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Drought hazard and annual precipitation predicted to increase in the Sirppujoki river basin, Finland

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HIGHLIGHTS

- Significant increase in agricultural drought hazard is predicted in 2040–2069 in South-West Finland.
- Agricultural drought hazard in growing seasons increase, despite rising annual precipitation.
- Multiple drought indices are essential in drought risk analysis involving climate change.
- Drought indices can assist local drought management, but local knowledge is required.

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ABSTRACT

Droughts pose a critical global risk that affect vast land areas and threaten almost all nations. Yet the impacts of droughts are most concretely felt at the local scale. Here, we assess drought indices in a Finnish basin with limited observations under current and future climate conditions in order to support local drought management. Long time series are needed for deriving drought indices, yet the available data is often a constraint. To increase the sample size available for analysis, we generated a thousand years of weather data with a stochastic weather generator based on observations and Regional Climate Model (RCM) data. The generated meteorological variables were fed into a hydrological model to simulate a large sample of hydrological variables. These large samples of simulated meteorological and hydrological variables were then used to analyse drought events and their characteristics in a past (1990–2019) and a future (2040–2069) time period. The results support the ongoing drought management work being done in South-Western Finland and specifically the Sirppujoki basin. Our results indicate that drought events will most likely become more frequent, especially during the growing season. Such changes would affect particularly the agricultural sector of Finland.

Practical Implications

Drought has major economic, social and environmental implications across sectors, with agriculture being often particularly strongly affected. Addressing the drought risks requires proactive drought management, as it is both cheaper and more effective than reactive mitigation of drought impacts. Given the increasing impacts of climate change, drought management should also consider the estimated future drought conditions with the help of e.g. drought indices. While this all would preferably build on extensive long-term time series, such data is rarely available: this emphasises the importance of generated (weather) data and modelling activities in drought management.

Our study focuses on understanding the future drought risk under climate change in a small Finnish river basin called Sirppujoki. It is also the national pilot area for developing the country's first-ever Drought Management Plan (DMP) at a river basin scale, for which our study directly contributed to. Our results indicate that drought events are likely to increase in the future even in a water-abundant Northern country such as Finland, emphasising the importance of cross-sectoral, basin-focused DMPs.

DMPs establish a general understanding of the drought in a given context, making use of data such as drought indices. While there is a plethora of such indices (GWP and WMO, 2016; Mishra and

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Singh, 2010), the challenge is finding the suitable indices for each context. Robust calculation of drought indices usually require a minimum of 30 years of high-quality data (GWP and WMO, 2016), which is not always available. Hydrological models and generated weather data can provide additional parameters and centuries-long time series, which can improve the performance of the associated drought indices. Generating data for predicted climate scenarios provides possibility for the DMPs to be better suited to the changing climate. This was also evident in our study, where we used large samples of simulated meteorological and hydrological variables to analyse drought events and their characteristics both in a past (1990–2019) and future (2040–2069), using multiple drought indices.

Our results show a significant increase in the amount of future drought events in the study area, despite the rising annual precipitation. Given the increase is particularly apparent in the growing season, the results are cause for concern particularly for the agricultural sector. Our study shows how generating long time series of weather data can help analysis in data scarce regions, although underestimation of low frequencies and uncertainties related to the method need also to be taken into account. This kind of analysis can provide the local planners valuable information about different drought indices as well as climate-related uncertainties.

The study also has broader policy implications particularly for Europe. While the European Union does not have a specific drought directive, the EU Water Framework Directive recommends drought management. Member states are also encouraged to implement drought management strategies and plans (Howarth, 2018). Finland does not currently have any national or local DMPs and there is no legislation demanding such plans. Yet, the major agricultural impacts and economic losses caused by recent droughts have emphasised the importance of proactive drought management – with climate change estimations just amplifying such need.

Data availability

Supplementary Data: "Drought hazard and annual precipitation predicted to increase in the Sirppujoki basin, Finland." https://doi.org/10.24342/d9dc5979-80fc-43e9-941e-0d8b9ac740e7

Introduction

Droughts cause major impacts and affect nationś water, food and energy security (e.g. de Amorim et al., 2018; Jääskeläinen et al., 2018; UNDRR, 2021). Droughts pose a risk even to nations with abundant water resources (Ahopelto et al., 2019). This risk should be managed proactively, as it is cheaper than reactive drought management and mitigates also societal impacts more effectively (e.g. Gerber and Mirzabaev, 2017; Wilhite and Pulwarty, 2017).

Drought risk can be generally understood to consist of three key components recognized by the IPCC risk framework, namely hazard, vulnerability and exposure (IPCC, 2014). This article focuses on drought hazard, which can be defined as the frequency and severity of droughts. Hazard assessments also need to factor in climate change, especially since drought hazard is estimated to increase in most places globally including Europe (e.g. Vogt et al., 2018).

There are several partly overlapping approaches for managing drought risk. A Drought Management Plan (DMP) is one common approach for proactive drought risk management. DMPs can be done at national, regional or local scale and their key elements usually include at least mitigation measures, drought indices, and organizational frameworks (e.g. Benítez Sanz and Schmidt, 2012; GWP CEE, 2015; UNDRR, 2021; Vogt et al., 2018). The drought indices and thresholds are essential for functional DMPs, and there is a plethora of indices to choose from (GWP and WMO, 2016; Mishra and Singh, 2010). The problem is choosing and fitting the right ones for each context.

While preparing the DMPs is typically a public-sector driven process, a diversity of (local) stakeholders should be engaged in both planning and implementing the drought risk management (Logar and van den Bergh, 2013). Communicating the uncertainty of climate variability and climate models for stakeholders is therefore central to the associated risk analyses (Hassan et al., 2014; Semenov et al., 1998).

Since the drought impacts are predominantly sectoral and occur largely at local scale, there is a need to study local and sectoral drought indices. For localized DMPs it would be highly valuable to have data about meteorological and hydrological variables that are linked to the identified sectoral drought risks and impacts. The link between drought indices and drought impacts has been considered a critical question e.g., by Blauhut et al., (2016), Stephan et al. (2021) and Trnka et al. (2018). To obtain robust drought indices, high-quality observational or modelled data are typically needed for 30 years or preferably for a longer period (GWP and WMO, 2016). Precipitation is the most common observation, whilst data for other hydrological and meteorological variables (i.e., soil-moisture, discharge, evapotranspiration, runoff) is scarcer (see e.g. Brunner and Tallaksen, 2019).

Hydrological models and generated weather data can provide additional parameters and long time series, which can improve the performance of the drought indices. Increasing the sample size by generating weather data is a common method in hydrology (Brunner et al., 2021), but drought risk management applications with climate change scenarios have been limited. Calculating and comparing several drought indices and their characteristics from long generated time series from climate scenarios has not to our knowledge been done previously. In addition, drought management plans, indices and climate change estimations for drought at local scale have not been studied previously in Finland.

In this article we address the aforementioned gaps in the following two ways. Firstly, to better understand how best to accommodate the indicator choosing process, we compare, test, and analyse local drought indices for a local DMP that take climate change into account. The indices are calculated by using observations, Regional Climate Model (RCM) simulated variables (for reference period and 2040–69), and hydrological modelling. We hypothesise that by generating long time series of hydrological and meteorological data for current and future climates, we can support local drought management and choose better drought indices for local DMPs compared to using precipitation and temperature observations for just some decades. Secondly, in order to improve the risk assessment, we provide localized drought hazard information for the case study area for the local DMP.

To test our hypothesis we increased the sample size of historical observation data and climate change scenarios significantly. We used a stochastic weather generator (WeaGETS) and hydrological model (Watershed Simulation and Forecasting System, WSFS) to generate a millennium's worth of weather data for our case study area in Finland, including climate scenarios for 2040–2069. Then, we identified drought events and calculated their characteristics utilising five drought indices: SPI (Standardised Precipitation Index), SPEI (Standardised Precipitation and Evaporation Index), SMA (Soil Moisture Anomaly), SRI (Standardised Runoff Index), and SSI (Standardized Streamflow Index). Afterwards, we compare our methods and findings with previous literature and discuss the implications in two ways: methodologically as well as practically in our case study area, in Finland and in Europe.

Study context: Drought risk management in the EU, Finland and Sirppujoki basin

Most of Europe has experienced severe drought events e.g., in 2002–2003 and 2018–2019 (Bakke et al., 2020; Boergens et al., 2020; García-Herrera et al., 2019), and the economic losses due to drought in the European Union (EU) have been estimated to be several billion euros annually (Naumann et al., 2021). As a reaction to drought risk and their growing impacts, the European Commission has taken a number of measures, including establishing the European Drought Observatory, drafting drought guidelines, and conducting studies to support drought management in its member states (GWP CEE, 2015; Vogt et al., 2018).

DMPs form a key approach in proactive drought risk management, and they can be applied in different scales. A local DMP can be used to both complement and implement national drought strategies (UNDRR, 2021). Drought indices are a key element of any functional DMP, since they are often used in assessing the current and future drought risk, early-warning systems, and estimation of the onset, severity, duration, and extent of the drought event. They are also used to trigger emergency drought mitigation measures in different stages of the drought (Steinemann and Cavalcanti, 2006).

To effectively address drought risks with the DMP, the drought risks need to be assessed. A thorough assessment can be a part of the planned mitigation measures, but a preliminary assessment is always needed. The most prevalent risk assessment method with natural hazard and climate change related assessments is the IPCC 2014 risk assessment framework (IPCC, 2014; UNDRR, 2019, 2021). The framework sees the (drought) risk as a combination of hazard, exposure, and vulnerability. The vulnerability and exposure components can be mitigated (e.g. with DMPs and increased resilience) or aggravated by human actions (e.g. clearing more crop fields or letting water-infrastructure deteriorate). Climate change affects the drought hazard component of the framework, making droughts generally more frequent and severe.

Previous studies on the effects of climate change on drought hazards in Finland have reported varying results (Grillakis, 2019; Roudier et al., 2016; Ruosteenoja et al., 2018; Spinoni et al., 2017; Stagge et al., 2017; Veijalainen et al., 2019). Finland has a relatively low drought risk and abundant water resources (Carrão et al., 2016; FAO, 2016). Thus, drought has not been seen as a major problem. However, past drought events of 2002–2003 and 2018 have had a clear impact in Finland (Ahopelto et al., 2019; Silander and Järvinen, 2004) and a need for better drought management has been acknowledged.

Drought risk varies around Finland due to differences in climate, hydrology, watershed properties, agriculture, industry, and population distribution (Ahopelto et al., 2019), yet comprehensive drought risk assessments have not been done. The 2002–2003 drought event in Finland was estimated to cost 100 million euros in direct costs (Silander and Järvinen, 2004), while the 2018–2019 event was estimated at 400 million euros for the agricultural sector alone (YLE, 2018), and lead to 50% lower crop yield of wheat in South-Western Finland (Natural Resources Institute Finland, 2015). The differing impacts were mainly due to the timing of the droughts as the 2002–2003 event started after the summer of 2002 and ended before next summer, whereas the 2018–2019 event started in spring 2018 and was severe at a critical time for crop development (see Fig. 6). In both events several water supply companies had to limit water use and after the 2002–2003 event, many built emergency connections to neighboring water supply companies.

The agricultural and economic impacts from recent droughts have emphasised the importance of drought management, and also the European Commission recommended in the latest Water Framework Directive's (WFD) feedback for Finland to consider DMPs (European Commission, 2019). Hence, a pilot was launched in 2020 to develop a drought management plan for Sirppujoki basin (Ahopelto and Veijalainen, 2020) in South-Western Finland, which had been identified to have elevated drought risk (Ahopelto et al., 2019). The pilot was a part of a larger project funded by the Ministry of Agriculture and Forestry (the ministry responsible for water resources management) and intended to study drought-related climate resilience in South-Western Finland (Ahopelto and Veijalainen, 2020). The project also included development of a drought early warning system and a guide on how to draft local DMPs in Finland.

The Sirppujoki basin was chosen as a test basin for this study since it is the planning area of the first, and at the moment only, local DMP of entire Finland. The planning process for its DMP is still ongoing, and the plan has not yet been implemented. The Sirppujoki basin covers an area of 438 km^2 with a 53 km long river and a few small lakes covering 1.85% of the basin area (Fig. 1). The basin is relatively flat and small without large geographical variations. Thus, observations from a single station can be seen to represent the conditions over the whole basin. The majority of the basin lies within the borders of two municipalities: Uusikaupunki and Laitila. The basin has a lot of agriculture and water intensive industry combined with relatively small aquifers. There is a large coastal reservoir at the end of the basin, which has been formed by enclosing a sea bay. This serves the urban areas of Uusikaupunki and water intensive industries nearby. All these features make the basin a suitable candidate for testing the first DMP of Finland. The IPCC (2014) risk framework was used in the Sirppujoki basin's DMP and is proposed to be used in future DMPs in Finland by the national guidance document for local DMPs.

Methods and data

To analyse different drought indices and the impact of climate change on drought hazard, several steps are needed: these are presented in Fig. 2. Numbers 3.1 to 3.5 in the figure indicate the associated subchapters.

First, we collected the observations (3.1) and RCM data (3.2) for the basin. Then, in section 3.3, we generated 990 years worth of precipitation and temperature data with the WeaGETS weather generator. Generation was based on observations (1980–2019) and daily simulated values from two RCMs for the reference period (1990–2019) and for the future period (2040–2069) with two Representative Concentration Pathways (RCPs) (3.3) (Moss et al., 2010; van Vuuren et al., 2011).

The generated precipitation and temperature data were then used as inputs for the hydrological model Watershed Simulation and Forecasting System (WSFS), developed by the Finnish Environment Institute (3.4) (Vehviläinen and Huttunen, 2001). Finally, we used WSFS to simulate 990 years worth of hydrological variables, and these were used together with the meteorological variables as inputs for the drought index calculation (3.5).

Observation data

The basin had 40 years of good quality daily precipitation (P) data and minimum, maximum and mean temperature (T) data from Laitila weather station from 1980 to 2019 observed by the Finnish Meteorological Institute. The study thus used a single weather station, which limits the ways the results can be generalised for the entire river basin (see also Section 5.3). The observation period for the used weather station is ten years longer than the RCM reference period and climate scenarios: to make the analysis representative, we wanted to use the full available observation data, instead of shortening it to match the other datasets. The precipitation data was corrected for aerodynamic, wetting and evaporation errors (Taskinen and Söderholm, 2016). Missing values were retrieved from the nearest weather stations.

Similar observations were also used from a second location at Siuntionjoki basin, Finland. This was done to compare and validate the results and index behavior in a different basin with different hydrological features. The Siuntionjoki upper basin has more lakes and less agriculture. All index and observation data for Siuntionjoki basin are available in the annex.

Regional climate model (RCM) data

To estimate the climate change impacts, we used temperature and precipitation scenarios from the Euro-Cordex data archive (Jacob et al., 2014), which provides regional climate change projections based on Coupled Model Intercomparison Project 5 models of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC,

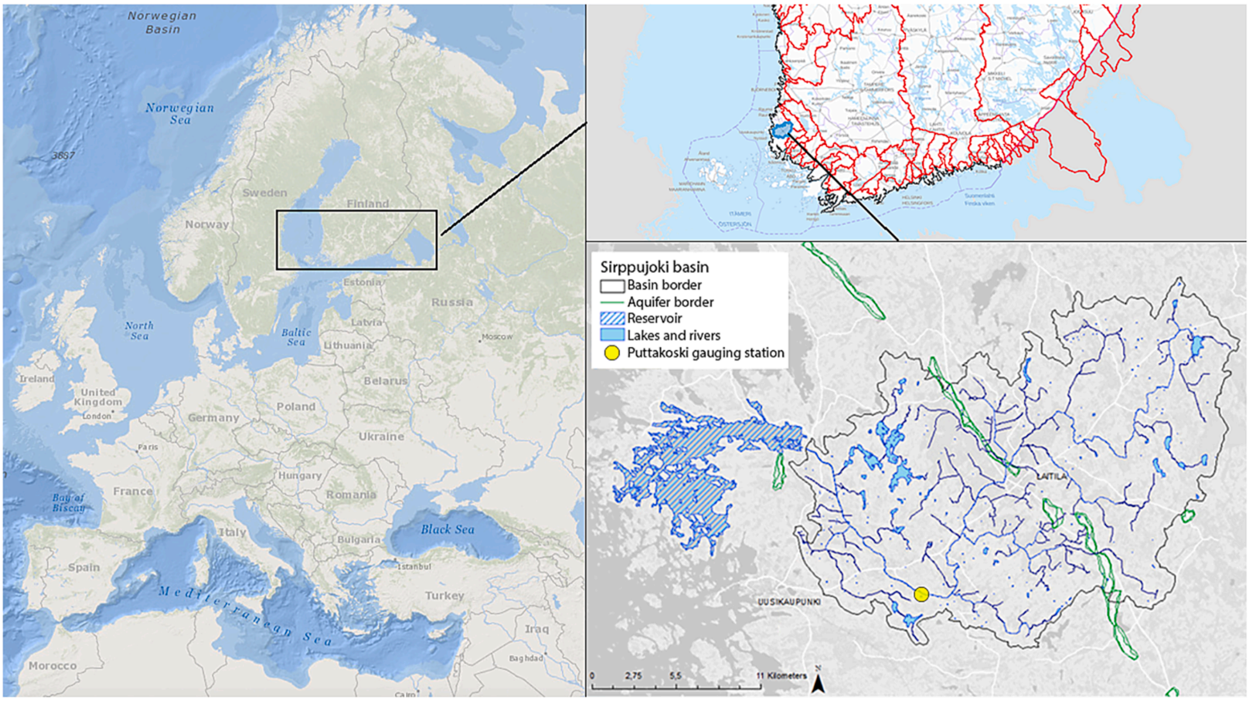

Fig. 1. Sirppujoki basin in South-Western Finland.

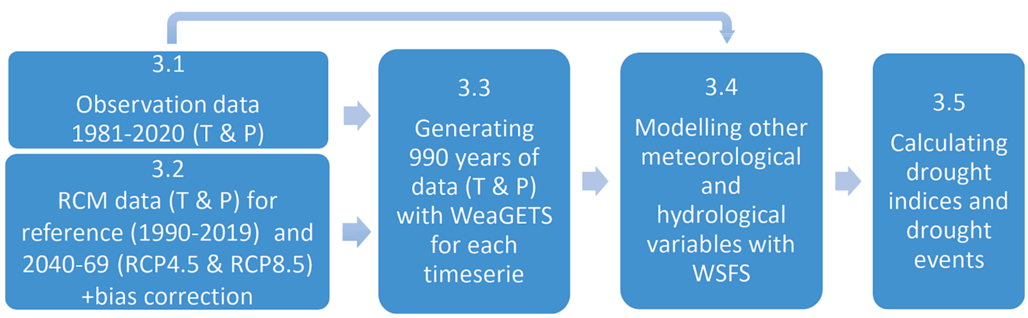

Fig. 2. Steps of the analysis. The number in each box refers to the subsection associated with the step. 'T' refers to temperature data and 'P' to precipitation data.

2014). We used two different global climate models (GCMs) and RCM combinations with two different RCPs: RCP4.5 and RCP8.5. From these combinations we selected data for two periods: 1) the reference period 1990–2019 and 2) years 2040–2069. Thus, for each RCM-GCM combination we get three different datasets: 1) reference 1990–2019, 2) 2040–69 with RCP4.5 and 3) 2040–69 with RCP8.5. The reference period 1990–2019 used historical experiment for 1990–2005 and RCP4.5 simulation for 2006–2019. All three datasets for both RCM-GCM combinations make a total of six individual datasets.

The first RCM-GCM combination was SMHI-RCA4 RCM using MOCH-HadGEM2 GCM as boundary condition (abbreviation Had-S) and the second was KNMI-RACMO22E RCM using EC-EARTH GCM (abbreviation EC-E-K). These were chosen from a larger set of scenarios to enable estimation of model and RCP influence on the results. These two scenarios were selected since their results function relatively well after the bias correction, they are from two different GCMs and RCMs, and produce variable results. A limited number of RCM-GCM combinations was chosen, since it was estimated to be sufficient to test the presented methodology and hypotesis. A larger amount of RCM-GCM would give more insight to the climate change uncertainties, and the full range of possible climate change impacts is therefore larger than presented in this study.

Since there can be significant biases in the RCM data (Christensen et al., 2008; Teutschbein and Seibert, 2012) we applied bias correction to the RCM temperature and precipitation. The daily precipitation and temperature data from the grid cell closest to the test catchments was bias corrected based on quantile–quantile mapping (Seguí et al., 2010; Teutschbein and Seibert, 2012; Veijalainen et al., 2012) using observed values for 1990–2019. In the quantile–quantile mapping method the cumulative density functions of the RCM simulated air temperature and precipitation are corrected to match their observed cumulative density functions during the control period. The same corrections are used also during the future period. The data from the two RCM-GCM combinations for years 1990–2019 provide a reference dataset for the climate change results to be compared against.

The years 2040–2069 were chosen as it was considered to be particularly suitable to aid practical drought management planning, being close enough for current time but still so far ahead that climate change impacts are already more clearly visible. RCPs 4.5 and 8.5 were chosen to support drought management planning, i.e., the preparedness of the society. The RCP4.5 representing the modest mitigation scenario that can be considered likely given current policies (Hausfather and Peters, 2020) and RCP8.5 representing the worst-case scenario.

Data generation

Weather data generation of temperature and precipitation was carried out with the WeaGETS stochastic weather generator using MatLab (Chen, 2021). The generated 990-year datasets represent the stationary climates of 1980–2019 (observations), 1990–2019 (RCM reference period) and 2040–2069 (RCM scenarios) without a trend in the dataset.

This particular generator was chosen because it features a low-frequency correction mechanism for temperature and precipitation, which is essential when estimating low frequency events like severe droughts (Chen and Brissette, 2014). Underestimation of the low probabilities is a well-known problem with weather generators (Chen et al., 2010; Khazaei et al., 2020).

WeaGETS is a parametric distribution-based model where different schemes are used to simulate the precipitation occurrence and amount. A Markov chain-based model is used for simulating precipitation occurrence and probability distributions to simulate daily precipitation amounts. Temperature is generated using a normal distribution and a first-order linear autoregressive model. The seasonal cycles of mean and standard deviation are modelled by finite Fourier series with two harmonics. Tmax and Tmin are conditioned on each other (Chen and Brissette, 2014).

We used a third-order Markov chain to produce precipitation occurrence, and a gamma distribution to generate daily precipitation amounts. A spectral correction approach was used for correcting the underestimation of interannual variability. Parameters of precipitation occurrence and quantity were not smoothed. The low-frequency variability of precipitation and maximum and minimum temperatures were corrected. Fig. 3 illustrates the performance of the weather generator by comparing generated data with the observed data. The frequency distributions of temperature match qualitatively, but there is an underestimation of temperatures near 0 °C in the generated data.

For climate change scenarios and references we used 30 years of daily precipitation (P), maximum temperature (T_{max}) and minimum temperature (T_{min}) as inputs and generated 990 years of daily P, Tmin and Tmax. Period of 990 years were generated due to restriction by WeaGETS for the number of generated years to be a multiple of the observation period (33 times 30 years of observations equals 990 years). These datasets do not experience any climate change during the 990 years and represent the climate of each 30-year period of input data. Similarly, 990 years were generated from 40 years of observation data as control for testing the hypothesis (1000 years were generated, but ten last dropped, to have equal-length time series). Next we calculated daily mean temperature (T_{mean}) from the generated Tmax and Tmin (Dall'Amico and Hornsteiner, 2006) for the WSFS hydrological model.

Hydrological model data

The generated daily P and T_{mean} values were then used as inputs to the WSFS model. The WSFS is a conceptual hydrological model developed and operated by the Finnish Environment Institute, used for operational flood forecasting and research purposes (Vehviläinen and Huttunen, 2001). The system is based on a watershed model, which was originally a HBV-type (Hydrologiska Byråns Vattenbalansavdelning) model (Bergström, 1976) and simulates the hydrological cycle using standard meteorological data. The watersheds are divided into small sub-basins each with their own parameters and water balance simulation. The runoff from different sub-basins is then connected with river routing and lake models. Sirppujoki catchment consist of ten subcatchments with a size varying from 10 to 136 km^2.

The inputs of the model are daily precipitation and mean temperature. In these simulations the potential evaporation is calculated from temperature, precipitation, and time of year, which is used to indicate the amount of available shortwave radiation. The model simulates snow accumulation and melt, soil moisture deficit, evaporation, runoff and discharges, and the water levels of main rivers and lakes.

The watershed model has been calibrated with approximately 40 years of observations of snow depths, water levels, and discharges. The procedure used is the direct search Hooke-Jeeves optimization algorithm (Hooke and Jeeves, 1961), which has been developed into a fully automatic procedure. This procedure minimises the error function weighted for observations of discharge, water level, and snow water equivalent. The weights of each observation in the objective function can be defined individually for the calibrated area to produce the best results with usually the largest weight given to discharge observations. The Nash–Sutcliffe model efficiency coefficient R^2, which can be used to evaluate model performance, was 0.78 for Sirppujoki (at Puttakoski gauging station) during 1981–2010. The performance of the hydrological model is further illustrated in Fig. 4, which presents the simulated and observed discharge at the Puttakoskis gauging station.

With WSFS we simulated 990 years of discharge at Puttakoski gauging station, soil-moisture, evapotranspiration, and runoff data

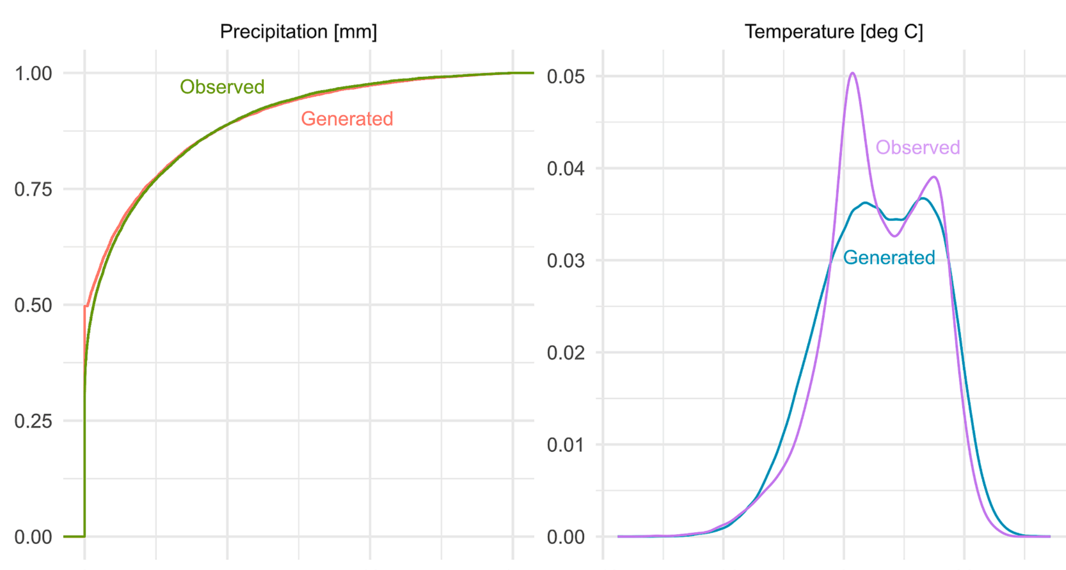

Fig. 3. The cumulative density function for precipitation and probability distribution function for temperature for observed data (1980–2019) from Laitila weather station and generated data (990 years).

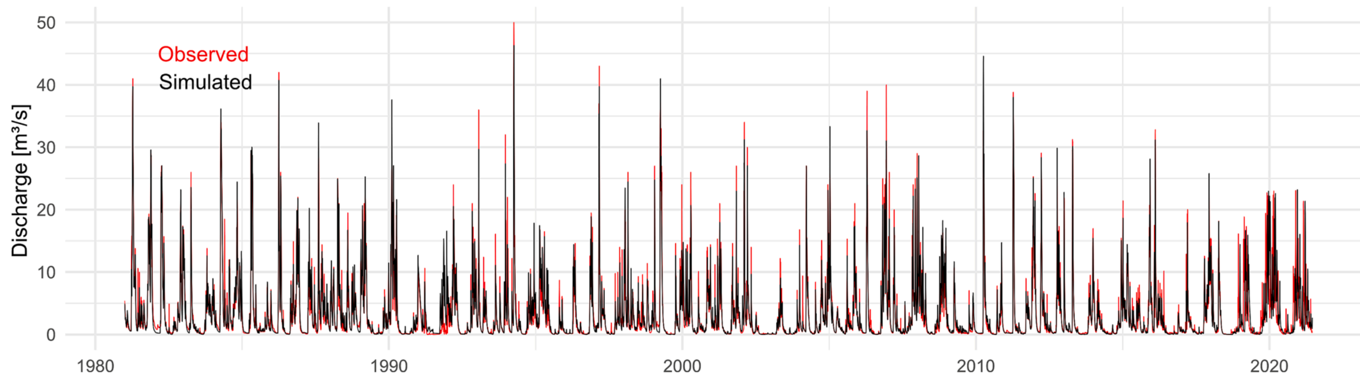

Fig. 4. Observed (red) and simulated (black) daily discharges (m3/s) at the Puttakoski gauging station for 1981–2021. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

based on the T and P data generated by the WeaGETS for the observation period (1980–2019), reference periods (1990–2019), and for climate scenarios (2040–2069).

Drought indices

After generating all the data, we calculated drought indices with the Standardized Precipitation Index (SPI) methodology for all obtained hydrological and meteorological variables. Table 1 shows the five different drought indices computed from the outputs of WeaGETS and WSFS with four different accumulation periods (McKee et al., 1993; Modarres, 2007; Sepulcre-Canto et al., 2012; Shukla and Wood, 2008; Vicente-Serrano et al., 2010). These standardized indices were chosen because they are widely used and are easy to interpret in an operative setting and comparable against each other. The different indicators and accumulations also support partly different sectors, as e.g. agriculture benefits from information on soil moisture and is particularly interested in 1- and 3-month accumulations, whereas ground water dependent sectors benefit from information on longer accumulations. Similar indices are also planned for Finland's national drought early warning system. The same set of indices were calculated for all generated datasets and for observed data for comparison. The indices were calculated using R (R Core Team, 2020) with package *SPEI* (Beguería and Vicente-Serrano, 2017). Several different distribution can be selected in the R-package *SPEI* for the calculation of indices. For SPI, SRI, and SSI accumulations we evaluated that the gamma distribution was the most suitable as is also suggested by Stagge et al. (2015). For SPEI and SMA log-logistic was the most suitable distribution. Evaluations were based on visual examination of the distributions. The reference period of 1990–2019 was used when calculating the standardised index values for years 2040–2069.

Understanding drought frequencies and severities is fundamental for drought management. To analyse the droughts further with the indices, we utilised Run Theory (Yevjevich, 1967), meaning that we identify continuous drought events as so-called runs and characterize them using concepts of duration, intensity, and severity (See Fig. 5). Analyzing drought events with Run Theory provides more insight to drought as a phenomenon, compared for example to analysing monthly index values only and has been used extensively (e.g. Jamro et al., 2019; Ma et al., 2023; Tian and Quiring, 2019).

We identified the drought events and calculated their characteristics (duration, severity, and intensity) using R (R Core Team, 2020). The thresholds for event thresholds are always case-specific and many different thresholds have been used in literature (e.g. Jamro et al. 2019; and Tian and Quiring 2019). Due to Finland being a water-abundant country and to limit the mild droughts from the analysis we set the threshold for drought event initiation to −1.5 of the index value, which is an often used threshold with standardized indices for severe drought (e.g. McKee et al., 1993). The event ending threshold was set to −0.5 which have been used as an threshold for *"normal conditions"* e.g. by Ma et al. (2023) and Ramadas (2014). When detecting a drought event, we allowed one-month of index value above the ending threshold without breaking the event, since it takes more than one month to recover from drought. This is especially relevant for indices with short accumulation since they fluctuate more than indices with long accumulation. We also set a threshold to indicate serious droughts, since they are most relevant for drought management. We defined a severe drought to have a severity of at least −12 (sum of monthly intensities within each event) for the Sirppujoki basin. The relevant thresholds and characteristics are shown in Fig. 5.

Results

Drought index analysis results for 1980–2019

First, we analysed the two most impactful drought events of the observation period 1980–2019: droughts of 2002–2003 and 2018–2019. This was carried out to understand how severe the drought events were according to each index. The propagation of both drought events can be seen in Fig. 6 with some selected indices to illustrate the events (all indices are available in supplementary materials). The drought initiation, duration, and severity by all calculated indices can be seen in Fig. 7.

Table 1
Indices and their accumulation periods chosen for the analysis.

Abbreviation	Full name	Accumulation (months)	Input(s)	Distribution for index calculation	Reference
SPI	Standardized Precipitation Index	1,3,6,12	Precipitation	Gamma	McKee et al., 1993
SPEI	Standardized Precipitation and Evaporation Index	1,3,6,12	Precipitation and potential evapotranspiration	Log-logistic	Vicente-Serrano et al., 2010
SMA	Soil Moisture Anomaly	1,3,6,12	Soil moisture deficit (WSFS calculates one soil layer)	Log-logistic	Sepulcre-Canto et al., 2012
SRI	Standardized Runoff Index	1,3,6,12	Surface runoff	Gamma	Shukla and Wood, 2008
SSI	Standardized Streamflow Index	1,3,6,12	Streamflow	Gamma	Modarres, 2007

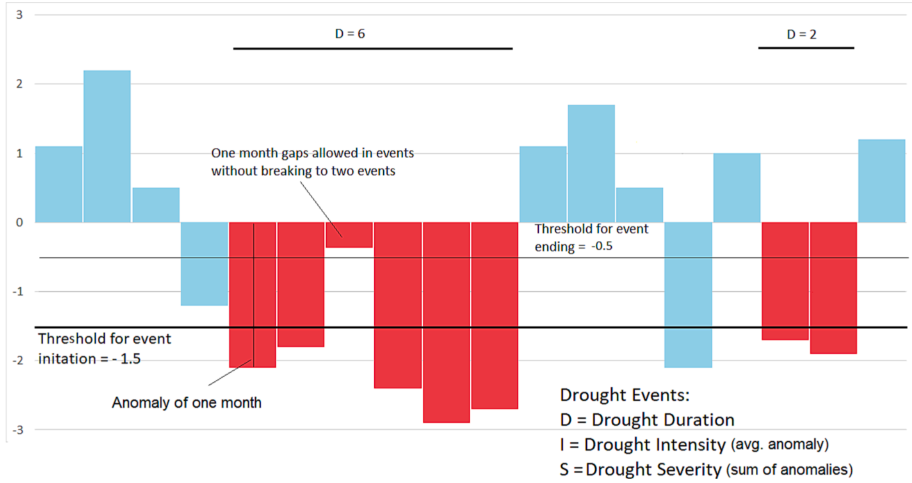

Fig. 5. Explanations how the drought events and their duration, intensity and severity are calculated with the run theory.

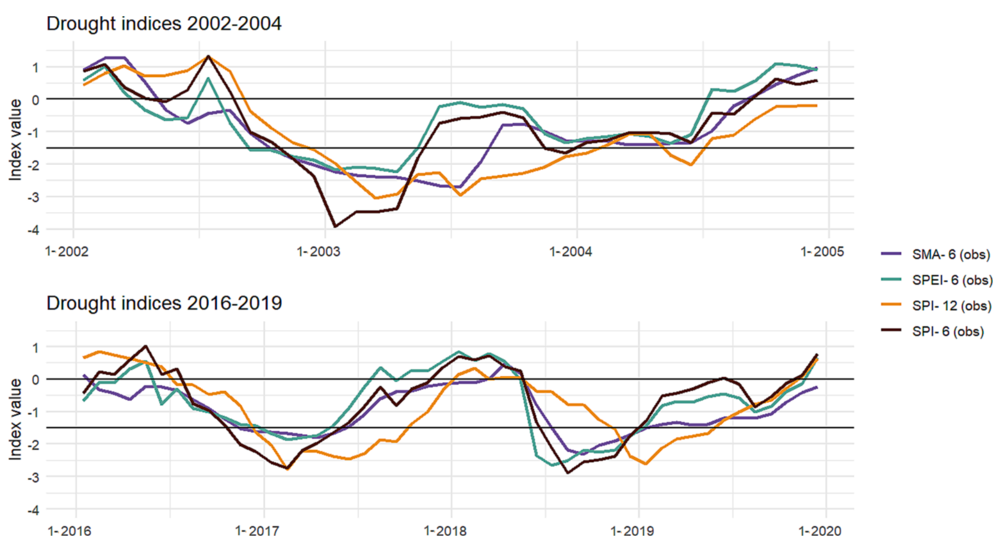

Fig. 6. Droughts of 2002–2003 and 2018–2019 with some selected indices. The lower bolded line presents the drought initiation threshold (-1.5).

The results show that the drought of 2002–2003 was much more severe than 2018–2019. The 2018–2019 drought was preceded with almost equally severe drought in 2016–2017, which was also experienced throughout Europe (García-Herrera et al., 2019), but this did not cause major impacts in Finland. Durations with shorter accumulations (one and three months) were quite similar, but with six- and twelve-month accumulations the durations were longer due to the deeper deficit. We can also observe which indices initiated first, which is important information for drought early warning systems. For the 2002–03 drought the one-month indices started earlier, but for 2018–19 the three-month indices were most often the first to initiate, suggesting that both accumulations should be used for the best results. The drought propagation from meteorological drought, to agricultural drought, and then hydrological drought is also visible, however, due to the small size of the basin, the transition is fast.

Analysing only two drought events provides a limited understanding about droughts in the study region. Applying the same drought indices to the generated 990-year dataset and identifying the drought events and their severity for this extended period (Table 2), provides more insight about the drought risk. The amount of drought events and severe drought events (event severity below −12) give an understanding about the frequency of events over the generated 990 years. A drought event triggered with the chosen threshold (-1.5), which is a common threshold for severe drought (McKee et al., 1993), but does not always proceed to a drought that requires actions (i.e. would not have a clear impact). In this study it was held as the latest limit in Finnish context when a water resources manager or water supply engineer should start to monitor the situation more closely. Roughly 5–20% of the time (depending on the index) the drought event proceeds to a severe drought, which in most cases would require emergency actions.

The shorter the accumulation period, the more events were recorded in the generated time series. This is due to the nature of the indices: shorter accumulation means more fluctuation in the indices. The threshold for severe drought is the same for all indices: −12. This means that the number of severe events is higher with longer accumulation periods, as was expected. In boreal conditions, shorter accumulation periods (one to three months) are generally more useful in drought management context. For example, the agricultural impacts of drought are mainly experienced in summer.

Using a single drought index is typically too limited to satisfy the diverse needs of different sectors affected by drought. At the same time, using too many indices is laborious and potentially also confusing in an operative setting. Thus, it is desirable to choose a comprehensive but limited set of indices that support each other and reflect the needs of the key sectors experiencing drought risk. To facilitate such a process, we analysed the correlations of the three-month accumulations of selected

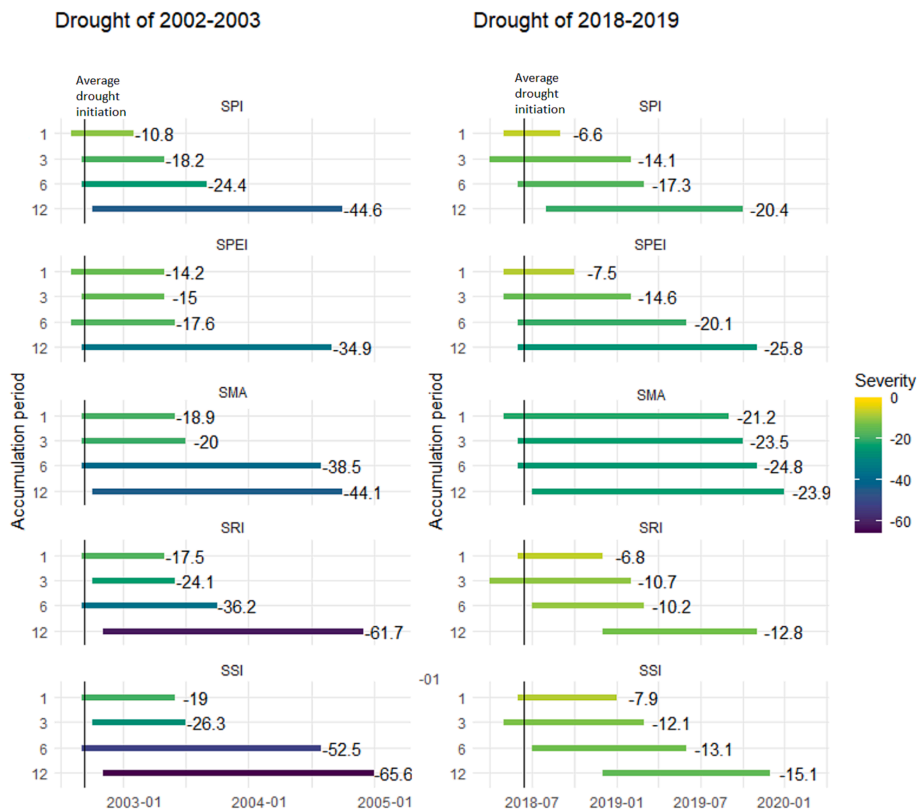

Fig. 7. Observed droughts of 2002–03 and 2018–2019 with their start, duration and severity (as calculated with run theory) according to all five studied indices and their respective accumulation periods (1, 3, 6 and 12 months). The average initiation of the droughts is also presented. Other than T and P values used to calculate the indices are simulated with the hydrological model, not direct observations. The 'average drought imitation' is the average drought initiation month of all the indices.

Table 2
Drought indices with drought characteristics calculated from 990 years of generated data for the reference period 1990–2019, based on 40 years of observations.

Index	Accumulation Months	Drought Events	Severe Droughts	Mean Duration	Mean Severity	Max Duration	Max Severity
SPI	1	709	2	2.3	−3.6	9	−16.5
	3	435	39	4.6	−6.6	17	−25.8
	6	265	80	8.1	−11.2	37	−60.3
	12	151	109	14.9	−20.3	51	−93.6
SPEI	1	602	3	2.5	−3.5	10	−13.7
	3	408	33	4.9	−6.7	17	−22.9
	6	247	83	8.5	−11.4	31	−41.9
	12	142	115	15.7	−21.0	53	−83.3
SMA	1	362	72	5.9	−8.1	20	−28.1
	3	243	97	8.4	−11.6	37	−54.5
	6	163	110	12.3	−16.9	39	−61.5
	12	97	93	22.0	−29.4	70	−92.8
SRI	1	485	4	2.8	−4.0	11	−12.7
	3	429	28	4.2	−6.1	13	−18.5
	6	311	90	6.8	−9.7	23	−40.3
	12	173	118	13.2	−18.4	51	−93.7
SSI	1	414	5	3.2	−4.5	11	−13.3
	3	408	30	4.4	−6.4	16	−25.0
	6	298	92	7.0	−10.0	24	−41.5
	12	176	122	13.0	−18.2	50	−94.6

indices with Pearson correlation. The correlation analysis revealed that SSI and SRI correlate strongly (Table 3). This is expected in a small catchment where streamflow and runoff are close related. Thus, both are not necessarily beneficial to follow in an operative setting. This is also true for SPI and SPEI in the current climate, however, when we examine the climate change results, SPI and SPEI behave differently (Figs. 6 and 7). Indices with low correlation are important to keep in risk analysis and operative plans since they most likely provide independent information about the drought situation.

Table 3
Pearson correlations between different indices calculated from 990-years of generated data based on 1980–2019 observation data.

	SPEI-3	SMA-3	SRI-3	SSI-3
SPI-3	0.95^{***}	0.51^{***}	0.62^{***}	0.58^{***}
SPEI-3		0.56^{***}	0.60^{***}	0.56^{***}
SMA-3			0.56^{***}	0.60^{***}
SRI-3				0.98^{***}

Climate model results for 2040–2069

The use of generated data provides an opportunity to study how climate change may affect droughts, by analysing the projected changes of drought characteristics and numbers of events. Fig. 8 shows the number of events and severe events for the generated 990 year time series in current climate (1990–2019) and in future climate (2040–69) with two different RCP scenarios and two different RCM-GCM combinations, allowing us to estimate how the frequency of drought events and severe drought events is likely to change over time.

The results show that SPI drought events and severity decrease between current climate and the four climate scenarios (Fig. 8). Such a finding is expected, given that climate change is projected to increase future precipitation in Finland (Ruosteenoja et al., 2016) and SPI has also previously been found to perform poorly in drought related climate change analysis (Vicente-Serrano et al., 2010). With SRI and SSI drought events increase (Fig. 8a) but the severe drought events (Fig. 8b) decrease with most scenarios. These changes are likely to be due to the changes in the seasonal rhythm of runoff, snow, and soil moisture. Higher temperatures mean less snow and longer summer periods with higher evaporation leading to drier summer and early autumn periods.

Also noteworthy is the relatively large differences in the different RCM-GCM combination results, especially with the EC-E-K RCP8.5 scenario (orange bars in Fig. 8): these differences are most likely explained by the larger increases in precipitation in the Had-S RCP8.5 scenario compared with the EC-E-K RCP8.5 scenario. This highlights the uncertainty in climate scenarios and the need to use several climate scenarios to project the future impacts of climate change on droughts.

Since drought particularly impacts agriculture, we calculated also how much the drought events are expected to change specifically during the growing season, namely between April and October (Fig. 9). As can be seen from Fig. 9, all studied drought indices except SPI show an increase of future drought events during the growing season, caused by the longer summer season with increased evaporation.

Generated data vs. observations

To test our hypothesis, that generating weather data provides useful information for drought management, we compared the number of events and drought characteristics from the observation period 1980–2019, against 990 years of weather data generated from the distribution characteristics of the observation period (SPEI-1, 3 and 6 presented in Table 4 and more indices in supplementary materials). In theory, a larger sample size should lead to more representative results.

The *annual event frequency* and *annual severe drought frequency* represents the number of events divided by the number of years in the timeseries (40 and 990 years). For all indices, the overall proportion of events is higher for generated data, but lower for severe droughts (except SPEI-6), meaning that the generated data indicate fewer severe droughts. This is expected since weather generators usually underestimate low frequencies. The mean duration and mean severity of events are similar. Maximum duration and maximum severity for one-month accumulation are similar for both datasets, however, the longer accumulation periods for generated maximum duration and maximum severity mostly have higher values than the observed data. The 990 years contain hundreds of drought events compared to the handful of observed ones, some of which are much more severe than in the observed 40-year period.

Discussion

Drought hazard increase despite rising annual precipitation

The analysis provides information about key aspects of drought hazard, namely frequency, maximum and average severity, and duration of drought events for both current and future climate. The predicted increase of annual precipitation in Finland with most climate change scenarios is evident also in the localised results for our study context, the Sirppujoki basin. However, the seasonal nature of runoff in Finland and increases in evapotranspiration mean that hydrological and agricultural droughts may be affected differently than meteorological droughts (Veijalainen et al., 2019). According to our results, the amount of drought events increases with all scenarios in all studied indices with three-month accumulation, except SPI that is purely precipitation driven. Future drought events and severe drought events increase significantly more with SPEI and SMA. The increases in drought events are largely due to the predicted longer growing season, earlier and less spring runoff, increased evapotranspiration (especially during late spring) and projected precipitation increase occurring more during winter season than during summer (see also Fig. 9). In addition to the presented results, additional drought characteristics are presented in supplementary materials (Ahopelto, 2021).

Previous studies related to drought hazard in Europe or Finland provide varying results, with some studies indicating decrease (Spinoni et al., 2017; Stagge et al., 2017), no significant changes in Southern Finland (Roudier et al., 2016), and increasing drought hazard for most of Finland (Grillakis, 2019; Ruosteenoja et al., 2018; Veijalainen et al., 2019). The differences between their results are most likely due to their differing scopes as well as different methods, scales, models and data

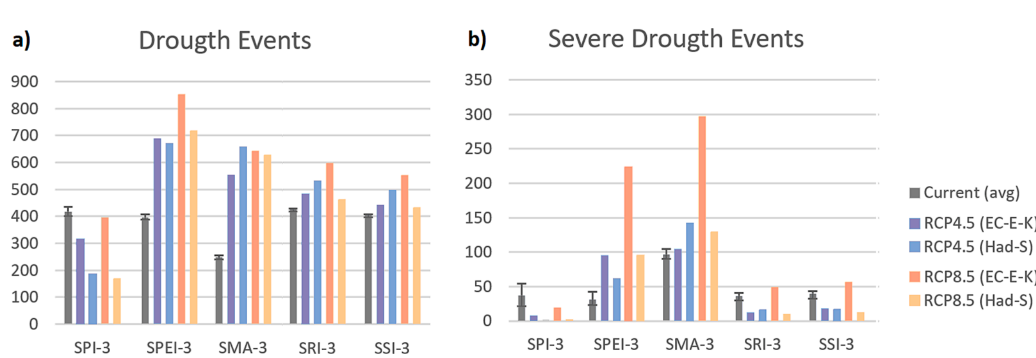

Fig. 8. Number of generated (a) drought events and (b) severe drought events (severity <−12) with all scenarios and three month accumulation. The current climate represent an average value of the two reference periods (1990–2019) and the data generated from observations. The error bar presents both model simulations in the reference period (EC-E-K and Had-S). The climate scenarios represent the period 2040–2069.

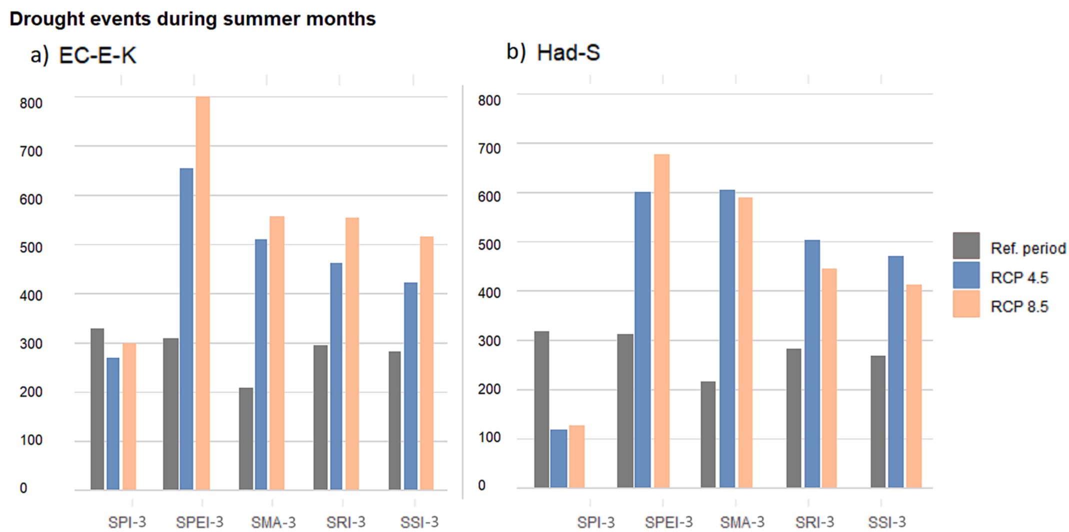

Fig. 9. Drought events during growing season with 3-month accumulation indices (at least one month of the event in April-October) for reference and RCP scenarios for a) EC-E-K and b) Had-S for 2040–2069.

Table 4
Generated and observed drought events and some characteristics for 1980–2019 with SPEI. SirC is the generated 990 years and sirObs40y is the observed data series without any generated data. The annual event frequencies represents the number of events per timeseries length (990/40 years).

Index	Time scale	Scenario	Events	Annual Event Frequency	Ann. Severe Drought Frequency	Mean duration	Mean severity	Max duration	Max severity
SPEI	1	sirC	602	61 %	0.3 %	2.5	−3.5	10	−13.7
		sirObs40y	18	45 %	2.5 %	2.8	−4.0	9	−14.2
SPEI	3	sirC	408	41 %	3.3 %	4.9	−6.7	17	−22.9
		sirObs40y	13	33 %	5.0 %	5.0	−6.9	9	−15.0
SPEI	6	sirC	247	25 %	8.4 %	8.5	−11.4	31	−41.9
		sirObs40y	5	13 %	7.5 %	9.2	−14.0	12	−20.1

used. Projected increases in precipitation would logically mean decreased drought risk, however a longer growing season with higher evapotranspiration acts to increase drought risk in southern and central Finland (Veijalainen et al., 2019). The finding is supported by Trnka et al. (2018) stating that the 'wet-getting-wetter and dry-getting-drier' paradigm is too simplistic and drought-related climate change impacts might be more complex than estimated earlier.

Despite the relatively small size of the basin analysed here, our findings on climate change impacts can be seen potentially relevant for Finland and possibly also Northern Europe more broadly. The soil moisture and SPEI results indicate a significant change in drought hazard during the growing season already by 2040–2069. This is troubling particularly for the agricultural sector, which is already exposed to the largest drought impacts. Agriculture in Finland is mostly rain-fed, with only 1–2% percent of the cultivated area being irrigated (Ahopelto et al., 2019), as most irrigation investments have not been seen as economically viable. However, Peltonen-Sainio et al. (2021) found that in most years irrigation would already be beneficial in early summers. Irrigation mitigates the drought risk effectively, as long as the water source does not run dry. While Finland generally has relatively abundant surface water resources that can provide water even during severe droughts (Peltonen-Sainio et al., 2015), the studied area in South-Western Finland has relatively less surface water resources, making extensive irrigation during droughts difficult.

The increasing agricultural drought risk is therefore something that the agricultural sector in (South-Western) Finland should both prepare for and study more – for example through cross-sectoral DMPs and, more broadly, through the concept of water security (Marttunen et al., 2019). This should also include active local involvement as well as consideration of local knowledge (Steinemann et al., 2015). While the possible implementation of the DMPs in Finland is still to be decided, there are plans for the establishment of so-called drought management groups in selected areas. Such groups would form an administrative body that initiates, monitors, and implements the local DMPs. This group is planned to consist of local stakeholders and officials, who would together have the required know-how to choose the right set of drought indices for their DMP. The results of this study can be used to support the planning of the Sirppujoki basin DMP, including the process of choosing the relevant drought indices for that context. The results can also support Finland's upcoming national Drought Early Warning System, when adjusting thresholds and choosing final indices.

Our study also emphasises the diversity if settings for drought management within Europe. Europe is hydro-climatically very diverse, and future climate change will affect the EU member states differently (e.g. Stagge et al., 2017). While a potential EU drought directive would undoubtedly increase the drought preparedness, it should also acknowledge the differing drought risks and contexts within Europe. While many EU member states have combined the DMPs with the River Basin Management Plans (RBMPs) of the EU Water Framework Directive (Benítez Sanz and Schmidt, 2012; GWP CEE, 2015), this may not always be feasible. This is very much the case in our study area: while the Sirppujoki basin (438 km^2) is the first area in Finland where the DMP process has been initiated, it is almost 200 times smaller than the vast RBMP area that it belongs to (83 360 km^2). Extending the DMP for the entire RBMP area in this context would therefore simply not be viable.

Data generation can help in local drought management in data scarce areas

Our study has three key methodological implications related to: 1) increasing the sample size with data generation, 2) communication of risks and uncertainties and 3) the need for multiple drought indices.

Firstly, the lack of an adequate time series to provide robust estimates for droughts or other hydrometeorological events is a well-known problem. It has been addressed already by Matalas (1967) and more recently from stochastic hydrology and climate change perspective by e.g. Nazemi and Wheater (2015), and considering droughts by Borgomeo et al. (2015) and Herman et al. (2016). Europe and Finland generally have good quality observation records, but globally many places lack long datasets to analyse droughts effectively. Generally, a larger sample size provides more accurate results. However, in this case the larger sample size is based on the distribution characteristics of the original observations. Brunner et al. (2021) mentioned stochastic data generation as a method to increase sample sizes in hydrology, and examples of data generation, and the challenges that it holds, have been presented in a number of studies e.g., by Ilich (2014) and Chen and Zhang (2021). Our combination of a stochastic weather generator combined with a hydrological model presents one optional solution to address challenges presented by Brunner et al. (2021) related to the need for continuous stochastic models. Another option to increase sample size would be to use more climate model chains. This would also provide more insight to the model uncertainties, but would provide less parameters. The best option would be to combine these two methodologies.

Secondly, our results also have implications for the effective communication of risks and uncertainties to decision makers and the public. This is listed as one of the eight golden rules of strategic drought risk management by Sayers et al. (2017). Our data generation methodology provides information about drought characteristics and examples of drought events that the area might experience in a hypothetical 990-year period, which may be easier to communicate to non-experts than statistical information or index values. On the other hand, data generation is known to underestimate low-frequency events (e.g. Chen et al., 2010; Khazaei et al., 2020). Also, uncertainties accumulate with every additional model and methodological step. Hence, the generation of weather data gives the analysis an illusion of statistical certainty, which should be communicated to users and policy makers. The uncertainties can be understood better by using multiple models and indices. Based on this analysis, our hypothesis of data generation helping in local drought risk management can be partly confirmed. The data generation aids in understanding extreme droughts better now and in future climates, but uncertainties accumulate in the process. Using a large ensemble of climate scenarios would also give a better understanding of uncertainties. Also using the RCP4.5 (i.e. modest mitigation scenario) or RCP8.5 (i.e. worst-case) scenarios as the basis of adaptation measures should be communicated and understood by end-users. However, the end-users should mainly focus on the RCP4.5 scenario, as it is the more plausible one.

Thirdly, the variations in the index results in all datasets and accumulation periods make it clear that using just one index is not sufficient for efficient drought risk management. A combination of indices is advisable as has been argued by many earlier studies and sources (e.g. GWP and WMO, 2016; Hao and AghaKouchak, 2013; Rajsekhar et al., 2015). The need for multiple indices is even more evident with the climate change scenarios. The most useful indices can be found with a correlation analysis, avoiding the usage of too many indices in an operative setting. Another option is to combine indices into a combined indicator, e.g. EDO combined drought indicator (Cammalleri et al., 2021). This can be a good solution for an operative setting but can possibly mask relevant information. The balance between usability and complexity is always case specific. Drought indices should also be linked with drought impacts (e.g. Stagge et al., 2017; Trnka et al., 2018). Since the drought impacts are local, it should be easier to link the indices to the impacts on a local level in a local DMP process. If this is repeated in several local DMPs, it can provide the national drought early warning system with the data to develop a working impact driven drought index.

Limitations and uncertainties

There are also some limitations related to our study concerning the study context as well as the data and methods used. Since droughts are not common in Finland, there are only two recent severe drought events with documented impacts from the two past decades. For reference purposes this is not ideal, especially since they were clearly different in severity and seasonal timing. Looking further into the past may not help, as the 1980s and 1990s were generally wet in the whole Northern Europe, and Finland did not experience any droughts with significant impacts.

The simulated 990-year results and climate change scenarios include several uncertainties. The results are simulated using a long chain of connected models including uncertainties in every step. The modeling chain includes the weather generator, the RCM scenarios, the bias correction method, and the hydrological model. A second test basin (Siuntionjoki basin) was used to have a better understanding of the uncertainties: the results from this test basin can be found from supplementary materials (Ahopelto, 2021).

To provide some idea of the uncertainties involved in climate change, we used four climate scenarios with two RCM-GCM combinations and two RCPs, but the full range of combinations available is significantly larger. A more comprehensive understanding of climate change impacts and uncertainties on droughts would require a more detailed analysis using a large ensemble of climate scenarios. The bias correction method used also adds uncertainties, especially the assumption that the same bias corrections of the reference period are still valid in future time periods (Christensen et al., 2008). From our selected scenarios especially the EC-E-K RCP 8.5 seems to stand out more than others, and the results from that scenario should be interpreted with caution.

The weather generator had a fairly short input timeseries (30–40 years). The inputs have significant natural variability which might amplify the impacts through the generator. Especially precipitation have large stochastic natural variations. Thus, it is possible that the results are more a product of natural variability than climate change.

The input data for the weather generator with the EC-E-K RCP 8.5 scenario had 14 drought events with the SPI-3 index, where the others had ten to twelve events. The longest event was also in the same scenario, eleven months. The others had 6 or 7 months. However, the most severe drought was in the scenario EC-E-K RCP 4.5.

The EURO-CORDEX RCM simulations have a systematic tendency to simulate too small summertime warming for the future, and the precipitation projections are excessively wet, compared to the driving global climate models (Boé et al., 2020). Due to the simplified aerosol forcing in the RCMs, it is likely the RCMs and therefore also our results produce too wet future climate. This could potentially lead to drought events becoming more frequent in the future than was estimated here, which should be considered when using the results.

Understanding the low frequency events are essential to analysing droughts (Hanel et al., 2018; Haslinger and Blöschl, 2017). The ability of the weather generator to estimate the frequencies and lengths of the dry periods correctly is one source of uncertainty. As stated previously, data generation is known to underestimate low frequencies (e.g. Chen et al., 2010; Khazaei et al., 2020). WeaGETS was chosen, since it tries to correct this feature, but based on the results and literature (e.g. Ng et al., 2017) some underestimation still occurs.

Data generation with WeaGETS works well for small areas, since the data is generated for one spot. For larger basins precipitation and temperature inputs should be extracted from multiple places that are naturally correlated. Some weather generators allow this, but as such, the method presented here does not support analysis of large basins directly. There should be no theoretical obstacles for the method to be used for large basins, but the complexity of the analysis will increase. However, it should be noted that the study used data from only one weather station and one gauging station due to constraints by the weather generator, which affects the way the results can be generalized to the entire river basin (even when the basin is relatively small and flat). Using just one location, may not characterize the whole basin accurately and generalizations should be done with caution. Further studies with additional data sources and multiple stations or gridded data, such as E-OBS, should therefore be explored to provide a more comprehensive view on the drought in the studied river basin. These studies could include a spatial analysis to quantify the spatial variability of precipitation and temperature in the study area, such as testing how the results change when using data from other nearby stations or when averaging data from multiple stations.

We use a relatively simple conceptual hydrological model, which has a simple model for potential evapotranspiration. These kinds of evaporation models using temperature as input have been shown to overestimate the increase in potential evapotranspiration (Mukherjee et al., 2018) compared to methods which also include other meteorological variables such as radiation, cloudiness, and relative humidity. Droughts are sensitive to changes in evapotranspiration, however, during long droughts the soil moisture will limit the evapotranspiration compared to the potential evapotranspiration significantly.

Conclusions

In this article we analysed drought indices for developing local drought management plans. In addition to observations, we used Regional Climate model (RCM) simulated variables for reference period and 2040–2069. We also used hydrological modelling to get additional data for the current climate and climate scenarios for 2040–2069. We generated 990-years of weather data using a weather generator to supplement the short time-series.

Based on the results, in the Sirppujoki basin in Finland, evapotranspiration sensitive indices showed significant increase in the amount of drought and severe drought events in 2040–2069, despite the rising annual precipitation. These findings are cause for concern, and may have significant repercussions, especially for the agricultural sector. Based on our results, generating a thousand years worth of weather data can assist drought management in data scarce regions, but underestimation of low frequencies and increasing uncertainties limit the usefulness of the method. However, it can provide the local drought management planners with valuable information about different drought indices and uncertainties of climate variability and climate models, hence improving the associated risk analyses and drought impact mitigation measures.

CRediT authorship contribution statement

Lauri Ahopelto: Conceptualization, Methodology, Visualization, Data curation, Formal analysis, Software, Writing - original draft, Writing - review & editing. **Marko Kallio:** Methodology, Visualization, Software, Writing - review & editing. **Noora Veijalainen:** Methodology, Data curation, Writing - review & editing. **Roope Kouki:** Software. **Marko Keskinen:** Funding acquisition, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Supplementary Data: "Drought hazard and annual precipitation predicted to increase in the Sirppujoki basin, Finland." https://doi.org/10.24342/d9dc5979-80fc-43e9-941e-0d8b9ac740e7

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Supplementary materials

Supplementary materials are available at Aalto University's research portal (Ahopelto, 2021).

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