The Danish Meteorological Institute

DMI Report 21-32 Implementation of New Radar-Based Weather Data in High Spatial Resolution into Agricultural Decision Systems

Final scientific report of the 2020 National Centre for Climate Research Work Package 3.2.2. Agriculture

DMI Report
15 January 2021

By Julie Pedersen (AU), Jens Grønbech Hansen (AU), Mette Balslev Greve (AU), Ying Wang (AU), Mathias Neumann Andersen (AU), Rashpal Gill (DMI), Thomas Bøvith (DMI), Bent Hansen Sass (DMI)

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Colophon

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Author(s)	Julie Pedersen (AU), Jens Grønbech Hansen (AU), Mette Balslev Greve (AU), Ying Wang (AU), Mathias Neumann Andersen (AU), Rashpal Gill (DMI), Thomas Bøvith (DMI), Bent Hansen Sass (DMI)
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Content

Abstract

Decisions in agricultural management are regularly supported by the input of measured and forecasted meteorological data. The weather conditions in 10 x 10 km grid interpolation have been used for weather based agricultural models and decision support systems, e.g. irrigation management, development of pest and diseases and nitrogen leaching at field and landscape level. A recently developed model, Surface Quantitative Precipitation Estimation (SQPE), allows grid size down to 0.5 x 0.5 km. The objective of this project was to implement new radar based precipitation data in higher spatial resolution into agricultural system models, in order to evaluate the potential and relevance of using these data with higher resolution. Two agricultural models were tested in use-cases: 1) soil water balance in crop fields for preventing water deficit, and 2) the risk of oospore-derived early late blight outbreaks, caused by the pathogen *Phytophthora infestans*, in potatoes. The new weather radar data was obtained from the Danish Meteorological Institute (DMI). A water balance model was used for measuring water balance and irrigation in different locations. A late blight oospore-risk model was used for modelling the potential risk of early outbreaks initiated by oospores.

The results showed differences in precipitation between the 10 x 10 km grid data and the radar-based data. The total accumulation of rainfall in 9 of the 10 locations, showed a tendency for more precipitation measured in the radar points, when compared to the 10 x 10 km grid data. It was observed that the estimated water balance and recommended irrigations occasionally changed due to the use of the different datasets, which indicated that the new data type had an effect on the decisions generated by the model. In the oospore model, 7.1 % of the potato fields changed due to the radar data. The results from this project indicates that the new weather radar data affects the output of agricultural models. The quality of the estimated precipitation data – time and amounts of rain – needs to be validated with data from a wider network of rain gauges not included in the model development.

Resumé

Beslutningstagning i landbruget understøttes ofte ved brug af målte vejrdata og vejrprognoser. Nedbørsdata i 10 x 10 km GRID baseret på vejrstationer har hidtil være kilden til vejrdata, men via et nyt produkt, en Surface Quantitative Precipitation Estimation (SQPE) model, kan man estimere nedbør helt ned til 0.5 x 0.5 km GRID størrelse. Formålet med dette projekt var at implementere det nye radardata i landbrugsmodeller og undersøge om dette kan give mere nøjagtig beslutningsstøtte helt ned på markniveau. To modeller blev brugt til undersøgelsen: 1) en jordvandsbalance-model for forebyggelse af vandunderskud i marken, og 2) en risikomodel for tidlige angreb af kartoffelskimmel forårsaget af oosporer fra patogenet *Phytophthora infestans*. De nye radardata er udviklet og leveret af Danmarks Meteorologisk Institut (DMI). En vandbalancemodel blev brugt til at simulere og generere vandbalancen og vandinger for forskellige lokaliteter. En oospore-risikomodel estimerede risikoen for tidlige angreb af kartoffelskimmel.

Resultaterne viste betydelige forskelle hvor modellerne anvendte hhv. 10 x 10 km data og radarkorrigerede 0.5 x 0.5 km data. Den totale akkumulerede nedbør for 9 ud af 10 lokaliteter, var højere i radar-punkterne end de relaterede 10 x 10 km GRIDS. Både vandbalance, samt tidspunkt og mængde af vanding ændrede sig, hvilket indikerer et potentiale i at bruge de nye radar korrigerede data med højere opløsning. I oosporemodellen ændrede 7.1% af kartoffelmarkerne risikoværdi ved anvendelse af de nye radardata. Resultaterne fra dette projekt giver anledning til opfølgende undersøgelser, dels mht. en egentlig validering af kvaliteten af de beregnede tidspunkter og mængder af nedbør for interpoleret nedbør og dels mht. validering af modelberegningerne af testede modeller for vandbalance og sygdomsrisiko.

1 Introduction

The Danish National Centre for Climate Research (Nationalt Center for Klimaforskning, NCKF) has completed its first year in 2020. It has been a source of funding for the Danish Meteorological Institute and collaborators for climate change related research during this year. The 18 work packages fall under 4 general themes:

1. Arctic and Antarctic Research
2. Climate change in the near future
3. Use of climate data
4. Support for the IPCC

Weather data, e.g. detailed information about precipitation are important sources of information for Agricultural Decision Support Systems. In a climate perspective weather data may gain further importance, e.g. if precipitation gets more extreme and variable in the future. In order to provide more detailed information to Agricultural Decision Systems in Denmark, DMI and Aarhus University, Department of Agro-ecology decided to test the impact of a new high resolution precipitation analysis on the diagnostic results of the Agricultural Decision Support Systems.

1.1 Water balance

Water is an essential component in plant production, and a sufficient amount of water has to be available throughout the season in order to achieve proper growth and maintain crop quality. Irrigations can be necessary in crop productions, yet, the water input should be quite accurate, to attain optimal water balance in the soil, serving the water exactly acquired to the plant. The software 'Vandregnskab' is a water balance model, which calculates the exact irrigation need in the field based on field information and weather data. The calculations are based on registered data, such as evapotranspiration, precipitation and own registered irrigation of the particular field. To make the water balance estimations more field specific, precipitation data in higher spatial resolution should be further analysed by implementing radar-based weather data into the model.

1.2 Disease Risk

Besides the influence on crop growth, the weather conditions also determine the potential risk of certain pests and diseases. Late blight, caused by the oomycete *Phytophthora infestans*, is a serious disease in potatoes. The pathogen is also commonly known to be the causal agent of the Irish Famine in 1845 (Fry and Goodwin, 1997) and today, more than 150 years later, it still troubles potato growers all around the world. The severity level of a late blight outbreak considerably depends on the environment and the weather conditions during the growing season. Conditions favourable to *P. infestans* may result in epidemics, ultimately leading to extensive use of pesticides (Cooke and Lees, 2004, Cooke et al., 2011). Since the 1920s, late blight forecasting models have been developed and applied as an effective tool to predict potential outbreaks, based on measured and predicted weather data (Singh and Pundhir, 2013). Currently, late blight forecast modelling is still a work in progress, attempting to develop the most accurate prediction that would assist growers in late blight management and to generate optimal spraying schedules throughout the season. However, the presence of both P. *infestans* mating types (A1 and A2) enables sexual reproduction, which results in the formation of viable resting spores, *oospores*. Oospores can survive in the soil for years and potentially constitute as primary inoculum source for early late blight attacks in the potato field the following seasons (Lehtinen and Hannukkala, 2004). The presence of oospores complicates the use of forecasting models, but the early attacks derived from oospore attacks are also believed to be predictable through modelling, by determining the exact time for disease onset and level of risk. In the GUDP project BlightManager, a geographical information system (GIS) based oospore model is developed, in order to predict the distribution of oospore-infested fields in Denmark and thereby detect early outbreaks. Since water is an essential factor in the formation and germination of oospores (Cohen et al., 2000), precipitation data is highly relevant to include in the oospore model. The new radar-based weather data may ultimately give more accurate calculations of the oospore risk in each individual field, and thus, assist growers in more precise applications based on each field profile.

This project aims to study new radar-based weather data in higher spatial resolution, by implementing and comparing data in two use cases; a water balance model, recommending irrigation based on precipitation and stress days and an oospore model for risk predictions of early late blight outbreaks initiated by oospores. It is expected that with a smaller grid-size (0.5 x 0.5 km) forecasting, it will be possible to detect differences between or within fields, which could affect the recommendations generated by the two systems.

1.3 Description of the Surface Quatitative Precipitation Estimates (SQPE) model

Aarhus University, Department of Agroecology (AU-Agro), have been using uncorrected rain gauge based precipitation product at a horizontal resolution of 10 x 10 km in their modeling prediction activities related to, amongst others, advising the farming community on water irrigation, risk of nitrous oxides in connection with applying fertilizers to the fields etc..

In the context of the NCKF (National Centre for Klima Forskning) funded project, DMI and AU-Agro started a collaboration to investigate the likely benefit of using instead the new DMI rain gauge and weather radar merged Surface Quantitative Precipitation Estimates (SQPE) product in the above mentioned modeling activities at AU-Agro. The detailed description of SQPE model is provided below. The SQPE product made available to AU-Agro has a horizontal resolution of 0.5 x 0.5 km. Further, 24 hours accumulations SQPE precipitation fields over four summer periods, April – September, from 2017 – 2020 were made available to AU-Agro for their evaluation. The rain gauge data used in the above SQPE model computations were also un-corrected so that a proper model comparison could be made with the traditional 10 x 10 km precipitation product, computed using only the rain gauge network, used by Aarhus Agro.

In recent years, an SQPE system has been developed at DMI, combining in situ rain gauge observations with a detailed analysis of data from meteorological radars. It has been pre-operational for several years, and it is now used in an operational context.

The precipitation analysis is based on a new DMI product to estimate the surface precipitation in near real-time by merging the rain gauge- and radar data. The theoretical techniques used to merge these two different types of data are based on Kriging methods. In recent years, Kriging methods have become very popular to merge rain gauge and radar data (Wackernagel, 2003). Kriging is a geostatistical method for estimating values of a random field at an unknown location by weighting the values from surrounding samples by minimizing the model error variances. Kriging assigns weights according to a data driven weighting function (variogram) rather than an arbitrary function. The weights add up to 1, so that the interpolated result is statistically unbiased. Kriging is preferred over other interpolated methods to merge rain gauge and radar data as the spatial variation of precipitation is too irregular to be modeled by a smooth function i.e., stochastic surfaces can better describe the spatial variation of precipitation. Some of the advantages of using Kriging methods, are how they help compensating for the effects of data clustering, such as many rain gauge data available from the Copenhagen region, by assigning individual points, within a cluster, less weight than isolated data points. Furthermore, Kriging gives estimates of the model variances, indicating the spatial quality of computed precipitation fields.

The Kriging methods used to merge rain gauge and weather radar data are; (i) Kriging with External Drift (KED), and (ii) Kriging with Radar based Error corrections (KRE), which are described in the open literature (Wackernagel, 2003; Goudenhoofdt and Delobbe, 2009; Sinclair and Pegram, 2005). Further, both parametric and non-parametric variograms, describing the spatial statistical variation of precipitation, have been used (Schiemann et. al., 2011, Velasco-Forero et. al., 2009). The final product evaluated, is the variance weighted mean of these four products (KED and KRE with both parametric and non-parameteric variograms). The products, at a horizontal grid size down to 500 m and accumulation periods varying from 10 minutes to 24 hours, have been pre-operational for the last few years, and they are now being used routinely by forecasters for monitoring of weather and by NWP model developers for model validation and verification.

2 Background Theory

2.1 Irrigation and soil water balance

Water is essential for plant growth and the adequate water supply in crop production can be crucial in achieving a sufficient yield, especially on sandy soils (Andersen and Ten Damme, 2018). Thus, irrigation can be necessary. However, due to the risk of leaching, irrigation should not exceed the soil's deficit of plant available water, otherwise water with dissolved nitrate will percolate to the ground water. Soil water balance can be difficult to measure, but models have been developed to simulate it. The components in a water balance model may consider factors such as: Soil evaporation, canopy transpiration, precipitation, irrigation, droplet evaporation, overspray/drift, runoff by overland flow, deep percolation and infiltration. The farmer enters certain information into the model, such as soil type, crop type, day of planting, and not least link to measured and forecasted weather data. Almost all this information can be drawn from the linked databases in systems like Vandregnskab (Thysen and Detlefsen, 2006). In fact, precipitation is the only variable that the advisory service strongly recommend farmers to measure themselves, due to its uneven distribution, which may vary within few hundred meters. Such variation may be large enough to bias the calculated soil water balance and thus increase the risk of both yield losses due to drought and nitrate leaching to the ground water. Manual entering of weather data should be avoided and if all input can be automated, it would largely facilitate the presentation of the soil water balance and irrigation advice on map based systems and interfaces.

2.2 Potato Late Blight - Oospores

Phytophthora infestans belongs to the phylum of Oomycota. Sexual reproduction between two individuals of two different mating types results in the formation of a single resting spore, an *oospore*. The oospore is spherical, smooth and hyaline (Ho, 2018), with a multi-layered cell wall containing a large amount of insoluble ß-glucans, which provide the energy for when germination is activated (Bartnicki Garcia and Wang, 1983, Strömberg et al., 2001). The thick cell wall, surrounding the spore, protects it from most environmental changes, thus, oospores can survive through winter and stay viable for years (Fernández-Pavía et al., 2004). In fact, oospores have been seen to survive outside a living host and resist extreme conditions within a range from - 80°C - 35°C to (Drenth et al., 1995), making them extremely resilient and difficult to eliminate. When the potato season ends, the oospores overwinter and may stay dormant for several years, and thus, serve as a source of primary inoculum for future late blight epidemics in the field (Lehtinen and Hannukkala, 2004). Clarification of the oospore extent, distribution and severity in Denmark is currently needed. Since it has been documented that oospores pose as a source of primary inoculum in Denmark (Cooke et al., 2011), the distribution of oospores, along with in-depth knowledge about viability and survival, could be highly beneficial in the management of late blight outbreaks from soil borne infections. Furthermore, oospores are known to initiate early outbreaks and can therefore be extremely challenging in a potato production, causing extensive sprayings and potential yield loss (Cooke et al., 2011). There is evidence that weather factors, such as temperature and precipitation, have great impact on the formation and germination of oospores (Drenth et al., 1995, Strömberg et al., 2001). Sexual sporulation and the production of an oospore occur effectively at moderate temperatures (10-15°C) (Strömberg et al., 2001)). Also, the occurrence of oospores have shown to be more frequent under heavy rainfall, compared to moderate rainfall (Cohen et al., 2000), which emphasises the importance of the weather conditions and precipitation, in the attempt to understand oospore development.

An oospore model should combine information about field, host, pathogen and meteorological data. It is believed that the risk of early outbreaks increases in fields where potatoes are grown in the proceeding years (Hannukkala et al., 2007), which suggests a cause of oospore-derived inoculum. Therefore, the number of years between potatoes is an important factor to include in the oospore model. Several factors could be included, but meteorological data and years between potatoes, are crucial parameters, along with the calculation of a daily risk value (DRV), calculated from temperature and humidity in the germination period and harvest periods (e.g. jul/aug, aug/sep) the previous seasons.

3 Materials and methods

3.1 Use case 1: Implementing new radar-based data into the water balance model

3.1.1 Water Balance Model

The water balance model was used to analyse the effect of using weather datasets with different resolutions by running simulations from a total of 10 different locations (Table 1);

Table 1: The 10 stations used for the simulations and the soil type on each location (the JB-type is the soil classification system in Denmark (Breuning-Madsen et al., 2001)).

Location	**Soil type (Danish soil classification system**	**JB-nr**
Hillerslev (Fyn)	Fine sandy clayey	6
Foulum	Fine clayey sandy	4
Hovborg	Coarse sandy	1
Flakkebjerg	Fine sandy clayey	6
Vendsyssel	Fine sandy	2
Renbæk	Coarse sandy	1
Vildbjerg	Coarse sandy	1
Galten	Fine clayey sandy	4
Skottemarke (Lolland-Falster)	Fine sandy clayey	6
Balling	Fine clayey sandy	4

For each location, three different crops were included in the simulations, based on difference in crop emergence date and irrigation schedules (Table 2).

Table 2: The crops used for the simulations and their input information

Crop	Date of emergence	Cuts (grass only)
Potatoes (starch)	May 20	
Winter wheat	April 1	
Grass	April 1	1 of June, July, August and September

The grids were selected based on their position in between weather stations and to ensure that the distribution of precipitation was representative for Denmark (Fig. 1). A farming design for each location was created, containing information such as crops, soil types and crop emergence date. For each simulation, three different crops were analysed; Potatoes (starch), winter wheat and grass (for biomass). Weather data files for each location were prepared, extracted from the meteorological data base at AU-Agro (Klimadatabasen – data supplied of DMI). The two weather dataset (10 x 10 km grid data and 0.5 x 0.5 km radar data) are both based on uncorrected weather data, with daily values from midnight to midnight, however, the Coordinated Universal Time (UTC) differs between the two weather data types, with radar based data being at UTC 0 and the 10 x 10 km grid weather data from Klimadatabasen, being UTC Danish local time (+1 and +2).

The weather data file included parameters such as air temperature, relative humidity, precipitation, etc. and was consistent for each simulation by location, precipitation being the only changed variable. The radar data product (SQPE file), was imported into the geographical information system, GIS (ArcGIS Pro).

A shapefile was created for each of the 10 selected grids, in which 5 different points were formed. Radar data from each points was extracted, and for each point a new weather data file was created. Each file with weather data was run through Vandregnskab, to calculate the water balance and the recommended irrigations. The outcome was analysed based on the calculated water balance and recommended irrigations generated by the program. Additionally, a program was programmed to calculate the potential yield loss.

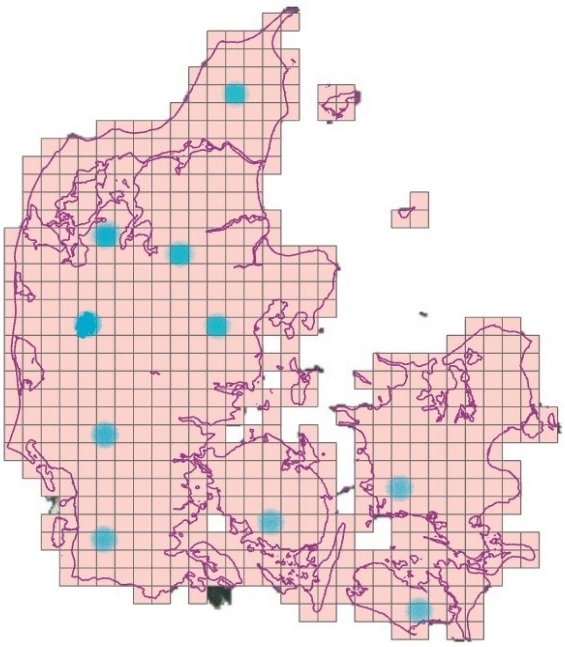


Figure 1: The 10 x 10 km grids on Denmark map with the selected locations/grids for the simulations

3.1.2 Vandregnskab

The Vandregnskab Online software calculates the soil water balance and estimates the irrigation need in the field based on the variables air temperature, evapotranspiration and precipitation, Vandregnskab Online automatically calculates the development in the content of plant-available water in the root zone and estimate the yield decrease due to drought when the crop evapotranspiration is constrained by soil water deficit. It outputs the specific need for irrigation of the individual fields every day and calculates the daily economic loss for a 5 day forecast period if no irrigation. The model automatically calculates and generates tables with output data. It also outputs figures illustrating water deficit in the root zone (Fig. 2), the water requirement (Fig. 3) and the green leaf area index for the crop throughout the period (Fig. 4).

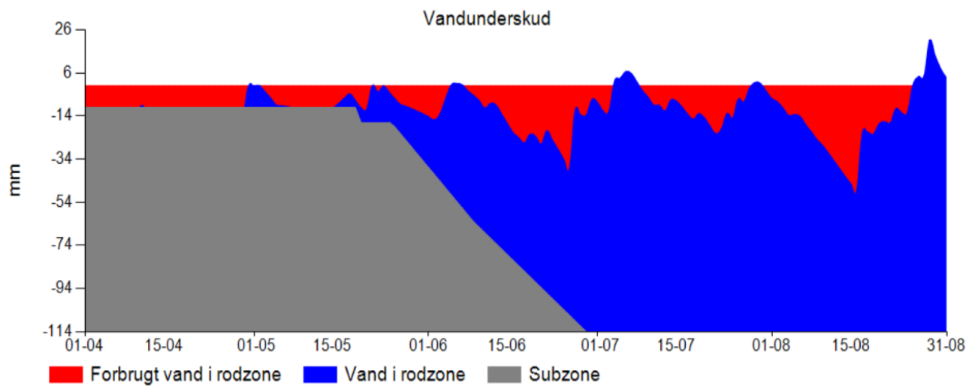


Figure 2: Root zone soil water deficit (Vandregnskab). Red = Utilised water in the root zone, blue = water available in the root zone and grey = subzone

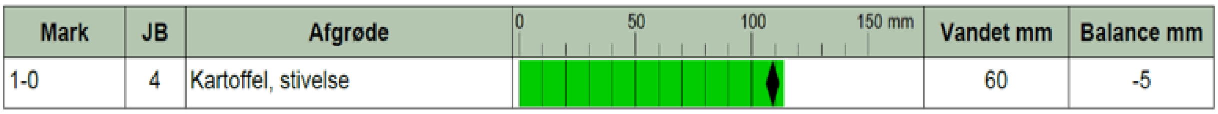


Figure 3: Water requirement. If the black rhomb is in the green area, irrigation is not necessary, but if in the yellow area, irrigation is needed. If the rhomb is in the red area, the crop is in crucial need of water and may already be damaged by drought.

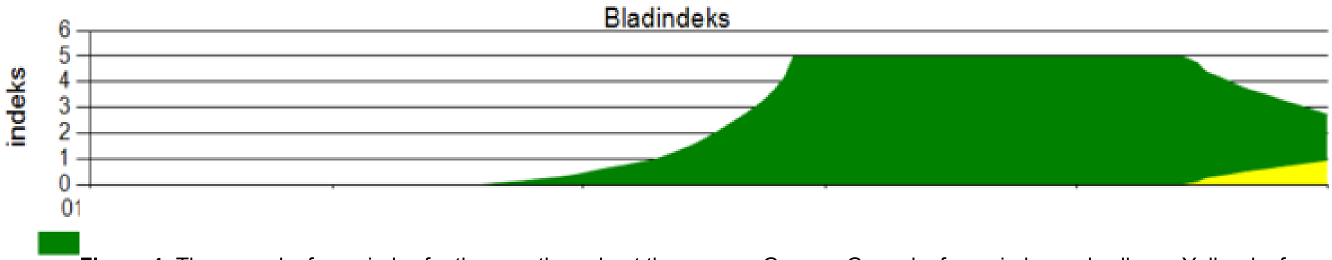


Figure 4: The green leaf area index for the crop throughout the season. Green = Green leaf area index and yellow = Yellow leaf area index

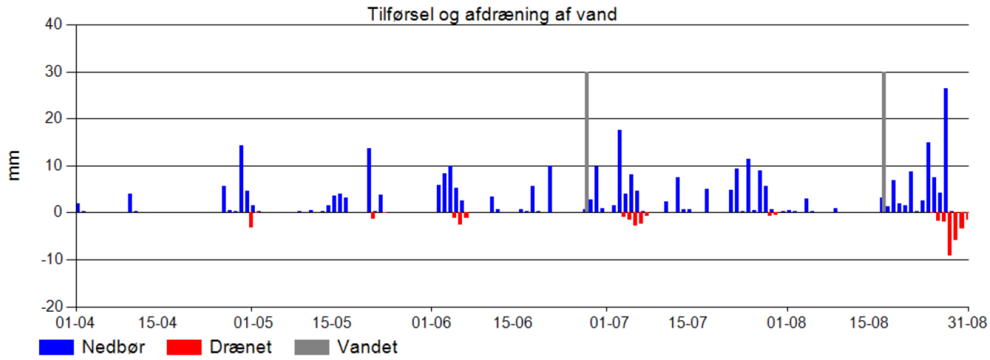


Figure 5: Recommended irrigations generated in Vandregnskab from the weather data file input.
Blue = precipitation, red = drainage, and grey = irrigation

3.1.3 Study design

The two weather dataset were compared in the water balance model: 0.5 x 0.5 km radar-based weather data and the 10 x 10 km interpolated rain-gauge data. Weather data files were prepared for each area. The required meteorological information was: the potential evapotranspiration, mm day^{-1}, daily mean air temperature, [°C] and precipitation on farm, mm day^{-1}. Furthermore, farm, field and crop data derived from the databases was required as well.

Three scenarios were tested: 1) Scenario 1 (S1): 10 x 10 km + weather file, 2) Scenario 2 (S2): Scaled-down 0.5 x 0.5 km precipitation + weather file, and 3) Scenario 3 (S3): Irrigations from scenario 1 + weather file from scenario 2

The output from Vandregnskab calculated the water balance and recommended irrigations in the field. A program in Rstudio (Team, 2020) was written to calculate the potential yield loss in the field. The results was plotted in Rstudio for graphical presentation.

3.2 Use case 2: Implementing new radar-based data into the oospore model

3.2.1 The oospore model

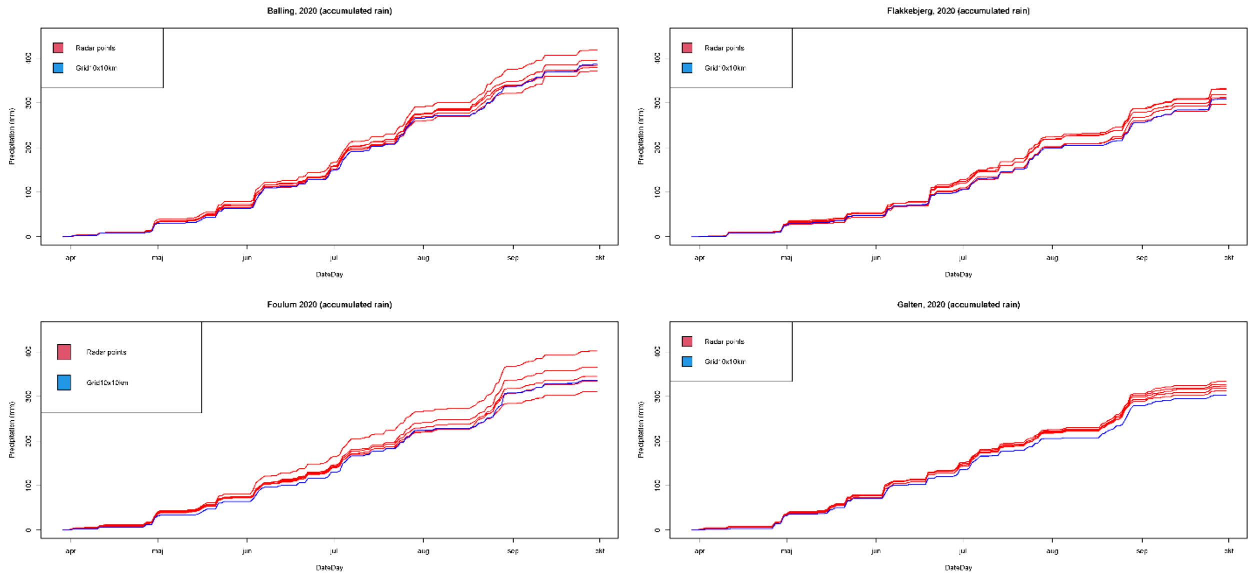
The oospore model was developed through the geoprocessing model builder in ArcGIS Pro for spatial analysis of the 10 x 10 km grid rain-gauge data and the high resolution radar data. The oospore model suggested the potential risk of oospore-derived outbreaks from a scoring system (1-10 scale) based on a range of different agricultural parameters: the calculated daily risk value for disease development (DRV – determined by temperature and relative humidity) at crop emergence stage, number of potato free years in the crop rotation, infection pressure late in the season when potatoes were grown in the same field and finally, precipitation at crop emergence. The DRV for a selected crop emergence-period for this season was summed (May 15-25, 2020) in which a graphical layer was created through the kriging interpolation method (the *Emperical Bayesian Kriging* tool). Furthermore, to include the factor of potato-free years, the DRV for the harvest periods the past three years (Aug/Sep; 2019, 2018 and 2017) was selected as well, which would give an indication of the disease pressure late in the season for the last years. The final risk score was calculated and visually mapped as a weighted overlay.

3.2.2 Data analysis

The risk score output for each file with precipitation data was compared in order to detect differences between the risk score when using different data types. The risk value for each field was extracted for each dataset and the score values were compared.

4 Results and discussion

The accumulated rainfall for the 10 x 10 km grid data and the five radar data points was plotted for each location (Fig. 6). The plots generally show a tendency of the radar points estimating a higher total amount of precipitation than the 10 x 10 km rain-gauge data, except for Vildbjerg.



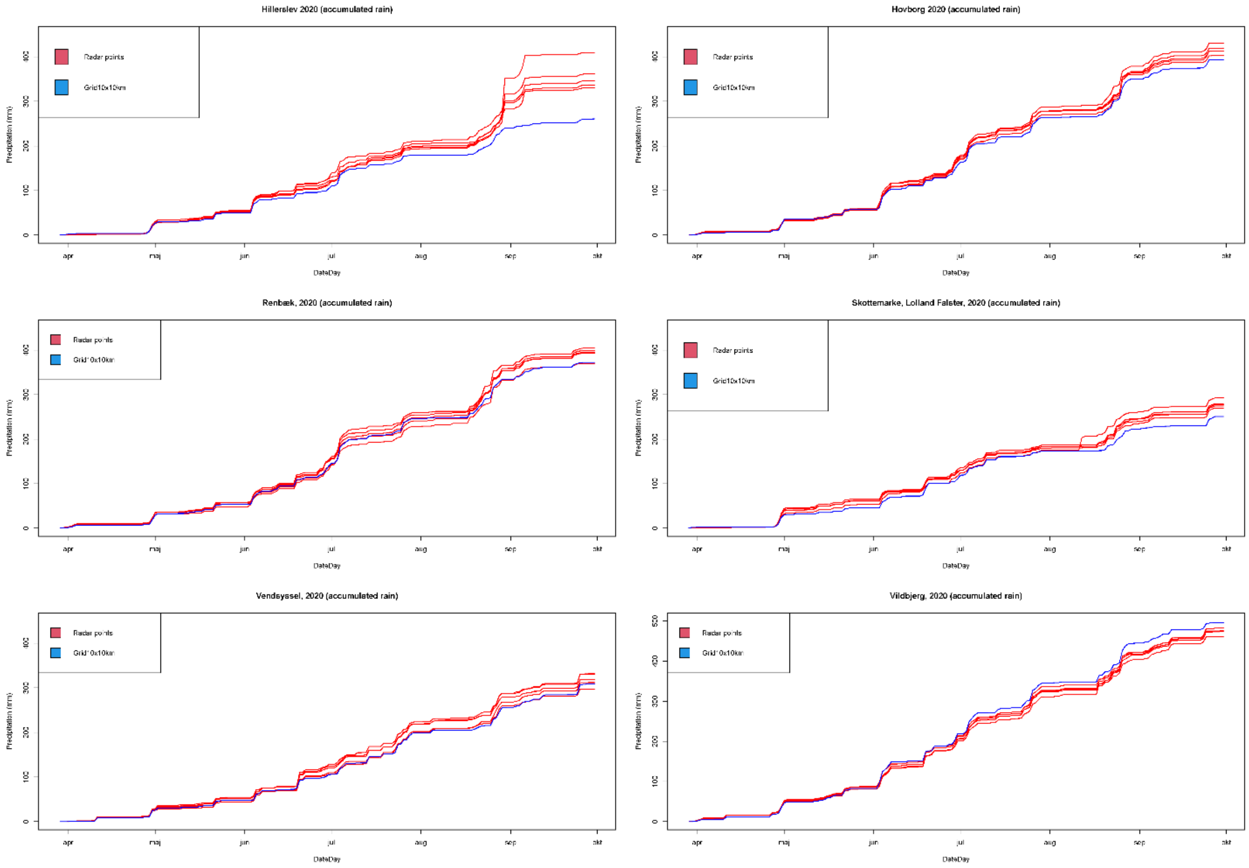
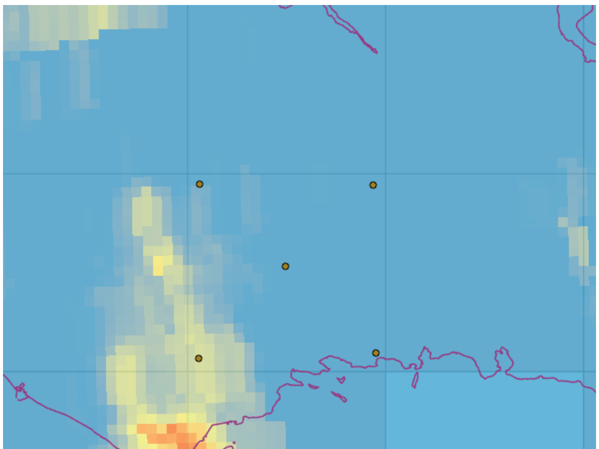


Figure 6: The accumulated rainfall plotted for each location. Red = precipitation data extracted from radar points, blue = 10 x 10 km grid rain-gauge data.

Still, the plots of accumulated rainfall visually demonstrate how the five different radar points graphs reasonably follow the 10 x 10 km grid precipitation, but with variation in the total amount. This gives an expression of the difference in precipitation within the same grids. For an example, the accumulated precipitation at Hillerslev differs with a total of 149 mm (Radar point 4 = 409.64 mm, PREC 10 x 10 km = 260.6) when comparing with one of the radar point.

Furthermore, the plot for Skottemarke, Lolland Falster, radar point 4 shows a noticeable jump in August (12th of August). The radar image for that particular day shows a large amount of precipitation in the left bottom corner of the grid, actually measuring 27.56 mm for the daily amount of precipitation for that single radar point, whereas the other points (and the 10 x 10 km grid data) only measured 0.5-2 mm in total (Fig. 7). This implies that the precipitation may occur differently within the same grid, which could have significantly changed the output in a model for fields located in that part of the grid. This will be further investigated in the next section.



4.1 Use case 1: Water Balance Model

The water balance was calculated for each grid and plotted ((Fig. 8) and **appendix 1**) to visualise the difference in the estimated water balance between the one of the radar points (point 5 – placed near the centre of the grid) and the 10 x 10 km grid data. In addition, the point 4 from Skottemarke, Lolland Falster was also compared to the 10 x 10 km grid, to see if the large difference in precipitation affects the output in the water balance model.

All 10 locations, each with the three selected crops, were plotted, to study the difference in water balance and irrigations. The plots for Balling are presented below (Fig. 8), to demonstrate an example of the final plots for each of the three crops. For potatoes and wheat (Balling), the recommended irrigations in Scenario 1 (1) and Scenario 2 (S2) were similar in timing and number of irrigations. Grass (Balling) showed a difference in irrigation time between scenario 1 (S1) and scenario 2 (S2), where the second irrigation for S2 was set 24 days later than S1 (S1 = 02-06-2020, S2 = 26-06-2020).

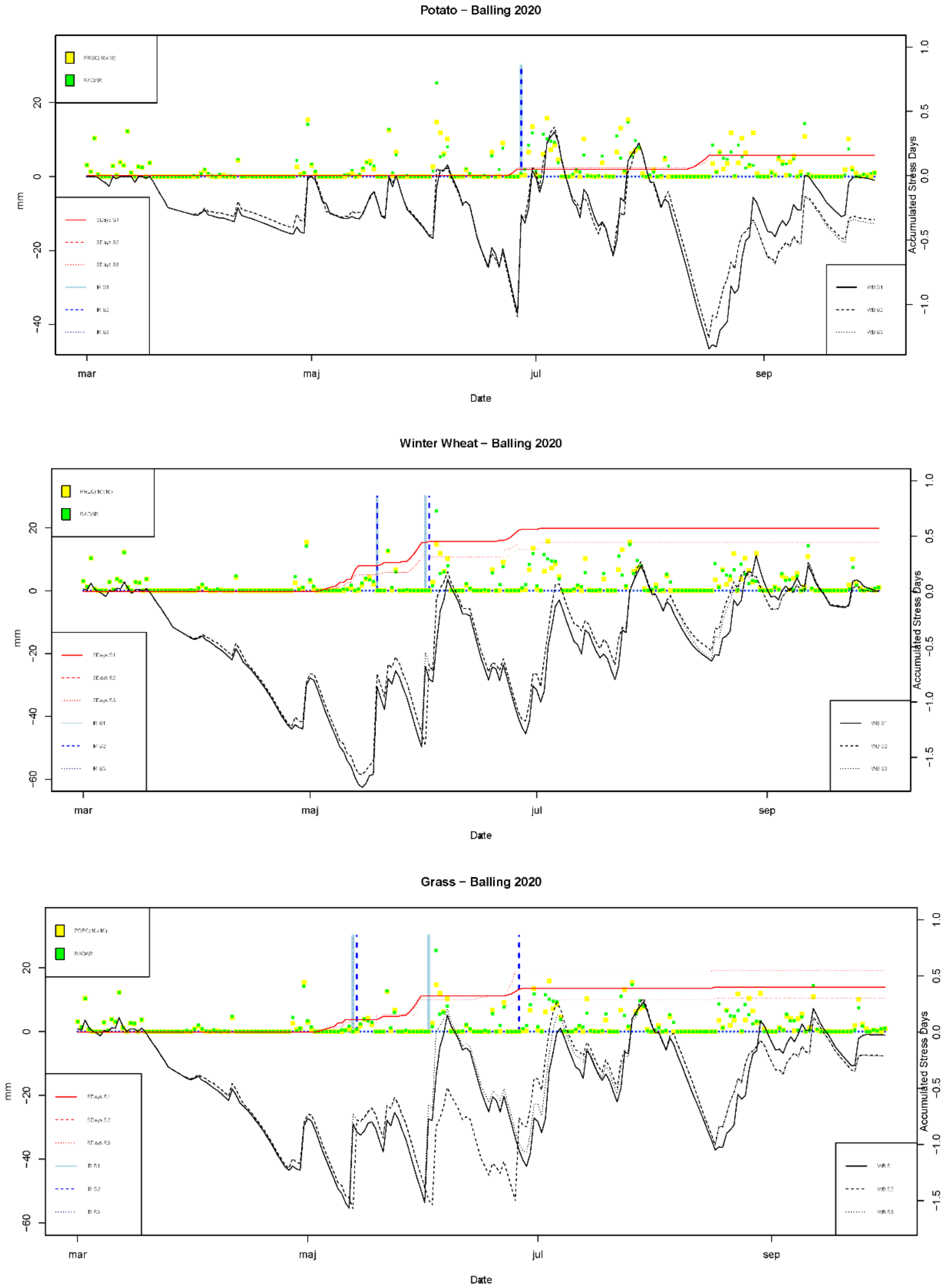


Figure 8: The irrigations and water balance generated in Vandregnskab, and the calculated accumulated stress days. PREC (10x10) = the precipitation data for the 10 x 10 km grid data, RADAR = the radar data, SDays S1 = the accumulated stress days for scenario 1, SDays S2 = the accumulated stress days for scenario 2, SDays S3 = the accumulated stress days for scenario 3, WB S1 = the water balance for scenario 1, WB S2 = the water balance for scenario 2, WB S3 = the water balance for scenario 3. IR S1 = Irrigation scenario 1, IR S2 = Irrigation scenario 2, IR S3 = Irrigation scenario 3. Y-axis left: Precipitation, irrigation and soil water deficit (mm) , y-axis right: accumulated stress days, and x-axis: date.

Each plot for location and crop are to find the **Appendix 1**. Potato and wheat (Flakkebjerg) generated 3 irrigations in S1 and 2 in S2. Grass (Flakkebjerg) had 5 irrigations in S1 and 4 in S2. Thus, all crops had one less irrigation in S2 than S1 in Flakkebjerg. Potato (Foulum) gave the same irrigations, but the irrigations for wheat and grass (Foulum) differed in timing. For potato (Galten), S1 was irrigated in the end of June, but S2 did not irrigate before the mid August. Wheat (Galten) differed in time, and Grass (Galten) had 3 irrigations in S1 and 2 in S2. All the irrigations for each crop in the simulations in Hillerslev were similar, except for a small difference in time for irrigation. For potato (Hovborg), S1 had one more irrigation than S2, but, in wheat (Hovborg), S2 generated one more irrigation than S1. There was no difference between S1 and S2 in the simulation of grass (Hovborg). Potato (Skottemarke, Lolland Falster) showed a difference in time for irrigation, and wheat (Skottemarke, Lolland Falster) had 3 irrigations in S1 and 2 irrigations in S2. Grass (Skottemarke, Lolland Falster) had 6 irrigations in S1 and 5 irrigations in S2. Potatoes and wheat (Renbæk) did not differ between irrigations, but grass (Renbæk) differed in timing for the last two irrigations. Potato (Vendsyssel) generated 2 irrigations in S1 and 1 in S2. There were no noticeable differences between the irrigations in wheat and grass (Vendsyssel), except for the irrigation time in the last irrigation for grass. Vildbjerg showed no major differences between the scenarios.

Thus, from a total of 30 simulations, 21 were similar in number of irrigations, but timing for irrigation varied. 8 of the simulations recommended one more irrigation in S1 than in S2, and 1 simulation recommended one more irrigation in S2 than in S1.

In addition to the radar points 5, the one particular interesting radar point 4 in Skottemarke, Lolland Falster, was also graphically illustrated (Fig. 9):

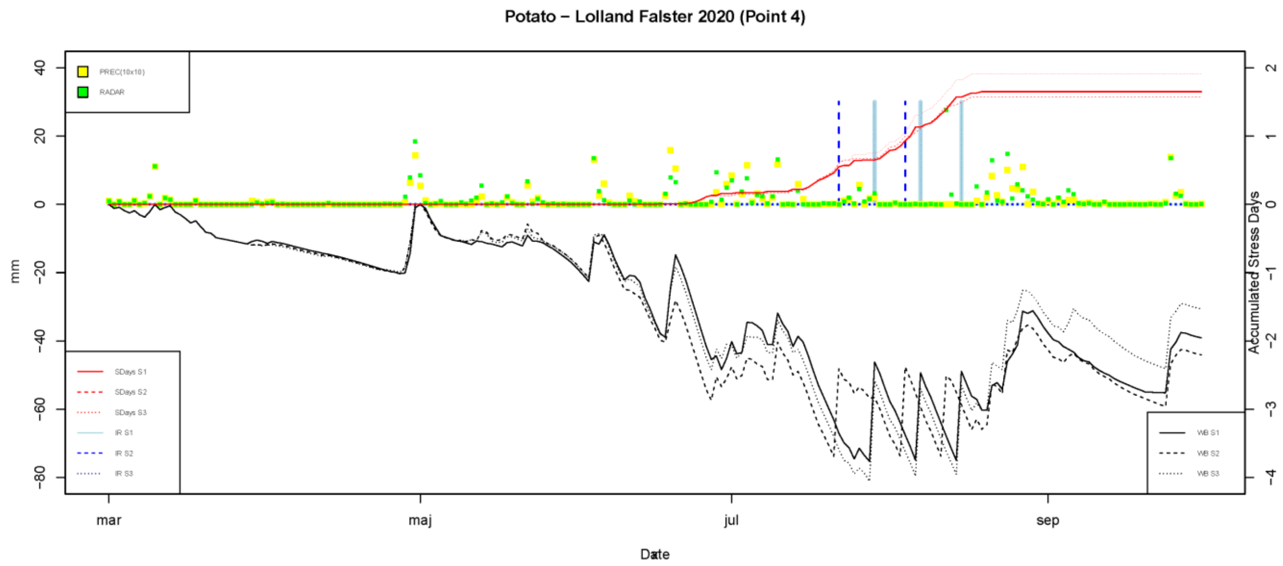


Figure 9: The radar point 4 plotted and compared in the Scenarios. The irrigations and water balance generated in Vandregnskab, and the calculated accumulated stress days. PREC (10x10) = the precipitation data for the 10 x 10 km grid data, RADAR = the radar data, SDays S1 = the accumulated stress days for scenario 1, SDays S2 = the accumulated stress days for scenario 2, SDays S3 = the accumulated stress days for scenario 3, WB S1 = the water balance for scenario 1, WB S2 = the water balance for scenario 2, WB S3 = the water balance for scenario 3. IR S1 = Irrigation scenario 1, IR S2 = Irrigation scenario 2, IR S3 = Irrigation scenario 3. Y-axis left: Precipitation, Irrigation and soil water deficit (mm), y-axis right: accumulated stress days, and x-axis: date.

It was observed that 3 irrigations were recommended in S1, while only 2 irrigations were recommended in the S2. Considering the heavy precipitation in the radar data on the 12 of August in S3, it can assumed that the model generated one irrigation less, which could assumedly be due to that one amount of rainfall, since an irrigation is recommended in S1 shortly after, but not in S2.

Table 3 shows the calculated yield loss (%) for each location and weather dataset. Flakkebjerg, Hillerslev and Lolland Falster calculated a slightly larger yield loss in the Scenario 1, than 3. The simulated irrigation in Scenario 1 and 2 were triggered automatically when the critical soil water deficit was reached. This depends on soil type, crop and crop development stage.

Table 3: The remaining yield [%] calculated from the precipitation and calculated stress days.

	Remaining yield [%]					
	Radar p1	**Radar p2**	**Radar p3**	**Radar p4**	**Radar p5**	**Scenarie 1: Grid 10 x 10 km**
Balling						
Potato	99.2	99.3	99.4	99.4	99.3	99.1
Winter wheat	98.4	98.6	99.2	98.4	98.5	97.8
Grass	99.7	99.7	99.8	99.6	99.7	99.5
Flakkebjerg						
Potato	95.4	95.4	94.6	93.1	95.1	91.1
Winter wheat	96	95.1	96.1	94.2	94.3	91.8
Grass	99.1	98.9	99.1	98.6	98.7	97.8
Foulum						
Potato	99.3	98.4	98.4	99.5	99	99
Winter wheat	99	98.5	98.8	99.5	98.9	97.3
Grass	99.7	99.6	99.6	99.8	99.7	99.3
Galten						
Potato	99.1	99	99	99.1	99.2	98.3
Winter wheat	98.3	98.6	98.7	98.3	98.9	97.7
Grass	99.4	99.6	99.6	99.5	99.6	99.2
Hillerslev						
Potato	97.1	95.3	95.7	96	94.2	92.7
Winter wheat	94.9	92.8	93.7	94.8	93.1	90.3
Grass	98.8	98.5	98.6	98.8	98.5	97.8
Hovborg						
Potato	99.2	99.1	99.1	99.3	99.2	98.9
Winter wheat	97.3	97.1	98.2	97.3	97.3	97.7
Grass	99.7	99.7	99.8	99.7	99.7	99.7
Lolland Falster						
Potato	92.4	89.9	87.8	87.2	87.7	90

Flakkebjerg						
Winter wheat	93.8	95.3	95.2	93.6	94.5	91.1
Grass	98	98.5	98.6	98.3	98.3	97
Renbæk						
Potato	99.1	99.3	99.1	99.1	99.1	99
Winter wheat	97.3	98.4	98.1	97.6	98.3	98.3
Grass	99.1	99.7	99.6	99.4	99.7	99.6
Vendsyssel						
Potato	98	99.2	98.9	95.3	98.8	96.8
Winter wheat	90.5	93.9	95.9	91.2	93.9	91.4
Grass	98.7	99.1	99.4	98.9	99.1	98.9
Vildbjerg						
Potato	98.9	99.1	99.1	99	99	98.8
Winter wheat	99.1	99.1	98.8	98.3	99.1	98.7
Grass	99.9	99.9	99.9	99.8	99.9	99.8

In some cases the suggested irrigations are triggered too late, i.e. some yield loss is induced. This is due to mismatch between the soil water deficit criteria and when reduction in actual evapotranspiration decreases below the potential rate, the latter, also being dependent on climatic conditions. Another reason is that irrigation has a cost and should not be triggered immediately when there is a small yield loss. In most cases, the yield loss was reduced in Scenario 3 (S3) when irrigations from Scenario 1 was used together with the climate (precipitation) data from Scenario 2 (radar). The reason for this is that precipitation from radar in most cases was higher than from the 10 x 10 km grid. Therefore, the crops had even better water supply than in Scenario 1 and 3 and the yield was thus less or similar affected by drought. On the other hand, this may lead to unnecessary irrigation that ultimately could give rise to increased drainage and loss of nitrate from the root zone. However, Vandregnskab does not simulate the increased loss of N and the effect this may have on yield.

4.2 Use case 2: The oospore model

The total precipitation sum for the 10 x 10 km grid data and the radar data, for the period 15-25 of May, 2020, was calculated and mapped (Fig. 10).

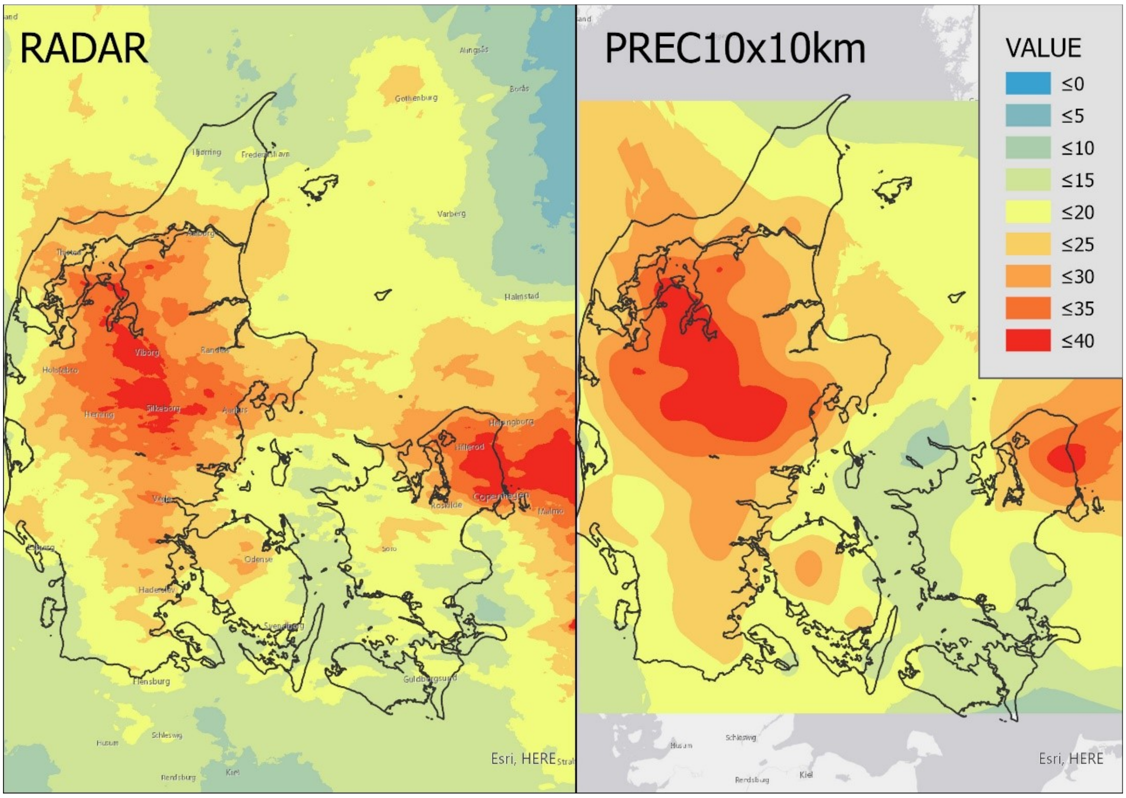


Figure 10: The precipitation (SUM from 15-25 of May, 2020) mapped in Denmark, ArcGIS Pro

The similarity and difference in risk score calculated for the fields for each of the datasets is illustrated below (Table 4).

Table 4: Risk score calculated for each dataset for the period 15-25 of May, 2020 (10 x 10 km grid data = PREC, and radar data = RADAR).

Risk score values (PREC vs. RADAR)	Number of fields	Percentage (%)
PREC = RADAR	7801	92.9
PREC = RADAR – 1	274	3.3
PREC = RADAR + 1	321	3.8
Total number of fields	8396	

From a total of 8396 fields, 92.9% of the potato fields had the same risk score when using either 10 x 10 km grid data or radar data. The percentage for 10 x 10 km grid data being one risk score value (10 x 10 km grid = radar -1) *below* the radar-data was 3.3%. The percentage for 10 x 10 km grid data being one risk score value *higher* than the radar data was 3.8% (10 x 10 km grid = radar +1). This means that 3.3% of the fields generated a risk score RADAR > PREC, and 3.8% where the risk score RADAR < PREC.

None of the values differed more than 1 risk score value.

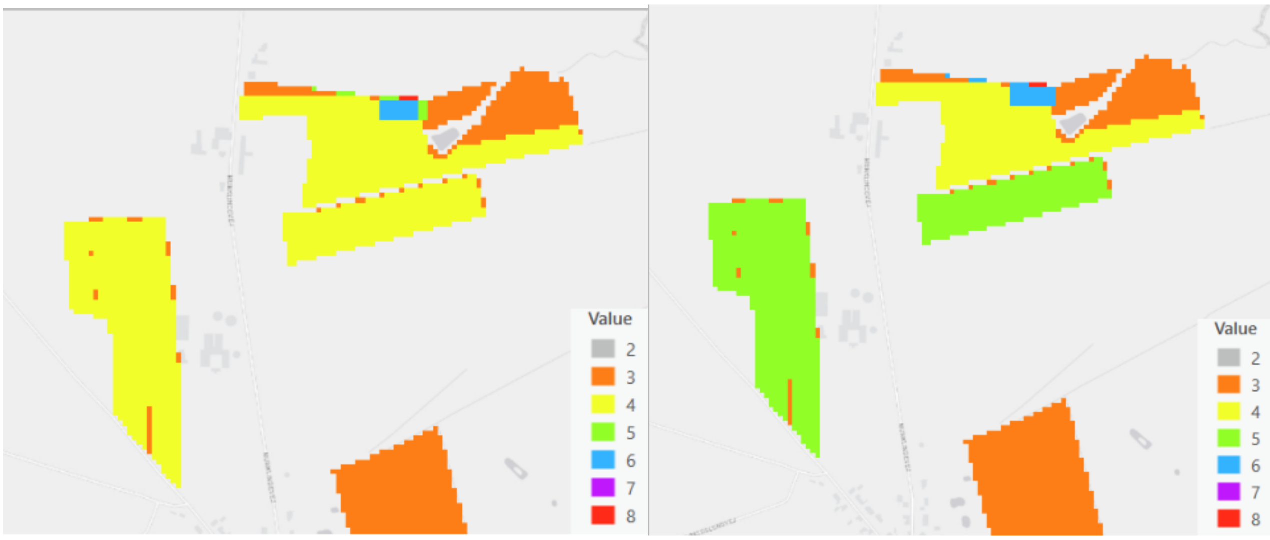


Figure 11: Munklinde, Ikast-Brande – the change in risk score from a risk score of 4 (PREC 10 x 10 km (left)), to a risk score of 5 (RADAR (right)).

A difference of risk score value of 1 (±) is not critical to the model, since group precipitation in classes with strict boundaries, e.g. if the precipitation for the 10 x 10 km grid data register 2.9 mm and the radar data register 3.1 mm, they will be classified in different score values, despite the fact that the values are rather close to each other. The results show that 7.1 % of the fields change in risk score due to the type of precipitation data, but the significance of the difference calls for further specification of the oospore model and its classification system.

5 Conclusion

Differences in precipitation within grids were observed, both when comparing the 10 x 10 km rain-gauge weather data with the radar-based data, but also between single radar points. In 9 of the 10 locations, the radar data points showed a tendency in suggesting more precipitation than the 10 x 10 km grid data, which may lead to the assumption that the 10 x 10 km grid data occasionally underestimates the precipitation in the grid. However, this requires further analysis of radar data and the 10 x 10 km grid data, in comparison to a wider independent rain-gauge network.
The results showed variations in the water balance output, when implementing the different types of precipitation data, both in time for irrigation and the amount. For 8 simulations, the model added an irrigation when using the 10 x 10 km grid data, compared to the radar data.
When implementing the data into the oospore model, it was observed that for 7.1% of the potato fields, the risk score changed due to change in precipitation datatype. Still, the significance of the differences observed calls for further specification of the oospore model and its classification system.

For future validation of the new radar based weather data, the data should be consistent with the comparing weather datasets, as the difference in UTC may potentially be of significance when comparing the daily precipitation. Therefore, we need to make sure that the daily accumulations refer to the same 24 hours. Furthermore, since the input rain gauge used in the computations of both the 10 x 10 km grid and the 0.5 x 0.5 km radar products are not quality controlled, it cannot be ruled out that the large difference between the two products are due to the uncontrolled quality of the input data. Due to the limited time for this initial study, it has not been possible to investigate this further. However, it is our intention that in the next phase of the study we shall use quality controlled input rain gauge data in both the gridded and the SQPE and investigate if our current conclusions needs to be re-evaluated.

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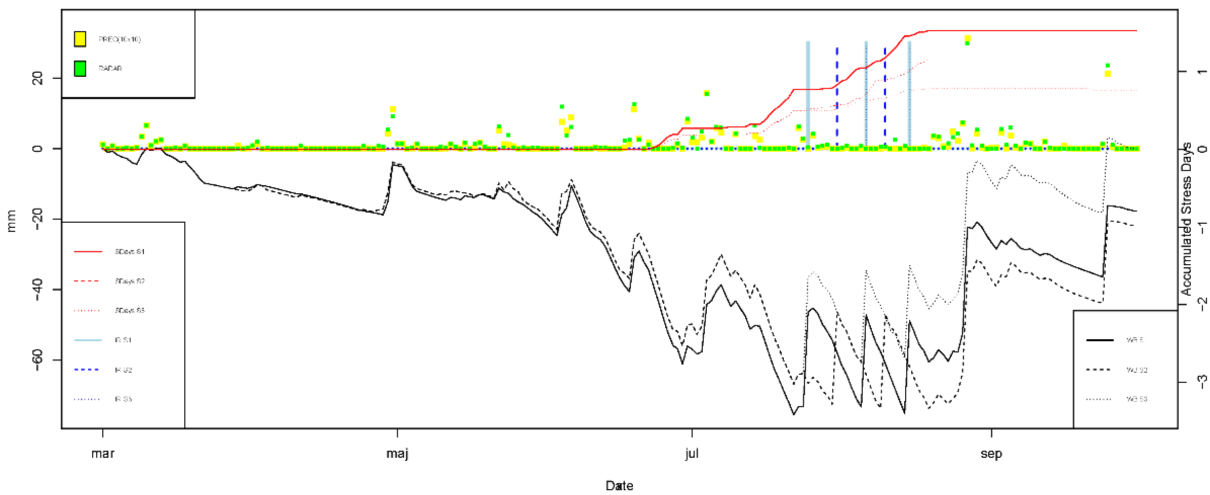
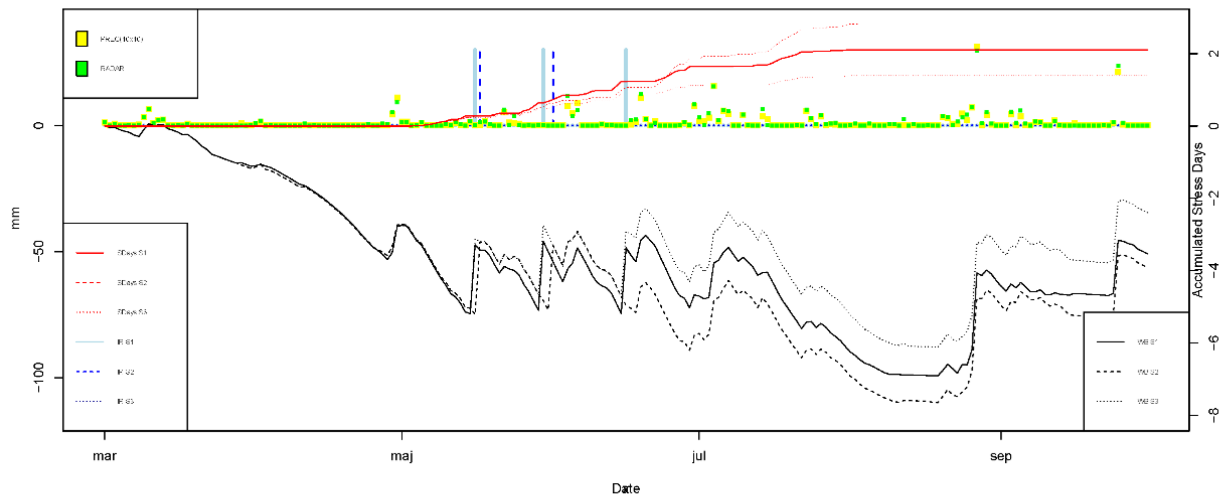
7 Appendices.

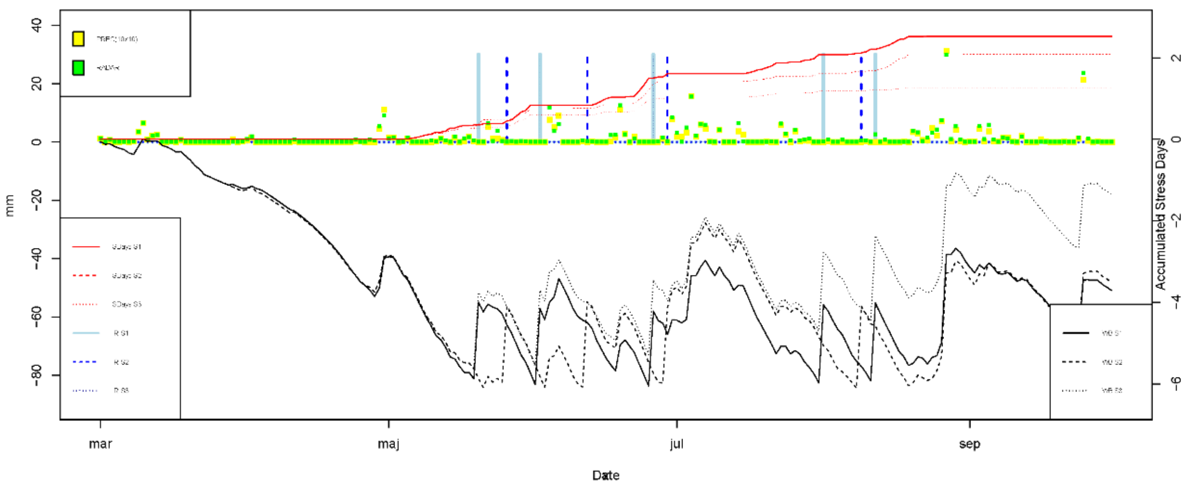
Potato – Flakkebjerg 2020



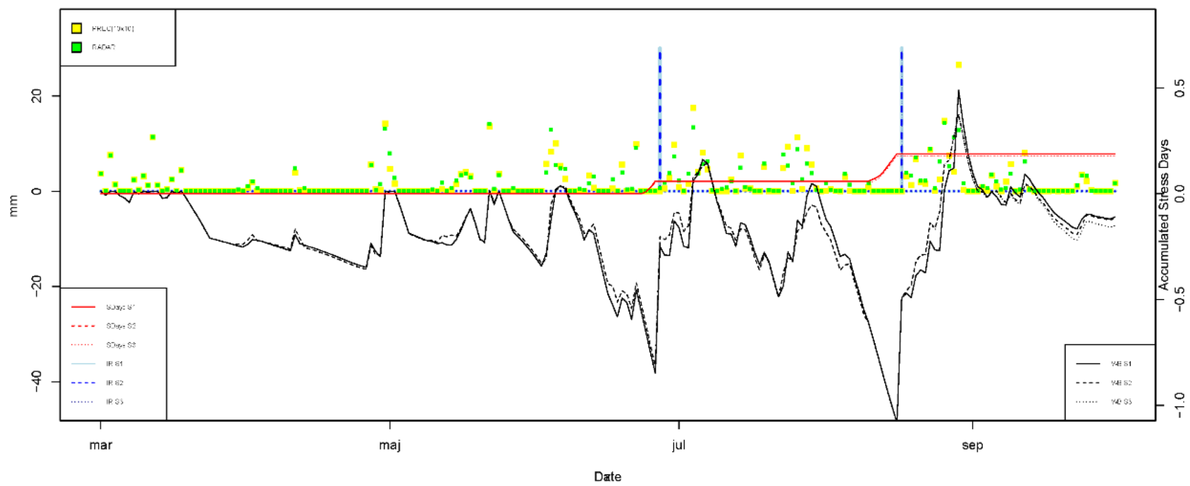
Winter Wheat – Flakkebjerg 2020



Grass – Flakkebjerg 2020



Potato – Foulum 2020



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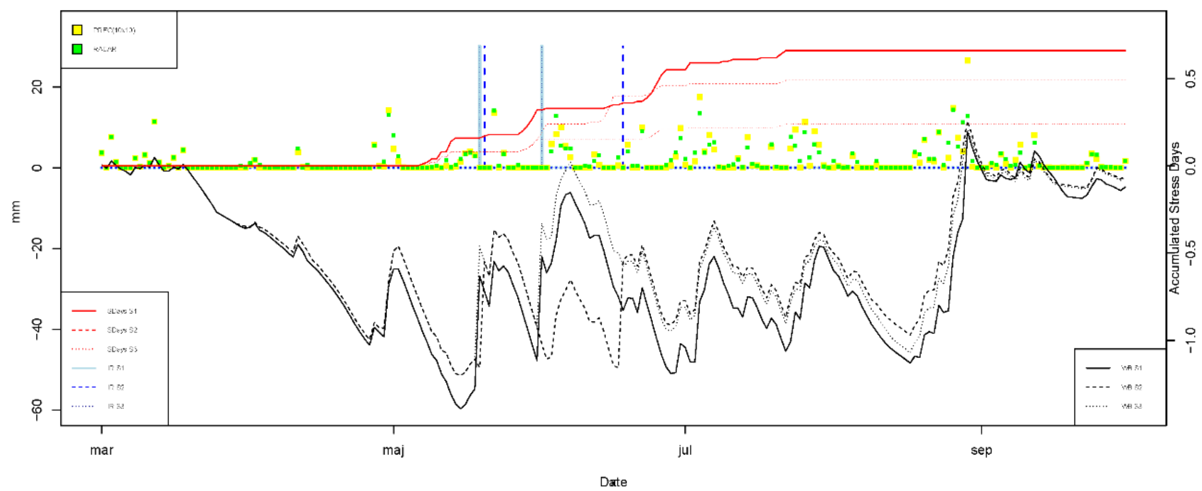

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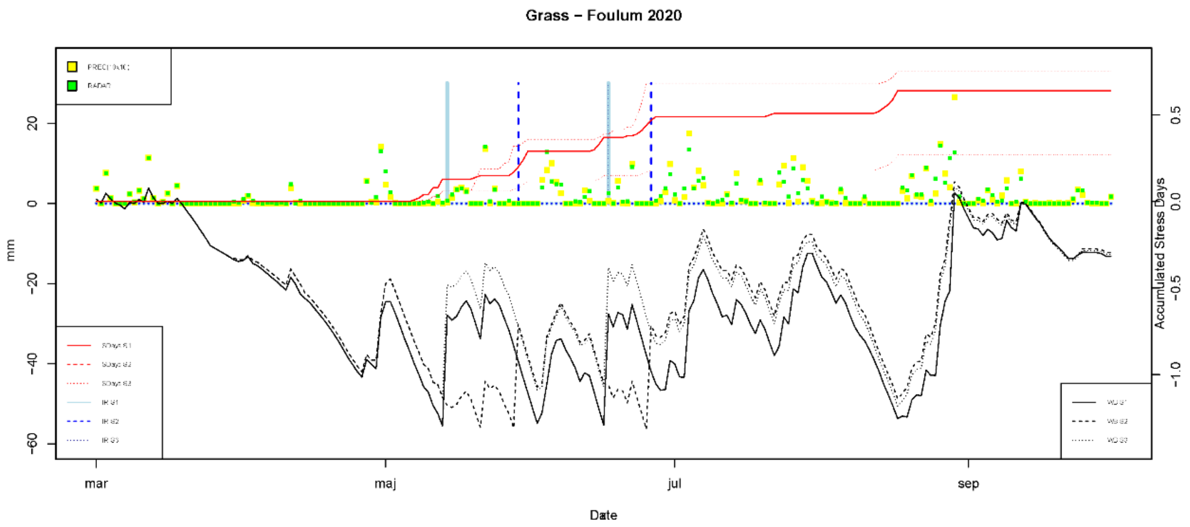

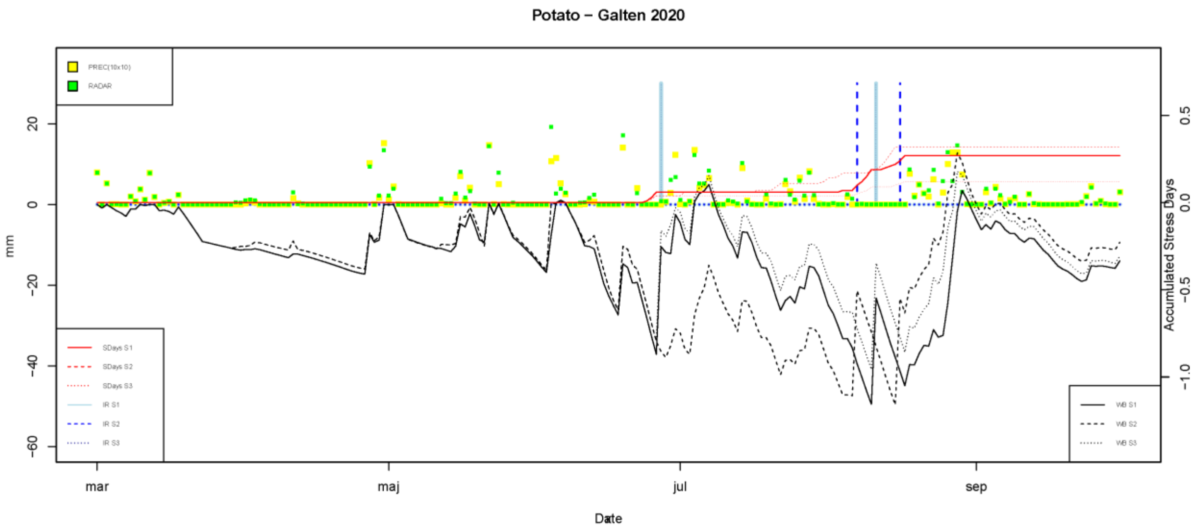

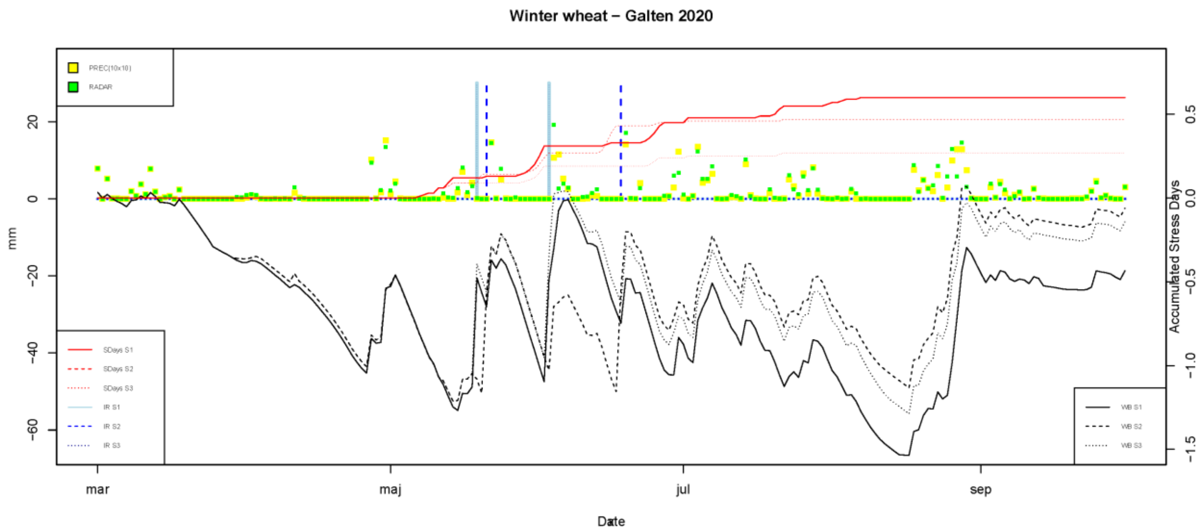

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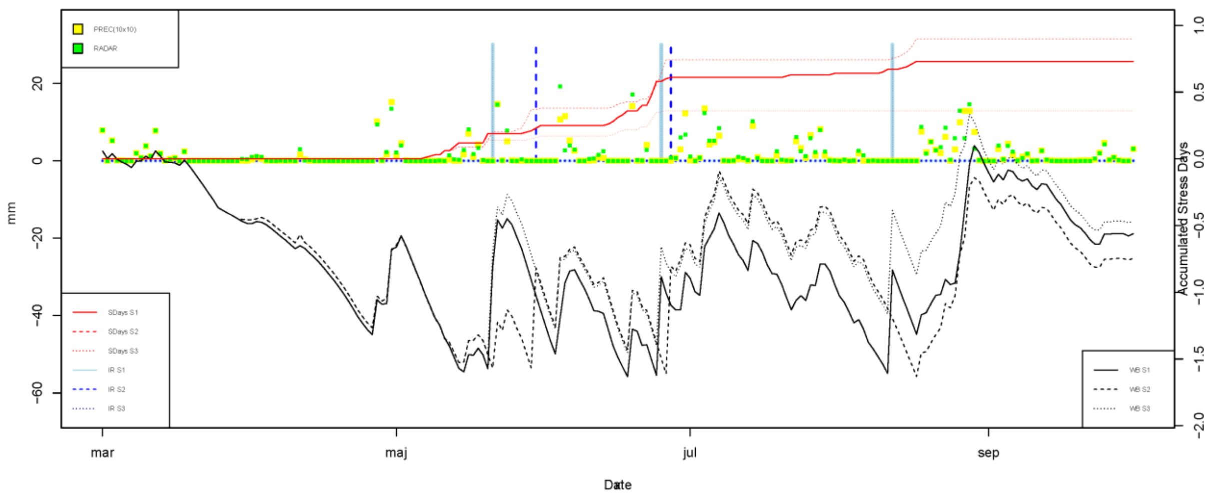
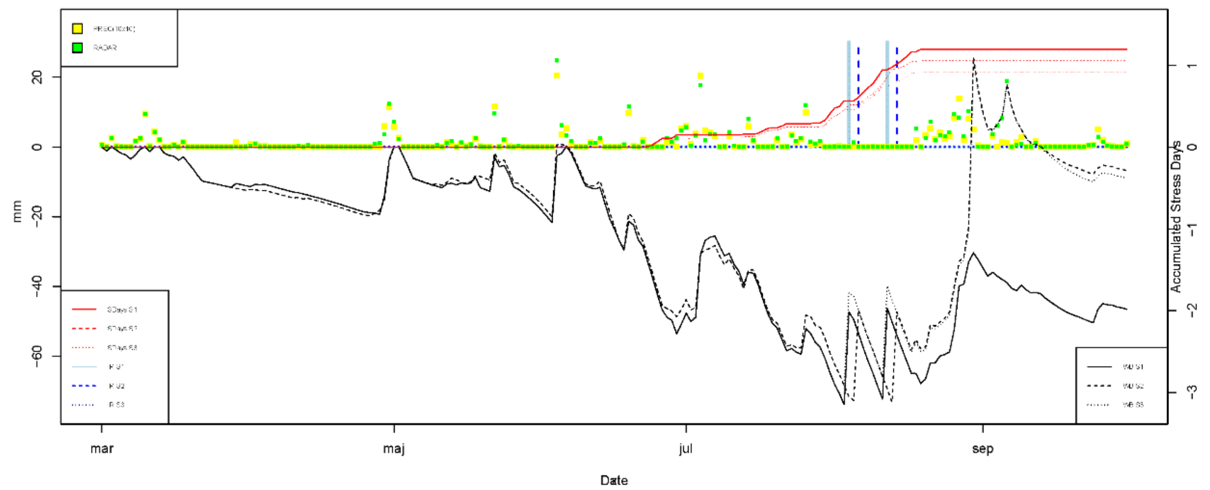
Grass – Galten 2020



Potato – Hillerslev 2020



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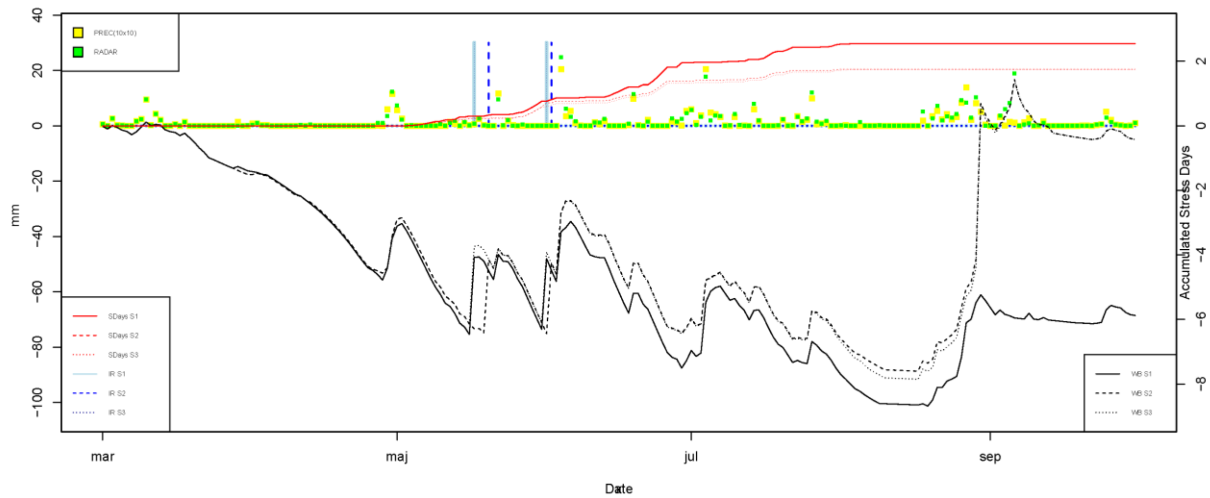

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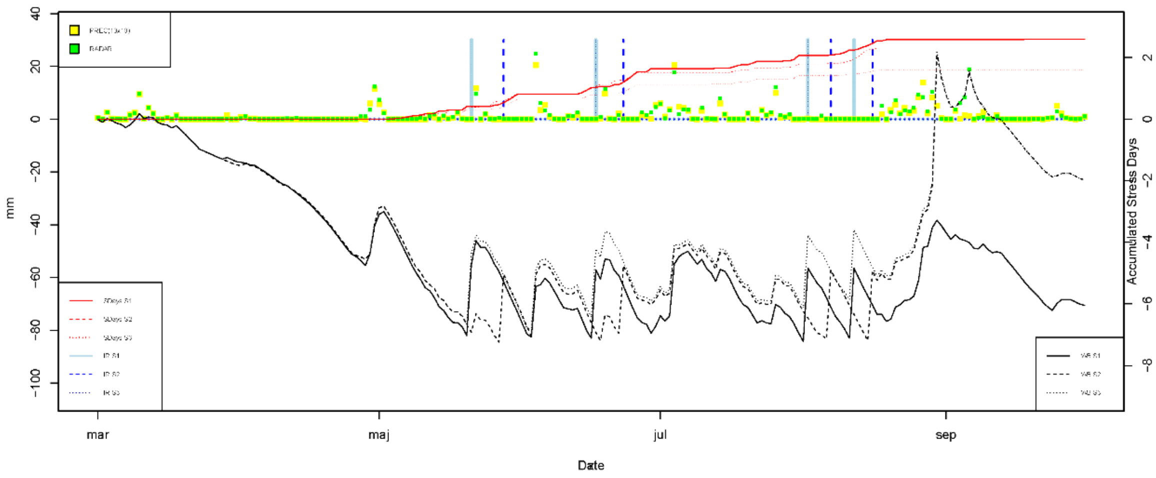
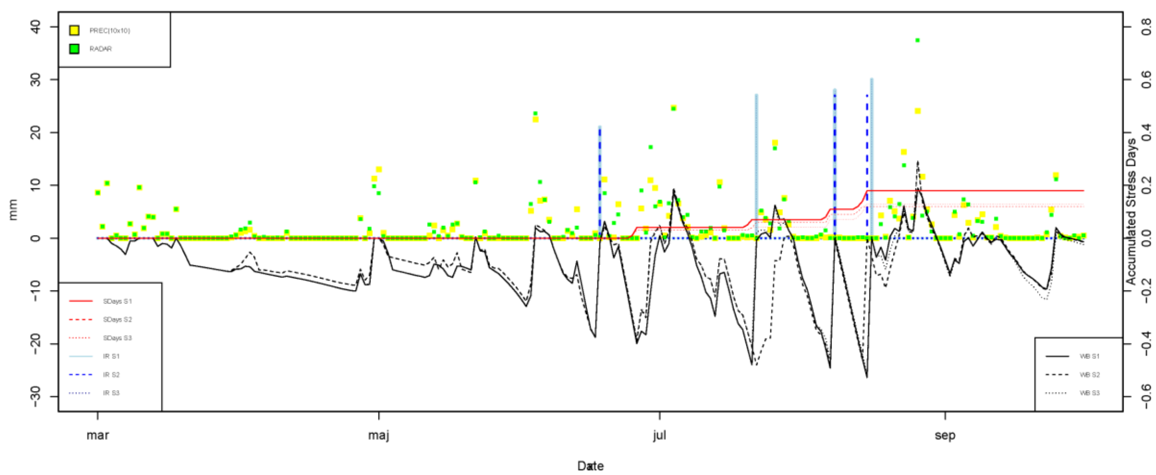


Potato – Hovborg 2020



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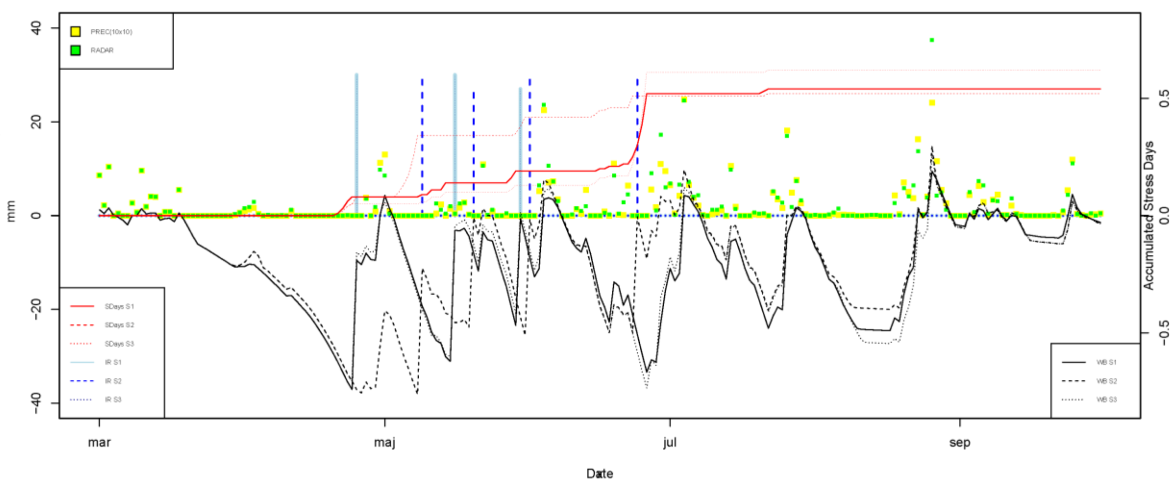

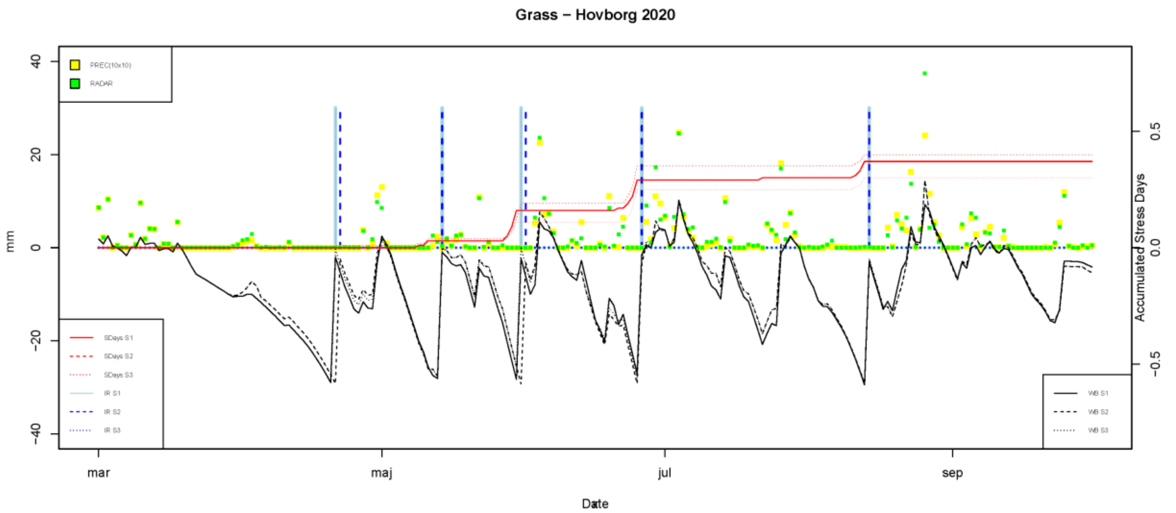
Grass – Hovborg 2020
PREC(10x10)
RADAR
SDays S1
SDays S2
SDays S3
IR S1
IR S2
IR S3
WB S1
WB S2
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mm
Accumulated Stress Days
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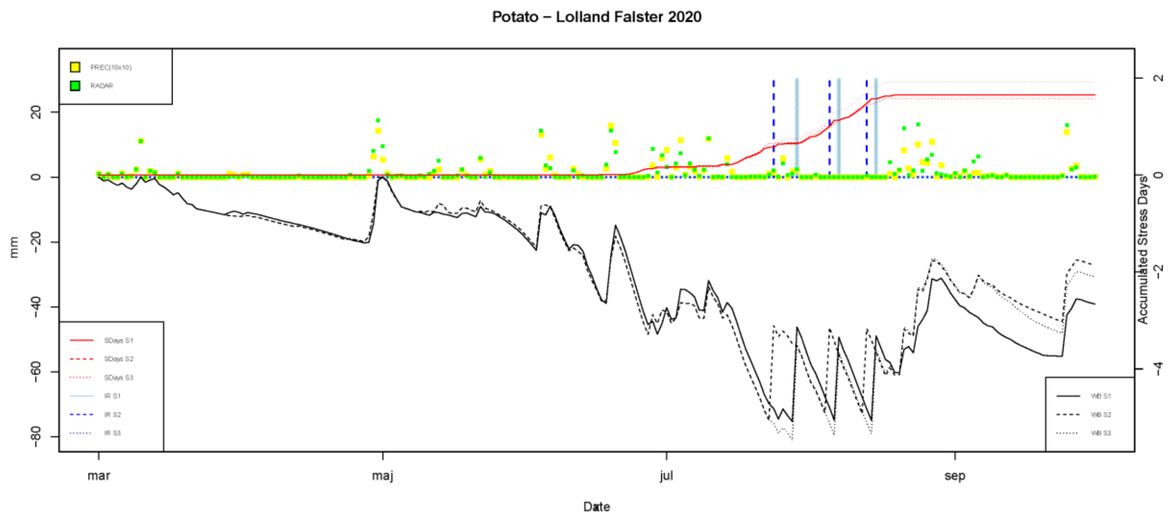
Date


Potato – Lolland Falster 2020
PREC(10x10)
RADAR
SDays S1
SDays S2
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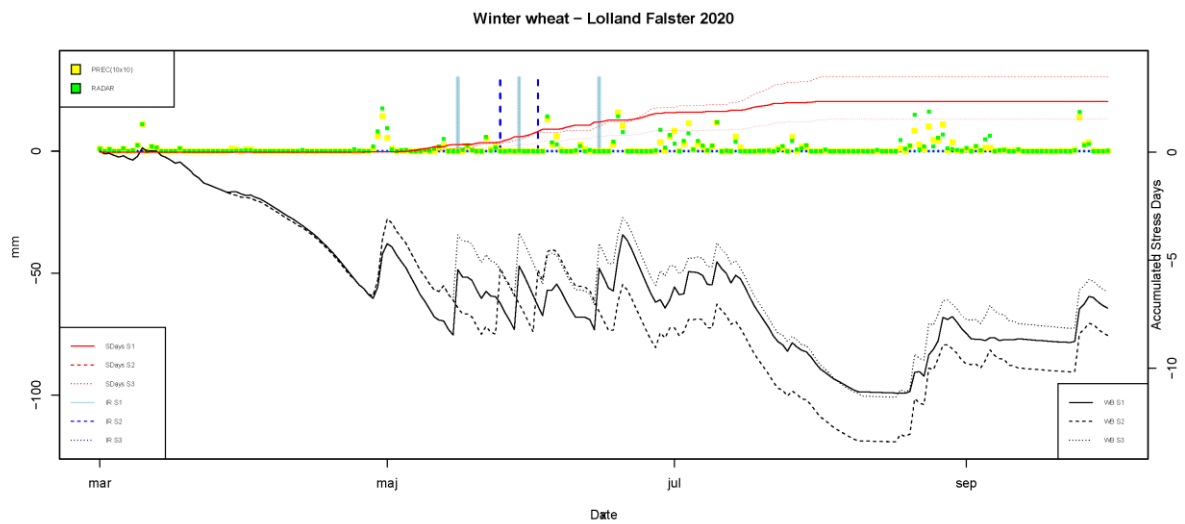
Winter wheat – Lolland Falster 2020
PREC(10x10)
RADAR
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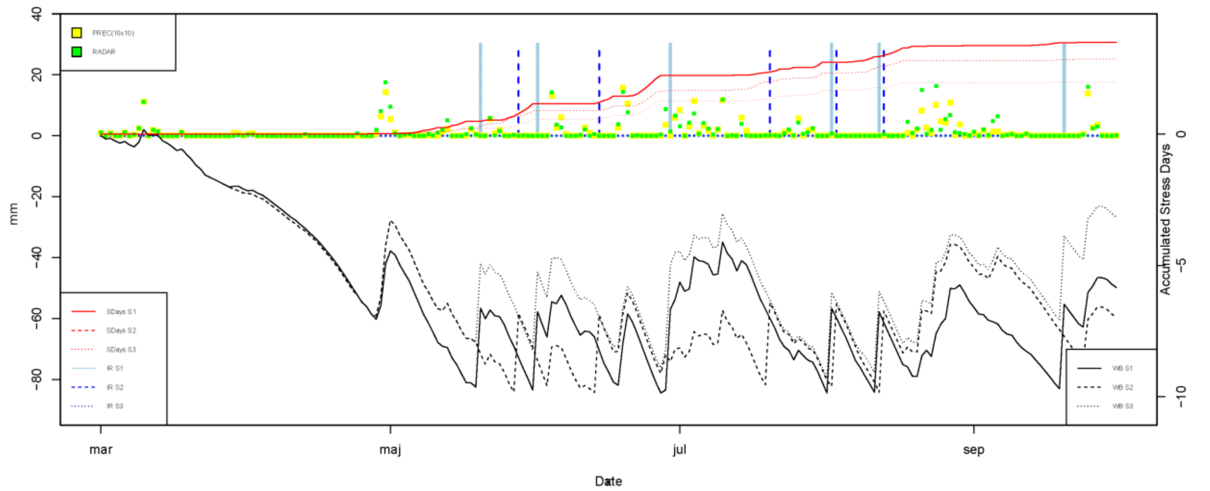
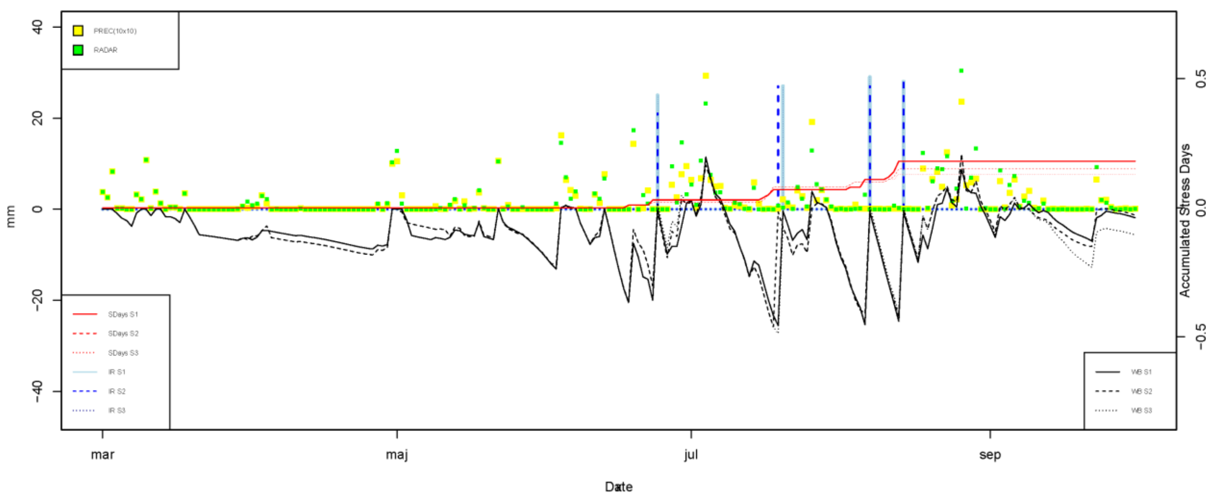
Grass – Lolland Falster 2020



Potato – Renbæk 2020



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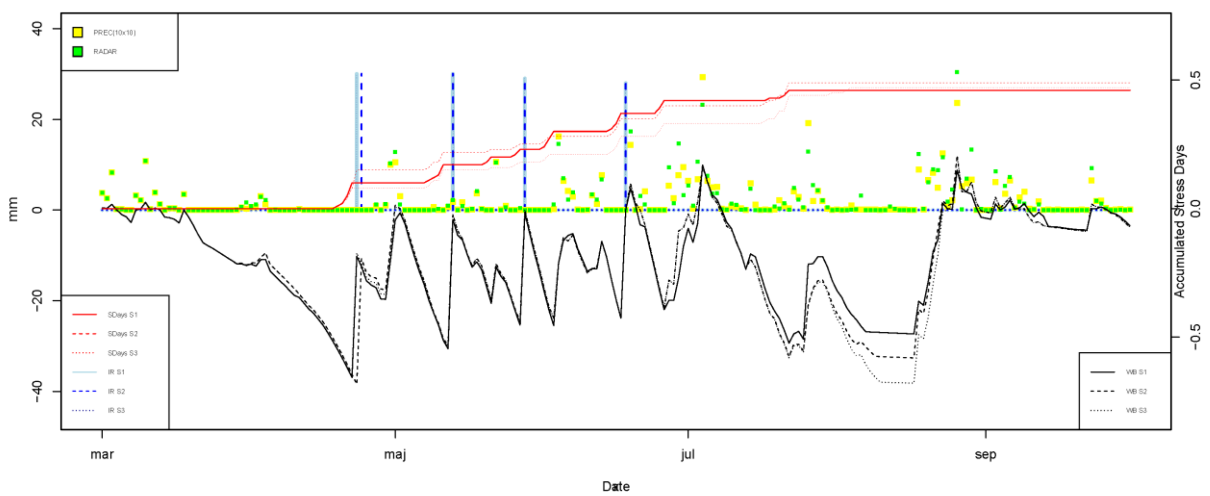

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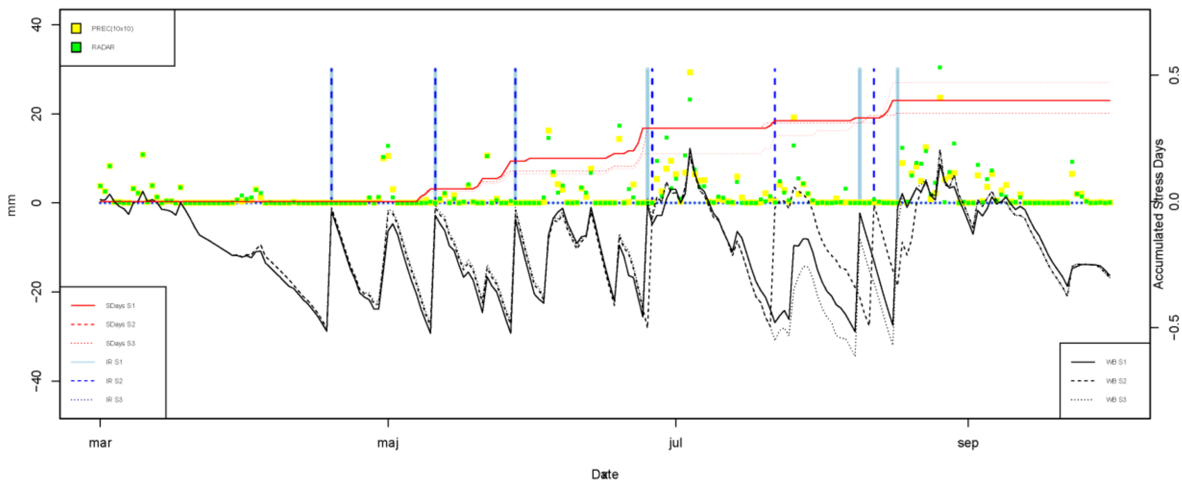
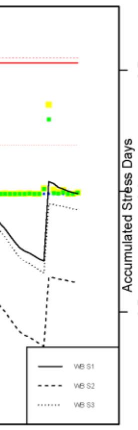
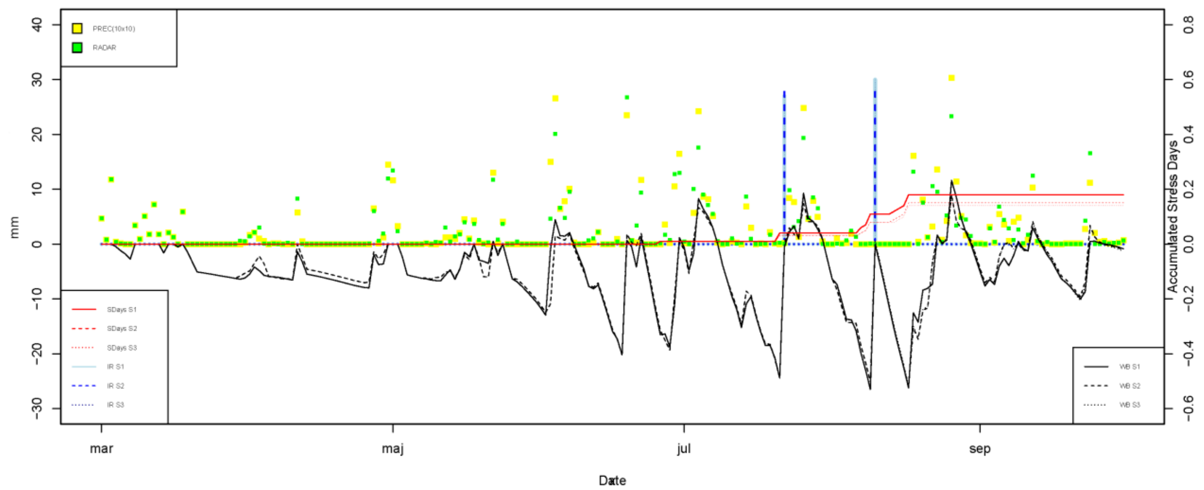
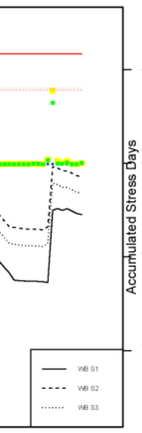


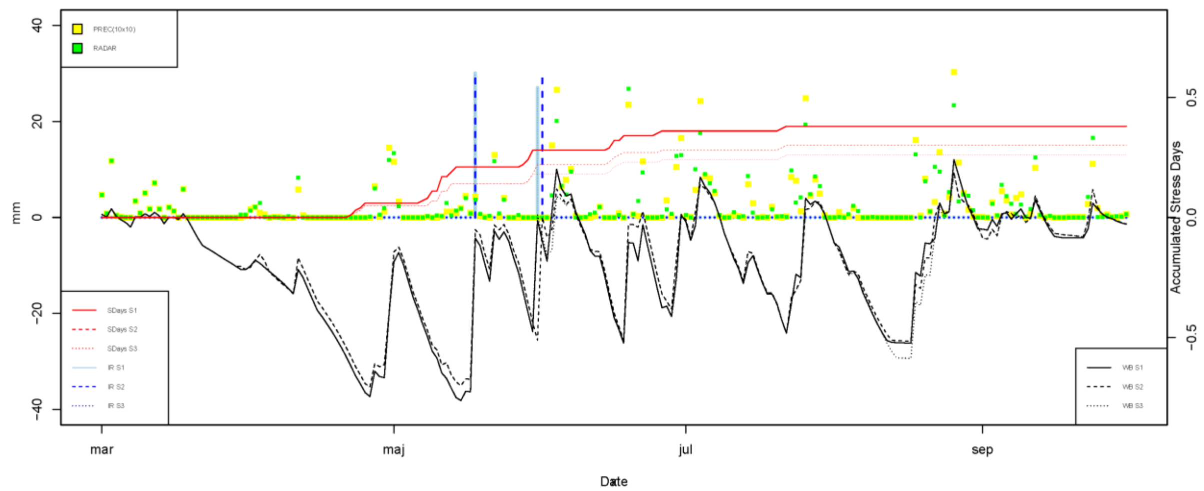


Potato – Vildbjerg 2020

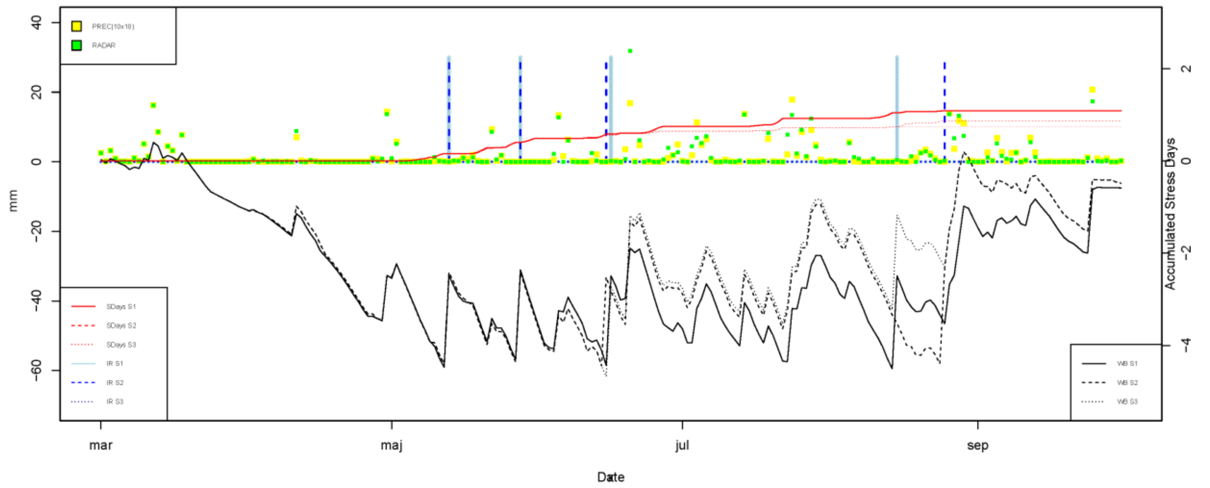




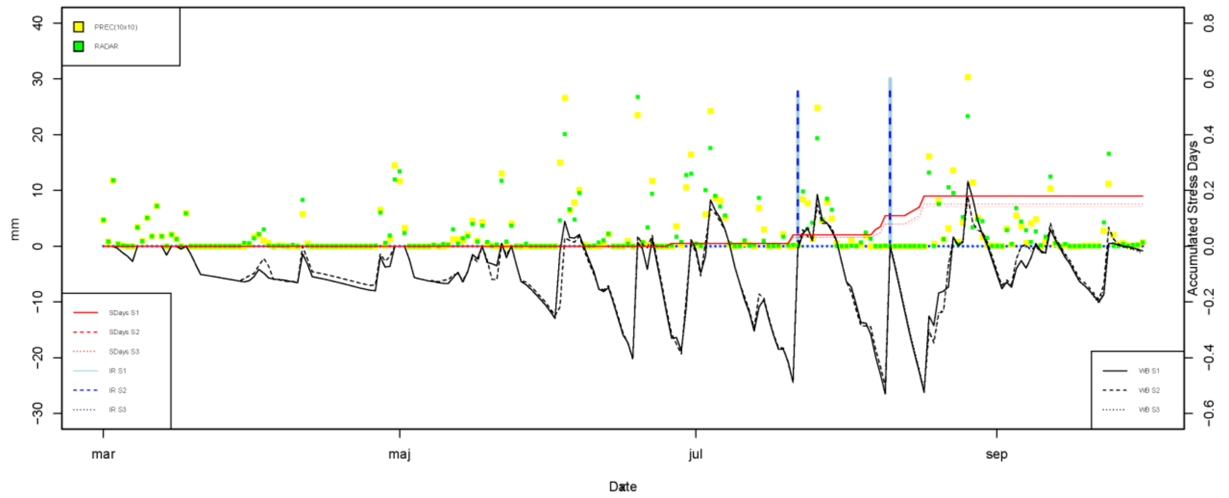
Winter wheat – Vildbjerg 2020



Grass – Vendsyssel 2020



Potato – Vildbjerg 2020



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