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Predicting and mapping productivity of short rotation willow plantations in Sweden based on climatic data using a non-parametric method

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ABSTRACT

In this study, estimates for yield of short rotation plantations are provided based on climatic variables using the *k* nearest neighbour method. The calculations were based on climatic data and yield records from 1790 willow plantations in central and southern Sweden, divided into three categories based on local performance. The chosen neighbours were weighted proportionally to the inverse squared distance measured in the feature space defined by the climatic variables. The climatic variables included monthly averages of maximum, minimum and mean temperatures and precipitation. These were weighted using empirical constants after an optimisation process. The best accuracy was obtained with $k = 4$ for the group of high performance plantations, and $k = 5$ for the other groups. The relative RMSE values were 37.9%, 24.4% and 38.9% for the high, medium and low local performance, respectively, and the corresponding relative biases were 2.10%, −0.95% and −1.30%. The method was applied to interpolate the yield values in order to perform maps of potential productivity for the whole area. The results of this approach indicate that it can provide faster and more accurate predictions than previous modelling approaches, and can offer interesting approaches in the field of yield modelling.

1. Introduction

Updated information regarding productivity, as well as potential yield, is fundamental for wood fuel supply chains based on short rotation plantations. Estimates of productivity are needed for numerous reasons including, predicting wood fuel supply, for harvest scheduling, and for the logistics and management of the fuels, as well as in the decisions associated with the location and establishment of future plantations and power plants.

Willow plantations for bioenergy are already at the commercial stage in Sweden, where about 16 000 ha have been established for bioenergy purposes, following a quick spread during the 1990s (Larsson and Lindegaard, 2003; Mola-Yudego and González-Olabarria, 2010). These plantations are grown on agricultural land, using a double row system with densities varying between 10 000 and 20 000 cuttings ha^{-1}. The expected lifespan of a plantation is considered to be about 25 years, and the same plantation can be harvested several times, with cycles around 4 years (Ledin and Willebrand, 1996). In general, the first cutting cycle is less productive than the latter ones, although high initial yields are an indicator of good establishment, which will result in higher yields during the remaining cycles (Mola-Yudego and Aronsson, 2008).

Excluding management practices, temperature and precipitation have been considered the most important factors for the growth of willow plantations (Perttu, 1999), and several initial studies have modelled the yields in Sweden based on climatic variables (e.g. Nilson and Eckersten, 1983). Lindroth and Båth (1999) proposed a model to calculate plantations yield as a linear function of precipitation during the growing season. The model was validated using experimental plots and commercial plantations. The results of the model provided maps of potential productivity for central and southern Sweden. However, one disadvantage of this approach was that the models systematically resulted in higher yields expectations than shown by empirical measurements based on commercial plantations (Mola-Yudego and Aronsson, 2008; Mola-Yudego, 2010).

The traditional methods to predict willow productivity have been based on regression models, where yield is predicted as a function of different parameters associated, for instance, to climate and soil. An alternative to this approach is the use of on non-parametric methods, where yield can be predicted as a weighted average of the yield of real plots measured in climatically similar locations (so-called most similar neighbour). As the nearest neighbours (NN) are chosen from a database of previously measured data, unrealistic yield estimates cannot occur. Furthermore, in non-parametric methods localisation can be made more efficiently than in regression models, resulting in more accurate maps of productivity. In addition, non-parametric methods retain the original variation of

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the data, preserve the correlations of dependent variables and do not require predefined functional forms. One of the main disadvantages is that non-parametric methods cannot predict without reference data, and thus cannot be applied in areas where there are not enough plantations. On the other hand, when the method has been applied to produce estimates, these can be easily updated once new data is added to the dataset.

The aim of this study is to use non-parametric methods to provide accurate estimates of yields for short rotation willow plantations, based on climate data. The results of this approach can aid, among others, the policy and economic considerations associated with short rotation plantations, as well as their future development.

2. Materials and methods

2.1. Origin of data

The field measurements from the willow plantations were provided by Lantmännen Agroenergi AB. The dataset used in the calculations was based on harvesting records from the first rotation of 1790 willow plantations in central and south Sweden. Data with inconsistent records (e.g. missing digits in the coordinates) or lacking information regarding the area planted or the location were excluded from the calculations. All plots were geo-referenced to a 1 km precision. The average yield was calculated by dividing the total harvested biomass by area planted and the number of years of the cutting cycle. The plantations were cut after the first growing season after planting in order to promote sprouting. The data used included 7753 ha planted during the period 1986–2005 in the area defined from 55°20′N to 61°29′N and from 11°33′E to 18°56′E (Fig. 1). The average size of the plantations was 4.3 ha (std dev: 4.2 ha).

The climatic data were based on the climate layers calculated for Sweden (WorldClim database Version 1.4). These data consist of a set of grid maps resulting from an interpolation process of temperature and precipitation averages (Hijmans et al., 2005), based on the reference period 1960–1990, in order to assess the average climatic conditions of the area.

The maps used in this study had a 30-s spatial resolution (which provides ~1 km precision). In order to link the climatic variables with the ground data, the maps were projected from the originally projected datum into the same coordinate system as the yield data (UTM, zone 33N). The precision of the interpolated climatic variables was 0.1 °C for temperature and 1 mm for precipitation. The monthly averages of maximum, mean, minimum temperatures, and precipitation (referred as *Tmax*, *Tmean*, *Tmin* and *P*, respectively) were obtained for each plantation.

2.2. Methods

Due to the high variability of the yields resulting from different management practices (Mola-Yudego and Aronsson, 2008), the plantations were classified according to their local performance, using municipalities as a unit of analysis. For each municipality, the plantations were ranked according to their measured yields, and then grouped in three categories of equal number of plantations (3 tiles). This resulted in three categories with enough records to perform the k-NN analysis. The categories were described as: low performance, medium performance and high performance (Table 1), with significant differences in their resulting yields (ANOVA, $p < 0.05$ between categories).

The working assumption was that high performance corresponded to intensive management, whereas low performance corresponded to minimum tending of the plantations. This assumption was based on previous work in this area (Mola-Yudego, 2009).

Table 1
Mean, standard deviation and number of willow plantations included in the performance groups used in the analysis. The plantations were first aggregated by municipalities, and then divided in three categories of equal number of plantations, according to their annual yield performance (odt ha^{-1} year).

Group	Mean	*N*	Std. deviation
Low	1.23	578	0.67
Medium	2.47	620	0.95
High	4.73	592	2.45

The initial hypothesis was that climatic variables would have a stronger effect on the medium performance plantations as the variability due to management would be lower.

The predicted variable was the mean annual growth per hectare, expressed as oven dry tonnes per hectare and year (odt ha^{-1} year^{-1}), and was estimated using the k-NN method (see Kilkki and Päivinen, 1987; Muinonen and Tokola, 1990; Tompo, 1990; Tokola et al., 1996). According to this, the variables from a specific pixel are predicted as a weighted average to the spectrally closest reference plots which are defined as nearest neighbours. In this study, the feature spectrum is defined by a vector of climatic variables, and the reference plots are the willow plantations. The chosen neighbours were weighted proportionally to the inverse-squared distance measured in the feature space defined by the climatic layers.

$$yield_p = \sum_{j=1}^{k} w_{pj} \cdot yield_{pj} \tag{1}$$

the weights being:

$$w_{pj} = \frac{1/d_{pj}^2}{\sum_{i=1}^{k} 1/d_{pj}^2} \tag{2}$$

where $yield_p$ is the mean annual biomass production per hectare for pixel p, $yield_{pj}$ is the measured mean annual biomass production per hectare of plantation j, and d_{pj} is the spectral Euclidean distance from pixel p to plantation j, which is defined as:

$$d_{pj} = \sqrt{\sum_{h=1}^{nc} (p_h \cdot (b_{ph} - b_{jh}))^2} \tag{3}$$

where nc are the number of climatic layers or variables used in the modelling, b_{pj} is the spectral value of pixel i on climatic band h, and p_h is an empirical constant for band h.

The empirical constants defined as p_h were used to weight the spectral importance of the climatic bands to improve the predictions and the interpretation results. The parameters were optimised using the Amoeba algorithm as described in Press et al. (1988), which is one implementation of the Nelder–Mead algorithm (1965). Different starting points were tested and evaluated in order to avoid local optima.

Different numbers and combinations of the climatic predictors defined (i.e. monthly averages of maximum, mean, minimum temperatures, and precipitation) were used. The predictors were chosen in order to show the influence of climatic characteristics on the yield performance of the plantations based on existing literature, and resulting in a minimal bias and RMSE. The combinations of predictors were also chosen so as to avoid excessive multicorrelation. Climatic variables resulting in empirical constants p close to 0 were also excluded. In addition, different values of k were used with all combinations of climatic predictors.

The performance of the method was evaluated qualitatively by examining the magnitude and distribution of the residuals for all variables, aiming at detecting obvious dependencies or patterns

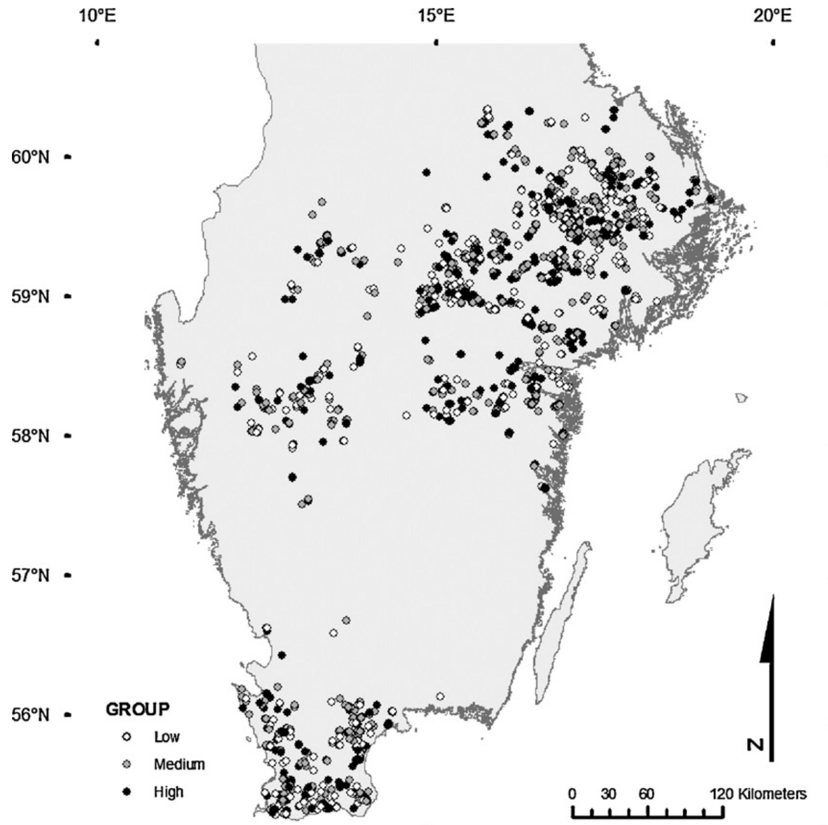

Fig. 1. Distribution of the commercial willow plantations ($N = 1790$) in Sweden included in the calculations. The groups correspond to the local performance of the plantations, at municipality level.

that indicate systematic discrepancies. The estimation accuracy of the predictions was evaluated by calculating the absolute and relative biases and root mean square errors (RMSEs) as follows:

$$bias = \frac{\sum(y_i - \hat{y}_i)}{n} \quad (4)$$

$$bias\% = 100 \times \frac{\sum(y_i - \hat{y}_i)/n}{\sum \hat{y}_i/n} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}} \quad (6)$$

$$RMSE\% = 100 \times \frac{\sqrt{\sum(y_i - \hat{y}_i)^2/n}}{\sum \hat{y}_i/n} \quad (7)$$

where n is the number of observations, and y_i and $\hat{y}_i$ are observed and predicted values. The significance of the overall bias was examined using a t-test. In addition, the spatial distribution of the residuals was analysed in order to detect possible geographical patterns, based on the Moran's I (Moran, 1950).

Finally, after the evaluation of the different combinations of parameters, prediction maps were produced for south and central Sweden. The predictions were restricted to those areas defined as agricultural land using the Corine 2000 classification for Sweden (EEA, 2000), 250 m resolution.

3. Results

The final model includes six climatic variables (Table 2). *Psum* was constructed by aggregating the precipitation for the months May to September. Some correlations between the predictors could not be avoided (Table 3). The variance inflation factors were in all cases below 5, being the highest 2.99, corresponding to *Tmax* Feb and *Tmin* Oct.

The use of nearest neighbours increased the accuracy of the predictions, whereas the relative bias did not present a clear pattern (Fig. 2). The final estimations were done using $k = 5$ for the groups of medium and low performance, and $k = 4$ for the group of high performance.

The weights of the climatic bands resulting from the optimisation method vary from 7% to 27% (Fig. 3). The variability due to the

Table 2
Mean, standard deviation and range of the willow yield data obtained and the variables used in the calculations.

	N	Minimum	Maximum	Mean	Std. deviation
Tmax Feb	1790	−2.1	3.1	0.11	1.23
Tmax Jul	1790	19.3	22.4	21.22	0.78
Tmax Aug	1790	18.6	20.6	19.91	0.30
Tmin Oct	1790	1.4	7	4.49	1.19
Tmean May	1790	8.7	11.3	10.31	0.36
Psum (mm)	1790	255	302	270.50	8.06
Yield (odt ha^{-1} year^{-1})	1790	0.03	30.29	2.8	2.1

The temperatures are expressed in Celsius degrees. Yield: average annual yield of willow plantations.

Table 3
Pearson correlation coefficients for the climatic bands used in the analysis.

	Tmax Feb	*Tmax* Jul	*Tmax* Aug	*Tmin* Oct	*Tmean* May	*Psum*
Tmax Feb	1.00					
Tmax Jul	−0.57	1.00				
Tmax Aug	−0.02	0.67	1.00			
Tmin Oct	0.82	−0.74	−0.09	1.00		
Tmean May	0.75	−0.10	0.42	0.61	1.00	
Psum	0.15	−0.17	−0.41	−0.16	0.03	1.00

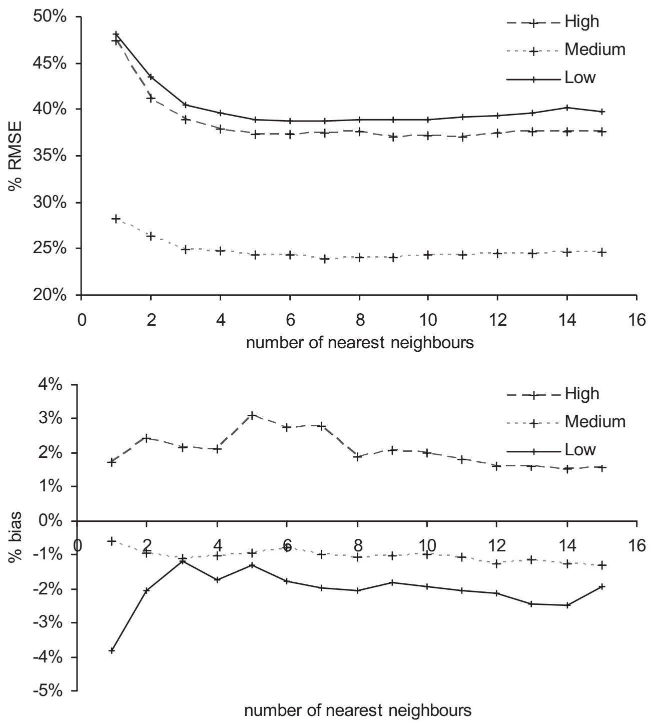

Fig. 2. Relative RMSE and bias for yield estimation for short rotation willow plantations for the high, medium and low local performance.

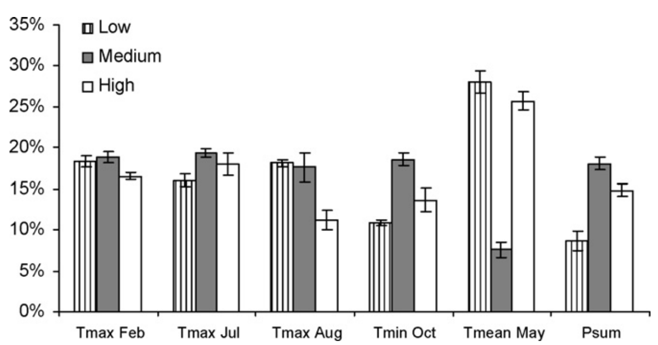

Fig. 3. Average weights of the bands for 1–10 starting points, used in the estimations for the low, medium and high local performance. The nearest neighbours used were 5, 5 and 4, for the groups low, medium and high, respectively.

use of different starting points was small. No optimisation cycle resulted in values close to 0, for any of the bands included.

The overall performance of the predictions was better for the medium and low productivity plantations. The coefficient of determination was of 0.50, 0.60, and 0.27 for the high, medium and low performance groups (Fig. 4), respectively. In general, the method failed to predict the highest yields of the best performance group, especially above 10 odt ha^{-1} year^{-1}.

The overall bias of the estimates was not significant (Table 4). In addition, the bias was examined by plotting the residuals as a function of the predictors (Fig. 5). No obvious dependencies or patterns that indicate systematic trends among the residuals and the independent variables were found in the predictions of the group of low and medium performance. On the other hand, some discrepancies were found in the high performance group, particularly in the predictions for the highest yields and for the *Tmax* in August, resulting in a higher overall bias. The amount of those biases was, however, low. The relative RMSE was similar for the groups of low and high performance.

Results of the Moran's *I* statistic indicated that there was no overall spatial autocorrelation in the residues of none of the three groups (Fig. 6).

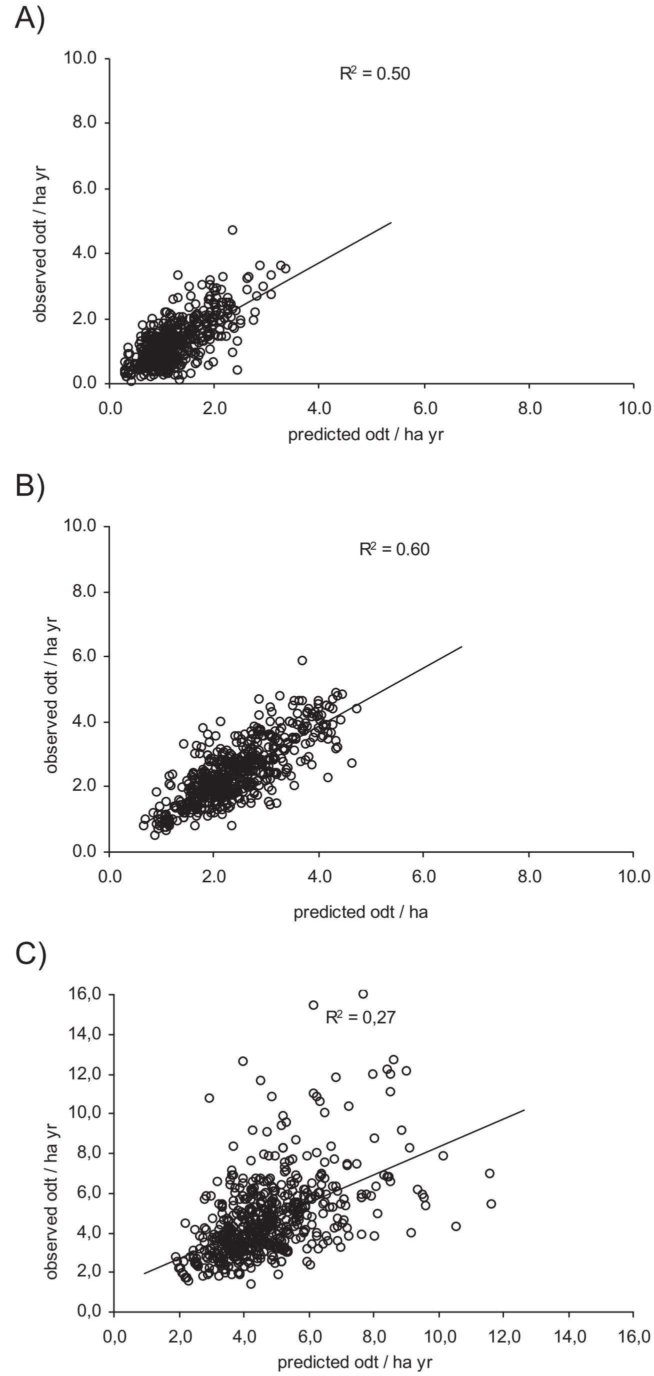

Fig. 4. Measured and predicted yield for willow plantations, according to the method proposed, for the (A) low, (B) medium and (C) high local performance, using 5, 5 and 4 nearest neighbours, respectively.

Table 4
Estimations of absolute and relative bias and RMSE, and coefficient of determination (R^2) of the predictions, for every group of plantations.

	N	Bias	*t*-Test	%bias	RMSE	%RMSE	R^2
Low	578	−0.0158	0.424	−1.30%	0.47	38.93%	0.50
Medium	620	−0.0233	0.330	−0.95%	0.60	24.39%	0.60
High	592	0.0991	0.176	2.10%	1.79	37.85%	0.27

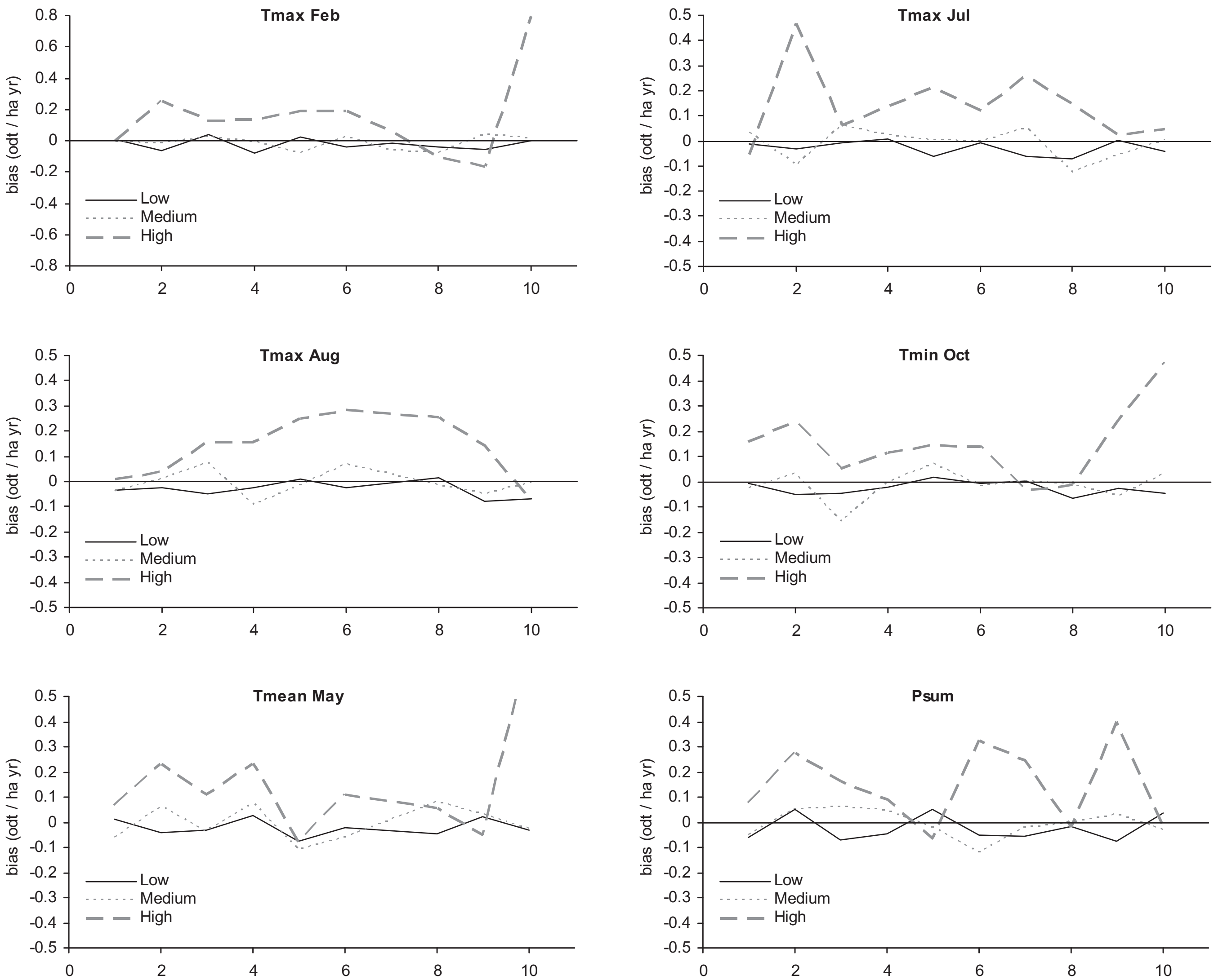

Fig. 5. Estimated mean residuals (bias) of the predictions as a function of the climatic bands used in the predictions for the three groups considered (low, medium and high local performance). The values have been grouped in 10 tiles of equal number of observations. *Psum*: Aggregated precipitation for the period May–September.

The resulting parameters were used to calculate productivity maps for central and south Sweden (Fig. 7). According to the estimates for the high performing group, around 100 000 ha would have estimated yields above 8 odt ha^{-1} $year^{-1}$, and 7900 ha would have yields above 10 odt ha^{-1} $year^{-1}$ (Fig. 8). Estimates for the medium group show 1 595 400 ha above 4 odt ha^{-1} $year^{-1}$, and 129 000 ha above 5 odt ha^{-1} $year^{-1}$, corresponding to 60% and 5% of the total agricultural land considered, respectively.

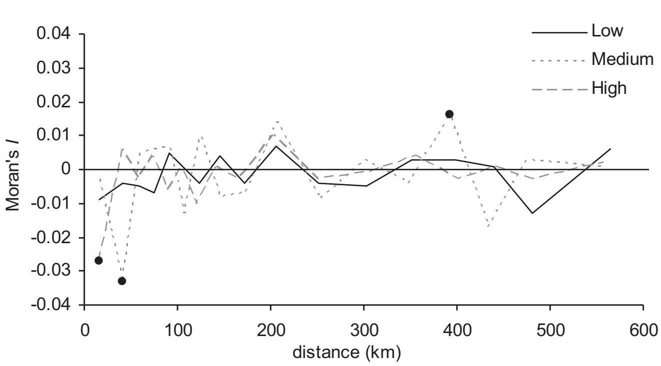

Fig. 6. Moran's I for spatial autocorrelation of the residues. Marked values showed significance autocorrelation ($p < 0.05$).

4. Discussion

This study presents estimations of biomass productivity from willow plantations in Sweden, based on harvest records from 1790 plantations for the period 1989–2005, using a *k*-NN based method. The large amount of data available allowed the inclusion in the models of almost 60% of the whole area planted with willow for bioenergy in Sweden, which enhances the reliability of the estimates. In addition, the records used in the calculations were based on harvested biomass, which have taken into account harvesting losses thereby providing more realistic information.

In general, different applications of the *k*-NN approach have been developed in forestry for different purposes during the recent years, oriented to, for example, forest inventory for the estimations of stand characteristics based on remote sensing imagery (Katila and Tomppo, 2001; McRoberts et al., 2007) or individual tree growth (Sironen, 2009). In Sweden, some applications in bioenergy have been developed, in order to get estimates of local assessments of forest fuels (Bååth et al., 2002). The *k*-NN is a highly computa-

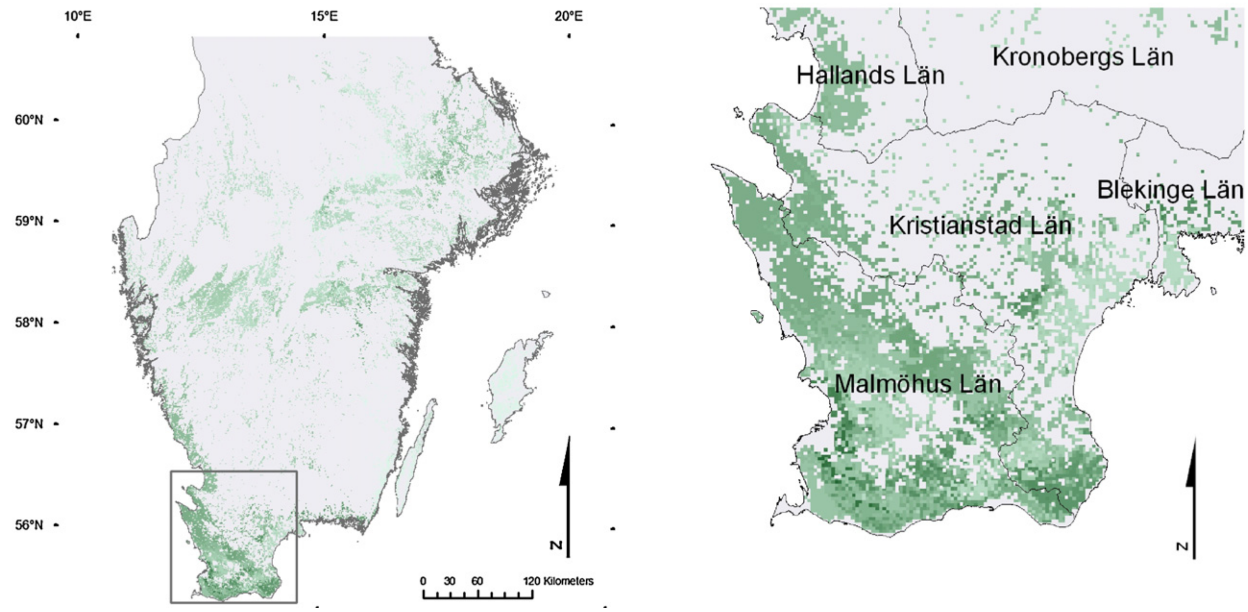

Fig. 7. Resulting yield estimates for willow plantations in the agricultural areas of central and south Sweden (left), and detailed for the counties of Malmöhus and Kristianstad (right). Darker colours indicate high productivity areas, according to the methodology applied. The estimates are based on high performance plantations (k = 4 nearest neighbours, Euclidean distance). The ranges are min 2 odt ha^{-1} year^{-1}, max 16 odt ha^{-1} year^{-1}.

tion demanding method the development of which is related to the recent improvement of computers.

The results of the analysis show that the application of the k-NN method to geographically dependent factors such as climatic variables can provide good estimates and can be used for the spatialisation of the productivity of plantations, with higher accuracy than previous models (Mola-Yudego and Aronsson, 2008). In general, temperature and precipitation are key parameters in order to explain willow productivity (Perttu, 1999; Lindroth and Båth, 1999). For instance, *Salix viminalis* clones are resistant to low temperatures during the winter, but at the same time, are very vulnerable to frost during the growing season. Usually cannot stand temperatures lower than −2 or −4 °C (Fircks, 1994) and in previous studies regarding performance of commercial willow plantations, the minimum temperatures in October proved to have a significant effect on biomass production (Tahvanainen and Rytkönen, 1999).

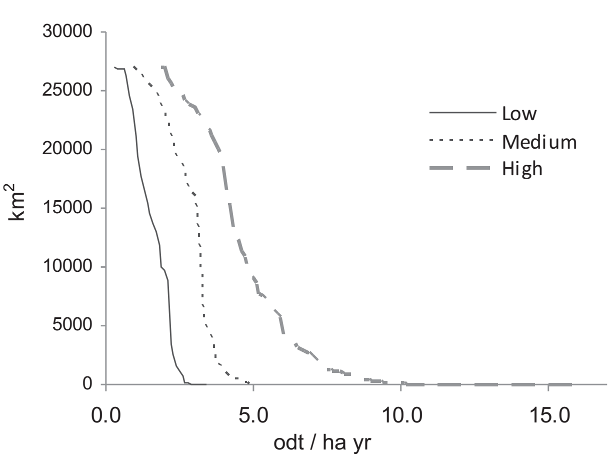

Fig. 8. Areas and productivity of short rotation willow plantations on agricultural land in south and central Sweden. The areas are presented aggregated under different productivity values, for the low, medium and high performance groups, according to the estimations.

The method, however, does not take into account factors, such as management, affecting the productivity with no spatial component. In fact, management is a key factor in willow productivity, as has been observed in previous studies (a review can be found in: Tahvanainen, 2004). In order to reduce the effect of these management practices and to homogenise the data, the plantations were divided into groups according to their local performance. The results show that this division enhances the effect of the climatic variables, although still different management practices can account for a significant part of the variability not explained.

The predictions for the group with high production were less accurate and seem to underestimate the plantations yield. This group included plantations with a more intensive management, and thus the variability due to these practices is proportionally higher than the effect of climate and location. This could also explain the biases in the predictions. In addition, the climatic conditions seem to moderately affect the performance of plantations properly tended and intensively managed, as possibly the use of adequate clones, together with proper irrigation, fertilisation and weeding, greatly reduces the effects of early frosts and water restrictions. Analogously, the lower accuracy of the low performance group versus the medium group could be explained as a result of the variability due to poor management practices.

Concerning the variability not explained by the method, it could be attributed to different management practices, as well as to specific variations of temperature and precipitation during the years prior to the harvest. Additionally, the overall performance of the predictions could be improved in future studies by including additional variables related to ground-water availability and soil conditions. Previous studies, however, have shown smaller effects of soil properties when compared to the effects of temperature and precipitation (Tahvanainen and Rytkönen, 1999). In addition, the availability of soil maps with a good level of definition can be more limited than the climatic data.

Variables with no spatial effect (such as management practices, which highly depend on the farmer, independently of the location) tend to have weights close to 0 after the optimisation process. This was one of the criteria in the process of selecting the variables. However, the weights of the bands are influenced by the starting points, since the optimisation can find local optima rather than global optima. The results for different optimisations based on arbitrarily chosen starting points have shown little variation in the weights of the climatic bands and in the overall performance of the predictions. On the other hand, different tests made during the application of the method revealed that outliers seem to have a stronger effect in the allocation of the weights of the bands, which is of particular importance in the group of high performance. These overall effects as well as the potential applications of using the weights of the bands as a valid parameter for interpretation of the spatial effects of the variables must be subject of further research.

One of the limitations of the method is that the predictions cannot be directly extrapolated to other areas out of the range of data, unless there is enough data to calibrate the new estimates. In general, estimations based on non parametric methods, such the *k*-NN method, require a large number of plots: e.g. Katila and Tomppo (2001) recommend at least between 400 and 600 plots for applications of similar *k*-NN methods using Landsat and based on the Finnish forest inventory. However, the new development of energy plantation programmes in other countries will potentially offer the necessary data to apply this methodology.

The future development of short rotation plantations will require fast estimations of productivity, calibrated to local conditions, in order to assist the energy planning needs of the bioenergy sector. The application of non-parametric methods to climatic data offers excellent tools to develop fast and accurate estimations of potential productivity. The method presented can be applied to develop site index models in new areas once there is enough data available to have accurate estimations. In addition, the method offers the possibility to calibrate the estimations in parallel to, for instance, incorporate the effects of new varieties with higher productivity. Also, the possibilities of improving the predictions by adding new variables must be explored. Finally, the application of similar approaches in plantations of other forest species (e.g. *Eucalyptus*) or to perform site indices for forest stands should be explored in the future.

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References

Bååth, H., Gällerspång, A., Hallsby, G., Lundström, A., Löfgren, P., Nilsson, M., Ståhl, G., 2002. Remote sensing, field survey, and long-term forecasting: an efficient combination for local assessments of forest fuels. Biomass and Bioenergy 22 (3), 145–157.

EEA (European Environment Agency), 2000. Environment Image & Corine Land Cover 2000 for Sweden. 250 m. Available from: http://dataservice.eea.eu.int/dataservice/ (accessed 11/05).

Fircks von, H.A., 1994. Frost hardiness and risk of damage in Salix plantations. Harvesting Techniques for Energy Forestry, vol. 14. Swedish University of Agricultural Sciences, Uppsala.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25, 1965–1978.

Katila, M., Tomppo, E., 2001. Selecting estimation parameters for the Finnish multisource National Forest Inventory. Remote Sensing of Environment 76 (1), 16–32.

Kilkki, P., Päivinen, R., 1987. Reference sample plots to combine field measurements and satellite data in forest inventory. In: Remote Sensing-aided Forest Inventory. Seminars Organized by SNS and Forest Mensurationist Club, Hyytiälä, Finland, December 10–12, 1996 , University of Helsinki, Department of Forest Mensuration and Management, pp. 209–215, Research Notes 19.

Larsson, S., Lindegaard, K., 2003. Full Scale Implementation of Short Rotation Willow Coppice, SRC, in Sweden. Agrobränsle AB, Örebro, Sweden.

Ledin, S., Willebrand, E., 1996. Handbook on How to Grow Short Rotation Forests. Swedish University of Agricultural Sciences, Department of Short Rotation Forestry, Sweden.

Lindroth, A., Båth, A., 1999. Assessment of regional willow coppice yield in Sweden on basis of water availability. Forest Ecology and Management 121, 57–65.

McRoberts, R.E., Tomppo, E.O., Finley, A.O., Heikkinen, J., 2007. Estimating areal means and variances of forest attributes using the k-nearest neighbors technique and satellite imagery. Remote Sensing of Environment 111 (4), 466–480.

Mola-Yudego, B., Aronsson, P., 2008. Yield models from commercial willow plantations in Sweden. Biomass and Bioenergy 32, 829–837.

Mola-Yudego, B., González-Olabarria, J., 2010. Mapping the expansion and distribution of willow plantations for bioenergy in Sweden: lessons to be learned about the spread of energy crops. Biomass and Bioenergy 34 (4), 442–448.

Mola-Yudego, B., 2009. Wood biomass production potential on agricultural lands in Northern Europe—achieving the goals of energy policy. Dissertationes Forestales, 84.

Mola-Yudego, B., 2010. Regional potential yields of short rotation willow plantations on agricultural land in Northern Europe. Silva Fennica 44 (1), 63–76.

Moran, P.A.P., 1950. A test for the serial independence of residuals. Biometrika 37, 178–181.

Muinonen, E., Tokola, T., 1990. An application of remote sensing for communal forest inventory. In: The Usability of Remote Sensing for Forest Inventory and Planning. Proceedings from SNS/IUFRO Workshop. Remote Sensing Laboratory, Umeå, Sweden, Report 4, pp. 35–42.

Nelder, J.A., Mead, R., 1965. A simplex method for function minimization. Computer Journal 7, 391–398.

Nilson, L.J., Eckersten, H., 1983. Willow production as a function of radiation and temperature. Agricultural Meteorology 30, 49–57.

Perttu, K., 1999. Environmental and hygienic aspects of willow coppice in Sweden. Biomass and Bioenergy 16 (4), 291–297.

Press, W.H., Flannery, B.P., Teukolsky, S.A., Vetterling, W.T., 1988. Numerical Recipes in C: The Art of Scientific Computing. Cambridge University Press, Cambridge.

Sironen, S., 2009. Estimating individual tree growth using non-parametric methods. Dissertationes Forestales, 94.

Tahvanainen, L., Rytkönen, V.-M., 1999. Biomass production of *Salix viminalis* in southern Finland and the effect of soil properties and climate conditions on its production and survival. Biomass and Bioenergy 16, 103–117.

Tahvanainen, L., 2004. Wood biomass production in Finnish farms during the EU-membership: environmental and economic approach. Academic dissertation. Faculty of Forestry, University of Joensuu.

Tokola, T., Pitkänen, J., Partinen, S., Muinonen, E., 1996. Point accuracy of a non-parametric method in estimation of forest characteristics with different satellite materials. International Journal of Remote Sensing 17, 2333–2351.

Tompo, E., 1990. Designing a satellite image-aided national forest survey in Finland. In: The Usability of Remote Sensing from Forest Inventory and Planning. Proceedings from SNS/IUFRO Workshop in Umea, February 26–28, 1990. Swedish University of Agricultural Sciences, Remote Sensing Laboratory, Report 4, pp. 43–47.