Operational adoption of new probabilistic point rainfall forecasts: the crucial role of a “user-oriented” approach

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# ABSTRACT

Numerical Weather Prediction (NWP) models produce forecasts that, although improve continuously in reliability/skill, represent an average over the model grid-box. For some applications, users require forecasts at specific locations instead. Forecasters can add value to model predictions issued for smaller scales than the model resolution as they understand model biases/errors, interpret how they might impact the weather at a location, and summarize the information to users. However, forecasters call upon past model performance experience, which can take years to build up, it is not easily adaptable to new model versions, and it might generate biased forecasts. A novel statistical post-processing methodology (ecPoint) that produces more reliable/skilful probabilistic forecasts at points can also help forecasters to overcome the challenges mentioned earlier. The formulation of ecPoint probabilities does not depend on personal experience. They are based on a global observational database instead. ecPoint probabilities adapt quickly to biases/errors in new model versions thanks to a dynamic calibration process. Finally, ecPoint summarizes in one intelligible probability distribution the complex raw probabilistic information. Thus, forecasters do not have to do it themselves. However, ecPoint adds layers of complexity to traditional probabilistic ensemble-based forecasts (PEFs). Is the current training provided on ecPoint-Rainfall sufficient to make forecasters fully appreciate ecPoint potentialities and to adopt the new post-processed forecasts operationally? A one-year trial with two different users showed that ecPoint-tailored training must be provided to improve the understanding of ecPoint forecasts, no matter what the previous experience of forecasters with probabilistic ensemble-based forecasts is. This study outlines revised guidelines to communicate ecPoint forecasts more efficiently to users.

# Introduction

Worldwide, extreme weather-related hazards (e.g. tropical cyclones, floods, landslides, droughts, heatwaves, wildfires, earthquakes, tsunamis, volcanoes) have cost millions of lives and billions of dollars in economic losses between 2000-2019 (UNDRR 2020). Moreover, such hazards are expected to become more frequent and damaging due to global warming (Hoegh-Guldberg et al. 2019) and due to an increased exposure and vulnerability of people and assets (Ward et al. 2020). The Sendai Framework for Disaster Risk Reduction 2015-2030 (UNDRR 2015) advocates reducing disaster risk by enhancing early response and preparedness.

Within this framework, several projects are building early warning systems at regional/national scale (Arnal et al. 2020; Demuth et al. 2020; Flack et al. 2019; Acosta-Coll et al. 2018) and international scale (Emerton et al. 2020; WMO 2017; Coughlan De Perez et al. 2015; Alfieri et al. 2012, 2013). All these projects recognize the practical importance of connecting forecast production and delivery systems to decision-making processes by a “user-oriented” approach (Golding et al. 2019). Such an approach asserts that enhancements in early warning systems do not depend only on mere forecast skill improvements. They also depend on establishing a two-way interdisciplinary communication system between developers and end-users (i.e. forecasters, decision-makers, emergency responders, or the public) (Zhang et al. 2019; Taylor et al. 2018). On the one hand, such system helps to convey to end-users the social, economic, and environmental value of forecasts (Fundel et al. 2019; LeClerc and Joslyn 2015; Joslyn et al. 2009a,b; Joslyn and LeClerc 2012; Joslyn and Savelli 2010; Joslyn and LeClerc 2013; Morss et al. 2008; Lazo et al. 2009). On the other hand, it helps to identify research targets to satisfy end-users’ needs (Demuth et al. 2020; Wilson et al. 2019; Losee and Joslyn 2018; Morss et al. 2016; Demeritt et al. 2013; de Roo et al. 2011; Demeritt et al. 2010; Morss et al. 2010; Novak et al. 2008).

In the above examples, forecast training appears to be a fundamental tool to inform the two-way communication system between developers and end-users. End-users tend, however, to highlight a series of issues about training content and its delivery. A series of studies (Demuth et al. 2020; Evans et al. 2014; Nobert et al. 2010; Novak et al. 2008) confirm what in the authors’ experience are the main issues with forecast training. Too often training content tends to be disproportionately heavy on the scientific developments of forecast products and to be much lighter on practical applications, e.g. what are the strengths and limitations of a forecast product, or how and when it applies to and benefits a forecast process by adding value rather than uncertainty to operational decision making. Training also tends to not mirror forecasters’ verification needs and language undermining their capability to assess and convey efficiently their confidence in the forecast to partners. Finally, training is not always effective in informing end-users about what forecast products are available and how to access them. Since users will naturally tend to inspect outputs from sources they are better acquainted with their strengths and weaknesses (Herman and Schumacher 2016), a not appropriate training can contribute to slow down or inhibit the adoption process of new forecast products.

A new statistical post-processing technique, called ecPoint-Rainfall, was developed at the European Centre for Medium-range Weather Forecasts (ECMWF) to provide global probabilistic rainfall forecasts at point-scale (Hewson and Pillosu 2020). A one-year global verification shows that, in the prediction of localized rainfall, the new post-processed forecasts are more reliable and skilful up to day 10 than ECMWF ensemble (ENS), especially for extremes (>50 mm/12h). However, compared to other raw or post-processed probabilistic forecast products, ecPoint-Rainfall adds some layers of complexity to the interpretation of its forecasts: (1) forecasts provide information on a point within the grid-box instead to the grid-box average, and (2) nothing can be said about the location of such point within the grid-box. If the implications of these features are not understood and applied correctly in the interpretation of forecasts and subsequent issuing of warnings, the perceived usefulness of ecPoint-Rainfall could be undermined. When Peru was affected by severe flooding in 2017, the Peruvian national hydro-meteorological service (SENHAMI) was provided with temporary free access to ECMWF forecasts (Pillosu et al. 2017). They were also provided with the newly developed ecPoint-Rainfall that, at the time, was running only internally at ECMWF in pre-operational mode. This provided an invaluable opportunity to collect field information about strengths, weaknesses, and usefulness of the new forecasts. Subsequent discussions with SENHAMI experts brought to the attention of ecPoint developers questions such as “Are ecPoint-Rainfall forecasts perceived as useful?”, “Are users interpreting ecPoint-Rainfall guidance correctly?”, “Will guidelines on ecPoint-Rainfall need to be user-tailored to increase the forecast usability?”. More collaborative projects of this kind were later pursued to collect further field information about ecPoint-Rainfall performance and usefulness (Pillosu and Hewson 2018). It was decided to limit the participation to forecasters at national hydro-meteorological services (NHMSs) as it was assumed that they might be the primary costumers of ecPoint-Rainfall forecasts. The Hungarian Meteorological Service (Országos Meteorológiai Szolgálat, OMSZ) and the Costa Rican Meteorological Service (Instituto Meteorológico Nacional de Costa Rica, IMN) participated to this study.

This study aims at collecting local-expert information about:

1. ecPoint-Rainfall performance in the prediction of extreme localized rainfall in diverse regions.
2. The perceived usefulness of ecPoint-Rainfall, focusing on (i) whether the available guidelines help to enhance ecPoint-Rainfall usefulness, and (ii) whether prior forecasters’ familiarity with probabilistic forecasts leads to different levels of guidelines efficacy.

# Data

ecPoint is a statistical post-processing technique that provides bias-corrected probabilistic forecasts at point scale. Potentially, different hydro-meteorological variables, from ensemble or deterministic numerical weather prediction (NWP) models, could be post-processed using the ecPoint technique. ecPoint-Rainfall is the branch of the “ecPoint family” that produces rainfall forecasts that mirror rain gauge measurements (Hewson and Pillosu 2020).

How do ecPoint-Rainfall and raw rainfall forecasts from NWP models differ? Let’s consider the rainfall forecast for an NWP model grid-box. Let’s also assume that the observed average rainfall over the grid-box is about 17 mm, while the minimum and maximum observed rainfall amounts are 2 and 60 mm, respectively. The entity of rainfall variability within a grid-box is associated to the type of weather affecting that grid-box, which from now on will be called “grid-box weather type” (G\_WT). A grid-box affected by a G\_WT that correspond to mainly convective rainfall and slow steering winds will have a higher probability to be affected by a higher rainfall sub-grid variability than a grid-box affected by mainly large-scale rainfall and fast steering winds. In the second the case, the rain will indeed tend to be more uniformly distributed within the grid-box. There are two issues that can be encountered when trying to forecast rainfall amounts. Firstly, there is a model sub-grid variability issue. NWP models provide rainfall forecasts that correspond only to a grid-box average. If correct, the NWP model will provide a forecast of 17 mm, but a user will not have any information about the variability of point rainfall values (which range from 2 to 60 mm in the example). The model sub-grid variability issue is enhanced in models with coarse resolutions (e.g. global or climate models), whilst km-scale models are better able to forecast the distribution of point rainfall values. Secondly, there is a model bias issue at grid-scale. Whatever is the extend of the observed rainfall variability within a grid-box, a completely accurate NWP forecast would predict 17 mm. However, depending on the G\_WT, the average grid-box rainfall forecast can be over-predicted (or under-predicted), for example, by 15%. This would deliver a forecast of 20 mm (or 14 mm) instead of 17 mm. ecPoint-Rainfall can help to anticipate model sub-grid variability and correct model biases at grid-scale by correcting the raw rainfall forecasts at each grid-box according to the correspondent G\_WT (see Fig. 1, left-red panel). From each raw single model grid-box forecast, ecPoint creates a distribution of X equally probable point-rainfall realizations (see Fig. 1, right-green panel). The value of X depends on available computational and storage capacity.

How does ecPoint differ from other post-processing techniques? The main difference between ecPoint and other post-processing techniques lies in the calibration dataset they use. First, rainfall post-processing techniques are generally site-specific. Rainfall observations should be collected at all those sites where post-processed guidance is desired (Hamill 2018). If no rainfall observations are available, post-processing becomes extremely difficult if not impossible. Rainfall observations should also span over several years to represent the site’s rainfall climatology and include relatively unusual rainfall events for that site. However, in situ observations are commonly sparse, might not have a long observational record, and even if they have, in situ observations of 20 years ago might not represent the weather today due to the general non-stationarity of rainfall trends over time. Second, forecasts that cover the same observational period and are consistent with the NWP model to post-process are needed (Hamill 2018). Due to continuous NWP models’ updates, it is almost impossible to have a long series of rainfall forecasts produced with the same model version. For this reason, the use of reforecasts (i.e. retrospective forecasts generated with a fixed NWP model version) has become increasingly popular in statistical post-processing of meteorological variables, including rainfall (Hamill et al. 2006). However, the creation of reforecasts represents a challenge in terms of computational and storage costs. The calibration dataset for ecPoint-Rainfall is built applying the so called "Remote Calibration" approach (Hewson and Pillosu 2020). Instead of creating a calibration dataset for a specific site, the "Remote Calibration" approach builds a calibration dataset for a G\_WT by pulling observations from all around the world where that G\_WT occurred. The principle behind this approach is that the physical processes that generate rainfall under a certain weather scenario are not site-specific. This approach has two main benefits. First, it allows to post-process rainfall forecasts in sites with no observations. Second, it allows to increase exponentially the calibration dataset for extremes. Indeed, the observations on sites where a G\_WT occurs relatively often inform the post-processing also for those sites where the same G\_WT generates extreme rainfall. In this case, a dataset created with the “Remote Calibration” approach can compare to a site-specific calibration dataset collected over hundreds or thousands of years.

In this study, ecPoint-Rainfall post-processes the ECMWF ENS (Hewson and Pillosu 2020). ecPoint-Rainfall produces 100 equally probable point rainfall realisations for each of the 51 ENS members and for each grid-box (Fig. 2). This creates 5100 values per grid-box, that are subsequently distilled down into 99 percentile fields (1st, 2nd, …, 99th). Outputs from ecPoint-Rainfall are produced at ECMWF twice per day (at 00 and 12 UTC), up to 10 days, for overlapping 12-hourly accumulation periods, namely (T+0,T+12), (T+6,T+18), ..., (T+234,T+246).

# Background

## IMN

### EXTREME (LOCALIZED) RAINFALL IN COSTA RICA

The climate of Costa Rica is mainly tropical. The mountains that run in a northwest-southeast direction split Costa Rica into two regions, Pacific and Caribbean, with their own rainfall regime. In the Pacific region, the wettest and the driest periods go from May to October and from December to March, respectively, being April and November transition periods. The Caribbean region is much wetter than the Pacific region, and it has not a defined wet season. However, the relatively wettest months are November to January and May to August. These two regions and their prevailing winds, the height and the orientation of the mountains and the influence of the Pacific and Atlantic ocean divide Costa Rica into seven main climatic regions: Región Pacifico Norte, Central and Sur, Zona Norte, Valle Central and Región Caribe Norte and Sur (see Fig.3d). Extreme rainfall events differ from region and time of year and are typically produced by cold fronts (coming from the northern hemisphere), affecting mainly Zona Norte, Región Caribe Norte and Sur and the eastern part of Valle Central between December-March; low-pressure systems (coming from the equatorial Pacific Ocean), affecting mainly Región Pacifico Norte, Central and Sur and the western part of Valle Central all year round; and hurricanes, between June and November, which affect mainly the Pacific Region due to winds circulation despite forming in the Caribbean Sea. These weather systems generate rainfall events that can last for several hours or days, accumulating large amounts of rain, and generating severe riverine floods. However, their interaction with the complex Costa Rican orography can enhance the rainfall amounts or produce severe localized storms and generate also severe flash floods.

### HOW IMN FORECASTERS PREDICT EXTREME (LOCALIZED) RAINFALL?

Given the small size of the country and its complex orography, IMN tend to not use guidance from global NWP models due to their typical coarse spatial resolution. Even if at occasions IMN forecasters look at the Global Forecast System (GFS) developed by the National Centers for Environmental Prediction in the USA, and at the ECMWF ENS from 2018, forecasters tend to rely mainly on guidance from km-scale models developed in-house. From the Weather Research and Forecasting (WRF) system, IMN has developed a series of model versions (WRF-1.5, WRF-5, WRF-AR, WRF-Sarapiquí, WRF, WRF-8, WRF-15) with different spatial/temporal resolutions, domains, and model configurations to tailor their use for specific hazards (e.g. tropical waves, tropical cyclones, cold fronts, hail, and forest fires). For example, WRF-1.5, developed in 2018, produces forecasts at 1.5 km resolution, up to 5 days, and aims to improve predictions for convective systems which can produce extreme localized rainfall events. These models are mainly deterministic, indeed *“95% of predictions at IMN are created using deterministic guidance, and only 5% derives from probabilistic models”*. Furthermore, predictions at IMN rely substantially on the examination of real-time observations of rainfall, river discharge, soil conditions which help experts to evaluate the impact that a certain rainfall event might have. Indeed, *“forecasts at IMN rely typically 60% on NWP guidance, and 40% on human expertise”.* For this reason, forecasters training is an important aspect at IMN. *“50% of forecasters have attended the NOAA’s Weather Prediction Centre International Tropical Desk, training in weather and climate forecasting for the Americas, and other forecasters have attended other training centres over the years”*.

## OMSZ

### EXTREME (LOCALIZED) RAINFALL IN HUNGARY

Hungary is located at the centre of the Carpathian basin. About two thirds of the country is flat, and the rest is mainly hilly. Peaks are all below 1000 m, except for Kékes (1014 m) in the “Heves” county. The climate of Hungary is mainly warm continental, and it is influenced by three main different climates: continental from the northeast, oceanic from the northwest, and Mediterranean from southwest. Such influences make average rainfall vary in space and time. May to September is the convective season, in which daily precipitation extremes can often exceeded 100 mm/day. June is often the wettest month, whilst February is the driest. The wettest areas in Hungary (> 850 mm, annual average) coincide with the hilliest parts of the country, mainly in the southwest (Vas, Zala, Veszprém, Somogy, and Baranya counties), and in the northeast (Pest, Nógrád, Heves and Borsod-Abaúj-Zemplén counties). On the contrary, the driest areas (< 500 mm, annual average) coincide with the flattest parts of the country in the southeast (Southern and Northern Great Plain), except for the east part of the Szaboics-Szatmár-Bereg county. In Hungary, extreme precipitation events are connected to large scale systems (e.g. cyclones, squall lines or cold fronts). However, local influences like those due to complex orographic can produce or enhance extreme precipitation. In certain occasions, small differences in the orography (e.g. 100-250 m) can be enough to trigger localized extreme rainfall.

### HOW OMSZ FORECASTERS PREDICT EXTREME (LOCALIZED) RAINFALL?

OMSZ has a long-standing experience (since the 1990s) in developing, using, and verifying EPFs. Therefore, extreme rainfall predictions are mostly generated and disseminated to the public using ensembles. OMSZ forecasters would typically look at a suite of ensemble models, including AROME (2.5 km horizontal resolution), ALADIN (8 km horizontal resolution) and ECMWF (ENS and high resolution, HRES, 9km horizontal resolution). OMSZ forecasters also take part regularly in educational and training programmes about the ECMWF ENS to keep updated on ensemble developments and improve the use of ECMWF probabilistic products. OMSZ is also experienced in rainfall post-processing which is regularly used at OMS to add value in the forecast of small-scale low-predictability phenomena like extreme localized rainfall (Matrai and Ihász 2017; Ihász et al. 2018).

# Methods

## Participants

This study aims at collecting independent local-expert feedback on (1) ecPoint-Rainfall performance in the prediction of extreme localized rainfall, and (2) its perceived usefulness in the creation of forecasts and warnings. The study is specifically interested at collecting such feedback from the perspective of operational forecasters at NHMSs as, currently, they are assumed to be the main users of ecPoint-Rainfall. To make any communication efficient between the NHMSs and ecPoint developers, a maximum of two contact people was identified at each NHMS. They helped as intermediaries between ecPoint developers and operational forecasters. For this reason, they were required to be operational forecasters themselves or have direct experience on the operational forecasters’ procedures and preferences when forecasting extreme rainfall events. Moreover, the contact people provided background information on the NHMS.

## Experiment design

An experiment in two phases was designed to analyse forecasters perspective on the new product’s performance and its perceived usefulness. The experiment design is represented by the flowchart in Fig. 3.

### “REAL-TIME” PHASE

The “real-time” phase aimed at observing how forecasters incorporate ecPoint-Rainfall in their forecasting routines, and at collecting information about forecasters perspective about ecPoint-Rainfall performance under real-time operational constrains.

The first step in the “real-time” phase was to provide remote training on ecPoint-Rainfall forecasts to the intermediaries. Links to all relevant online training material produced prior to the experiment (see Table 1) were sent out via email, with intermediaries then invited to email the ecPoint developers (Fatima Pillosu and Tim Hewson) with any related questions. Answers were also provided by email. This “email-exchange” approach to training is consistent with how the bulk of user support at ECMWF functions.

Whilst the remote training was taking place, the NHMSs began to receive the ecPoint-Rainfall forecasts via file transfer protocol (ftp) for 12 months. Table 2 contains the details of the forecasts provided to IMN and OMSZ.

The expected outcome from the “real-time” phase was a report from IMN and OMSZ. They were left free to organize the report as preferred. However, they were asked to at least answer the following questions:

* Did you developed any specific products from ecPoint-Rainfall? If so, describe them.
* Was ecPoint-Rainfall used in operations? If so, what were the forecasters’ impressions?
* Perform a subjective evaluation (i.e. via case studies) or objective evaluation (i.e. evaluation of verification scores) of the ecPoint-Rainfall performance in predicting extreme localized rainfall.
* Was the information provided by ecPoint-Rainfall useful in the prediction of localized extreme rainfall?

### OFF-LINE” PHASE

The “offline” phase aims at discussing the content of the reports prepared at the end of the “real-time” phase, and aspects that might limit the adoption of ecPoint-Rainfall forecasts in the operational environment of IMN and OMSZ. Informal discussions about the content of the reports were carried out. As shown by Harding (2018), this approach can help interviewers to put respondents at ease and do not inhibit or constrain their comments about the topic of the discussion, in this case ecPoint-Rainfall performance and its perceived usefulness. The informal discussions were conducted over two main steps.

The first step consisted in a remote discussion via videocall of one hour, conducted on each NHMS in turn. It was decided to guide the conversation with a list of open-ended questions (that can be found in Appendix A). Harding (2018) shows that this approach allows the conversation to start without compromising the following of its own path when required (e.g. when forecasters thought there were important points to highlight about ecPoint-Rainfall performance that were not coming out from the questions). videocall The list of questions was structured in two main sections. The first section focused on collecting background information to understand the context under which forecasters formulate their predictions for extreme rainfall. The second section focused mainly on ecPoint-Rainfall performance and its perceived usefulness. At the end of the first step, ecPoint developers summarized forecasters answers and needs, products- and training-wise, via a thematic analysis (Harding 2018) to highlight similarities and/or differences between forecasters at IMN and OMSZ. The outcomes of that analysis allowed ecPoint developers to create two new sets of ecPoint-Rainfall products tailored to IMN and OMSZ needs, respectively. Such new products were also accompanied by a new set of specific training material, whose language was better tailored to users’ and ecPoint-Rainfall forecasts’ characteristics than the original documentation provided.

The second step consisted in a remote discussion about the new products and training material created by the ecPoint developers. The discussion was carried out via email to be consistent with how the bulk of user support at ECMWF functions. After sending via email the new set of products and training, forecasters were asked to revise their initial forecasts for the case studies included in the report written at the end of the “real-time” phase. Specifically, they were asked whether they would have changed their initial forecasts. For example, would they have changed the level of warning initially forecast for an area? Would they have changed the areas at higher risk of experiencing the highest rainfall? Finally, forecasters were asked whether they perceived that the new set of products and training were more useful in the creation of the revised forecasts compared to the products IMN and OMSZ developed and the training material they received at the beginning of the real-time phase.

## Data analysis

The main points that allow ecPoint developers to assess whether the ecPoint forecasts were used correctly in both the “real-time” and the “offline” phase, and how well the training provided helped users in an efficient use were:

* Did IMN and OMSZ combined the percentiles and the probabilities products correctly to identify the location of the areas at highest risk of localized rainfall?
* Did IMN and OMSZ understood that it is best to use the highest percentiles to assess the location and the magnitude of the localized rainfall event?
* Did IMN and OMSZ comprehend the difficulties on verifying extreme local rainfall events within a limited region (e.g. the 99th percentile shows a rainfall event with a 1 in 100 chance of being observed, this might not be observed in a not very dense observational network)?
* Did IMN and OMSZ forecasters understood the differences between the spread in traditional raw NWP model outputs and the spread in the ecPoint output?

# Results

## Products developed from ecPoint-Rainfall

### IMN

IMN developed a product based on ecPoint-Rainfall which consists in a map plot displaying the ecPoint-Rainfall 85th percentile (Fig. 4a). IMN reported that it was not conducted a specific study to choose that specific percentile. They reported that, based on past experienced, the 85th percentile would have probably provided a “*balanced*” forecast, avoiding overestimations.

### OMSZ

OMSZ created two products from ecPoint Rainfall. The first one is a meteogram (Fig. 4b) that displays 12-hourly precipitation from the ECMWF ENS in blue and ecPoint-Rainfall in orange (first panel), rate of convective precipitation ratio (second panel), 700 hPa wind speed (third panel), and CAPE (fourth panel) from ECMWF ENS. The second, third and fourth panel represent the values of three out of the five predictors used in the 12-hourly post-processed rainfall. The second product consists in a map plot that displays the 90th (top number), 75th, 50th, 25th and 10th (bottom number) percentiles for ecPoint-Rainfall for each grid box (of 0.5 degree resolution).

## Results of the independent verification carried out on ecPoint-Rainfall

Due to the limited volume of data available (only one year of forecasts), both countries decided to provide feedback on ecPoint-Rainfall performance using a case study.

### IMN

IMN chose an extreme rainfall event occurred between October 3rd and 5th, 2018 to evaluate the performance of ecPoint-Rainfall in predicting extreme localize rainfall events. A trough evolved into an almost stationary low pressure over the Caribbean Sea, generating extreme rainfall in Region Pacifico Norte (especially in the Nicoya Peninsula), Pacifico Central and Pacifico Sur. On October 3rd the Nicoya Peninsula was badly affected, especially near the coast with values up to 140 mm/24h. High rainfall totals were also observed in Region Pacifico Central and Sur. The most intense rainfall was observed on October 4th reaching 400 mm/24h in the south of the Nicoya peninsula, 200 mm/24h in the Region Pacifico Central, and 90 mm/24h in Region Pacifico Sur. On October 6th Costa Rica was out of the influence of the low-pressure system as it moved northwards. See 12-hourly rainfall observations for the event in Fig. 5a-f. The rainfall event caused severe flash floods and local landslides, generating severe widespread impacts: one person died, hundreds were moved to refuges, and around 1500 people were somehow affected, for example by electricity or water service interruption or road closures.

Forecasts (from the ecPoint-Rainfall product developed at IMN) from day 1 to 7 were used to evaluate both short and medium range forecasts (see Fig. 6, first column). IMN used only 12 UTC runs for ecPoint-Rainfall as those were the only ones usable for daily warnings considered the time difference between Europe and Central America (UTC-6). IMN’s conclusions on the performance of ecPoint-Rainfall for this case study can be summarized in the following main points:

* ecPoint-Rainfall predicted well the beginning and the end of the rainfall event in every run from September 27th.
* On October 4th, ecPoint-Rainfall pointed out that Región Pacifico Central and Pacifico Sur would have been the most impacted areas, underestimating the rainfall amounts in Región Pacifico Norte, especially in the Nicoya peninsula where totals of up to 400 mm/24h were observed. No ecPoint-Rainfall forecasts [based on the 85th percentile of ecPoint-Rainfall] reached such totals. Only the run on October 4th predicted values higher than 100 mm/12h.”
* Most runs [based on the 85th percentile of ecPoint-Rainfall] predicted with one day of delay [October 5th] the wettest day which was on October 4th.

### OMSZ

OMSZ examined a flash flood event in Szilvásvárad, occurred between June 10th and 11th, 2018 due to localized extreme rainfall (Tóth and Ihász 2020). The formation of unstable atmospheric conditions was due to the shallow cyclone in southeast Europe, which gradually marched over the country. As a result, there was a strong cumulus cloud formation in the Northern Central Mountains in the afternoon, to which the lifting effect of the mountains significantly contributed. Due to the slow flow system, the rapidly developing thunderstorm cells did not move from the area for hours, which led to the accumulation of extreme rainfall. The most intense rainfall was reported in the Bükk mountains (in Northern Hungary, between Heves and Borsod-Abaúj-Zemplén counties), where 174 mm/24h was measured. Such events occur rarely in Hungary, approximately every 10-20 years, and are challenging to forecast even with km-scale NWP models. See Fig. 7a for the 12 hourly rainfall observations on June 11th between 0 and 12 UTC (when the majority of the rainfall fell). The highest rainfall value (92 mm/24h) was measured in Bükkszentlélek (purple circle with a cross in Fig. 7a). The rainfall event caused severe flash floods and generate severe impacts in the Bükk area.

ecPoint-Rainfall probabilities (in %) of not exceeding 10 and 30 mm/12h for day 2 (Fig. 7b and Fig. 7d, respectively) and 4 (Fig. 7c and Fig. 7e, respectively) were evaluated. OMSZ’s conclusions on the performance of ecPoint-Rainfall for this case study can be summarized in the following main points:

* Based on the forecasts, the expectation of higher rainfall amount in the Bükk area was expected.
* The map for probabilities of not exceeding 30 mm/12h outlines nicely where the local precipitation is likely to occur.
* Although the probabilities of not exceeding 30 mm/12h are relatively low, this information is very important for forecasters. ecPoint-Rainfall could be a consequential tool for the early detection of such localized extreme rainfall events.

## Results of the informal discussions about the ecPoint-Rainfall usefulness in the prediction of extreme rainfall

During the “offline” phase of the experiment, participants were asked to reflect on the usefulness of the guidelines provided, what was their impression about the performance of the forecasts, and how the provision of such guidelines could be improved. Both IMN and OMSZ forecasters’ representatives provided their perspectives through active discussion via email and videocalls. The responses, alongside observations from the team of ecPoint developers, are incorporated throughout the following subsections.

### IMN: ON THE SELECTION OF ECPOINT-RAINFALL'S 85TH PERCENTILE TO PREDICT EXTREME LOCALIZED RAINFALL

IMN reported that the 85th percentile was selected to predict extreme events because higher percentiles might make them overlook much more frequent events that might already cause an impact in some regions:

“Events of around 50 mm/12h can already cause some impacts on the Pacific coast of Costa Rica or in the capital city, San José. Those events are relatively frequent. If we look at the 99 percentile all the time, we will miss such more frequent events.”

However, by looking only at the 85th percentile (which would forecast events that have, on average, a 1 in 7 chance to occur), forecasters would miss the opportunity to be aware of what could be the possible local "worst-case scenario".

Therefore, it was discussed the possibility to make available to forecasters two different products: the probabilities of exceeding a certain threshold (e.g. 50 mm/12h for the Pacific coast of Costa Rica) and the 99th percentile map plot to identify the areas that could be possibly affected by the worst local rainfall (i.e. events with 1 in 100 chance to occur). See a mock-up product in Fig. 8. In this way, forecasters could display assess the probabilities of the Pacific coast being affected by a rainfall exceeding 50 mm/12h but also can assess the magnitude of the worst local rainfall event that can affect the region.

“This product could help us to forecast an event that can already generate an impact in the Pacific coast but at the same time, have an idea what could be the local maxima. For example, the Nicoya peninsula was affected by much higher rainfall, and we would have not had any idea of the possible amount by looking only at the probabilities product.”

Furthermore, examination of different extreme rainfall cases around the world has shown that raw ENS and ecPoint-Rainfall’s CDFs tend to cross around the 85th percentile. This can be seen also for the case study presented by IMN, by comparing the forecasts of the 85th percentile of ecPoint-Rainfall (first column) and the 85th percentile of the Raw ENS (second column) in Fig. 5. This means that by using the 85th percentile of ecPoint-Rainfall, users will not be making the most of the post-processed product.

# Lessons learnt and recommendations for using ecPoint-Rainfall more efficiently

The section discusses the lessons learnt when communicating ecPoint-Rainfall forecasts with IMN and OMSZ and attempts a first generalization of how to modify the structure and the content of ecPoint-Rainfall guidelines for future training.

# Tables

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| **ecPoint training/guidance provided** | **IMN** | **OMSZ** |
| Links, sent via email, to all online resources published until 2018\*. | X | X |
| Direct contact, via email, to explain:   * How are ecPoint-Rainfall forecasts structured? * Is the rainfall data provided accumulated over 12-h? * Is the data provided in grib or netCDF format? | X | X |
| Direct contact, via email, on how to interpret percentiles? | X | - |
| Direct contact, via email, on how to compute probabilities and how to interpret them? | X | - |
| \*Links to the material provided:   * <https://www.ecmwf.int/en/newsletter/153/news/new-point-rainfall-forecasts-flash-flood-prediction> * <https://confluence.ecmwf.int/display/FUG/Point+Rainfall> * <https://www.ecmwf.int/en/elibrary/18331-ecpoint-rainfall-global-probabilistic-rainfall-point-scale-ecmwf-ensemble> * <https://www.ecmwf.int/en/newsletter/159/news/new-point-rainfall-products-eccharts> * <https://www.ecmwf.int/en/newsletter/152/news/ecmwf-supports-flood-disaster-response-peru> | | |

Table 1 – ecPoint training/guidance provided to IMN and OMSZ at the beginning of the “real-time” phase of the project. The training in red correspond to default training provided by the ecPoint developers to all participants; the training in blue is the training that was provided under request by the participants. The mark “X” under the name of a meteorological service indicates that the correspondent training was provided; The mark “-” indicates the that the correspondent training was not provided.

|  |  |  |
| --- | --- | --- |
| **Forecasts received** | ecPoint-Rainfall percentiles (from 1st to 99th) | |
| **Runs** | 00 and 12 UTC | |
| **Rainfall Accumulation** | 12 hours | |
| **Number of accumulation periods** | 4 overlapping accumulation periods per day. The valid times (in UTC) of such periods correspond to (0 to 12), (6 to 18), (12 to 00\*) and (18 to 6\*).  \* on the following day | |
| **Lead time** | Up to day 10, (t+246) | |
| **Files format** | Grib | |
| **Coordinates of the corners of the spatial domain over which the forecasts were provided**  **(N / S / O / E)** | Cost Rica  (12°N / 7°N / 87°W / 82°W) | Hungary  (49°N / 45°N / 15°E / 24°E) |

Table 2 – Characteristics of the ecPoint-Rainfall forecasts provided to IMN and OMSZ.

# Figures

Diagram

Description automatically generated

Fig. 1 - ecPoint workflow. The left (red) panel represents the ecPoint's offline calibration process. The right (green) panel represents the ecPoint's forecast generation process and the products that can be derived from the post-processing output. The variable "rainfall" was used in this figure two illustrate both processes, calibration and forecast generation, but they can be used to post-process also other variables, e.g. "temperature".

Map

Description automatically generated

Fig. 2 – Panel (a) shows the climatological regions in which Costa Rica is divided. The box shows the location of Costa Rica in Central America. Panel (b) shows the administrative regions (colours shades) and counties (white lines) in which Hungary is divided. The box shows the location of Hungary in Europe. Panels (c) and (d) show the orography in Costa Rica and Hungary, respectively. Panels (d) and (e) show the annual rainfall (in mm) in Costa Rica and Hungary, respectively.

Diagram

Description automatically generated

Fig. 3 - Experiment design. The grey boxes describe the different steps carried out during the “real-time” and the “offline” phase of the project. The yellow rhombus contained the questions asked at key moments of the study to define the path to take in the experiment. The green boxes represent the actions taken based on the followed path. Finally, the red, blue, and cyan frames encompass the steps done by ecPoint developers, volunteer testers, and developer & testers, respectively.

Graphical user interface, chart

Description automatically generated

Fig. 4 – Products developed by IMN and OMSZ based on ecPoint-Rainfall. Panel (a) is a map plot displaying the 85th percentile of ecPoint-Rainfall over Costa Rica. Panel (b) is a meteogram displaying 12-hourly precipitation from the ECMWF ENS in blue and ecPoint-Rainfall in orange (first panel), rate of convective precipitation ratio (second panel), 700 hPa wind speed (third panel), and CAPE (fourth panel) from ECMWF ENS. Panel (c) is a map plot displaying the 90th  (top number), 75th, 50th, 25th and 10th (bottom number) percentiles for each grid box (of 0.5 degree resolution).

# Diagram, map Description automatically generated

Fig. 5 - Panels from (a) to (f) show 12-hourly rainfall observations during the extreme rainfall event occurred between October 3rd and 5th, 2018. The times the figure refer to are indicated in UTC time and local time (LT).

A picture containing background pattern

Description automatically generated

Fig. 6 - Forecast evolution (from day 7 to day 1) for the rainfall event occurred between October 4th at 12am and October 5th at 0am (local time, LT). See Fig. 5d to compare the forecasts with the observations. From the left, the first column shows the 85th percentile for ecPoint-Rainfall (as used operationally by IMN), the second column shows the 85th percentile for the raw ENS, the third column shows the 99th percentile for ecPoint-Rainfall, the fourth column shows the wettest member of the raw ENS, and the fifth column shows the deterministic forecast from WRF-1.5 (spatial resolution of 1.5 km) typically used by IMN in the forecasts of extreme localized rainfall events. The shown raw ECMWF ENS and ecPoint-Rainfall forecasts correspond to runs at 12 UTC, which is the first available run from Europe to IMN forecasters in the morning due to time difference between Europe and America (UTC-6). The WRF-1.5 forecasts correspond to runs at 18 UTC, which are the first run available to IMN forecasters in the morning. The colour scheme of the first column plots have been modified, compared to the original IMN products (see Fig. 4a), to standardize all the plots in this figure, and make easier the forecasts comparison between models.

Map

Description automatically generated

Fig. 7 – Panel (a) shows the 12 hourly observations for the intense rainfall event on June 11th, 2018 between 0 and 12 UTC time. The purple circle with a cross refers to a manually added record of 92 mm/24h in Bükkszentlélek between 12 UTC June 10th and 12 UTC June 11th (most of the rain fell on June 11th). Panels (b), (f), and (j) show the probabilities (in %) of not exceeding 10 mm/12h for day 2 forecasts for ecPoint-Rainfall, Raw ENS and AROME, respectively; panels (c), and (g) show day 4 forecasts for ecPoint-Rainfall and Raw ENS (such lead time is not available for AROME). Panels (d), (h), and (k) show the probabilities (in %) of not exceeding 30 mm/12h for day 2 forecasts for ecPoint-Rainfall, Raw ENS and AROME, respectively; panels (e), and (i) show day 4 forecasts for ecPoint-Rainfall and Raw ENS.

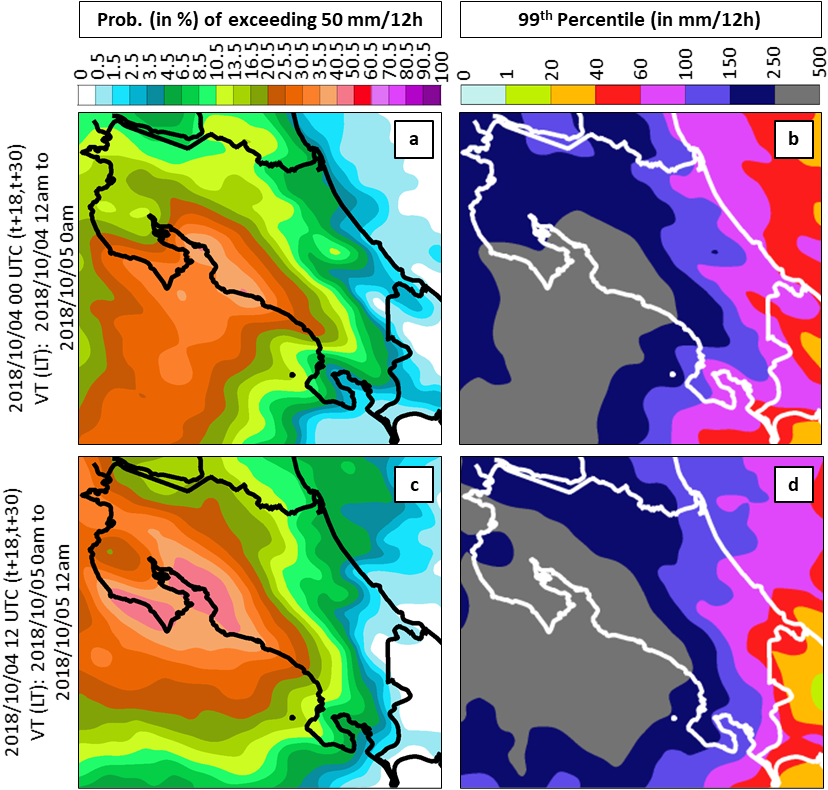


Fig. 8 - Panels (a) and (c) show the probabilities of not exceeding 50 mm/12h, and panels (b) and (d) show the 99th percentile, both for ecPoint-Rainfall forecasts. Panels (a) and (b) correspond to the forecast on 2018/10/04 at 00 UTC (t+18, t+30), which correspond to the rainfall observed between 2018/10/04 12 am and 201/10/05 0 am (local time, , see Fig. 5d). Panels (c) and (d) correspond to the forecast on 2018/10/04 at 12 UTC (t+18, t+30), which correspond to the rainfall observed 2018/10/05 0am and 201/10/05 12am (local time, see Fig. 5e).

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# Appendix A – Guide questions for the informal discussions with IMN and OMSZ

**BACKGROUND QUESTIONS**

**PREGUNTAS DE CONTEXTO**

***On the general Met-Service experience with ensemble forecasts***

***Sobre la experiencia general del servicio meteorológico con pronósticos de conjunto***

1. Has the Met-Service any experience with ensemble forecasts? If so, which ensemble forecasts are mainly used?

¿El servicio meteorológico tiene experiencia con pronósticos por ensembles? Si es así, ¿qué pronósticos de conjunto utilizan principalmente?

1. If there is some access to ensemble forecasts in the Met-Service, how are they used? Are they used as the primary source to issue alerts and create products for end-users and inform them also about the uncertainty on the forecast? Or are they used as a background knowledge to complement the information provided by a deterministic model, and if so, why?

Si tiene acceso a pronósticos por ensembles, ¿cómo los usan? ¿Los usan como fuente primaria para emitir alertas y crear productos para usuarios finales e informarlos también sobre la incertidumbre en los pronósticos? ¿O los usan para complementar la información proporcionada por un modelo determinista? Si es así, ¿por qué?

1. What is the general impression of ensemble forecasts and their use in operational environments? Is there any internal disagreement on the practical value of ensemble forecasts (e.g. due to issues in the communication of probabilistic forecast or their reception by end-users)? Is there any discomfort surrounding how to deal with probabilistic forecasts in an operational environment?

¿Cuál es la impresión general sobre las predicciones por ensembles y su uso en entornos operativos? ¿Existe algún desacuerdo interno sobre el valor práctico de los pronósticos de conjunto (por ejemplo, debido a problemas en la comunicación del pronóstico probabilístico o su recepción por parte de los usuarios finales) ? ¿Hay alguna molestia sobre cómo lidiar con pronósticos probabilísticos en el entorno operativo?

***On the general Met-Service experience with rainfall forecasts calibration***

***Sobre la experiencia general del servicio meteorológico con calibración de pronósticos de lluvia***

1. Has the Met-Service any experience of post-processing or calibrating rainfall forecasts? If so, for what purpose (e.g. improving quality of operational forecasts for end-users, making the forecasts more suitable for downstream applications such as hydrological forecasts)?

¿El servicio meteorológico tiene experiencia con el postproceso o calibración de pronósticos de lluvia? Si es así, ¿con qué propósito se hacen (por ejemplo, para mejorar la calidad de los pronósticos operativos para los usuarios finales, hacer que los pronósticos sean más adecuados para segundas aplicaciones como pronósticos hidrológicos)?

***On the background of the people who worked with ecPoint-Rainfall***

***Sobre las personas que trabajaron con ecPoint-Rainfall***

1. Who has been receiving ecPoint-Rainfall forecasts? What is their background (e.g. operational, research)?

¿Quién recibió los pronósticos de ecPoint-Rainfall? ¿Cuáles son sus antecedentes (por ejemplo, operativos, investigación)?

1. Do those particular people have general experience working with ensemble forecasts? Do they have experience working with post-processed forecasts? If not, do they have much time to devote to learning?

¿Las personas que recibieron las predicciones de ecPoint-Rainfall tienen experiencia de trabajo con predicciones de conjunto? ¿Tienen experiencia trabajando con predicciones calibradas? Si no es así, ¿tienen tiempo para dedicar al aprendizaje?

**QUESTIONS ON ECPOINT-RAINFALL**

**PREGUNTAS SOBRE ECPOINT-RAINFALL**

1. Was ecPoint-Rainfall used operationally, experimentally, or for research?

¿Se usó ecPoint-Rainfall de manera operacional, experimental o para investigación?

1. Was it difficult to become accustomed to the meaning/structure of ecPoint-Rainfall forecasts? Did the fact that ecPoint-Rainfall products you received did not provide grid box forecasts create any issues?

¿Fue difícil acostumbrarse al significado o a la estructura de ecPoint-Rainfall? ¿El hecho que los productos de ecPoint-Rainfall que recibieron no proporcionan predicciones a escala de celda creó problemas?

1. If ecPoint-Rainfall was used operationally, were there any technical issues to integrate the forecasts in your operational workflows? Evaluation would include configuration of ecPoint-Rainfall, data volumes, run times, displaying the forecasts, etc.

Si se utilizó ecPoint-Rainfall operacionalmente, ¿hubieron problemas técnicos para integrar las predicciones en sus sistemas operativos? La evaluación incluiría configuración de ecPoint-Rainfall, volúmenes de datos, tiempos de ejecución, o representar gráficamente productos, etc.

1. Did you develop products from ecPoint-Rainfall? Did you use percentiles? Which percentiles? Why? Did you use probabilities? Which probabilities? Why?

¿Desarrollaron productos basados en ecPoint-Rainfall? ¿Usaron percentiles? ¿Cuáles percentiles? ¿Por qué? ¿Usaron probabilidades? ¿Qué probabilidades? ¿Por qué?

1. Where (e.g. over mountainous, coastal, flat areas), in which weather situations or for which type of events (e.g. deep convection, flash floods, etc.) do you think you could get most benefit from ecPoint-Rainfall? Why?

¿Dónde (por ejemplo, en zonas montañosas, costeras y planas), en qué situaciones climáticas, o para qué tipo de eventos (por ejemplo, convección, inundaciones, etc.) creen que podría obtener mayor beneficio de ecPoint-Rainfall? ¿Por qué?

1. Was ecPoint-Rainfall found useful? Do you think it added value to raw ECMWF ensemble and/or the model used in-house?

¿Se encontró ecPoint-Rainfall útil? ¿Te parece que añade valor a las predicciones de ECMWF y/o al modelo que utilizan comúnmente?

1. Do you think that ecPoint-Rainfall could change the way that alerts are issued for localized extreme rainfall, flash floods, etc? Perhaps increasing the lead-time at which alerts are issued (e.g. up to medium ranges)? Why?

¿Cree que ecPoint-Rainfall podría cambiar la forma en que se emiten las alertas para lluvias extremas localizadas, inundaciones repentinas, etc.? ¿Quizás podrían aumentar el plazo con el que se emiten las alertas (por ejemplo, hasta un plazo medio)? ¿Por qué?

1. Do you think ecPoint-Rainfall is useful information to have? If so, in which way, as preliminary information to raise internal awareness to prompt increase preparedness within the forecasting centre? Or would it also be used to trigger early actions to mitigate or manage high risk events?

¿Cree que ecPoint-Rainfall proporciona información útil? Si es así, ¿de qué manera? ¿Cómo información preliminar usada internamente para aumentar rápidamente la preparación el centro de predicción? ¿O también se usaría para activar acciones tempranas con el objetivo de mitigar o gestionar eventos de alto riesgo?

1. If you think ecPoint-Rainfall has improved raw model rainfall forecasts, based on your experience, what aspects stand out as being better (e.g. less false alarm rates, better representation of point rainfall values, etc)?

Si cree que, en base a su experiencia, ecPoint-Rainfall ha mejorado las predicciones de lluvia, ¿cuáles son lo que aspectos se destacan por ser mejores (por ejemplo, la menor frecuencia de falsas alarmas, una mejor representación de los valores puntuales de lluvia, etc.)?

1. Can you think of other useful applications for ecPoint-Rainfall (e.g. predicting dry weather)?

¿Tiene sugerencias para otra útil aplicaciones para ecPoint-Rainfall (por ejemplo, la predicción de no-lluvia)?

1. Currently the maximum percentile available is 99th (1 in 100 chance). We could in principle deliver up to percentile 99.98th (1 in 5000 chance), or, let’s say, we could even restrict the maximum available percentile to 95th (1 in 20 chance). What level do you think we should use as the maximum?

Actualmente el percentil máximo disponible es el 99° (1 entre 100 posibilidades) . En principio, podríamos computar hasta el percentil 99,98° (1 en 5000 posibilidades) o podríamos restringir el percentil máximo al 95° (1 en 20 posibilidades). ¿Qué nivel cree que deberíamos usar como máximo?

**QUESTIONS ON THE ECPOINT-RAINFALL CASE STUDY**

**PREGUNTAS SOBRE EL CASO DE ESTUDIO BASADO EN ECPOINT-RAINFALL**

1. Have you used/verified ecPoint-Rainfall for a particular event or case study? Briefly describe the geographical region and the weather conditions for which the tests were conducted.

¿Ha utilizado / verificado ecPoint-Rainfall para un evento o un caso de estudio en particular? Describa brevemente la región geográfica y las condiciones climáticas para las cuales se realizaron las pruebas.

1. Why was this particular case study or event chosen (e.g. the forecasts for the region or the particular synoptic situation are usually not very good)?

¿Por qué fue elegido ese particular caso de estudio o evento (por ejemplo, los pronósticos para la región o para la situación sinóptica considerada no son muy buenos por lo general)?

1. With hindsight, did ecPoint-Rainfall provide useful guidance for this particular situation? How would you rate its performance?

En retrospectiva, ¿ecPoint-Rainfall proporcionó información útil para esta situación en particular? ¿Como evaluaría su rendimiento?

1. Are there any improvements that you would like to see in ecPoint-Rainfall (e.g. 12-hourly rainfall accumulations were ok for your needs, or would you like to see other durations, etc.)?

¿Hay alguna mejora que le gustaría ver en ecPoint-Rainfall (por ejemplo, las acumulaciones de lluvia de 12 horas fueron adecuadas para sus necesidades o le gustaría ver otras acumulaciones, etc.)?