Flow intermittence prediction using a hybrid hydrological modelling approach: influence of observed intermittence data on the training of a random forest model

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Abstract. Rivers are rich in biodiversity and act as ecological corridors for plant and animal species. With climate change and increasing anthropogenic water demand, more frequent and prolonged periods of drying in river systems are expected, endangering biodiversity and river ecosystems. However, understanding and predicting the hydrological mechanisms that control periodic drying and rewetting in rivers is challenging due to a lack of studies and hydrological observations, particularly in non-perennial rivers. Within the framework of the Horizon 2020 DRYvER (Drying River Networks and Climate Change) project, a hydrological modelling study of flow intermittence in rivers is being carried out in 3 European catchments (Spain, Finland, France) characterized by different climate, geology and anthropogenic use. The objective of this study is to represent the spatio-temporal dynamics of flow intermittence at the reach level in mesoscale river networks (between 120 km^2 and 350 km^2). The daily and spatially distributed flow condition (flowing or dry) is predicted using the J2000 distributed hydrological model coupled with a Random Forest classification model. Observed flow condition data from different sources (water level measurements, photo traps, water temperature measurements, citizen science applications) are used to build the predictive model. This study aims to evaluate the impact of the observed flow condition dataset (sample size, spatial and temporal representativity) on the performance of the predictive model. Results show that the hybrid modelling approach developed in this study allows to accurately predict the spatio-temporal patterns of drying in the 3 catchments, with a Sensitivity criteria above 0.9 for the prediction of dry events in the Finnish and French case studies, and 0.65 for the Spanish case study. This study shows the value of combining different data sources of observed flow condition to reduce the uncertainty in predicting flow intermittence.

1 Introduction

River systems are an essential link in terrestrial biodiversity. They are habitat to many animal and plant species within the riverbed and in the riparian zone (Leigh and Datry, 2017). They also serve as ecological corridors by providing a connection between upstream and downstream for mobile species and by transporting nutrients and sediments necessary for the survival

of species located downstream (Deiner et al., 2016). In particular, ecologists assume that intermittent rivers are biodiversity hotspot thanks to the succession of different flow phases (e.g. flowing, isolated pools, dry) which promotes species richness (Datry et al., 2014).

25   By impacting the hydrological cycle and increasing the risk of drought (Gudmundsson and Seneviratne, 2016; Tramblay et al., 2021), climate change threatens river biodiversity (Bond et al., 2008). Prolonged drying and shifting of river sections from perennial to intermittent flow can endanger ecosystems and limit the access to water resources useful to our society (Steward et al., 2012; De Girolamo et al., 2017; Tonkin et al., 2019).

The term intermittent rivers refers to all rivers with a non-perennial flow. This includes ephemeral rivers with short periods
30   of flow in direct response to rainfall or snow melt events, rivers with seasonal flow, and nearly perennial rivers with infrequent periods of drying (Buttle et al., 2012; Snelder et al., 2013; Shanafield et al., 2021). In this study, the term "flow intermittence" will refer to the alternation between flowing phases and phases with interrupted flow (completely dry riverbed or disconnected pools).

Although they represent a large proportion of terrestrial rivers (Messager et al., 2021), intermittent rivers are still poorly
35   known (Acuña et al., 2014; Meerveld et al., 2020; Fovet et al., 2021) and their study in hydrology is relatively recent. Modelling the hydrological functioning of drying river networks (DRNs) can help understanding the impact of drying on ecosystems and to predict the evolution of the drying spells and possible tipping points in flow regimes under climate projections.

Studies have already looked at modelling intermittent rivers with a physical hydrological model (Jaeger et al., 2014; Tzoraki et al., 2016; Llanos-Paez et al., 2023). One major difficulty in modelling flow intermittence is that hydrological models have
40   difficulties to simulate zero flows (Shanafield et al., 2021). First there is a numerical challenge: the flow routing scheme implemented in the models to propagate the streamflow across the river networks cannot represent sudden transitions from wet to dry. Second, the origins of intermittence are multiple (disconnection between the river and the water table, drying up following a long period without precipitation, infiltration from the river bed into a fault or a karstic subsoil, drying up following anthropic withdrawals, etc.) (Datry et al., 2016) and sometimes very local. Representing all these processes in the
45   models is thus complex and requires a large amount of data. A more common modelling approach to model intermittent rivers is the use of artificial neural networks (ANN) (Daliakopoulos and Tsanis, 2016; Beaufort et al., 2019) and random forest (RF) (González-Ferreras and Barquín, 2017; Beaufort et al., 2019; Belemtougri, 2022; Jaeger et al., 2023) models. These models are easier to implement, do not require a priori knowledge of the origins of drying, and show good performances to predict the spatial distribution of flow regimes (perennial or intermittent) in the river networks. The covariates used to predict the river flow
50   regime are usually the stream physical characteristics (width, length, slope, geological context, etc.) and climate variables such as precipitation, temperature and evapotranspiration. Predicting the spatial and temporal dynamics of drying in intermittent river systems requires providing the RF models with additional covariates on the spatialized hydrological conditions along the river systems at a sufficiently fine time step and fine spatial resolution. This can be achieved using spatially distributed hydrological models at a daily or smaller time step.

55   Another challenge in the study of intermittent river networks is to collect observed data of flow intermittence to train or validate the models. Studies of river intermittence on a large scale mainly use gauging station data (Belemtougri, 2022; Mes-

sager et al., 2021; Tramblay et al., 2021; Beaufort et al., 2019; Reynolds et al., 2015). Gauging station data are easy to retrieve and analyse and have the advantage of providing data at a regular time step over long periods. But stations are mainly located on rivers with perennial flow (Eng et al., 2016; Meerveld et al., 2020) and their spatial distribution is not dense enough to understand the flow intermittence patterns along river networks. On the contrary, studies focusing on smaller catchments use data from field campaigns (Jaeger et al., 2023; Llanos-Paez et al., 2023; Sefton et al., 2019), which allow the collection of data at regular time steps with a denser network of observations. But field campaigns can be costly and time consuming, and usually cover short periods of time (several weeks or month), with a risk of over-representing drying events when the campaign is focused on the summer season.

The objective of the study is to present a hybrid modelling approach to simulate spatio-temporal patterns of drying in the river networks. To do so, we developed a flow intermittence model by coupling a distributed hydrological model (JAMS-J2000) with a Random Forest classification model. The models are applied in 3 European DRNs from the DRYvER project (Datry et al., 2021) located in Spain, France and Finland to evaluate the ability of the models to predict the drying patterns in contrasted climate, hydrological, geological and anthropogenic contexts.

This study also investigates the different types of observed flow state data available to drive the RF model (gauging stations, field campaigns, crowdsourced data, remote sensing, expertise), their ability to represent the actual drying patterns in the DRNs, and how they can be combined to improve the modelling of flow intermittence.

2   Material and methods

2.1   Study area and data

2.1.1   Focal DRNs

This study focuses on 3 meso-scale DRNs located in Spain, France and Finland (Table 1, Fig. 1) that are part of the DRYvER project on drying rivers and climate change (Datry et al., 2021). The 3 catchments have similar surface areas ranging between 200 and 350 km^2 and are characterized by different climates and flow intermittence patterns.

The Genal catchment, located in southern Spain, is characterized by a dry and warm climate and scarce natural vegetation. Long periods of drying are observed in the smaller reaches. The main Genal river is known to be perennial except in the downstream part of the catchment where the Genal river dries up in the summer season due to water abstraction for irrigation.

On the opposite, the Lepsämänjoki catchment in Finland is characterized by a wetter and colder climate. Flow intermittence is only observed in the smallest reaches but seems to have intensified in recent years due to climate change.

The Albarine in France is characterized by a more temperate climate. Flow intermittence is particularly observed in the upstream and downstream parts of the catchment. Drying is mainly due to the seepage of the Albarine river in the soil at geological discontinuities.

Name	Country	Area [km^2]	Outlet lat. [°]	Outlet lon. [°]	Range of elevations [m.a.s.l]	Mean temperature [°C]	Mean Precipitation [mm]
Albarine	France	354	45.906	5.234	212 - 1497	10.0	1439
Genal	Spain	343	36.318	-5.312	3 - 1718	15.9	743
Lepsämänjoki	Finland	208	60.238	24.984	8 - 145	5.6	899

Table 1. Characteristics of the studied catchments. Mean annual precipitation and temperature are computed from the ERA5-land reanalysis for the period 1991-2020.
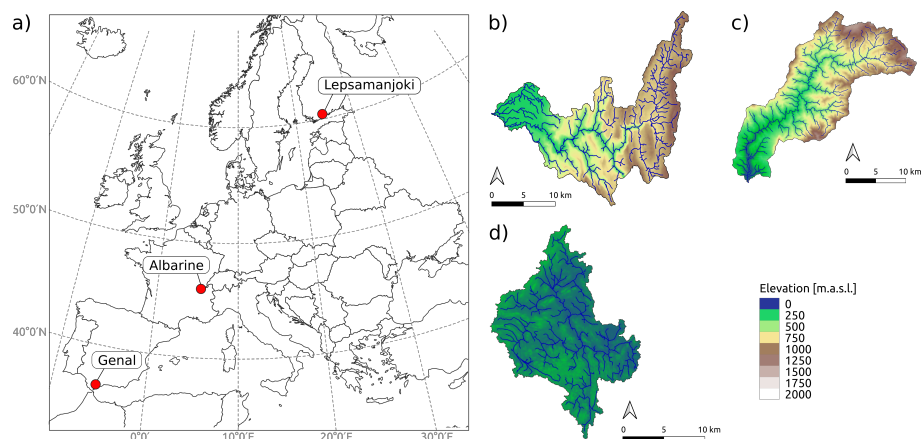
Figure 1. a) Location of the 3 studied DRNs. b,c,d) River networks and elevations of the Albarine, Genal, and Lepsämänjoki DRNs.

2.1.2 Spatial data

Topography, soil types, land use and hydrogeology information is needed as input to the spatially distributed hydrological model. The following data sources were used:

90   – Topography: EU-DEM v1.1 (Copernicus, 2016) with a 25 m resolution for the Albarine DRN, the Andalucía DEM (Portal Ambiental de Andalucía. 2010) with a 10 m resolution for the Genal DRN, and the 10 m DEM Finland (National Land Survey of Finland[1]) for the Lepsämänjoki DRN.

    – Soil: Soil classes were used from the European Soil Database v2.0 (European Commission; Panagos et al. (2012)). Physical parameters were also used from the European Soil Database v2.0 (field capacity, saturated water content, depth 95   to rock). In the Genal DRN (Spain) texture and bulk density data was used from soil profiles (Llorente et al., 2018) for the calculation of parameters using pedotransfer functions (Ad-Hoc-AG, 2005; Baxter, 2007).

    – Land use: Corine Land Cover (CLC) 2012, Version 2020-20u1 Level 3 (44 classes) was used (Copernicus Land Monitoring Service 2020) to establish the LULC classes. Parameters such as albedo, crop coefficients, LAI, root depth, and

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[1] https://asiointi.maanmittauslaitos.fi/karttapaikka/tiedostopalvelu/korkeusmalli

impervious fraction area, were adapted to local conditions from different sources (Allen et al., 1998; Krause, 2001;
Kralisch and Krause, 2006; Neitsch et al., 2011; Faroux et al., 2013).

– Hydrogeology: IHME1500 – International Hydrogeological Map of Europe (aquifer and lithology layers)(Duscher et al., 2015) was used to establish the classes for all DRNs.

2.1.3 Climate data

The ERA5-land reanalysis (Muñoz-Sabater et al., 2021) was used to as climate forcing data for the hydrological modelling. The following hourly ERA5-land climate variables were used to compute the reference evapotranspiration using the Penman-Monteith equation (Allen et al., 1998): 2 m air temperature (°C), 2 m dew point temperature (°C), 2 m relative humidity (%), 10 m u and v wind speed components (m/s, incoming solar radiation (W/m^2), incoming thermal radiation (W/m^2), and surface pressure (Pa). Hourly ERA5-land precipitation, air temperature and computed reference evapotranspiration were then aggregated at the daily time step to be used as climate forcing data in the hydrological model.

2.1.4 Flow state and and discharge data

In order to validate the models' ability to simulate flow intermittence at the reach level multiple data sources of flow observations were used:

– Hydrological stations: (i) discharge daily time series from gauging stations (http://leutra.geogr.uni-jena.de/DRYvER). The streams are considered as dry if the measured discharge is equal to 0 m^3/s, and flowing otherwise. (ii) the ONDE network (Observatoire National des Etiages, https://onde.eaufrance.fr): this French network of hydrological stations was specifically developed to monitor intermittent rivers and gives a monthly qualitative information about the state of flow (visible flow, non-visible flow, dry).

– Crowdsourced data from smartphone applications: DRYRivERS (https://www.dryver.eu/app) and CrowdWater (https://crowdwater.ch/en/data/).

– Measurements from field campaigns for the DRYvER project : phototraps installed along the river networks took daily pictures from 2018-11-07 to 2022-04-30 in the Albarine DRN and from 2021-06-17 to 2021-09-26 in the Lepsämänjoki DRN.

– Observations on Google Earth images: the state of flow of the reaches was observed on the images for several dates between 2010 and 2022. The observation with Google Earth images was only possible in the Genal DRN which has a scarce vegetation.

– Expertise of local DRYvER project partners : some members of the DRYvER project have been studying these DRNs for several years and have a deep understanding or their hydrological behaviours. Their expertise was used to identify reaches characterised by a perennial flow. Those reaches are assumed to be flowing every day during the field campaign period.

130 These data sources are available either as disconnected points in time and space (Fig. 2), recurrent observations at the sampling sites or time series of daily data over periods ranging from a few months to several years.

As a result of acquiring data from multiple sources, there may be several flow state observations on the same day in the same reach. By grouping the data by reach and by date, we observe that there is simultaneity in only 0.26% of cases on average for the 3 catchments (Albarine: 83 cases of simultaneity over 28852 total cases, Genal: 16 cases over 7146, Lepsämänjoki:

135 12 cases over 6307). The small amount of data observed on the same day on the same stretch of river can be explained by the complementary nature of the different sources, which each focus on different areas and periods. Of the 111 cases of simultaneity, the different sources give the same state of flow in 88% of cases. In case there are several flow state observations on the same day in a reach, only one observation is kept to train the RF model. First a filter is applied to prioritize data from direct observations (e.g. ONDE stations, crowdsourced data, phototraps, Google Earth) and remove data from indirect

140 measurements (gauging stations). If after this selection, there are still more than one observation per reach and per day, only one observation with the predominantly observed flow state is (flowing or dry) is kept.

A detailed analysis of the flow state observations and their ability to represent the drying in the river networks is presented in the Results section (Table 5 and Fig. 5).
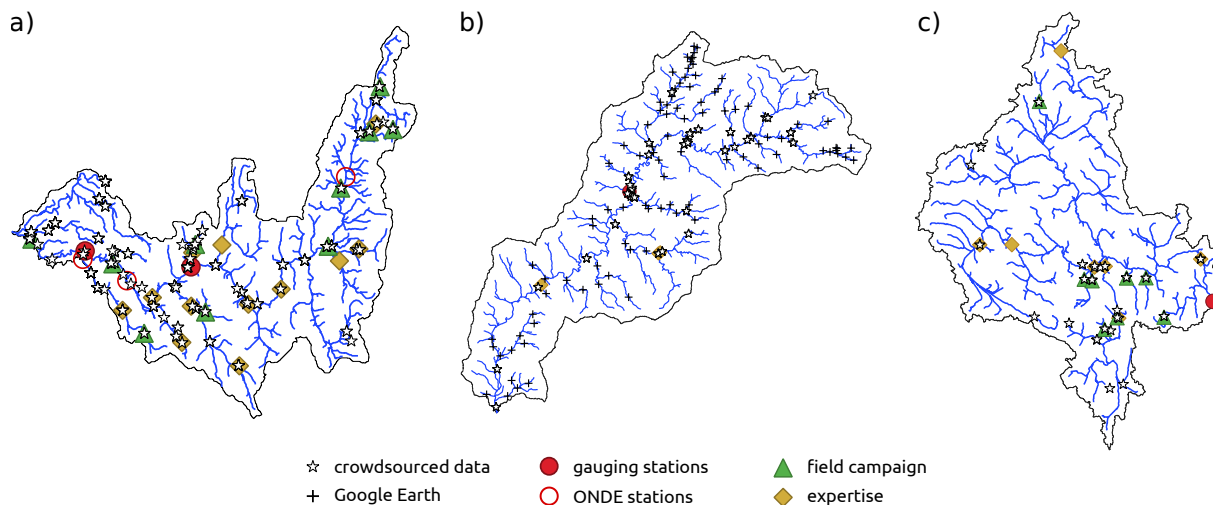
Figure 2. Observed state of flow data in the a) Albarine, b) Genal, c) Lepsämänjoki DRNs.

2.2 Flow intermittence model

145 In order to simulate flow intermittence, a spatially distributed process-oriented hydrological model (JAMS-J2000) was implemented on the 3 mesoscale DRNs (detailed description of the model in Section 2.2.1). Once calibrated and validated, the JAMS-J2000 hydrological model enables to simulate daily streamflow time series in each reach of the river network.

Then, the deterministic hydrological model was coupled with a stochastic model, using the model outputs and physical information to train a Random Forest (RF) classification model with some flow-state observations. The outputs of the RF

150 model enables to predict the daily flow state (flowing or dry) in each reach of the DRN, and thus predict the spatio-temporal patterns of flow intermittence.

The modeling method to simulate flow intermittence is summarized in Figure 3 and is described in detail in the following sections.
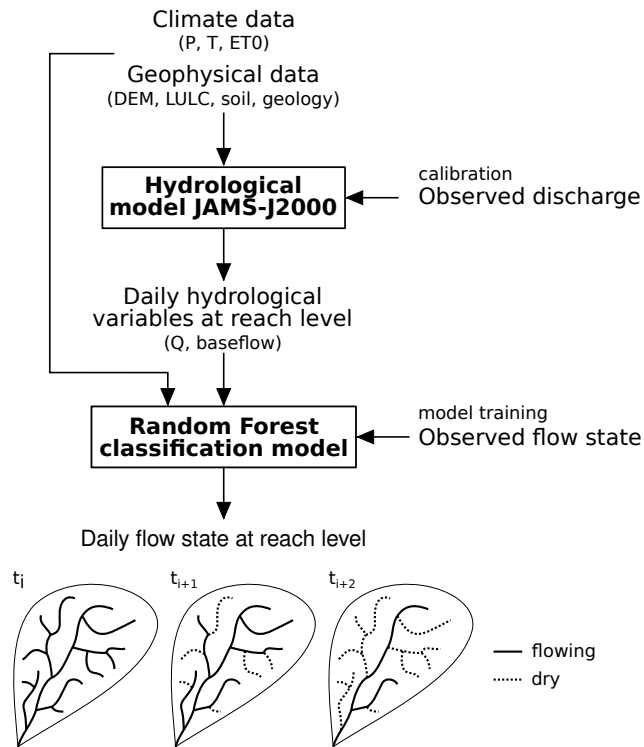
Figure 3. Modelling approach to simulate flow intermittence in river networks by coupling a distributed hydrological model to a Random Forest classification model.

2.2.1 JAMS-J2000 hydrological model

155 The process-oriented JAMS-J2000 hydrological model (Kralisch and Krause, 2006) is used to simulate spatially distributed hydrological variables in the DRNs. The catchment represented in JAMS-J2000 is discretized in Hydrological Response Units (HRU). From climate forcing data, JAMS-J2000 simulates evapotranspiration, snow processes, soil water balance and groundwater processes at the HRU level and computes lateral flow routing to account for surface, sub-surface, and groundwater flow from hillslopes into the stream and along stream segments until the outlet of the river network (Figure 4).

160 The J2000 river networks were generated from the flow directions and flow accumulations computed from the DEMs. Observed river networks were used to validate the generated river networks and make sure that the J2000 river networks corresponds to the observed river networks (see Fig. S1, S2, and S3 in supplementary material).

Some modifications from the standard J2000 hydrological model were made for this study using the evapotranspiration module from Branger et al. (2016) to compute potential evapotranspiration using the reference evapotranspiration and spatially distributed crop coefficients. Besides, the J2000 snow module adapted by Gouttevin et al. (2017) was used.
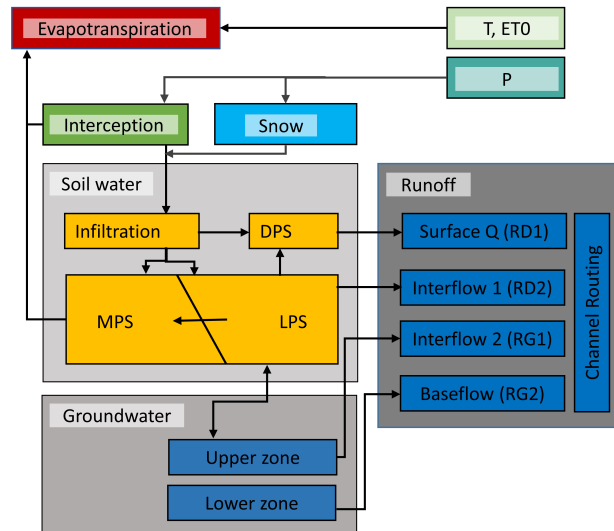
Figure 4. Schematic representation of the hydrological processes modeled in JAMS-J2000 at the HRU and reach level according to Krause (2001), Figure adapted from Watson et al. (2020). DPS: Depression Storage, MPS: Middle Pore Storage, LPS: Large Pore storage

2.2.2 Calibration of JAMS-J2000 model

This section describes only the general aspects of the method used to calibrate the JAMS-J2000 model. A full description of the calibration method as well as parameter values for each DRN are presented in the supplementary material (Tab. S1 and S2).

Calibration of the JAMS-J2000 parameters was performed on larger catchments (1500 to 3700 km^2) corresponding to the intermediate-scale basins studied in the DRYvER project (to bridge the gap between the DRN scale and the continental scale).

First, for the Albarine and Lepsämänjoki catchments, 4 lumped parameters for snow processes were calibrated to optimize the simulated snow cover area (Hall et al., 2007). Then, 15 lumped parameters and 4 distributed parameters were calibrated in order to optimize the simulated discharges at the gauging stations. The Kling-Gupta-Efficiency (Gupta et al., 2009) as well as different evaluation criteria focusing on low flows, such as the 10th percentile of the discharge were used to assess model performance. The calibration and validation periods for the 3 DRNs are presentented in Table 2. For the Genal catchment, the discharge data measured at the Jubrique gauging station indicated potential errors between 2004 and 2012, this period was therefore not taken into account in the calibration and validation of the model.

DRN	Initialization period	Calibration period	Validation period
Albarine	1990-1995	1995-2009	2009-2020
Genal	1998-2001	2001-2004	2012-2018
Lepsämänjoki	2000-2005	2005-2014	2014-2020

Table 2. Calibration and validation periods. Hydrological years start on the 1st of October and end on the 30th of September.

Table 3 shows the performance of the JAMS-J2000 model to simulate the discharge at the locations of the gauging stations in the 3 DRNs. KGE values for the calibration and validation periods show that the discharge is well simulated by the hydrological model. The comparison between the simulated and observed 10th percentile of discharge also shows that JAMS-J2000 gives good results for low flows. In the Albarine DRN, the Saint-Denis-en-Bugey station is located in the downstream part of the river, which is intermittent due to the seepage of the Albarine river in the aquifer. This explains the poorer results on this station as the seepage of the Albarine river is not represented in JAMS-J2000 model. More details on the validation of the JAMS-J2000 model on low flows are available in the supplementary material.

DRN	Gauging stations	KGE calib. / valid.	Q10sim calib. / valid. [m^3/s]	Q10obs calib. / valid. [m^3/s]
Albarine	Saint-Rambert-en-Bugey	0.76 / 0.79	0.94 / 0.50	0.74 / 0.51
	Saint-Denis-en-Bugey	0.55 / 0.69	0.86 / 0.45	0 / 0
Genal	Jubrique	0.75 / 0.76	0.01 / 0.02	0.11 / 0.05
Lepsämänjoki	Lepsämänjoki	0.74 / 0.81	0.56 / 0.40	0.56 / 0.33

Table 3. Validation of the JAMS-J2000 model. KGE values for the calibration and validation periods, and comparison between simulated and observed 10th percentile of discharge during the calibration and validation periods.

Once calibrated, the JAMS-J2000 model is used to simulate daily hydro-meteorological variables such as spatially distributed discharge and groundwater contribution, as well as evapotranspiration, snowmelt, soil saturation and groundwater saturation at the catchment scale from 01/10/2005 to 30/04/2022 in the 3 DRNs.

2.2.3 Random Forest classification model

Results of the JAMS-J2000 hydrological models are used as input data to a Machine Learning model to predict the flow intermittence at the reach level. The Random Forest (RF) classification and regression model (Breiman, 2001) is used to predict the daily state of flow (dry or flowing) at the reach level. The RF model uses 20 covariates based on Beaufort et al. (2019) (Table 4):

– Reach physical characteristics: drainage area, slope, type of land use, type of soil, hydrogeological class around the reaches),

195   – Daily hydro-meteorological variables aggregated at the catchment scale: incoming liquid water, temperature and actual evapotranspiration during the 10, 20 and 30 previous days as well as soil and groundwater saturation,

     – Spatially distributed hydrological variables simulated with JAMS-J2000: discharge and groundwater contribution (at t_0, and averaged over the 10 previous days).

Abbreviation	Description	Spatial / temporal distribution	Data source
drained_area	Drainage area of the reach	reach / constant	Albarine: EU-DEM v1.1 Genal: Andalucia DEM Vantaanjoki : DEM Finland
slope	Slope of the reach	reach / constant	Albarine: EU-DEM v1.1 Genal: Andalucia DEM Vantaanjoki : DEM Finland
landuse	Majority landuse class of HRUs crossed by the reach	reach / constant	Corine Land Cover 2012
soil	Majority soil class of HRUs crossed by the reach	reach / constant	European Soil Database v2.0
hgeo	Majority hydro-geological class of HRUs crossed by the reach	reach / constant	IHME1500
R10, R20, R30	Sum of incoming liquid water (rainfall + snowmelt) during the 10, 20 and 30 previous days	catchment / daily	simulated with JAMS-J2000
T10, T20, T30	Mean air temperature during the 10, 20 and 30 previous day	catchment / daily	ERA5-land
ET10, ET20, ET30	Sum of actual evapotranspiration during the 10, 20 and 30 previous days	catchment / daily	simulated with JAMS-J2000
SoilSat	Mean saturation of the soil reservoirs	catchment / daily	simulated with JAMS-J2000
GwSat	Mean saturation of the groundwater reservoirs	catchment / daily	simulated with JAMS-J2000
Q	River discharge	reach / daily	simulated with JAMS-J2000
Q10	Mean river discharge over the 10 previous days	reach / daily	simulated with JAMS-J2000
GW	Groundwater contribution to the river discharge	reach / daily	simulated with JAMS-J2000
GW10	Mean groundwater contribution to the river discharge during the 10 previous days	reach / daily	simulated with JAMS-J2000

Table 4. List of the covariates used in the RF model to predict the spatially distributed daily state of flow.

The RF models were implemented and calculated using the R package "ranger" (Wright et al., 2020).

200 For each DRN, the RF models are trained using flow state observations, and then used to extrapolate spatially and temporally the daily state of flow in each reach during the simulation period (01/10/2005 - 30/04/2022). To use the most of the observed flow state data (Section 2.1.4), the RF model is trained with all available data.

During the training phase of a RF model, a subset of variables is randomly selected at the node's splitting point in each random forest tree (Breiman, 2001). In this study, the RF is trained 20 times in order to take into account this structural
205 uncertainty.

The ability of the RF model to represent flow intermittence is evaluated with four efficiency criteria: Sensitivity (probability of correctly detecting drying events), Specificity (probability of correctly detecting flowing events), Accuracy (probability of correctly simulating the flow condition), and False Alarm Ratio (FAR) (probability of wrongly predicting a drying event). These criteria are calculated as follows:

210 $$\text{Sensitivity} = \frac{a}{a+c}$$

$$\text{Specificity} = \frac{d}{b+d}$$

$$\text{Accuracy} = \frac{a+d}{a+b+c+d}$$
215

$$\text{FAR} = \frac{b}{a+b}$$

with a the number of dry observations correctly simulated by the model, b the number of flowing observations that were simulated as dry, c the number of dry observations that were simulated as flowing, and d the number of flowing observations correctly simulated by the model.

220 **2.3 Sensitivity analysis of the RF model**

2.3.1 Sensitivity to the size of the training sample

First, the sensitivity of the RF model to the size of the training sample is tested by randomly selecting 75% of the flow state observations to train the RF model for each of the 20 runs. The RF model is then evaluated on the remaining 25%. For the 20 runs, the selection of the 75% of training data is based on a different random draw. This first test aims at evaluating the impact
225 of using a reduced training dataset on the prediction of flow intermittence. It also aims at evaluating the error of the RF model on a validation sample.

2.3.2 Sensitivity to the type of flow state observed data

As presented in Section 2.1.4, the collected flow state observation datasets used to train the RF model are heterogeneous in terms of spatial and temporal distributions of the observations, and representativity of different types of flow regimes. The
230 sensitivity of the RF model to each type of observed data (stations, field campaign, crowdsourced data, Google Earth, expertise) is evaluated by removing in turn each type of data from the training dataset, and then comparing the RF performance and the

predicted flow intermittence patterns. The RF performance is evaluated on the whole dataset of flow state observations in order to compare the performance on the same validation dataset. The objective of this analysis is to assess the amount of useful information brought by each type of data.

2.3.3 Sensitivity to the geology data

The last test aims at analysing the sensitivity of the RF model to different degrees of accuracy of covariates. Here, we focus on the study case of the Albarine DRN, in which a main cause of intermittence is the infiltration of the riverbed in moraine deposits and karstic soils.

The European IHME1500 map used to define the geological classes in the hydrological model (JAMS-J2000 + RF), with a scale of 1:1500000, shows 3 classes of geology in the Albarine catchment (karst, fine sediments, and coarse sediments). On the other hand, the French BD Charm-50 map (BRGM, 2020), with a scale of 1:50000, shows 71 different geological classes.

The RF is trained with the geological classes from the BD Charm-50 map to evaluate the impact of the precision of geological data in a catchment where flow intermittence is very influenced by the geological context. In this test, the JAMS-J2000 is still parameterized based on the IHME1500 map, only the input geology classes of the RF are modified.

3 Results

3.1 Observed flow state data analysis

Table 5 shows general statistics on the distribution of the observed flow state between the different datasets and the coverage of the river networks. The gauging stations are the main source of observed data in term of number of observations. They give information on long time periods with regular time step, but the number of stations in the DRN is limited (1 station in the Genal and Lepsämänjoki DRNs and 5 stations in the Albarine DRN), which means that stations cannot bring useful information about the spatial patterns of drying in the DRNs. The field campaigns (with expertise) is the second source of observed data. They cover a shorter time period than the stations (3 months in Lepsämänjoki and 3.5 years in the Albarine), but have a better spatial coverage of the river network than the stations. In the Genal DRN, observed data from Google Earth images show a very good spatial coverage with about 38% of the river network with at least one observation along the period of available data. It also covers a long time period (11.5 years) but with only a few observations per reach (between 1 and 8 observations per reach). Crowdsourced data only represent a very small fraction (0.6 to 2.8%) but have a good spatial coverage, with around 14% of the Albarine and Genal river networks covered.

DRN	Data type	Period of available data	Number of observations	Number of reaches with observations	Length of river network [%]
Albarine	Stations	2005-10-01 to 2021-12-01	10681	5	1.2
	Crowdsourced	2019-06-26 to 2022-04-23	299	56	14.7
	Field campaign	2018-11-07 to 2022-04-30	5184	9	2.4
	Expertise	2018-11-07 to 2022-04-30	12688	10	1.9
	All	**2005-10-01 to 2022-04-30**	**28852**	**61**	**15.7**
Genal	Stations	2005-10-01 to 2021-10-19	5845	1	0.3
	Crowdsourced	2021-05-20 to 2022-02-12	88	28	14
	Google Earth	2010-10-08 to 2022-04-01	319	98	38.2
	Expertise	2021-03-28 to 2022-01-21	894	3	1.0
	All	**2005-10-01 to 2022-04-01**	**7146**	**119**	**47.7**
Lepsämänjoki	Stations	2005-10-01 to 2020-05-26	4761	1	0.1
	Crowdsourced	2021-06-18 to 2021-11-02	28	19	6.2
	Field campaign	2021-06-17 to 2021-09-26	807	8	2.6
	Expertise	2021-06-17 to 2021-09-26	711	7	1.6
	All	**2005-10-01 to 2021-11-02**	**6307**	**23**	**7.3**

Table 5. Flow observations in the studied DRNs (from 2005-10-01 to 2022-04-30)

Observed data have different distributions in time and space in the DRNs (Fig. 5). For the three DRNs, there are observed data on the different classes of reaches (classified according to their drainage area), but there is more available data in the class of reaches with the largest drainage area. This is due to the gauging stations data that are located along the main river and which represent the largest share of the data. The Albarine basin is the only one to have a full seasonal coverage on the different types of reaches. Reaches with small drainage areas in the Genal and Lepsämänjoki DRNs have observed data mainly between June and September, and have missing data during the other months of the year (especially December and January). This shows that the collection of observed data on flow intermittence tends to be focused on the dry season and that there is almost no information on the state of flow for small river sections during winter.

Figure 5 also shows a seasonal distribution of the no-flow observations along the river networks. There is a clear spatio-temporal distribution of the no-flow observations in Lepsämänjoki DRN, with most of the drying events occurring in June and July in reaches with the smallest drainage area. Drying events gradually decrease with the size of the reaches drainage area, and the main river is perennial. However, drying events seems to be over-represented during the summer season, because in the smallest reaches, 100% of the observations are dry, whereas it is know that in this catchment, not all small reaches dry up, and they do not dry for more than a few weeks. In the Genal DRN, the peak of the drying season seems to be between June and September, but drying events are also observed in early spring and autumn. Most of the dry events are observed in the small

reaches but a few dry events are also observed in the downstream part of the Genal river due to water abstraction of irrigation (around 4% of the observations in June and July). Drying events are observed later in the season - from August to October - in

275   the Albarine DRN and are localized in small reaches but also in the main river due to the seepage of the Albarine river in the soil (around 30% of dry observations in the Albarine between July and August). The smallest reaches (with a drainage area lower than the 25th percentile) only show flowing observation, which shows that no-flow observations may be lacking in these reaches.
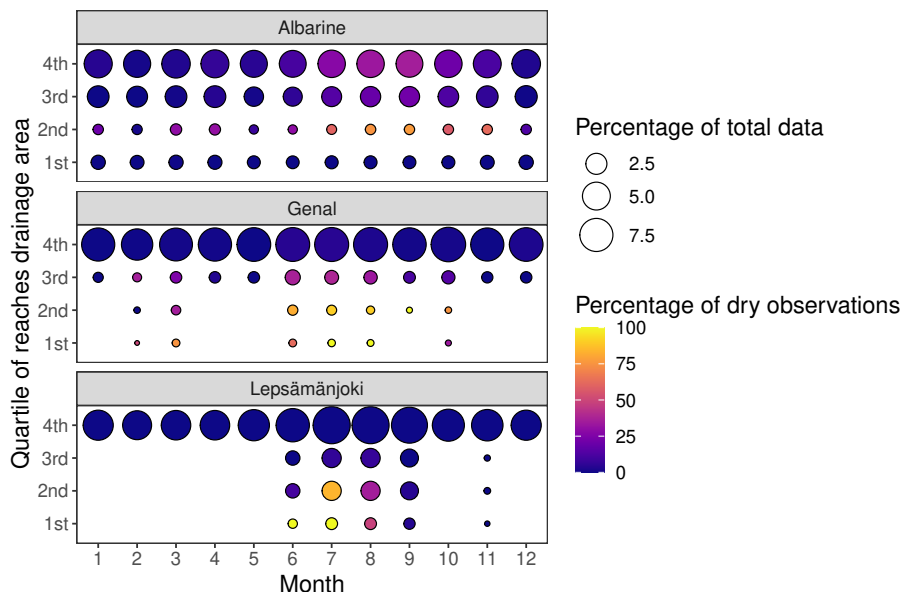
Figure 5. Distribution in space and time of flow state data. The size of the dots indicates the percentage of total available data per month and per class of drainage area, and the color the percentage of dry observations per month and class of drainage area.

3.2   Prediction of flow intermittence

280   This section presents the results of the simulation of flow intermittence with the JAMS-J2000+RF modelling.

Figure 6 shows an example of the state of flow prediction in one reach of the Albarine DRN. Comparin the observed state of flow and the discharge simulated with the JAMS-J2000 model shows that the hydrological model alone is not sufficient to reproduce the periods with no flow. The transition from a flowing to a dry state cannot be easily inferred from the simulated flows alone since there are periods when the simulated discharge is relatively high (e.g. in late 2020) while the phototrap

285   indicates a dry state whereas on other periods, the simulated discharge is low while the phototrap indicates a flowing state (e.g. late summer 2019). However, the flow state predicted by the RF model is in good agreement with the observed flow states, which shows the usefulness of the coupling between the spatialized hydrological JAMS-J2000 model and the RF model.
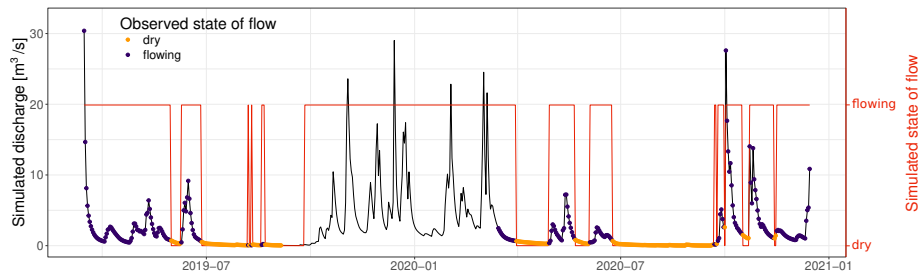
Figure 6. Daily state of flow predicted by the RF model (red) in the reach 2443600 in the Albarine DRN compared to the discharge simulated by JAMS-J2000 model (black) and the observed state of flow collected from a phototrap (orange: dry, purple: flowing).

To enhance the precision of evaluating the coupled JAMS-J2000+RF model to represent flow intermittence across the entire river systems, the model underwent training and testing using two distinct configurations: configuration 0 involved training the
290   RF model with 100% of the observed data, while configuration 1 involved training the RF model with 75% of the observed data and validating its performance on the remaining 25%. The Sensitivity, Specificity, Accuracy, and FAR values obtained with the reduced training sample (configuration 1) are indicators of the RF model error to extrapolate the prediction of the state of flow on reaches and dates that are not represented in the training dataset. With configuration 0, the model perfectly reproduces the observed drying and flowing events in the three DRNs (Sensitivity and Specificity = 1), whereas the performance of the
295   RF model is decreased with configuration 1 (Fig. 7). The Albarine and Lepsämänjoki DRNs only show a slight decrease of the performance: the model still correctly predicts more than 90% of the no-flow observations and has a FAR around 5%. The Genal DRN is more impacted by the removal of some of the observed data, the mean Sensitivity drops to 65% and the mean FAR is 19%. Specificity is above 0.99 for the 3 catchments, which means that the RF model predicts flowing events almost perfectly with configuration 1. Accuracy is also very close to 1 (> 0.98), this is due to the fact that flowing events are much
300   more represented than drying events in the observed dataset, so prediction errors for dry events are negligible compared with the near-perfect predictions of flowing events.

These results show that there is a high confidence of the prediction in the general dynamics of drying in the Albarine and Lepsämänjoki DRNs, but higher uncertainty for the Genal DRN (see discussion in Section 4.2).

The next sections present firstly flow intermittence modelling results obtained with configuration 0 in Sections 3.3 and 3.4
305   and secondly the uncertainty related to the input data (size of the training sample with configuration 1, type of flow state observed data, and geology data) in Section 3.5.
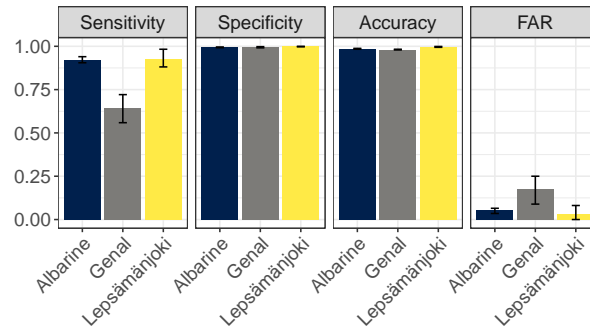
Figure 7. Performance of the RF model when the model is trained with 75% of observed data and tested on the remaining 25% (configuration 1). Bars show the mean value and error bars show the range of values of for the RF model 20-members with configuration 1. FAR: False Alarm Ratio.

3.3 Simulated spatial and seasonal patterns of flow intermittence

Regarding the spatial pattern of flow intermittence, the model simulates more drying in the small tributaries for the three DRNs (Fig. 8). For the Albarine and Genal DRNs, the flow intermittence of the main river in the downstream part of the catchment, due to seepage for the Albarine and water abstraction for irrigation in Genal, is well reproduced by the model. Simulated spatial patterns of drying have been validated by local experts who confirmed that they are consistent with their observations (Fig. S13 and S14).

Figure 9 shows the mean interannual variations of the fraction of dry river network through the year. It shows that the drying is limited to end of May until end of August in the Lepsämänjoki DRN, and than the mean annual maximum of drying usually does not exceed 9% of the river network. In the Albarine DRN, the mean annual maximum of drying occurs in early September with between 24 and 27% of dry river network. More than 10% of the river network is continuously dry between July and the end of September. The model predicts some flow intermittence throughout the year (between 1 and 4% of dry river network during the winter season). In the Genal DRN, the river network can dry up to 78-80% in August, and more than 50% of the river network is dry from June to mid-September. The fraction of dry river network in Genal during the winter season stays relatively high (between 6 and 26%), but the lack of observed data over this period makes the results particularly uncertain.

Overall, the model successfully represents the general spatio-temporal patterns of drying in the 3 contrasted European DRN, with intense and long periods of drying in the Genal catchment characterized by a dry and warm climate, regular and localized drying up due to the geological context in the Albarine catchment, and short and limited in space drying in the Lepsämänjoki catchment characterized by a more humid climate but mild in summer.
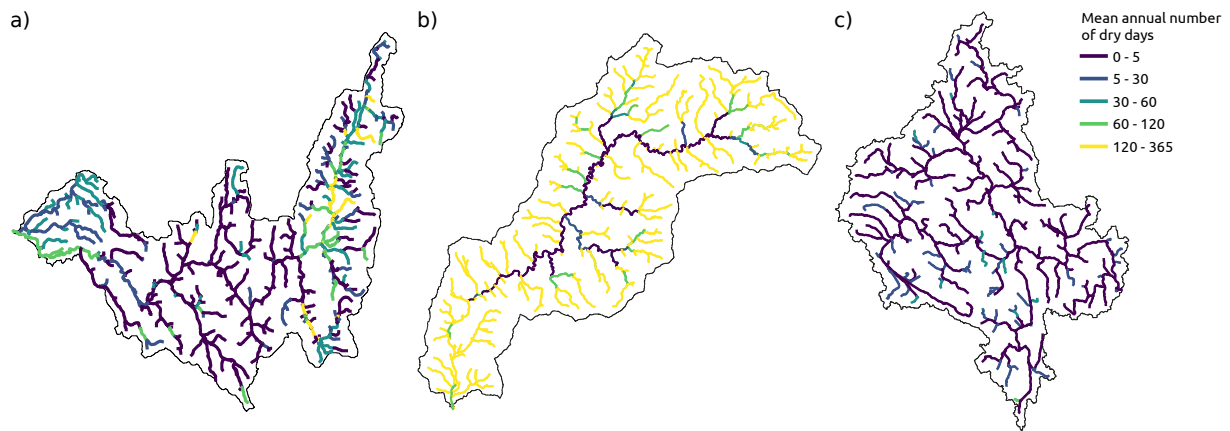
Figure 8. Predicted average annual number of dry days for each reach of the a) Albarine, b) Genal, c) Lepsämänjoki DRNs.
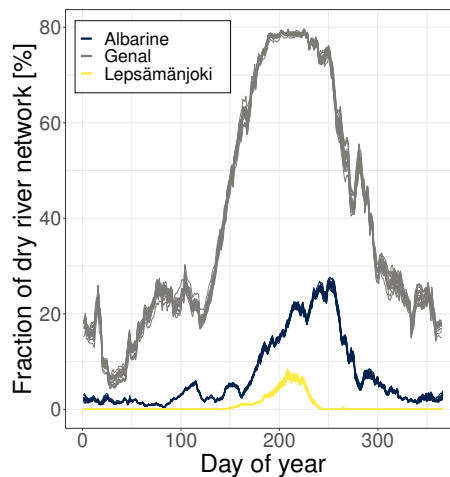
Figure 9. Seasonal variability of the fraction river network that gets dry (inter-annual average of the percentage of total number of kilometers of rivers). For each DRN, the lines represent the ensemble of the 20 runs of the RF model.

325 **3.4 Analysis of the covariates**

The ranking of the most important covariates in the RF models reflects the different contexts of flow intermittence in the DRNs. In the DRNs with more complexe spatial patterns of drying, the RF gives more weight to the variables describing the reaches characteristics. For all three DRNs, the drainage area of the reaches and their slopes are the 2 most important variables for the prediction of the flow state (Fig. 10).

330 For the Lepsämänjoki DRN, the next most important variables are the mean catchment air temperature during the previous 30 days (T30), the simulated discharge, and simulated groundwater contribution to the discharge (GW10 and GW). These three variables give information on the hydro-meteorological situation in the catchment, and define the temporal variability of

drying. T30 allows seasonal variability to be captured, and makes a distinction between winter low flows, when precipitation is stored as snow in the basin, and summer low flows, when drying is observed in small streams.

For the Genal DRN, the third and fourth most important covariates are the mean discharge during the 10 previous days and the current discharge, which shows that the temporal dynamics of drying is mainly controlled by the simulated discharge in the reaches. The fifth most important variable is the landuse which reflects the more concentrated agricultural areas, with a water demand for irrigation, in the downstream part of the basin.

In the Albarine DRN, the most important variables, after the reaches drainage area and slope, are the land use and soil types around the reaches and the current discharge. The four most important variables do not reflect the main cause of drying in the Albarine, which is the seepage of the river in moraine deposit areas. The classes of geology causing flow intermittence in the Albarine are not represented in the IHME1500 dataset, which may explains why other spatial characteristics are used in the RF model to reproduce the spatial pattern of drying.
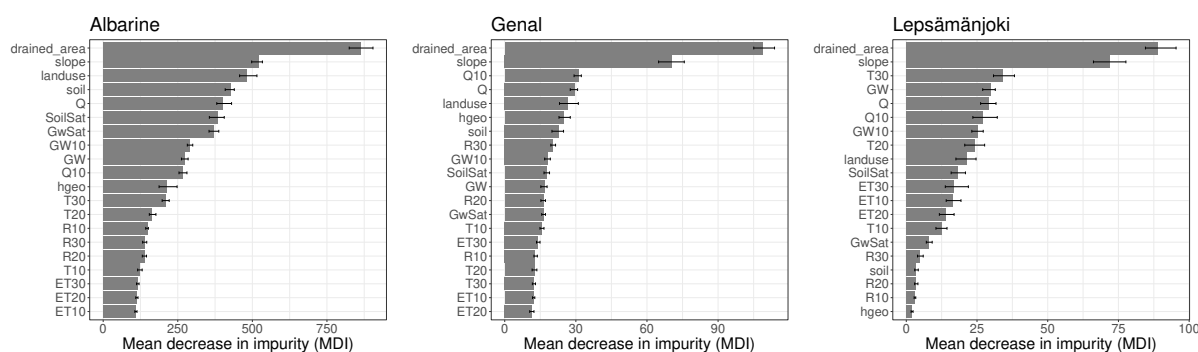
Figure 10. Importance of the covariates in the RF models (mean decrease in impurity (Archer and Kimes, 2008)) for the 3 DRNs. Bars represent the mean MDI and the error bars the minimum and maximum values of MDI for the 20 runs of the RF model.

3.5 Sensitivity to the input data

3.5.1 Sensitivity to the size of the training sample

Figure 11 shows the impact of the size of the training sample on simulated seasonal pattern of drying in the DRNs. The RF model is either trained with 100% of available observed data (configuration 0), or 75% of the observed data (configuration 1). For the Lepsämänjoki DRN there is no visible impact of reducing the training dataset on the predicted flow intermittence. In the Albarine and Genal DRNs, the results show that the uncertainty increases particularly during the winter season, when there are fewer observations.

These results show that the RF model is more sensitive to the representativity of drying in the observed data recorded than in the amount of data itself. The Lepsämänjoki DRN has fewer observations and a poorer spatial and temporal coverage of the observed data than the Genal DRN, but the model is more robust in Lepsämänjoki than in Genal. The higher sensitivity of the Genal DRN to the training dataset can be explained by the fact that the DRN is more affected by drying, a very large part of

355 the river network dries every year, and during long periods (several weeks to several months). It thus needs a larger amount of observed data to fully capture the seasonal dynamics of drying along the river network.

The importance of the covariates obtained with configuration 1 is very close to that obtained with configuration 0 (Fig.10) which shows that for this study the importance of the covariates is not very sensitive to the size of the training sample (see Fig.S15 in supplementary material).
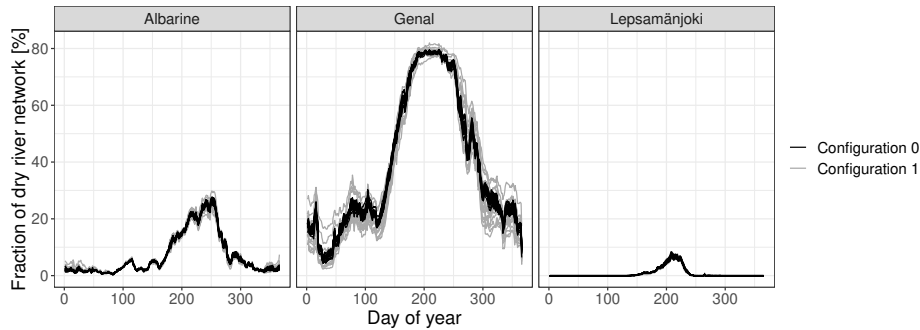
Figure 11. Sensitivity of the simulated length of dry river network to the size of the raining sample. Configuration 0 (black): the RF model is trained with 100% of the observed data. Configuration 1 (grey): the RF model is trained with 75% of the observed data.

360 **3.5.2 Sensitivity to the type of flow state observed data**

Figures 12 and 13 show the sensitivity of the model to the type of observed data used to train the RF. The first result is that the prediction of flow intermittence is very sensitive to the expertise data. Indeed, when this dataset is removed from the training sample, the FAR increases (43% for Albarine, 40% for Genal, and 7% for Lepsämänjoki), the drying is more intense during the summer in Lepsämänjoki (maximum annual of dry fraction of the river network between 6 and 8% without expertise data

365 versus 8 to 11% with expertise), and the drying is twice more intense and last much longer in the Albarine DRN.

Field campaign data also have a large impact on the prediction of flow intermittence, especially in the Albarine DRN where the model is only able to predict 50% of the dry days without the field data. The drying is much reduced during the summer and there is no drying simulated from November to June. On the opposite, in the Lepsämänjoki DRN, the FAR is increased without the field campaign data and the drying is very over-estimated. Expertise and field campaign data are the two most impactful

370 datasets in Albarine and Lepsämänjoki.

In the Genal DRN, the results show that the simulated seasonal pattern of drying is very different without the Google Earth data, with a lot of drying predicted during the winter season, which can reach unrealistic values (up to 70% of dry river network in January) (Fig. 13). In a DRN characterised by high intermittence of flows, and with little field observations, flow intermittence observation from remote sensing dataset can be very useful to better constrain the RF model.

375 In the Lepsämänjoki DRN, the removal of the station data from the training dataset does not impact the prediction of drying. However, in the Albarine and Genal DRNs some of the stations are located on intermittent reaches and their removal decreases the sensitivity criteria to 61% for the Albarine, and 77% for Genal.

Crowdsourced data, which represents at most 1% of all observations collected in the DRNs, have a visible impact on the prediction of dryness, especially during the summer. For the Albarine, the mean annual maximum of dry river network decreases

380 from 27 to 23% without the crowdsourced data in early September. In the Genal DRN, the uncertainty increases without the crowdsourced data, for example, in late July - early August, the fraction of dry river network ranges between 78 and 80% when the RF model is trained with all of the observed data, and ranges between 78 and 85% when the crowdsourced data is removed from the training dataset. This shows that, even is they only represent a very small fraction of the observed data, crowdsourced data, have a significant impact on the prediction of flow intermittence through the spatial information they provide.
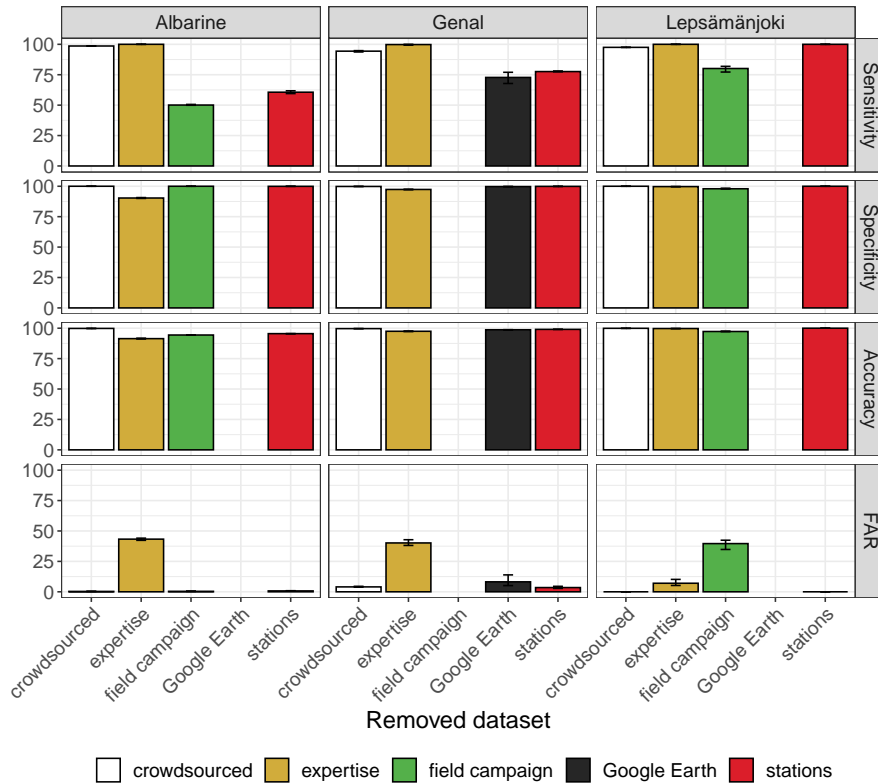
Figure 12. Impact of removing a source of observed data from the training sample on the performance of the RF model.
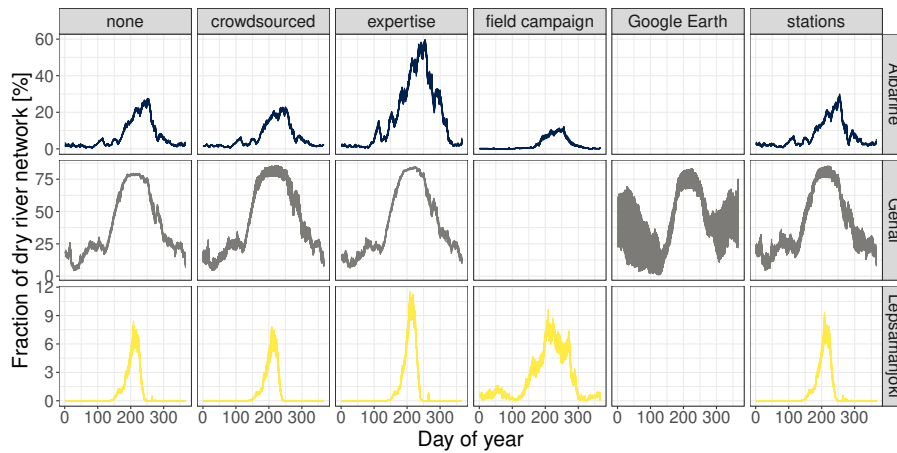
Figure 13. Impact of removing a source of observed data from the training sample on the prediction of flow intermittence.

3.5.3 Sensitivity to the geology data in the Albarine DRN

When the BD CHARM-50 geology map is used to define the geology classes in the covariates of the RF model, geology becomes the most important variable in the RF (versus 11th most important variable with IHME1500) (Fig. 15). The RF model also gives more weight to the mean catchment ground water and soil saturation, which shows that the physical processes causing flow intermittence in the Albarine DRN are better taken into account in the RF model when using more accurate geological data.

The seasonal pattern of drying is rather similar but with a bit less drying in winter and spring and a bit more drying in summer and autumn. When looking at the spatial patterns of drying we can see some differences, especially in the upstream and downstream parts of the catchment. We presume that this is due to moraine deposits, which are represented more widely in the catchment by the BD CHARM-50 map. With the coarser geology map (IHME1500), the RF manages to predict rather accurately the main spatio-temporal patterns of drying, but the use of more detailed geology map (BD CHARM-50) can help improving the prediction of drying at the reach scale.
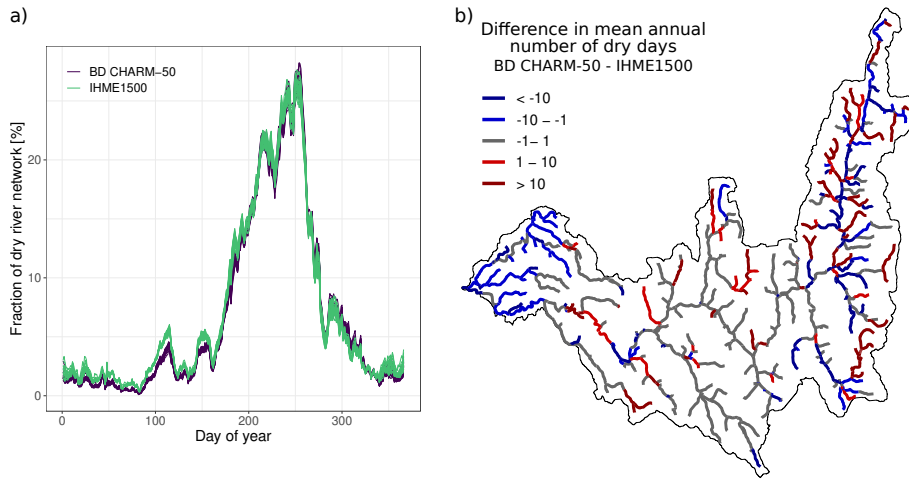
Figure 14. Sensitivity of the prediction of flow intermittence to geological data in the Albarine DRN. Note that in b) values can locally largely exceed the range of [-10,10] difference represented here.
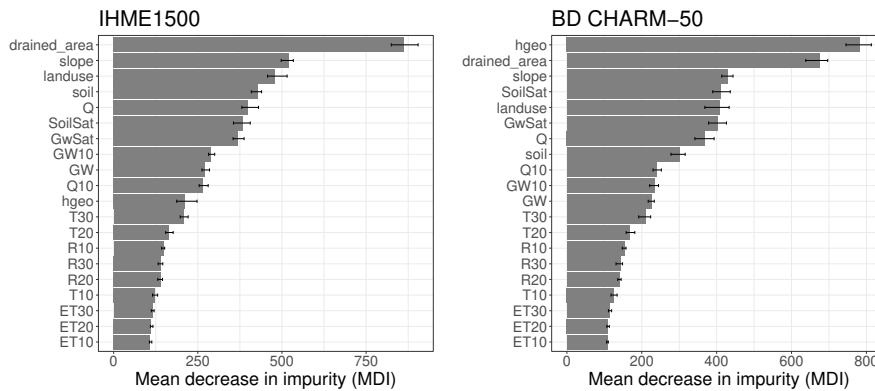
Figure 15. Importance of the covariates (mean decrease in impurity (Archer and Kimes, 2008)) when the RF model is trained with the IHME (left) and the BD CHARM-50 (right) geology maps. Bars represent the mean MDI and the error bars the minimum and maximum values of MDI for the 20 runs of the RF model.

4 Discussion

4.1 Hybrid modelling to predict flow intermittence at the reach scale

The coupling between a spatially distributed model and a random forest model has a number of benefits for predicting intermit-
400 tence in river systems. First, the JAMS-J2000 model represents the spatially distributed hydrological physical processes in the catchments. This enables to simulate several hydrological variables at the HRU and the reach scale, such as evapotranspiration, soil water content, groundwater level, discharge, that can be used as spatially distributed covariates in the RF model. Second,

the JAMS-J2000 represents lateral flow routing between the HRUs and the reaches, and thus represents the hydrological con-
nectivity which cannot be represented in a RF model. However, the simulation of flow intermittence with JAMS-J2000 alone
405   is not yet possible. The JAMS-J2000 model has difficulties to simulate periods with no flow. Even after long periods without
precipitation input, the model tends to simulate residual low flows, and the reaches never completely dry up. There are also a
multitude of processes causing the drying of rivers (e.g. interaction between the riverbed and the water table, seepage into karst,
pumping of water from aquifers and rivers) and it is difficult to represent them all and accurately in a physical model (Fovet
et al., 2021; Shanafield et al., 2021). Despite the JAMS-J2000 model ability of simulating seepage through the alluvial river
410   bed (Watson et al., 2021), or water abstraction for anthropogenic uses (Branger et al., 2016), the data needed to parameterize
these processes are seldom available and were not available in our case studies (e.g. daily amounts of water withdrawals and
their precise locations). The use of the RF model enables to simulate flow intermittence even if the processes causing the drying
up are not known or understood precisely beforehand since it does not require a representation of physical processes, but links
covariates to observed states of flow. In addition, RF models have the advantage to provide variable importance metrics (Tyralis
415   et al., 2019) which, in our case, allow to better understand the processes leading to the drying in the DRNs.

The question can be raised about the contribution of the RF model compared to applying a threshold on the discharge
simulated by the JAMS-J2000 model below which would determine zero flows. Figure 16 shows the distributions of simulated
discharges for the two types of flow conditions (flow or dry) in reach 2443600 of the Albarine (same example as in Figure 6).
For simulated discharges ranging from 0 to 4 m^3/s, there is an intersection of the distributions for observed dry and flowing
420   events. Setting a threshold would mean truncating the tails of these distributions. For instance, by setting a threshold to achieve
a Sensitivity of 98% on this reach, a FAR of 26% is obtained, as low discharges are all predicted as dry events. In contrast, with
the RF model, the intersection of the distributions is well reproduced, and a FAR of 1.7% is achieved for the same Sensitivity
(98%). The differences in distributions between observed and simulated flow conditions can be explained by the fact that
there are few "flowing" observations during winter periods with high flows in this reach. It is also challenging to extrapolate a
425   discharge threshold value across all reaches of the network. Looking at the spatial pattern of flow intermittence in the DRNs
(Fig.8) it is clear that the threshold value should be spatially distributed to take account of local effects, but this raises the
question of how this spatial distribution should be achieved.

The use of a spatialized hydrological model combined to a RF model is therefore very advantageous in order to be able to
simulate flow states at fine time steps and in a spatialized way over the entire river network.
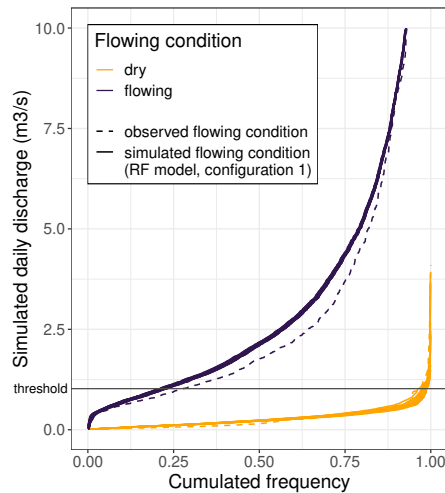
Figure 16. Distribution of simulated discharge with JAMS-J2000 model for observed and simulated (RF model 20-members ensemble with configuration 1) flowing conditions for reach 2443600 in the Albarine DRN (same reach as in Fig.6). The horizontal black line shows an example of an applied threshold to predict flow condition from the simulated discharges (on the figure, the threshold value is set to correctly predict 98% of the observed drying events).

430   However, the use of a RF model has several limitations. A first limitation is that the RF model can predict the right state of flow for the wrong reasons if the causes of drying are not represented in the covariates. For the 3 studied DRNs, drainage area is the most important covariate, which is consistent with other studies using RF models to predict flow intermittence (Jaeger et al., 2023; González-Ferreras and Barquín, 2017; Snelder et al., 2013), but in the Albarine and Genal DRNs we know that the drying is in fact due to the geology and water abstraction, respectively. The results of the RF model do not necessarily provide

435   a better understanding of the origin of drying in river networks if the covariates are not sufficiently precise. Most importantly, this means that a RF model trained on a specific DRN may not be robust enough to predict flow intermittence in another DRN.

One major application of this flow intermittence modelling approach is to simulate the flow states under different climate change scenarios and predict tipping points in the flow regime of the river sections, such as transitions from a perennial to an intermittent flow regime. However, the robustness of such a model for extrapolating flow intermittence in climate change

440   projections is questionable. The RF model is trained with observed data over a relatively short period, with no observed change in the flow regime of the reaches and it is known that RF models cannot predict events that have never been observed before (Hengl et al., 2018; Tyralis et al., 2019), which represents a major limitation for predicting the future evolution of drying spells in the DRNs. While it can be expected that the drying spells of currently intermittent reaches will be prolonged under climate change scenarios, the ability of the RF model to predict a shift from a perennial to an intermittent flow regime is not assured.

445   However, the results of this study show that the average annual number of dry days simulated for the reaches known to have perennial flow is rarely zero, but can vary between 0 and 3 days per year. This means that in the present period, the model simulates completely perennial flow only in a few reaches. This bias in predicting the state of flow in the present period is a

drawback for characterising current drying dynamics in river systems and studying the impact on biodiversity, but may facilitate the prediction of drying in the context of climate projections as most of the reaches are already considered as intermittent in
450 the present period.

4.2 Observed flow state data for the modelling of flow intermittence

The results of the RF model are highly dependent of the training dataset. This study highlights the challenges of obtaining observed flow state data to train or validate the models. To accurately represent flow intermittence along river networks, the observed data ideally need to be uniformly distributed both spatially and temporally, which can be difficult to achieve.

455 Most studies focusing on the catchment scale collect observations from field campaigns (e.g., Llanos-Paez et al., 2023; Jaeger et al., 2023; Van Meerveld et al., 2019; Sefton et al., 2019), but such surveys generally do not allow rivers to be monitored over many years and are usually limited to portions of the river network as they can be very time-consuming.

This study shows the interest of combining different types of data with heterogeneous spatial and temporal patterns in order to maximise the information on flow condition in the river networks. This is consistent with the results of Gallart et al. (2016)
460 who showed that combining data from citizen science and aerial photographs afforded more robust information.

The results obtained in the 3 basins demonstrate the need to adapt the data collection to the context of each DRN. Ideally, a large amount of homogeneously distributed data along the river network and throughout the year will introduce the least possible bias into the model, like in the Albarine DRN for instance. However, the case of the Lepsämänjoki DRN shows that even with a small amount of data concentrated on the summer season, the predicted patterns of drying are consistent with
465 the observations made by local experts. In contrast, with a similar amount of data, the variability of the prediction of flow intermittence in the Genal DRN is higher due to more complex spatio-temporal patterns of drying. To reduce the uncertainty in the Genal DRN, more years of observed data would be necessary, with data more evenly spread over the year to better capture the length of dry spells.

The analysis of the Albarine and Lepsämänjoki DRNs shows that data from field campaigns provide essential information
470 on the spatial and temporal dynamics of drying, making it the most useful type of data for predicting flow intermittence in river networks. However, in the Genal DRN, where phototraps were not installed during field campaigns, remote sensing seems to be a good alternative for collecting data. Although remote sensing data can be used to detect the state of flow adequately, Gallart et al. (2016) have nevertheless pointed out several limitations: images are available at too low a frequency to study temporal patterns and dense vegetation near the rivers may prevent the detection of the state of flow.

475 As shown in the results of this study, citizen science can also be a useful way of obtaining intermittence data and increasing the spatial coverage of observations. Several studies have shown the advantages of working with citizens to monitor temporary streams, especially to obtain observations in streams that would otherwise not be monitored (Turner and Richter, 2011; Buytaert et al., 2014; Gallart et al., 2016; Kampf et al., 2018). Gallart et al. (2016) and Strobl et al. (2019) studied the accuracy of data provided by citizen scientists and showed these data give an overall good indication of the hydrological state of the streams.

480 Expertise data indicating reaches with perennial flow proved to be crucial in reducing the over-representation of data from intermittent reaches in the RF model training data across all three DRNs. However, this raises questions about the value of

such data, which is based on human perception and the error it may contain. Expert elicitation in hydrology has already shown benefits, particularly when tangible data are missing (Ye et al., 2008; Warmink et al., 2011; Sebok et al., 2016, 2022). These studies do show differences in the individual perceptions of the experts consulted, but by consulting a larger number of experts (in this study, only 1 or 2 experts were consulted per studied DRN) and by applying protocols similar to the ones proposed in these studies, the uncertainty linked to individual perception could be reduced, or at least quantified.

The general indications for data collection emerging from this study are to 1) favour a good spatial distribution of the observations by collecting data reaches with different characteristics (e.g. in terms of drainage area, geology and water abstractions), 2) collect data on intermittent sections as well as on reaches with a permanent flow regime, 3) have time series of observations covering at least a whole year on a few points of the river network.

4.3   Delineation of the river networks

Another limitation of the study arises from the delineation of river networks. The delineation needs to be as accurate as possible to ensure that observations of flow state are assigned to the correct reaches. However, several studies such as those by Prancevic and Kirchner (2019), Van Meerveld et al. (2019), and Godsey and Kirchner (2014) have shown that river networks are dynamic systems: they extend or retract according to landscapes and climatic conditions and can also be disconnected. It is therefore difficult to delineate a fixed reference river network with a density enabling to predict accurately the spatial variability of drying in the DRNs.

In this study, the density of the delineated river networks was chosen so that all observations could be assigned to a reach, but the results show that the density of the river network has an impact on the simulated patterns of drying in the DRNs. In the 3 studied DRNs, contradictory states of flow were observed in reaches at the same day indicating that the density of the river networks is not high enough to capture very local processes of drying. In contrast, the density of the river network should not be too high, as it may lead to the representation of reaches with an unrealistically small drained area, for which there is no observed data available to train the RF model. This situation occurred in the Albarine DRN where the resolution of the river network had to be increased in order to capture the locations of observed data (Fig. S2), resulting in some unrealistic prediction of small perennial reaches in the upstream part of the catchment (Fig. 8).

5   Conclusions and perspectives

The modelling approach, coupling a spatially distributed physical hydrological model (JAMS-J2000) with a random forest classification model, developed in this study allows to predict the daily state of flow (dry or flowing) at the reach scale along river networks. The results show that the models allow to successfully predict the main spatio-temporal patterns of drying in 3 contrasted European river networks.

This study also discusses the difficulty of collecting flow intermittence data to train and validate random forest models. The results show that the combination of various sources of observed flow state data is essential to form a training dataset that is

representative of the actual spatio-temporal drying patterns in the drying river networks and to reduce the uncertainty of the prediction of flow intermittence.

515   In order to improve the modelling of flow intermittence, further improvements could be made to the models and to the collection of flow state data to train the RF model. Regarding the modelling approach, a first perspective is to add a third class of state of flow in the RF model to predict the pools condition (i.e. stagnant water in disconnected pools) which is as important as the dry or flowing conditions for studying the ecological impact of flow intermittence (Datry et al., 2017; Bourke et al., 2023). Another perspective is to improve the parameterization of the groundwater reservoir in the JAMS-J2000 models by

520 using observed data of groundwater level to optimize the groundwater parameters and by using a more precise geology data to define the geological classes in JAMS-J2000 for the DRNs where flow intermittence is influenced by geology. Regarding the collection of flow state data, a perspective is to use satellite products to collect flow intermittence data. Cavallo et al. (2022) showed that Sentinel-2 images can be used to detect flow intermittence along river networks. The use of satellite products could allow the modelling method to be transposed more easily to other river networks without the need for extensive field

525 campaigns.

    The hydrological modelling approach presented in this study will be used to project the evolution of flow intermittence in the river networks under climate change scenarios and provide flow intermittence indices to characterize the spatio-temporal dynamics of drying in the DRNs in the present and future periods. These indices will then be used to study the impact of drying on the freshwater ecosystems. One of the challenges will therefore be to analyse the hybrid model's ability to extrapolate the

530 flow state of river sections in a future climate. In particular, it will be necessary to analyse the model's ability to simulate changes in flow regime (for example, the transition from perennial to intermittent flow) outside its training period.

Code and data availability. The calibrated JAMS-J2000 hydrological models for the 3 study catchments, the R scripts used to predict flow intermittence with a Random Forest algorithm, as well as the observed flow state data used in this study an be obtained from the corresponding author upon request.

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