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Coupling field monitoring with crop growth modelling provides detailed insights on yield gaps at field level: A case study on ware potato production in the Netherlands

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ABSTRACT

Context: Yield gap analyses are useful to assess and benchmark the productivity of cropping systems. Often such analyses are performed at higher aggregation levels. As a result, these studies lack the detail to explain yield gaps at field level and hence make it difficult to translate findings into precise recommendations to farmers and extensionists.
Objective: This study provides a detailed approach for yield gap assessments at field level through coupling frequent field monitoring in farmers' fields with crop growth modelling. We used ware potato production in the Netherlands as a case to study yield gaps at field level, as average productivity is high whilst yields are still highly variable among fields, and as ware potato is an important cash crop for farmers.
Methods: Over two growing seasons, 96 ware potato fields were monitored throughout the growing season on a biweekly basis, taking measurements on soil, crop growth and yield. The crop growth model SWAP-WOFOST was used to simulate potential and water-limited potential yields. Various statistical methods were used to quantify yield gap explaining factors.
Results: The average yield gap ranged from 20 to 31% depending on the year and soil type. Among fields, the yield gap ranged from 0 to 51%. On clayey soils, the yield gap was attributed mostly to oxygen stress. On sandy soils, the yield gap was determined mostly by drought stress in 2020, a relatively dry year, and by reducing factors (pests, diseases and poor agronomic practices) in 2021, an average year in terms of precipitation. The type of reducing factors differed per field. Furthermore, we found that earlier planting and later harvesting can increase yields, as Yp is radiation-limited.
Conclusions: Overall, there is limited scope to narrow the yield gap as current ware potato production is already close to 80% of the potential yield, which is assumed to be approximately the maximum farmers can attain. However, yield and resource use efficiency gains are to be made for individual fields. Furthermore, we conclude that frequent field monitoring coupled with crop growth modelling is a powerful way to assess yield gap variability and to get detailed insight in the yield gap explaining factors at field level.
Significance: This study showed that coupling frequent field monitoring with crop growth modelling allows to gain detailed insight in yield gap variability among fields. This method provides detailed information about yield gap explaining factors which can be used to improve yield and resource use efficiency at field level.

1. Introduction

The productivity per unit area of a cropping system can be assessed using yield gap analyses. Yield gaps are referred to as the difference between potential or water-limited potential yield and actual farmers' yield (Lobell et al., 2009; Van Ittersum et al., 2013; Van Ittersum and Rabbinge, 1997). Potential yield is defined by radiation, CO_2 concentration, temperature, and cultivar characteristics. Water-limited

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potential yield is defined by the same factors but also accounts for yield limitation due to drought or oxygen stress due to waterlogging. Actual yield levels are further limited by nutrients and/or reduced by the impact of pests and diseases or other yield reducing factors (Lobell et al., 2009; Van Ittersum et al., 2013; Van Ittersum and Rabbinge, 1997). Next to an assessment of productivity levels, yield gap analyses are used to assess which factors explain yield gaps (Beza et al., 2017). In addition, yield gap analyses can be coupled with resource use efficiency assessments to improve ecological sustainability of cropping systems (Getnet et al., 2016; Rong et al., 2021; Tittonell et al., 2008).

Yield gaps have been estimated for various crops in different environments (Caldiz and Struik, 1999; Dadrasi et al., 2022; Espe et al., 2016; Gobbett et al., 2017; Rattalino Edreira et al., 2017; van Loon et al., 2019; Wang et al., 2018). In these yield gap assessments, actual yield levels are usually based on national or regional statistics data (Dadrasi et al., 2022; Espe et al., 2016; Gobbett et al., 2017; Wang et al., 2018) or farmer reported survey data (Caldiz and Struik, 1999; Rattalino Edreira et al., 2017). This provides useful information on yield and yield gap levels in different contexts. However, these levels are often determined at higher aggregation levels or could contain inaccuracies as they are based on farmer reported data (Fraval et al., 2019). Moreover, data is mostly collected after the growing season, making it impossible to ground truth measurements on yield and yield gap explaining factors. As such, yield gap analyses often lack detailed information to explain yield gaps at field level, which could be used by farmers and extensionists to adjust management.

Detailed explanations of yield gaps at field level are important for highly productive cropping systems with large field-to-field yield variability. While a high average yield in such systems suggests limited scope for improving yield at regional level, yield and/or resource use efficiency gains can still be made for particular fields. An example of a highly productive cropping system with large field-to-field variability is ware potato production in the Netherlands. For this system, average actual yields were reported to be at 70–75% of potential yield (Silva et al., 2020, 2017). However, simultaneously large yield variability was reported among farms (Ravensbergen et al., 2023; Silva et al., 2017) and fields (Mulders et al., 2021; Ravensbergen et al., 2023), resulting in relatively low productivity in some fields, as well as low resource use efficiency when such low yielding fields are cultivated with similar input levels as the higher yielding fields (Silva et al., 2021). Furthermore, it was recently shown that yield variability among fields was much larger than yield variability among regions (Ravensbergen et al., 2023). Therefore, improving productivity and resource use efficiency of relatively poorly performing fields requires proper understanding of the yield gap variability and the associated yield gap explaining factors at field level rather than at regional level.

Analyses on yield and yield gap variability have been performed for ware potato production in the Netherlands (Mulders et al., 2021; Ravensbergen et al., 2023; Silva et al., 2021, 2020, 2017; Vonk et al., 2020), and have provided useful insights in the yield gap explaining factors for this production system. However, these studies were performed for a single farm only (Mulders et al., 2021), for single production parameters as fertilizer application rates or soil organic matter content (Ravensbergen et al., 2023; Vonk et al., 2020), at farm level neglecting the variation that exists within a farm (Silva et al., 2017) or using farmer reported data which contain uncertainties as to data accuracy (Silva et al., 2021, 2020). In addition, data was collected after the growing season, limiting the possibility of ground truthing observations, especially in relation to the effect of yield reducing factors. Hence, these studies lack detailed information to assess yield gap variability at field level across a wide range of farms and fields.

In this study, we provide a detailed approach for estimating yield gaps at field level. We estimated yield levels and yield gaps by coupling frequent field monitoring with detailed crop growth modelling of potential and water-limited potential yield. We used various statistical methods and field observations to quantify and describe the effect of yield gap explaining factors on the yield gap at field level in a high-input cropping system. We used ware potato production in the Netherlands as a case study as productivity is high, whilst yields are still highly variable among fields, and as ware potato is an important cash crop for farmers (Goffart et al., 2022).

2. Conceptual framework

2.1. Yield levels

Potential yield represents the yield that can be obtained under optimal growing conditions in which the crop is not limited by water stress or nutrients, pests and diseases are effectively controlled, and poor agronomic practices do not limit yield in another way (Van Ittersum et al., 2013; Van Ittersum and Rabbinge, 1997). In this study we define two different potential yield levels: maximum and field-specific potential yield. Maximum potential yield (Yp_{max}) is the potential yield considering optimal planting and harvesting dates (planting as early and harvesting as late in the growing season as possible taking into account temperatures and accessibility to the field), which results in maximum radiation interception throughout the growing season. At farm level, limited availability of machinery and/or labour prevents farmers from planting all crops and fields on the optimal planting dates. We therefore consider the field-specific potential yield (Yp_{fs}) as the potential yield considering field-specific planting and harvesting dates. Yp_{max} and Yp_{fs} are always provided in tonnes (t) dry matter ha^{-1}.

Water-limited potential yield is determined by water stress caused by drought stress due to insufficient rainfall or irrigation, or oxygen stress as a result of waterlogging (Van Ittersum and Rabbinge, 1997). Commonly, this yield level is calculated as the maximum yield that can be obtained when a crop is cultivated under rainfed conditions (without receiving irrigation). The Dutch potato farming system is a partially irrigated system. Therefore, two distinct levels of water-limited potential yield are defined. Water-limited potential yield under partially irrigated conditions (Yw_{irr}) represents the yield that can be obtained with the actual irrigation applied by the farmer and can be calculated as it is known for each field how much irrigation is applied (see Section 3.2.4). Yw_{irr} equals Yp when farmers apply full irrigation completely avoiding water stress. Likewise, Yw_{irr} is lower than Yp when farmers apply partial irrigation. Water-limited potential yield under rainfed conditions (Yw_{rf}) represents the yield that can be attained if no irrigation is applied. Yw_{irr} and Yw_{rf} are always indicated in t dry matter ha^{-1}.

Actual yield (Ya) is the yield that is obtained in farmers' fields. Ya is lower than Yp and Yw_{irr} when a lack of nutrients limits optimal growth or when weeds, pests and diseases or poor agronomic practices reduce yields. Ya can be higher than Yw_{rf} if farmers apply irrigation. Actual yields are both expressed in t dry matter ha^{-1} (Ya_{DM}) and in t fresh matter ha^{-1} (Ya_{FM}). Fig. 1 provides a schematic overview of the different yield levels.

2.2. Yield gap levels

Different yield gap levels are considered in this study. The (Yp_{max} – Yp_{fs}) yield gap is explained by radiation limitation and indicates the extra yield that can potentially be gained if the crop is planted earlier or harvested later, which is determined by temperature and accessibility to the field. At farm level it is not always possible to close this gap because of limited availability of machinery and/or labour around critical moments. The (Yp_{fs} – Yw_{irr}) yield gap is explained by water limitation as a result of drought and/or oxygen stress. This gap represents the extra yield that can be obtained if farmers apply an optimal irrigation and drainage strategy, compared to their current practice. An important condition for closing the (Yp_{fs} – Yw_{irr}) gap is that the crop is not limited by nutrient availability and that pests and diseases are effectively controlled. The (Yw_{irr} – Ya) yield gap is explained by nutrient limitation and/or yield reduction by pests and diseases. The (Yp_{fs} – Ya) yield gap is

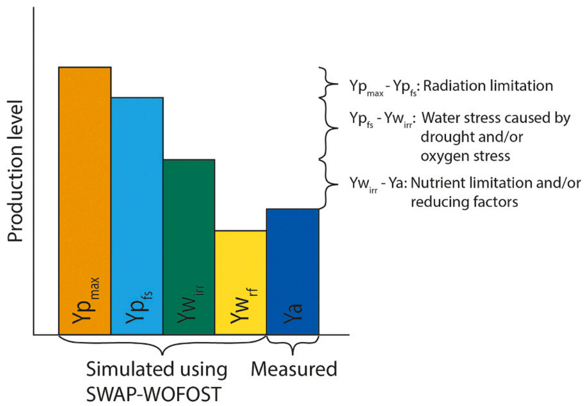

Fig. 1. Conceptual framework for visualising yield levels and associated yield gaps. Production level refers to the yield in t ha^{-1}. Yp_{max} is the maximum potential yield with earliest possible planting and latest possible harvesting dates. Yp_{fs} is the potential yield based on farmers' planting and harvesting dates. Yw_{irr} is the water-limited potential yield considering the amount of irrigation (which may equal zero if no irrigation was used) applied by the farmer. Yw_{rf} is the water-limited potential yield under rainfed conditions. Ya is the actual yield. Yp_{max}, Yp_{fs}, Yw_{irr} and Yw_{rf} are simulated using SWAP-WOFOST (see Section 3.3), Ya is measured in the field (see Section 3.2.3).

used to assess the yield gap at field level that is determined by the combined effect of drought and/or oxygen stress, nutrient limitation and reducing factors. The (Yp_{max} – Ya) yield gap is used to determine the maximum potential yield gain, compared to Ya, if also planting and harvesting dates were changed.

3. Materials and methods

3.1. Study area

We collected data from 96 different commercial ware potato fields in 2020 and 2021 (Fig. 2). Fields were selected in six different important potato growing regions in the Netherlands: Tholen/West-Brabant (1), Zuid-Holland (2), Flevoland (3), Noord-Brabant (4), Limburg (5) and Drenthe (6). Soils in the first three regions are characterized as clayey soils and in the latter three regions as sandy soils. In the regions with clayey soils, we selected fields with the variety Innovator and in regions with sandy soils, we selected fields with the variety Fontane. These varieties were chosen as they are among the main cultivated varieties on the respective soil types. We selected eight potato fields per region per year to get an equal number of the sampled fields. Hence, we collected data from a total of 48 fields for each soil type and for each year. Further on in this manuscript fields from 2020 are labelled with 2 digits and fields from 2021 are labelled with 3 digits.

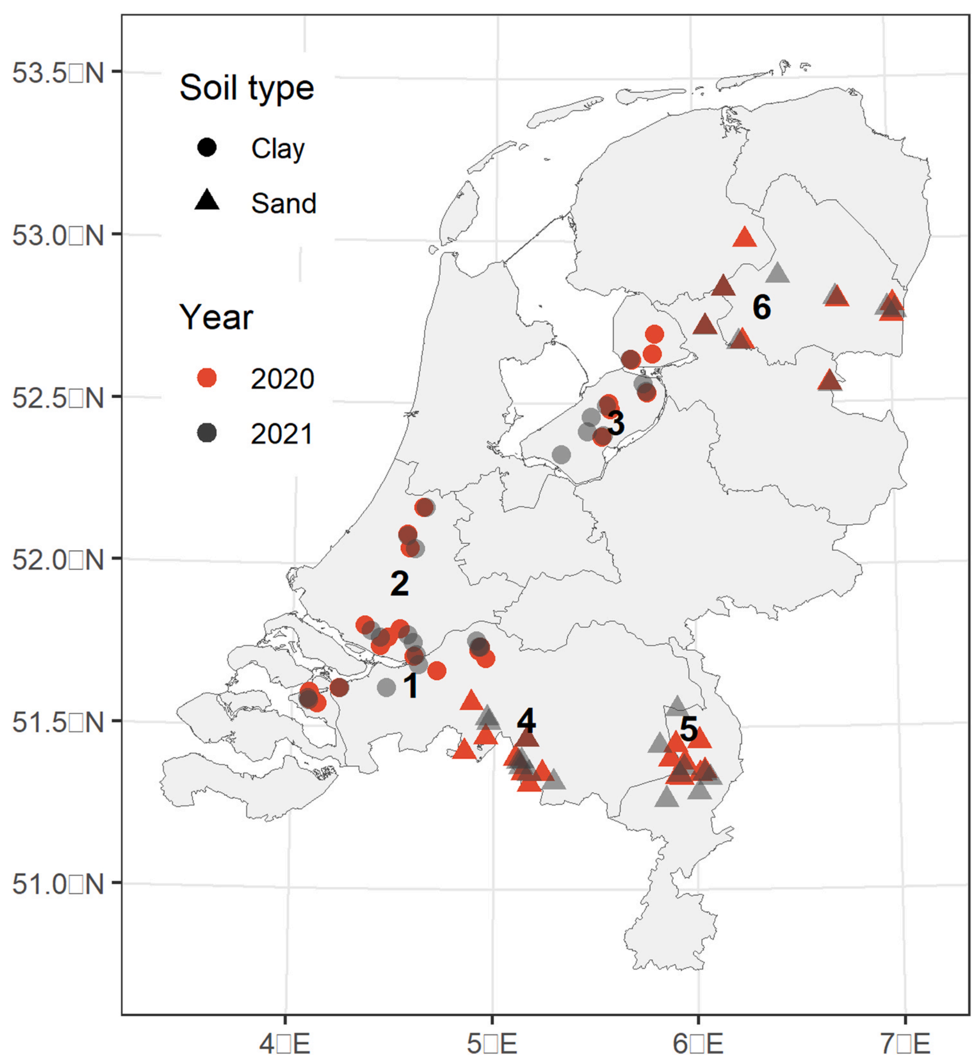

Fig. 2. Map of the Netherlands with field locations. Different colours indicate different years. Different symbols indicate different soil types. Different numbers indicate different potato growing regions in the Netherlands.

Farmers and fields for this study were selected in several ways. In 2020, farmers were selected based on established contacts from earlier research, via contacts from the potato processing industry and via the network of participating farmers. Most farmers who participated in 2020 also participated in 2021. However, some farmers dropped out as they were growing different cultivars in 2021. Newly participating farmers were selected from the respondents lists of an unpublished survey in which farmers could indicate if they were interested to participate in the study. Over the two years, in total 55 different farmers participated in this research. From each farmer, 1 to 2 fields per year were selected. Overall, the selected fields represented a broad range in soil conditions and nutrient management (Table 1).

The years 2020 and 2021 were distinct in terms of weather conditions. The first year could be characterized as dry to average in terms of rainfall, with cumulative precipitation over the growing season ranging from 153 to 387 mm (long-term average 416 mm) (Fig. 3A). The second year of the study could be characterized as an average year, with cumulative precipitation over the growing season ranging from 317–461 mm. The cumulative precipitation deficit was on average 200 mm in 2020 and 70 mm in 2021. Cumulative global radiation was 15% higher in 2020 and 3% higher in 2021 than the long-term average (Fig. 3B). Lastly, temperatures in 2020 were different from those in 2021. In 2020, the summer was relatively warm with a heat wave in August, while in 2021 spring was relatively cold (Fig. 3C).

In each field, we selected a small measurement area to minimize heterogeneity effects within fields. The selected measurement area was always located in a part of the field where limited effect of other factors was expected. For instance, the measurement area was never in the headlands where heavier soil compaction is expected due to machine traffic, nor was it located directly adjacent to a neighbouring field to prevent irrigation from the neighbouring field influencing potato growth in the measurement area. The selected measurement area was divided into four plots which served as measurement replicates. In 2020 the size of each plot was 7 m long and 6 m (8 ridges) wide. In 2021, the size of each plot was 7 m long and 9 m wide (12 ridges). Fields within one region were sampled within one day (or two days when conditions were very wet) and fields within the same soil type were always sampled within five subsequent days.

3.2. Data collection

3.2.1. Soil measurements

In each field, one composite soil sample was taken from the plots at the beginning of the growing season. Soil organic matter (SOM) was measured using the loss on ignition method by placing the sample in a furnace at 550 °C for 3 h. SOM was corrected for clay content using Hoogsteen et al. (2015), where clay content was provided by the farmer or taken from a soil map. Soil pH was measured in water in a 1:2.5 soil: water ratio. Plant available N and P were measured spectrophotometrically with a Skalar san+ + system from a 0.01 M $CaCl_2$ extraction (Houba et al., 2000). Total N and P were measured in the same way after a digestion with a mixture of H_2SO_4–Se and salicylic acid. Plant available K was measured with a Varian AA240FS fast sequential atomic absorption spectrometer from the same extracts. All soil samples were analysed by an external laboratory. Soil penetration resistance was measured using a penetrologger (Royal Eijkelkamp, 2022) at the beginning of the growing season when it could be assumed that the soil moisture content was at field capacity. The measurements were repeated on three locations per plot. Lastly, potato cyst nematode pressure was measured in each field in 2021. From the final harvest area one square meter was intensively sampled for potato cyst nematodes at the start of the growing season. For each sample, the number of living eggs and larvae per gram dry soil was counted. Supplementary Material 1 provides a full overview of the measurements performed for this study, including the measurements that were not used for analyses.

3.2.2. Crop growth monitoring

Each field was visited at least once every two weeks from planting to harvest, resulting in 10–13 field visits per field during the entire growing season. Crop developmental stages were recorded throughout the growing season. Emergence was assumed when 80% of the plants in the middle two ridges of a plot emerged. Tuber initiation was assumed when three out of four plants formed three or more tubers with a diameter of at least 1 cm. Flowering was assumed to take place when 50% of the plants flowered (Appendix A provides an overview of the dates of the different developmental stages). Furthermore, crop health was scored at each visit using a scale from 1–5. A score of 5 indicates a healthy crop and a

Table 1
Soil properties and fertiliser application rates of the 96 fields (2020 and 2021). Indicated for each parameter are the mean, standard deviation, minimum value, and maximum value. See Section 3.2 for more details on the measurements and calculations.

Variable	Soil type	2020 Mean	SD	Min	Max	2021 Mean	SD	Min	Max
SOM (%)	Clay	3.9	1.4	2.4	8.2	4.1	0.7	2.7	5.4
	Sand	5.0	2.2	2.5	9.5	4.9	3	2.7	17.4
pH (-)	Clay	7.6	0.2	7.3	7.9	7.5	0.2	6.7	7.7
	Sand	5.5	0.4	4.7	6.2	5.3	0.5	4.2	6.1
Plant available N ($mg\ kg^{-1}$)	Clay	116	60	12	238	91	46	14.5	167
	Sand	60	50	16	202	60	53	11.4	227
Plant available P ($mg\ kg^{-1}$)	Clay	2.1	2.1	0.3	6.9	1.6	1.2	0.5	4.9
	Sand	5.8	3.9	0.6	15.2	5.8	5.1	0.3	16.4
Plant available K ($mg\ kg^{-1}$)	Clay	132	94	39	459	157	71	82	305
	Sand	95	62	27	265	133	72	37	341
Total N ($g\ kg^{-1}$)	Clay	1.8	0.7	1.0	3.7	1.8	0.4	1.0	2.6
	Sand	1.6	0.5	0.8	2.7	1.6	0.7	1.0	4.1
Total P ($g\ kg^{-1}$)	Clay	0.9	0.1	0.7	1.2	0.9	0.1	0.8	1.2
	Sand	0.7	0.2	0.3	1.3	0.9	0.3	0.4	1.5
N applied ($kg\ ha^{-1}$)*	Clay	429	146	248	956	420	129	250	696
	Sand	287	62	123	379	299	72	136	503
Effective N applied ($kg\ ha^{-1}$)*	Clay	347	74	248	545	337	66	234	450
	Sand	222	52	88	304	226	47	98	334
P applied ($kg\ ha^{-1}$)	Clay	55	32	0	154	58	35	0	133
	Sand	28	14	12	66	33	17	9	85
K applied ($kg\ ha^{-1}$)	Clay	340	165	131	720	332	140	124	643
	Sand	280	87	49	431	277	103	41	552

* N applied is calculated as the total N applied between the harvest of the previous crop and the harvest of the potatoes. Effective N applied is calculated over the same period, but then the nitrogen fertiliser replacement values of the organic manures are taken into account (Section 3.2).

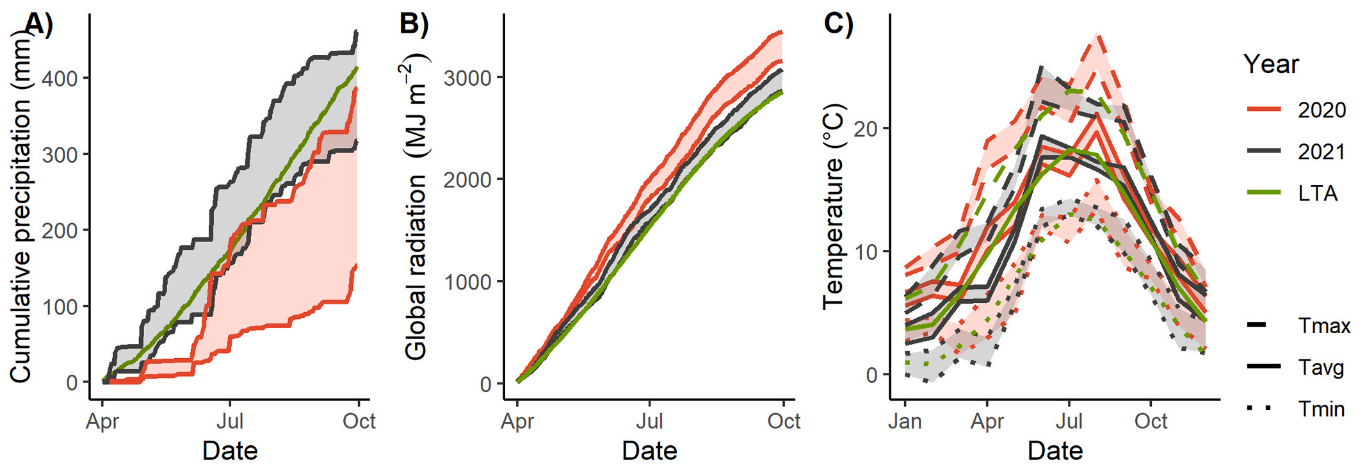

Fig. 3. Cumulative precipitation (in mm) (A), cumulative global radiation (in MJ m^{-2}) (B) and temperature (in °C) (C) over time. Different colours indicate different years. Shaded areas present the range of observed values across the six regions. LTA = long-term average (period 1991–2021).

score of 1 indicates a very diseased crop. Scoring was done based on visual inspection. The average crop health score was calculated by averaging all scores of the crop throughout the growing season. Before full canopy closure, the emergence rate was assessed by counting the number of emerged plants per plot.

3.2.3. Yield and yield quality measurements

Yield was measured during and at the end of the growing season. Sampling strategies differed between the two years. In 2020, two intermediate harvests were done in August on a 2 m^2 area to measure gross tuber yield, which is referred to as the total harvested tuber weight. Final yield sampling was done from a 3 m^2 area after haulm killing or natural senescence, or just before harvesting by the farmer in case haulms had not senesced. From each plot of the final harvest, a 6 kg subsample was taken to measure underwater weight. In 2021, throughout the growing season four intermediate harvests were done for Innovator and five intermediate harvests were taken for Fontane from a 2 m^2 area. We measured gross tuber yield at each harvest. A composite tuber sample (from all plots) was analysed for dry matter concentration early in the season and for underwater weight when the weight of the composite sample reached more than 5 kg. Final yield was measured in the same way as in 2020.

3.2.4. Crop management information

Farmers were asked to report their crop management information for each field. Farmers informed us when they applied irrigation and how much they applied per event. Information was collected on the type, timing and quantity of the applied fertilizers and crop protection products. We processed the information on applied fertilizers to calculate the total applied nitrogen, phosphorus, and potassium. The amounts were calculated as the sum of famer applied nutrients starting from the harvest of the previous crop till the end of the potato growing season and exclude deposition and mineralisation. We calculated effective applied nitrogen in the same way, but used nitrogen fertilizer replacement values from the Dutch government to correct for the readily available nitrogen (RVO, 2018). We further processed the information on crop protection products to calculate the total amount of active ingredients and the Environmental Impact Points of the product application, using the Environmental Yardstick tool (Reus and Leendertse, 2000). It is a tool that combines information on the applied quantity and harmfulness of the applied product to soil and aquatic organisms and ground water. It can be used to calculate the environmental pressure of the applied crop protection products. Farmers reported planting, haulm killing and harvesting dates (Appendix 1). From two fields the crop management information was incomplete, and these fields were excluded in analyses that required crop management information.

3.3. Using SWAP-WOFOST to estimate different yield levels and water stress

The model SWAP-WOFOST was used to estimate Yp_{max}, Yp_{fs}, Yw_{irr}, Yw_{rf} and the respective yield gaps. WOFOST (de Wit et al., 2019) is a process-based crop growth model that has recently been calibrated for the varieties used in this study using experimental data and was evaluated against on-farm data from a period of seven years (ten Den et al., 2022). The model simulates dry matter accumulation of the crop as a function of irradiation, temperature and crop characteristics, with daily time steps (de Wit et al., 2020). Soil water availability is simulated using a classical water balance in which it is assumed that soil water can drain freely to deeper groundwater layers.

For more detailed simulations of soil water availability in the rooted zone, WOFOST can also be coupled with the soil hydrological model SWAP (Kroes et al., 2017). In SWAP, the soil profile can be divided into multiple compartments with different soil characteristics for each compartment. Furthermore, SWAP can deal with interactions between available water in the rooted zone and the groundwater level. Using SWAP, it is possible to simulate not only the effect of drought stress on crop growth, but also the effect of oxygen stress. In the case of drought stress, it is assumed that actual transpiration decreases linearly with decreasing pressure head after a critical pressure head has been reached until a level at which water uptake does not take place anymore (Metselaar and de Jong van Lier, 2007). In the case of oxygen stress, similar assumptions are considered, whereby actual transpiration decreases linearly with increasing pressure head (Bartholomeus et al., 2008). Supplementary material 2 shows that for the collected data simulations of water-limited potential were better in line with observed yields using SWAP-WOFOST than using WOFOST. In addition, it shows that SWAP-WOFOST is able to capture yield variability signals over a longer time period with variable weather conditions.

SWAP-WOFOST was run with two different assumptions on the interaction between water in the rooting zone and the groundwater level. In the first run, we assumed no interaction between the two. In this case, water in the rooting zone was assumed to drain freely to deeper groundwater layers below the rooting zone. In the second run, we assumed that there was an interaction between water in the rooting zone and the groundwater level via capillary rise. We used the free drainage situation for yield gap calculations and statistical analyses in the sandy soils, as groundwater levels in these soils are relatively deep during the growing season. We used the interaction situation for yield gap calculations and statistical analyses in the clayey soils, as groundwater levels in these soils are relatively shallow during the growing season. In both runs, drought stress was simulated using Feddes (1982) and oxygen stress using Bartholomeus et al. (2008).

Field-specific values needed to run SWAP-WOFOST were assigned based on our measurements or publicly available data. Weather data from the nearest weather station of the Royal Netherlands Meteorological Institute (KNMI) were used for simulations. However, rainfall data was replaced with farmer's rainfall measurements in case a farmer owned a weather station. Rooting depth was estimated as the average depth at which the measured soil penetration resistance was larger than 2 MPa, with a maximum rooting depth of 50 cm (Silva et al., 2020). Soil type and profile were taken from the BOFEK soil map (Heinen et al., 2022). Crop management information (planting, irrigation, haulm killing) was taken from the crop management information provided by the farmer. The groundwater levels were collected from the 'Landelijk Hydrologisch Model' (NHI, 2023).

SWAP-WOFOST was used to simulate different yield levels and estimate water stress. Yp_{max} was modelled assuming planting on April 1 and haulm killing on September 21 on clayey soils and on September 30 on sandy soils and correspond approximately to the 5th percentile for planting date and the 95th percentile for harvesting date of the studied fields. In practice, planting date is determined by temperatures and accessibility to the field. Harvesting date is determined by an anticipation on trafficability of the field in autumn. Only if the farmer planted earlier or harvested later than these dates, the farmer's planting or harvesting dates were used. Yp_{fs}, Yw_{irr} and Yw_{rf} were modelled with field specific planting and harvesting dates. Total water stress was estimated as the difference between potential transpiration and actual transpiration and expressed in mm per growing season. The reduction in transpiration that was attributed to insufficient water availability is referred to as drought stress and the reduction in transpiration as a result of waterlogging is referred to as oxygen stress.

3.4. Statistical analysis

ANOVA was used to test for significant yield differences between years and soil types, where Tukey HSD was used a post-hoc test.

Various statistical methods were used to explain yield and yield gap variability among the studied fields. First, a comparison was made between the best and worst performing fields in terms of Ya_{DM}, Ya_{FM}, the (Yp_{fs} – Ya) yield gap or the (Yw_{irr} – Ya) yield gap. This was done per soil type and variety and for both years together and separately. Groups were made with the highest yielding fields (or fields with smallest yield gap) and lowest yielding fields (or fields with largest yield gap) and consisted of 12 fields when the analyses were done for both years together and of 6 fields when done for a single year. Following, we assessed whether there was a significant difference between the two groups for each of the measured yield gap explaining factors. A student t-test was used for normally distributed data and a Mann-Whitney U test was used for non-normally distributed data. Normality was assessed using a Shapiro-Wilks test.

Linear regression models were used to test for correlations between yield or the yield gap and measured parameters. To avoid risk of overfitting, a selection of parameters that were to be included in the statistical models had to be made. First, a full model was made using either Ya_{DM}, Ya_{FM}, the (Yp_{fs} – Ya) yield gap or the (Yw_{irr} – Ya) yield gap as a dependent variable and all measured parameters as explanatory variables. Then, we used the dredge function from the MuMIn package (Barton and Barton, 2015) to run all possible combinations of reduced models, using R version 4.2.2. We added a restriction to the function that only one to a maximum of four explanatory variables could be included in the reduced linear models. Furthermore, we excluded all combinations of parameters that were correlated to each other (Pearson correlation test > 0.5). After running all models, the top-ranking models were selected based on the AICc criterium, where all models with ΔAICc < 3 were considered to be top-ranking models. Finally, a model was built with all explanatory variables that were included in one or more of the top-ranking linear models. However, if explanatory variables were correlated to each other, we included only the variable that was used in the majority of the top-ranking models. If explanatory variables were correlated to each other and were used in an equal share of top-ranking models, multiple models were built and the model with the lowest AICc was chosen as the final statistical model. This analysis was performed for only the fields on sandy soils (cv. Fontane), only the fields on clayey soils (cv. Innovator), or all fields together. For the latter group, we included variety as an explanatory variable in all linear models and the maximum number of explanatory variables to be included in the reduced models was changed from four to five.

To further understand the relationships between yield or yield gap and the measured parameters, yield or yield gap was plotted against each of the measured parameters that had a significant effect on the yield or yield gap in one of the earlier performed statistical analyses. Following, quantile or linear regression was used to test if there was a significant correlation.

4. Results

4.1. Actual yield

For Innovator on clayey soils, final gross yield averaged 63 t ha^{-1} and ranged from 48 to 77 t ha^{-1} in 2020 and averaged 54 t ha^{-1} and ranged from 34 to 61 t ha^{-1} in 2021 (Fig. 4). Already early during the growing season, large significant yield differences were observed between the two years, i.e., a 16 t ha^{-1} yield difference between the average yields in week 31 and a 14 t ha^{-1} yield difference between the average yields in week 33. For Fontane on sandy soils, the average final yield was similar for both years with 62 t ha^{-1} in 2020 and 64 t ha^{-1} in 2021. However, a difference in yield range was observed at the end of the growing season. In 2020, the final yield ranged between 40 and 83 t ha^{-1}, and in 2021 between 53 to 81 t ha^{-1}. Earlier on during the growing season, the yield difference between the means of the two years was 6 t ha^{-1} in week 32 and 2 t ha^{-1} in week 34, both differences were significant in favour of 2020.

4.2. Potential and water-limited potential yields as compared to actual yields

Simulated results for Innovator cultivated on clayey soils in 2020 showed that Ya_{DM} was below or similar to Yp_{fs} in all fields (Fig. 5). Furthermore, for most of the Innovator fields Ya_{DM} was around the same level as Yw_{irr}. However, for a few fields (46–48, 65–68) Ya_{DM} was higher than simulated Yw_{irr}. Irrigation resulted only in a few fields with Innovator in higher water-limited potential yields compared to rainfed

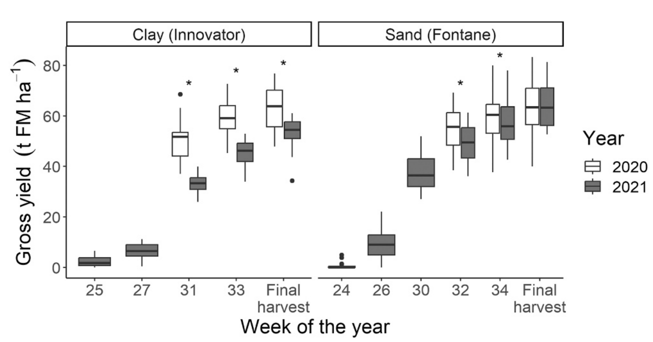

Fig. 4. Gross yield (in t fresh matter ha^{-1}) over time for two different soil types (with respective varieties) and in two years. Final harvest refers to the final harvest of the growing season and depended on the maturity of the crop. * indicates significant differences between the two years using ANOVA ($p < 0.05$).

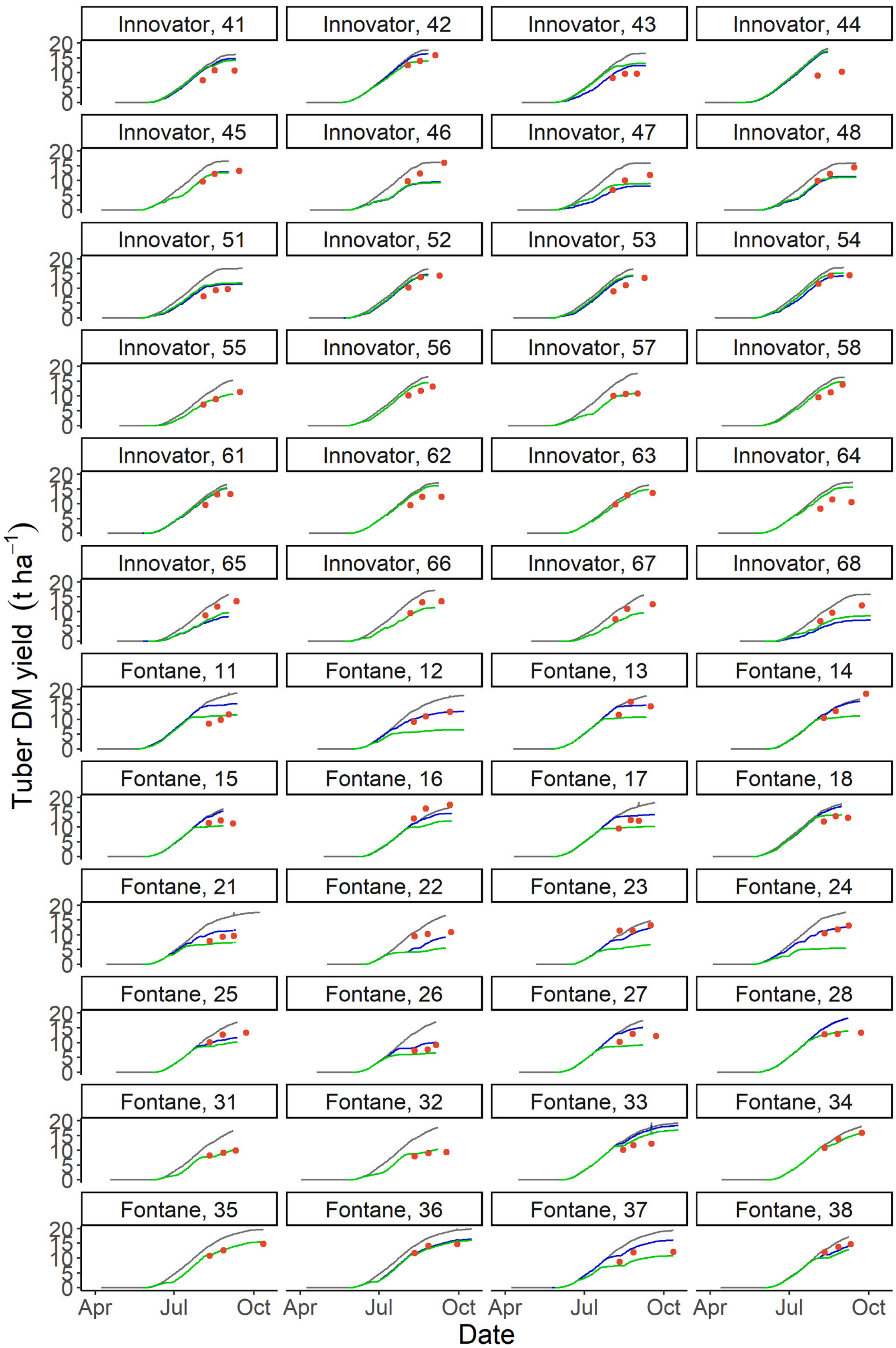

Fig. 5. Potential (Yp), water-limited potential (Yw) and actual (Ya) tuber yield (in t DM ha^{-1}) over time for the year 2020. Red dots indicate Ya. Grey lines indicate Yp_{fs}. Blue lines indicate Yw_{irr}. Green lines indicate Yw_{rf} (for explanation of all abbreviations, see Fig. 1). Innovator was grown on clayey soils; Fontane on sandy soils. Continuous lines indicate simulated values and dots indicate measured values. Numbers in the headers of the plots indicate field numbers.

conditions ($Yw_{irr} > Yw_{rf}$), but resulted in lower water-limited potential yields (which SWAP-WOFOST attributed to oxygen stress) in other fields ($Yw_{irr} < Yw_{rf}$). Simulated results for Fontane on sandy soils in 2020 showed that in almost all fields Ya_{DM} remained below or at Yp_{fs}. Only in one field Ya_{DM} was slightly higher than the Yp_{fs}. Irrigation resulted in higher water-limited potential yields in most fields compared to rainfed conditions ($Yw_{irr} > Yw_{rf}$). Yw_{irr} simulations using SWAP-WOFOST were at the same level or higher than Ya_{DM}.

Simulated results of 2021 show a similar model performance compared to the results of 2020. For Innovator on clayey soils, Yp_{fs} was higher than the Ya in all fields (Fig. 6). Furthermore, Ya measurements were in a fair agreement with Yw_{irr}. Only in a few fields, Yw_{irr} was

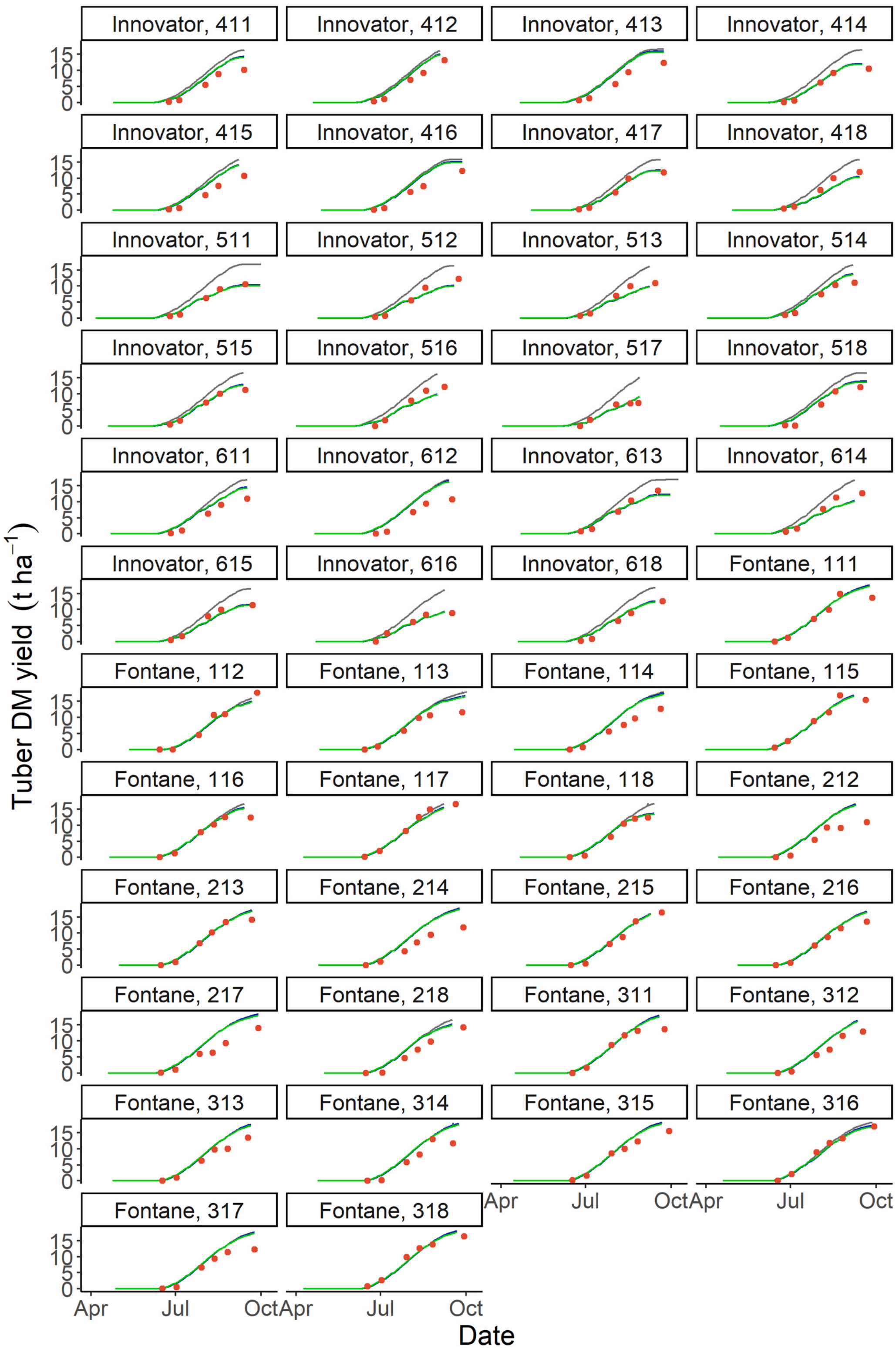

Fig. 6. Potential (Yp), water-limited potential (Yw) and actual (Ya) tuber yield (in t DM ha^{-1}) over time for the year 2021. Red dots indicate Ya. Grey lines indicate Yp_{fs}. Blue lines indicate Yw_{irr}. Green lines indicate Yw_{rf} (for explanation of all abbreviations, see Fig. 1). If lines are not visible they are at the same level. Innovator was grown on clayey soils; Fontane on sandy soils. Continuous lines indicate simulated values and dots indicate measured values. Numbers in the headers of the plots indicate field numbers.

slightly lower compared to Ya. For Fontane in 2021, Ya of most fields remained at or below Yp_{fs} and Yw_{irr}. Furthermore, only in a few fields mild water limitation was observed ($Yw_{irr} < Yp_{fs}$).

Average Ya_{DM} was 12.7 t ha^{-1} for Innovator in 2020 and 11.3 t ha^{-1} in 2021 (Fig. 7). In 2020, average Yw_{irr} and Yw_{rf} were similar to the average Ya_{DM}, whereas in 2021 average Yw_{irr} was 1.2 t ha^{-1} higher than average Ya_{DM} and average Yw_{rf} was 1.4 t ha^{-1} higher. Yp_{fs} was similar for both years (around 16.5 t ha^{-1} on average). Extending the growing season resulted in average Yp_{max} levels which were 1.0 t ha^{-1} higher than Yp_{fs} in 2020 and 0.6 t ha^{-1} higher than Yp_{fs} in 2021.

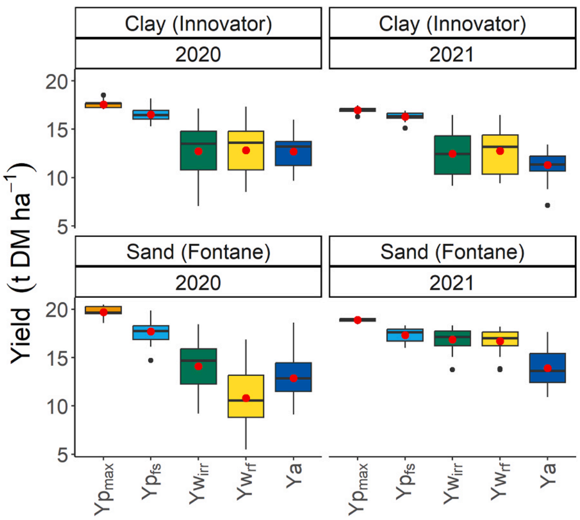

Fig. 7. Different yield levels (for abbreviations, see Fig. 1; all in t DM ha^{-1}) for two different years and soil types (and respective cultivars). Red dots indicate average values. Values of Ya were measured, while other yield levels were modelled.

For Fontane, Ya_{DM} was 12.9 t ha^{-1} in 2020 and 13.9 t ha^{-1} in 2021. Yw_{rf} was on average 10.8 t ha^{-1} in 2020 and 16.7 t ha^{-1} in 2021. Applying irrigation increased Yw_{irr}, on average, by 3.2 t ha^{-1} in 2020 and by 0.2 t ha^{-1} in 2021 compared to Yw_{rf}. Yp_{fs} was 17.7 t ha^{-1} in 2020, whereas it was 17.3 t ha^{-1} in 2021. Extending the growing season resulted in average Yp_{max} levels which were 2.0 t ha^{-1} higher than Yp_{fs} in 2020 and 1.6 t ha^{-1} higher than Yp_{fs} in 2021.

4.3. Yield gap components

The average total (Yp_{fs} – Ya) yield gap, was 3.8 t DM ha^{-1} for Innovator in 2020 (23% of Yp_{fs}, range 1 – 43%), 5.0 t DM ha^{-1} for Innovator in 2021 (31% of Yp_{fs}, range 19 – 53%), 4.8 t DM ha^{-1} for Fontane in 2020 (27% of Yp_{fs}, range 0 – 47%) and 3.4 t ha^{-1} for Fontane in 2021 (20% of Yp_{fs}, range 0 – 36%) (Fig. 8). For Innovator, yield limitation was largely attributed to oxygen stress in both years. However, there was large variability among fields, i.e., in some fields there was no yield limitation attributed to oxygen stress, whereas in other fields yield was limited by more than 5 t ha^{-1}. Considering that the actual yield development (Ya over time) matched yield development of Yw_{irr} in most fields (Figs. 5 and 6), yield seemed to be limited by drought and/or oxygen stress and little of the Innovator yield gap seemed to be attributable to nutrient limitation and/or reducing factors. The (Yp_{max} – Yp_{fs}) yield gap was 1.1 t DM ha^{-1} in 2020 and 0.7 t DM ha^{-1} in 2021, suggesting a modest gain from a longer growing season.

For Fontane, drought stress limited yields on average by 3.6 t DM ha^{-1} in 2020 and 0.5 t DM ha^{-1} in 2021. Drought stress variability was large among fields, as in some fields no drought stress was simulated whereas in other fields drought stress resulted in a 7 t DM ha^{-1} yield limitation. Nutrient limitation and/or reducing factors were responsible for an additional 1.2 t DM ha^{-1} yield gap in 2020 and an additional 3.0 t DM ha^{-1} yield gap in 2021, with again large variability observed among fields. Planting earlier or harvesting later could have increased potential yield by 2.0 t DM ha^{-1} in 2020 and 1.6 t DM ha^{-1} in 2021.

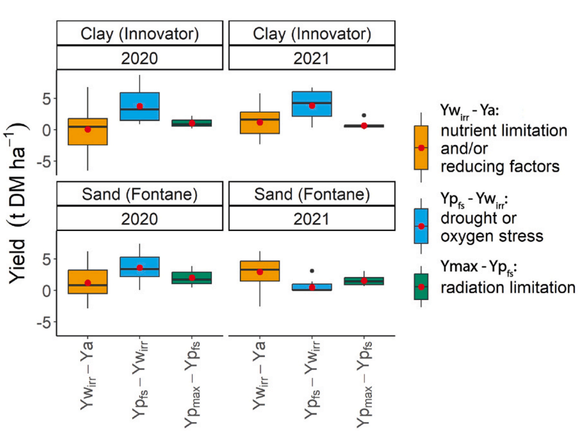

Fig. 8. Yield gap components (for abbreviations see Fig. 1; all in t DM ha^{-1}) for two different years and soil types (and respective cultivars). Different coloured boxplots indicate different yield gap levels. Red dots indicate average values.

4.4. Explaining yield (gap) variability

A detailed overview of the results from the statistical analysis is provided in Supplementary Material 3. Here, only main findings are provided. Statistical analysis showed that for both Innovator on clayey soils and Fontane on sandy soils, water stress caused lower yields and larger yield gaps. On clayey soils, water stress was assumed to be caused by waterlogging, whereas on sandy soils water stress was caused by drought. Crop health score and emergence rate were found to correlate to both the yield and yield gap, where higher crop health score and emergence rate were related to a higher yield or lower yield gap. Furthermore, for Innovator on clayey soils a positive relationship was found between the use of active ingredients and environmental impact points of crop protection agents and the yield levels. Both for Fontane and Innovator, insignificant or counterintuitive relationships were found between actual yield or the yield gap and soil properties or fertilizer application rates. From the data it could not be concluded that yield increased or the yield gap decreased with increasing fertilization rates or soil fertility, suggesting limited effect of soil conditions and fertilization on actual yield or the yield gap.

4.5. Yield gap decomposition and field observations

Considering the (Yp_{max} – Ya) yield gap, 12–31% of the yield gap could be explained by a limitation in radiation, which can be attributed to late planting or early harvesting (Fig. 9). Drought stress explained, on average, 8–18% of the Innovator yield gap and 9–52% of the Fontane yield gap. In both years, 59% of the Innovator yield gap and less than 1% of the Fontane yield gap was attributed to oxygen stress. Nutrient limitation and/or reducing factors jointly explained 1% and 21% of the Innovator yield gap in 2020 and 2021, respectively. For Fontane, nutrient limitation and/or reducing factors jointly explained 18% of the yield gap in 2020 and 59% of the yield gap in 2021.

The reducing factors that explained the yield gap constituted a multitude of factors and varied widely across fields (Table 2). For almost all fields with a (Yw_{irr} – Ya) yield gap (Figs. 5 and 6), logical factors were found to qualitatively explain the remaining yield gap. Diseases were an

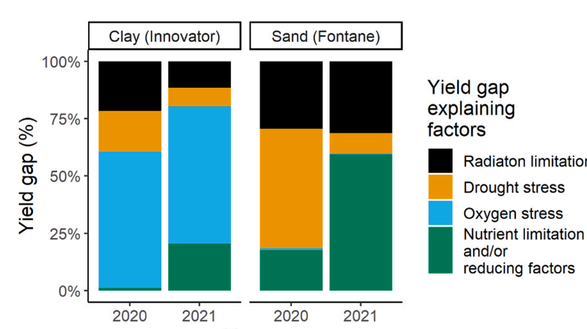

Fig. 9. Yield gap explaining factors in percentage of the (Yp_{max} – Ya) yield gap. Different colours indicate different yield gap explaining factors.

Table 2
Yield reducing factors and in which fields these occurred. See Supplementary material 4 for pictures and more elaborate information on the affected fields.

Yield reducing factor	Field number
Pectobacterium (causing black leg disease or soft rot)	11, 18, 27, 28
Tubers rotten away before emergence, disease unclear	33, 114, 314
Cut seed, irregular emergence	41, 64
Alternaria (causing early blight)	62, 411
Potato cyst nematodes	37*, 317
Fusarium rot	413
Damaged planting machine	612
Senesced sprouts	311
Tuber rust, possibly because of Ca deficiency	44
Multitude of yield gap explaining factors	113, 212, 214, 217, 415
Unclear	15

* For field 37 potato cyst nematode pressure was not tested, but based on the irregular canopy closure we assumed potato cyst nematodes were the cause of the lower yields.

important component of the reducing factors in most of the fields, but in other fields yield reduction was related to poor agronomic practices such as mal-functioning planting machines or planting cut seeds. In a number of fields, a multitude of yield gap explaining factors reduced yields. In field 113, part of the seed tubers rotted away leading to a lower emergence rate. In the same field, rotting also affected the ware potato tubers at the end of the growing season, resulting in a reduced yield. Furthermore, there was a light late blight infection in this field. In field 212, seed and ware tuber rot were also important reducing factors, caused by a *Pectobacterium* infection (formerly Erwinia). Field 214 suffered from bacterial wilt due to *Pectobacterium*, late blight and early senescence of plants, starting from mid-June. For field 217, we hypothesized that excessive canopy growth slowed down tuber growth, possibly because of overfertilization with nitrogen on an already rich soil. In addition, there was a late blight infection in this field. In field 415 there was a second flush of tuber initiation in July, which was expected to have slowed down tuber growth in this field. Only for field 15 no logical explanation could be found for the (Yw_{irr} – Ya) yield gap.

5. Discussion

5.1. Yield gap levels and yield gap explaining factors

This study revealed that by combining frequent field monitoring throughout the growing season with crop growth modelling, we were able to provide detailed insight in variability in yield gaps and yield gap explaining factors at field level for ware potato in the Netherlands. We estimated the average (Yp_{fs} – Ya) yield gap (i.e., potential yield given farmers' planting dates minus actual yield) for the variety Innovator cultivated on clayey soils at 23% of Yp_{fs} in 2020 and 31% in 2021, and for the variety Fontane cultivated on sandy soils at 27% of Yp_{fs} in 2020 and 20% in 2021. At field level, the (Yp_{fs} – Ya) yield gap ranged from 1 to 53% for Innovator and from 0 to 47% for Fontane.

A yield gap decomposition analysis showed that the Innovator yield gap could be attributed mostly to oxygen stress in both years, and that the Fontane yield gap was determined mostly by drought stress in 2020 (a relatively dry year) and by reducing factors in 2021 (an average year in terms of precipitation) (Figs. 8 and 9). Combining crop growth modelling with statistical analyses was useful to determine the overall effect of reducing and or nutrient limiting factors on the yield gap, but could not be used to identify specific problems at individual fields. Using the field observations throughout the growing season, we could establish that the reducing factors that impacted crop growth were diverse (Table 2). A large part of the reducing factors was related to the use of diseased planting material, such as *Pectobacterium* infected tubers. In other fields, there were problems with airborne diseases, such as early and late blight. Poor agronomic practices also caused part of the yield gap in a few fields, where for instance one farmer reported a broken planting machine and other farmers planted cut seed tubers resulting in heterogeneous plant densities. In two fields, yields were reduced by the presence of potato cyst nematodes.

Based on our results, we argue that there is limited scope to narrow the average ware potato yield gap in the Netherlands. Yield gains are only to be made for specific individual fields. At the same time, it is also important to consider resource use efficiency when targeting fields with lower productivity. Our study shows that yield gains can be made through earlier planting, increased irrigation, improved drainage and planting healthy seed material using the same inputs. However, these recommendations are given at field level, while farmers operate at farm level. At farm level it is not always possible to apply optimal or timely management because of limited availability of labour and machinery (Kingwell, 2011; Reidsma et al., 2015), or adverse weather conditions (van Oort et al., 2012). For example, in one specific field in this study, a farmer still had to harvest leeks in April. Therefore, the farmer could not plant earlier than in May. In other fields, farmers were unable to irrigate. In these fields, rather than to increase yield, we would argue to adjust inputs to the expected yield levels based on the biophysical conditions at field level and socio-economic constraints at farm level, with the aim to use resources more efficiently.

5.2. Frequent field monitoring compared to big data approaches

In our study, yield (gap) variability was partly attributed to the same yield determining factors as in earlier studies. Previous studies concluded that ware potato yield levels are determined by sowing and harvesting dates (Mulders et al., 2021; Silva et al., 2020), irrigation (Mulders et al., 2021; Silva et al., 2020), variety (Mulders et al., 2021; Silva et al., 2020), fungicide use (Silva et al., 2017) and preceding crops (Mulders et al., 2021). In addition, less clear or contradicting effects were found of soil properties and fertilizer application on yields (Mulders et al., 2021; Ravensbergen et al., 2023; Silva et al., 2021; Vonk et al., 2020). Our study provided new insights in the potato yield gap variability in the Netherlands. Previous studies did not clearly quantify the yield limiting effect of oxygen stress and yield reducing effects of pest, diseases and poor agronomic practices. Neither did these previous studies show the variability in yield gaps and yield gap explaining factors among fields. Furthermore, the variability explained by (similar types of) regression models was much lower in Silva et al. (2020) (R^2 = 0.34) than in our study (R^2 = 0.39–0.65) (Supplementary Material 3, Table S.4). This underpins effectiveness of our method to perform detailed yield gap variability assessments at field level. This contrasts with big data approaches which "*are useful to characterize cropping systems at regional scale and to develop benchmarks for farm performance, but not as much to explain yield variability or make predictions in time and space*" (Silva et al., 2020, p. 11). Nevertheless, frequent field monitoring is a time consuming and therefore costly activity. Hence, there is a need to assess how big data approaches can be coupled with field monitoring to save costs while still maintaining agronomic rigour to assess causes of yield variability among fields.

While we were not able to quantify the relative contribution of different reducing factors on the yield gap, the qualitative analysis through field observations did provide an overview of the reducing factors at individual fields, and showed that the reducing factors affecting yield were very diverse. This is another benefit compared to other studies where yield gaps were attributed to reducing factors, but where lack of information prevented drawing conclusions as to which pests and diseases or other factors were reducing yields (Deguchi et al., 2016; Silva et al., 2017). When field observations were included, observations were done in only a few fields (Sinton et al., 2022), or excluded important aspects of cultivation, such as water stress (Grados et al., 2020), limiting the applicability to a wider group of farmers.

5.3. Methodological considerations

The reported (Yp_{fs} – Ya) yield gap in this study is similar to earlier reported yield gaps of 25–30% for ware potato in the Netherlands (Silva et al., 2020, 2017). However, these earlier analyses reported lower levels of both Yp_{fs} and Ya. The higher simulated potential yields in our study can be attributed to the fact that we used a recently calibrated version of WOFOST (ten Den et al., 2022) to estimate potential yield. Higher observed Ya levels can be explained by different ways of determining Ya. In earlier studies, Ya was assessed at farm level (Silva et al., 2017) or at field level (Silva et al., 2020), which includes non-yielding areas such as spraying tracks and lower yielding areas such as headlands. We measured Ya from a delineated plot, excluding non and lower yielding parts of the field. In addition, manual harvesting prevented loss of small tubers during harvest.

The yield gap analysis in this study is largely based on crop growth model outputs. Model results from the recently calibrated version of WOFOST showed a fair agreement with measured crop growth (Figs. 5 and 6). However, there were also some uncertainties around the use of SWAP-WOFOST, especially around simulating oxygen stress. In a few fields with clayey soils, modelled water-limited potential yield was lower than measured actual yield, which should not be possible according to the yield gap concept. Underestimation seemed to be related to a particular soil type class from the BOFEK soil map (Heinen et al., 2022) in regions 1 and 3 (Fig. 2), which we expect to be a result of incorrect soil property classifications for these particular fields. Furthermore, there are other possible reasons for overestimating the effect of oxygen stress. First, groundwater levels were taken from the 'Landelijk Hydrologisch Model' (NHI, 2023). These groundwater levels are simulated levels and have not been validated in the field. Second, rooting depth was estimated using penetrologger measurements. However, the oxygen stress function within SWAP-WOFOST is sensitive to rooting depth (Bartholomeus et al., 2008). Therefore, overestimating rooting depth may have resulted in overestimating oxygen stress. Lastly, oxygen stress is related to waterlogging, which can be a result of high intensity rainfall events. Such events are erratic and very local. Hence, the employed precipitation from the KNMI weather stations could have overestimated precipitation in farmers' fields and therefore have led to higher simulated oxygen stress levels.

The negative effect of oxygen stress on potato yields in the Netherlands has not been clearly reported earlier. Excessive rainfall was earlier identified as a climate risk (Diogo et al., 2017; Schaap et al., 2011), and it was identified that it can cause a delay in planting and harvesting (van Oort et al., 2012) or resulted in severe waterlogging during the growing season (Wustman, 2005). However, these studies describe the effect of water excess on the timing of management activities and relatively extreme wet cases of standing water in the field. In our study, we showed that also in wetter periods during the growing season which do not coincide with flooding, waterlogging can negatively affect potato yields. This was the case for clayey soils, and not for sandy soils, which are usually well drained and therefore have a low risk of waterlogging (Wagg et al., 2021). An important consideration is that our result is solely based on crop model outputs and have not been validated in the field. Although the crop model simulations align strongly with our observations in the field and it has been shown before that waterlogging can reduce potato yields (Benoit and Grant, 1985) and yields of other crops (Hack-ten Broeke et al., 2019), the extent to which we assessed that oxygen stress limited yield requires experimentation and evaluation in the field.

6. Conclusions

By combining frequent field monitoring and crop growth modelling, we gained detailed insight in the yield gap and yield gap explaining factors at field level for the Dutch ware potato production system. We found that the average (Yp_{fs} – Ya, i.e., potential yield given farmers' planting dates minus actual yield) yield gap ranged from 20 – 31% depending on the soil type and variety, but that the (Yp_{fs} – Ya) yield gap in individual fields ranged from 0 – 53%. On clayey soils with the variety Innovator, the yield gap was mostly attributed to oxygen stress caused by waterlogging. While this attribution is based on the crop model results, oxygen stress effects must be better examined and measured in the field. On sandy soils with the variety Fontane, the yield gap was mostly determined by drought stress in 2020, a relatively dry year, and by reducing factors in 2021, an average year in terms of precipitation. The reducing factors that affected potato yields varied from field to field and were mostly related to diseases, but in some cases to pests or poor agronomic practices also. Extending the growing season by earlier planting or later harvesting could potentially increase yields as well, but it is constrained by availability of labour and machinery and adverse weather conditions, and is only possible if no other factors limit or reduce yield. Overall, we see limited scope to narrow the average yield gap as current ware potato production is already close to the exploitable yield (i.e., which is assumed to be ca. 80% of potential yield considering economic and environmental efficiency). However, yield gains are to be made for individual fields given they are not constrained by other factors.

We showed that combining frequent field monitoring with crop growth modelling provided detailed insight in the yield gap variability at field level. The crop growth modelling allowed us to break down the yield gap in different components. Through the frequent field monitoring we could closely observe plant development over time and identify the wide diversity of yield reducing factors at field level. As such our method contrasts to other yield gap analyses using big data approaches which were less powerful to assess crop yield variability among fields.

CRediT authorship contribution statement

Ravensbergen Arie Pieter Paulus: Conceptualization, Formal analysis, Data curation, Writing – original draft, Methodology. **van Ittersum Martin K.:** Conceptualization, Project administration, Resources, Supervision, Writing – review & editing. **Kempenaar Corné:** Conceptualization, Supervision, Writing – review & editing. **Ramsebner Nicole:** Conceptualization, Data curation, Formal analysis, Writing – review & editing. **de Wit David:** Conceptualization, Data curation, Formal analysis, Writing – review & editing. **Reidsma Pytrik:** Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fcr.2024.109295.

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