Assimilation of remotely sensed soil moisture data in a hydrological forecasting model of the Overijsselse Vecht.

Thesis report

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Illustration cover page: Overijsselse Vecht at Dalfsen
https://beeldbank.rws.nl, Rijkswaterstaat/ Harry van Reeken

Preface

First, I want to thank Jelle de Jong, for the opportunity to do my master thesis at the Water board Drents Overijsselse Delta, but especially for the support during these weird corona times, when working from home was the standard. He always made time for me and he helped me with all my questions.

Furthermore, I want to thank Denie Augustijn and Martijn Booij, my supervisors from the University of Twente. They helped me defining my research objective and scope.
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Last but not least, I would like to thank my family and friends for their support during my thesis.

I hope you enjoy reading my thesis.

Geert Luijkx
Silvolde, 16 September 2020

Summary

Hydrological models are widely used in the field of water management and are used, among other things, to support decisions which are made by water managers. One example of such a model that supports the decision making is the Flood Early Warning System (FEWS). By water board Drents Overijsselse Delta (WDOD), FEWS is used to forecast the discharge and water levels in the Overijsselse Vecht. This model consists of two sub-models, a hydrodynamic model, and a hydrological model. In this study there was looked at the hydrological model of the FEWS, the HBV model. Due to the increased resolution and availability of satellite data, the water board wants to know what the added value of this data could be for them. One of the questions of WDOD is whether the HBV model performance could be improved by assimilation of remotely sensed soil moisture data.

In this study, 3 (out of 14) sub-catchments of the Overijsselse Vecht are investigated, namely the Ommerkanaal, Sallandse Wetering and the Dinkel. For these 3 sub-catchments, the following steps were executed. First, the HBV models of the 3 used sub-catchments were recalibrated. For this step, the parameter sensitivity was studied, from which the parameters for the calibration were selected. The calibration was done with a Monte Carlo simulation with 2.5 million runs. For all sub-catchments, the model performance did improve in comparison to the HBV models used in FEWS.

The sensitivity analysis (different then the parameter sensitivity) for the initial conditions showed that the model is the most sensitive for the initial condition of the soil moisture, for 2 out of the 3 sub-catchments. For the Dinkel, the sensitivity for the soil moisture was not the highest but still relatively large. Therefore, it was expected that changes in the initial condition of the soil moisture have an effect in the simulated discharge.

Subsequently, the correlation between the HBV modelled soil moisture and the remotely sensed soil moisture content was investigated. For both the daily measured soil moisture content and the 3-day moving average, a good correlation was found for all of the 3 sub-catchments, meaning there are similarities in the pattern of both datasets. The correlation between the 3-day moving average and the HBV modelled soil moisture was higher for all of the 3 sub-catchments because the peaks are smoothed. The values of the correlation coefficients are ranging from 0.85 for the Sallandse Wetering to 0.91 for the Ommerkanaal. The daily measured data is highly depending on the moment when the satellite passes over. If it has just rained, all the water is still in the top few centimetres of the soil, so the value is an overestimation of the real situation. Using the 3-day moving average instead dampens this effect and reflects the behaviour of the HBV modelled soil moisture better.

The remotely sensed soil moisture delivered by VanderSat is in the unit of m^3/m^3 while the HBV soil moisture is in mm, therefore a transformation was needed. This is done by using two methods which linearly transformed the data. The transformed data was assimilated into the HBV model as initial condition for the soil moisture storage, which is one of the three storages the HBV model has. The other two initial conditions are made by a model run with a warm-up period of 1 year. With the assimilation the model forecasted a discharge for the next 5 day, with as input the measured precipitation and the potential evaporation.

The assimilation of remotely sensed soil moisture in the HBV model did not showed an improvement overall. There are a few exceptions in which the model with assimilation showed an improvement; this was sometimes the case when the peak flow occurred during a dry period. The approach of the HBV model without assimilation is to store the precipitation in the soil moisture, which will lead to a lower discharge. With the assimilation, in this case, there was a higher forecasted discharge, because the initial soil moisture is higher. In the rest of the cases, the HBV simulated soil moisture was performing better than the assimilated soil moisture. This can be explained if looked at the transformation done with the remotely sensed soil moisture, this transformation is not representing the pattern in the data, which is not linear.

Out if this research a few recommendations are derived both for the water board and for the study. One of which is to further research another transformation of the remotely sensed soil moisture content to the unit used in the HBV model. The method used is an oversimplification of the pattern which can be found in the data. Furthermore, the HBV model could have been calibrated with the use of remotely sensed soil moisture content as input. By already using the soil moisture data in the calibration the parameters could be adapted to the remotely sensed soil moisture content. This could improve the performance of the assimilation. Furthermore, the high correlation found in this study, between the remotely sensed soil moisture and HBV modelled soil moisture, could be a potential for the use of remotely sensed soil moisture in a other way in the HBV model or in other models. At last the recalibration of the model leads to an improvement of the simulated discharge and could therefore be done for the other sub-catchments of the Vecht in order to improve the model performance.

Contents

1 Introduction

The introduction of this thesis is structured as follows: first, a general introduction will be given in section 1.1 which is about the problem that Water board Drents Overijsselse Delta (WDOD) wants to tackle. Subsequently, in section 1.2, the state of the art of the available methods to address this problem is presented. The difference between the state of the art and the problem of WDOD gives us the research gap, in section 1.3. Based on this research gap, the research aim, and research questions will follow in section 1.4. In section 1.5, the study area for this study is described. The last section (1.6) describes the outline of the report.

1.1 Aim water board

Water board Drents Overijsselse Delta (WDOD) is responsible for water safety, sufficient water, and clean water. Therefore, the protection of their service area against floods is one of their responsibilities. To fulfil this task, they want to be able to forecast the water levels in the Overijsselse Vecht, which lies partly in the area managed by WDOD. They use a Flood Early Warning System (FEWS), which is based on a hydrodynamic and hydrological model of the Vecht. This system provides the water board with the necessary information about the water levels in the Vecht for five days in advance. Based on this information, decisions such as the build-up of temporary dikes or evacuation of cattle from the floodplains can be made.

In FEWS, two components can be distinguished: the hydraulic model, which describes the movement of the water in the Vecht and the hydrological model, which describes the runoff of rainfall into the Vecht. The hydraulic model used in FEWS is a separate Sobek model, and the hydrological model is based on a model called Hydrologiska Byråns Vattenbalansavdelning (HBV) (Bergström & Forsman, 1973). Because the Vecht catchment has been divide into 14 sub-catchments, the hydrological model of FEWS is divided into 14 HBV models. The sub-catchments are shown in Figure 1 and Table 1 in section 1.5.

The water board would like to have a forecast which predicts the water levels in the Vecht as accurately as possible. The current model can become more accurate by decreasing different uncertainties that are present in the current model. One of them is the fact that the model is based on an initial soil moisture content, which is not always reflecting the actual state of the soil at that moment. Given the fact that in the model, the discharge out of a sub-catchment is partly determined by the amount of water present in the soil, there could be an error in the generated runoff by the model. This could result in differences between the actual and forecasted water levels.

In recent years, new methods and products to use satellite data have become available for the water board. One of these data products offers information about soil moisture, which creates the possibility to add extra information to the hydrological part of the model (Zhuo & Han, 2016). Therefore, this study will look at the use of satellite soil moisture data for assimilation of soil moisture in the hydrological part of the model, the HBV model. One of the possibilities to provide information about the initial condition of the soil moisture content is the use of satellite products. There are different satellite products available which could give information about the soil moisture; the satellite products used in the study are supplied by VanderSat. There is chosen for the satellite products of VanderSat because the product is very user friendly.

1.2 State of the art

Soil moisture data collected from satellites have many hydrological and agricultural applications, such as water level management and crop yield optimization. According to Van der Velde et al. (2018), for this reason, several studies have focused on the development of methods for estimating soil moisture from satellite data.

Specific attention is paid to the microwave range of the spectrum emitted by the satellite, because of the ability to see through clouds, vegetation, and parts of the soil. In general, the longer the wave, the deeper into the soil can be looked at, and the less the signal is influenced by vegetation. For soils, the maximum penetration depth is approximately a quarter of a wavelength (Schmugge, 1983). This means that with radiation in the L-band (1.4 GHz, 21.4 cm wavelength), the frequency band that is most sensitive to water, the soil moisture content of the top five centimetres of the soil can be determined. Sentinel satellite-1A and 1B ensure that large parts of the Netherlands have an image available every two days with a pixel size of 10 x 10 meters. Although Sentinel-1 is not specifically designed as a soil moisture satellite, there is evidence that these observations can also be used to obtain soil moisture information (Benninga et al., 2018). VanderSat uses a variety of satellites to produce the soil moisture product delivered by them (VanderSat, 2020), which are based on the principal describe above.

Hydrological models are often used to support operational water management, for example, for flow forecasting. The soil moisture maps based on satellite data offer additional information that can be used to reduce uncertainties in the model. A way to combine soil moisture products with a hydrological model is data assimilation (Renzullo et al., 2014). With this method, the state variables (such as soil moisture content and groundwater level) in the model are adjusted based on observations from satellite data or field measurements. The purpose of this is to limit deviations from reality. This gives water managers a more reliable representation of the actual situation within a management area and enables them to respond better to local problems. The interesting thing about data assimilation is that it improves not only the model outcome of the assimilated state variable, but it could also improve the calculated water fluxes, such as current evaporation, groundwater replenishment, and river discharge.

A lot of studies have been done about assimilating soil moisture data into the HBV model. Different methods of data assimilation are available. A lot of these studies are using a technique called a Kalman filter. For example in a study done by Komma et al. (2008), a Kalman filter is used in combination with a flood forecasting system. With the use of a Kalman filter, the soil moisture is updated at real-time. The result of this data assimilation was positive for both a short lead time of a few hours but also for a two days lead time. The Kalman filter is a data assimilation method which is challenging to implement in the model. Alternatively, the method of direct insertion could also be used as done, for instance, by López et al. (2016). In this method the simulated data is replaced by the observed data.

Several studies have been done in which remotely sensed soil moisture data I used in combination with the HBV model. In a study by Liu et al. (2007), the remotely sensed soil moisture content is related to the HBV simulated soil moisture. In this study, a difference was found between these two different soil moistures, and this could be partly explained by the fact that the remotely sensed soil moisture measurement is representative for only the top layer of the soil while the soil moisture in the HBV model represents water storage for larger depths. To cope with this issue, soil moisture values of deeper layers could be used both remotely sensed but also measured in situ. Another method used by Liu et al. (2007) is smoothing the remotely sensed soil moisture content with the neighbouring grid cell; this gave a better result for the comparison.

Another application of remotely sensed soil moisture data is for calibration of a hydrological model. An example of this is the study done by López et al. (2017) in which they made use of satellite measured soil moisture to calibrate a poorly gauged catchment. This is done by comparing the soil moisture modelled by the HBV model and the soil moisture measured with the satellite. With this technique, it is possible to calibrate catchments from which the discharge is not adequately measured on the ground.

1.3 Research gap

It is unknown to what extent the use of satellite information about soil moisture results in a more accurate forecasted discharge for the river Vecht by the HBV model. Previous studies showed (Komma et al., 2008) the expectation that soil moisture data derived from satellites can improve the forecasting of discharges. But it is not clear if this is also the case for the situation in which WDOD operate. In their case it about an operational flood early warning system with a lead time of 5 days. Furthermore, the area is different, and the satellite data used is also different and therefore the result could be different.

1.4 Research aim and questions

This research aims to examine to what extent it is possible to improve the forecasted discharge of the HBV models of the 3 selected sub-catchments of the Overijsselse Vecht for peak discharges by assimilating remotely sensed soil moisture content as initial condition into the model.

There are 5 steps needed to see if the data assimilation improves the output of the HBV model. The first step is to see if the model can be improved by doing the calibration over. The second step is to see if there is an effect on the forecasted discharge by changing the initial soil moisture condition of the HBV model. The third step is to see if there is a correlation between the HBV modelled soil moisture, and the remotely sensed soil moisture. If there is no correlation, then the assimilate of remotely sensed soil moisture data in HBV is not likely to give a big improvement. The fourth step is to make the remotely sensed soil moisture data applicable to the HBV model. The unit of the used satellite soil moisture data provided by VanderSat (in m^3/m^3) is not the same as the soil moisture in HBV (in mm), and therefore conversion of the data is necessary. The last step is to assimilate the data into the model and find out what the effect is on the forecasted discharge and compare it to the observed discharge.

To achieve the research objective and complete the necessary steps, the following research questions have been formulated:

1. To what extent could the HBV model performance be improved by recalibrating the model?
2. How sensitive is the HBV modelled discharge for change in the three different initial conditions, the initial level of the three different storage components (mainly focused on the soil moisture storage) of the HBV model?
3. What is the correlation between the HBV simulated soil moisture and the remotely sensed soil moisture content?
4. To what extent could the assimilation of remotely sensed soil moisture improve the forecasted discharge by the HBV model, in comparison to the observed discharge and the forecasted discharge without assimilation?

1.5 Study area

The area used for this research will be the Overijselse Vecht. The Overijsselse Vecht is a rainwater river in Germany and the Netherlands. It is 167 kilometres long, of which 60 km is in the Netherlands. Its origin lies in Münster land, and it flows out into the Zwarte Water near Zwolle. The catchment area of the Overijsselse Vecht covers 4780 km^2. Important tributaries that join the Overijsselse Vecht are the Steinfurter Aa, the Dinkel, the Afwateringskanaal and the Regge. The runoff of the Vecht is highly fluctuating; at Dalfsen, the discharge varies between 2 and 550 m^3/s (Verdonschot & Verdonschot, 2017).

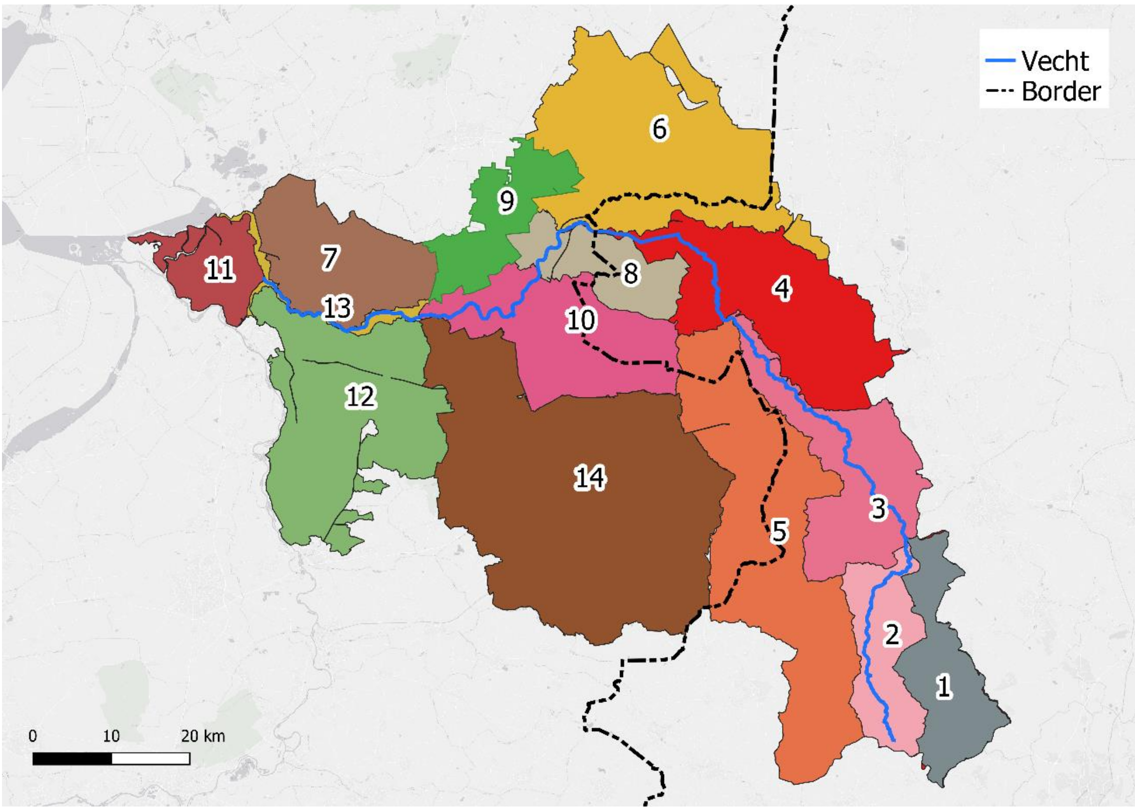

Figure 1: Overview of the Vecht catchment, the numbers in this figure are corresponding with the numbers of the sub-catchments in Table 1

The location of 14 sub-catchments is shown in Figure 1. In Table 1, the name of the sub-catchments and their areas are given. Al these sub-catchments have an inflow point into the hydrodynamic model (the SOBEK model) of the Vecht in FEWS. Furthermore, the whole Vecht is not a natural river; at many places, there are weirs in place to control the water levels and the discharge. Also, at some of the tributaries of the Vecht weirs are in place to control the discharge and water levels.

Table 1: name of sub-catchments and their area.

Nr.	Sub-catchment	Area (km^2)
1	Steinfurter Aa	204.52
2	Vecht A	183.33
3	Vecht B	315.51
4	Vecht C	409.02
5	Dinkel	643.13
6	Afwateringskanaal	579.27
7	Streukelerzijl	246.00
8	Radewijkerbeek	154.27
9	Ommerkanaal	170.67
10	Itterbeek	337.39
11	Mastenbroek	125.57
12	Sallandse Wetering	449.10
13	Vecht	34.10
14	Regge	1014.90

1.6 Outline report

This thesis is further organized as follows. Chapter 2 describes the methodology used to arrive at the research aim described. The results are presented in Chapter 3. Chapter 4 is dedicated to the discussion of this work and treats this research’s potential and limitations in detail. Finally, the conclusions and recommendations for further research are to be found in Chapter 5.

2 Method

In this chapter, the method for this study is described in line with the research questions formulated in section 1.4. First, the model used for the study is described in section 2.1. As the second part the method for the calibration will be described in section 2.2. Subsequently, the method used to investigate the sensitivity of the HBV model for its initial conditions will be presented in section 2.3. After this, the method used for finding the correlation between the HBV modelled soil moisture, and the remotely sensed soil moisture will be shown in section 2.4. Finally, the method used for the data assimilation will be elaborated in section 2.5.

2.1 HBV model

The Hydrologiska Byråns Vattenbalansavdelning (HBV) model has been developed by Bergström at the Swedish Meteorological and Hydrological Institute in 1972. The HBV model is a conceptual rainfall-runoff model and can be used as a distributed, semi-distributed or lumped model (Bergström & Forsman, 1973). There is chosen for this model due to its fast model time and also because it is used in other forecasting systemin, for example, FEWS of the Rijn catchment(Renner et al., 2009).

Since the model was developed in Sweden, also snowfall and snow cover are considered. Furthermore, the storage of water in lakes is taken into account in HBV. The water balance that is used for this model is given in Equation 1.

Equation 1:

$$P - E - Q = \frac{d}{dt}[SP + SM + SUZ + SLZ + Lakes]$$

In which:
P = precipitation (mm)
E = evapotranspiration (mm)
Q = runoff (mm)
SP = snowpack (mm)
SM = soil moisture (mm)
SUZ = upper groundwater zone (mm)
SLZ = lower groundwater zone (mm)
lakes = lake volume (mm)

Since the 70s, many versions of the HBV model have been developed. A comprehensive re-evaluation of the model was carried out during the 1990s and resulted in the present model version called HBV-96 (Lindström et al., 1997).

The HBV model, as described by Lindström et al. (1997), is used to build an HBV model in Python. This is done with the changes made by Deltares to the HBV model in the FEWS model. The HBV model used has two routines, the soil, and the runoff routine. In the next section, the two different routines in the model will be described.

2.1.1 The soil routine

The schematization of the soil routine can be seen in Figure 2. The soil routine consists of one storage box with maximum storage as an input parameter (FC in mm). The variable SM (in mm) describes the total soil moisture stored in a time step. Out of the soil moisture storage box, there are three outgoing fluxes: the evaporation, the recharge (or seepage) and direct runoff. The only ingoing flux is the infiltration of the precipitation.

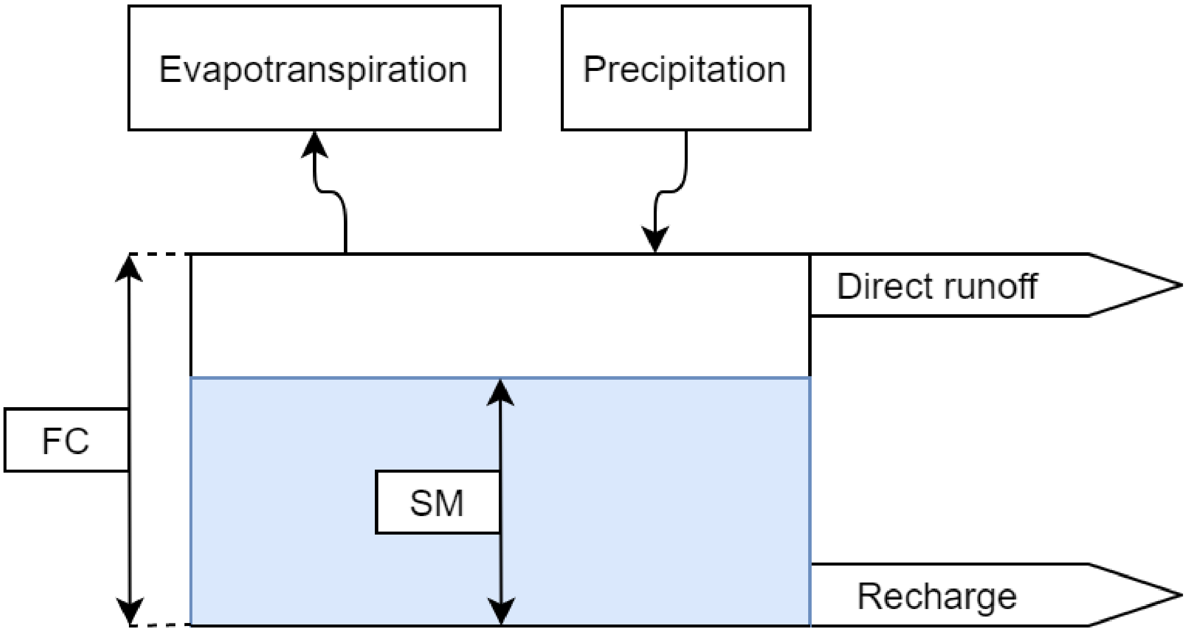

Figure 2: The schematization of the soil routine

The actual evapotranspiration is limited by parameter LP (-), which is a fraction of FC. If the soil moisture is lower than LP*FC, then the actual evapotranspiration is smaller than the potential evapotranspiration (Equation 2), if the soil moisture exceeds LP*FC, then the actual evapotranspiration will be equal to the potential evapotranspiration (Equation 3) (Lindström et al., 1997).

Equation 2:

$$ET_a(\mathrm{t}) = ET_P(\mathrm{t}) * \frac{SM(t)}{LP * FC} \qquad\qquad if\ SM(t) < LP * FC$$

Equation 3:

$$ET_a(\mathrm{t}) = ET_P(\mathrm{t}) \qquad\qquad if\ SM(t) \geq LP * FC$$

ET_a	Actual evapotranspiration (mm/day)
ET_P	Potential evapotranspiration (mm/day)
SM	Soil moisture storage (mm)
FC	Maximum soil moisture content (mm)
LP	Limit for potential evapotranspiration (-)

If the storage has reached its maximum (SM > FC), the excess rainfall will be converted to direct runoff (Equation 4). The recharge (R in mm) is calculated according to Equation 5 (Lindström et al., 1997).

Equation 4:

$$Qd(t) = P(t) + SM(t) - FC$$

Qd	Direct runoff (mm)
P	Precipitation (mm)

Equation 5:

$$\mathrm{R(t)} = \mathrm{INET(t)} * \left(\frac{SM(t)}{FC}\right)^{Beta}$$

R	Recharge(mm)
$INET$	Netto Infiltration (mm), which is the precipitation minus the direct runoff
SM	Soil moisture (mm)
FC	Maximum soil moisture content (mm)
$Beta$	Soil parameter (-), controls the increase of the lower zone for every mm of precipitation, >1

The recharge and direct runoff, which is the excess water out of the soil moisture storage box, are divided by the runoff routine into an upper and lower storage zone, controlled by the maximum percolation (PERC). In the HBV model used in the FEWS model, there is no capillary transport taken into account.

2.1.2 Runoff routine

The runoff routine consists of 2 storage boxes, the upper zone (SUZ in mm) and lower zone (SLZ in mm), out of the two storage boxes three discharge fluxes are generated (Jungermann et al., 2012). In Figure 3, the schematization of the runoff routine can be seen.

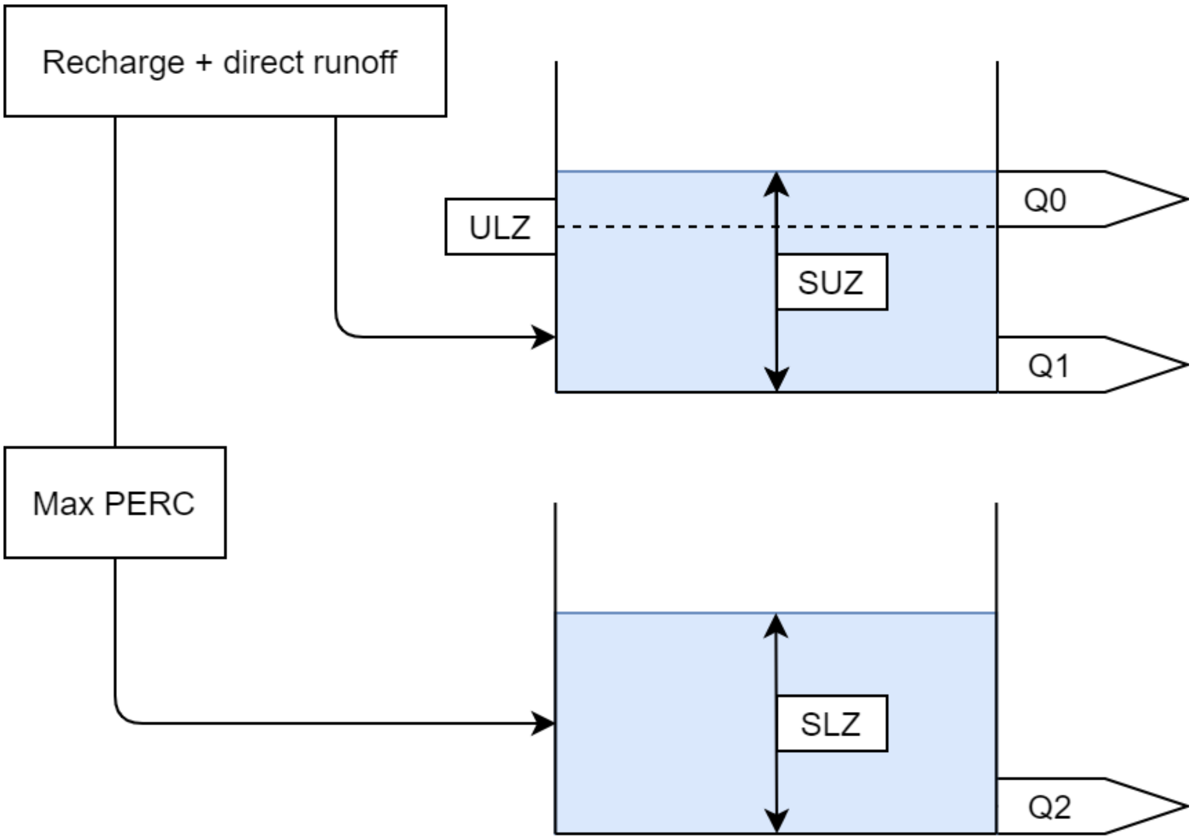

Figure 3: The schematization of the runoff routine

The available water from the soil routine, the direct runoff and recharge, will in principle end up in the lower zone (SLZ), unless the percolation threshold, PERC (mm), is exceeded, in this case, the redundant water ends up in the upper zone (SUZ) (Deltares, 2013).

Out of the upper zone, there are two discharge fluxes generated. The first one is the quick flow (Q_0), as described in Equation 6 (Gendzh, 2018). The quick flow will only occur when the storage in the upper zone is above a given storage, ULZ (mm). The second discharge flux from the upper storages box is the interflow (Q_1), as described in Equation 7.

Equation 6:

$$Q_0(t) = K_0 * (SUZ\ (t) - ULZ) \qquad\qquad if\ SUZ(t) > ULZ$$

Q_0	Quick flow (mm/d)
K_0	Recession coefficient of the quick flow (d^{-1})
SUZ	Storage upper zone (mm)
ULZ	Threshold value for Q_0 (mm)

Equation 7:

$$Q_1(t) = K_1 * SUZ(t)$$

Q_1	Inter flow (mm/d)
SUZ	Storage upper zone (mm)
K_1	Recession coefficient for the interflow (d^{-1})

The lower zone is responsible for the third discharge component. This is the base flow and is calculated according to Equation 8.

Equation 8:

$$Q_2(t) = K_2 * SLZ(t)$$

SLZ	Storage lower zone (mm)
Q_2	Base flow (mm/d)
K_2	Recession coefficient for the base flow (d^{-1})

The total runoff, in mm, of the model is the summation of the tree individual discharge fluxes. Using the area of the catchments, the total runoff in m^3/s can be calculated (Lindström et al., 1997).

The used HBV model has eight parameters which are summarized below. The values for these parameters are found by calibrating the model. The HBV model uses three initial conditions, i.e. the initial storage of the three storage boxes (SM, SUZ, SLZ), and two time series as input, the precipitation, and the potential evapotranspiration.

FC	Maximum soil moisture storage (mm)
LP	Limit for the evapotranspiration (mm)
$Beta$	Soil parameter, which controls the increase of the lower zone for every mm of precipitation (-)
$Perc$	Maximum percolation (mm/d)
K_0	Recession coefficient of the quick flow (d^{-1})
K_1	Recession coefficient for interflow (d^{-1})
K_2	Recession coefficient for base flow (d^{-1})
ULZ	Threshold value for the quick flow (mm)

The model described above is built from FEWS to a version in Python. In Figure 4, the simulation of the HBV model in Python used for this study and the HBV model from FEWS can be seen. This comparison is made with data of the Ommerkanaal for the period of 2007 till 2008. The parameters and initial conditions used are exactly the same and could be found in Appendix B. As can be concluded, the models provide the same results. The difference between the HBV model used in FEWS and the HBV model build in Python will be expressed with the mean absolute percentage error (MAPE) (Brooks et al., 2017), which is given in Equation 9:

Equation 9:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Q_i^{FEWS} - Q_i^{HBV}}{Q_i^{FEWS}}\right|$$

Q^{Fews} Discharge modelled by FEWS (m^3/s)
Q^{HBV} Discharge modelled by the HBV model (m^3/s)

The MAPE of this run is $4*10^{-5}$ %, this error is caused by the rounding of which is done in FEWS.

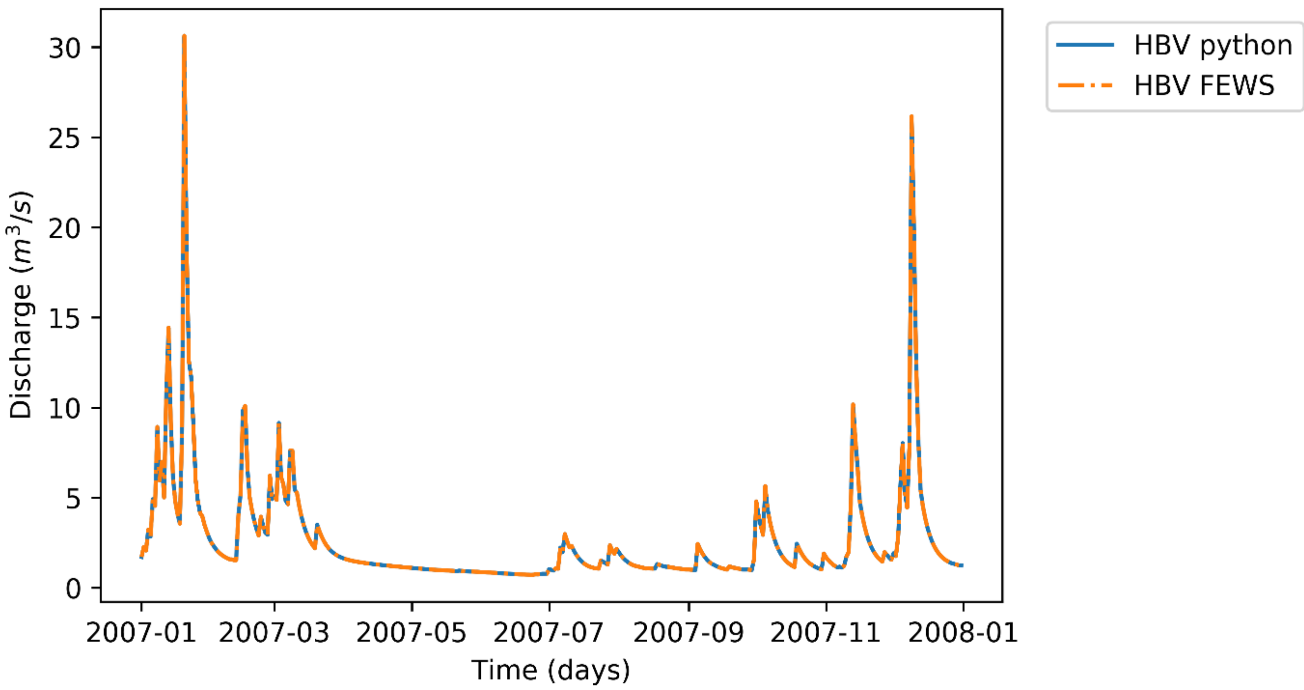

Figure 4: The comparison of FEWS HBV vs the HBV model in Python for the Ommerkanaal for the year 2007, before calibration.

2.2 Sensitivity analyses and calibration.

In this section, the steps taken for the calibration of the model will be described. The calibration of the model is done because the calibration done before by Deltares could be improved. This calibration was only performed with 1000 iterations, with a randomly chosen parameter set, out of which the best parameter set is chosen (Jungermann et al., 2012). Calibrating with more iterations could improve the modelled discharge, which could make the assimilation of satellite data into the model better.

For the calibration of the HBV model, three aspects are important. First the calibration process, this will be described in section 0. To find the parameters which are most important for the calibration, the sensitivity of the HBV model was investigated as a second step. The method for this is described in section 2.2.2. Third, for both these steps, it is necessary to make use of an objective function. Therefore, the objective functions which were used are described in 2.2.1.

The sensitivity analysis and calibration were done for different sub-catchments of the Vecht, namely: the Ommerkanaal, Sallandse Wetering and Dinkel, with data from 2005 up to and including 2010, where 2005 was used as warmup period. There is chosen for these 3 catchments because there is measurement data available for the outflow.

2.2.1 Objective function

The root mean square error (RMSE, Equation 9) and an adapted form of the Kling-Gupta efficiency (KGE; (Mizukami et al., 2018), Equation 11) are chosen as objective functions for the sensitivity analysis and the calibration.

Equation 10:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Q_{sim} - Q_{obs})^2} \;\; With\ optimal\ value\ 0$$

Equation 11:

$$KGE = 1 - \sqrt{\left(S_r(r-1)\right)^2 + \left(S_a(\alpha-1)\right)^2 + \left(S_\beta(\beta-1)\right)^2} \;\; With\ optimal\ value\ 1$$

In which

α is the ratio between the r variability in the simulated and observed values

$$\alpha = \frac{\sigma_{sim}}{\sigma_{obs}}$$

In which

σ standard deviation

β is representing the bias, which is the ratio between the mean observed flow and mean simulated flow.

$$\beta = \frac{\mu_{sim}}{\mu_{obs}}$$

In which

μ mean of the discharge

r is the linear correlation coefficient

$$r = \frac{\sum_{i=1}^{n}(Q_{obs} - \overline{Q_{obs}})(Q_{sim} - \overline{Q_{sim}})}{\sqrt{\sum_{i=1}^{n}(Q_{obs} - \overline{Q_{obs}})}\sqrt{\sum_{i=1}^{n}(Q_{sim} - \overline{Q_{sim}})}}$$

In which

$\overline{Q_{obs}}$ Average of observation discharge (m^3/s)

$\overline{Q_{Sim}}$ Average of simulated discharge (m^3/s)

Q_{obs} observed discharge (m^3/s)

Q_{sim} simulated discharge (m^3/s)

S_r, S_α, and S_β are user-specified scaling factors

In a balanced formulation, S_r, S_α, and S_β are all set to 1.0. By changing the relative sizes of the S_r, S_α, or S_β weights, the calibration can be altered to emphasize more strongly the reproduction of flow timing, statistical variability, or long-term water balance. For this study, a value of 3 will be used for S_r, since the reproduction of the flow timing is most important for the FEWS model. This is because the discharge from different sub-catchments is used as input for the hydrodynamic model; therefore, an error in the peak flow of the different sub-catchments could lead to bigger errors in the simulated discharge for the entire Vecht catchment. The range for the scaling factors given by Mizukami et al. (2018) is between 1 and 5, where the difference between a value of 3 and 5 is small. Therefore, the value of 3 for the S_r is chosen due to the fact that there is not only an error with the peak flows in the model but also the base flow, with a higher value the baseflow would not be improved.

2.2.2 Sensitivity analysis

In order to select the parameters that need to be calibrated, it is necessary to know which parameter has the biggest influence on the objective functions given in Equation 9 and Equation 10. This was investigated by conducting a sensitivity analysis. During the analysis, the 8 parameters of the HBV model were changed one by one, with steps of 5% from -50% to +50%. If an increase or decrease of 50% of the parameter leads to a change in one of the objective functions with more than 25%, the parameter was selected for the calibration. The selection criteria were determined on forehand.

2.2.3 Calibration

The calibration is done with the use of an algorithm called a Monte Carlo simulation (Lidén & Harlin, 2000) for the period of 2006 to 2010. This algorithm is probably the simplest one for a calibration purpose and does not learn or adapt its method during the sampling. In principle, this algorithm can solve any parameter search problem. But with an increasing number of parameters, the number of required iterations to reach a global optimum, rises exponentially. It relies on repeated random parameter samplings which are tested in the simulation function. In Table 2, the range for the parameters during the calibration can be found. With the random parameter set, the model is run, and the objective function of this run was saved in a database.

Table 2: Parameter range for the HBV model during calibration (Karamouz et al., 2013)

Parameter	Lower boundary	Upper boundary
FC	50 (mm)	700 (mm)
LP	0 (-)	1(-)
BETA	1 (-)	6 (-)
PERC	0 (mm/day)	15 (mm/day)
ULZ	0 (mm)	100 (mm)
K0	0.1 (d^{-1})	0.9 (d^{-1})
K1	0.01 (d^{-1})	0.3 (d^{-1})
K2	0.001 (d^{-1})	0.1 (d^{-1})

This process was repeated for 2.500.000 times, and the best parameter set was selected. In order to select the best parameter set, the KGE, as defined by Equation 11, was used as the main objective function. The RMSE was used as verification objective function.

2.3 The sensitivity of the HBV model for its initial conditions

In order to determine the effect of a possible error in the initial condition of soil moisture on the discharge, it is necessary to find out how sensitive the model is for its initial conditions. This step is done in order to see if it is useful to improve the initial conditions with the use of remotely sensed soil moisture. If the outcome of this step is that the model is not sensitive to the initial conditions for soil moisture, there is likely to be no improvement with better initial conditions for soil moisture.

There are three initial conditions for the HBV model: the soil moisture (SM), the storage in the upper zone response box (SUZ) and the storage in the lower zone response box (SLZ). In the FEWS model, the initial conditions are based on the content of the storage boxes of outcome the run of the day before. However, in this study, there was no data available from the previous day. Therefore, the model will have a warmup period of 1 year. From that moment on the outcome of the previous run will be used as an initial value for the model. The sensitivity analysis is done by changing the initial conditions with steps of 1% from -50% to +50%. In this case 2005 is used as a warmup period and 2006 as the period to evaluate the sensitivity.

The model will be run for 1 year, resulting in a forecasted discharge for each day for the next 5 days. Therefore, there will be 5 simulated time series per sub-catchment with a lead time of 1 to 5 days. Lead time is the length of time between the issuance of a forecast and the occurrence of the phenomena that were predicted. This is done because the effect of the initial condition could be seen as a function of lead time.

The sensitivity of the model for the initial parameters is determined by changes in the value of the objective functions (RMSE and KGE) for the different lead times. Additionally, a hydrograph will be made to see the effect of the changes in the initial condition on the discharge.

2.4 Correlation of the HBV modelled and remotely sensed soil moisture.

The HBV model is a conceptual model; therefore, not all the model parameters are directly related to physical characteristics in the real world (Pechlivanidis et al., 2011). In the case of the soil moisture, is it necessary to investigate whether this variable is correlated with the remotely sensed soil moisture content delivered by VanderSat. If there is not a high degree of correlation, it is not meaningful to use the satellite data instead of the currently used initial condition with a good result.

For the correlation both the 3-day moving average of the remotely sensed and the daily measured soil moisture content (remotely sensed soil moisture content), both delivered by VanderSat, will be compared with the soil moisture modelled with the HBV model. The model is run from 2014 up to and until 2017, where 2014 will be used as a warmup period for HBV.

The correlation between the remotely sensed soil moisture by VanderSat, and the HBV modelled soil moisture will be checked with the linear correlation coefficient as can be found in equation 12, where a value of 1 means a perfect correlation and a value of 0 no correlation.

Equation 12:

$$r = \frac{\sum_{i=1}^{n}(SM_{HBV} - \overline{SM_{HBV}})(SM_{RS} - \overline{SM_{RS}})}{\sqrt{\sum_{i=1}^{n}(SM_{HBV} - \overline{SM_{HBV}})}\ \sqrt{\sum_{i=1}^{n}(SM_{RS} - \overline{SM_{RS}})}}$$

SM_{HBV}	HBV model soil moisture
$\overline{SM_{HBV}}$	Average of the HBV model soil moisture
SM_{RS}	Remotely sensed soil moisture content
$\overline{SM_{RS}}$	Average of the remotely sensed soil moisture content

2.5 Assimilating soil moisture into the HBV model

2.5.1 Selection of the periods for assimilation.

For the data assimilation, different periods are selected. Because the FEWS model is mainly used for the forecasting of floods, (short) periods of high flow are evaluated. Therefore, there will be looked in this study at the 6 highest peaks in the period of June 2015 till 2020; this is the period for which the data of VanderSat is available. In Figure 5, the selection of the peak discharges for the Ommerkanaal is shown. For the Ommerkanaal, two peaks are very close to each other and therefore taken as one period. For the Sallandse Wetering also two peaks are close to each other and therefore taken as one period. For the Dinkel, only 3 peaks were present in the data.

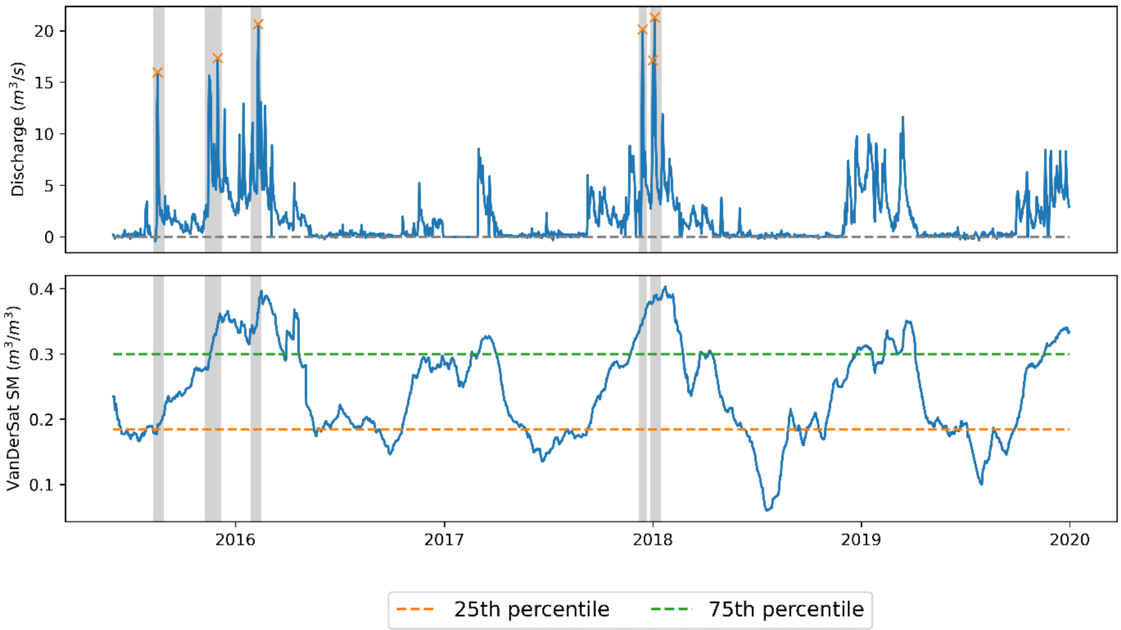

Figure 5: The selection of periods with peak discharges for the Ommerkanaal

2.5.2 Transforming the remotely sensed soil moisture

The unit of the soil moisture content delivered by VanderSat is in m^3/m^3, and the unit of the soil moisture used in the HBV model is mm. Therefore, to assimilate the soil moisture data in the HBV model, the remotely sensed soil moisture should be transformed. For this, two methods are used. The first method is given in Equation 13, the second method in Equation 14. The second method is based on the assimilation done by López et al., (2016) the first method is not based on a study but on mathematical normalization of the data set and introduced in this study. In both equations, the values of VanderSat are the average values of the sub-catchment.

Equation 13:

$$SM_{new}(t) = \frac{\theta(t)}{\theta_{max}} * FC$$

With:

θ	the soil moisture provided by VanderSat (m^3/m^3)
θ_{max}	The maximum soil moisture content measured by VanderSat in the given period

Equation 14:

$$SM_{new}(t) = SM_{min} + \frac{SM_{max} - SM_{min}}{\theta_{max} - \theta_{min}}(\theta(t) - \theta_{min})$$

With:

$SM_{min/max}$	Is maximum/minimum soil moisture simulated by the HBV model in the given period without data assimilation (mm)
θ_{min}	The minimum soil moisture content measured by VanderSat in the given period

The two methods give a soil moisture value which can be used during the assimilation in the HBV model. The other two initial conditions, SUZ and SZL, will be simulated by the model with a warmup period of a year.

The model with the assimilated soil moisture will be run for the periods selected as can be seen in 2.5.1, resulting in a daily forecasted discharge for lead times up to 5 days. Therefore, there will be 5 simulated time series per sub-catchment per selected period with a lead time of 1 to 5 days. This is done so the effect of the assimilation of soil moisture as the initial condition can be seen for different lead times.

The effect of the assimilation on the forecasted discharge will be expressed in objective functions (in comparison to the simulation without assimilation): the RMSE and the linear correlation coefficient, both are suggested by CAWCR (2017) as an objective function for a deterministic forecast. The combination of the RMSE and the Pearson correlation is chosen because the RMSE is giving information about the absolute difference between the simulated and observed discharges while the correlation is giving information about the similarities in the pattern of the discharge curve. If both are getting closer to the perfect value for the simulation with data assimilation, the forecasted discharge with assimilation is better than without assimilation. For the forecasted discharge, it is important that the error is small, expressed by the RMSE, otherwise, the forecasted discharge peak is overestimated or underestimated. Furthermore, the timing of the peak is important because, in the SOBEK model, the discharges of the different sub-catchments contribute to the discharge of the entire Vecht. Therefore, the correlation is used in order to check the similarities in the patterns of the forecasted discharge and the observed discharge.

3 Results

In this chapter, all the result of this thesis will be shown according to the steps described in the methodology. In section 3.1, the results of the calibration will be presented. In section 3.2, the sensitivity of the HBV model to its initial conditions will be presented. The correlation between the remotely sensed soil moisture and the HBV modelled soil moisture will be pretended in section 3.3. and finally, the result of the assimilation of remotely sensed soil moisture will be presented in section 3.4.

3.1 Calibration

The first result is the calibration done for 3 sub-catchments, for the period of 2006 up to and including 2010 where 2005 is used as a warmup period. First, a sensitivity analysis is done for the 3 sub-catchments, in order to select the parameters for the calibration. With the selected parameters, the 3 models of the different sub-catchments are recalibrated with a more extensive Monte Carlo simulation.

3.1.1 Sensitivity analysis

A sensitivity analysis was performed to assess the sensitivity of the simulated discharge to changes in the model parameters. The results are shown in Figure 6 and 7 for the two objective functions. If the change in one of the objective functions was more than 25%, by an increase or decrease of 50% in the parameter value, the parameter was selected for the calibration. Based on this criterion, the parameters selected for calibration for the Ommerkanaal are K0, FC and ULZ. BETA will also be calibrated due to the interest of this study in the soil moisture. Also, PERC will be calibrated because, during the calibration, it became clear that without the calibration of PERC, the model performance was not as good as with the calibration with the PERC. This can be explained if looked at the simulated runoff before calibration in Figure 8. In the situation before calibration, there is a higher base flow than observed, by calibrating the PERC this could be altered. For the Dinkel and Sallandse Wetering also a sensitivity analysis has been conducted, which can be found in appendix E and D, respectively. The parameters selected for calibration for the Dinkel and Sallandse Wetering can be found in Table B.1 in Appendix B.

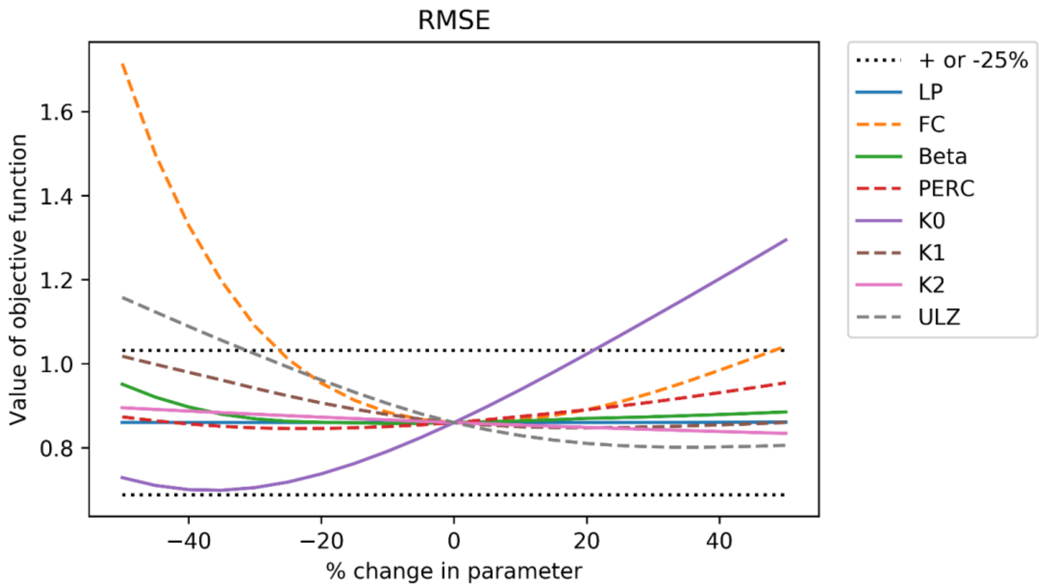

Figure 6: The parameter sensitivity of the HBV model of the Ommerkanaal reflected by the RMSE

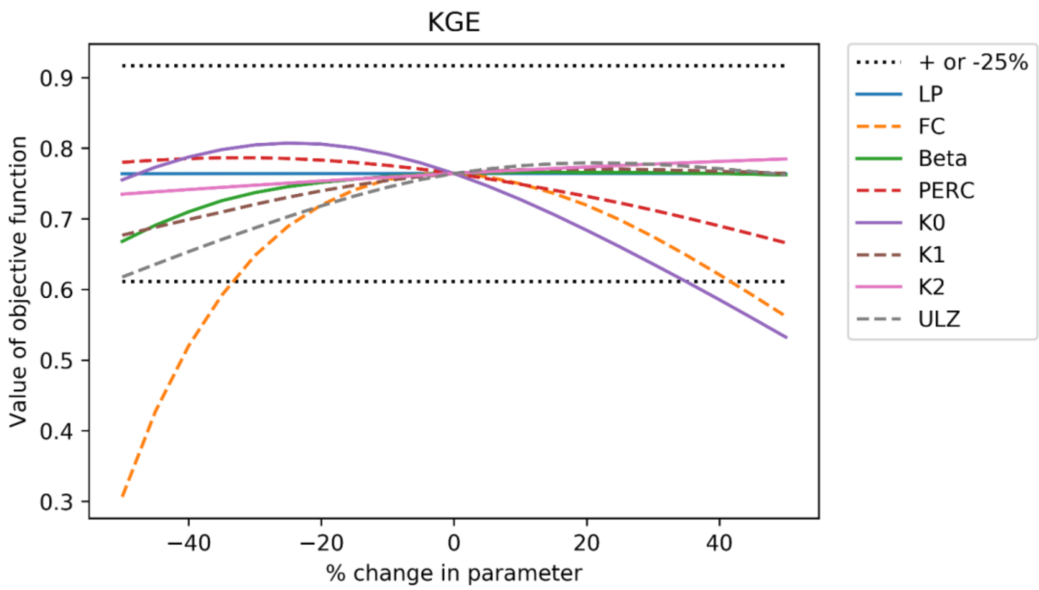

Figure 7: The parameter sensitivity of the HBV model of the Ommerkanaal reflected by the KGE

3.1.2 Calibration

The model is calibrated by using a Monte Carlo approach where 2.500.000 runs were performed with values for the five parameters randomly sampled from the ranges given in Table 2. In Table B.1 in Appendix B the calibrated values for the HBV model of the three sub-catchments are given. Table 3 shows the values for the objective functions before (as used in the FEWS system) and after calibration. In Figure 8 the hydrograph for the Ommerkanaal is given. When considering both the value of the objective functions and the hydrograph, there is an improvement of the model visible. The calibration conducted in this study is more rigid than the one done for the FEWS model (as described in section 2.2.3), and therefore it is reasonable to assume that the model would improve. The biggest improvement is in the base flow of the model, as can be seen in Figure 8, but also in the peak flows, there is an improvement visible.

Table 3: Values of the objective functions before and after calibration

Objective function	Before calibration	After calibration
Ommerkanaal		
KGE	0.76	0.90
RMSE	0.86 (m^3/s)	0.57 (m^3/s)
Sallandse Wetering		
KGE	0.65	0.87
RMSE	2.57 (m^3/s)	1.62 (m^3/s)
Dinkel		
KGE	0.42	0.77
RMSE	3.72 (m^3/s)	2.74 (m^3/s)

For the Dinkel and the Sallandse Wetering, the calibration did also improve the model performance, similar as for the Ommerkanaal (Table 3). For this reason, it can be concluded that the calibration has improved the model performance for all the 3 sub-catchments. After calibration, the model is performing better for the Ommerkanaal than for the Sallandse Wetering and the Dinkel. This is reflected in the value for KGE closer to 1 and a lower RMSE for the Ommerkanaal than for the Dinkel and the Sallandse Wetering.

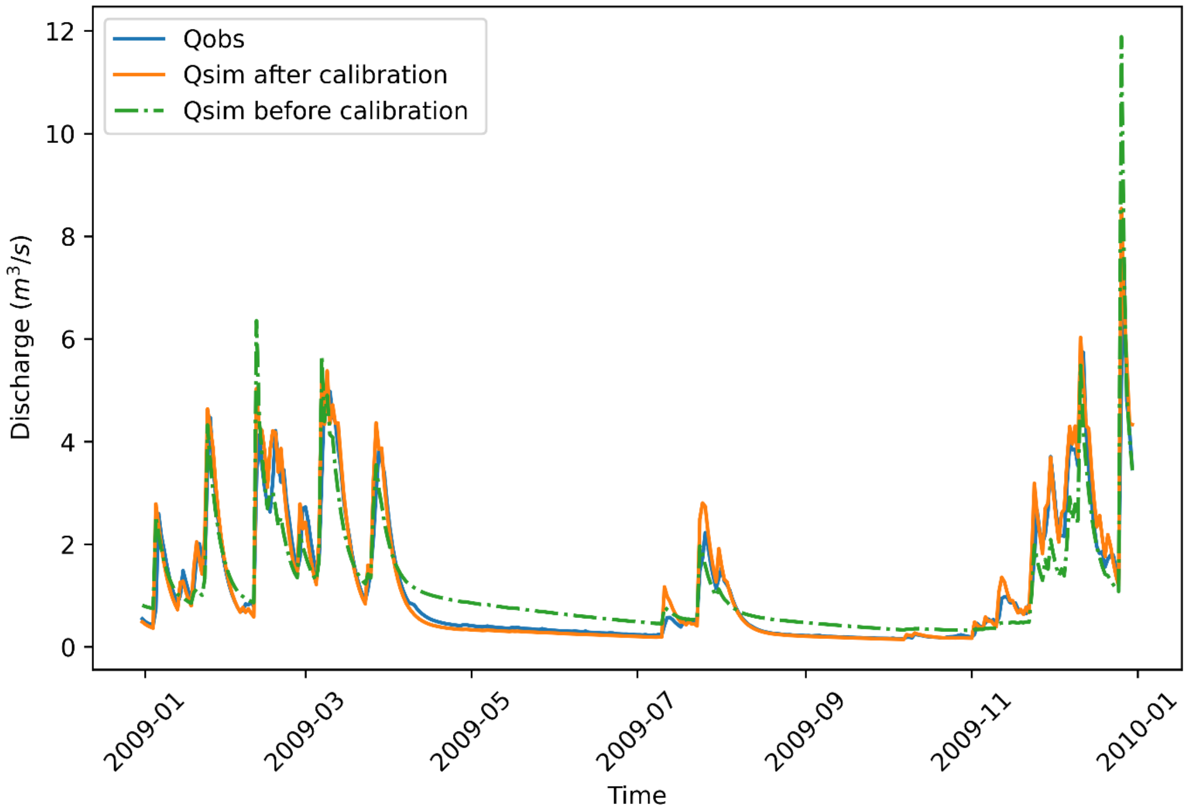

Figure 8: Hydrograph for the Ommerkanaal for 2009 only, to illustrate the effect of the calibration on the simulated discharge, with the observed and simulated discharge before and after calibration.

3.2 The sensitivity of the HBV model to its initial conditions

In this section, the results of the sensitivity analysis for the initial conditions will be presented for the Ommerkanaal, the Sallandse Wetering and the Dinkel.

Figure 9 shows the outcome of the sensitivity analysis of the HBV model for the Ommerkanaal for the initial conditions: soil moisture (SM_0), upper groundwater zone (SUZ_0) and lower groundwater zone (SLZ_0). It was found that the model is most sensitive for the initial condition of the soil moisture (SM_0), because the change in the initial condition for the SM_0 has the largest effect on the RMSE, which can be seen in Figure 9. With an increase of the lead time, the sensitivity of the model for the changes in the initial condition of SM_0 increases. The higher sensitivity with a higher lead time can be explained due to the fact that there is no runoff out of the soil moisture storage. Therefore, the water has to move to the lower 2 storage compartments in order to contribute to the run, which will take time. Due to the fact that there is a delay in changes in the discharge, there will also be a delay to see the effect of the changes in SM_0 in the objective function used.

In Figure 10 the effect of the sensitivity analysis is shown for the Ommerkanaal, for a period of only one peak discharge, in order to see the effect of the changes in initial condition on the simulated discharge. The conclusion that can be drawn from this figure is the same as the conclusion that can be drawn from Figure 9: the sensitivity of the discharge for the initial conditions of the HBV model is the highest for SM_0. This applies to all lead times, with one exception: the 1-day lead time. With an increase of 25% for the SUZ_0, there is a relatively large change in the simulated discharge in Figure 10, which cannot be seen in the RMSE in Figure 9. Therefore, the conclusion is that the HBV model of the Ommerkanaal is most sensitive for the initial value of SM_0, especially for higher lead times. The same conclusion can be drawn for the Sallandse Wetering, as can be seen in figure D.2 in Appendix D. The only difference between this sub-catchment and the Ommerkanaal is that the sensitivity for SLZ_0 for the Sallandse Wetering is higher. However, the sensitivity of the Sallandse Wetering for SLZ_0 is still lower than the sensitivity for SM_0.

Unlike the Sallandse Wetering and the Ommerkanaal, the highest sensitivity for the initial conditions of the Dinkel is not SM_0, as can be seen in Figure 11, but SLZ_0. A possible explanation for this result could be that the maximum SM for the Dinkel is only 60 mm (which is small in comparison to the maximum storage of both the Sallandse Wetering and Ommerkanaal), while the storage of SLZ reaches values of more than 400 mm. Therefore, in comparison to the SLZ storage, the effect of a change in the percentage of the SM storage leads to a smaller change in the storage (in mm).

Nevertheless, the conclusion is that the HBV model is sensitive to the initial conditions of the SM_0. For the Ommerkanaal and the Sallandse Wetering, the model is most sensitive for the initial condition of SM_0, for the Dinkel it is not, but the initial condition of SM_0 still has a relatively large effect on the objective function of the simulated discharge of the Dinkel, especially for higher lead times. Therefore, for all the sub-catchments, it is expected that an improvement of the initial conditions for the SM_0 leads to an improvement in the simulated discharge.

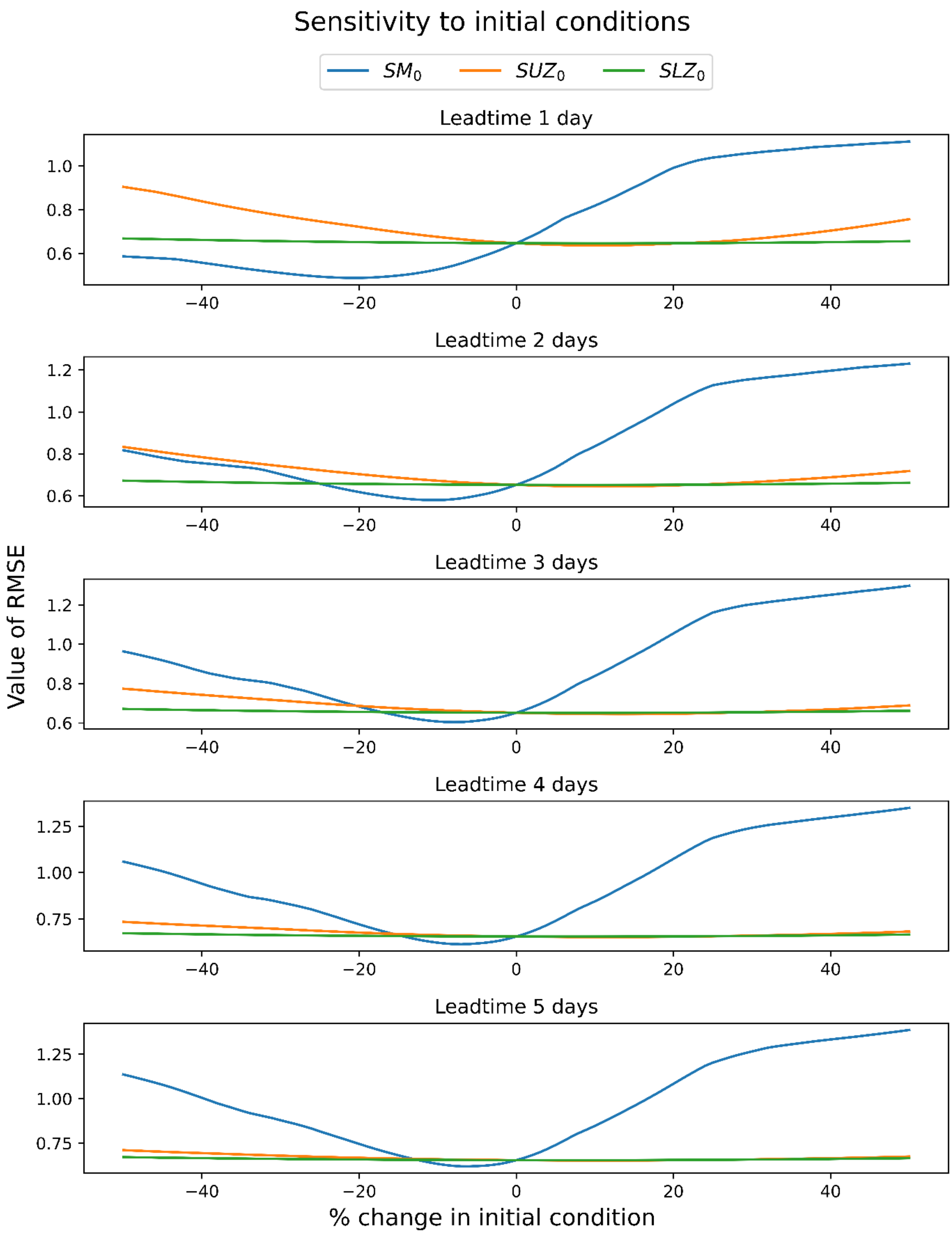

Figure 9: Outcome of the sensitivity analysis of the HBV model for the Ommerkanaal for its initial conditions reflected by the RMSE for different lead times of 1 to 5 days

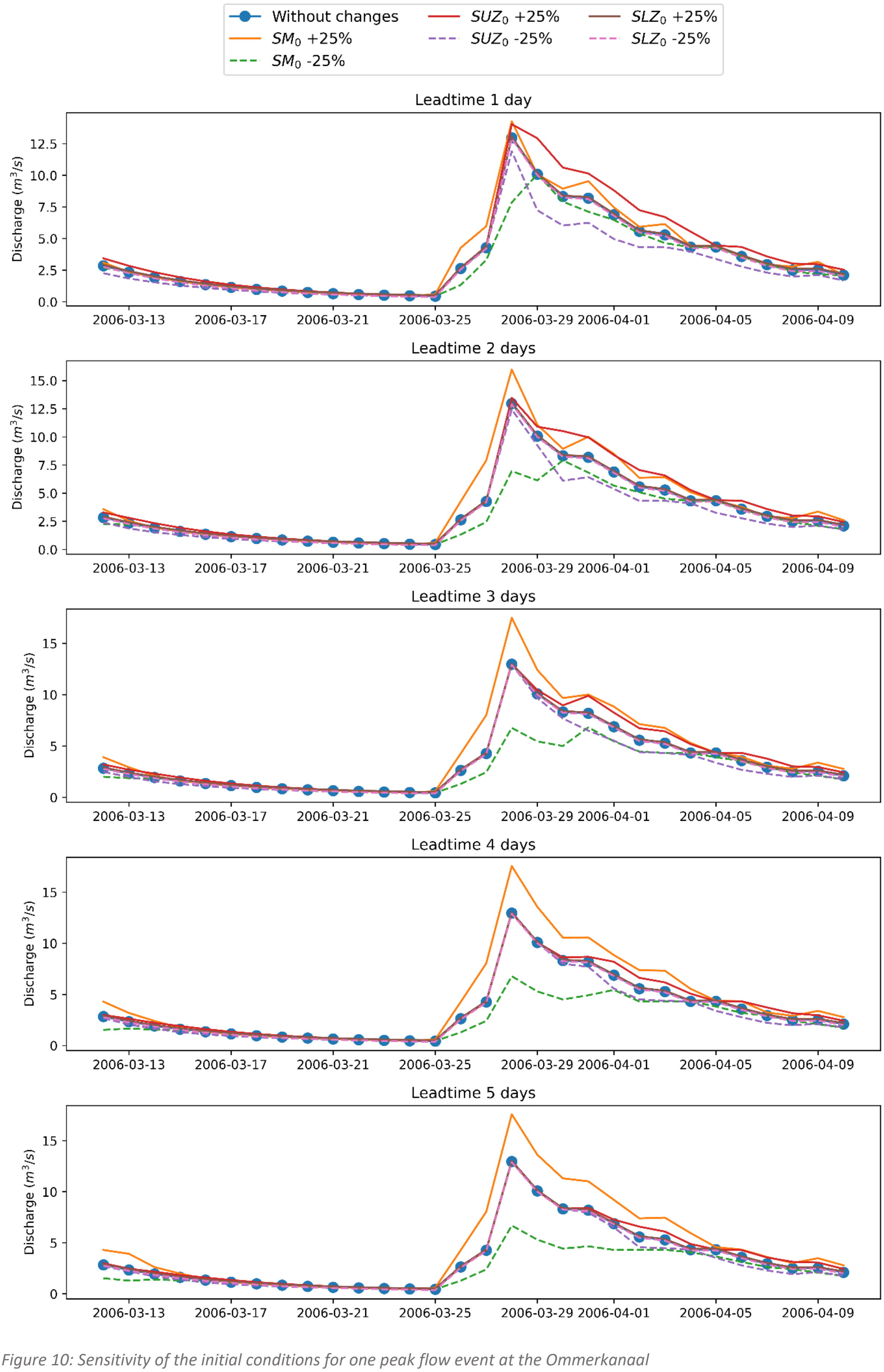

Figure 10: Sensitivity of the initial conditions for one peak flow event at the Ommerkanaal

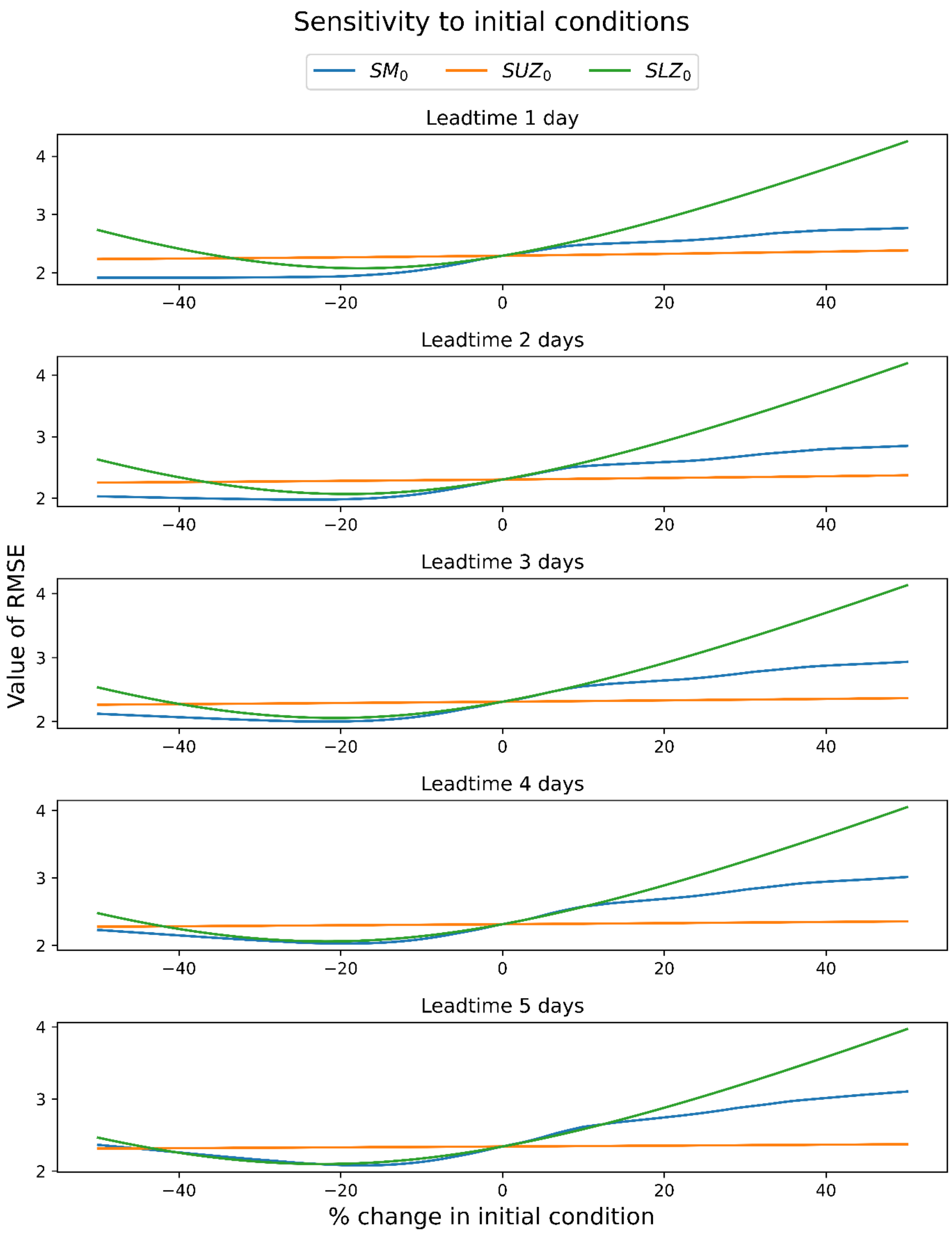

Figure 11: Outcome of the sensitivity analysis of the HBV model for the Dinkel for its initial conditions reflected by the RMSE for different lead times of 1 to 5 days

3.3 Correlation of the HBV simulated soil moisture and the remotely sensed soil moisture.

In this section, the results of the correlation between the soil moisture simulated by HBV and the remotely sensed soil moisture will be presented for the Ommerkanaal, the Sallandse Wetering and the Dinkel.

3.3.1 Ommerkanaal

In Figure 12 the daily remotely sensed soil moisture content by VanderSat (with interpolation of the missing data, as can be seen in appendix A) and the soil moisture modelled by the HBV model is plotted for the Ommerkanaal. The correlation coefficient between the VanderSat daily measured soil moisture content and the soil moisture simulated by HBV has a value of 0.81. Figure 13 shows the moving average (3-day window) of the remotely sensed soil moisture content by VanderSat and the soil moisture simulated by the HBV model for the Ommerkanaal. Clearly, there is a high correlation between the 3-day moving average and the soil moisture simulated by HBV. This is also reflected by the correlation coefficient, with a value of 0.91. With this result, it can be concluded that the HBV model and the remotely sensed soil moisture have a high degree of similarity.

As can be seen in Figure 13, the moving average smooths the peaks, and therefore the short term response of the soil moisture content to precipitation events is removed from the data set. The peaks in the data set are caused by the fact that the satellite is only measuring the top 5 cm of the soil. Therefore, if the satellite overpass is directly after a precipitation event, the top 5 cm will be wet, whereas the rest of the soil could be dryer. But it could also be that the remotely sensed soil moisture has noise introduced by the measurement with satellites.

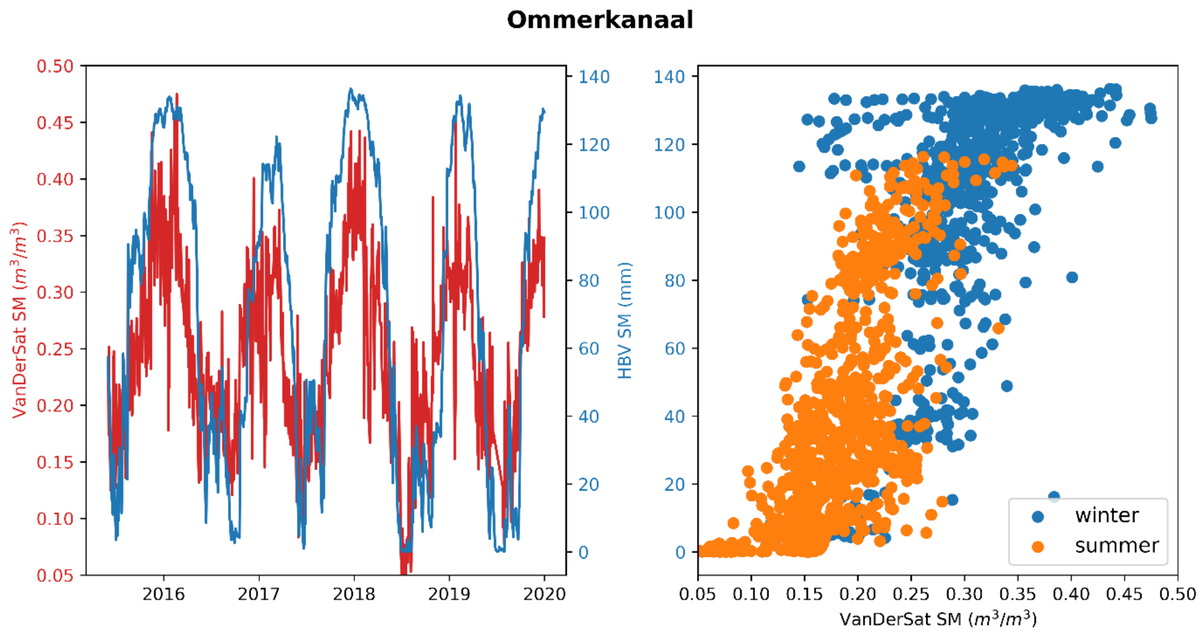

Figure 12: The soil moisture simulated by the HBV model and the daily remotely sensed soil moisture for the catchment of the Ommerkanaal and the scatter plot of the same data

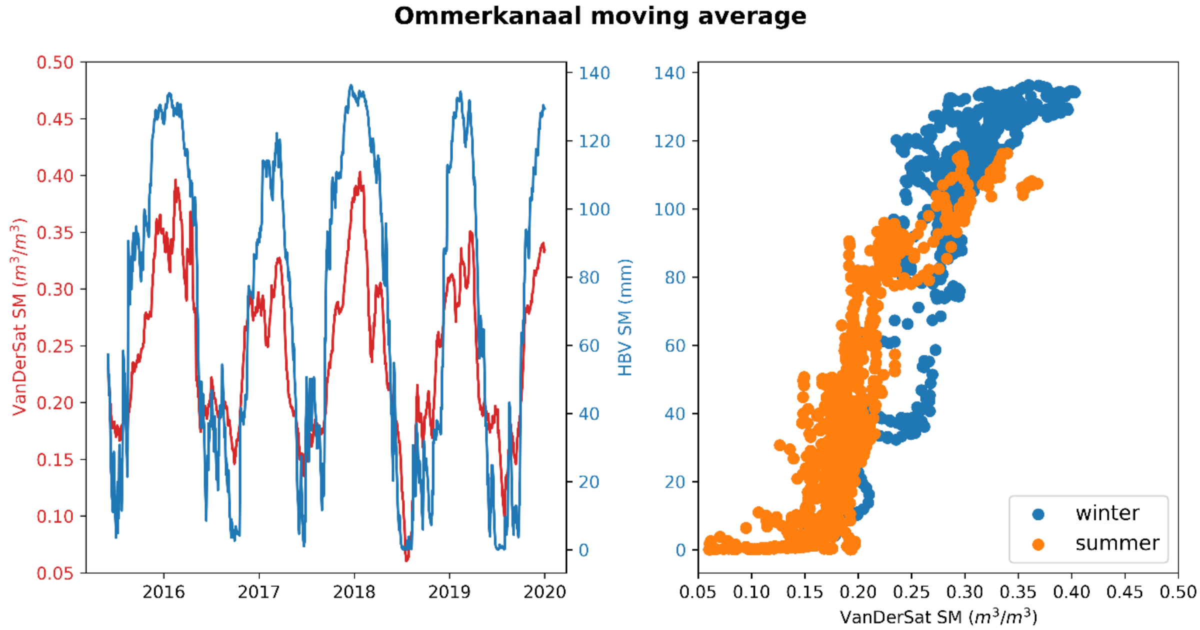

Figure 13: The soil moisture simulated by the HBV model compared with the moving average of the remotely sensed soil moisture for the Ommerkanaal and the scatter plot for the same data

On the right-hand side of Figure 12, a scatter plot of the HBV-simulated soil moisture and the remotely sensed soil moisture content delivered by VanderSat, is shown as well. As can be seen in the figure, for low values of soil moisture content until 0.10 (m^3/m^3), measured by VanderSat, the HBV modelled soil moisture shows a relatively low value. Furthermore, the spread of values is large: for a single value of the soil moisture content, a whole range of values is present for the HBV-simulated soil moisture (and vice versa).

Similarly, on the right-hand side of Figure 13, the scatter plot of the HBV-simulated soil moisture and the moving average of the soil moisture content, delivered by VanderSat, is shown. In this figure, the clustering of the low values of the measured soil moisture content is even better visible than in Figure 12. Meaning that the HBV model is modelling a soil moisture storage close to 0 mm, while the values measured by VanderSat are ranging between 0.05 and 0.15 m^3/m^3. In contrast to the scatter plot in Figure 12, the spread of the values is less; this is also reflected in the higher correlation coefficient.

Onwards from a value of the soil moisture content of approximately 0.15 (m3/m3) in Figure 13, there is an upward trend, which levels off at the higher values for the soil moisture of the HBV model. The flattening of the trend is more visible at lower values (of the simulated soil moisture) in summer than in winter, this is caused by the soil moisture content modelled by the HBV model, these are typically lower in the summer than in the winter. This trend has some linear behaviour in it (at some intervals the trend is, but especially at the lower and upper part of the data there is some nonlinear behaviour visible.

3.3.2 Dinkel and Sallandse Wetering

The relevant figures for the Sallandse Wetering and Dinkel can be found in appendix C and D, respectively. In Table 4, the values for the correlation coefficient for the Sallandse Wetering and Dinkel are given. For both catchments, a higher correlation is found for the 3-day moving average than for the original data points, as can be seen in Table 4, similar as for the Ommerkanaal. For both, especially for the Dinkel, the correlation (between the simulated soil moisture and remotely sensed soil moisture), is lower than for the Ommerkanaal. Nevertheless, the correlation between the remotely sensed soil moisture and the HBV modelled soil moisture is still high. But there should be taken into account that even though the correlation is high if looked at the scatter plots, there is still a large difference in the pattern of the HBV model soil moisture and the remotely sensed soil moisture.

Table 4: correlation coefficient for the measured on daily bases and 3-day moving average data set for the different sub-catchments

	Ommerkanaal	Sallandse Wetering	Dinkel
Daily	0.82	0.75	0.81
3-day moving average	0.91	0.87	0.85

Concluding, there is a good correlation between the HBV-simulated soil moisture and the soil moisture data delivered by VanderSat, especially for the 3-day moving average. The only correlation coefficient used is a linear one, but the scatter plots show that the correlation between the remotely sensed soil moisture content and the simulated soil moisture is not completely linear. Therefore, a higher correlation could have been found if a nonlinear correlation coefficient would have been used. Furthermore, the highest correlation is found, for both data sets used, with a lag of zero days.

In line with the findings above, it can be concluded that data assimilation of the remotely sensed soil moisture has potential (due to the relatively high correlation) and could have a positive effect on the accuracy of the simulated discharge. Even though the correlation for the moving average data is always higher than the correlation for the daily measured soil moisture content, both data sets will be used in the assimilation discussed in the next section, because the difference in the value of the correlation coefficient is relatively small. Another reason to use both data sets is that there is a possibility that the daily measured soil moisture content gives a better result during the assimilation because, in the moving average, the peaks are smoothed.

3.4 Data assimilation of soil moisture into the HBV model.

In this section, the transformation of the data delivered by VanderSat and the assimilation of soil moisture as an initial condition for the HBV model will be presented. The assimilation is done for all 3 sub-catchments.

3.4.1 Transformation of VanderSat data.

In Figure 14, the transformation of the soil moisture content delivered by VanderSat in m^3/m^3 to mm can be seen, in comparison to the HBV modelled soil moisture without assimilation. For both data sets, the daily remotely sensed soil moisture content, and the 3-day moving average of the soil moisture content, 2 methods are used. For both methods, the trend in the soil moisture data is the same; only the absolute value is different. Therefore, the linear correlation coefficient between the transformed soil moisture (both for the daily measured data and the 3-day moving average) and the HBV modelled soil moisture does not deviate from the values found in section 3.3.

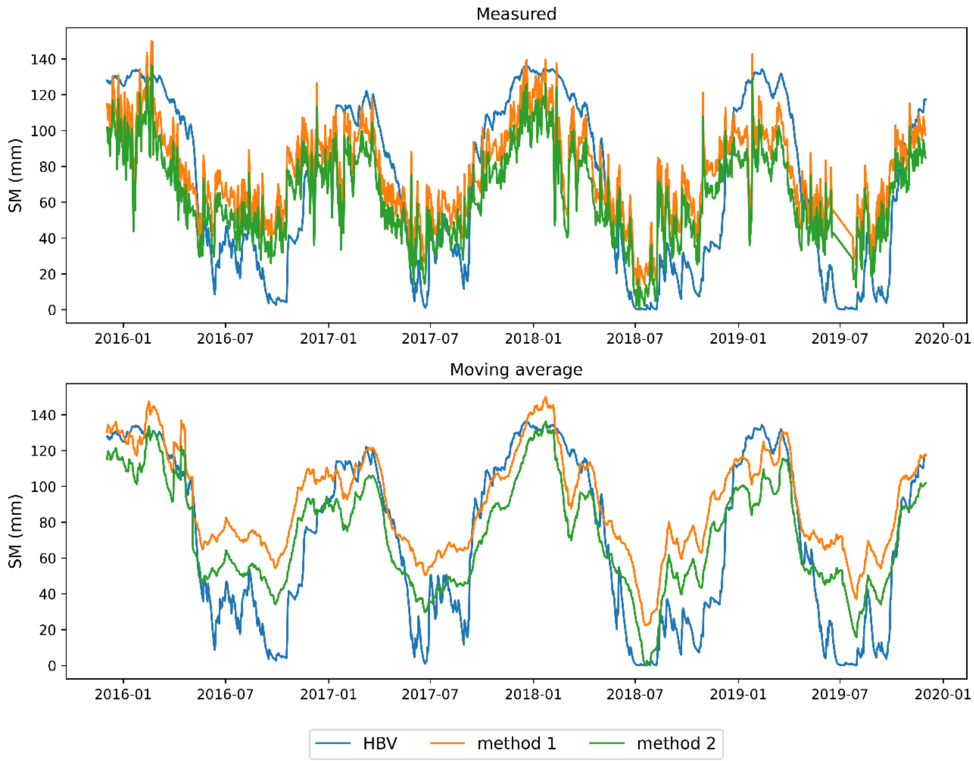

Figure 14: Soil moisture simulated by the HBV model (in mm) and the soil moisture derived from VanderSat data with method 1 (equation 13) and 2 (equation 14), also in mm for the Ommerkanaal for the period 2016 to 2018. The latter two are used for the data assimilation.

In Figure 15, the transformed soil moisture could be seen in comparison to the remotely sensed soil moisture for the Ommerkanaal. In this figure it could clearly be seen that the remotely sensed soil moisture is linear transformed to the units used in the HBV model. The figures for the Sallandse Wetering and Dinkel could be found respectively in the Appendix D and E.

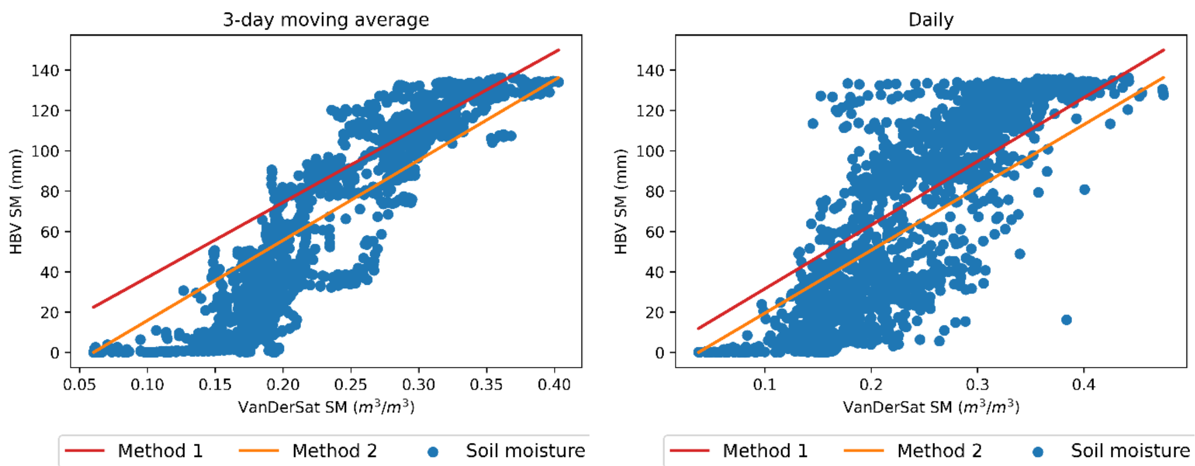

Figure 15: The remotely sensed soil moisture in comparison to the transformed soil moisture.

3.4.2 Data assimilation

In this section, the results of the assimilation for the different sub-catchments will be presented. The results will be presented in two different graphs. The first graph shows the effect of the assimilation on the objective functions (RMSE and the correlation coefficient) for the selected periods. Also, the effects of the use of 2 different methods, as described in 2.5.2, are shown. The values of the objective functions for the reference situation are shown too. The reference situation is the newly calibrated HBV model without the assimilation of the remotely sensed soil moisture. The effect of the assimilation is expressed by the improvement of the objective functions in percentages. So, if the RMSE goes from 1 to 0.9 m^3/s, the improvement is 10%. The second graph is showing the forecasted discharge of the different methods and data sets used as well as the forecasted discharge without assimilation and the observed discharge. Furthermore, in this graph, the initial SM for the model run for that day is shown, both for the HBV modelled soil moisture and the assimilated soil moisture. The lead time giving in this figure is the between the forecasted discharge and the initial condition used, so for the forecast with a lead time of 5 days the initial condition is the value of 5 days before from the lowest subplot in the figure.

Ommerkanaal

In Figure 16 and Figure 17, the results of the assimilation for the Ommerkanaal are shown. In Figure 16, the two methods and the two data sets used for the five selected periods are shown. In Figure 17, the effect of the assimilation is shown for a peak flow event; the hydrographs of the other periods can be found in Appendix C.

The assimilation did not lead to an overall improvement in the forecasted discharge. Moreover, only for period 1 and 4, an improvement can be observed, for all other periods, both the objective functions scored worse. For period 1, both the correlation coefficient and the RMSE showed an improvement, for period 4 only the RMSE improved in some cases. For period 4, the effect of the assimilation is not useful. When looked at Figure C.3 in Appendix C, it can be seen that the effect of the assimilation is not an improvement for period 4, the simulation is still not adequate, even though there is an improvement in the RMSE. In Figure 17, the effect of the assimilation on the forecasted discharge is shown for period 1. The forecasted discharge without assimilation is not very accurate, because the difference between the forecasted peak discharge and the observed peak discharge is nearly 10 m^3/s, this inaccuracy is also represented by the RMSE with a value of 4.31 (m^3/s) for this period. The improvement of the assimilation can be explained when looking at the lowest subplot of Figure 17, in which the original initial SM of the HBV model is compared with the initial SM used in the assimilation. The HBV model shows an increase in the soil moisture content. Therefore, a part of the precipitation of the HBV model is not transformed to discharge, but it is stored in the soil moisture. With the assimilation, this behaviour is partly removed, mainly because the assimilated soil moisture uses a higher soil moisture content and therefore there is less precipitation stored in the soil moisture, and hence the forecasted discharge is closer to the observed discharge. The overall effect of the assimilation for period 1 is positive, but there are differences in the accuracy of the forecasted discharge. The effect of the assimilation during a dry period as seen for period 1 of the Ommerkanaal could also be seen in another, which is not one with a high peak flow and therefore not selected as described in section 2.5, in Figure C.5 in Appendix C. This period has only a small discharge in comparison to the period 1 of the Ommerkanaal, but the behaviour of the HBV model and the assimilation is the same.

For the forecasted discharge with a lead time of one day, the methods using the daily measured soil moisture content are performing better than the ones using the 3-day moving average. However, with an increase in lead time, this change in favour of the 3-day moving average. With a lead time of more than 3 days, the methods using the 3-day moving average are performing better than the methods using the daily measured soil moisture content, as can be seen in Figure 16. The general conclusion which can be drawn from Figure 16 is that method 1 with the 3-day moving average as inserted data, is performing the best. But overall, it can be concluded that the assimilation is not giving a better model performance

In general, the deviation from the reference situation is quite large. This is indicated by the value of the RMSE, which is above 3 (m^3/s) for period 1, 4 and 5. For period 2 and 3, the value of the RMSE is smaller, but still quite large. Therefore, the overall conclusion is that the model performance is suboptimal without assimilation for all the selected periods, and with assimilation soil moisture, the performance is even worse. This can be explained by Figure 15 in which clearly could be seen that the transformation of the remotely sensed soil moisture is introducing a large error.

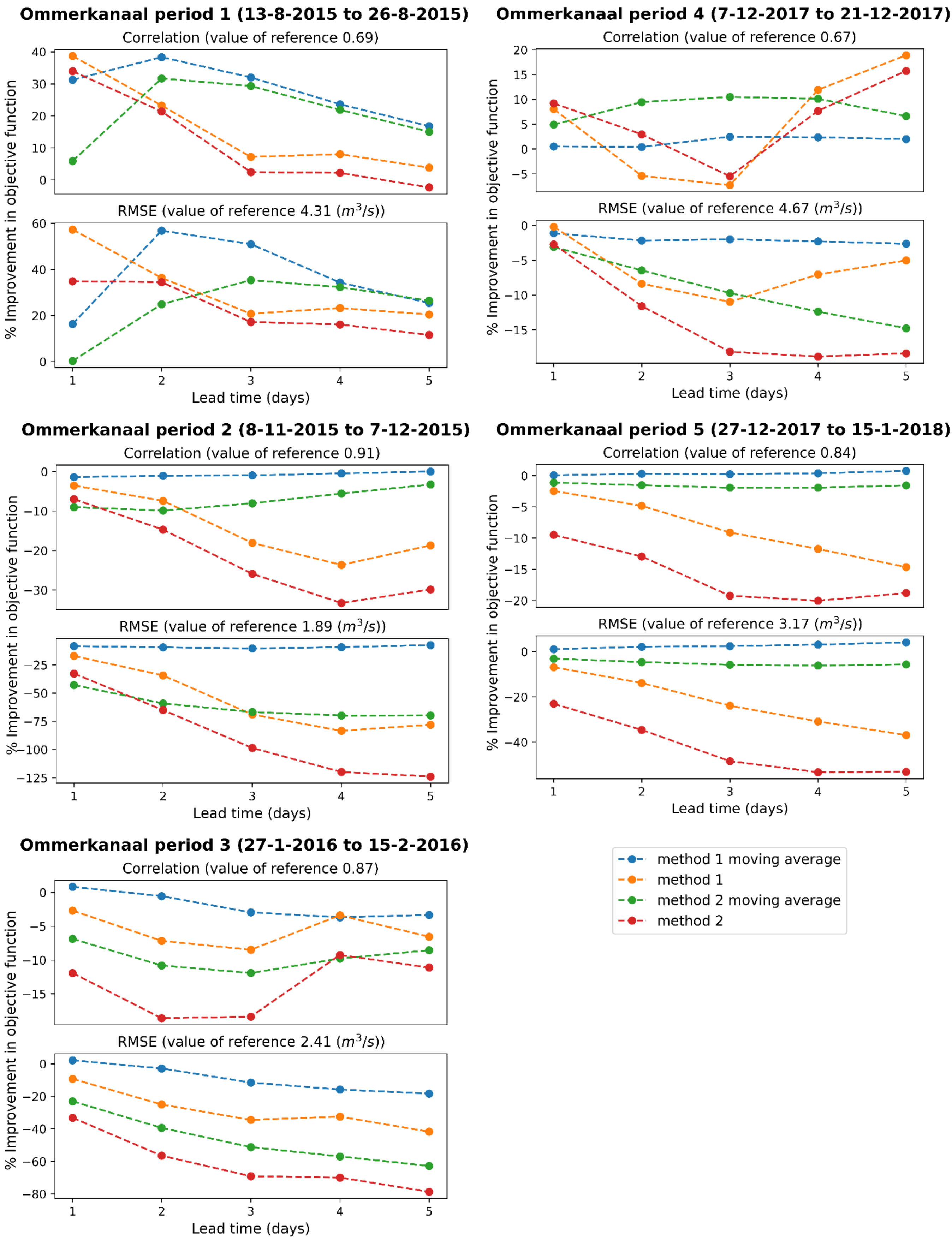

Figure 16: The result of the assimilation for 5 periods for the Ommerkanaal, expressed in the objective functions used.

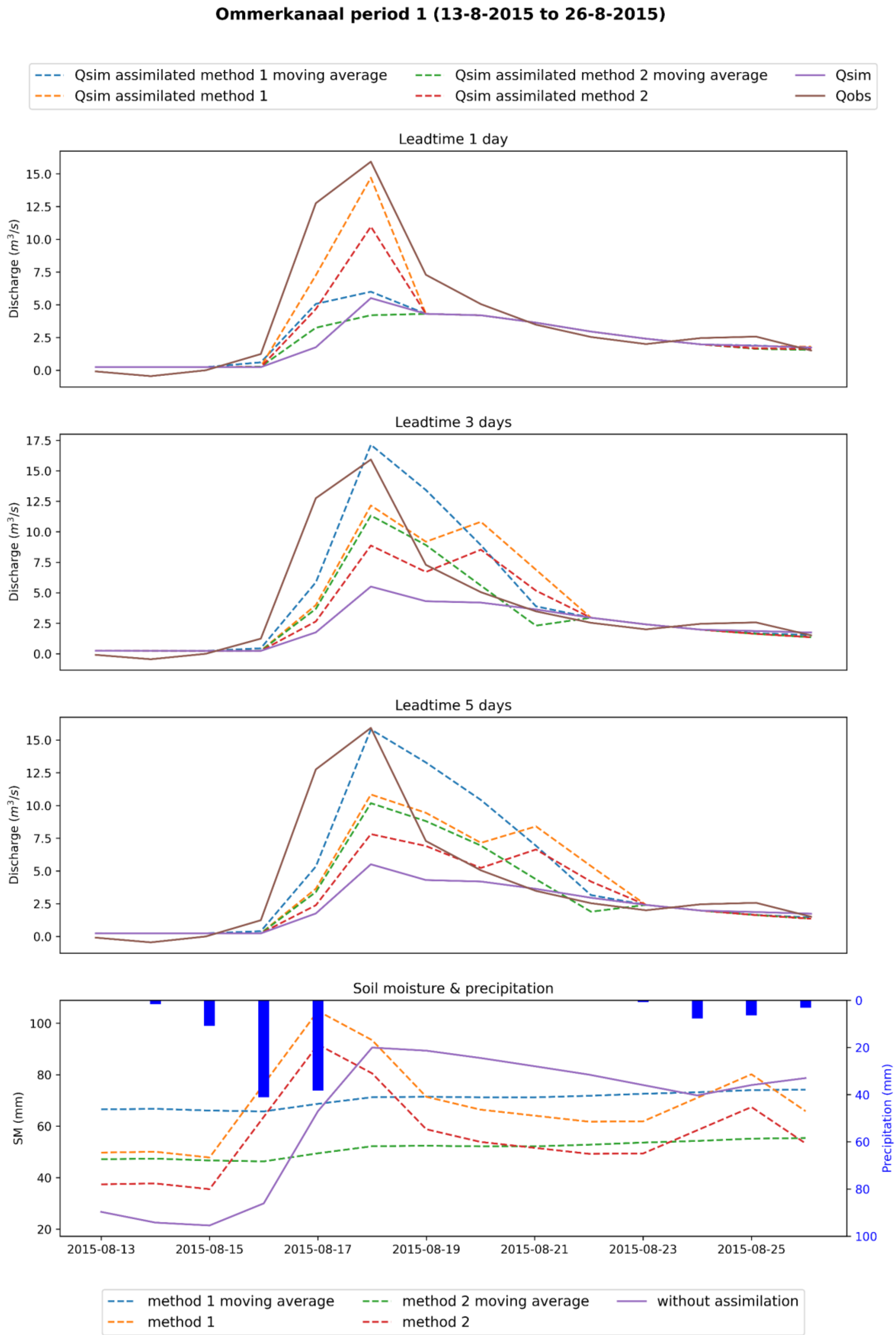

Figure 17: The effect of the assimilation of soil moisture on the discharge of one peak flow event

Sallandse Wetering and Dinkel

In this section a summary of the result for the Sallandse Wetering and the Dinkel could be found, a more elaborated result for the Sallandse Wetering and the Dinkel can be found in, respectively, Appendix D and E.

The same conclusion, as for the Ommerkanaal, can also be drawn for the Sallandse Wetering, the assimilation of remotely sensed soil moisture data does not improve the forecasted discharge. For all periods, the value of the RMSE is above 4 (m^3/s), which is relatively high for a flow of approximately a peak discharge of 30 (m^3/s) which is in line with the findings for the Ommerkanaal.

The conclusion for the Dinkel is the same as found by the Ommerkanaal, in which this assimilation is also not leading to an improvement of the model performances for the periods. Furthermore, one of de selected periods for the Dinkel is during a dry period, in which the assimilation did not have the same effect as found for the Ommerkanaal. The assimilation did not for this period lead to an improvement in model performance as found for two dry periods for the Ommerkanaal.

A general conclusion of 3.4

The effect of the assimilation of soil moisture in the HBV model does not result in an improvement of the model performance, expressed in the RMSE and the correlation coefficient. In general, in comparison to the methods using the daily measured soil moisture data set, the methods which are using the moving average have a better model performance, but the overall performance of the assimilation is not an improvement. That the methods using the 3-day moving average are performing better could be explained because there is a higher correlation between this data and the HBV simulated soil moisture, possibly because the peaks are smooth. The daily measured data is highly depending on the moment when the satellite passes over. If it just has rained, all the water is still in the top few centimetres of the soil, so the value is an overestimation of the soil moisture content in deeper layers. Using the moving average instead of the daily measured soil moisture content partly dampens this effect, which reflects the simulated soil moisture of the HBV better.

In the periods where the assimilation is leading to a decrease in model performance, there could be concluded that the HBV simulated soil moisture is performing better than the assimilated soil moisture. This can be explained by looking at the transformation which is done to the remotely sensed soil moisture content delivered by VanderSat, as shown in Figure 14 and Figure 15. At some point, the assimilated soil moisture is close to the HBV simulated soil moisture, but there are also periods where the difference is huge. Especially in Figure 15 this effect could be clearly seen. But also, the physical difference between the remotely sensed soil moisture and the HBV modelled soil moisture are a source of the error.

There are 2 periods found for which the assimilation leads to an improvement of model performance, both for the Ommerkanaal. For both periods, the peak flow occurred during a dry period. During a dry period, the HBV model stores water in the soil moisture storage, which will lead to a lower discharge. With the assimilation, this is partly solved because the assimilated soil moisture is higher than the soil moisture simulated by the HBV model.

Therefore, with assimilation, the HBV model simulates more discharge. This effect of the assimilation is not shown for the other sub-catchments, even though there is a relatively dry period used for the Dinkel.

In addition to this, it can be concluded that the models of all three considered sub-catchments that the error of the models is relatively large, and consequently there is a large difference between the forecasted discharge and the observed discharge. For some peak flows the model is performing not adequately, for example, period 4 for the Ommerkanaal and period 1 for the Dinkel.

4 Discussion

The results and implications of this study are discussed in this chapter. At first, the potential of this research is described in Section 4.1. In Section 4.2, several limitations of the methodology and overall study are presented, and in section 4.3, the generalization of the results will be presented.

4.1 Potential

This study shows that there is a relatively high correlation between the HBV modelled soil moisture and the remotely sensed soil moisture. This is in line with the finding of Liu et al. (2007), who found a large correlation between the remotely sensed soil moisture content and the HBV modelled soil moisture content. Liu et al. (2007) found that smoothing (with neighbouring measurements) the measurement from the satellite leads to a better correlation, which is in line with the findings of this study. However, Liu et al. (2007) found that the response to precipitation of the remotely sensed soil moisture was quicker than the HBV model soil moisture, the best correlation they found was for a lag of several days. This was not found in this study, for all the sub-catchments of the Vecht, the highest correlation is found with no lag.

Although the HBV simulated soil moisture and the remotely sensed soil moisture data are physically different, the remotely sensed soil moisture content is only telling something about the top layer, while the HBV model is some conceptual soil moisture storage, there is a good correlation between them. Therefore, there is a potential to use this data in the HBV model for different purposes, such as the calibration of poorly gauged areas.

During the calibration, the remotely sensed soil moisture data has not been used. Therefore, an improvement of the effect of the assimilation could be made by using the data during calibration. This is something that has been done in other studies, for example, by López et al. (2017). By using the remotely sensed soil moisture during the calibration, the parameters could be changed such that model better responds to the assimilated data, in order to partly overcome the problem caused by the physical differences.

In this study, remotely sensed soil moisture delivered by VanderSat was used, but there are other soil moisture products available as well. Theses soil moisture products could be used with the same approach. An example of other remotely sensed soil moisture is SMAP (van der Velde et al., 2019). This product is validated with a network of in situ soil moisture sensors in Twente, the Netherlands.

During this research, it was discovered that the HBV model is having problems with the simulation of peak flows during a dry period. After a long dry period, when the soil moisture content (SM) is low, rainfall will consequently add very little to the runoff, while after a wet period the situation is the opposite (Bergström & Forsman, 1973). This behaviour of the HBV model is also found by Rakovec et al. (2012), after a dry period the model showed a smaller discharge than in a situation where the soil moisture content was higher. In this study, it was shown for the Ommerkanaal that the HBV model with assimilation could simulate the peaks better in dry periods. This could be a potential for using the assimilation of soil moisture content.

4.2 Limitations

This study knows some limitations, the first limitation is that the perfect forecast was used, which means that measured precipitation is used instead of forecasted precipitation. This will lead to less uncertainty in the forecasted discharge because the uncertainty of the precipitation is largely filtered out. Therefore, the results of this study for a real forecasting situation would lead to more uncertainty in the forecasted discharge, and probably to worse results.

This study has not looked at the effect of the assimilation for the whole catchment of the Vecht, but only at the effect for 3 individual sub-catchments of this river. The ultimate goal of the WDOD is to improve the accuracy for the whole catchment. The assimilation is done in standalone simulations for each sub catchment, the effect of the assimilation of the 3 areas is not translated to the Vecht as a whole. Furthermore, the discharge of the Vecht, which is 150 to 200 m^3/s during peak flow events, is relatively large compared to the discharge of the 3 sub-catchments used during this research.

The calibration is done for a period of 4 years, in this period several peak flow events are present; most of them are in the periods when the soil is wet. Therefore, during the calibration, more emphasis is put on peak flow events with a high soil moisture content. This means that peak flow events with low soil moisture content are not calibrated as good as the peaks in the wet situation.

The remotely sensed soil moisture content is linearly transformed and used in the HBV model, while, when looking at the data, there is not a completely linear correlation. The shape of the curve in the scatterplot is more like an S-shape. This could lead to a lower performance of the assimilation, especially at the lower and upper limits of the interval of the curve. Another interpolation of the data to transform the VanderSat data to SM in HBV could possibly lead to better results.

The HBV models used in this study are lumped models. As the HBV models cover a large area, the input of satellite data has to be averaged over the area, which leads to a loss of information and regional variability.

The discharge of the sub-catchments is not free, the water level in the Vecht has an impact on the outflow of the sub-catchments. Therefore, the measurements of the sub catchment are not completely in line with the simulations of the HBV model. Furthermore, at the end of the Ommerkanaal, there is a weir which is controlling the water level and flow. Therefore, even if the model has a perfect simulation, there could be a difference in the observed a forecasted discharge. But the effect of the weir will be the biggest in low flow situations.

The satellite gives information about the top 5 centimetres of the soil, while the HBV model gives information about a conceptual soil moisture storage. The effect of precipitation is more pronounced when only looking at the top 5 centimetres of the soil, then with measurements deeper in the soil. Therefore, the correlation and the assimilation will be different with measurements done at another dept (in situ).

4.3 Generalization

The findings of this study could be used in other models in the same catchment but also in other catchments. A high correlation was found between the modelled soil moisture and the remotely sensed soil moisture content. Although they are not physically the same, it could be that this correlation (of two variables giving information about the wetness of the soil) is the same in other models, like for example WALRUS (Brauer et al., 2014), another model used by WDOD for the catchment of the Vecht. Also, there could be looked at the option of the use of remotely senses soil moisture for different models used by the water board. In order to implement the assimilation of remotely sensed soil moisture content in other models, there should be investigated what the shortcomings of the use of this assimilation are what kind of error the assimilation is introducing.

5 Conclusion and recommendations

In this finial chapter the conclusions and recommendation of this study will be presented.

5.1 Conclusion

The research aim of this study was to examine to what extent it is possible to improve the forecasted discharge of the HBV models of the 3 selected sub-catchments of the Overijsselse Vecht for peak discharges by assimilating remotely sensed soil moisture content as initial condition into the model. The research was guided by the 4 following research questions which will be answered in this section, and also the conclusion of the research aim will be presented:

1. To what extent could the HBV model performance be improved by recalibrating the model?
2. How sensitive is the HBV modelled discharge for change in the three different initial conditions, the initial level of the three different storage components (mainly focused on the soil moisture storage) of the HBV model?
3. What is the correlation between the HBV simulated soil moisture and the remotely sensed soil moisture content?
4. To what extent could the assimilation of remotely sensed soil moisture improve the forecasted discharge by the HBV model, in comparison to the observed discharge and the forecasted discharge without assimilation?

The recalibration leads to an improvement in model performance. For the 3 sub-catchments, the values of both the KGE and the RMSE improves with the recalibration. For the Ommerkanaal, this improvement was, in comparison with the improvement for the Sallandse Wetering and especially the Dinkel, relatively small. The overall model performance of the Ommerkanaal is the best of the 3 sub-catchments, both before and after recalibration.

The HBV model is most sensitive to the initial condition of soil moisture content for the sub-catchment of the Ommerkanaal and Sallandse Wetering. For the Dinkel, the storage of the lower zone is the most sensitive initial condition. Nevertheless, the sensitivity for the soil moisture initial condition is also relatively high for the Dinkel.

In the study there was found that a relatively high correlation exists between the remotely sensed soil moisture content and the HBV simulated soil moisture, especially when using the 3-day moving average. The correlation between the 3-day moving average and the HBV modelled soil moisture is higher because the peaks of the remotely sensed data are smoothed. The daily measured data is highly depending on the moment when the satellite passes over. If it just rained, all the water is still in the top few centimetres of the soil, so the value can be an overestimation or underestimation of the soil moisture content. Using the 3-day moving average moisture content instead partly dampens this flashy behaviour, which reflects the behaviour of the HBV simulated soil moisture better. Therefore, the correlation between the 3-day moving soil moisture content average and the HBV model soil moisture is higher.

The assimilation of remotely sensed soil moisture data by direct insertion does not lead to an improvement in the forecasted discharge with high peak flows. It can be concluded that for this study the simulated soil moisture is performing better than the assimilated soil moisture. This can be explained due to the large difference created with the transformation between the modelled soil moisture and remote sensed soil moisture. Furthermore, the remotely sensed soil moisture content is physically different then the HBV modelled soil moisture. This difference is also creating an error in the assimilation. The HBV soil moisture is telling information about a conceptual storage with a depth of in the order of magnitude of 100 mm water storage, while the remotely sensed soil moisture content is only giving information about the volume of water present in the top 5 centimetres of the soil. Therefore, the remotely sensed soil moisture is telling information about shallower depts then the conceptual HBV model.

However, there is a possibility that the assimilation of soil moisture could lead to a better forecasted discharge in very dry periods. In these periods the HBV model stores more precipitation in the soil moisture storage, which leads to lower peak discharges. In this study 2 periods for the Ommerkanaal have been found in which the assimilation leads to a better forecasted discharge in a dry period. Because the result only improved for these two periods while for the other periods the model performance decreased, it could also be a coincidence. More research is needed to find if other assimilation methods will improve the model in general as well.

5.2 Recommendation

In this section both the recommendations for this research and for WDOD will be presented in line with the points described in the discussion.

5.2.1 Recommendation for research

During this research, a very simple transformation of VanderSat data from m^3/m^3 to mm was used. This is probably an oversimplification. There are better ways to transform this with a nonlinear function. With a better transformation the performance of the assimilation could be better.

Also, the data assimilation used is relatively simple, therefore there could be looked into data assimilation methods which are more advanced. A relatively simple one could be to use a warmup period after the assimilation of the remotely sensed soil moisture because the effect of the assimilation is not directly visible in the discharge. This lag could also be seen in the sensitivity of the HBV model for its initial conditions. Furthermore, there are more sophisticated methods of assimilation than direct insertion, for example a Kalman filter, which is used by Komma et al. (2008) in a flood forecasting system.

Furthermore, VanderSat is only one of the providers of remotely sensed soil moisture content. With the use of data from other providers (e.g. SMAP) of remotely sensed soil moisture content, the effect of the assimilation of soil moisture could be different.

In addition, the calibration of the HBV model could be done with the use of the remotely sensed soil moisture. By already using the soil moisture data in the calibration the parameters could be adapted to the remote sensed soil moisture content. This could improve the performance of the assimilation.

5.2.2 Recommendations for water board WDOD

The investigated assimilation technique does not appear useful in the FEWS model, if the water board wants to use assimilation of remotely sensed soil moisture content there is more research necessary. With the assimilation used in this study the model performance does not improve, and even gets worse. This study is done with a perfect forecast, while in the situation WDOD is using this model, the precipitation forecasts are used. With the use of forecasted precipitation, the uncertainty increases, and the uncertainty in the precipitation forecast is probably bigger than the uncertainty in the initial conditions.

In order to ensure that the model stays up to date, it is important to calibrate the model now and then with newly available data. With recalibration, for both the HBV models and the SOBEK model, an improvement in model performance is achievable.

Another possibility is to look further into the use of the assimilation of soil moisture data in other models. The correlation found in this study could also be found for other models, even though the model and satellite measurements are not physically representing the same. For the HBV model it is easy to gather initial conditions with a warmup period of a year, but for other models it can be more cumbersome to get the right initial conditions for the model. For these models, the satellite information could be useful to determine the initial conditions.

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Appendix A: Data used

A.1 Satellite data

VanderSat delivered data of the measured soil moisture content for every pixel in the area. A the size of the pixel in de dataset is 1km*1km and is available for 230 days a year (VanderSat, 2020), an overview of how this data looks can be seen in Figure A.1. This is the soil moisture content measured by a satellite for a depth of 5 to 10 cm. Also, by VanderSat a regional average based on a user defined area is delivered, of this regional average also a moving average is delivered by VanderSat. In Figure A.2 the data delivered by VanderSat, as regional averaged, for the period of 2015 till 2020 for the Ommerkanaal could be seen.

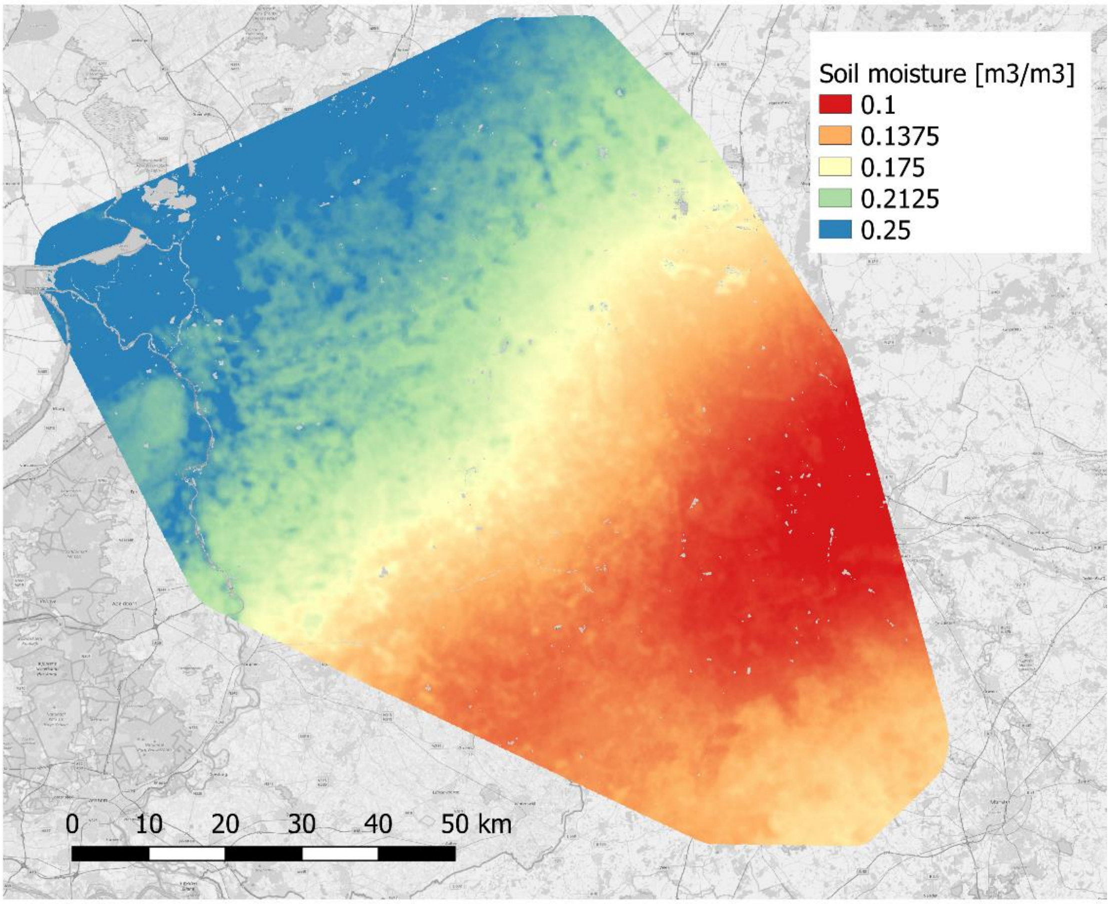

Figure A.1: Satellite image for 24-01-2017 as delivered by VanderSat

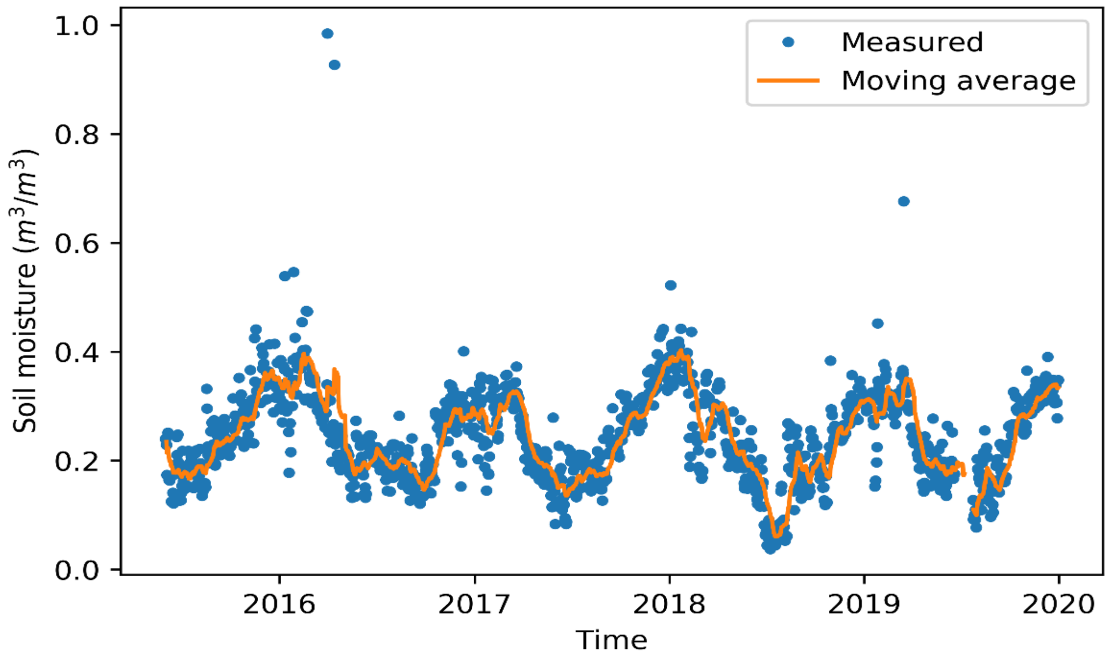

Figure A.2: Remoted sensed soil moisture measured by VanderSat for the area of the Ommerkanaal for the period of 06-2015 up to and including 12-2019.

In Figure A.2 there are some outliers, one of them is 31 March 2016 with a value higher than 0.9. In the Figure A.3 below the image of soil moisture of that day can be seen (for the first days delivered by VanderSat). Due to a large rain event on this day the quality of the satellite image is not good, or even not present. Therefore, the missing data will be linear interpolated. Also, the outliers will be removed from the data and the value for that day will be interpolated.

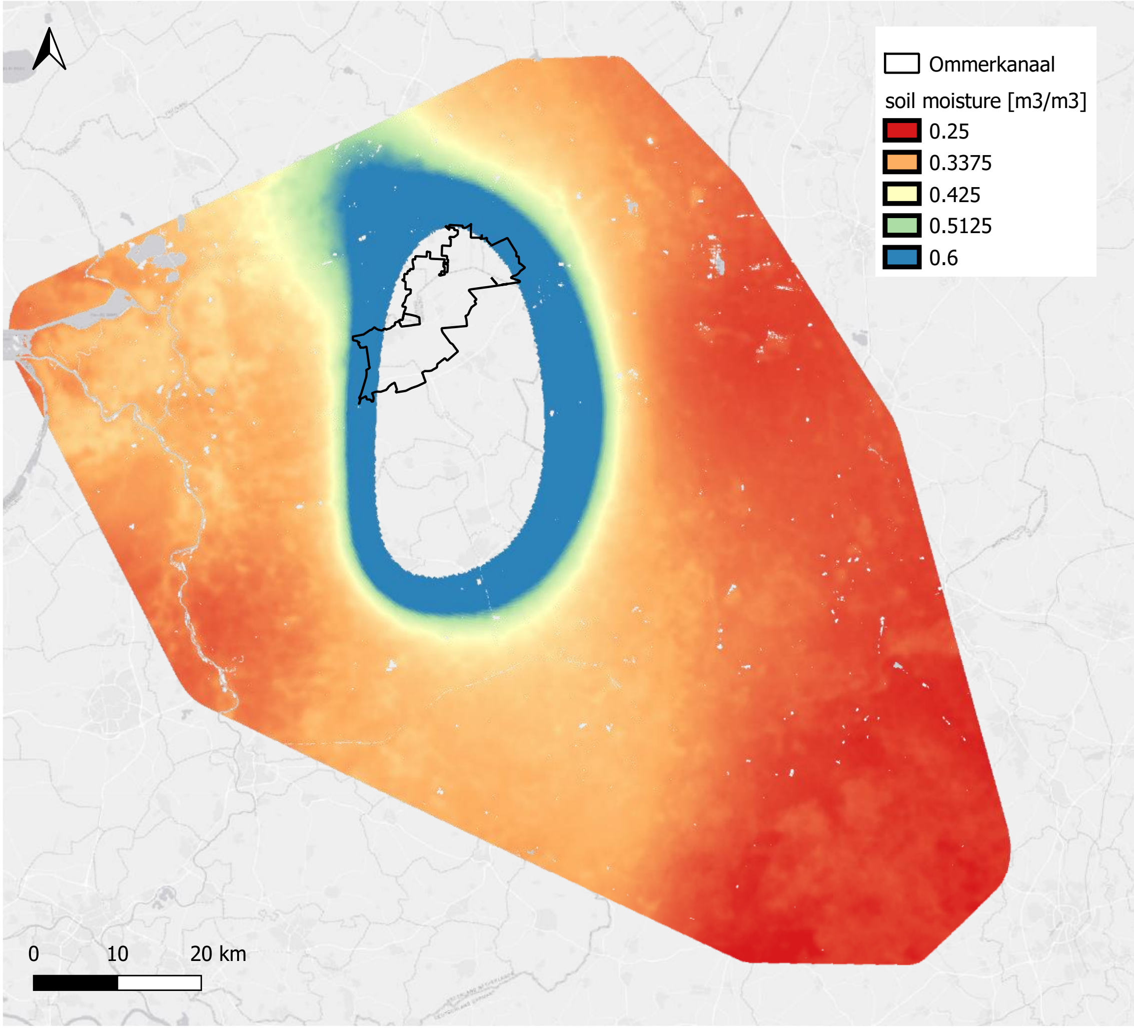

Figure A.3: Satellite image of 31-06-2016 with a large rain event, with the Ommerkanaal outlined.

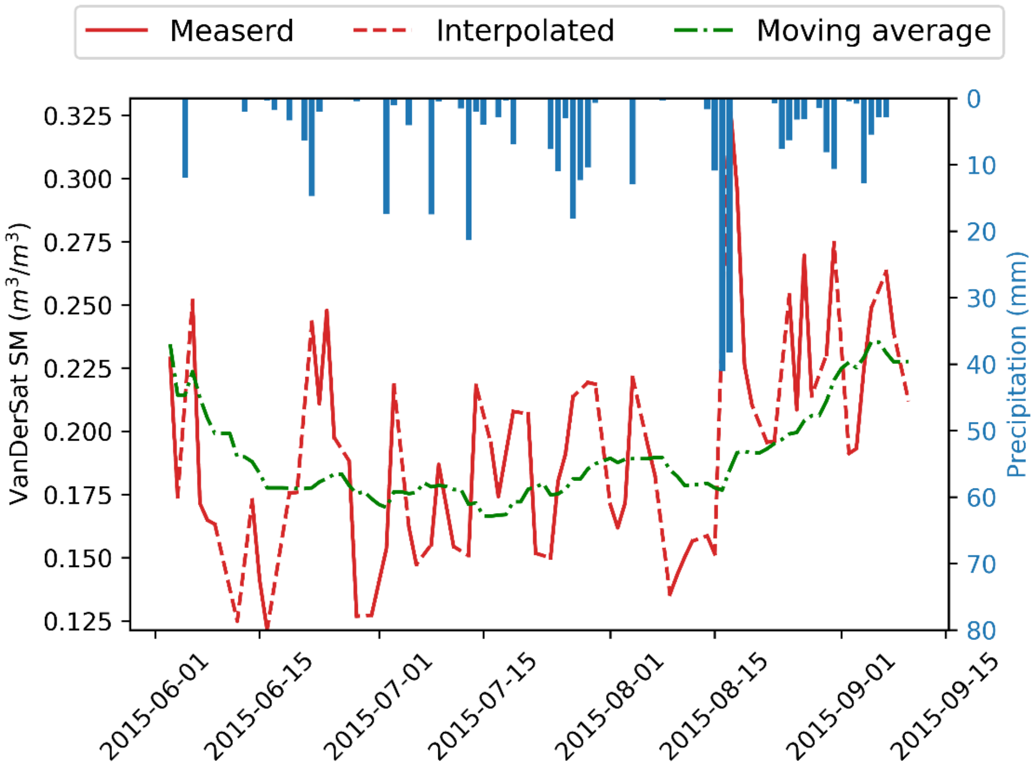

Figure A.4: Soil moisture measured by VanderSat, averaged for the area Ommerkanaal and the measured precipitation from the radar measurements for the Ommerkanaal

A.2 Metrological data

The meteorological data from 2005 till 2010 is provided by the water board. For the period of 2015 to 2020 the data of the Koninklijk Nederlands Meteorologisch Instituut (KNMI) is used, retrieved via Metobase. The precipitation used in this study is based on radar measurements averaged over the sub catchment. In Figure A.5 the precipitation measured with radar could be seen for the Ommerkanaal. Also, in Figure A.5 the precipitation of the measurement stations in Hoogeveen and Heino could be seen. In Figure A.6 the location of the 2-precipitation measurement station in respect to the location of the Ommerkanaal could be seen. The precipitation measured for the Ommerkanaal with the radar is in line with the precipitation measured by the ground stations.

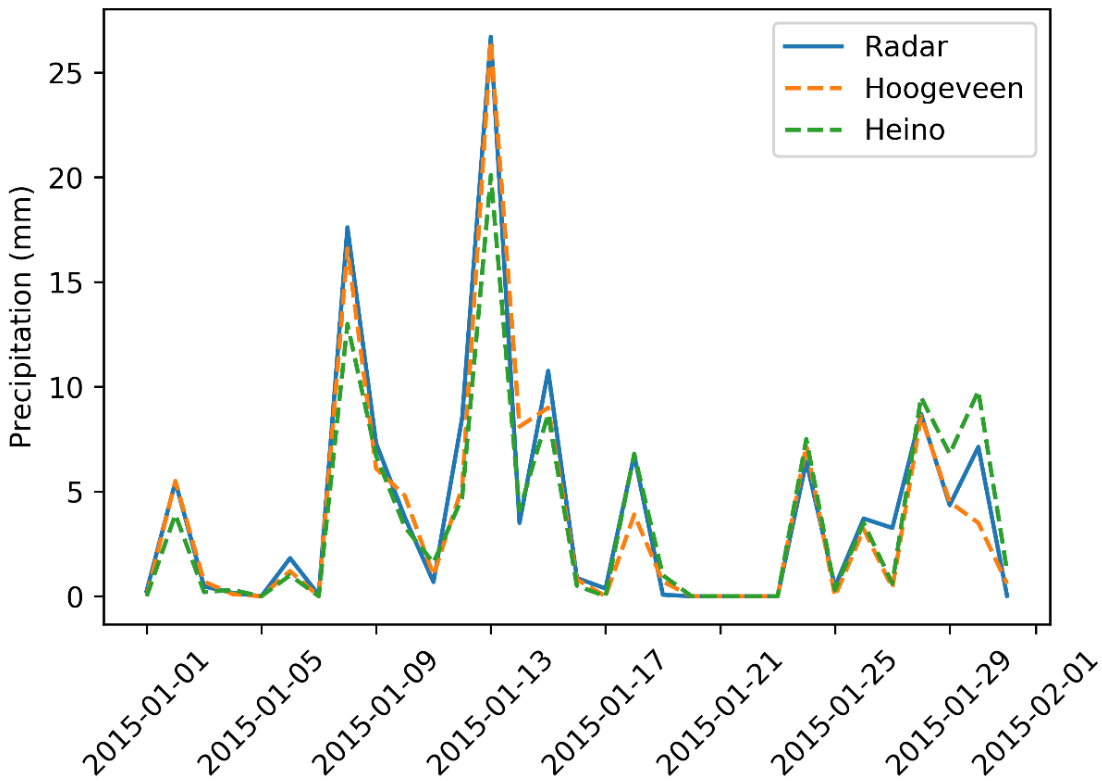

Figure A.5: Precipitation derived for the Ommerkanaal compared to 2 KNMI measuring stations close by the Ommerkanaal.

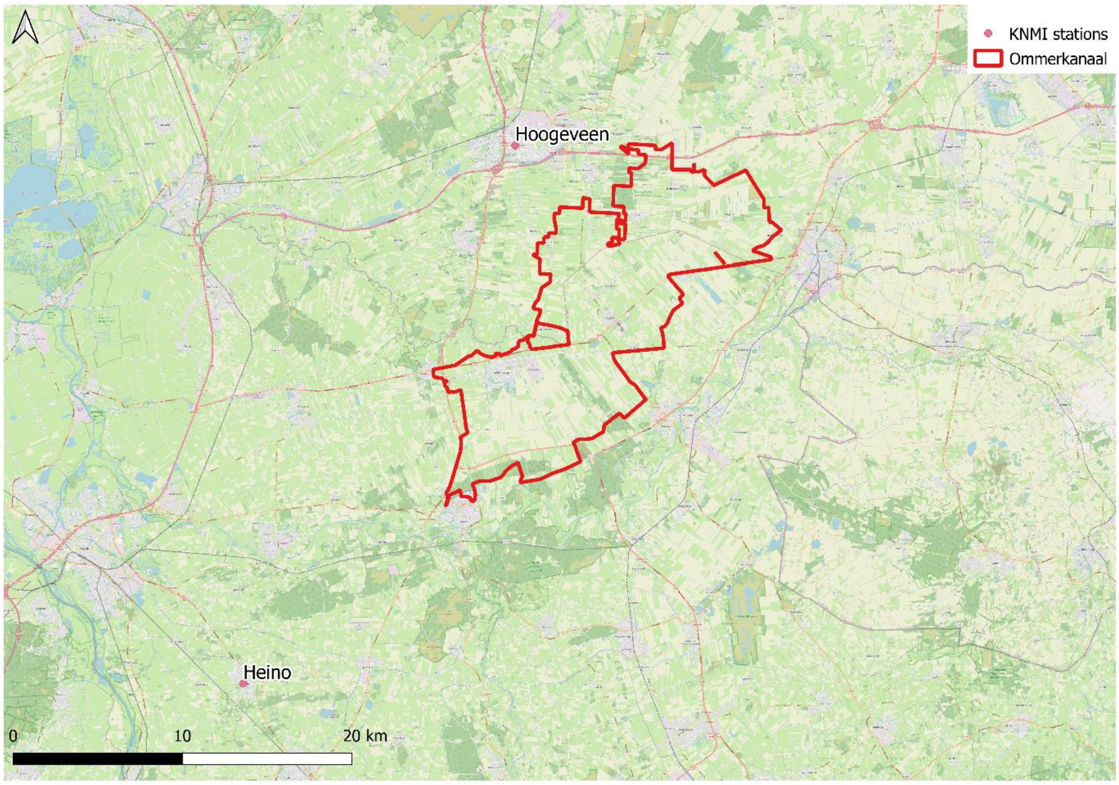

Figure A.6: Location of the Ommerkanaal to the 2 KNMI measuring stations

A.3 Discharge data

At some of the outflow points of these tributaries into the Vecht, the discharge is measured with gauges. For this thesis, the following gauges of the sub-catchments will be used: the Ommerkanaal and the Sallandse Wetering (measured by water board WDOD) and the Dinkel (measured by water board Vechtstromen).

Appendix B: Parameters HBV model

Table B.1: Parameters for the HBV model for the different sub-catchments

Sub catchment	**Ommerkanaal**	
Parameter	**Before calibration**	**After calibration**
FC	140 (mm)	138.43 (mm)
LP	0.1 (-)	-
BETA	3 (-)	3.40 (-)
PERC	2.2 (mm/day)	0.57 (mm/day)
K0	0.4 (d^-1)	0.228 (d^-1)
ULZ	10 (mm)	12.4 (mm)
K1	0.2 (d^-1)	-
K2	0.01 (d^-1)	-
Sub catchment	**Sallandse Wetering**	
Parameter	**Before calibration**	**After calibration**
FC	200 (mm)	307.81 (mm)
LP	0.4 (-)	0.66 (-)
BETA	3 (-)	5.8 (-)
PERC	11 (mm)	-
K0	0.6 (d^-1)	0.2 (d^-1)
ULZ	10 (mm)	-
K1	0.3999 (d^-1)	-
K2	0.05 (d^-1)	0.099(d^-1)
Sub catchment	**Dinkel**	
Parameter	**Before calibration**	**After calibration**
FC	100(mm)	61.17 (mm)
LP	0.1(-)	-
BETA	3 (-)	-
PERC	8 (mm)	6.69 (mm)
K0	0.45 (d^-1)	-
ULZ	20 (mm)	12.90 (mm)
K1	0.011 (d^-1)	-
K2	0.15 (d^-1)	0.04006 (-)

Table B.2: Initial conditions for the HBV model for the different sub-catchments

Sub catchment	**Ommerkanaal**
SM_0	0.95 (-)
SUZ_0	14.4 (mm)
SLZ_0	10 (mm)
Sub catchment	**Sallandse Wetering**
SM_0	0.95 (-)
SUZ_0	0.5 (mm)
SLZ_0	25 (mm)
Sub catchment	**Dinkel**
SM_0	0.95 (-)
SUZ_0	6.6 (mm)
SLZ_0	450 (mm)

Appendix C: Results Ommerkanaal

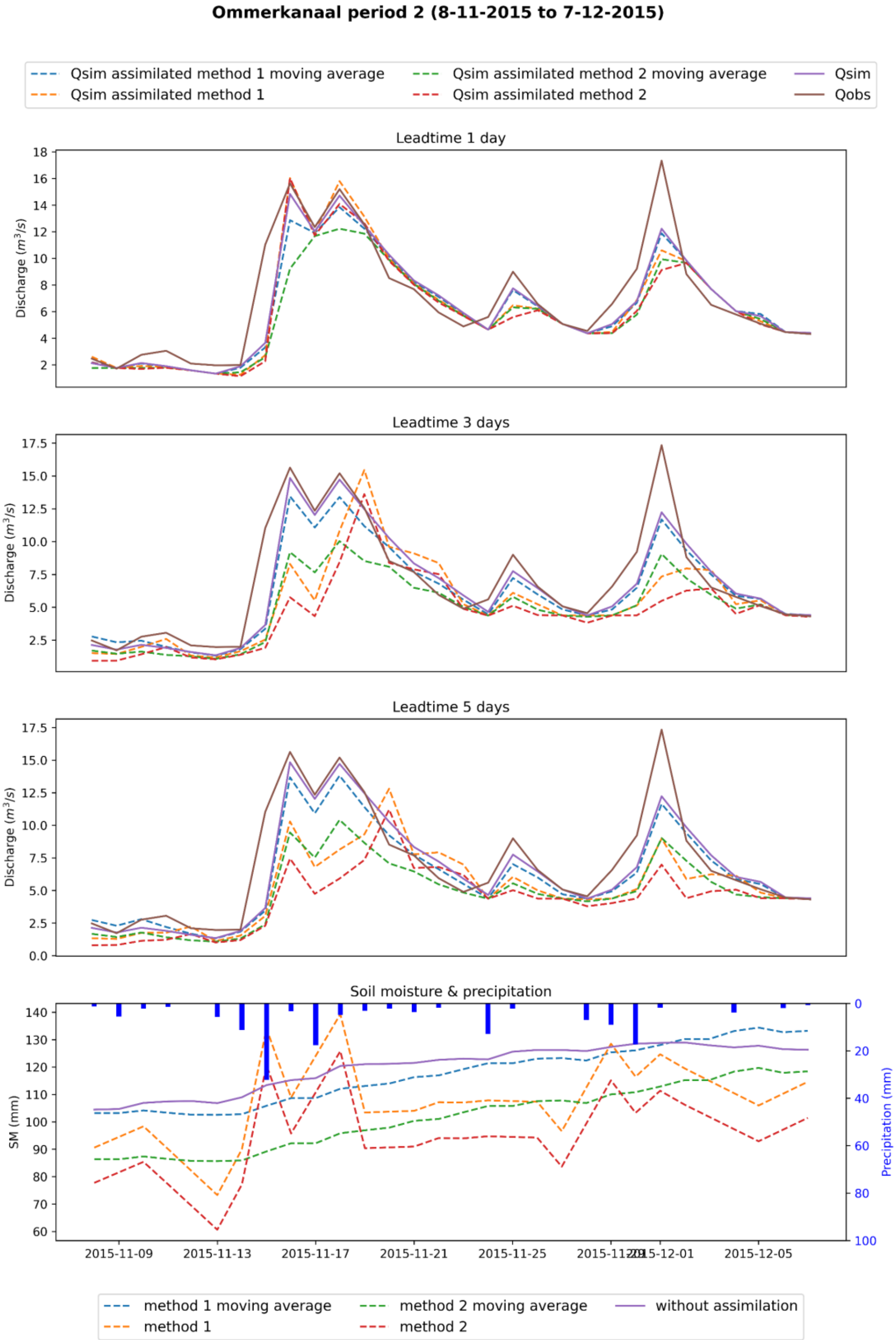

Figure C.1: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Ommerkanaal for the period of 8-11-2015 to 7-12-2015

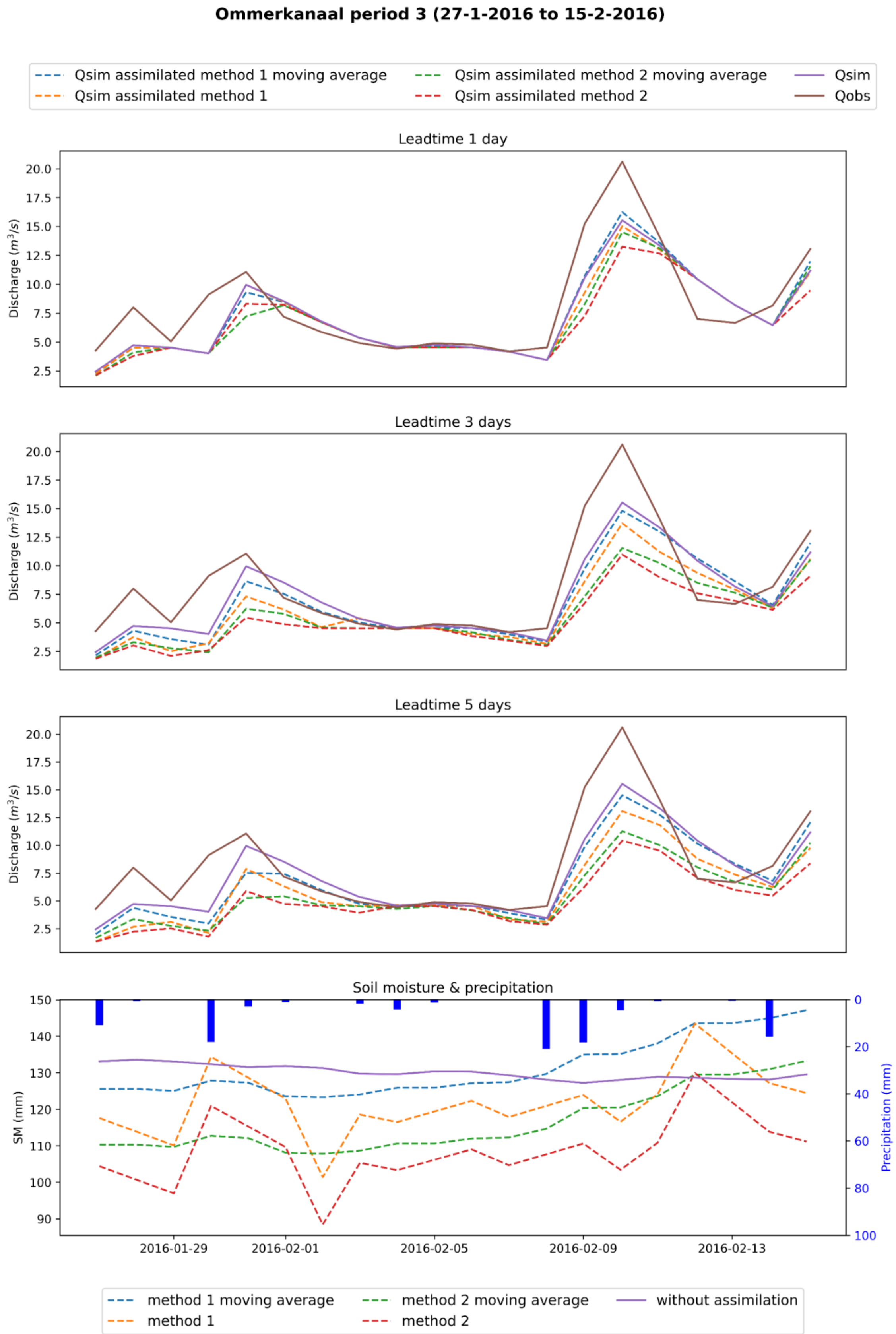

Figure C.2: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Ommerkanaal for the period of 27-1-2016 to 15-2-2016

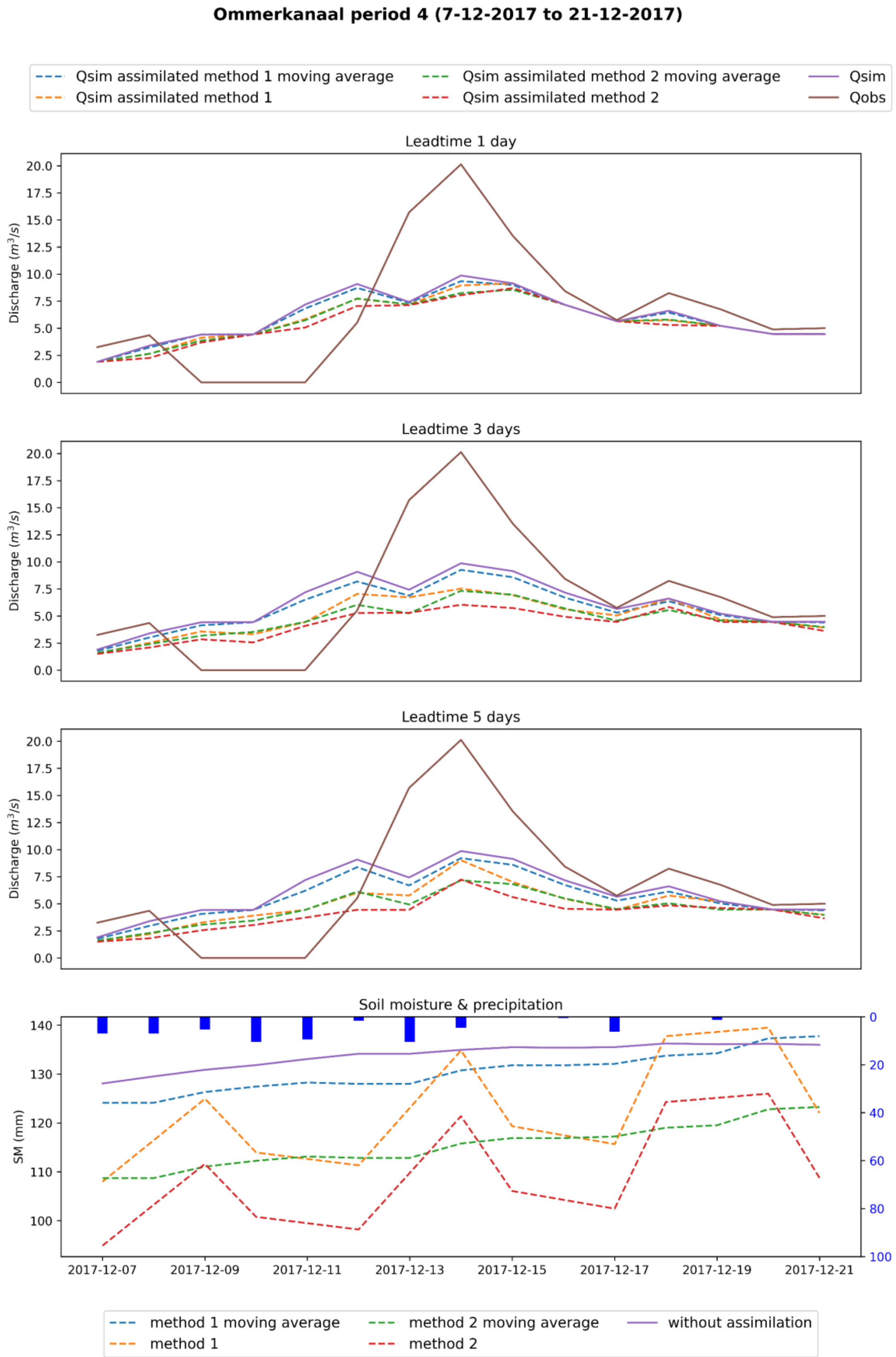

Figure C.3: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Ommerkanaal for the period of 7-12-2017 to 21-12-2017

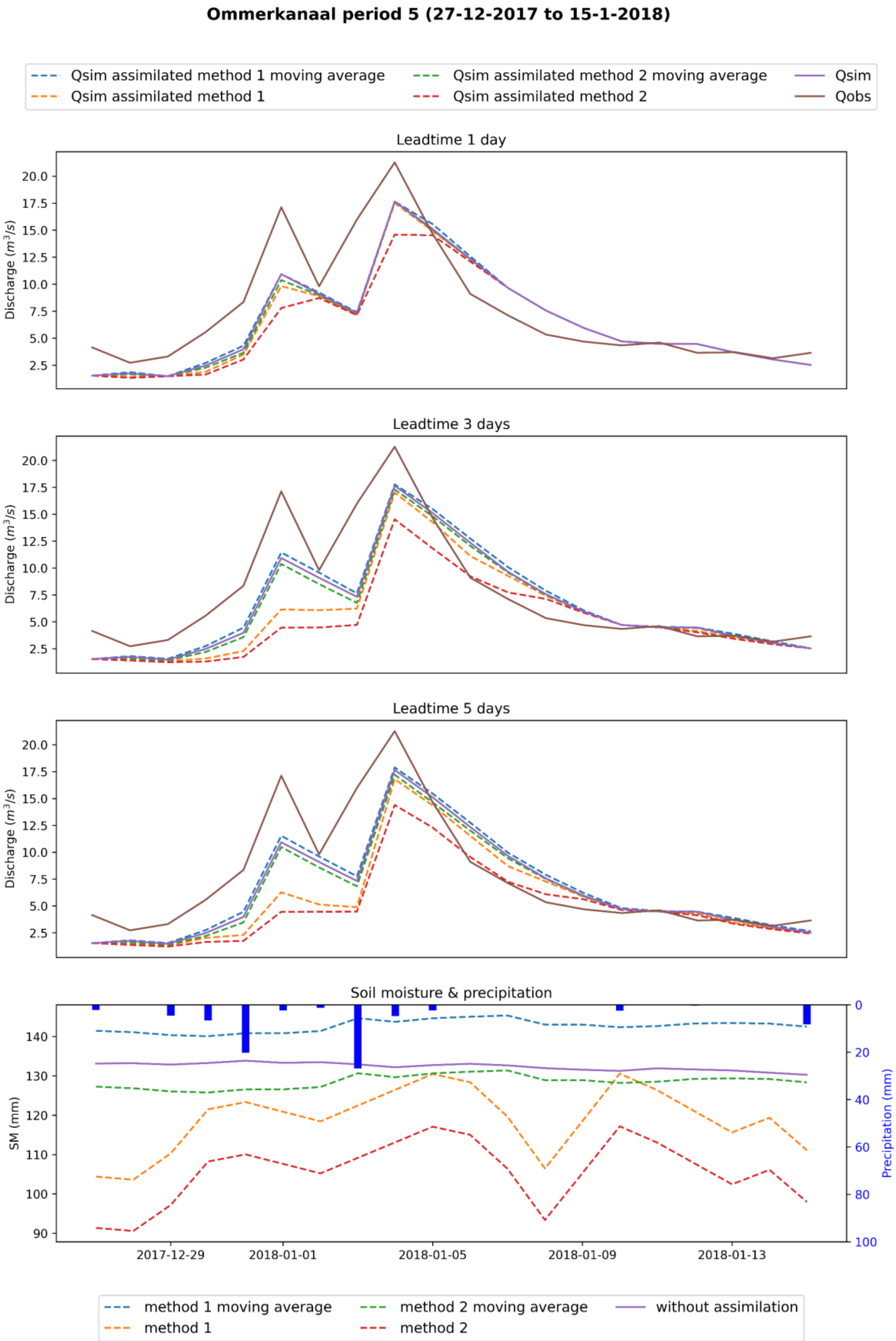

Figure C.4: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Ommerkanaal for the period of 27-12-2017 to 15-1-2018

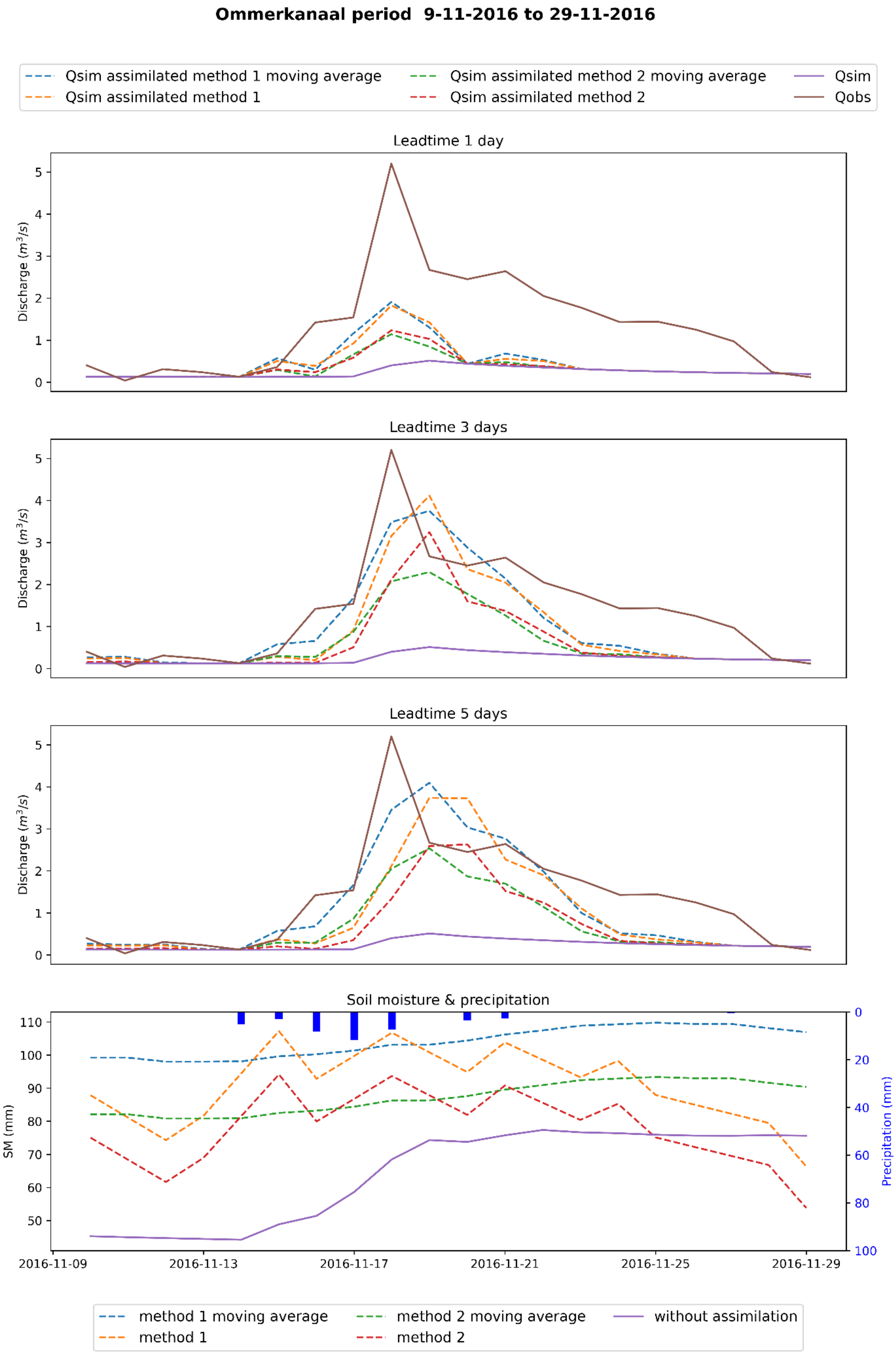

Figure C.5: Extra period used during the assimilation, in which the HBV model does an under estimation of the discharge during a dry period.

Appendix D: Results Sallandse Wetering

D.1 Parameter sensitivity

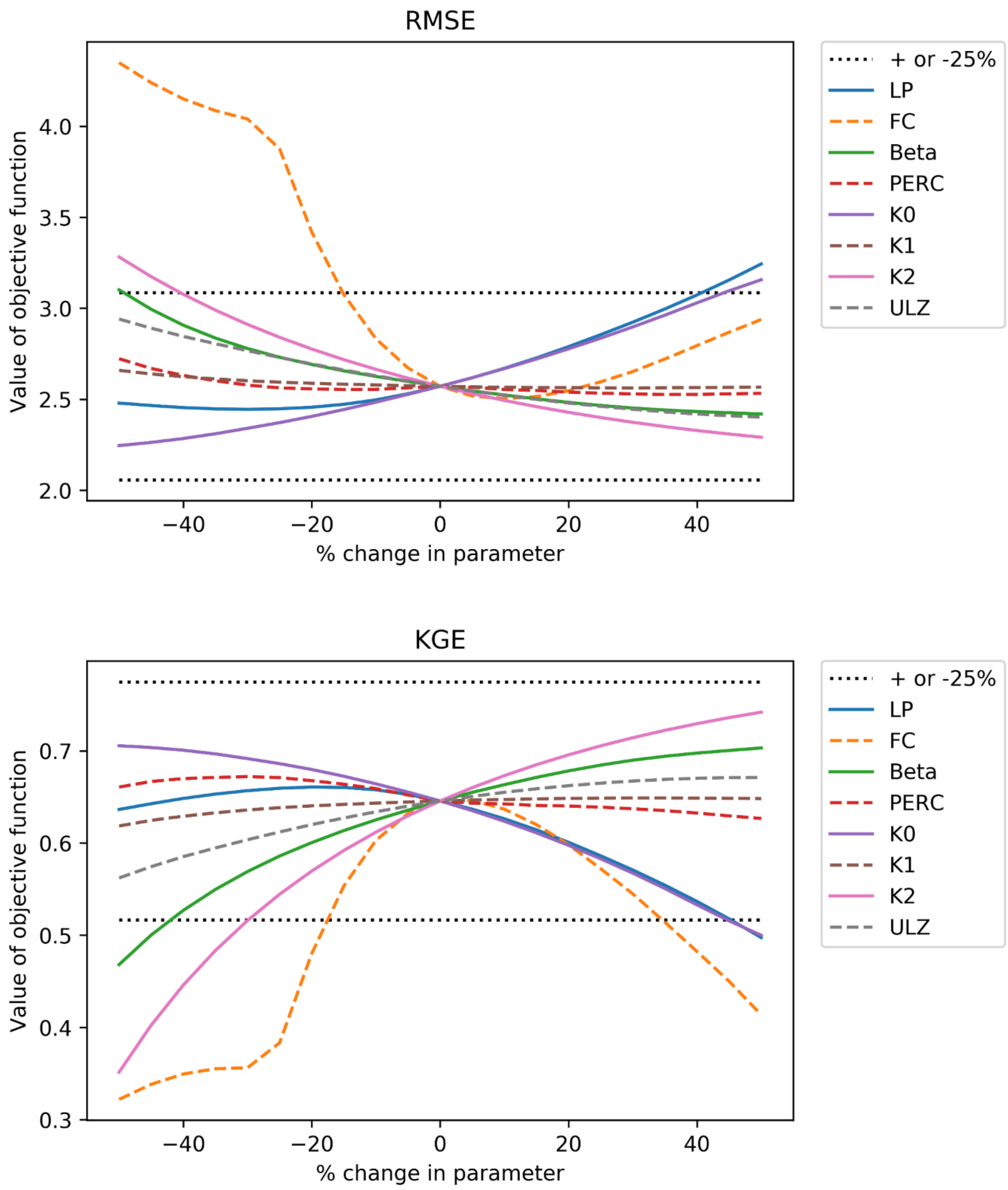

Figure D.1: The parameter sensitivity of the HBV model of the Sallandse Wetering reflected by the RMSE and the KGE

D.2 Sensitivity to Initial conditions

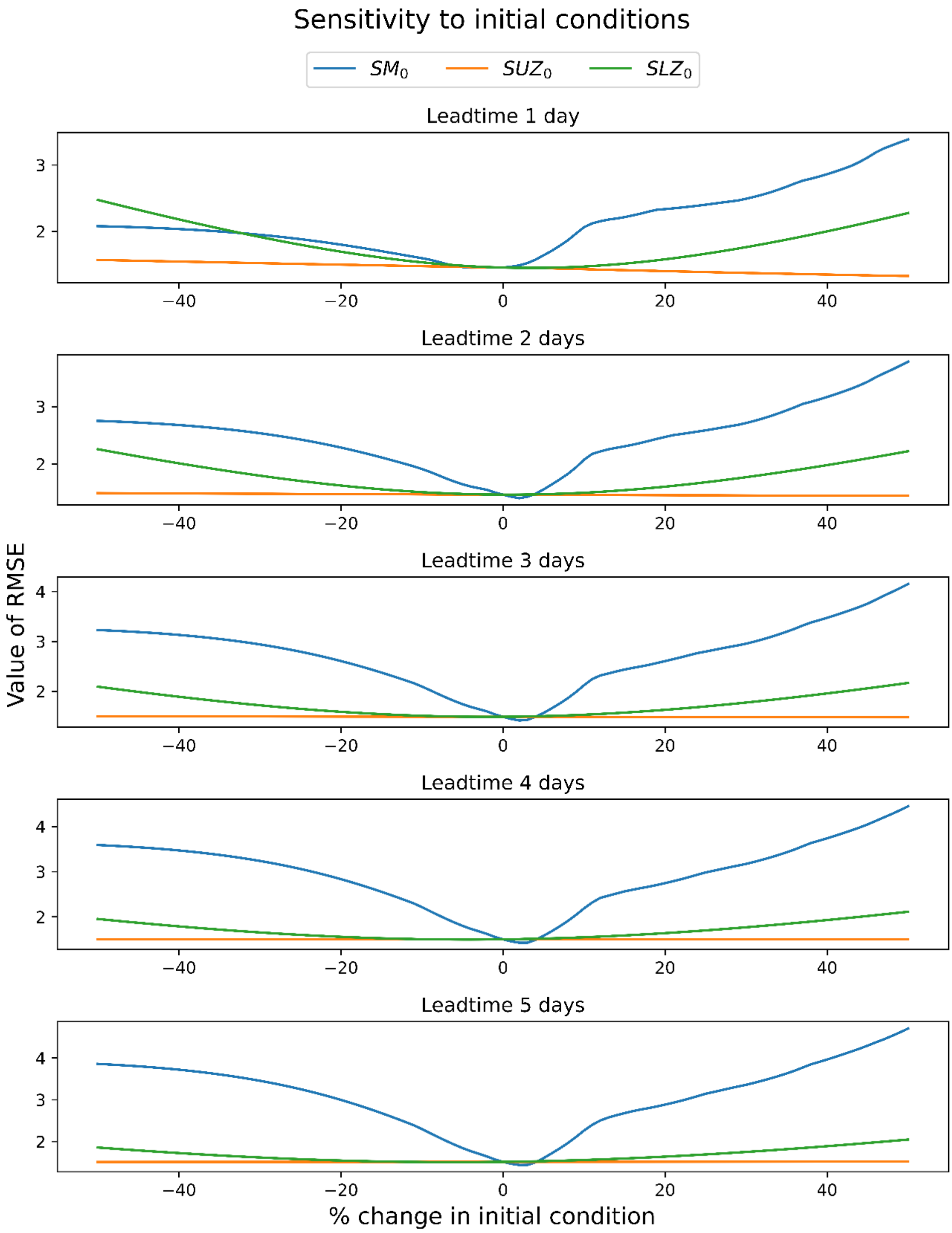

Figure D.2: Outcome of the sensitivity analysis of the HBV model for the Sallandse Wetering for its initial conditions reflected by the RMSE for different lead times of 1 to 5 days

D.3 Correlation

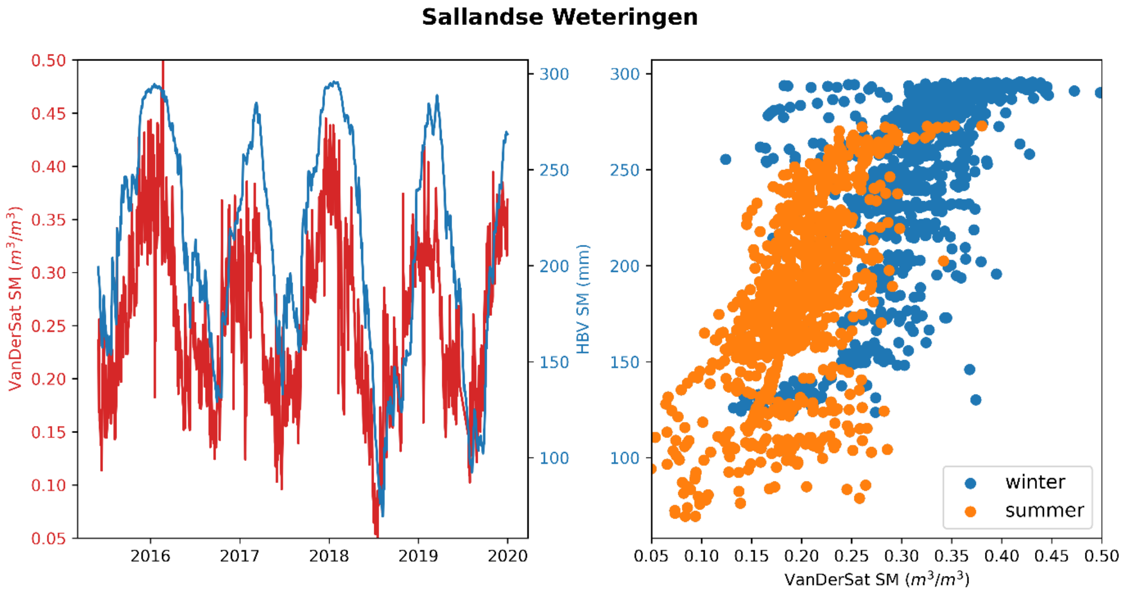

Figure D.3: The soil moisture simulated by the HBV model and the remotely sensed soil moisture for the catchment of the Sallandse Wetering and the scatter plot of the same data

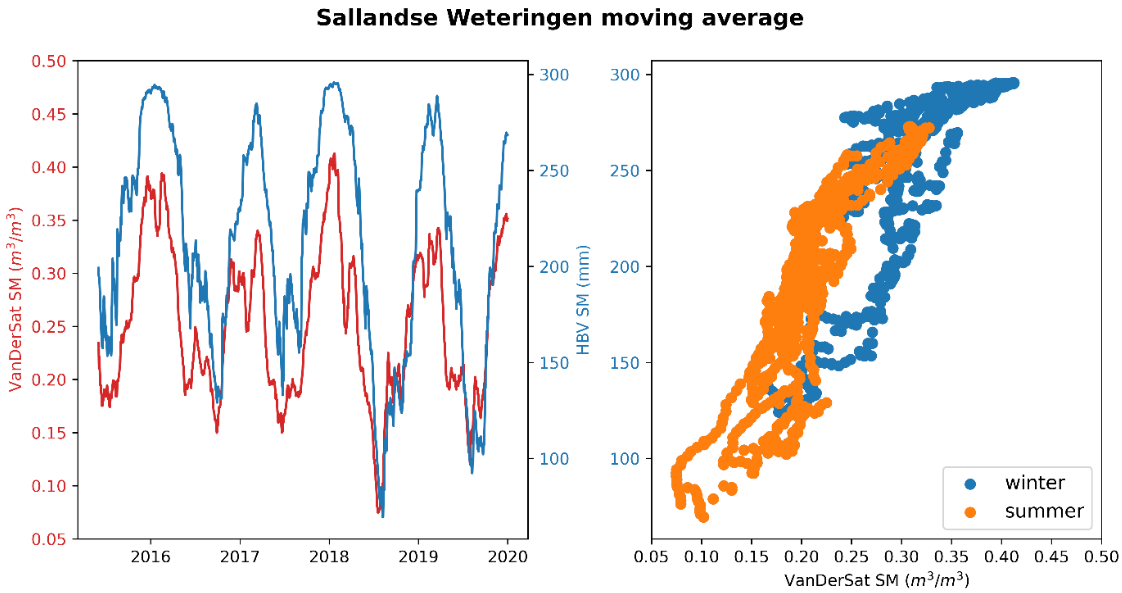

Figure D.4: The soil moisture simulated by the HBV model compared with the moving average of the remotely sensed soil moisture for the Sallandse Wetering and the scatter plot for the same data

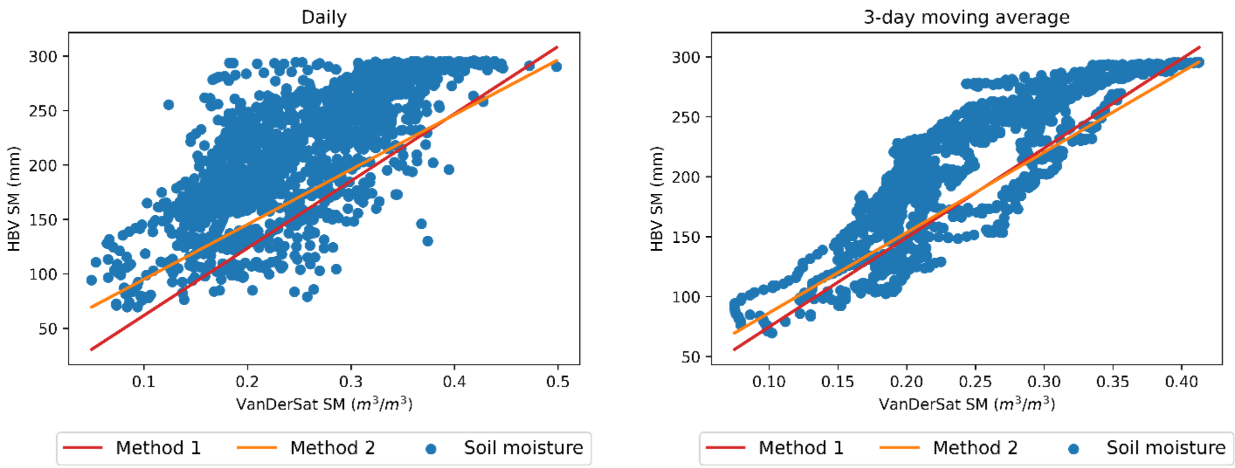

Figure D.5: The remotely sensed soil moisture in comparison to the transformed soil moisture.

D.4 Assimilation

In Figure D.11, the two methods and the two data sets used for the five selected periods are shown. Overall, the figure shows that the methods using the moving average are performing the least worse, but still, the forecasted discharge does not show an overall improvement. Furthermore, it shows that the method used (as described in section 2.5) does not make a big difference in the model performance. Most of the differences in the model performance can be explained by the different data sets (the daily measured vs the 3-day moving average) used. This can be related to the higher correlation coefficient for the moving average data set than for the measured data set, as found in section 3.3. But still, there is no improvement in the model performance with the assimilation.

The same conclusion, as for the Ommerkanaal, can be drawn for the Sallandse Wetering: the assimilation of remotely sensed soil moisture data does not improve the forecasted discharge. For all periods, the value of the RMSE is above 4 (m^3/s), which is relatively high for a flow of approximately a peak discharge of 30 (m^3/s).

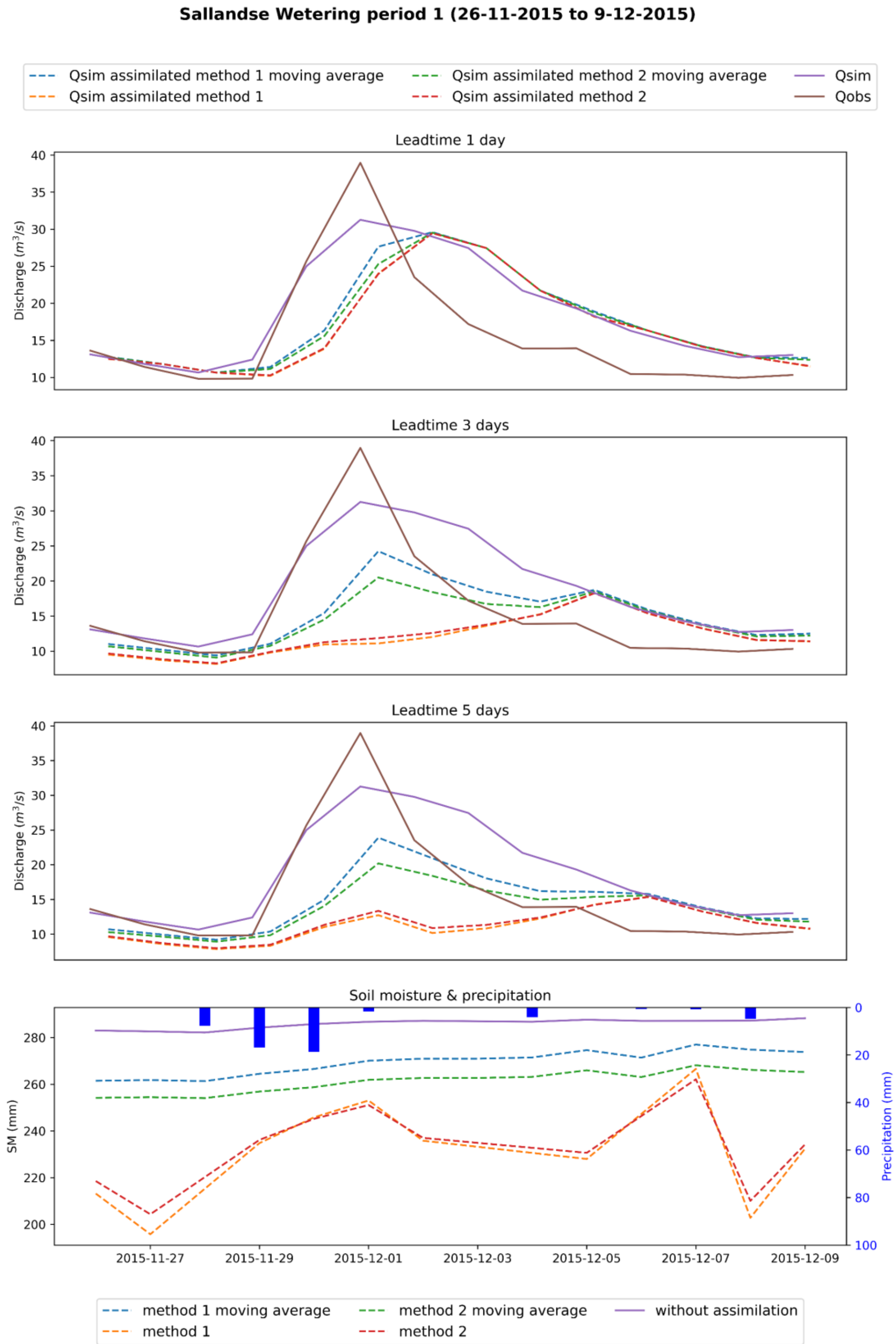

Figure D.6: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Sallandse Wetering for the period of 26-11-2015 to 9-12-2015

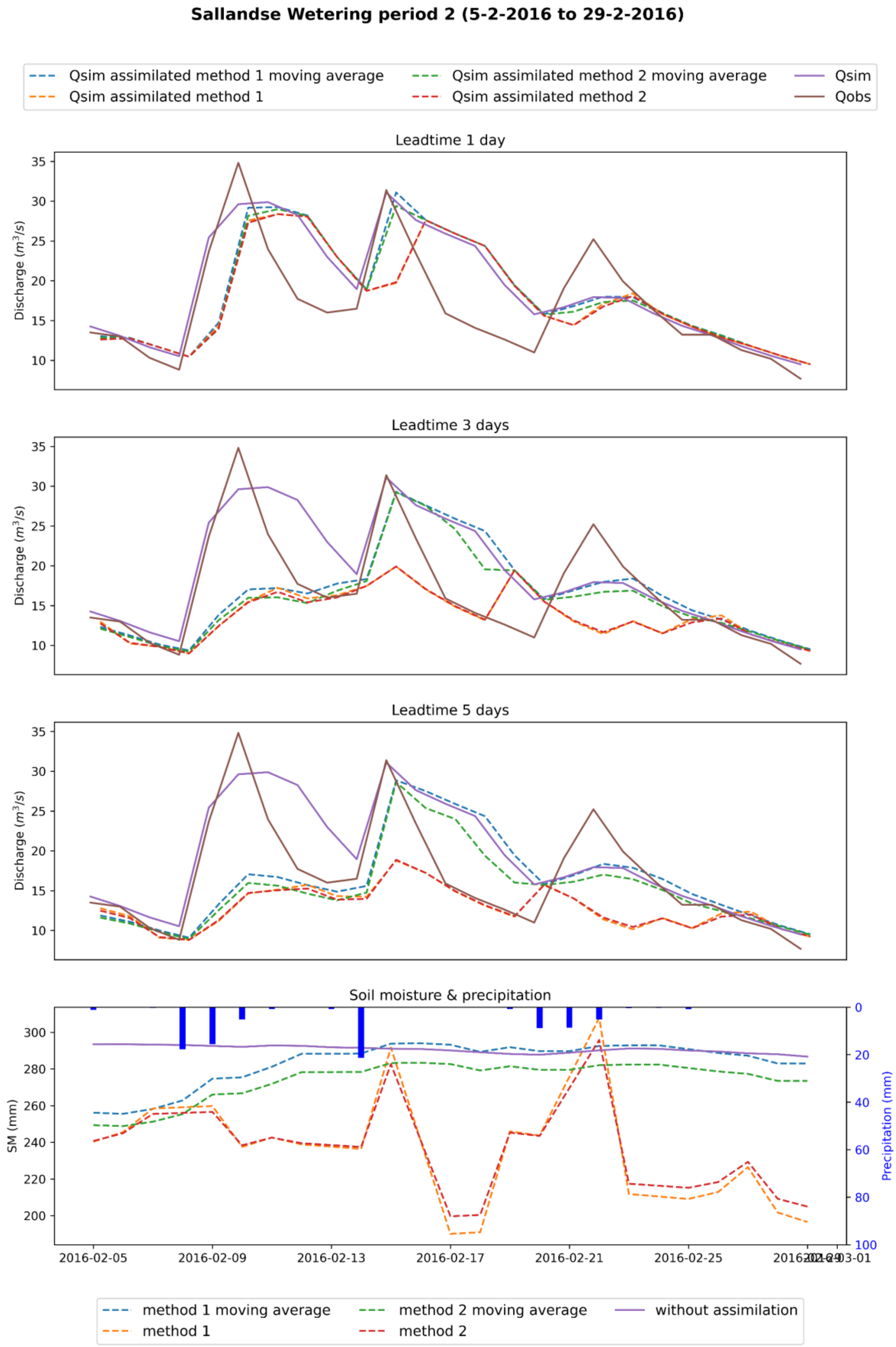

Figure D.7: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Ommerkanaal for the period of 5-2-2016 to 29-2-2016

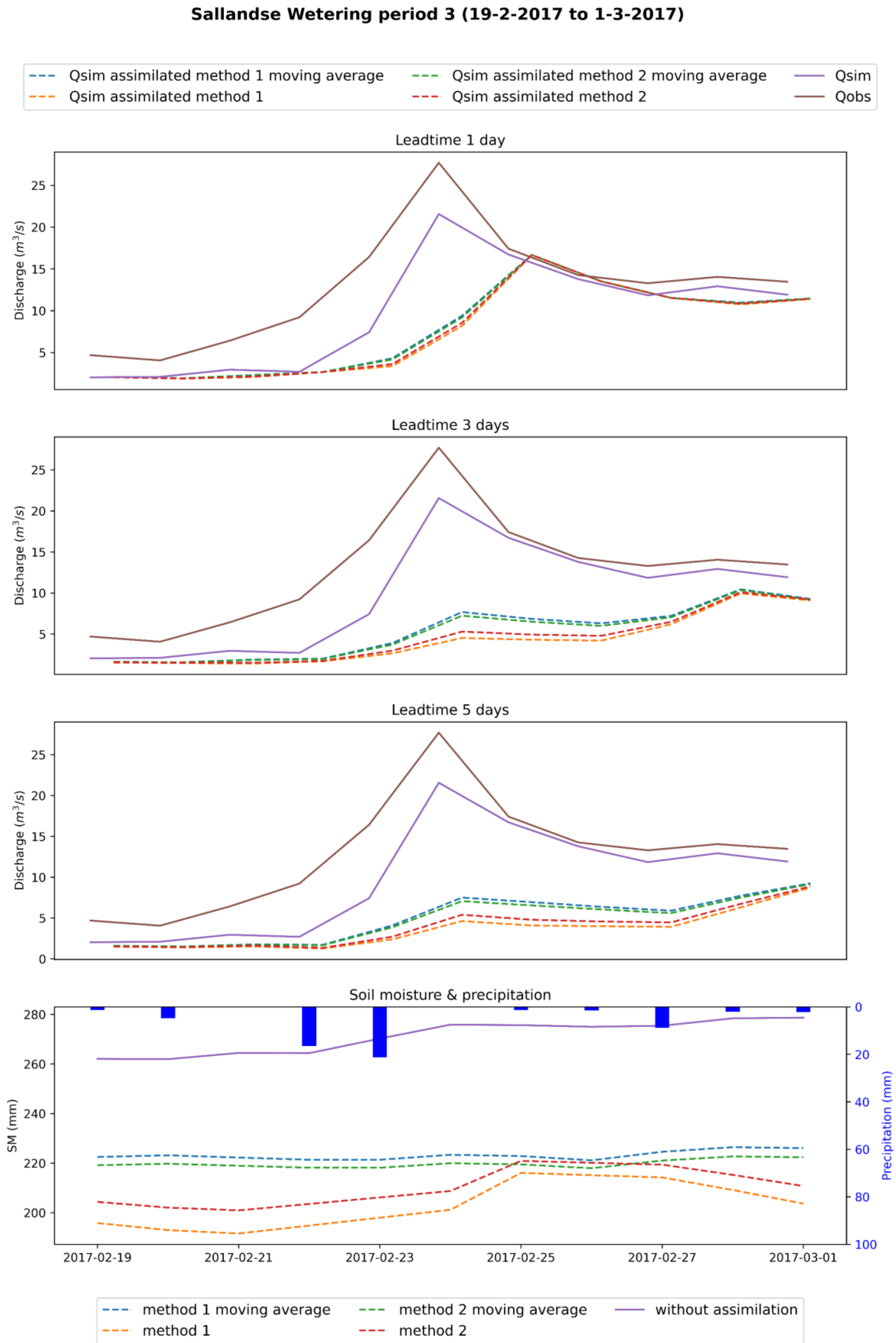

Figure D.8: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Sallandse Wetering for the period of 19-12-2017 to 1-3-2017

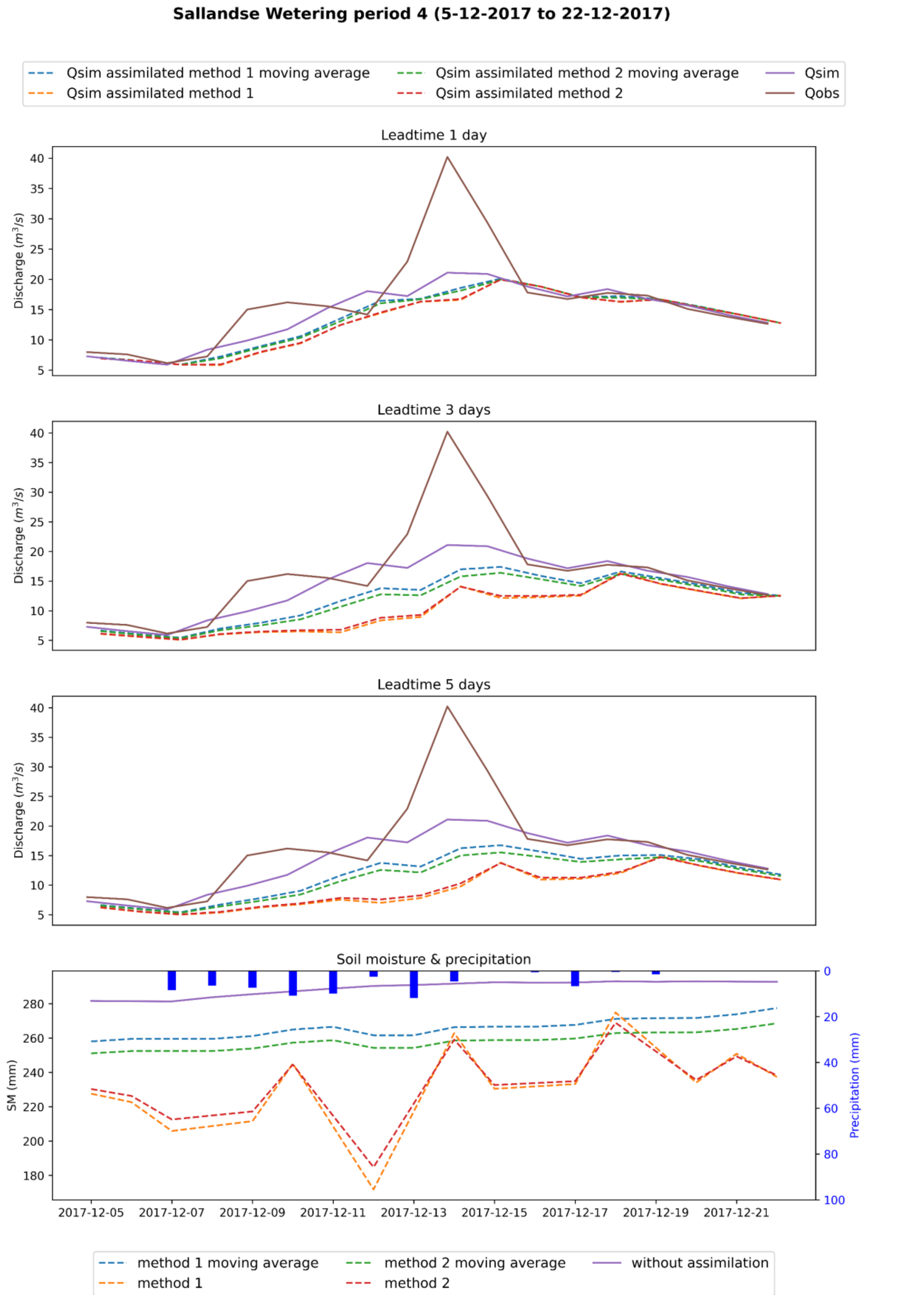

Figure D.9: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Sallandse Wetering for the period of 5-12-2017 to 22-12-2017

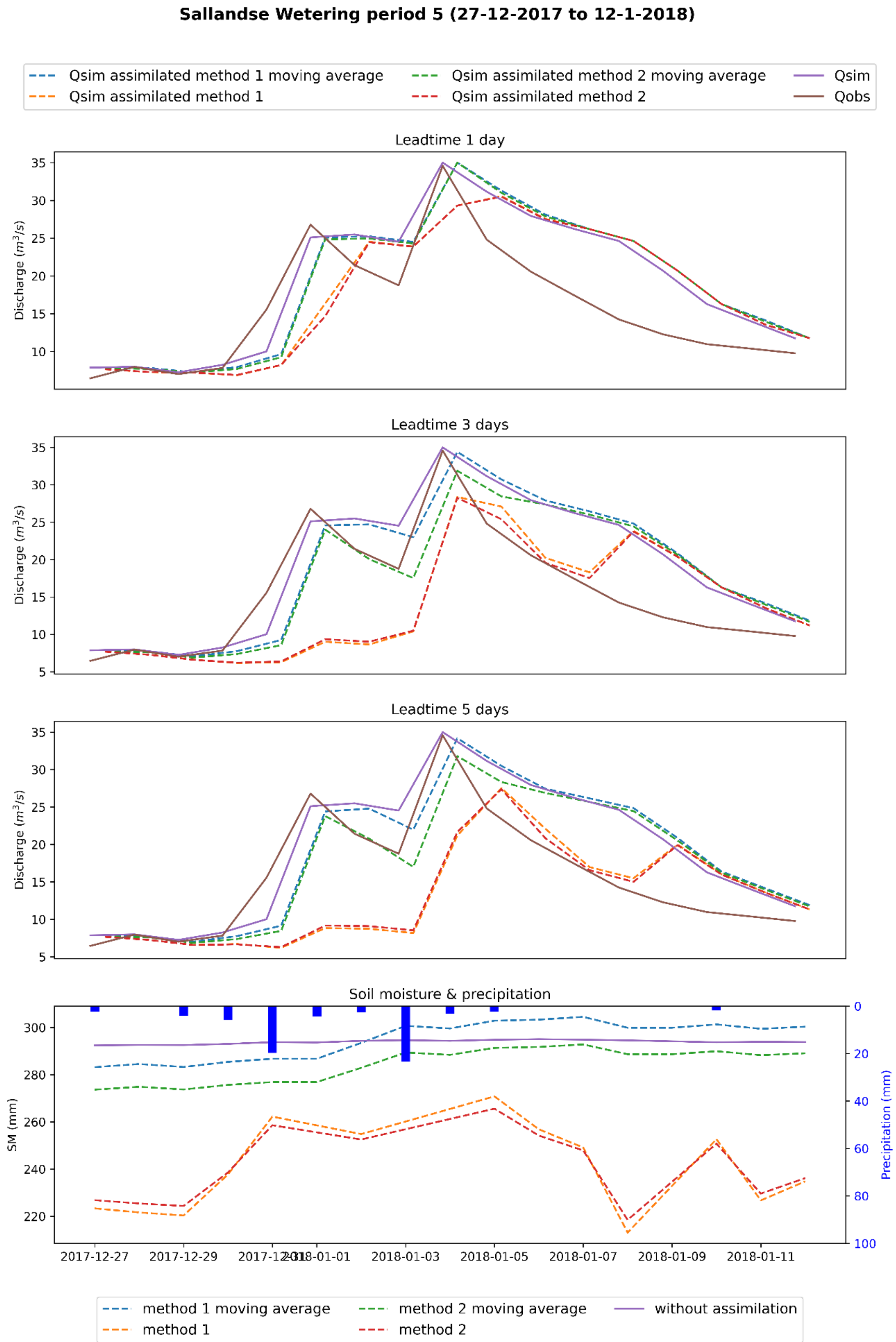

Figure D.10: The effect of the assimilation of soil moisture on the discharge of one peak flow event

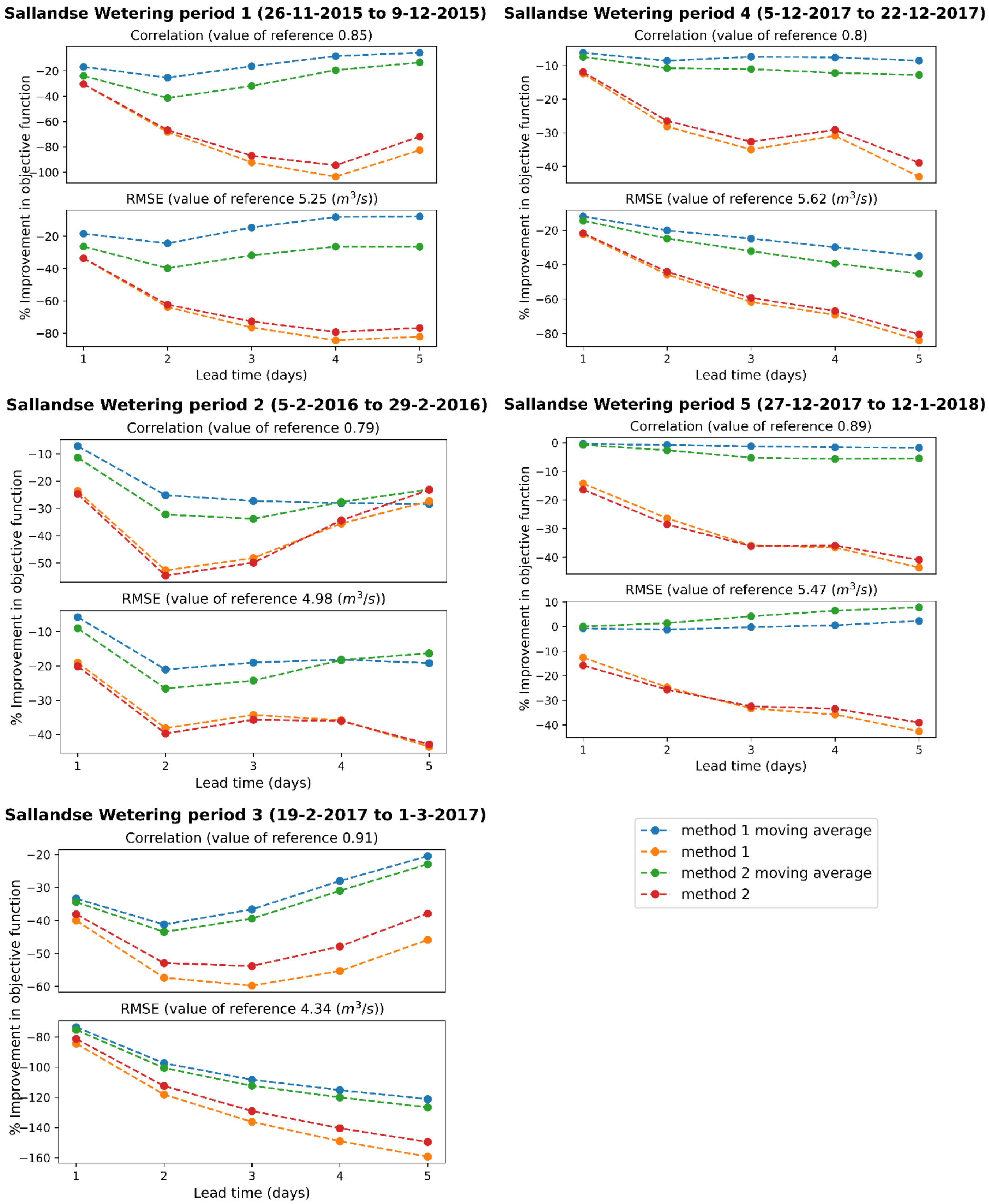

Figure D.11: The result of the assimilation on 5 periods, expressed in the objective functions used.

Appendix E: Results Dinkel

E.1 Parameter sensitivity

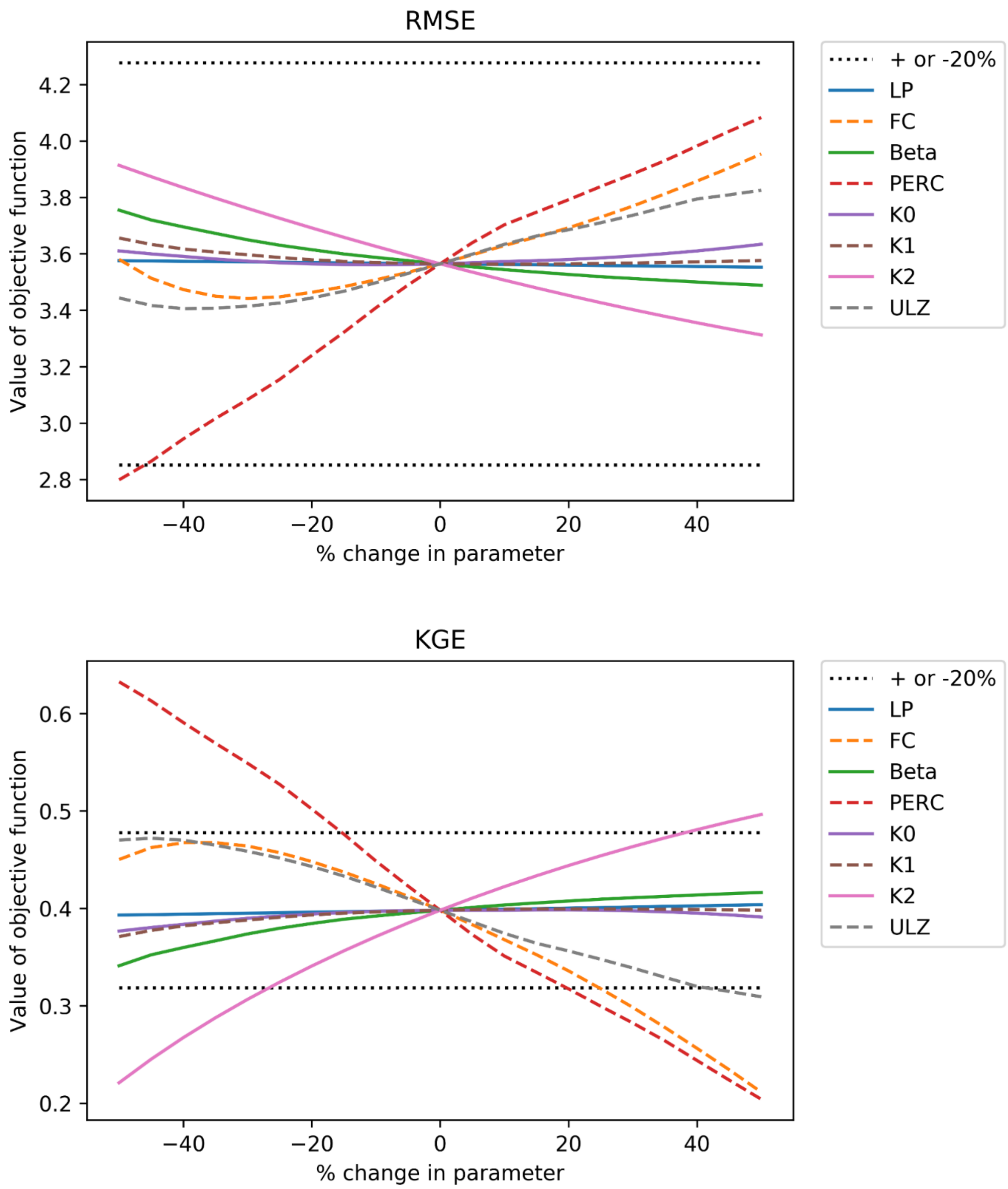

Figure E.1: The parameter sensitivity of the HBV model of the Dinkel reflected by the RMSE and the KGE

E.2 Correlation

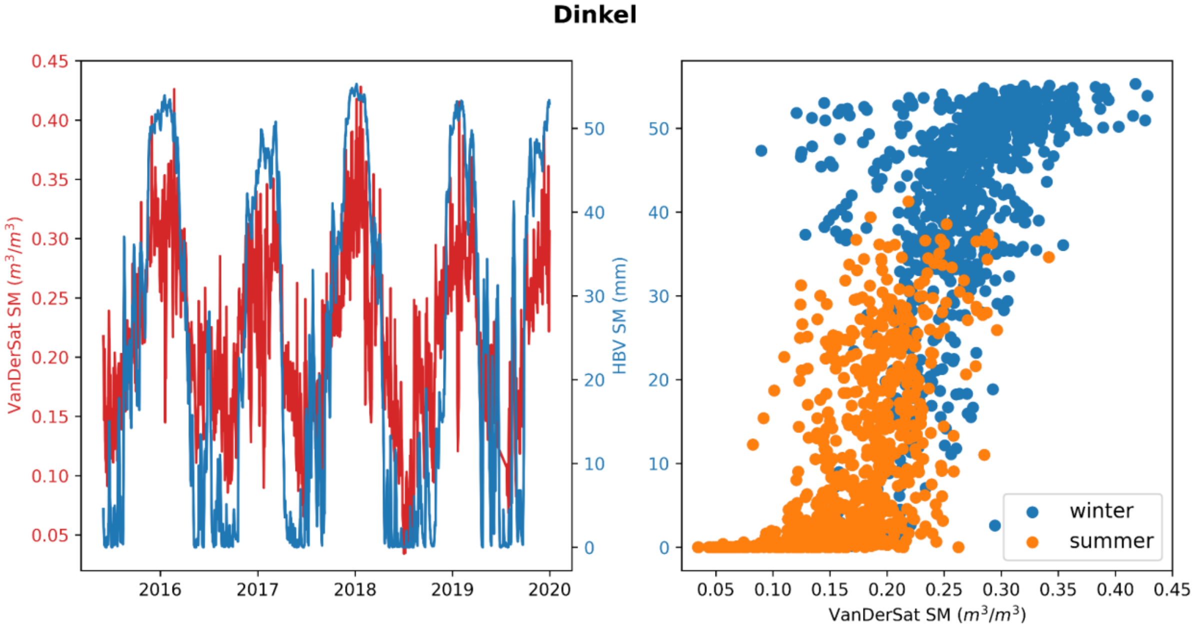

Figure E.2: The soil moisture simulated by the HBV model and the remotely sensed soil moisture for the catchment of the Dinkel and the scatter plot of the same data

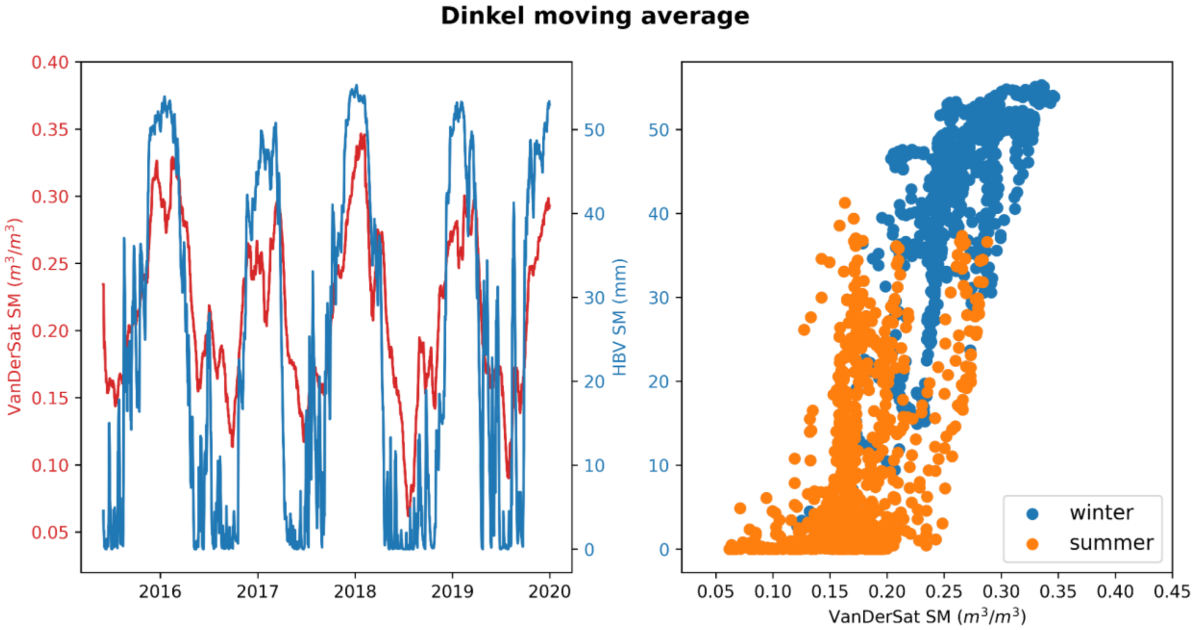

Figure E.3: The soil moisture simulated by the HBV model compared with the moving average of the remotely sensed soil moisture for the Dinkel and the scatter plot for the same data

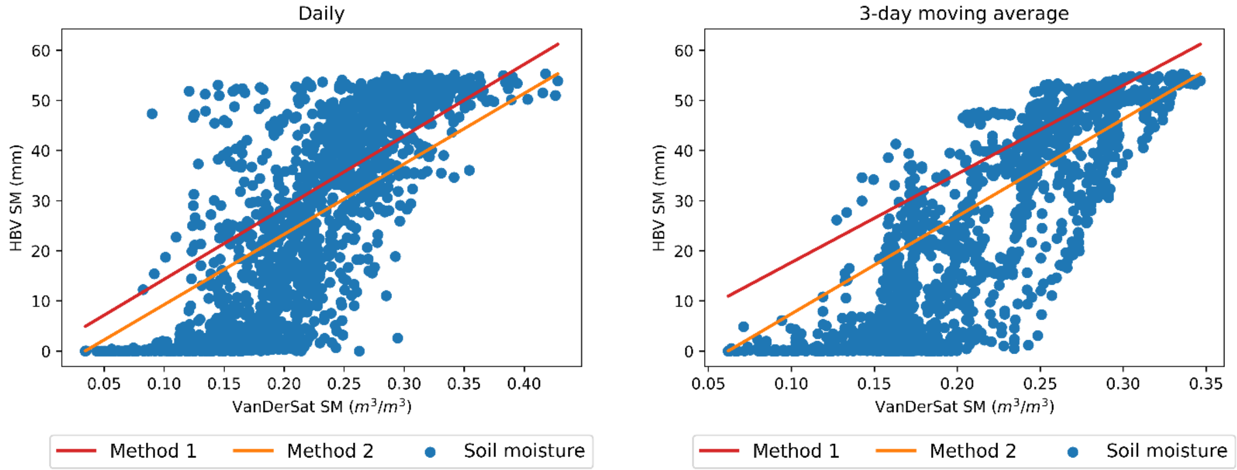

Figure E.4: The remotely sensed soil moisture in comparison to the transformed soil moisture.

E.3 Assimilation

In Figure E.4, the results of the assimilation for the Dinkel are shown. As can be concluded from this figure for period 2 and 3, the assimilation does not lead to an improvement in the forecasted discharge. For period 1 Figure E.4 shows an improvement, however when looking at Figure E.5, the forecasted discharge (with or without assimilation) is very inadequate, this is also reflected in Figure E.4, with the values for the objective functions. For the other two periods, the result of the assimilation is no improvement, but method 1 using the 3-day moving average is also not giving a decline in the performance, the improvement of the objective function stay around the 0% for all lead times. This is the same as found by the Ommerkanaal, in which this method is also not leading to a deterioration of the performances for some of the periods but also no improvement in the model performances.

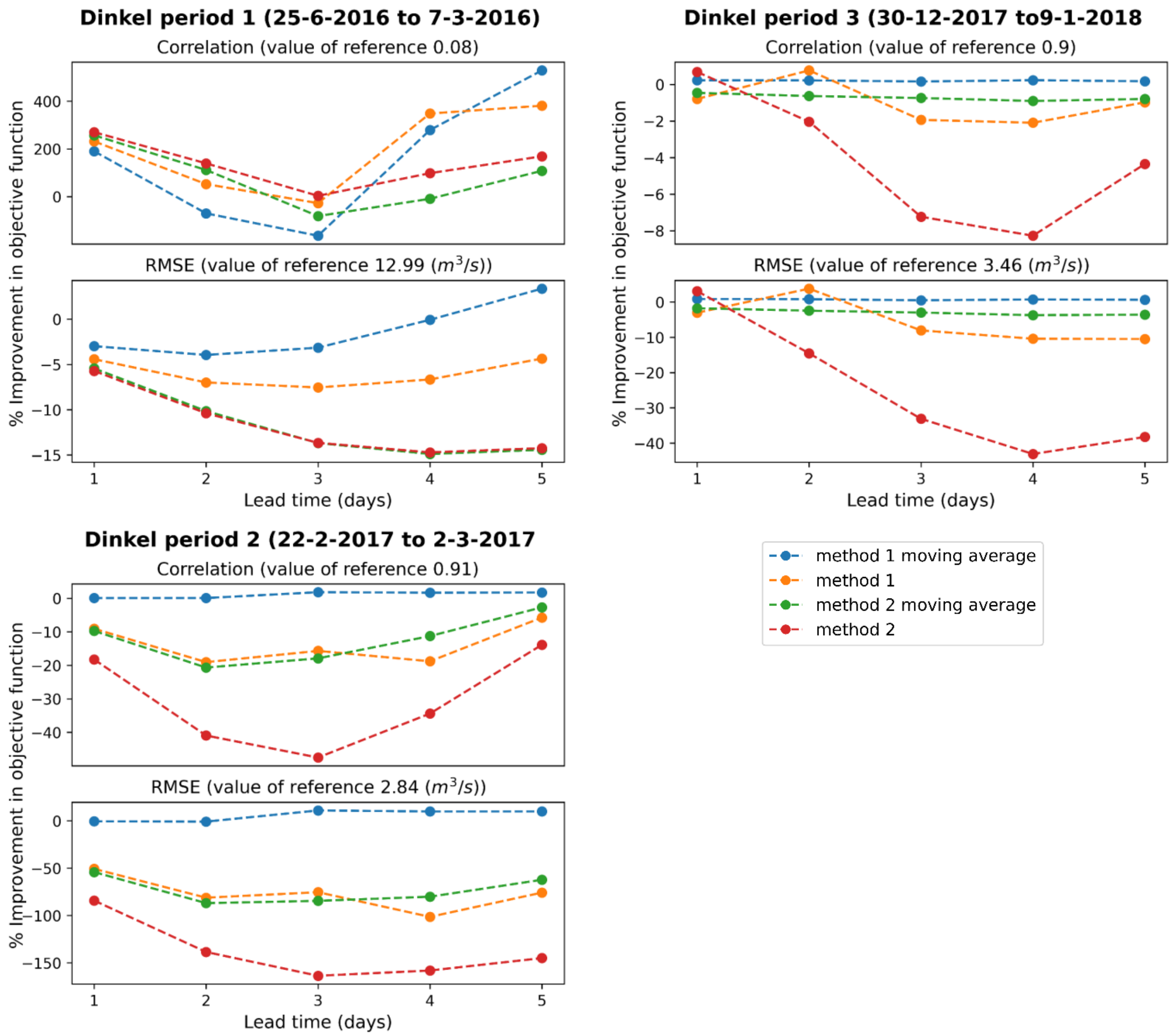

Figure E.5: The result of the assimilation on the 3 periods for the Dinkel, expressed by the objective functions used.

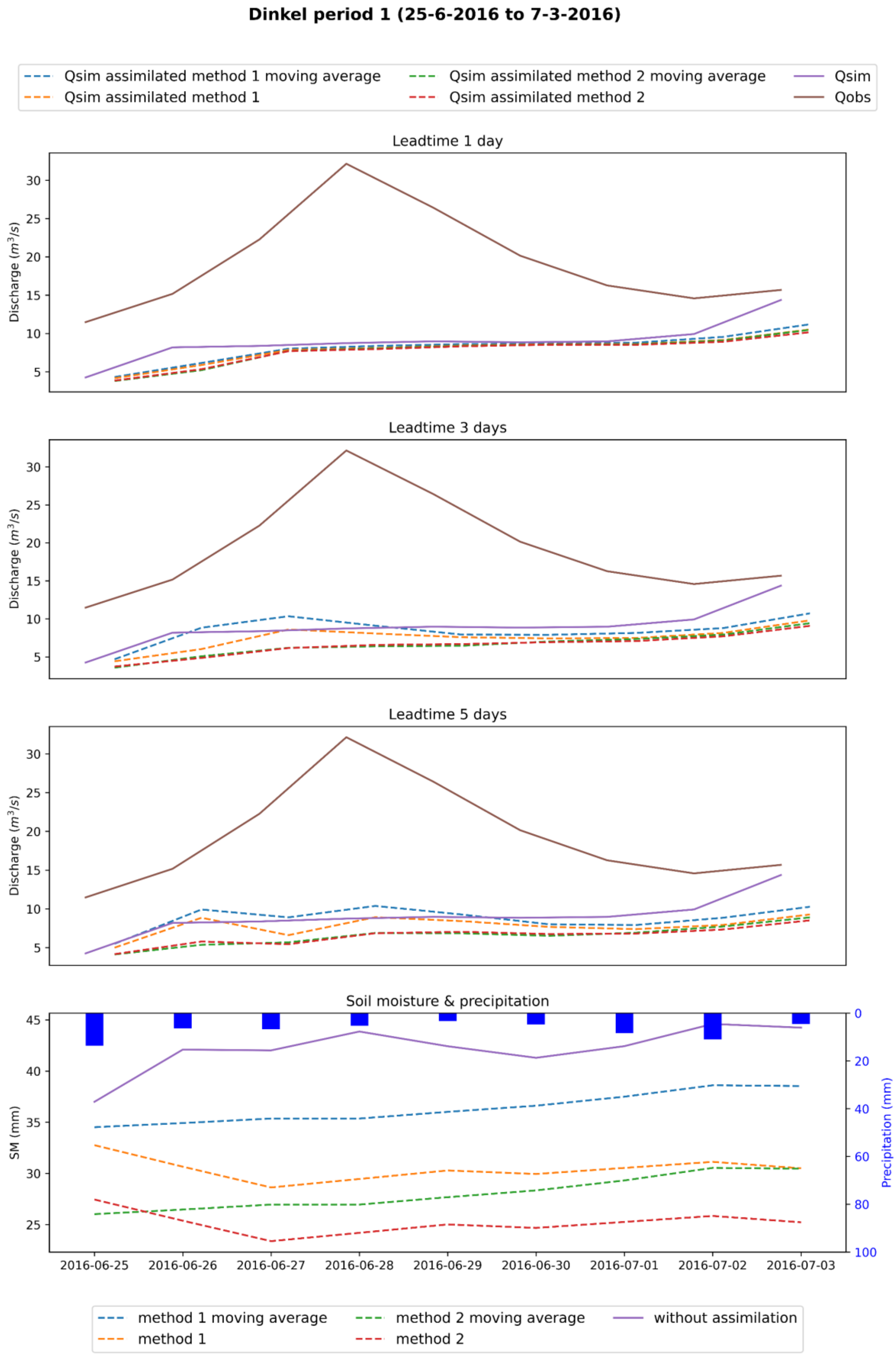

Figure E.6: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Dinkel for the period of 25-6-2016 to 3-7-2016

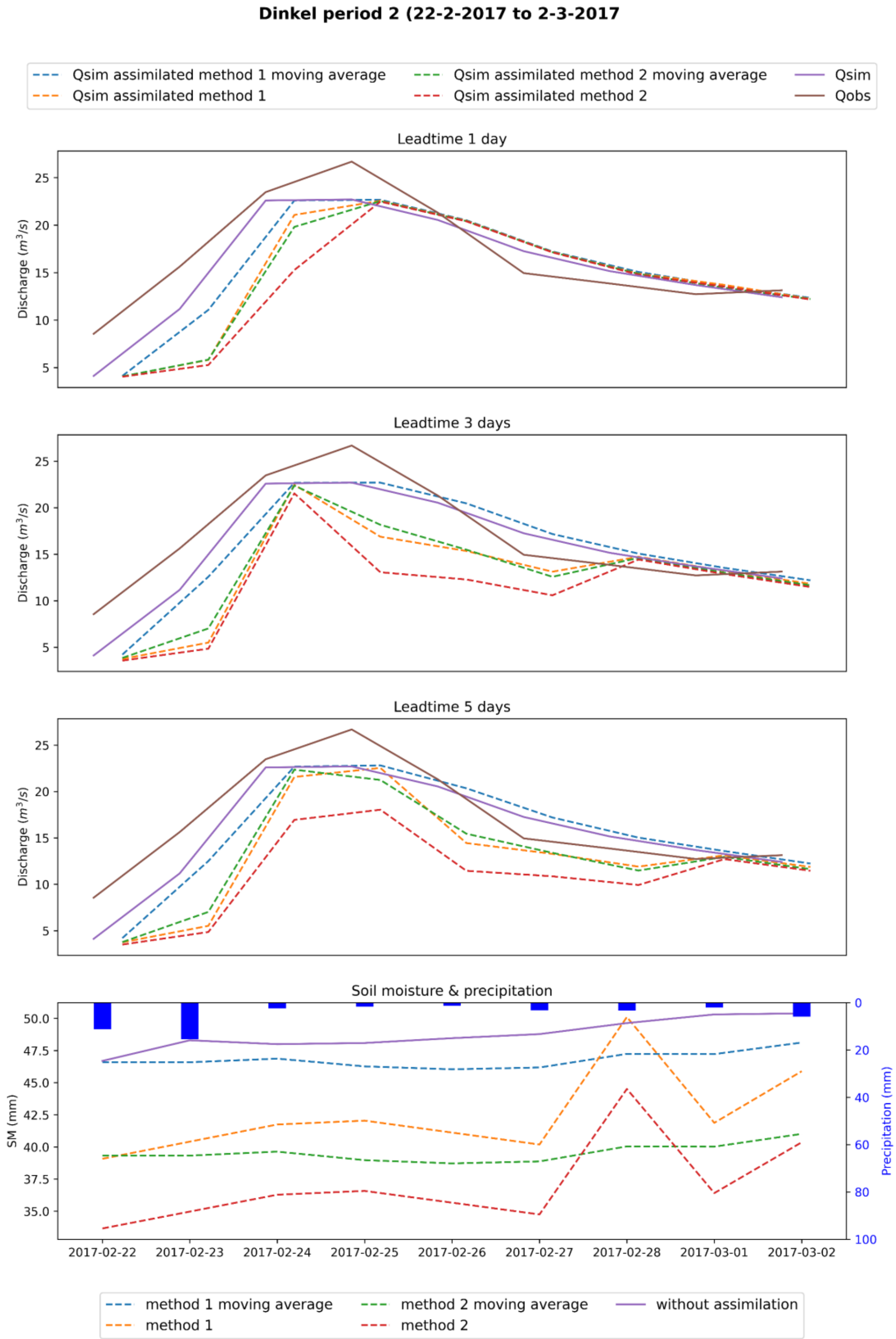

Figure E.7: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Dinkel for the period of 22-2-2017 to 2-3-2017

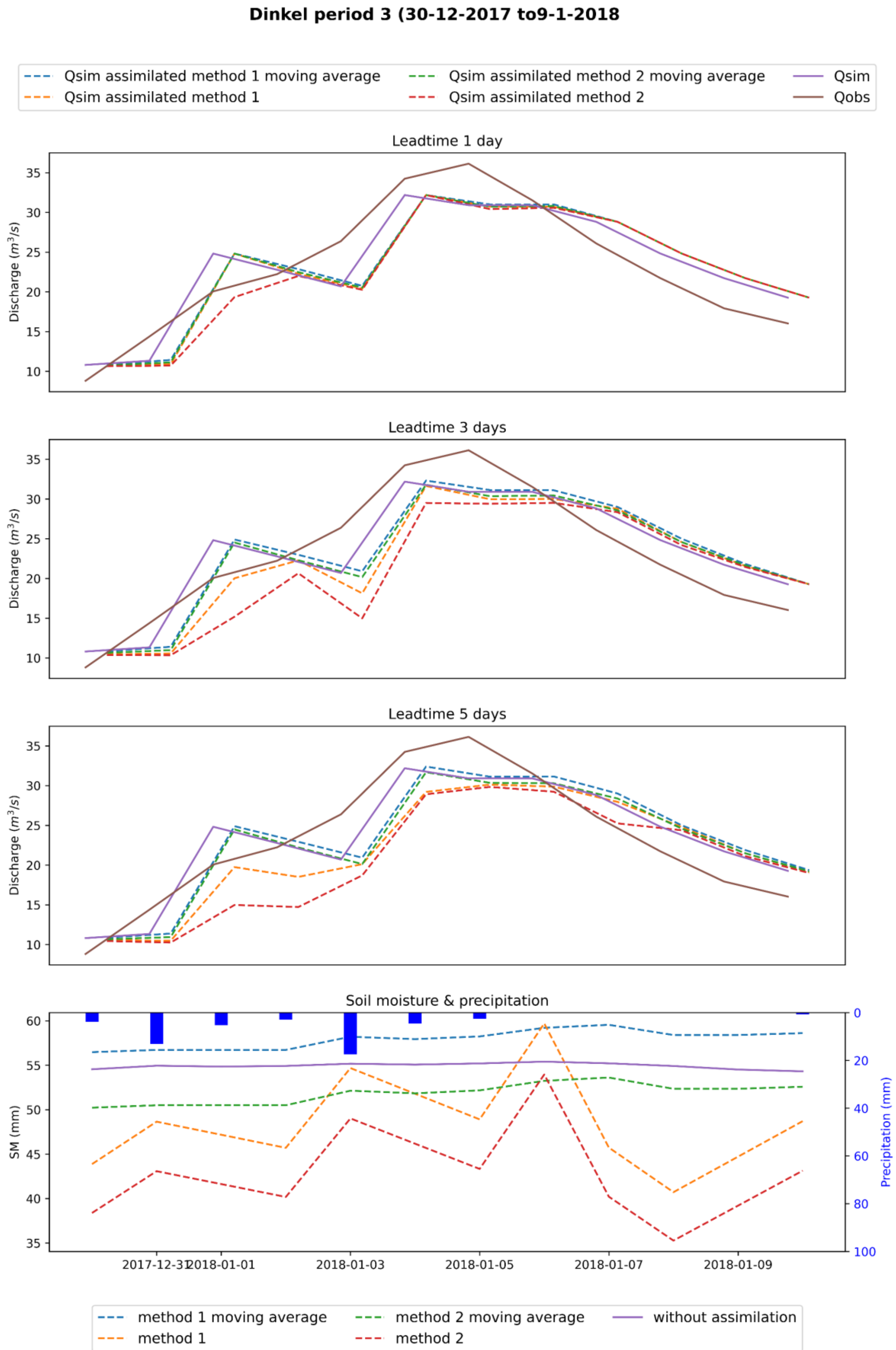

Figure E.8: The effect of the assimilation of soil moisture on the discharge of one peak flow event for the Dinkel for the period of 30-12-2017 to 1-9-2017