



Yield variability across spatial scales in high input farming: Data and farmers' perceptions for potato crops in the Netherlands

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ABSTRACT

Crop yields are determined by the biophysical environment and by farm management decisions, which in turn depend on socio-economic conditions of the farm(er). The interaction of these factors results in spatial and temporal yield variability. We assessed ware potato yield variability in the Netherlands across four agronomically relevant scales (among provinces, farms and fields and within fields) using five datasets with data on potato yield across space and time. Furthermore, we disseminated an online questionnaire among farmers to identify the perceived yield gap and the key yield gap explaining factors at farm level. Spatial yield variability was largest among fields, with a standard deviation of 8.5–11.1 t ha⁻¹, and within fields, with a standard deviation of 7.7–8.7 t ha⁻¹. Spatial yield variability decreased at higher aggregation levels, i.e., the standard deviation of among-farm yield variability was 4.0–6.1 t ha⁻¹ and that of among-provinces 1.6–3.5 t ha⁻¹. Mean yields of the datasets ranged from 46 to 52 t ha⁻¹. Temporal yield variability explained 10–55 % of the total observed variation in crop yield and its magnitude was equal or larger than the spatial yield variability for almost all datasets. Farmers estimated the ware potato yield gap at 13–18 t ha⁻¹, corresponding to 20–24 % of estimated yield potential, depending on the soil type and variety. Water deficit and water excess were considered the most important yield gap explaining biophysical factors. In addition, soil structure was an important biophysical factor on clay soils and diseases on sandy soils. Irrigation and fertilization were identified as the most important yield gap explaining management factors, whereas legislation and potato prices were identified as the key socio-economic factors influencing potato yields. However, the perceived yield gap explaining factors varied with soil type, variety and year. We conclude that reducing potato yield variability in the Netherlands can be achieved best at the field and within-field level, rather than at farm or regional level. When reducing yield variability is not feasible and/or desirable, inputs should be adapted to actual yield levels to achieve optimal environmental and economic sustainability.

1. Introduction

Crop yields are determined by the biophysical environment and by farm management decisions, which in turn depend on the socio-economic conditions of the farm(er) (Beza et al., 2017; van Ittersum et al., 2013). These factors affect crop yield differently over time and space resulting in temporal and spatial yield variability (Grassini et al., 2015). Analysing yield variability across different scales can be useful to determine at which scale addressing yield variability is most impactful. Yield variability analyses can be used to prioritize policies at regional

scale (van Dijk et al., 2020), tailor management advices to specific farms, or justify the promotion of precision agriculture technologies to manage yield variability at field or within-field scale. Examples of policy measures are to stimulate irrigation in regions that are more severely affected by drought or to use variable rate application of fertilizers in heterogeneous soils. Relatively low yields, associated with large yield variability, are undesirable because they translate into lower resource use efficiency and lower profitability if inputs are not adjusted to target yield levels (Silva et al., 2021). Addressing yield variability could thus increase crop production, while reducing the impact of crop production

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on the environment and improving farmers' income.

In the Netherlands, ware potato was found to be more impacted by weather extremes than other arable crops (van Oort et al., 2023), and a large yield variability can be expected for this crop as a result. A regional analysis of the effect of weather extremes on potato yield found that the lowest yields were up to 20 % lower than the average yield (van Oort et al., 2023). At farm level, ware potato yield averaged 51 t ha⁻¹, with a range from 30 to 80 t ha⁻¹ (Silva et al., 2017). At field level within a single farm, Mulders et al. (2021) found that average potato yield ranged from 50 to 60 t ha⁻¹ with a 95 % confidence interval of 30–90 t ha⁻¹. In another study at field level, ware potato yield was, on average 50–54 t ha⁻¹, depending on the maturity group, with a range between 30 and 90 t ha⁻¹ (Silva et al., 2020). Year-to-year variation is also an important constituent of yield variability as in 10 % of the years yields were more than 20 % lower than the average long-term yield (van Oort et al., 2012). Despite early assessments of ware potato yield variability in the Netherlands, the cited literature does not provide consistent methodologies of yield variability analysis across different spatial scales. The latter limits comparisons of yield variability across spatial scales, making it difficult to devise and prioritize strategies to manage yield variability. This study adds to the existing knowledge by quantifying yield variability across agronomically relevant spatial scales with a consistent protocol.

Beyond quantifying yield variability across temporal and spatial scales, it is also important to identify the factors explaining yield variability (Taylor et al., 2018). Studies on yield gaps often rely on farm-field data with detailed information on crop management and biophysical conditions (e.g., Hochman et al., 2016; Mourtzinis et al., 2018; Mulders et al., 2021; Silva et al., 2017). However, such analyses often neglect socio-economic factors (Beza et al., 2017), which are important to understand farmers' decision making. Moreover, measuring which factors are constraining yields is time consuming (van Bussel et al., 2015) as a wide variety of factors could explain yield gaps (Beza et al., 2017). Farmer-based assessments may thus help identifying the most important yield gap explaining factors influencing yield variability. This could provide insights in the socio-economic constraints at farm level in addition to biophysical and crop management limitations (Kwambai et al., 2022). Variability in ware potato yield in the Netherlands was previously associated with planting and harvesting dates, irrigation, fungicide use, and preceding crops, rather than with soil properties and fertilizer application rates (Mulders et al., 2021; Ravensbergen et al., 2023; Silva et al., 2020, 2017). Yet, the aforementioned analyses did not include farmers' perceptions on yield gap explaining factors.

In this study, we analysed different datasets with yield data for ware potato in the Netherlands across multiple spatio-temporal scales. We quantified actual yield and yield variability across years and four agronomically relevant spatial scales using a consistent protocol. Despite inconsistencies across datasets, our approach was helpful to understand and draw numerical conclusions on how yield levels and variability are affected by different scales of observation and analysis. We also identified the yield gap explaining factors for ware potato based on farmers' expert knowledge. We hypothesized that (1) yield variability increases from regional to farm, field, and within-field levels, and that (2) ware potato production in the Netherlands is more constrained by water stress and yield-reducing factors, particularly pests and diseases, than by nutrient limitations.

2. Materials and methods

2.1. Yield variability analysis across spatial scales

2.1.1. Spatial scales

Yield variability is conditional on the spatial scale at which data are analysed. Therefore, we considered spatial scales that are relevant for targeting policies, extension services or management interventions. The

four spatial scales considered in this study were thus region, farm, field, and within-field (Table 1). At the regional scale (i.e., 2000–5000 km²), we compared yield variability across provinces (i.e., administrative boundaries) in the Netherlands as such information is commonly available in yield datasets. At the farm scale (i.e., 10–1000 ha), different farms were compared within a province. At the field scale (i.e., 1–20 ha), we compared different fields within a single farm. At the within-field scale (90 m²), yield variability was assessed within a single field.

Ideally one single dataset should be used to compare yield variability from within-field to regional level. Yet, to the best of our knowledge such a dataset is not available. Therefore, we analysed multiple datasets in this study (Table 1). The first dataset contained average yield per year per province collected by Statistic Netherlands (CBS, Dutch governmental organisation) (CBS, 2021) and was used to analyse yield variability among provinces. The second dataset consisted of yield data measured by the potato processing industry and was also used to analyse yield variability among provinces. The third dataset was derived from the Farm Accountancy Data Network (FADN; cf. Silva et al., 2017) to analyse yield variability at the provincial and farm scale. The fourth dataset included yield data at provincial and farm scale as well and was obtained through a questionnaire that was disseminated among farmers. The last dataset was obtained from two large scale commercial farms in the Netherlands, named 'Van Den Borne Aardappelen' and 'Scholtens-zathe'. This dataset was used to analyse yield variability at the field and within-field scale. All datasets refer to ware potato yield only and thus excluded data for seed and starch potato.

2.1.2. Data sources and processing

Statistics Netherlands (CBS) requests Dutch farmers to report marketable ware potato yields at farm level every year. This dataset did not report potato yield for different varieties, which could then not be controlled for in the analysis. Yields are summarized per province per year and made publicly available (CBS, 2021). From the dataset, we filtered out the province of Utrecht as no yield data was available for this province in the other datasets (see below). This resulted in 297 province x year observations from 1994 till 2020.

The industry samples dataset consisted of marketable yield data of varieties used to produce french fries. Yield data were collected at field level by four different potato processing companies. These companies took biweekly tuber samples from multiple potato fields to assess tuber weight and size distribution throughout the growing season. In our case, samples were collected from week 30 onwards from a total harvested area of 3–4.5 m², which resulted in a time series of yield measurements per field. For each field with at least three measurements, final yield estimated using regression analysis. Three regression models were used for that purpose: linear, quadratic plateau, or linear upper plateau models (Grassini et al., 2013). The three estimated regression models were compared based on the Akaike Information Criterion (AIC) and the model with the lowest AIC was selected as the best model to describe yield development for each field. Each of the three functional forms was most appropriate for about one-third of the data. After processing, the industry dataset contained yield observations from 1393 field x year combinations (2013–2019).

The FADN dataset for the Netherlands contained marketable ware potato yield data at farm level from a representative group of 1500 Dutch farms for the period 2000–2020, without differentiating between varieties. After removing missing values, a dataset with 2471 observations of farm x year combinations remained. We removed data from the period 2000–2005, for which no information on soil type was available, and two more observations were discarded (which was the only observation available for the province of Utrecht and the only observation for the peat soil type resulting in 1889 observations over the period 2006–2020).

We disseminated an online questionnaire for the growing seasons 2020 and 2021 requesting farmers to report the yield obtained on their farm. In addition, farmers who cultivated the variety Innovator on clay

Table 1

Overview of different data sources and their respective spatial and temporal scales for yield variability analysis. Resolution refers to the lowest spatial unit at which the data was available in each dataset.

Data source	Spatial scale				Temporal scale	Resolution
	Province	Farm	Field	Within-field		
CBS statistics	x				1994–2020	Province
Industry samples	x				2013–2019	Field
FADN database	x	x			2006–2020	Farm
Questionnaire	x	x			2020–2021	Field
Commercial farms			x	x	2015–2020 ^a	Grid cell (3–4 m ²)

^a For the commercial farm 'Scholtenszathe' no data from 2017 were available.

soils or the variety Fontane on sandy soils were specifically asked to report yields for these varieties as they are the most cultivated varieties in the country, for the respective soil types. Farmers were also asked to indicate the yield of the highest and lowest yielding fields for these two varieties. Information was specifically requested for the two varieties to remove confounding effects of genotype and soil type in the analysis. For the comparative analysis with other datasets (Section 2.1.3) we used the yield data at farm level, hence yield of different varieties were pooled.

Potential respondents to the questionnaire were reached through different communication channels (i.e., newsletters, farmers' webpages, targeted e-mails, news article in a farmers' magazine, and social media). In total we received 170 useful responses for the 2020 growing season. Of the 170 responses in 2020, 41 farmers cultivated Fontane on sandy soils and 40 farmers cultivated Innovator on clay soils. For growing season 2021, we asked the respondents of 2020 to fill in the questionnaire once more. In this way, we received in total 62 responses in 2021 with 20 observations from farmers who cultivated Innovator on clay soils and twelve observations from farmers who cultivated Fontane on sandy soils.

The last dataset consisted of yield measurements on two large commercial farms in the Netherlands. We note that these two farms are not representative of an average Dutch potato farm, due to their large cultivated area, specialization towards potato production, and large share of potato cultivation on rented land. Yet, the spatial and temporal coverage of these datasets make it valuable to study yield variability at field and within-field scales. The first farm, 'Scholtenszathe', is an arable farm in the northeast of the Netherlands in a sandy soil region. On this farm, ca. 1000 ha are cultivated each year of which approximately 200 ha are used for ware potato cultivation. The second farm, 'Van Den Borne Aardappelen', is an arable farm in the south of the Netherlands in a sandy soil region, mostly focused on potato production (Mulders et al., 2021). On this farm, ca. 1000 ha are cultivated each year of which approximately 600 ha are allocated to ware potato (land renting makes it possible to grow potato on such large shares of the total area). On both farms, gross yield was measured using a harvesting machine, resulting in yield maps per field. The resolution of these yield maps ranged between 3 and 4 m² per grid cell, depending on the driving speed of the harvesting machine. From these maps, all measurement points with yield values equal to 0 t ha⁻¹ and above 150 t ha⁻¹ were discarded. Values of 0 t ha⁻¹ are registered when the harvesting machine is driving on the field without harvesting. For Scholtenszathe, all headlands and any parts of the field with irregular driving patterns (for harvesting) were removed. For van den Borne Aardappelen, the outer 10 m of each field was removed. Finally, from all measured values 15 % tare was subtracted to represent marketable yield (Mulders et al., 2021), consistent with the other datasets. For both farms, only fields with the variety Fontane were selected to remove confounding effects of genotypes. Yield per field was determined by averaging the yield of all grid cells. Yield for within-field sub-area was determined in a similar way for grid cells of 30 × 30 m resolution, excluding grid cells with less than 50 observations per cell. After processing, the dataset of Scholtenszathe included 68 field x year combinations from the years 2015, 2016, 2018, 2019, 2020 with a total cultivated area of 806 ha, resulting in an average field size of 11.9

ha. The dataset of Van Den Borne Aardappelen included 789 field x year combinations between 2015 and 2020 with a total cultivated area of 2681 ha, resulting in an average field size of 3.4 ha.

2.1.3. Comparing yield variability across spatial scales

Different descriptive statistics were used to determine the average yield and yield variability at each spatial scale because datasets differed in available variables (e.g., variety or soil type) and resolution at which data were collected. A comparative analysis was performed to assess yield variability across the four spatial scales using a consistent protocol, built upon linear mixed models. When boxplots were used for visualisation, whiskers were set to represent the 10th and 90th percentile of the data.

At the regional scale, linear mixed models were used to estimate the average yield per province for the CBS, industry samples, and FADN datasets using the 'lmerTest' package in R version 4.2.0 (Kuznetsova et al., 2015). For all three datasets, potato yield was set as the dependent variable, province as a fixed factor, and year as a random factor. Variety and company were also added as fixed factors to the linear mixed model of the industry samples dataset and soil type was added to the model of the FADN dataset. ANOVA was used for all three datasets to test for significant yield differences among provinces, using a Tukey's HSD test as post-hoc test. Temporal yield variability among provinces was visualised using boxplots for each year x dataset combination.

At the farm scale, two different approaches were used to describe among-farm yield variability for two datasets. For the FADN dataset, yield variability was assessed by comparing long-term average yields among farms. First, we excluded all farms with less than 5 years of yield observations. For the remaining observations, yield was rescaled as follows:

$$Y_{ij\text{scaled}} = \frac{Y_{ij}}{M_j} \quad M \quad (1)$$

where $Y_{ij\text{scaled}}$ is the scaled yield of farm i in year j , Y_{ij} is the actual yield of farm i in year j , M_j is the median yield in year j , and M is the overall median yield of the whole dataset. The long-term average yield was then calculated by taking the farm average of $Y_{ij\text{scaled}}$. Furthermore, we calculated how often each farm had a higher than median yield. Finally, boxplots were used to visualise the among-farm long-term yield variability for a given province and to assess if a farm consistently obtained a higher or lower yield than the median yield of the pooled data. Results are only shown for provinces with at least ten farms, to adhere to privacy regulations. Hence, we employed data from 104 farms and 1255 farm x year combinations. For the questionnaire dataset, responses were divided into three groups: farms with Fontane cultivated on sandy soils, farms with Innovator cultivated on clay soils, and farms with none of these cultivars cultivated on the respective soil types. Among-farm yield variability was visualised for each group and for the two years separately using boxplots.

For the questionnaire dataset, among-field yield variability was calculated as the difference between the highest and lowest obtained yield per field within a single farm. This was calculated for farms with Innovator cultivated on clay soils and farms with Fontane cultivated on

sandy soils. We used quantile regression to assess if there was a significant relation between among-field yield variability and farm size for the 10th percentile ('quantreg' package in R version 4.2.0; Koenker et al., 2018). For the commercial farms datasets, among-field yield variability was summarized for each year using boxplots. The range, expressed as the difference between 10th and 90th percentile of among-field yield variability, was calculated for each year.

At the within-field scale, boxplots were used to visualise the within-field yield variability for each field x year combination. The range, expressed as the difference between 10th and 90th percentile of the within-field yield variability per field, was calculated for each field and averaged across all fields per year.

Finally, we compared yield variability across spatial scales and years with a random effects model fitted with year and spatial scale as random effects (see also Silva et al. 2023). Random effects models are a particular type of linear mixed models that consider only random effects. Within the tested models, spatial scales were nested within each other if a dataset contained yield data of multiple scales (Table 1). Year and province were used as random effects for the CBS and industry samples dataset. Year and farm nested within province were used as random effects for the FADN and questionnaire datasets. Finally, year and within-field nested within fields were used as random effects for the commercial farm datasets. Interactions between year and spatial scales were not included to ease interpretation of the results. Spatial and temporal yield variability were expressed as a standard deviation in $t\ ha^{-1}$. For a fair temporal comparison across scales, we included for this analysis data from the same growing seasons (2015–2020). However, there were some exceptions due to the structure and availability of the data. We already noted that no data were available for 2020 in the industry samples dataset and no data were available for 2017 in the Scholtenszathe dataset. Thus, these datasets miss one year for the comparative analysis. For the questionnaire dataset, only data from 2020 and 2021 were available and hence 2021 was included in the comparative analysis.

2.2. Expert-based assessment of yield gap explaining factors

The questionnaire described in Section 2.1.2 was also used to ask farmers which factors affected potato production at their farm, which was done in two steps. First, farmers were asked to estimate the potential yield at farm level under optimal cultivation conditions. We indicated to farmers that potential yield refers to the maximum achievable yield under given climatic conditions, assuming agronomically perfect crop management (van Ittersum et al., 2013). Farmers who cultivated Innovator on clay soils or Fontane on sandy soils were asked to estimate the potential yield for these specific varieties. Farmers who did not cultivate these varieties on the respective soil types were asked to estimate the average potential yield at farm level for the varieties they cultivated. From the estimated potential yield, the yield gap was calculated as the difference between the farmer estimated potential yield and the reported actual yield (van Ittersum et al., 2013).

In the second step, we requested information about what farmers perceived as the most important factors explaining the potato yield gap on their farm. The yield gap explaining factors were divided into three categories (Table 2): biophysical, management, and socio-economic factors. For each category, farmers were asked through a multiple-choice question which factors explained the yield gap on their farm. Farmers were then given the opportunity to explain their selection through an open question.

The questionnaire disseminated in 2021 was expanded based on the answers to the 2020 questionnaire. For 2020, two results were striking (Section 3.3): (1) 'too little fertilization' was an important management factor and 'legislation' was an important socio-economic factor explaining the yield gap and (2) farmers indicated that low potato prices (due to the COVID-19 pandemic) was one of the reasons to invest less in inputs, particularly irrigation. To explore these results further, farmers

Table 2

Possible yield gap explaining factors in relation to biophysical conditions, crop management practices, and socio-economic conditions in the disseminated questionnaire.

Biophysical factors	Management factors	Socio-economic factors
Heat	Planting too early	Lack of irrigation guns
Frost damage	Planting too late	Lack of machinery
Water deficit	Too little irrigation applied	Lack of labour
Water excess	Irrigation applied too late	Farm is too large to manage optimally
Nutrient deficit in the soil	No irrigation applied	Economically not interesting to aim for potential yield
Poor soil structure	Poor drainage	Aim of cultivation is not maximum yield
Hail damage	Too little fertilization	Legislation
Presence of diseases	Use of heavy machinery	No successor
Presence of nematodes	Preceding crop	
	Too narrow rotation	
	Insufficient use of crop protection products	
	Crop damage due to herbicide treatment	

were asked additional questions in 2021, based on a Likert scale, to indicate to what extent input use was reduced due to low potato prices and how more lenient legislation would affect soil and crop conditions and yield on their farm.

3. Results

3.1. Yield variability analysis

3.1.1. Among provinces

Ware potato yield was significantly different among provinces in all three datasets, with maximum yield differences ranging from 8 to 14 $t\ ha^{-1}$, depending on the dataset. In the CBS dataset, average yield per province ranged from 45 to 53 $t\ ha^{-1}$ (Fig. 1A). Based on the industry samples dataset, average yield ranged from 45 to 51 $t\ ha^{-1}$ (Fig. 1B). In the FADN dataset, average yield ranged from 39 to 53 $t\ ha^{-1}$ (Fig. 1C). In all three datasets, yield in Flevoland and Noord-Brabant were among the top three, indicating these were the highest yielding provinces.

Large temporal yield variability was observed in all three datasets as well. Over time, median yield ranged from 41 to 53 $t\ ha^{-1}$ in the CBS dataset, 45–57 $t\ ha^{-1}$ in the industry samples dataset, and 40–51 $t\ ha^{-1}$ in the FADN dataset (Fig. 1D). Although average yield in the industry samples dataset was slightly higher, yield variability among the years followed similar patterns for the different datasets.

3.1.2. Among farms

Large among-farm yield variability was observed in both the FADN and questionnaire datasets. For the FADN dataset, long-term average yield at farm level ranged from 37 to 60 $t\ ha^{-1}$ (Fig. 2A). Based on the questionnaire dataset, among-farm yield variability ranged from 42 to 68 $t\ ha^{-1}$, but varied by variety/soil type and year (Fig. 2B). For Innovator on clay soils, average yield was approximately 10 $t\ ha^{-1}$ lower in 2021 than in 2020, whereas the yield variability range was similar between the two years. For Fontane on sandy soils, both the average yield and yield range were similar across the two years.

The FADN dataset showed that 9 % of the farms obtained higher than median yield (across all farms) in all years, 12 % of the farms never obtained higher than median yield, and the remaining farms obtained higher and lower than median yield (Fig. 2C). Farms with higher than median yield were found in all provinces. However, in Noord-Brabant and Flevoland there were relatively more farms which obtained higher

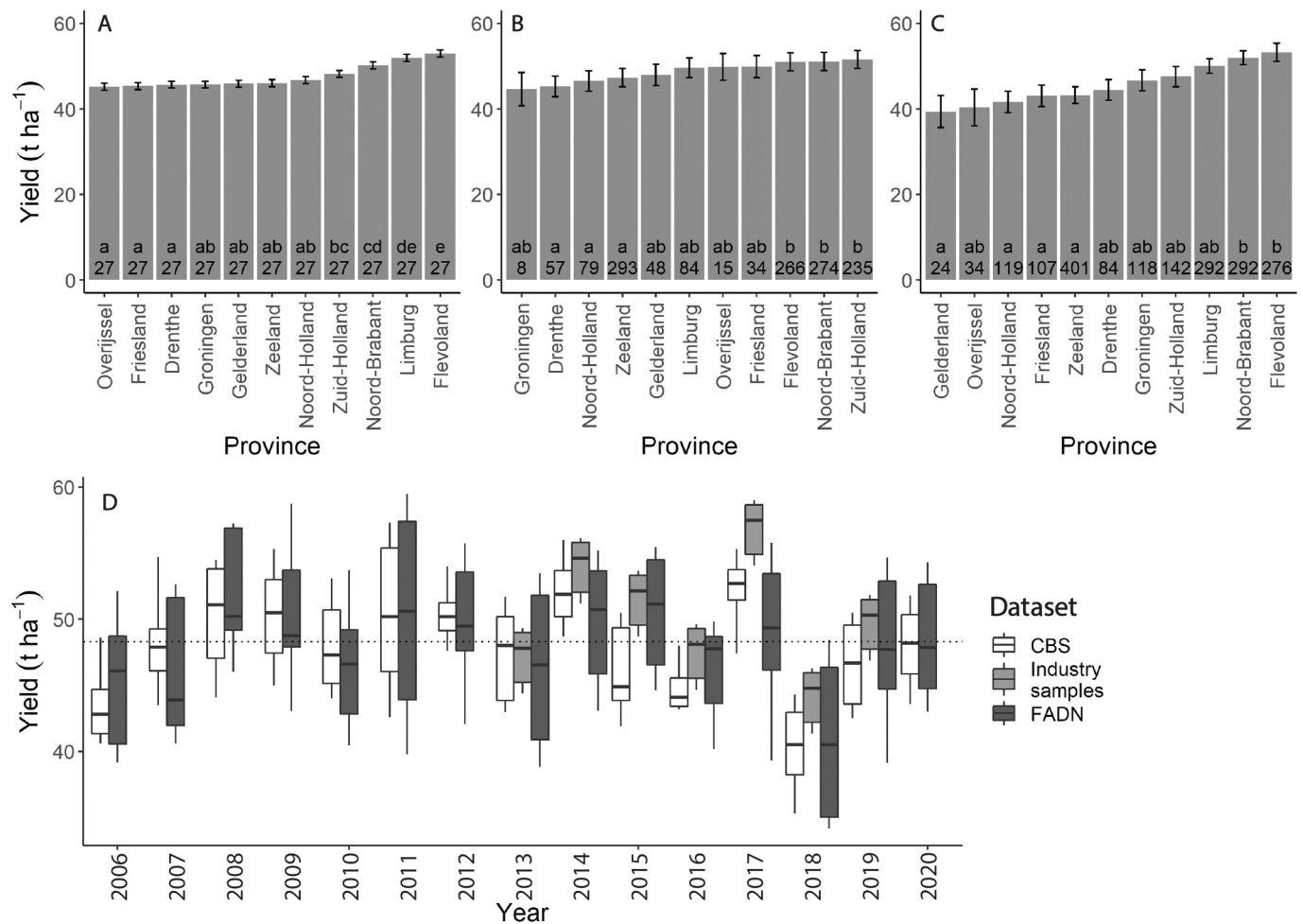


Fig. 1. Average yield (in t ha⁻¹) for different provinces in the Netherlands calculated with the CBS (1994–2000) (A), industry samples (2013–2019) (B) and FADN dataset (2006–2020) (C). Panel D shows variability among provinces for each year from 2006 onwards. Error bars in panels A–C indicate standard errors. Different letters indicate significant differences between provinces. Numbers at the bottom of the bars indicate the number of observations (number of years for panel A, number of field x year combinations for panel B and number of farms x year combinations for panel C) an estimate is based on. Boxplot whiskers in panel D indicate 10th and 90th percentile of the data.

than median yield. Among farms, the yield range was roughly 20–30 t ha⁻¹ and varied from year to year (Fig. 2D).

3.1.3. Among fields

Large among-field yield variability within a single farm was observed in both the questionnaire and commercial farm datasets. For the questionnaire dataset, among-field yield variability (i.e., difference between the highest and lowest yielding field, Section 2.1.3) averaged 10 t ha⁻¹ on clay soils with cv. Innovator and 23 t ha⁻¹ on sandy soils with cv. Fontane (Fig. 3). There was no clear difference in yield variability between the two years. Furthermore, for sandy soils with cv. Fontane, quantile regression showed that among-field yield variability increased with increasing cultivated potato area for the 10th percentile, indicating larger among-field yield variability in larger farms. This relation was robust when excluding the three farms with cultivated potato area above 400 ha.

The yield range among fields (i.e., the difference between the 90th and 10th percentiles) varied from 13.5 to 20.2 t ha⁻¹ for Scholtenszathe and 22.6–34.8 t ha⁻¹ for Van Den Borne Aardappelen (Fig. 4). Median yield differed considerably across years at both farms, while yield variability was similar across years with standard deviations ranging from 12 % to 21 % of the mean for Scholtenszathe and 19–39 % of the mean for Van Den Borne Aardappelen.

3.1.4. Within fields

Large differences were observed among fields in terms of within-field yield variability. The yield range per field (i.e., the difference between the 90th and 10th percentiles) varied from less than 10 t ha⁻¹ to more than 40 t ha⁻¹. The average range of within-field yield variability per year and farm varied from 9.6 to 16.8 t ha⁻¹ for Scholtenszathe and from 18.5 to 25 t ha⁻¹ for Van den Borne Aardappelen. Fig. 5 presents results for two extreme years. In 2016 (year with highest yield variability), the southern sandy soils of Van Den Borne Aardappelen experienced high intensity rainfalls. In 2018 (year with lowest yield variability), an extreme drought affected potato cultivation across the Netherlands. Supplementary Material 1 shows that mean ranges are slightly different across years, but that the distribution of within-field yield variability remained similar.

3.1.5. Yield variability across spatial scales over the period 2015–2020

Random effects model results, using only data for the period 2015–2020, indicated that yield variability was lowest at the regional scale, greater at farm scale, and even greater at both field and within-field scales (Fig. 6). The standard deviation of among-field yield variability ranged from 8.5 to 11.1 t ha⁻¹. Within-field yield variability was at a similar or slightly lower level, with a standard deviation from 7.7 to 8.7 t ha⁻¹. Standard deviation of among-farm yield variability ranged from 4.0 to 6.1 t ha⁻¹ and of among-province yield variability ranged

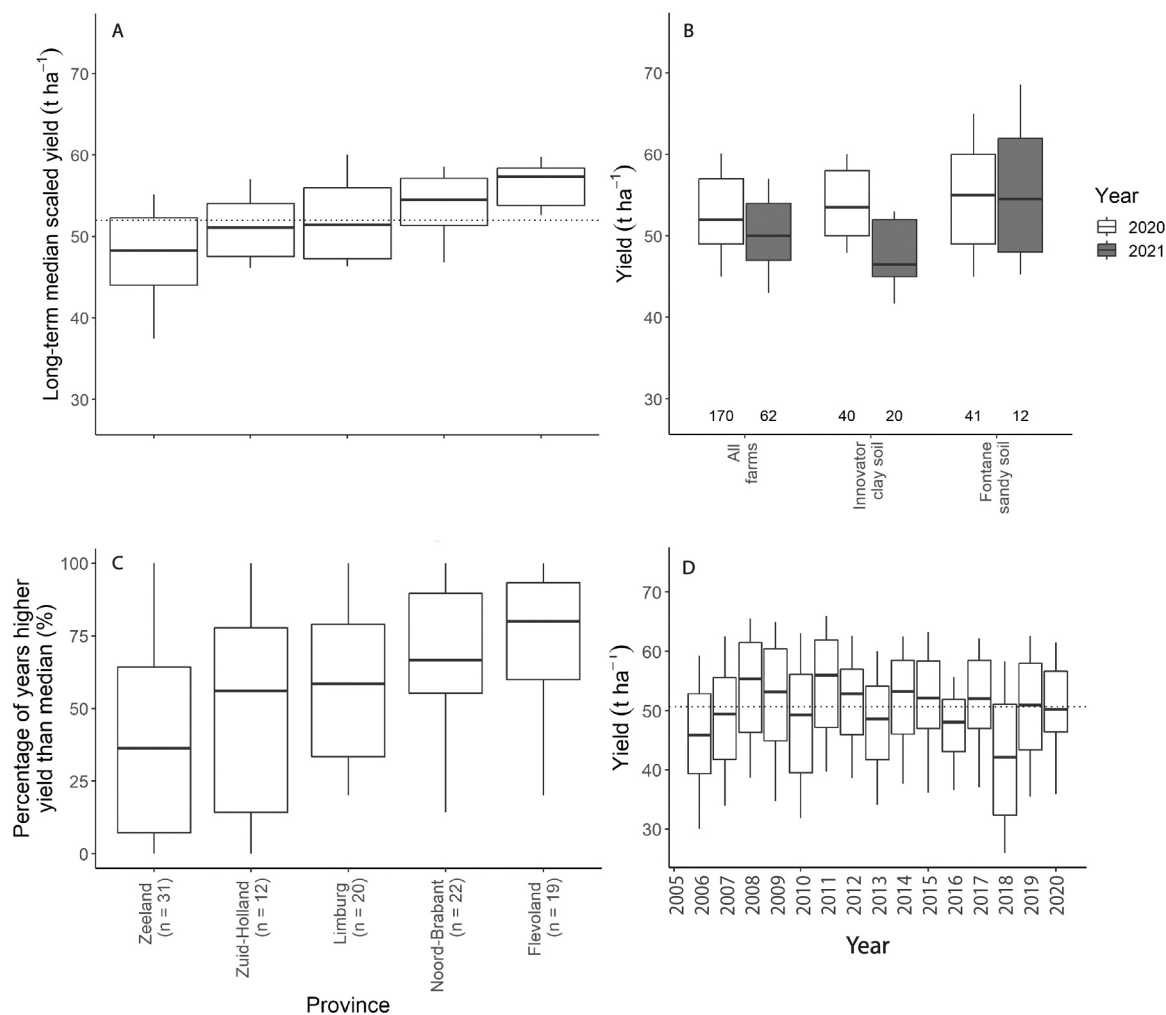


Fig. 2. Long-term median scaled yield per farm (in $t\ ha^{-1}$) for five different provinces based on the FADN dataset (A). Yield per farm (in $t\ ha^{-1}$), based on the questionnaire dataset (B). Percentage of years that a farmer had a higher than median yield for all yield observations of that year, based on the FADN dataset (C). Among-farm yield variability for each year, based on the FADN dataset (D). The dotted line in panels A and D indicates the median yield of all farms and years. Different greyscales in panel B indicate different years. Whiskers of the boxplots indicate 10th and 90th percentile of the data. Number of observations indicated in panel C apply to panel A and C. Numbers in panel B indicate number of observations per group.

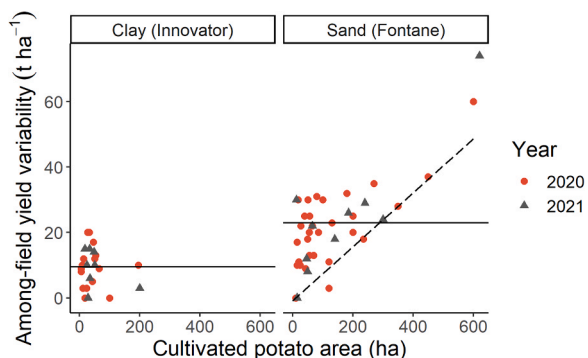


Fig. 3. Among-field yield variability (in $t\ ha^{-1}$) calculated as the difference between the highest and lowest yielding fields against the total cultivated potato area per farm (ha). Different colours indicate different years. The solid lines indicate the average among-field yield variability per soil type. The dashed line indicates the quantile regression line for the 10th percentile including all data points. Figure is based on the questionnaire dataset.

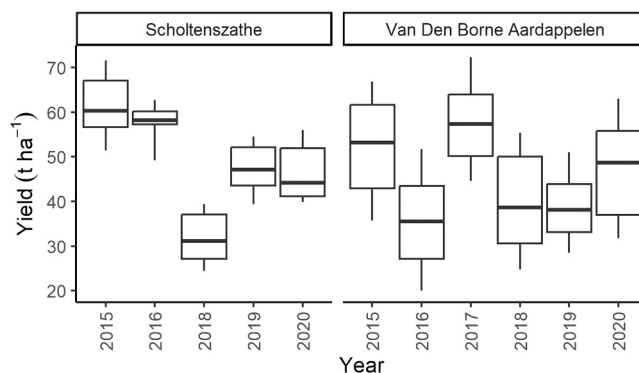


Fig. 4. Boxplots showing among field yield variability (in $t\ ha^{-1}$) per year for the farms Scholtenszathe and Van Den Borne Aardappelen. Figure is based on the commercial farms dataset. Whiskers of the boxplots indicate 10th and 90th percentile of the data.

from 1.6 to 3.5 $t\ ha^{-1}$. The mean yields of the different datasets ranged from 45 to 52 $t\ ha^{-1}$ (Fig. 6).

The temporal scale was another important source of yield variability. In the CBS, industry samples, and Scholtenszathe datasets, temporal

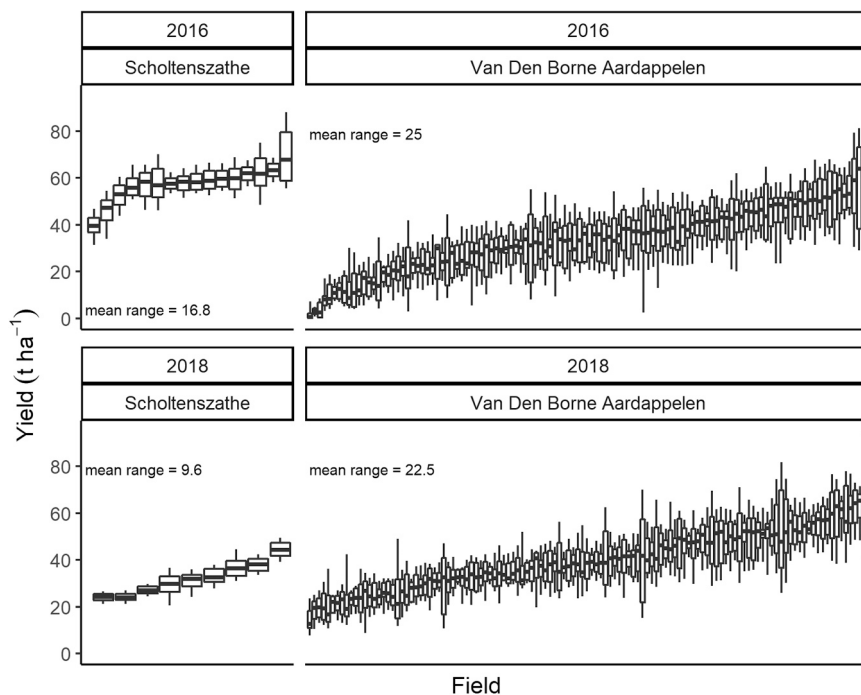


Fig. 5. Boxplots showing within-field yield variability (in $t\ ha^{-1}$) per field per year for the farms Scholtenszathe and Van Den Borne Aardappelen for 2016 (an exceptionally wet year) and 2018 (an exceptionally dry year). Figure is based on the commercial farms dataset. Boxplot whiskers indicate 10th and 90th percentile of the data. The mean range provided in each figure represents the average range of within-field yield variability per year (in $t\ ha^{-1}$).

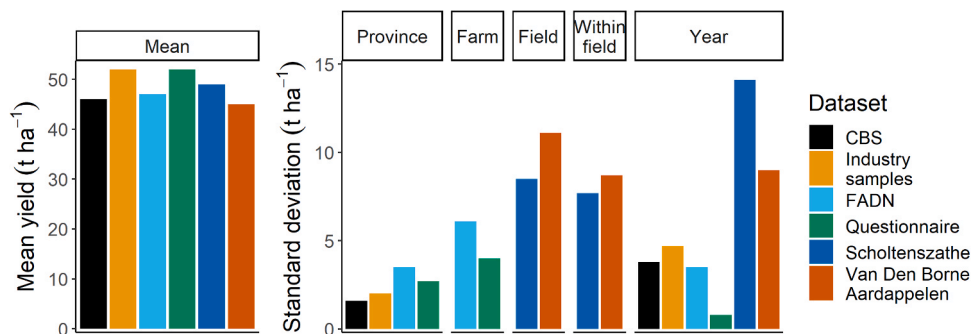


Fig. 6. Mean yield per dataset and standard deviation (in $t\ ha^{-1}$) for each scale and data source for the period 2015–2020. For the industry samples dataset, no data were available for 2020. For Scholtenszathe, no data were available for 2017. For the questionnaire dataset, only data from 2020 and 2021 were available.

yield variability was approximately twice that of the observed spatial yield variability (Fig. 6). In the FADN dataset, temporal yield variability was similar to the spatial yield variability among provinces and roughly half of the yield variability among farms. For the dataset of Van den Borne Aardappelen, temporal yield variability was similar to within-field yield variability and almost 20 % lower than among-field yield variability. Supplementary Material 2 provides a comparison of yield variability across scales for all available years in the datasets.

Roughly half of the yield variability in all datasets was explained by temporal and spatial variability (Fig. 7). Differences among provinces explained 3–14 % of the observed variation. Among-farm yield variability explained 28–32 % of the observed variation. Variation among fields was about 15–21 % and variation within fields was about 12–13 % of the total variance. Excluding the questionnaire dataset, 10–55 % of the total variance in all datasets was explained by temporal variability. In all datasets, 30–75 % of the yield variability remained unexplained (Fig. 7), which may be attributed to other factors not included in the analysis (e.g., crop management practices, disease pressure) or measurement errors. Supplementary Material 3 presents a comparison of explained variance for all available years in the datasets.

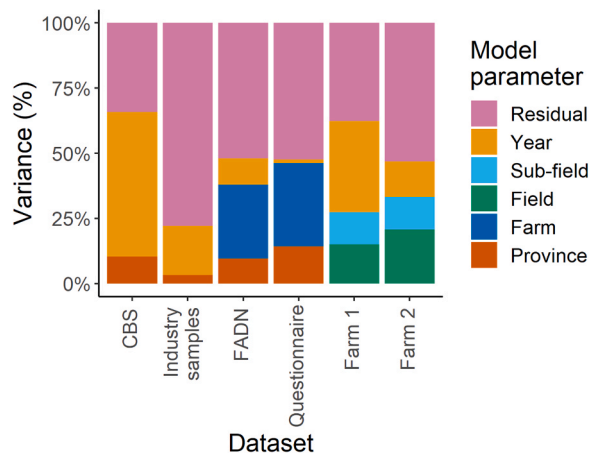


Fig. 7. Variance explained (in % of total variance) by the different model parameters for each dataset for the period 2015–2020. Different colours indicate different sources of variance.

3.2. Constraints to potato production based on farm survey

On average, farmers estimated the potential yield at farm level, including all varieties, at 63 t ha^{-1} . Potential yield for Innovator on clay soils was estimated at 64 t ha^{-1} and for Fontane on sandy soils at 75 t ha^{-1} (Fig. 8A). Nonetheless, there was large variability in the estimated potential yield with a lower range of $50\text{--}65 \text{ t ha}^{-1}$ and an upper range of $73\text{--}95 \text{ t ha}^{-1}$. Large variability was also observed in the estimated yield gap between potential and actual yield, ranging from nil to ca. 40 t ha^{-1} (Fig. 8B). The average yield gap was ca. 13 t ha^{-1} at farm level, including all varieties, 13 t ha^{-1} for Innovator on clay soils, and 18 t ha^{-1} for Fontane on sandy soils, corresponding to a yield gap of 20–24 % of potential yield.

Among the two years, farmers identified different biophysical factors as yield gap explaining factors (Fig. 9). For 2020, heat and water deficit were mentioned (each by 69 % of the respondents) as the most important yield gap explaining factors by all three respondent groups. For 2021, water excess was considered an important yield gap explaining factor on clay and sandy soils (51 % on average). Diseases were indicated as a yield gap explaining factor by farmers who cultivated Fontane on sandy soils in 2021 (70 %) but not by farmers who cultivated Innovator on clay soils (11 %). Conversely, farmers on clay soils considered soil structure an important yield gap explaining factor in both years (37 % in 2020 and 42 % in 2021), but only few farmers on sandy soils considered soil structure a yield gap explaining factor (9 % in 2020 and 20 % in 2021).

Farmers indicated several management factors that could explain the yield gap (Fig. 9). For 2020, farmers mainly mentioned irrigation as an important yield gap explaining factor (60 % on average). Applying too little irrigation was most often mentioned on sandy soils (51 %), whereas delayed irrigation (26 %) or no irrigation (26 %) were considered more relevant to explain the yield gap on clay soils. Lack of fertilization was selected as a yield gap explaining factor by 16–35 % of the farmers in both years, which contrasts to the fact that nutrient deficit was not selected by any farmer as a biophysical yield gap explaining factor. Preceding crop, use of heavy machinery, and crop protection were relevant yield gap explaining factors according to 9–20 % of the farmers. Timing of planting, drainage, spraying damage, and crop rotation were hardly mentioned by farmers as plausible causes for yield gaps.

Both in 2020 and 2021, legislation was mentioned as a relevant yield

gap explaining factor by 20 % of the farmers on average (Fig. 9). Moreover, in 2020 socio-economic factors related to drought stress were indicated as important to explain yield gaps. For instance, farmers pointed out that it was not always economic to strive for high yields (35 %), i.e., the cost of irrigation did not compensate the expected additional income. The answers to the open questions revealed that it was mainly the low potato price in 2020 that negatively affected the economic return of using inputs. Lastly, for some farms on sandy soils with cv. Fontane, availability of irrigation guns was deemed insufficient (36 %) and/or the cultivated potato area was too large to be fully irrigated (30 %).

The additional questions in the 2021 questionnaire (Section 2.2) revealed that 29 % of the farmers irrigated less frequently if potato prices were (expected to be) low (Fig. 10). Moreover, 20 % of the farmers indicated to apply less water per irrigation event because of low potato prices. At the same time, farmers indicated negligible effect of potato prices on the use of other inputs, i.e., only 14 % of the farmers applied less mineral fertilizers due to low potato prices, and even fewer farmers reduced pesticide or organic manure inputs due to low potato prices.

Legislation had a large effect on potato cultivation according to most farmers. Over 90 % of the farmers indicated that soil fertility could be improved if they were allowed to apply more organic fertilizers. Almost 70 % of the farmers indicated that yield would increase if higher nitrogen and/or phosphorus applications would be allowed on their fields. A slightly smaller percentage of farmers indicated that plant health would increase if they were allowed to apply more manure under the assumption that plants would better cope to stresses under high fertility conditions. In 2020, some farmers also stated that yields were lower because the herbicide Reglone was no longer allowed for haulm killing at the end of the growing season, which forced farmers to use other herbicides or haulm killing methods. The questionnaire of 2021 revealed that an equal share of farmers agreed or disagreed with this statement.

4. Discussion

4.1. Spatial and temporal yield variability

This study assessed ware potato yield variability in the Netherlands across four spatial scales. We found that yield variability was lowest at

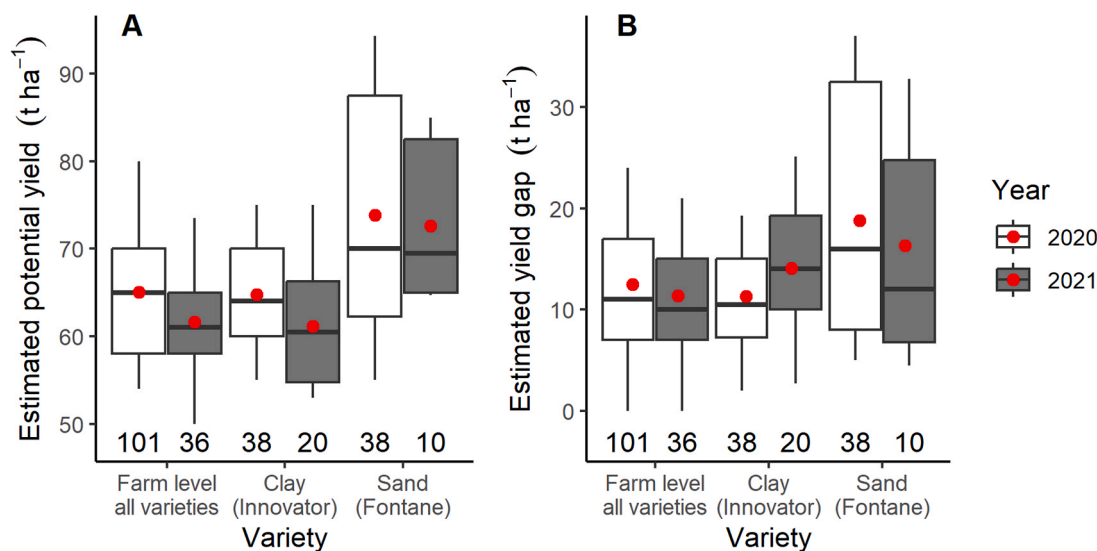


Fig. 8. Potential yield estimated by farmers (in t ha^{-1}) (A) and yield gap (in t ha^{-1}) for three different groups (B): Farm level estimates including all varieties, estimates for Innovator on clay soil and for Fontane on sandy soil. Different greyscales indicate different years. The red dots indicate the mean estimated potential yield or yield gap. Numbers at the bottom of the graph indicate number of observations.

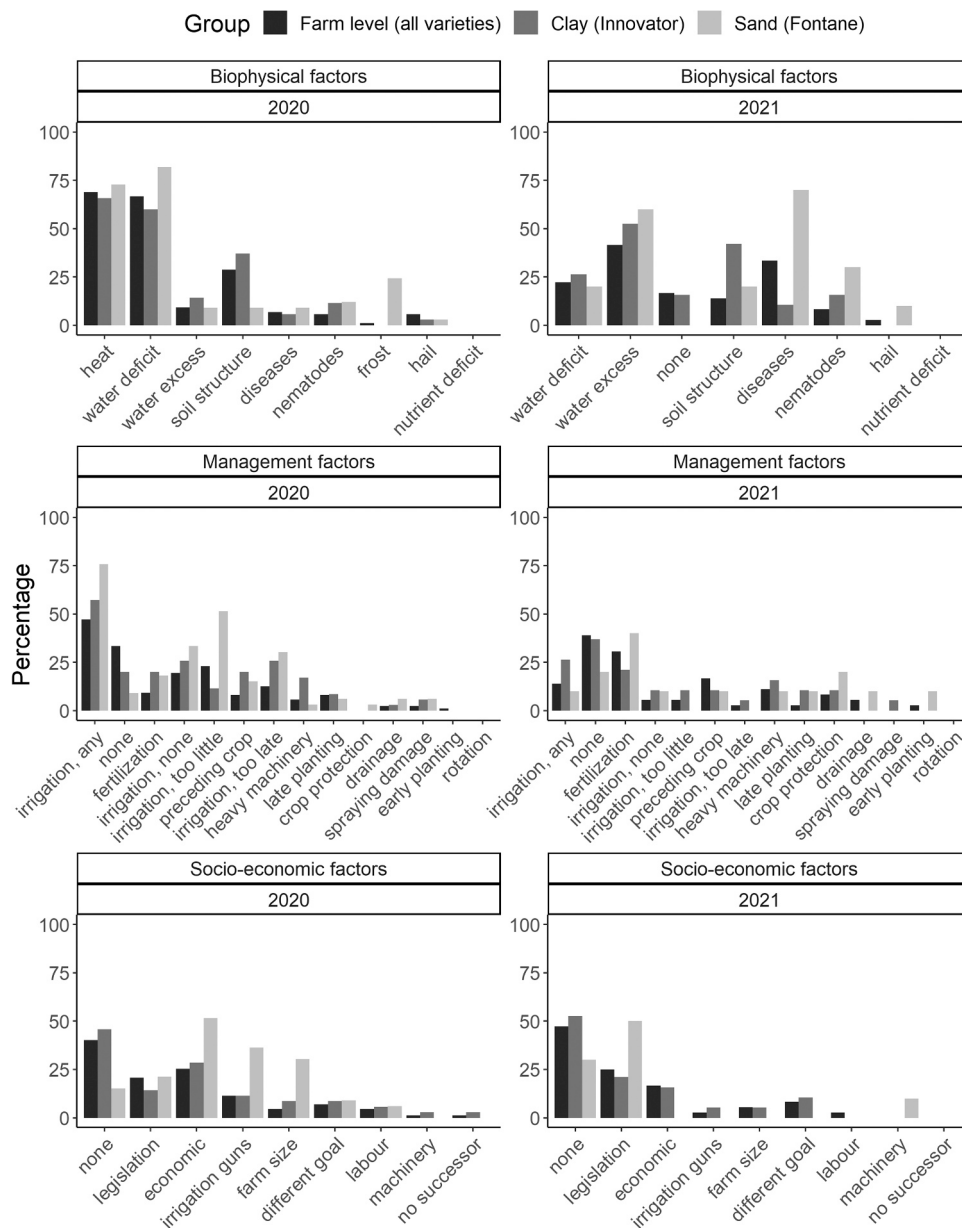


Fig. 9. Percentage of farmers that considered one of the indicated biophysical, management, or socio-economic factors relevant for explaining the yield gap at their farm in 2020 and/or 2021. Different greyscales indicate different groups of farmers.

the regional scale, greater at farm scale, and even greater at both field and within-field scales. Our findings are in agreement with our hypothesis and confirm earlier findings that yield variability decreases at higher aggregation levels (Debrah and Hall, 1989; Górski and Górska, 2003; Lobell et al., 2007). However, this study showed for the first time that the latter does not necessarily apply to the lowest spatial scale as yield variability within a field was comparable with yield variability among fields. Temporal variability was another important constituent of yield variability explaining 10–55 % of the yield variation in all datasets, highlighting the importance of weather conditions on yield at all scales (Fig. 7; see also Ray et al., 2015; Silva et al., 2023). Our method allowed us to compare temporal yield variability with spatial yield variability revealing that temporal yield variability was particularly important for the two large commercial farms, for which most fields were distributed across a relatively small area. We also note that potato fields at Van Den Borne Aardappelen were irrigated, while at Scholtenszathe potato was cultivated under rainfed conditions, further explaining the differences in temporal yield variability between the farms.

Weather extremes have a large influence on crop yield variability (Brown, 2013; van Oort et al., 2012), as captured by the period covered in our analysis. In 2018 there was an extremely dry period (van Oort et al., 2023) resulting in far below average yields in all datasets. Conversely, 2016 was an extremely wet year in the south of the Netherlands, with almost one-third of the annual precipitation occurring in June when the potato crops started to establish. The latter had a strong impact on the commercial farm ‘Van Den Borne Aardappelen’ (Fig. 4). As extreme weather events are likely to occur more frequently in future (van den Hurk et al., 2014), yield variability is also expected to increase in space and time, particularly at lower aggregation levels (Adams et al., 2003). The sandy regions in the south and east of the Netherlands are specifically vulnerable because of somewhat larger temperature increases and larger risk of water deficits (Diogo et al., 2017).

The comparison of yield variability across spatial scales and the fact that yield variability increased with farm size on sandy soils suggest that local variability in biophysical conditions and crop management have a

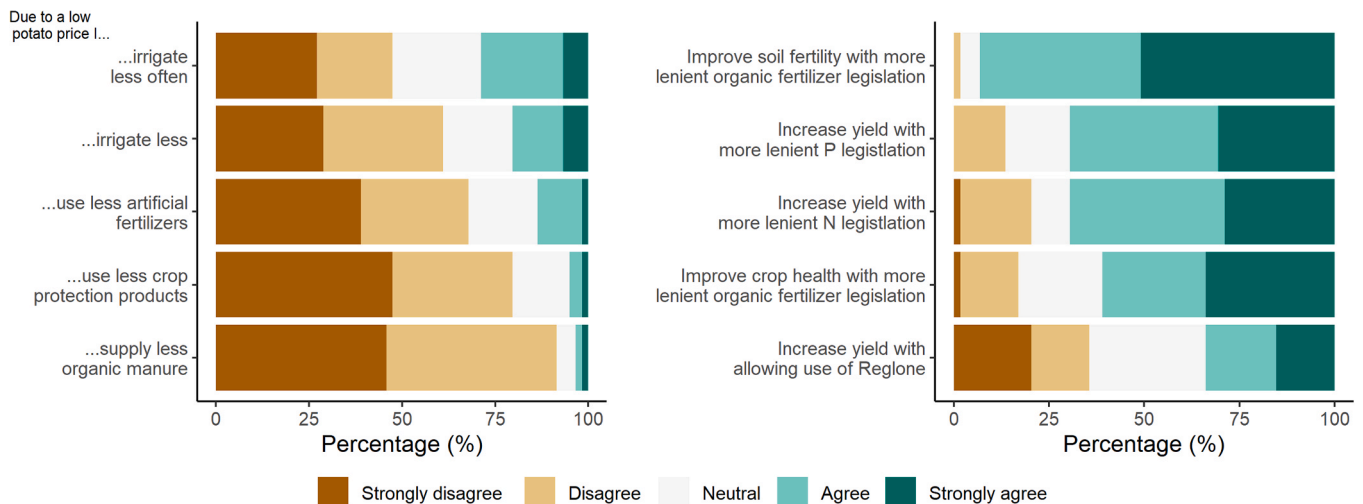


Fig. 10. Percentage of farmers that agreed or disagreed with the indicated statements in the 2021 version of the questionnaire. Different colours indicate whether a respondent (strongly) agreed, (strongly) disagreed or was neutral regarding the statement (n = 59).

larger impact on yield variability than farm(er) characteristics. Yield variability across space can be best addressed at field and within-field level, but this requires understanding the drivers of yield variability (Mulders et al., 2021; Silva et al., 2021), and needs to consider temporal yield variability. Precision agriculture offers potential to manage yield variability, but it should be focused at within-field and among-field yield variability assuming yield potential is comparable within and between fields, respectively. In case of differences in yield potential within and among fields, precision agricultural techniques based on real-time observation of crop conditions can help attuning crop management to realistic target yields under field conditions (Al-Gaadi et al., 2016; van Evert et al., 2012a, 2012b). The latter will likely not reduce yield variability per se but contributes to increasing resource use efficiency and achieving environmental and economic sustainability. However, temporal variability affects crop production each year differently, and therefore it can be challenging for farmers to adjust precision farming techniques to seasonal weather patterns.

Whether addressing spatial yield variability is beneficial, depends on the farm characteristics and the socio-economic context. The economic break-even point for investing in precision agriculture techniques is lower on farms with larger observed variability (English et al., 1999) or with larger acreage (Barnes et al., 2019; Kempenaar et al., 2010). Furthermore, crop yield could be constrained by persistent factors that are difficult to overcome (Lobell et al., 2010). Some farmers indicated in the questionnaire that in 2020 (a relatively dry year) the irrigation capacity was limited (Fig. 9) or that it was not economically viable to irrigate (Fig. 10), leading to larger yield variability. Similarly, time bound activities such as planting are dependent on the availability of machinery and labour, and a lack of these translates into wider planting windows and greater among-field yield variability.

4.2. Methodological considerations of the yield variability analysis

Ideally one dataset containing yield data across all four studied scales should be available to analyse spatial and temporal yield variability. This would allow to make a direct comparison between the highest and lowest spatial scales and to study the impact of yield data aggregation from one spatial scale to the next. To the best of our knowledge such a dataset combining yield levels across all scales is not available. Instead, regional to farm level data are more readily available to replicate our analysis to other crops and geographies. Within-field yield data will remain a challenge to access in most regions despite new developments to study yield variability at lower aggregation levels (Basso and Antle, 2020).

The use of multiple sources of data, as presented in this study, makes it difficult to properly control for different varieties and management practices when quantifying yield variability. We acknowledge that some of our analysis suffers from such limitation, particularly at farm and regional levels, but note that the magnitude and patterns of yield variability among provinces were similar for the different datasets analysed in this study (Figs. 1 and 6). Beyond differences in data sources, some other considerations are required for proper interpretation of the results. First, estimates of among-field and within-field yield variability are based on yield data from two atypical large farms. The questionnaire dataset revealed that yield variability was larger on sandy soils than on clay soils (Fig. 2B and Fig. 3) and increased with cultivation area on sandy soils (with cv. Fontane; Fig. 3). Hence, among-field and within-field yield variability estimates are likely to be lower for smaller farms or other soil types than analysed in this study. Second, interactions between spatial and temporal variability were not analysed to avoid complexity, despite their importance to understand yield stability over time (e.g., Maestrini and Basso, 2018). Lastly, datasets differed in the way yield data was aggregated (Table 1). For instance, yield data was aggregated at province, farm, and field level in the CBS, FADN, and industry samples datasets, respectively. These different aggregation levels could potentially explain differences in standard errors for the yield estimates per province (Fig. 1), differences in yield variability attributed to the time scale (Fig. 6), or differences in unexplained variability (Fig. 7).

4.3. Yield gap explaining factors of potato production

Farmers indicated a yield gap for ware potato in the Netherlands of 13–18 t ha⁻¹, corresponding to 20–24 % of the potential yield (Fig. 8). This yield gap is slightly lower than that reported in other studies (25–30 % of potential yield), where crop growth models were used to simulate the potential yield (Silva et al., 2020, 2017). Farmers may have a different interpretation of the potential yield than researchers, which then explains the slightly lower yield gap found in this study. As the highest farmers' yield is generally lower than the potential yield and only reached by few farms (Silva et al., 2017), farmers may underestimate the potential yield as defined based on what is achievable with optimal farm management as simulated by crop growth models (van Ittersum et al., 2013).

Yield gap explaining factors indicated by farmers were largely in agreement with our hypothesis that ware potato yield is constrained by water stress and yield reducing factors. Indeed, farmers specified that water stress and use of irrigation were the most important biophysical

and management factors explaining the yield gap on their farm (Fig. 9). Yield-limiting factors related to drought stress were acknowledged as yield gap explaining factors for potato production in the Netherlands in other studies as well (Mulders et al., 2021; Silva et al., 2020). The questionnaire revealed that disease management and (poor) soil structure were other important yield gap explaining factors at farm level as also found by Silva et al. (2017). In addition to earlier findings, our analyses revealed that farmers consider legislation and potato prices important socio-economic constraints to potato production on their farms. Contrary to our hypothesis, farmers considered fertilization among the most important yield gap explaining factors at farm level. Roughly 70 % of the farmers indicated that potato yield could be increased if they were allowed to apply higher rates of N and P fertilizers (Fig. 10). Yet, in earlier studies the relationships between fertilizer application and yield in farmers' fields were weak or absent (Ravensbergen et al., 2023; Silva et al., 2021; Mulders et al., 2021; Silva et al., 2017). These studies thus indicate that empirical data do not confirm farmers' perception that nutrients are limiting potato yield in the Netherlands.

5. Conclusion

In this study we quantified potato yield variability in the Netherlands across four agronomically relevant spatial scales. We showed that spatial yield variability was largest among fields, with a standard deviation of 8.5–11.1 t ha⁻¹, and within fields, with a standard deviation of 7.7–8.7 t ha⁻¹. Spatial yield variability decreased at higher aggregation levels, i. e., the standard deviation of among-farm yield variability was 4.0–6.1 t ha⁻¹ and that of among-provinces 1.6–3.5 t ha⁻¹. Mean yields of the datasets ranged from 46 to 52 t ha⁻¹. Temporal (year-to-year) variability was another important constituent of yield variability, explaining between 10 % and 55 % of the total observed variation in crop yield. Moreover, temporal yield variability was equal or larger than spatial yield variability. We conclude that reducing yield variability can best be addressed at field and within-field level, which requires site-specific crop management practices attuned to local field conditions. However, when reducing yield variability is not feasible or desirable, inputs should be tailored to realistic target yield levels under field conditions to increase resource use efficiency and farm profitability.

We also assessed farmers' perceptions about the magnitude and causes of potato yield gaps at farm level. Depending on the soil type and variety, farmers estimated the ware potato yield gap at 13–18 t ha⁻¹, corresponding to 20–24 % of the estimated potential yield. Water deficit, water excess, heat, diseases, and soil structure were indicated as the most important biophysical factors explaining the yield gap. Irrigation and fertilization were indicated as the most important management factors and legislation and potato prices were identified as the most important socio-economic factors. Farmers' perceptions were not always confirmed by empirical data, which shows that there is a need to better understand the socio-economic context of the farmer.

CRedit authorship contribution statement

Arie Pieter Paulus Ravensbergen: Conceptualization, Methodology, Software, Formal analysis, Data Curation, Writing – Original draft. **Martin van Ittersum:** Conceptualization, Methodology, Writing – Review & Editing, Supervision, Project administration. **João Vasco Silva:** Methodology, Software, Writing – Review & Editing. **Bernardo Maestrini:** Methodology, Software, Data Curation, Writing – Review & Editing. **Corné Kempenaar:** Conceptualization, Methodology, Writing – Review & Editing, Supervision. **Pytrik Reidsma:** Conceptualization, Methodology, Writing – Review & Editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests co-author part of the editorial board of Agricultural Systems - P.R.

Data Availability

The authors do not have permission to share data.

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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.eja.2023.126925.

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