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Mapping water table depths in wetlands and polder areas by probability sampling

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ABSTRACT

Information on water table depth (WTD) in polder areas and wetlands is important in, for example, estimating emissions of greenhouse gases, assessing the agricultural and ecological potential, and flood risk management. The seasonal variation of WTDs is summarized with averages of the yearly highest (shallowest) and lowest (deepest) water tables (MHW and MLW). These characteristics show short-distance variations within the fields in polder areas, which cannot be mapped using geostatistical interpolation techniques or physical modelling against reasonable costs or with acceptable accuracy. The within-field variations depend on soil type and water management. MHW and MLW were determined from auger hole measurements of WTDs at locations being selected following stratified simple random sampling in subareas classified by soil type and water management. Within these subareas, a further classification was made on the basis of distance to ditches. For each subarea spatial distribution functions of MHW and MLW were made, taking censored observations into account. Uncertainty was quantified by 10,000 bootstrap realisations of the spatial distribution functions. From these realisations maps depicting summary statistics for the spatial distribution of WTD-characteristics within the subareas were derived, as well as a map with probabilities of exceedance of a critical level that can serve as input for risk analysis.

1. Introduction

Fan et al. (2013) estimated that the water table or its capillary fringe is within plant rooting depth in 7–17% of the global land area. In this area, the water table is important to the agricultural and ecological potential, leaching of nutrients and pesticides. Furthermore, in areas with organic soils the water table depth is an important factor in emissions of CO_2 as a result of oxidation caused by drainage. For these reasons, accurate and actual information on water table depth (WTD) is needed to support policy on climate, agriculture, environment, and nature restoration.

This study focuses on mapping characteristics that describe the seasonal fluctuations of WTDs in flat coastal plains built-up by Holocene sediments such as clay and peat, in a temperate climate. We refer to these characteristics as WTD-characteristics. These WTD-characteristics are for instance the average upper and lower bounds of the yearly seasonal fluctuation, summarized with averages of the yearly highest (shallowest) and lowest (deepest) water tables (MHW and MLW), see Ritzema et al., 2018 for definitions. In wetlands and ditch-dissected polder areas most of the spatial variation of WTD-characteristics occurs within the fields between the ditches. These variations can be described in several ways.

Spatial patterns of WTD-characteristics can be described with a physical-mechanistic model of groundwater flow, *e.g.*, Kelbe et al. (2016) or Xiao et al. (2016). These models require inputs on the locations of the ditches, the drainage resistance, transmissivity, hydrological conditions and soil physical properties which are generally not available at a field scale for large areas.

Alternatively, spatial patterns of WTD-characteristics can be modelled by geostatistical techniques. A geostatistical approach on the basis of observations only would require considerable and unrealistic efforts in fieldwork, which can be reduced by incorporating exhaustively available ancillary information that is strongly related to WTD-characteristics in the geostatistical algorithms (Finke et al., 2004; Hoogland et al., 2010; Calzolari and Ungaro, 2012). Schumann and Zaman (2003) applied geostatistical interpolation with electromagnetic measurements as ancillary variable. Kaiser et al. (2012) used a regression model to predict WTDs and ecological moisture levels from thermal remote sensing data in a grassland area. Manzione and Castrignanò (2019) and Manzione et al. (2021) used multiple sources of remote

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sensing data as ancillary information in geostatistical interpolation of mean WTDs and risk assessment of shallow WTDs, respectively. Geostatistical techniques can be combined with time series models for the relation between precipitation surplus and water table depth, to describe the spatiotemporal variation of WTD (Changnon et al., 1988; Knotters and Bierkens, 2001; Yuan et al., 2008; Manzione et al., 2010). The applied time series models can be linear or nonlinear, less or more physically based, purely deterministic or with an additional noise component. Bierkens and te Stroet (2007) regionalized a physically based, nonlinear time series model to describe the dynamics of WTD. Instead of a geostatistical model, they used detailed grid information on landsurface elevation, drainage networks, soil conditions, hydrogeology, and land use for regionalizing the parameters of the time series model. Bierkens and te Stroet (2007) indicate that the resulting model is particularly suited for systems with deep permeable soils, shallow water tables and intensive drainage, whereas our focus is on areas with Holocene sediments of low permeability, such as clay and peat.

For the eastern parts of the Netherlands, generally built up from sandy sediments, with a slightly undulating topography and free drainage, Finke et al. (2004) mapped WTD-characteristics at a resolution of 25×25 m. For the remaining western part of the Netherlands, with polders and wetlands built up from clayey and peaty sediments, WTD-information is only available from the Soil Map of the Netherlands 1: 50,000 (van Heesen, 1970). This information is outdated. Besides this, the classification of MHW and MLW into so called water-table classes (WTCs) is too coarse for actual applications in water management, environmental policy and nature restoration. Furthermore, the accuracy of the WTD-information is not quantified which makes the maps less suitable for application in uncertainty and risk analysis.

The aim of this paper is to introduce a new method based on probability sampling and robust regression for mapping WTDs in polders and wetland areas where existing methods were not proficient enough. The presented method has been tailor-made for ditch-dissected polder areas built up of clayey and peaty sediments, and where most of the spatial variation of WTD-characteristics occurs at short distances within the fields between the ditches. The resulting maps contribute to the Dutch National Key Registry of the Subsurface, an initiative to bring together all available subsurface information in a single data portal, in addition to the maps for the eastern parts of the Netherlands made by Finke et al. (2004).

2. Why probability sampling to map WTD-characteristics?

Making maps by probability sampling might not seem obvious, since with probability sampling global information on the spatial distribution of WTD-characteristics for specific areas of interest is obtained, rather than local information on spatial patterns within these areas (Brus and de Gruijter, 1997; de Gruijter et al., 2006). In this Section we motivate our choice for mapping by probability sampling.

In designing a mapping strategy we followed the recommendation by de Gruijter et al. (2006, p.28) to pay attention to the agreement between data acquisition and data processing. In developing the mapping strategy we followed the scheme proposed by de Gruijter et al. (2006, p. 29–30). This scheme provides a detailed specification of the objectives, takes budgetary, practical and quality constraints into account, facilitates a motivated choice between design-based or model based inference from sample data, and ends in a well-defined protocol on data collection and field work and a description of the methods to be used for statistical inference. We designed a mapping strategy that answers to the following constraints:

1. the map must be applicable for policy and decision making at a national and regional scale, *i.e.*, provinces and district water boards, but is not required to support decision making on farm or field level;
2. the map must be suitable as a benchmark in the validation of physically-based models such as the National Hydrological Instrument (de Lange et al., 2014; Verkaik et al., 2021). Therefore the quality of the map must not depend on the validity of model assumptions, which implies that the mapping method must be model-free or at least that the validity of model assumptions can easily be verified;
3. the map must be suitable for uncertainty and risk analysis, which implies that uncertainty must be quantified;
4. fieldwork must answer to budgetary constraints, which in this study implies that fieldwork must be restricted to one year, and the number of locations for borehole measurements of WTD should not exceed 300.

Ad 1: In areas with free discharge, the WTD is strongly correlated with ground surface elevation, and therefore the use of a digital elevation model (DEM) as ancillary information in spatial interpolation of WTD characteristics is obvious. For instance, Finke et al. (2004) mapped WTD-characteristics in the eastern parts of the Netherlands, with generally sandy soils, slightly undulating topography and free discharge. The availability of a DEM enabled mapping at a resolution of 25×25 m. This high resolution might suggest applicability of the map at farm or field scale. High resolution should not be confused with high accuracy, however. If information on accuracy is presented separately from a map showing spatial predictions with high resolution, users of this map might neglect the information on accuracy and might use the map in taking decisions at farm or field level. Yet, the accuracy of such a high resolution map might allow decision support at regional or national scale only. In summary, it is important to find balance between resolution and accuracy, and information on accuracy should be integrated with the map of "best estimates", to prevent for neglect of uncertainty in decision making.

Ad 2: All methods summarized in Section 1 are based on models, either geostatistical models, time-series models or physical models. The quality of the resulting maps depend on the validity of model assumptions. The outcome of a validation study should preferably not depend on the validity of model assumptions that were used to construct the reference.

Ad 3: With geostatistical methods it is possible to quantify uncertainty. However, the uncertainty is quantified *given* the model assumptions. In quantitative uncertainty and risk analysis the information about uncertainty should preferably cover all sources of uncertainty, and not depend on the validity of model assumptions.

Ad 4: In ditch-dissected polder areas the spatial variation of WTD-characteristics such as the MHW and MLW occurs mainly at short distances within the fields. Geostatistical mapping of these within-field patterns at high resolution raster maps on the basis of WTD-characteristics that have been derived from observed WTDs only, would require an unrealistically dense monitoring network. Ancillary variables can be used in some form of co-kriging or regression-kriging (*e.g.*, Finke et al. (2004)) to construct high resolution raster maps, provided that a relationship with WTD-characteristics is sufficiently strong to obtain accurate spatial predictions. Alternatively to high resolution raster maps with spatial predictions of MHW (MLW), maps with mean MHW (MLW) for larger spatial units can be constructed by block-kriging, and information about the distribution within blocks can be obtained by spatial aggregation of point kriging estimates. A model of spatial variation is needed, however.

Probability sampling enables model-free estimation of the spatial distribution of WTD-characteristics (constraints 2 and 4) for subareas (domains of interest) that fit to the regional or national scale of decision making (constraint 3), with quantification of uncertainty (constraint 3). A key factor in the sampling strategy is to separate subareas on the basis of knowledge of the drainage conditions which explain the within-field variations of WTD-characteristics. This knowledge is provided by the Soil Map of the Netherlands, scale 1:50,000, because this map reflects

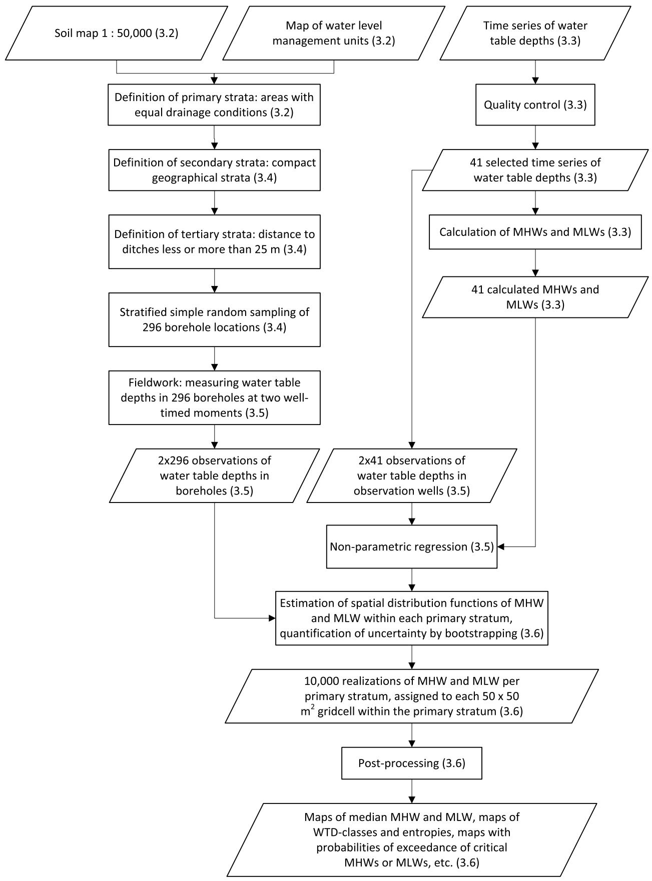

Fig. 1. Flowchart of the mapping strategy, references to Subsections in parentheses.

the spatial distribution of soil types with different hydraulic properties. Information on water level management is provided by district water boards. Stratified simple random sampling enables to utilise this knowledge in mapping WTD-characteristics.

3. Materials and methods

3.1. Design of the mapping strategy

Fig. 1 gives a flow chart of the mapping strategy. In the remaining Subsections the stages of the procedure will be described.

3.2. Study area, priory information

The study area (1,945.09 km^2 non built-up area, excluding surface water, roads, farmyards) is located in the eastern part of Friesland, a province located in the northern part of The Netherlands, see Fig. 2. The study area consists of polders and wetlands with artificial water management and is built up from Holocene, mainly clayey and peaty sediments. Most dominant soil types in the study area are gleysols, vertisols and histosols (FAO, 2015). Most common land use is agricultural land which can be divided in arable land to grow crops and semi-permanent pastures to feed livestock with. Arable land is mainly found in the northwestern part of the study area where more sandy clayey soils can be found, which are easier to cultivate and generally have better drainage conditions than peaty soils and heavy clay soils which are located in the central and eastern part of the study area. Semi-permanent pastures are found on these type of soils and make up for the major part of land use.

The soil map of the Netherlands, 1: 50,000, shows 226 map units in the study area. These were clustered on the basis of drainage properties into eleven units. The study area consists of polders in which fixed surface water levels are maintained. The water level management units were combined with the eleven units derived from the soil map to obtain a map with 26 subareas, see Fig. 3. We assume that these subareas have relatively homogeneous drainage conditions. These 26 subareas are the domains of interest for which the distribution functions of WTD-characteristics are estimated. In the sampling design these 26 domains of interest are the primary strata.

3.3. Calculating WTD-characteristics from time series of water table depths

From the national database on groundwater data (Zaadnoordijk et al., 2019) we selected time series of 41 observation wells to calculate WTD-characteristics MHW and MLW, see Fig. 4, on the basis of the following criteria:

1. The well screen must be situated in or slightly below the fluctuation zone of the water table;
2. The observation well must be situated in the target area, *i.e.*, non built-up area, not in farmyards, gardens, pavements, roadsides, or slopes to ditches or channels;
3. The time series must have been observed without interruptions for at least four recent years. In addition, the water table fluctuations must not have been affected by changes in water management;
4. The observation frequency must be at least semi-monthly;
5. Automated measurements must be available for the fieldwork days (Subsection 3.5).

From the selected time series the WTD-characteristics the Mean Highest (MHW) and Mean Lowest (MLW) Watertable are estimated according to Ritzema et al. (2018). First, for each hydrological year, measures for the upper and lower bounds of the seasonal fluctuation are calculated, *i.e.* the HW3 and LW3 respectively. These are the averages of the depths to the three highest (lowest) water tables in a hydrological year (1 April/31 March) at a semi-monthly measuring frequency (the 14th and 28th). Next, the MHW and MLW are estimated. The MHW (MLW) is defined as: average of the HW3 (LW3) over a period of 30 years under the given climatic and hydrological conditions (Ritzema et al., 2018). It is assumed that MHW and MLW can be estimated from observed series with lengths of at least four years in polder areas, since in these areas the seasonal fluctuation depends more on water level management than on seasonal fluctuation of precipitation and evapotranspiration. Fig. B.11 in B gives details of the 41 time series and the calculated MHW's and MLW's.

3.4. Selection of locations for well-timed WTD-observations

Borehole locations were collected by probability sampling. The primary strata are given in Fig. 3. We only have estimates of WTD-characteristics for the 41 locations of observation wells. This number is too limited to model the spatial variation in the 26 domains of interest. To obtain more information on the spatial distributions of WTD-characteristics within the 26 domains of interest, the WTD was observed in a large number of boreholes. WTD-characteristics were estimated for these borehole locations following the method described in Subsection 3.5. Because of budgetary and practical constraints the number of borehole locations was limited to a maximum of 300. The borehole locations were selected by probability sampling, as motivated in Section 2. The sampling strategy was focused on estimating the spatial distribution functions of WTD-characteristics, including the within-field variations, in subareas with homogeneous drainage conditions. A stratified simple random sampling design with three levels of stratification was developed. The primary strata are the 26 domains of interest, *i.e.*, the 26 subareas of homogeneous drainage conditions, see Fig. 3. To

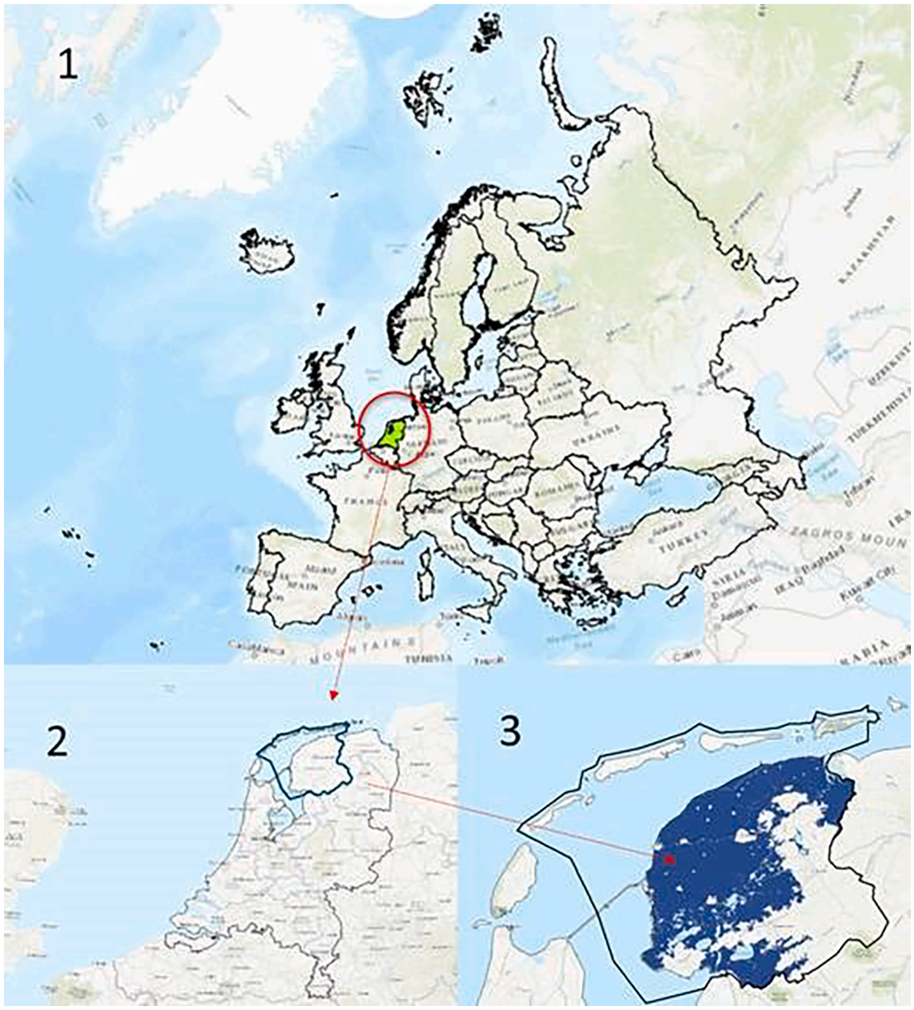

Fig. 2. Study area.

improve the spatial coverage of the borehole locations, each primary stratum was divided into secondary, compact geographic strata using the R-package spcosa (Walvoort et al., 2010). To improve spatial coverage within fields, the compact geographic strata were further divided into areas relatively close to ditches ($<$ 25 m) and more farther away from ditches ($\geqslant$25 m). These areas are the tertiary strata.

Within each secondary stratum four borehole locations are selected: two in each of the tertiary strata. Note that two is the minimum number of sampling units needed in a simple random sample for variance estimation. Because the maximum number of borehole locations allowed due to budgetary constraints is limited to 300, the total number of borehole locations is 296 ($= 2 \times 2 \times 74$), distributed over 74 secondary strata. Fig. 5 shows the selected 296 borehole locations.

3.5. Regression with well-timed WTD-observations

WTD-characteristics were estimated for the 296 borehole locations following a method described by te Riele et al. (1991). In this method the WTD is observed simultaneously in the $n = 41$ observation wells and in a large number of boreholes ($m = 296$), at “well-timed moments”. At these moments, it is assumed that the WTDs in the observation wells approximate the MHWs and MLWs that were estimated from the time series observed in these wells. Next, a linear regression model is fitted to the $n = 41$ observations made in the observation wells, explaining the MHW (MLW) from the WTDs observed at the well-timed moments:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i \tag{1}$$

with y_i the MHW (MLW) for the ith observation well, $i = 1 \ldots n$, x_i the observed WTD in the ith observation well, β_0 the intercept coefficient, β_1 the slope coefficient, and ϵ_i the regression residual. This linear regression model is used to estimate the MHW (MLW) for the 296 borehole locations. It is implicitly assumed that the seasonal fluctuation of WTD reaches its upper and lower bounds at the same moment in the study area. This assumption is reasonable for fast-reacting groundwater systems like polder areas and wetlands.

Observations of WTD can be right-censored, which means that it is only known that the water table is below the well screen or range of the borehole. 15 (5%) of the 296 well-timed observations for MHW-estimation were right-censored, and 12 (4%) of the 296 well-timed observations for MLW-estimation were right-censored. Leaving these censored observations out or replacing them by the censor depth would introduce bias. Censored observations can be taken into account in regression analysis by maximum-likelihood regression or by nonparametric regression. We followed the advice of Helsel (2004) to apply nonparametric regression if the number of observations is less than 50. The linear relationship between MHW (MLW) was modelled with the Akritas-Theil-Sen method for nonparametric linear regression (Akritas et al., 1995). In this method the slopes between all possible pairs of points in the scatterplot (Fig. 6) are calculated. If a pair of points contains a censored observation, then it is only known that the slope is below or above a certain value. Next, the slope coefficient β_1 of the linear regression model is estimated by the median of the slopes between all pairs of points. The intercept coefficient β_0 is estimated by the median

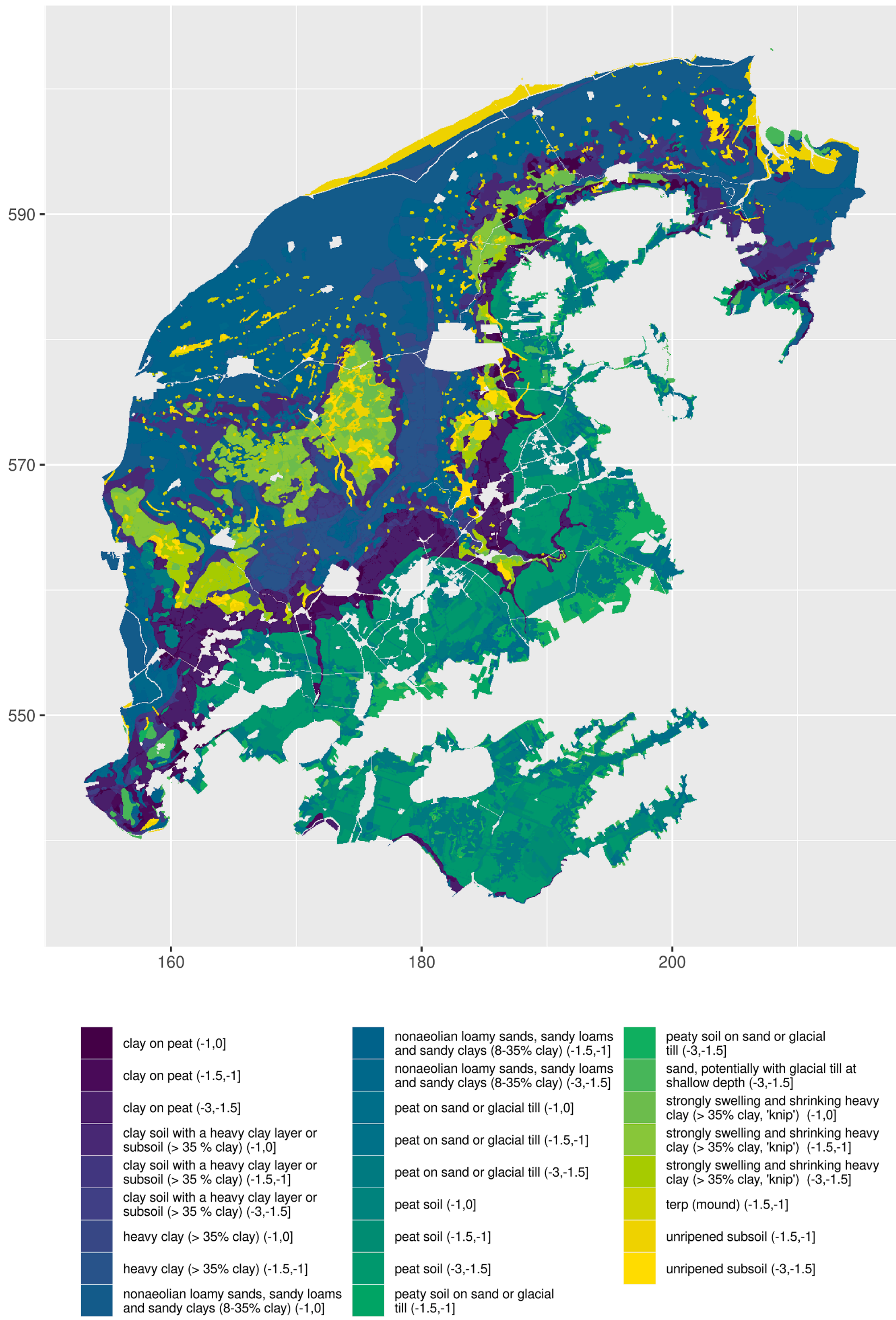

Fig. 3. Subareas (a.k.a. domains of interest or primary strata) with homogeneous drainage conditions. Range of surface water levels in interval notation.

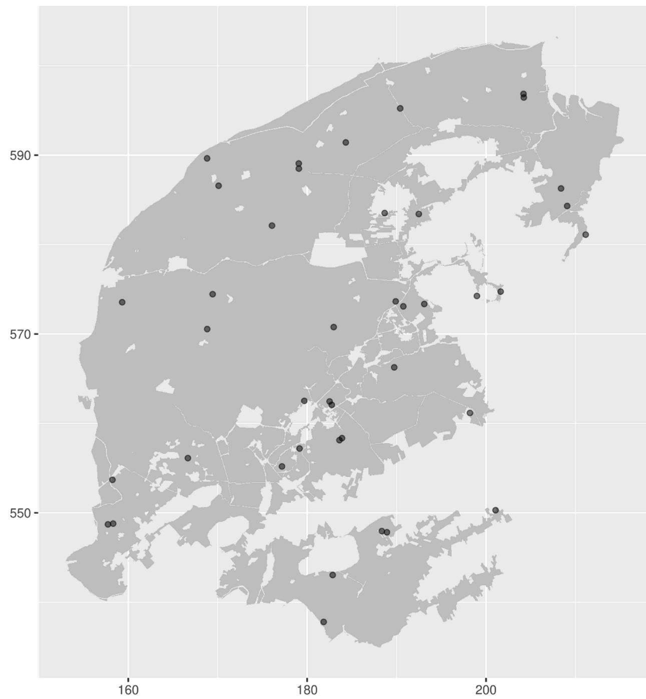

Fig. 4. Locations of the selected 41 observation wells.

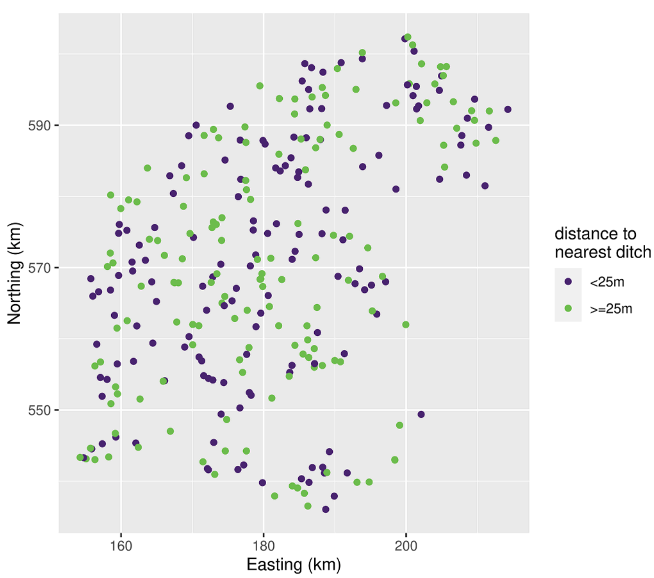

Fig. 5. Selected 296 borehole locations.

of $y_i - \widehat{\beta}_1 x_i$.

The accuracy of the estimated coefficients $\widehat{\beta}_0$ and $\widehat{\beta}_1$ is quantified by a nonparametric bootstrap of the residuals ϵ_i (Efron and Tibshirani, 1993). In this procedure a large number N_R of samples are taken with replacement from the Kaplan–Meier estimate of the empirical distribution of the residuals ϵ_i (Kaplan and Meier, 1958), to account for censored values of y_i and thus ϵ_i. In this study the number of samples N_R was set at 100. Each sample has size $n = 41$. Next, each of the N_R samples is added to the fitted values $\widehat{y}_i = \widehat{\beta}_0 + \widehat{\beta}_1 x_i$, resulting in N_R replications of y_i. Finally, N_R nonparametric regression models are fitted to each replication by the Akritas-Theil-Sen method, resulting in a distribution of N_R estimates of β_0 and β_1 reflecting the precision of the estimated regression coefficients.

3.6. Estimation of spatial distributions of WTD-characteristics for primary strata

For each primary stratum, spatial cumulative distribution functions of the WTD-characteristics MHW and MLW are estimated as follows:

1. Using the N_R estimates of the regression coefficients β_0 and β_1 and the well-timed WTD-observations in the 296 boreholes, N_R sets of estimates of MHW and MLW are made for the 296 borehole locations.
2. For each of the N_R sets of MHW (MLW) estimates N_S bootstrap samples are selected by random sampling with replacement, and using the relative areas of the tertiary strata as selection probabilities. In this study $N_S = 100$.
3. From each bootstrap sample a spatial cumulative distribution function of MHW (MLW) is calculated by Kaplan–Meier estimation (Kaplan and Meier, 1958), because MHW (MLW) can be censored. We don't have to take relative areas into account, as this has already been taken care of during the bootstrap (step 2).

This procedure results in $N_R \times N_S = 10,000$ spatial cumulative distribution functions (SCDF) of MHW and MLW per primary stratum, reflecting two sources of uncertainty. The first source of uncertainty arises from estimation errors in MHW (MLW) estimated by the regression procedure described in Subsection 3.5. The second source of uncertainty arises from the sampling error in the selection of the borehole locations, see Subsection 3.4.

Summary statistics are calculated from the 10,000 realisations of SCDF of MHW and MLW, and visualised in maps with the primary strata as map units. Summarizing statistics are for example the medians and interquartile ranges of MHWs (MLWs), and probabilities of exceedance of critical depths.

MHWs and MLWs can be classified as water table classes (WTCs), see A. The estimation of SCDF of WTCs is analogous to the procedure followed by MHW and MLW. For each of the N_S bootstrap realisations the probability is calculated that a WTC occurs in a primary stratum. It is assumed that MHW and MLW are not correlated within primary strata, which is justified by an exploratory analysis of the well-timed observations made in the boreholes.

4. Results

Fig. 6 shows the nonparametric linear regression models for the relationship between MHW (MLW) and WTDs observed at well-timed moments in the 41 observation wells. These models were applied in the estimation of SCDFs of MHWs (MLWs) in the primary strata, see Subsection 3.6.

Fig. 7 shows maps of the estimated median MHW and MLW. This map depicts the estimated depth that is exceeded in 50% of the primary stratum.

The spatial variation in MHW (MLW) within primary strata is shown by the estimated interquartile ranges in Fig. 8.

It should be noted that Fig. 7 and 8 reflect estimates only and do not inform about the associated uncertainty. The uncertainty is quantified by the $N_R \times N_S = 10,000$ bootstrap realisations, from which statistics can be derived that express uncertainty. For example, maps depicting probabilities of exceedance of some critical value of MHW or MLW can be constructed from the 10,000 bootstrap realisations. As an example, Fig. 9 shows a map with the probability of MHWs shallower than 30 cm. A probability equal to 1 means that the MHW is certainly shallower than 30 cm at any location within a map unit, whereas a probability equal to 0 means that the MHW is certainly deeper than 30 cm at any location within a map unit. A probability of 0.5 reflects the maximum uncertainty, which means that it is equally likely that the MHW is deeper than or within 30 cm for any point in the primary stratum. Probabilities such as in Fig. 9 can be translated into risks by multiplying them by effects.

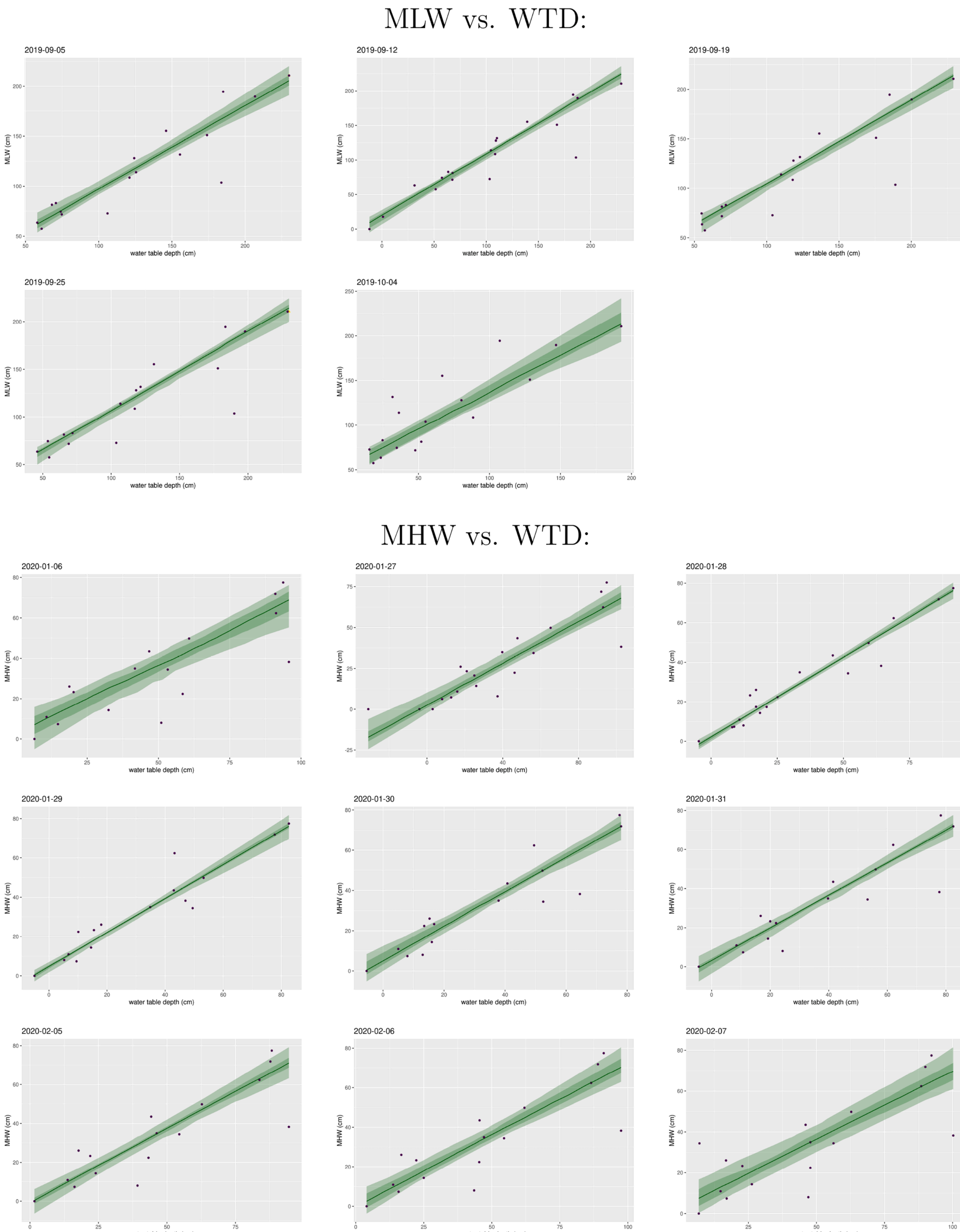

Fig. 6. Nonparametric linear regression models for the relationship between MHW (MLW) and WTD at well-timed moments in 41 observation wells (Fig. 4). Dark green: 50% confidence interval. Light green: 90% confidence interval.

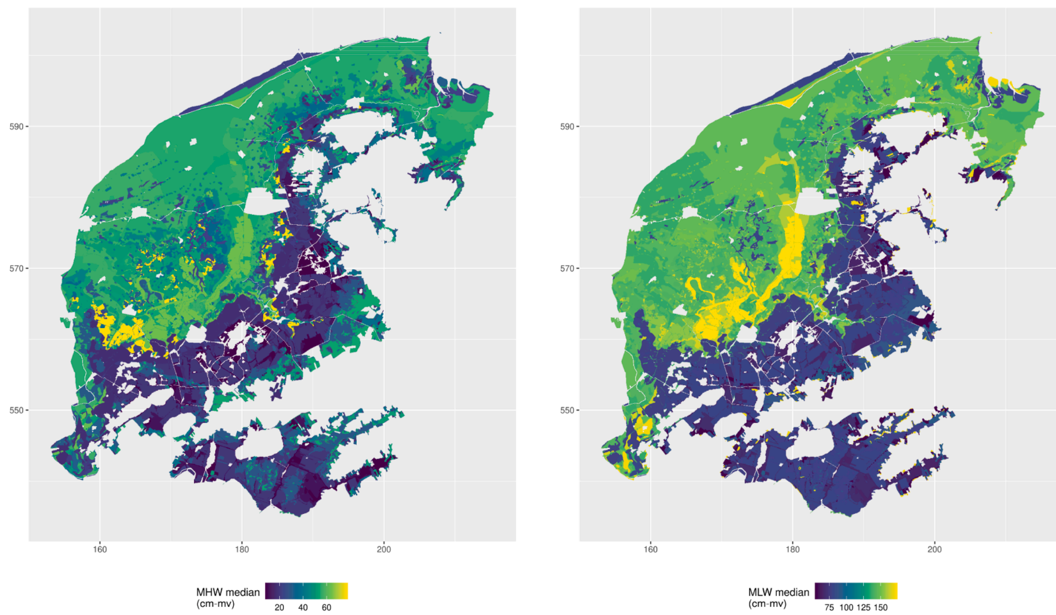

Fig. 7. Estimated median of MHW (left) and MLW.

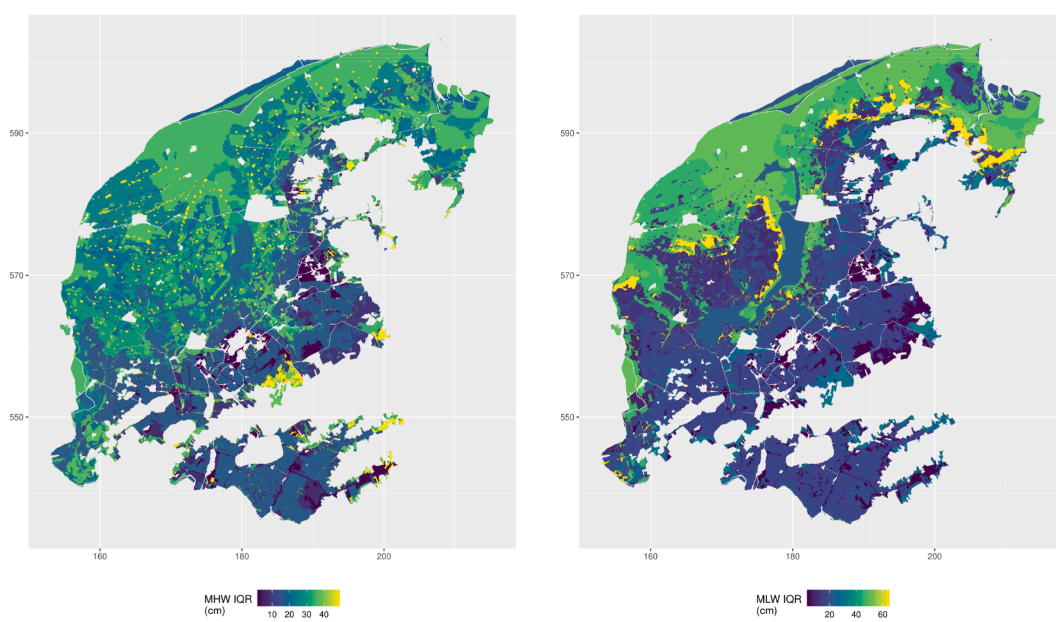

Fig. 8. Estimated interquartile ranges of MHW (left) and MLW.

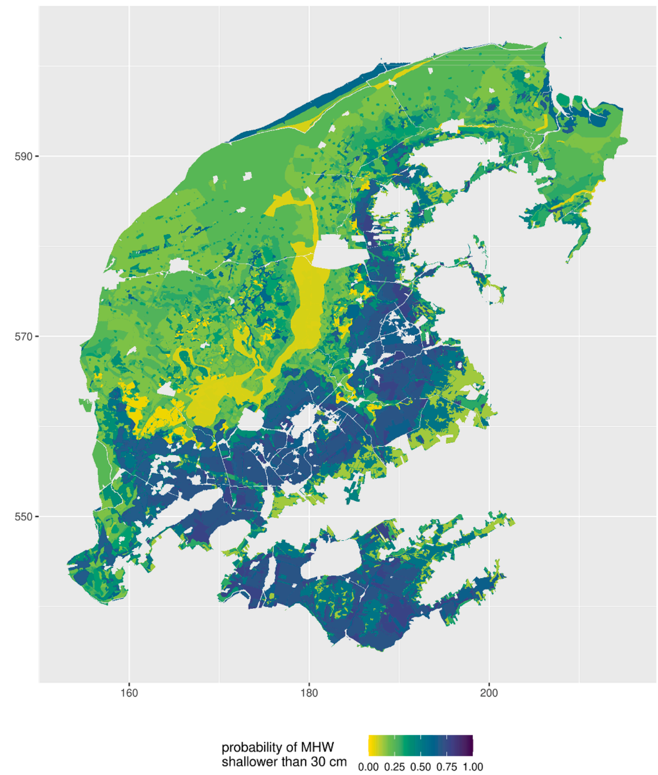

Fig. 9. Probabilities of MHW shallower than 30 cm in subareas of homogeneous drainage conditions (primary strata).

For instance, high probabilities of MHW < 30 cm in cropland areas can be translated into high risks of crop yield reductions because of wet soil conditions, whereas high probabilities of MHW > 30 cm in peat soils can be translated into high risk of soil subsidence due to oxidation of soil organic matter.

Fig. 10 shows the prevalent WTC and the variation in WTCs. The left map shows the mode, *i.e.*, the WTC that covers the largest part of a primary stratum. The right map shows the normalized Shannon's entropy, which represents the degree of heterogeneity. Zero entropy means the presence of only one WTC, whereas an entropy value of one means that all WTCs are equally present.

5. Discussion

The presented method not only has potential in mapping WTDs in 7–17% of the global land area (Fan et al., 2013), but could also be applied in mapping other soil properties. We discuss the results in light of spatial detail and objectivity. We compare mapping by probability sampling as presented in this paper with mapping based on geostatistical and physical modelling.

5.1. Spatial detail

The maps in Figs. 7–10 are basically choropleth maps, showing statistical data aggregated over predefined regions, *viz.* the primary strata based on homogeneous drainage conditions (Fig. 3). This is an important difference with high resolution raster maps depicting continuous fields of quantitative variables, resulting from geostatistical modelling (Knotters and Bierkens, 2001; Schumann and Zaman, 2003; Finke et al., 2004; Hoogland et al., 2010; Calzolari and Ungaro, 2012; Kaiser et al., 2012; Manzione et al., 2010; Manzione and Castrignanò, 2019), and physical modelling (Xiao et al., 2016). We refer to these maps briefly as 'raster maps' in the following. The difference between choropleth maps and raster maps is associated with the difference between global and local information, that follows from the questions "How much?" and "Where?", respectively, as discussed in Brus and de Gruijter (1997). High resolution raster maps answer the "Where?" question to a high extent since they answer the "How much?" question for small spatial units, *i.e.* raster cells. Choropleth maps answer the "How much?" question with global statistical data for predefined regions or strata. The extent to which a choropleth map provides an answer to the "Where?" question, depends on the spatial detail in the stratification. However, in answering the "Where?" question not only the level of spatial detail is important, but also the rationale behind the definition of spatial units. In this study balance was pursued between the level of spatial detail with which the "Where?" question can be answered, the accuracy of the map and fieldwork restrictions, resulting in a division into 26 primary strata. These were defined as regions with homogeneous drainage conditions, on the basis of the soil map and a map of water level management units. This stratification makes the map obviously more useful in water management than an arbitrary division into 26 contiguous geometric areas such as grid squares.

Since maps are viewed on digital screens rather than on paper, map users should be aware that the accuracy of the map does not change when zooming in or out. Furthermore, high spatial resolution does not

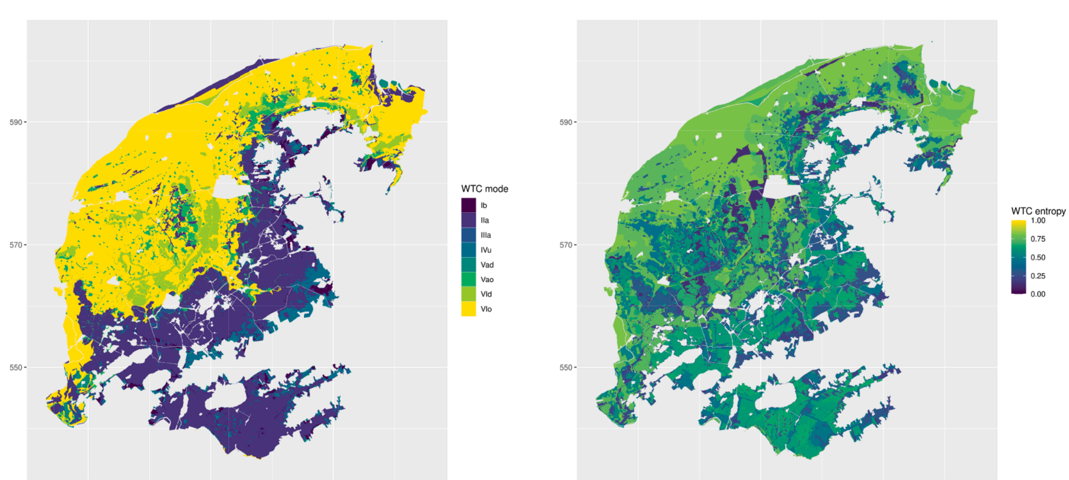

Fig. 10. Modus (left) and entropy of the water-table classes in subareas of homogeneous drainage conditions(primary strata).

necessarily mean a high accuracy of spatial predictions. The resolution of the choropleth maps in Figs. 7–10 is determined by the primary strata, which were chosen with the utilisation of the map in mind. If spatial distributions of continuous variables are visualised with raster maps in geographic information systems, then map users can make their own choice of resolution in property space, which may result in a bad balance between resolution and accuracy. High resolution might suggest high accuracy, particularly if best estimates are presented separately from the associated uncertainty measures like standard errors and prediction intervals, or if uncertainty is neglected at all. Bad balance between resolution and uncertainty can be prevented by integrating best estimates and uncertainty measures into a single map, *e.g.*, a map with probabilities of exceedance (Fig. 9). These probabilities of exceedance can be used as input in statistical models for decision making. Preferably the information on uncertainty used in decision making, *e.g.* calculated probabilities of exceedance, does not depend on subjective assumptions or judgements, see Subsection 5.2.

5.2. Objectivity

With objectivity we mean that the results do not depend on assumptions or judgements the validity of which cannot easily be verified. The first source of subjectivity is in the selection of the locations where observations are collected (the sampling locations). In stratified random sampling objectivity is realized by random selection of the sample locations within the strata and by accounting for the stratum weights in the estimation of WTD-characteristics. Note that regions in a stratum that are not part of the study area (like built-up area) are excluded from the random selection. In geostatistical modelling and physical modelling no restrictions need to be made on the selection of sampling locations. As Brus and de Gruijter (1997) mentioned subjective judgement on 'representativity' of sampling locations are allowed, and locations can be selected preferentially or by convenience in low or high grade zones.

The second source of subjectivity is in the models used in estimating WTD-characteristics. So-called design-based estimates that are based on probability sampling can be perfectly model-free. However, in this study the introduction of a model was unavoidable, because time series of WTDs were only available for a restricted set of observation wells, the locations of which were selected purposively. We assumed a linear relationship between MHW (MLW) and water table depth at well-timed moments (Eq. 1) when the WTD approximates the MHW (MLW). The validity of the linearity assumption can be verified from Fig. 6. As explained in Subsection 3.5 we implicitly assume that the seasonal fluctuation of WTD reaches its upper or lower bound at the same moment in the study area, which is reasonable in fast-reacting systems with shallow water tables.

As compared to geostatistical and physical mechanistic modelling, the role of model assumptions is limited in the presented method of mapping WTD-characteristics by probability sampling. Furthermore, the model assumptions could be verified easily. It should be noted that subjective assumptions and judgements not only affect best estimates, but also the quantitative information on uncertainty and hence outcomes of uncertainty analyses and risk assessments.

6. Some concluding remarks

Maps of WTD-characteristics that result from geostatistical or physical mechanistic modelling can be considered as models of the spatial variation of WTD-characteristics, the quality of which can be assessed by validation. Contrary to this, the maps based on probability sampling presented in this study can be considered as summaries of descriptive statistics that inform about spatial variation, and the quality of this information is implicitly quantified. This makes the maps based on probability sampling useful as benchmarks in quality assessments of geostatistical and physical mechanistic models.

In this study stratified simple random sampling was applied, with three levels of stratification. In future projects this sampling strategy can easily be adjusted to new conditions. For example, for areas with fields that are poorly accessible, a two-stage sampling strategy can be considered. The strategy can roughly be designed as follows: i) definition of primary strata as in this study, ii) random selection of fields within these primary strata, and iii) random selection of borehole locations within the selected fields.

An important reason for developing the presented method was that a large part of the spatial variation of WTD-characteristics in polder areas and wetlands occurs within ditch-dissected fields, and that this short-distance variation could not be mapped with geostatistical and physical mechanistic models against reasonable costs or with acceptable accuracy. The choropleth maps presented in this study might reflect less spatial detail than high resolution raster maps obtained by geostatistical and physical mechanistic modelling might reveal. However, map resolution should always balance map accuracy. This is not only true for WTD-maps, but for maps in general. A high resolution map with unknown but low accuracy may hamper decision making. In the presented method, the resolution is determined by the primary strata, which are defined with respect to use of the map in water management, and the accuracy is quantified for each map unit.

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.

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Appendix A. Water-table classes

Table 1.

Table 1
Water-table classes. MHW: mean highest water-table. MLW: mean lowest water-table. Depths in cm below ground surface.

Water-table class	MHW	MLW
Ia	< 25	< 50
Ib	> 25	< 50
IIa	< 25	50 –80
IIb	25 –40	50 –80
IIc	> 40	50 –80
IIIa	< 25	80 –120
IIIb	25 –40	80 –120
IVu	40 –80	80 –120
IVc	> 80	80 –120
Vao	< 25	120 –180
Vad	< 25	> 180
Vbo	25 –40	120 –180
Vbd	25 –40	> 180
VIo	40 –80	120 –180
VId	40 –80	> 180
VIIo	80 –140	120 –180
VIId	80 –140	> 180
VIIIo	> 140	120 –180
VIIId	> 140	> 180

Appendix B. Observed time series and estimated MHW's and MLW's

Fig. B.11.

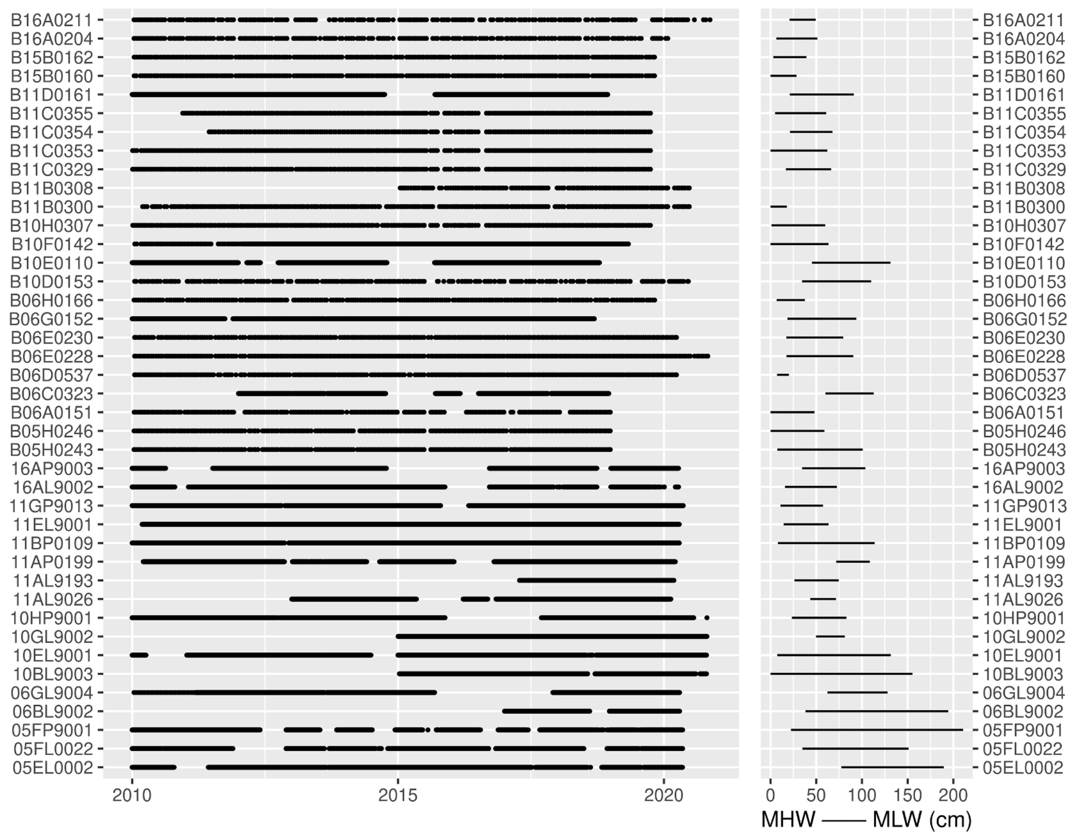

Fig. B.11. Details of the time series, observed in 41 wells. The dot plot depicts the distribution of the observations in time for each well. The line plot depicts the mean highest (shallowest) and mean lowest (deepest) water table (MHW and MLW, respectively) that were calculated from each time series.

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