Development and testing of climate service DroogteNL

Rainfall radar for soil moisture forecasts in the Netherlands

REPORT 225

CLIENT **Provinces of Gelderland and Overijssel, Regio Twente**

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DATE **June 2021**

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A case study within the "Daring Applications & Innovations in Sensor Systems" (DAISY2) project

FutureWater Report 225

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Summary

In this report, the methodology behind the DroogteNL product is presented and tested, which uses rain radar as a key input. This service provides operational soil moisture forecasts on high resolution for the entire Netherlands. This development was partially financed by the “Daring Applications & Innovations in Sensor Systems” (DAISY2) project.

To test the methodology behind the service, relative soil moisture short-term forecasts initialized with bias-corrected radar-based were compared with station-based rainfall derived initial conditions. This quality analysis has taken place during a summer period when soil moisture patterns are more variable and relevant to end-users (July to September 2019).

Main results point out to a significant difference for all considered lead times (1 to 6 days) on average between the radar vs the station-based setup over the entire Netherlands. As rain-radar patterns are of higher quality than station-based rainfall patterns, this shows that there is an added value of using rainfall radar inputs to produce soil moisture forecasts.

The analysis also investigates these differences based on land use type and lead time extent and found a significant difference of about 20% for all considered lead times over agricultural areas occupying 20% of the entire surface of the Netherlands. Especially in agricultural areas, soil moisture forecasts can be of relevance to mitigate drought impacts. The report further presents the DroogteNL service and some examples of the outputs.

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1 Introduction

1.1 Introduction and background information

Radar sensors have a strong increasing influence on society (Andrejevic and Burdon 2015). Such detection systems come in all shapes and sizes and are used in a wide range of applications in the field of management and safety (i.e. coastal and port surveillance, protection of critical infrastructure, predicting and monitoring of precipitation events and measuring changes in water flows). The use and further development of such sensors is of high importance to Dutch society today as they allow to reinforce adaptation schemes against large societal and economic impacts associated with hazard risk.

In the field of water management, having the correct quantitative hydrological information at a given time and location is crucial to guarantee safety and resilience. Good soil-moisture estimates at key moments such as in the 2018 drought that occurred over Europe provides concerned end-users (i.e. farmers, irrigators and decision-makers) with the possibility to adapt to extreme weather conditions (Hirschi et al. 2011). Operationally, this can guide them to optimize their irrigation planning in time and/or inform water boards on best timely strategies to adopt.

The current state of warning systems is based on the use of models that simulate the hydrological processes at the watershed scale. As our ability to model the hydrological system in its complexity has improved, uncertainties throughout the modeling chain remain a limiting component for accurate outputs. These uncertainties stem from errors in model structure, or uncertainties in model inputs: forcing data, model parameters, and initial conditions (Gupta et al. 2012). Forecast skill is limited by our knowledge of initial conditions, this is especially true for short lead times (up to one month) where initial conditions are considered to be the principle source of error in the forecast (Li et al. 2009).

1.2 Main objective

For hydrological forecasting, good data on initial conditions of the system are critical. These initial conditions mainly refer to the land surface state, which are related to water storage components of the system: soil moisture and snow cover. Unfortunately, exact initial conditions can never be known because of lack of accurate, complete description of the land surface state (Gupta et al. 2012). The latter are often obtained by forcing a hydrological model with our best estimates of forcing conditions (i.e. temperature and precipitation). In relation to precipitation, frequent use is made of the rainfall stations, e.g. the network of KNMI precipitation stations for the Netherlands, although these are point measurements and do not offer a full plane-covering precipitation image. An alternative is the use of radar sensors that do offer a seamless record of precipitation for The Netherlands.

Within the Daisy2 project, FutureWater investigates the applicability and potential of radar data to provide improved initial conditions needed for hydrological simulation. These improved inputs are included in the climate service DroogteNL. Users of this service, like for example Dutch Water Authorities, need to be served with high-quality and high-resolution soil moisture forecasts, for early warning, ex-post drought impact assessments, and drought management plans.

To test the methods and rainfall inputs used in the drought early warning climate service, two setups of the system are compared which provide 6-day soil moisture forecast at a spatial resolution of 250 x 250 meters for the whole of the Netherlands. One setup is initialized with bias-corrected radar precipitation derived data while the other with a best estimate derived from a network of 51 KNMI precipitation stations (See Figure 1 for an overview over the adopted simulation scheme). Although a larger network of stations is made available by the KNMI database, we limit the study to 51 stations as these are regularly checked for consistency and quality by the KNMI[1]. The other setup uses the rainfall radar product provided by KNMI. The testing takes place over a period in which drought assessment are especially relevant (summer period 2019 going from July to September). The analysis compares forecast output made with those two systems over the different lead times and will pay close attention to the difference in output among the different identified land use types. The comparison of these two systems provides insight into the added value of high-resolution precipitation radar for soil moisture early warning systems in The Netherlands.

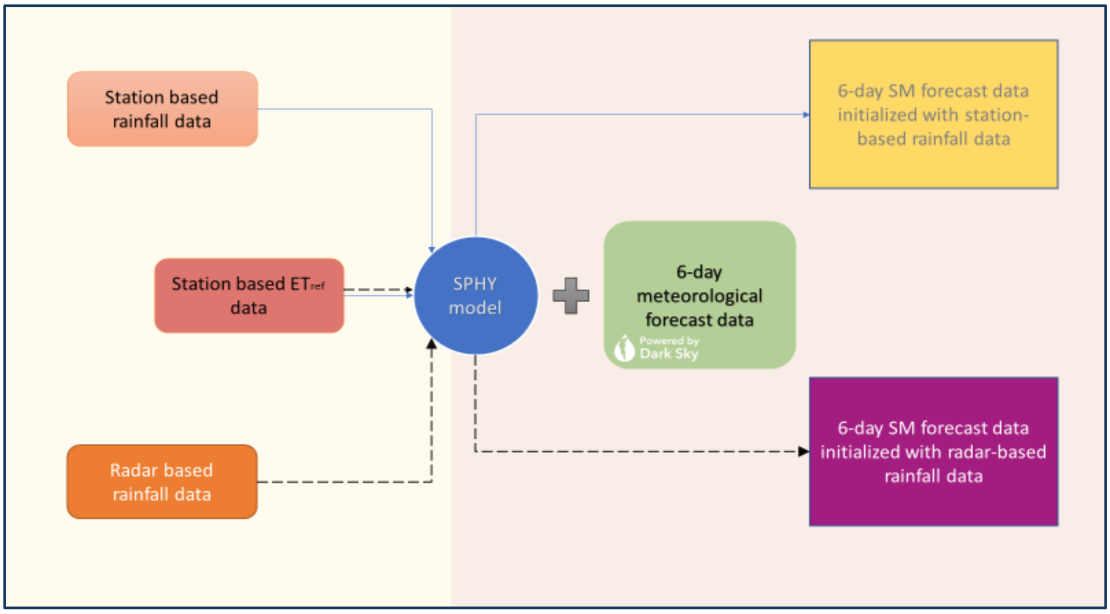

Figure 1: Overview of the adopted simulation scheme for this report

[1] [Daggegevens van het weer in Nederland]. Retrieved on August 20th, 2019, from https://www.knmi.nl/nederland-nu/klimatologie/daggegevens

2 Data and Methods

2.1 Soil Moisture and the SPHY model

Previous research has shown soil moisture levels to be strongly associated with summer hot extremes in Europe (Hirschi et al. 2011). In consequence, skillful soil moisture forecasts provide increased capacity for climate change adaptation measures against potential damaging drought conditions. In order to investigate the added value of high - resolution precipitation radar for soil moisture forecasts, the Spatial Processes in Hydrology (SPHY) model (Terink et al. 2015) is used. Absolute soil moisture values are expressed as relative soil moisture values fluctuating between (0 and 1) where -0- represents permanent wilting point conditions and -1- a saturated soil. The latter has been done in order to facilitate the comparison between pixels as each differ from the other in terms of storage capacity, root depth and soil properties.

The SPHY model is a model developed by FutureWater able to simulate soil moisture in the root zone. A detailed description of SPHY (See Figure 2 for model schematization) can be found in (Terink et al. 2015).The SPHY model for the Netherlands was calibrated and validated against measured soil moisture (Terink et al. 2015). This calibrated version of SPHY has also been used for this study.

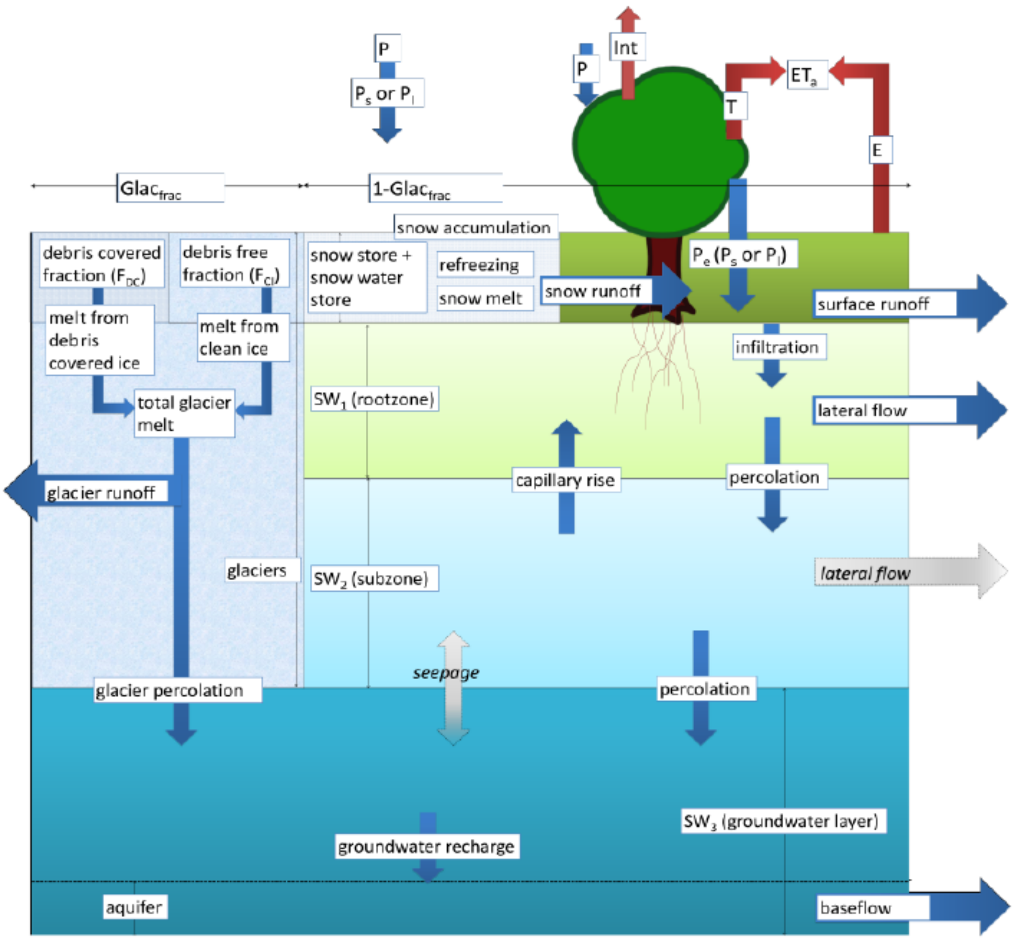

Figure 2: SPHY model schematization

2.2 Model input

2.2.1 Static model input

To simulate soil moisture in the root zone, the SPHY model requires both static and dynamic model input. Physical soil and land use data fall under the static model input. A soil map is needed to determine the following soil properties:

- Field capacity;
- Saturated volume;
- Wilting point;
- Permanent wilting point;
- Saturated permeability (k value).

A land use map is primarily needed to determine the root depth and crop factor, and therefore the potential and current evaporation. A detailed description of the static SPHY model input can be found in (Terink et al. 2015; Terink, Immerzeel, and Droogers 2013).

2.2.2 Dynamic model input

<u>Station based precipitation and ETref data</u>

For a correct simulation of soil moisture, it is essential that the meteorological input is adequate. This applies to both the precipitation and the reference evapotranspiration ET_{ref}. Partly because approximately 70% of the precipitation that falls in the Netherlands evaporates, it is important that both meteorological fluxes are of high accuracy. ET_{ref} and rainfall are obtained from the KNMI data center based on a network of 51 stations (see Figure 3) located around the country where ET_{ref} is calculated according to the Makkink method (Cristea, Kampf, and Burges 2013). Because this data is measured per location, and is therefore not seamless, the data must be spatially interpolated. Here we make use of the 'Automap' package (Hiemstra et al. 2009) available for the R programming language. This package contains the 'autoKrige' function that automatically fits the best variogram and then uses Kriging interpolation. The same method has been applied by (Soenario and Sluiter 2010) for the spatial interpolation of KNMI precipitation data.

Figure 3: Location of the 51 KNMI stations considered for the study

Radar data

Gridded files of radar-derived 24-hour precipitation accumulations are obtained from the KNMI data center. Radar reflectivity is measured by both radars (De Bilt at 52.1017 N, 5.1783 E and Den Helder at 52.9533 N, 4.7900 E) in scans with elevation angles of 0.3, 1.1, 2.0, and 3.0 degrees. These scans are used to generate a single image per radar at 1500 m by linearly interpolating radar reflectivity in altitude. Radar reflectivity is then converted to rainfall intensities by using the Z=200R^1.6 formula, and these rainfall intensities are accumulated to 24-hour sums. The entire rainfall product is then corrected using the KNMI network of manual gauges. This step is crucial to overcome well documented sources of error associated with radar weather data (Hazenberg, Leijnse, and Uijlenhoet 2011).

Forecast data

A 6-day precipitation and temperature forecast dataset is obtained from the Dark Sky API [Data Sources]. Retrieved on August 20th, 2019, from https://darksky.net/dev/docs/sources. This global dataset is backed by a wide range of weather data sources out of which we highlight the EUMETNET's Meteo-alarm weather alerting system for EU countries. These datapoints have been extracted for the same locations marked by the network of 51 stations used to obtain the station-based precipitation and Et_{ref} data. Similarly, the data is spatially interpolated using the 'autoKrige' function. Potential evapotranspiration is calculated according to the modified Hargreaves method (Farmer et al. 2011).

2.3 Evaluation criteria

The effect of having different initial conditions over the forecasting system has been assessed by comparing the difference in relative soil moisture outputs over the different lead times considered (1 to 6 days). In addition, we consider the difference over different land use types identified according to the National Land Use File for the Netherlands (LGN-6, see Figure 4) (Hazeu et al. 2012). The LGN file is a raster file for the Netherlands, which shows 39 forms of land use. Since 1986, this file has been updated with a frequency of 3-5 years. This land use map has been expanded with the LGN crop database in which 7 crops are distinguished: grass, maize, potatoes, beets, grains, other crops and flower bulbs (Hazeu et al. 2012).

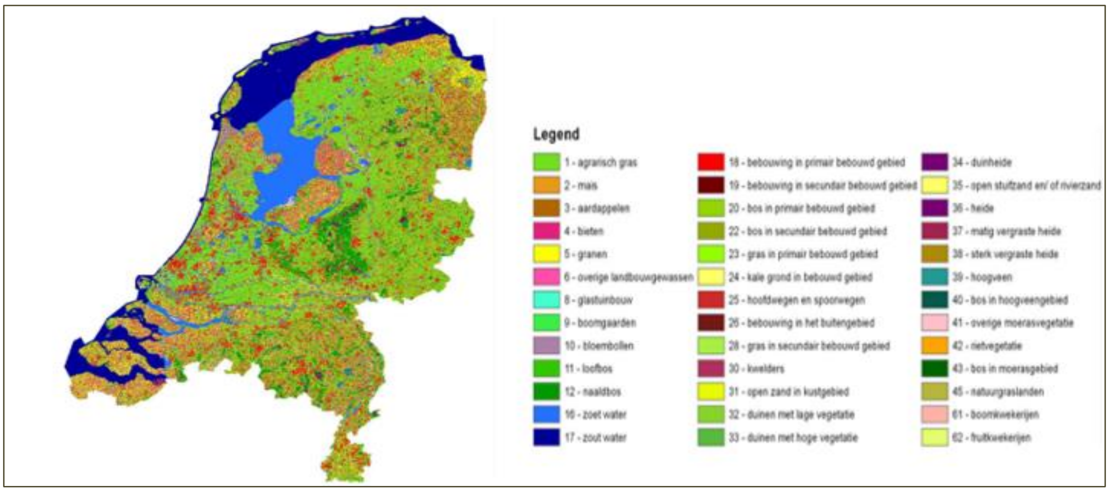

Figure 4:Land use map and legend taken from the LGN-6 report (Hazeu et al. 2012)

Statistical significance of the difference between the two simulation branches is computed using an unpaired two-samples, two-sided Wilcoxon test with p-value set to be strictly smaller than 0.05. In order to quantify the extent of the difference between the two simulations, we calculate the "percentage difference value" where the percentage difference equals the absolute value of the change in value, divided by the average of the 2 numbers, all multiplied by 100 (see equation 1).

$$\text{Percentage difference} = \frac{\left| V_1 - V_2 \right|}{\left[\frac{(V_1 + V_2)}{2} \right]} \times 100 \qquad (1)$$

3 Testing Results

3.1 Historic difference between radar and station-based rainfall data and consequent differences for relative soil moisture values

To gain insight into the differences between radar and station-based rainfall over the Netherlands, we plot an example in Figure 5 of gridded rainfall and consequent relative soil moisture values recorded and simulated on the 31st of July 2019.

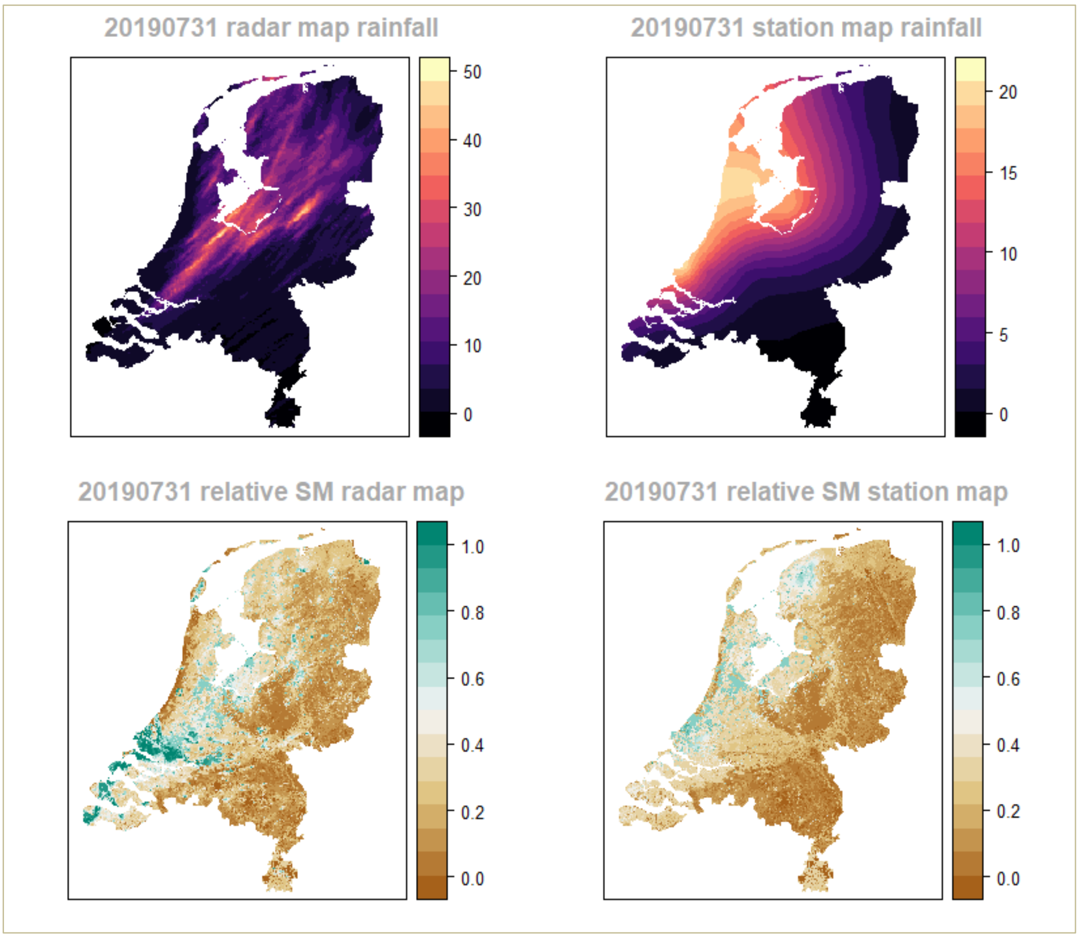

Figure 5:Gridded rainfall (mm/d) and relative soil moisture values for the 31st of July 2019

The rainfall map following station-based data interpolation shows higher regularity in rainfall pattern compared to the radar product in addition to lower intensities in millimeter per day values. Similarly, soil moisture maps reflect higher relative soil moisture levels when forced with radar-based rainfall; in addition to a slight difference in the spatial pattern.

Figure 6 shows the difference between the two relative soil moisture distributions for historic runs over a period of 2 months. Significant difference has been established with a (Wilcoxon test | p-value < 0.05) confirming higher levels of soil moisture values on average over all the Netherlands when considering the radar-based rainfall product. Whether these differences persist or not when using radar versus station-based forcing to initialize an early warning system is key to understand the value of radar data unto short-term soil moisture forecasting.

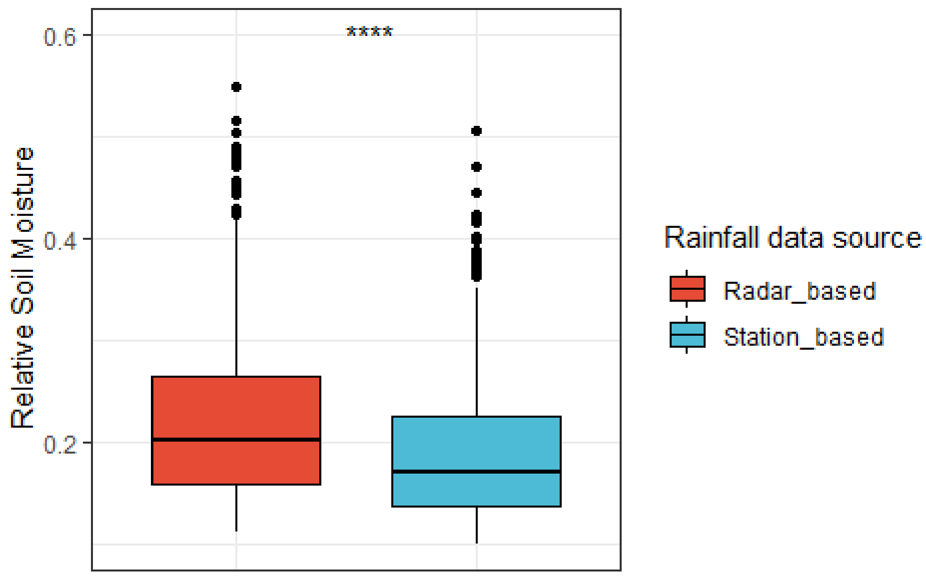

Figure 6: Relative soil moisture distriburtions for the historic run (July – September 2019). (*: p < 0.05,: p < 0.01, ***: p < 0.001, ****: p < 0.0001)**

3.2 Differences between short term soil moisture forecasts initialized with radar vs station-based forcing data

For simulating a short-term soil moisture forecast, we rely on a similar meteorological forecast input for the two simulation setups. The only difference resides in the initial conditions, and in consequence, the difference between the two simulation branches is expected to decrease in time until a point when the two simulation outputs become similar. Figure 7 plots the percentage difference between the two simulation branches over the 6 different lead times. On average, the percentage difference drops from 13% to 9% over the 6 days considered and from 15% to 13% after one day of simulation (Comparing Historic to lead time 1).

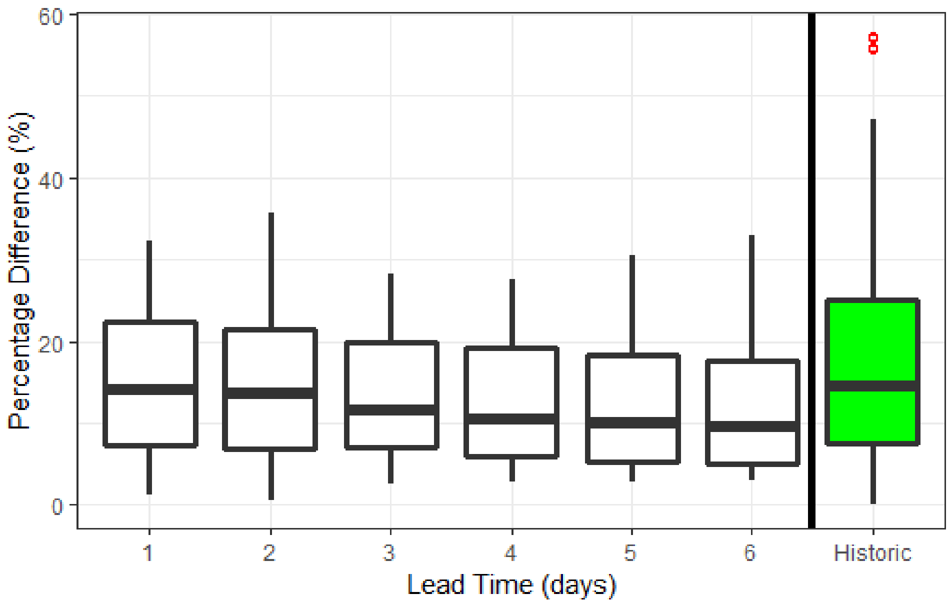

Figure 7: Percentage difference in soil moisture between radar and station based over the 6 different lead times and over historic conditions

Figure 8 similarly to Figure 7, plots the two relative soil moisture distributions although considered for the forecast output over the different lead times. Significant difference between the means is found for all lead times when considering a Wilcoxon test with p-value set to 0.05.

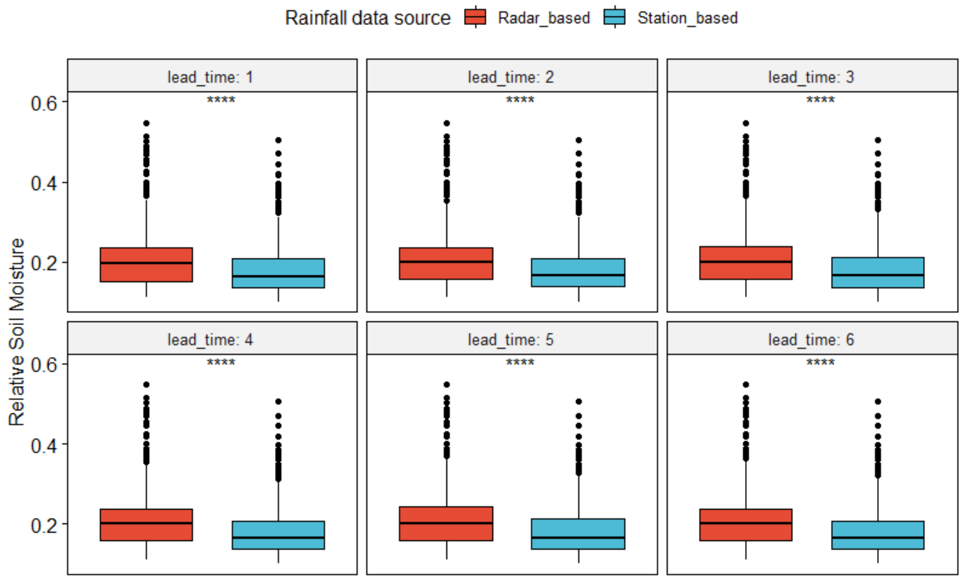

Figure 8: Relative soil moisture distriburtions for the forecast output over the different lead times considering an average over all the Netherlands. (*: p < 0.05,: p < 0.01, ***: p < 0.001, ****: p < 0.0001)**

3.3 Differences between short term soil moisture forecasts for different land use types

Difference between radar based and station-based soil moisture forecast output has different value over different land use types. Comparing differences as spatial mean over the whole country might lead to averaging out some local differences with potential high socio-economic value. For that reason, we investigate the differences in output for the two systems using the LGN-6 map (See Figure 4) which identifies 39 forms of land uses for The Netherlands. Difference between the two relative soil moisture distributions has been tested for all lead times and land use types considered in this report using a Wilcoxon test with p-value set to 0.05.

Figure 9 shows the percentage difference between the two setups for the different land use types for which significant difference has been found for all considered lead times. A percentage difference of around 20% on average for most agricultural land use types is noted at lead time 1 and drops to around 17% at lead time 6. We highlight a particular large difference for “nature” identified land use forms where a percentage difference of around 70% for ID-33 at lead time 1 goes to 40% at lead time 6.

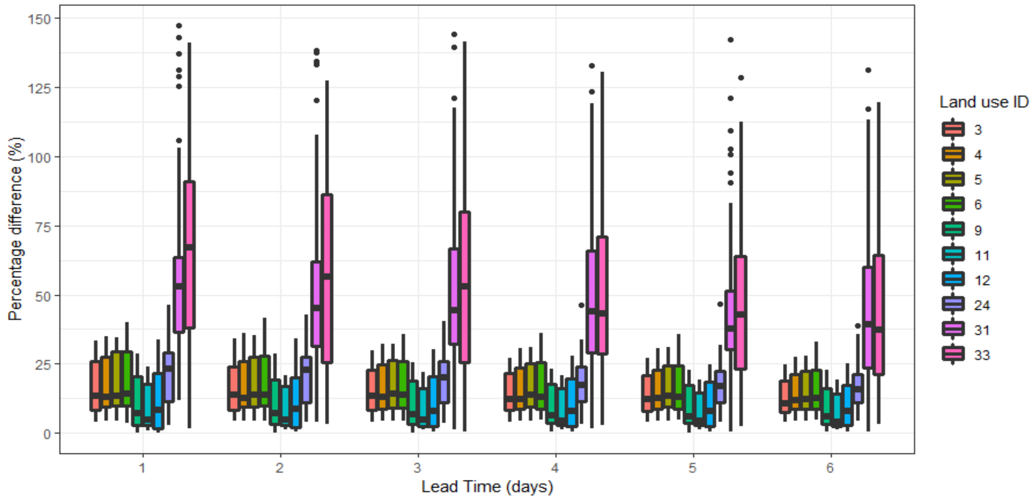

Figure 9: Percentage difference between radar and station-based simulations for the different land use types and lead times considered. Plotting are only land use types where significance (Wilcoxon test| p-value < 0.05) was found across all lead times.

Table 1 provides a summarized legend of land use IDs over which significant difference was found for all lead times between radar based and station based short-term forecast. The orange color groups agricultural land use forms, green groups forest types, grey for built up area and brown for nature. For a complete table representing portion (%) of each land use ID, see Appendix 2. In line with previous sections, Figure 10 plots the two relative soil moisture distributions over the different identified land use types where significant differences are noted over all considered lead times.

Table 1: Table summarizing the legend for the IDs plotted in Figure 9- Percentage column refer to the portion of Land occupied by this land use compared to the total surface area of the Netherlands (The orange color groups agricultural land use forms, Green groups forest types, Grey for built up area and Brown for nature). Source: (Hazeu et al. 2012)

ID	Legend	%		ID	Legend	%
3	Potatoes	5.3		11	Deciduous forest	4.0
4	Beets	3.3		12	Coniferous forest	5.0
5	Cereals	5.4		24	Bare land in built up area	3.3
6	Other Agri-crops	5.2		31	Open sand in coastal area	0.2
9	Orchards	0.8		33	Dunes with high vegetation	0.4

Figure 10: Relative soil moisture distriburtions for the forecast output over the different lead times and land use IDs considered (*: p < 0.05,: p < 0.01, ***: p < 0.001, ****: p < 0.0001) - Plotted are only land use types where significance (Wilcoxon test| p-value < 0.05) was found across all lead times. [Complete table found in Appendix 1]**

For a complete plot of all distributions with significant and non-significant differences between the distributions, see Appendix 1. The latter highlights cases where differences between radar and station-based simulations have become non-significant throughout the forecast period in addition to land use types where no significant difference was found over all considered lead times.

4 Climate Service Outputs

A very persistent high-pressure system across Northern Europe in the summer of 2018 resulted in an extremely dry summer in the Netherlands and neighboring countries. Precipitation in the months May, June, July and September was extremely low while temperatures between April-September were extremely high, combined with a higher-than-average number of sun hours resulting in very high potential evapotranspiration[1]. In the Netherlands, the most common way to measure drought is to calculate the cumulative potential precipitation deficit, which is the difference between the potential evapotranspiration and the precipitation in the growing season (1 April – 30 September). A precipitation deficit in summer is normal for the Netherlands and is not an issue because normally the winters are wet enough to make up for this deficit.

However, not only the summer of 2018 was extremely dry with a cumulative potential precipitation deficit of over 300 mm in certain areas, the fall and winter of 2018 - 2019 were not wet enough to completely make up for the potential precipitation deficit of 2018. On top of that, the following summer of 2019, was also dry, but more regional differences were eminent (Figure 11).

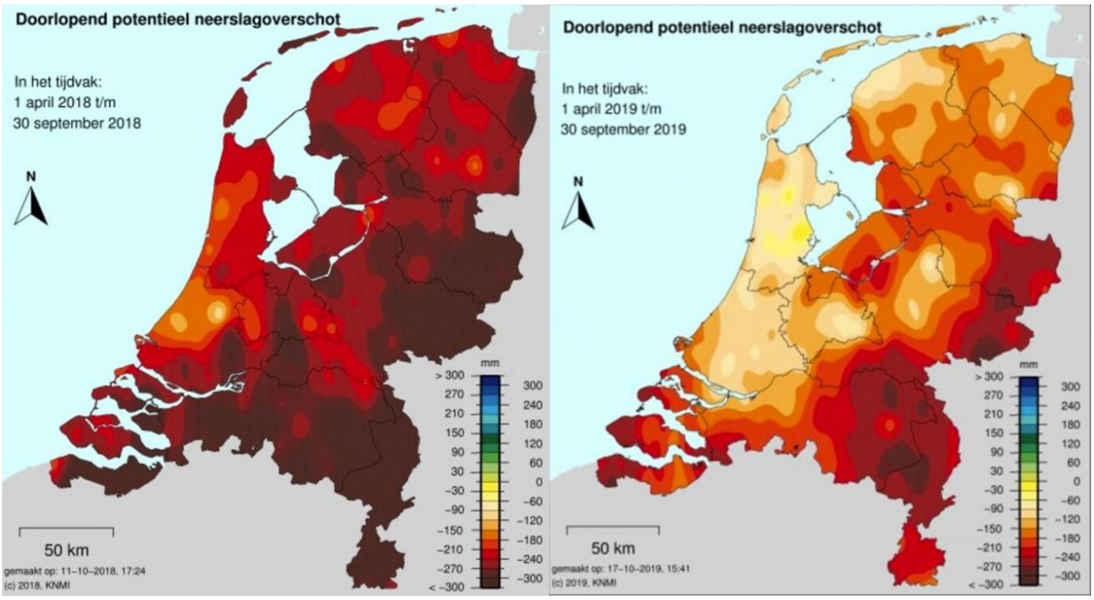

Figure 11 Cumulative potential precipitation deficit in the Netherlands for the growing season (1 April - 30 September) of 2018 (left) and 2019 (right). Source: KNMI.

During the dry summers, yields were greatly reduced because not enough water was available for irrigation and restrictions on water use by different sectors were in place. In times of drought, especially for agriculture and nature reserves, soil moisture becomes more and more relevant since this is the only water available to plants for transpiration when ground water tables are lowering.

Given the interest in and importance of soil moisture during droughts, a platform was developed in which the soil moisture status in the Netherlands can be tracked over time. This platform was named **DroogteNL (https://www.futurewater.nl/droogtenl/)**. It is an online, interactive platform to support decision makers at for example waterboards by providing them with current and historical soil moisture data for their management area.

[1] https://www.knmi.nl/kennis-en-datacentrum/achtergrond/attributie-van-de-droogte-van-2018-in-nederland

The DroogteNL portal contains multiple dropdown menu items on the left where the type of aggregation (waterboard, municipality, provincial or the full country) and the date can be selected. It is also possible to download the soil moisture timeseries by clicking on the "Download .csv" button. An interactive map with average monthly soil moisture values per aggregation unit is visible in the middle and on the right a graph with the timeseries of the actual and the average, 10% driest and 10% wettest soil moisture concentration in a particular month is shown (Figure 12). Soil moisture data in the DroogteNL portal is expressed as a percentage, giving the relative soil moisture content between the permanent wilting point of the soil and the saturated water content of the rootzone. A percentage of 100% means that the soil is completely saturated, while a percentage of 0% means that the water content is at permeant wilting point.

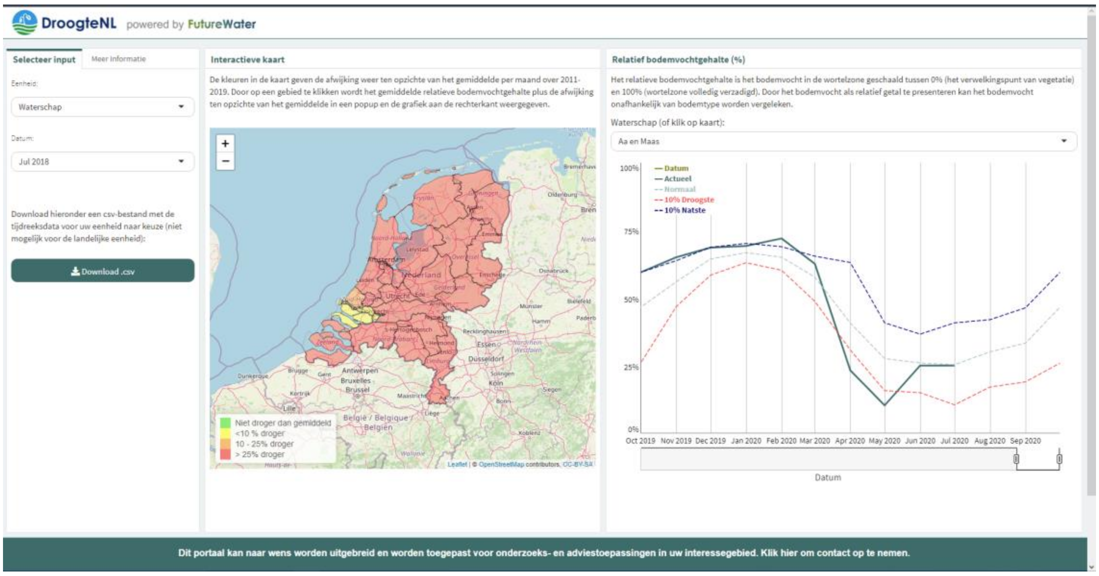

Figure 12 Screenshot of the DroogteNL portal.

The DroogteNL portal was developed using soil moisture data as calculated by the SPHY model that was developed to compare soil moisture estimates using radar-based data with station-based data. The static input and dynamic input data of that model was not changed. The model was run for the period 2011 – July 2020. The soil moisture time series as presented on the right in the portal contain all data for this period (Figure 13).

The data shows the soil moisture in time is increasing and decreasing with the seasons. There is a clear peak in soil moisture content in fall and winter (October – March) while a clear minimum in soil moisture content is visible in spring and summer (April – September). Zooming in to the years of 2018 and 2019 (Figure 14), soil moisture in winter 2017 - 2018 was among the 10% wettest months of the data series, while, given the fact that the summer of 2018 was very dry, soil moisture had decreased during the spring and summer of 2018 to the 10% driest months. The winter of 2018 – 2019 was clearly not among the wettest, because soil moisture was below average and close to the 10% driest observed for the winter months. Because of the relatively dry winter of 2018 - 2019, soil moisture content decreased to below average very early in the growing season (soil moisture content in April 2019 was below average).

This type of analysis can be very useful for decision makers at for example waterboards, because when they have early insight in soil moisture conditions they could act and for example allow farmers to start irrigating early in the season when plenty of surface water is available. This could create a soil moisture buffer for periods when less water is available. However, prolonged periods without rain will quickly decrease soil moisture content because no precipitation in summer is often related to high evapotranspiration.

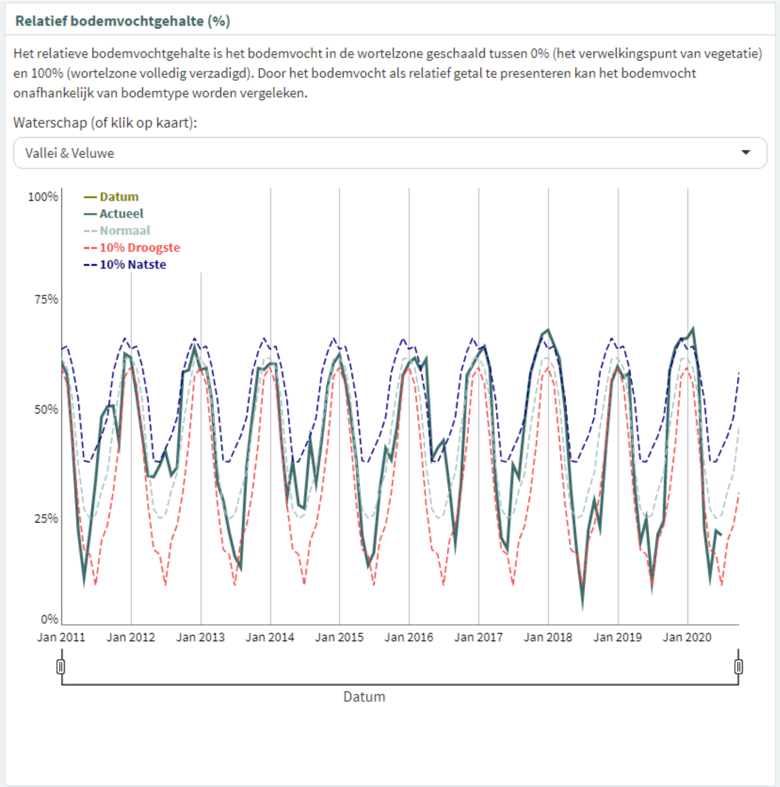

Figure 13 Screenshot of the timeseries (2011 – July 2020) of soil moisture in waterboard Vallei & Veluwe' management area.

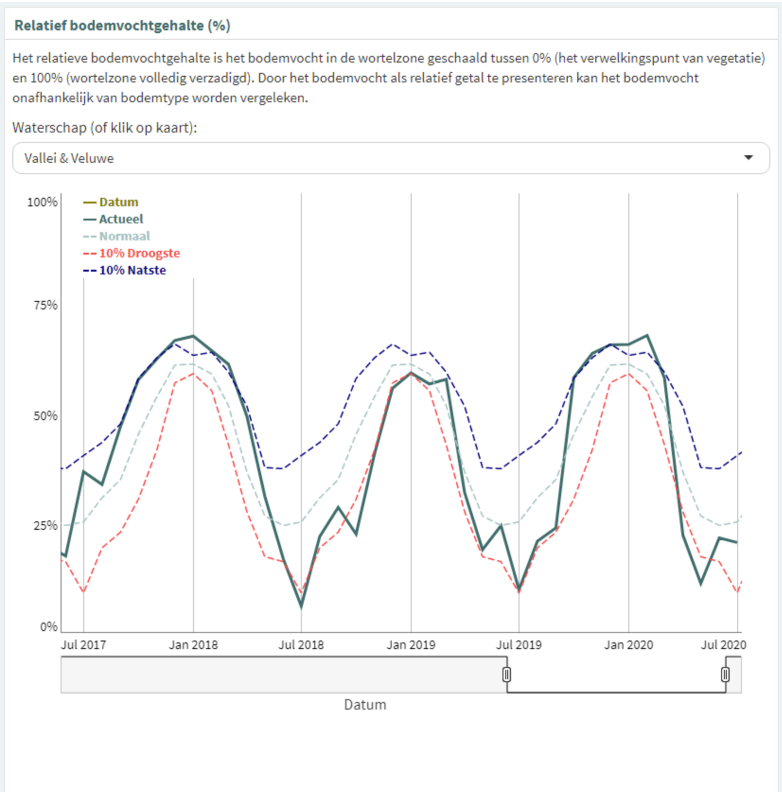

Figure 14 Screenshot of the soil moisture in waterboard Vallei & Veluwe' management area focussing on 2018 and 2019.

The DroogteNL service is currently being used to engage with Dutch water boards for consultancy work related with (i) drought early warning, (ii) ex-post drought impact assessments (iii) drought management plans and drought mitigation actions. User-specific adjustments are foreseen so the soil moisture information can be embedded in the decision-making processes and existing tools of the water boards.

5 Discussion and Conclusion

In this report, we investigated the outputs of two setups of the climate service DroogteNL: one using rainfall radar, and the other based on a rainfall station network, to assess how the initial conditions of the system affect the soil moisture forecasts of one week ahead. Main results point out to a significant difference for all considered lead times on average between the two setups over the entire Netherlands (see Figure 8). Although a slight decrease in percentage difference is observed throughout the simulation (see Figure 7), difference remain significant after 6 days. This is related but not restricted to the memory of the system; where initial conditions of soil moisture are expected to impact a forecast output weeks after issuance (Li et al. 2009). It is important to note that this study took place over the warmer summer season where higher contribution of initial hydrological conditions is predicted compared to the cold winter season. This is due to drier initial soil moisture states in summertime (Shukla and Lettenmaier 2011).

Statistically significant difference does not necessarily mean operationally valuable impact. A change in mean relative soil moisture value going from 0.2 to 0.17 (see Figure 8) on average over all the Netherlands might have little practical implication to potential users of the tool. To appreciate further the change between the two setups, we study how differences are spread spatially over the different land use types identified according to the LNG-6 map (Figure 4). We find that in some nature identified land types, this percentage difference can be of up to 75% (see Figure 9). This shows that differences can be substantial and relevant for management of areas where drought early warning is critical to prevent harmful impacts, for example in agricultural areas or areas with high environmental value.

This assessment was done against a situation in which rainfall station data are available on a very high density. Generally though, dense station networks are not available. In this case, the differences can be expected to be even higher, and the added value of rainfall radar is even higher (Terink et al. 2018). In such cases, equipping and maintaining a higher density rain gauges will include large costs that should be carefully weighted out against other measuring techniques (Pardo-Igúzquiza 1998). Still, it could be that in some remote areas, accurate meteorological information is not deemed crucial. For that reason, we look further at the portion of land represented by each land use ID as a percentage of total surface area of the Netherlands in addition to the functional dependence of a specific land use on accurate soil moisture forecasts. This allows us to better understand the value of considering different rainfall products for such an application over the Netherlands.

To illustrate the previous point, we take as example the two land use IDs (31 & 33) over which we observe the largest difference; the portion of land occupied is of less than 1% of the total surface. Another example is the significant difference over bare land in built up area where soil moisture value and prediction has little potential value for users. On the other hand, results point out to a significant difference of about 20% over agricultural land use types occupying a total of 20% of the entire surface area of the Netherlands. Established links between crop yield and soil moisture (Dorigo et al. 2017; Rossato et al. 2017) presupposes higher sensitivity to differences between model outputs in agricultural areas. This leads to potential hotspots that should be of interest to users of climate services like DroogteNL.

A limitation throughout this analysis is the non-availability of an observation dataset on soil moisture, against which a validation of the results could have been performed. Still, we argue that: (i) As the radar data has been bias-corrected using KNMI network of manual gauges, it is likely that the radar-based simulation represents real-world conditions best; (ii) this study serves as a sensitivity analysis and not a validation study. The analysis showed that for soil moisture forecasts, one week ahead, the service is sensitive to improved data (rainfall radar) driving initial conditions.

Ultimately, when designing an early warning system tool, end-user preference should be taken at the core of the development process. This is supported by large European projects that have investigated the development of climate services and prototype forecasting tools for a wider community of users (Christel et al. 2018; Hanlon et al. 2018). In this study, we reported land uses over which significant difference between the two setups has been found for all lead times. A more detailed result section can be found in Appendix 1 where reader can track significant difference per land use for each lead time considered.

For future iterations of this work, we suggest validating the model outputs with real world soil moisture observations. In addition, we suggest further co-development action with users in order to better understand the needs in terms of requested hydrological variables, lead-time extent and other practical aspects that are crucial for increasing the value of such early warning system tools. Currently, the DroogteNL service is being used in engaging with Dutch water authorities and consultancy activities related to drought.

The DroogteNL service shows the potential of radar-based precipitation data for practical uses as soil moisture assessments. The soil moisture content clearly follows meteorological forcings and by using a hydrological model such as SPHY, a clear indication of the soil water availability at the start of the growing season can be predicted. This can be very useful for decision makers because they can implement (temporary) measures to increase soil moisture content by for example allowing farmers to start irrigating with surface water early in the season. Future development of DroogteNL portal are planned and will focus on tailoring the tool to water authorities and develop soil moisture forecasts for specific areas of interest.

6 References

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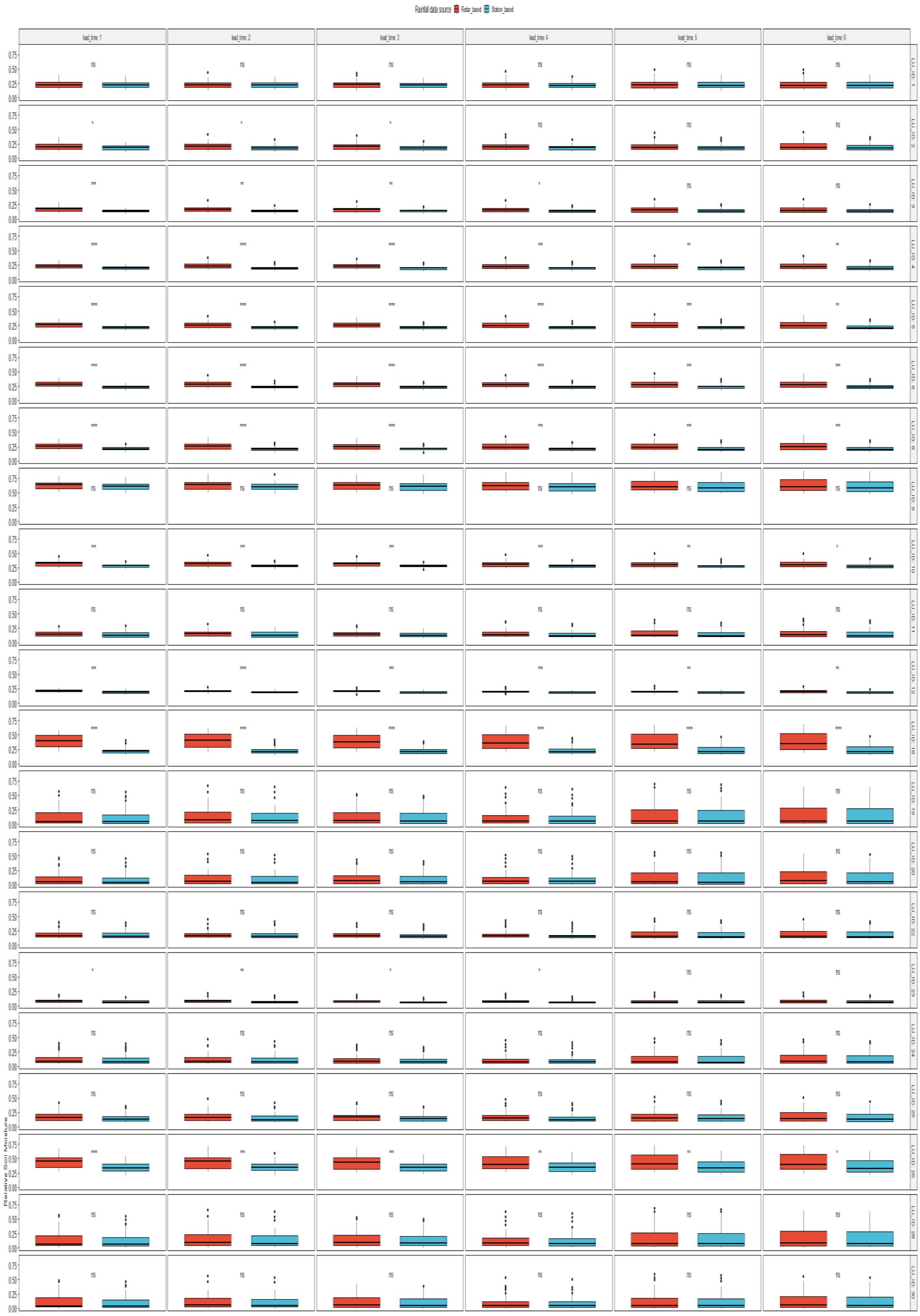
Annex 1


Rainfall data source Radar_based Station_based
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lead_time: 2
lead_time: 3
lead_time: 4
lead_time: 5
lead_time: 6
Relative Soil Moisture

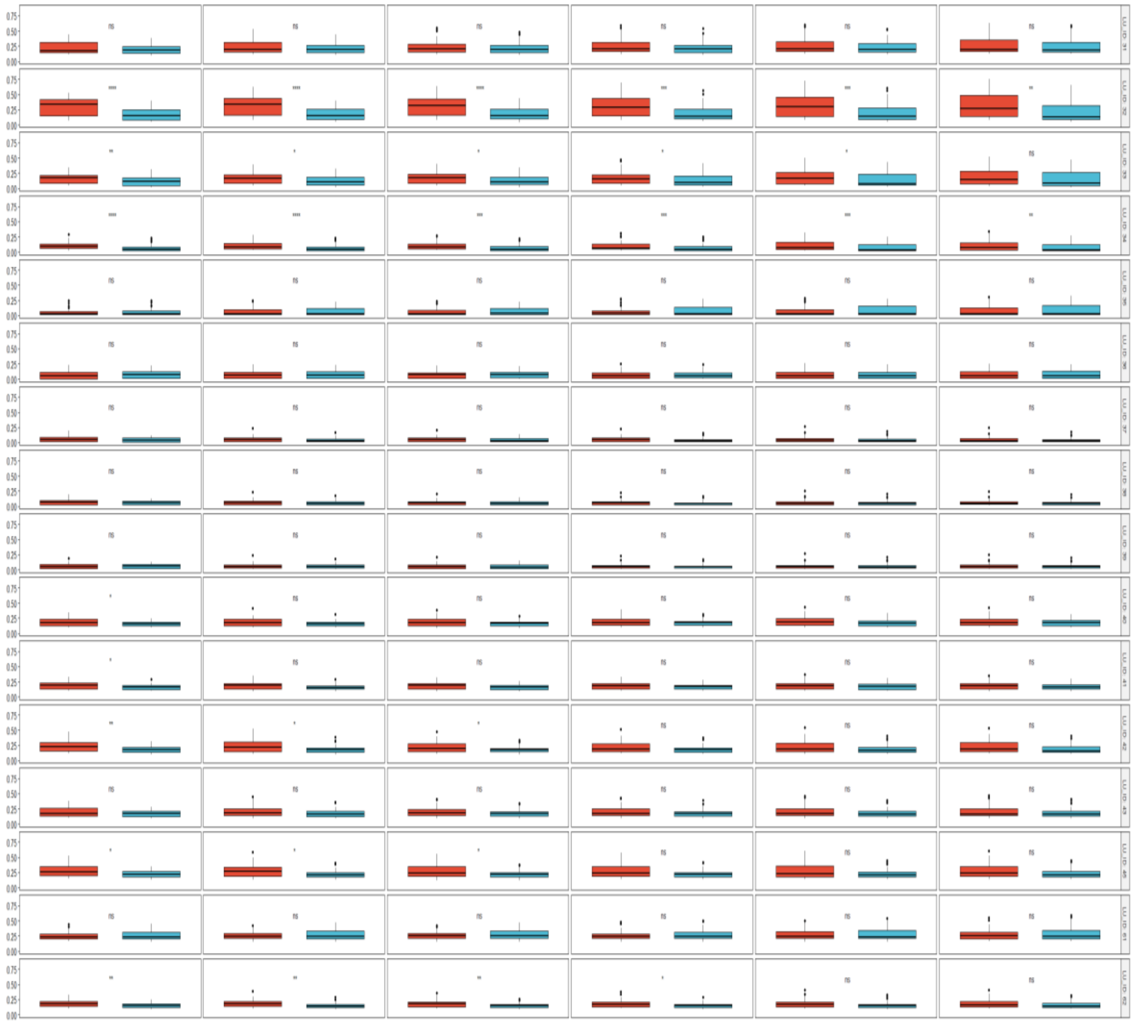

Figure 15 Complete table for Wilcoxon test per land-use and lead-time (P-value=0.05)

Annex 2

ID	Portion of the total area (%)	ID	Percentage portion of the total area (%)	ID	Percentage portion of the total area (%)	ID	Percentage portion of the total area (%)	ID	Percentage portion of the total area (%)	ID	Percentage portion of the total area (%)
1	38.25	9	0.78	19	0.28	28	0.50	36	0.34	43	0.19
2	7.40	10	0.66	20	0.42	30	0.13	37	0.23	45	0.07
3	5.30	11	3.96	22	0.12	31	0.22	38	0.20	61	1.43
4	3.31	12	5.06	23	0.42	32	0.29	39	0.18	62	0.04
5	5.37	16	13.39	24	3.32	33	0.38	40	0.06		
6	5.19	17	0.27	25	0.10	34	0.02	41	0.22		
8	0.37	18	9.17	26	1.99	35	0.05	42	0.30		

Figure 16 Complete table for Portion and Land use IDs- (Orange: Agriculture; Green: Forest; Blue: Water; Grey: Built up area; Red: Infrastructure; Brown: Nature)