefficient between CN and the averaged surface moisture for all analyzed averaging periods and rainfall events. The best fit is achieved when 16 days prior to the rainfall onset are averaged, yielding a high R^2 value of 0.96. The clear consistency in the correlation coefficient changes as the antecedent period is varied reinforces the validity of this result.

The presented relationship between CN and EO based on surface moisture has been obtained for five rainfall events modelled in the small Boadella reservoir catchment. Despite the limited representativeness of the presented case, the quality and consistency of the relationship strongly suggests the potential of EO data to provide updated estimates of the CN value. The accuracy in the estimation of this parameter has crucial implications in the volumes of runoff predicted by hydrological models and, hence, in the flood prevention measures taken by water resources managers.

4.3. DISCUSSION: IMPACT OF FLOODING AND POTENTIAL BENEFITS OF MERGING REMOTE SENSING DATA IN WATER RESOURCES MANAGEMENT DECISION SUPPORT SYSTEMS

Among the five events presented herein, the events 20110313_4d and 20130304_3d were the ones that caused more flood damages from an economic point of view. The economic evaluation of the flood risk associated to the released discharges, and of the water resources lost or preserved after the extreme rainfall episodes, are part of the outputs of the system developed under the PGRI-EPM project for the operational management of reservoirs in the region (Sanz-Ramos et al. 2018). The application of management measures obtained as outputs from the system for the aforementioned events, would have significant benefits in minimizing the flood risk and maximizing the preservation of water resources. For 20110313_4d for instance, the damages to property would have been reduced by 15 %, expected injury by 62 % and expected fatalities by 48 %, while a volume of 0.9 hm^3 of water released from the reservoir would have been preserved. These values represent a reduction of the episode impact of approximately 3.3 M€. For 20130304_3d, material damages would have been reduced by 28 %, injury by 81%, expected fatalities by 58 % and 0.2 hm^3 of preserved water volume. In this last case, the reduction of the impact would have been around 2.9 M€ (Bladé et al. 2018).

EO data represent a valuable source of information for hydrologic purposes and for water resources management, in general, through mapping water resources and monitoring hydrological parameters. Remote sensing techniques contribute to management systems modelling providing updated estimates of different parameters which can significantly improve the efficiency of such models and their robustness for forecasting. In this case, we focus attention on the benefits that can be obtained in water management modelling through the updated assessment of the CN value after the consideration of remotely sensed soil moisture information as described in previous section 4.2.

Once the numerical model is calibrated, the final system is supported up with only two sets of data: quantitative precipitation forecasts and soil moisture from EO. The model is executed continuously, updating the inputs with the last available ESA CCI SM data and precipitation forecasts (Roux et al. 2020). Threshold alerts and pre-established dam operation protocols are included in the model, though the protocols can also be manually adjusted for the assessment of different operations of the dam outflow systems.

5. CONCLUSIONS

On-site and Earth observation (EO) data were used for the calibration of the NRCS-CN parameter of an Eastern Pyrenees basin, as it is the most important parameter of the hydrological model when correctly assessing water balance so as to evaluate the basin hydrologic response. The model developed for this purpose consists of a coupled fully-distributed hydrological and hydraulic model, which constitutes the central core of an operational system for the Boadella reservoir management. The main aim of the operational system is the prediction of flood risk and final water resources estimates associated to a forecasted extreme rainfall. The use of a distributed model integrating hydraulics and hydrology has been proven to be a robust tool so as to obtain in a single simulation, results of water resources (discharges, reservoir volumes) and flood hazard (depths, velocities).

Solid correlations were found between the estimated moisture data and the CN value obtained through numerical modelling forced by ground data, suggesting the potential of available remote sensing data for the updating of the CN values in continuous hydrological models. The optimal averaging period for the SM was, for the present case, 16 days. It would be valuable to check the validity of this period in other basins, which is proposed for future work.

The relationship between CN and EO based on surface moisture has been obtained for five rainfall events modelled in the small Boadella reservoir catchment. The accuracy in the estimation of the CN parameter strongly affects the volumes of runoff simulated by the hydrological model and, consequently, the flood mitigation measures informed by those.

Thanks to the SM-CN relationship, the information needed to continuously support the operational system for the reservoir management has been reduced to two sets of data: observed meteorological data in raster format, and the observed soil moisture. The consistency of the achieved SM-CN relationship strongly suggests the potential of EO data to provide updated estimates of the CN.

The present results of the application to the case study suggest the usefulness of incorporating remotely sensed proxies. This work is a step towards physical descriptors of soils based on remote sensing and its integration in water resources management and flood forecasting systems, thus providing a beneficial direction for future work on optimized management strategies.

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7. DATA AVAILABILITY STATEMENT

The data used during the study, and provided by a third party are listed below:

- Precipitation data (Table 2), generated by Servei Meterològic de Catalunya (https://meteo.cat), was provided by Agència Catalana de l'Aigua (http://aca.gencat.cat/ca/inici) within the PGRI-EPM project.
- Dam outlet and water level data (Table 2) was provided by Agència Catalana de l'Aigua (http://aca.gencat.cat/ca/inici) within the PGRI-EPM project.

Direct requests for these materials may be made to the provider.

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FIGURES & TABLES

Fig. 1. Location and characteristics of the study area. (a) Topography of La Muga basin, extension of the study area and location of the Boadella Dam and rain gauge station. (b) Land use map of the study area. Source: Institut Geològic i Cartogràfic de Catalunya (a), CORINE (b) and own elaboration.

Fig. 2. Computational mesh of the study area.

Fig. 3. Sensibility analysis for the Manning coefficient (n) associated with forest-dense land use. Water level evolution for the events 20130304_3d and 20150320_3d.

Fig. 4. Representation of a non-distributed (top: rain gauge registrations, triangle: rain gauge localization) and distributed (bottom: radar observations) rainfall records for events 20131116_3d, 20141129_2d and 20150320_3d.

Fig. 5. Evolution of the water level in the Boadella reservoir (dam point-check) for the observed data (dotted line) and the simulations (rain gauge: dashed line; radar: continuous line) using the selected CN.

Fig. 6. Scatter plot of CNs calibrated for five events versus Earth observation based soil moisture measurements averaged for different antecedent number of days.

Fig. 7. R^2 coefficient of the linear correlation between the calibrated CNs and the Earth observation based soil moisture averaged for different antecedent periods.

Table 1. Extreme rainfall events registered in the study area used for the model calibration. Rainfall information sources are identified as: (rg) for rain gauge, (r) for radar images.

Event ID	**Date**	**season**	**Source of data**	**Total rainfall depth [mm]**		**Maximum intensity [mm/5-min]**	**[mm/h]**
				(rg)	**(r)***	**(rg)****	**(r)*****
20110313_4d	March 2011	spring	(rg)	127	-	62	-
20130304_3d	March 2013	spring	(rg)	181	-	30	-
20131116_3d	Nov 2013	autumn	(rg), (r)	123	98	54	9
20141129_2d	Nov 2014	autumn	(rg), (r)	151	132	61	13
20150320_3d	March 2015	spring	(rg), (r)	197	77	67	9

**Cumulated rainfall for the study area*
***Intensity registered in 5 minutes at the raingauge*
****Intensity registered in the study area*

Table 2. Summary of the data used for the upper La Muga sub-catchment study case.

Data type	Characteristics	Source	Data description
Digital Terrain Model (DTM)	2x2 m ASCII raster file	Institut Cartogràfic i Geològic de Catalunya (ICGC)	Elevation data based on LIDAR (RMSE of 0.15 m)
Land uses	Shapefile converted into 2x2 m ASCII raster file	CORINE Land Cover project (EEA 2007)	Land uses classification and spatial representation for the year 2012
Soil moisture (SM)	0.25º degrees spatial resolution	European Space Agency Climate Change Initiative for Soil Moisture (ESA CCI SM)	ESA CCI SM
Precipitation	Rainfall intensities	Agència Catalana de l'Aigua (ACA) and Servei Meteorològic de Catalunya (SMC)	Rainfall intensities from 5-minutal raingauge (hyetograph) and 1-hour radar (1x1 km ASCII raster file)
Dam outlet / water level	Discharges and water level	Agència Catalana de l'Aigua (ACA)	5-minutal series of the outlet hydrograph and the water level in the reservoir

Table 3. CN values resulting from the calibration process.

Event	season	CN_{rg}	CN_r	$CN_{selected}$
20110313_4d	spring	94	*	**94**
20130304_3d	spring	81	*	**81**
20131116_3d	autumn	50	55	**55**
20141129_2d	autumn	60	65	**65**
20150320_3d	spring	50	85	**85**

**No data available on this format*

Table 4. Cumulated and effective rainfall using the selected CN (Table 3) at the end of the event.

Event	Total rainfall [mm]		Effective rainfall [mm]	
	(rg)	(r)	(rg)	(r)
20110313_4d	127	*	109	*
20130304_3d	181	*	125	*
20131116_3d	123	98.3	16	12
20141129_2d	151	132.3	59	49
20150320_3d	197	76.7	152	41

**No data available on this format*

Table 5. Model performance between observed and simulated flow and water balance using the corresponding CN for each rain source.

Event	MAE (m)		RMSE (m)		NSE	
	gauge	radar	gauge	radar	gauge	radar
20110313_4d	0.735	*	0.873	*	**	*
20130304_3d	0.261	*	0.389	*	0.987	*
20131116_3d	0.193	0.152	0.209	0.172	0.637	0.754
20141129_2d	0.770	0.371	0.948	0.532	0.518	0.848
20150320_3d	0.383	0.242	0.432	0.260	0.861	0.941

**No data available on this format*

***Statistic not applicable due to lack of data*

Table 6. Mass balance at the end of the rainfall event using the selected CN (Table 3).

Event	GAUGE							
	WL_{start} [m]	WL_{end} [m]	V_{start} [hm³]	V_{end} [hm³]	ΔV (sim)	ΔV (obs)	Difference [hm³]	Difference [%]
20110313_4d	151	158	36.9	60.2	23.3	22.2	1.1	4.9
20130304_3d	147	156	26.7	51.8	25.1	25.2	0.1	0.4
20131116_3d	151	152	37.0	40.2	3.23	3.07	0.16	5.2
20141129_2d	149	152	31.1	41.2	10.1	10.0	0.1	1.0
20150320_3d	155	163	48.5	80.2	31.7	9.0	22.7	252

Event	RADAR							
	WL_{start} [m]	WL_{end} [m]	V_{start} [hm³]	V_{end} [hm³]	ΔV (sim)	ΔV (obs)	Difference [hm³]	Difference [%]
20131116_3d	151	152	37.0	40.2	3.23	3.07	0.16	5.2
20141129_2d	149	152	31.1	41.0	9.87	10.0	-0.14	-1.4
20150320_3d	155	157	48.5	56.8	8.24	8.95	-0.71	-7.9