Improving the use of artificial neural networks for site-specific nitrogen fertilization

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Abstract. *For the planning of site-specific nitrogen fertilization, adequate decision rules are needed. Prerequisite for site specific nitrogen fertilization is the site specific forecast of yield. For this the use of artificial neural networks (ANN) has proven particularly interesting. Therefore, ANN based small-scale yield forecasts are realized in order to deviate the economic optimum of fertilization. The basis of yield forecasts with ANN are different site-specific input variables that have presumable impact on yield expectation. These input variables for instance could be recorded yield, electrical conductivity, relief (e.g. topographic wetness index (TWI)), draft force resistance, vegetation indices like red edge inflection point (REIP), previous fertilizer applications and so on. In many years the economic advantage of using ANN for nitrogen fertilization is approved. The results are largely promising, but not sustainable in every case. The data survey for the training set underlies natural disturbance. So the accuracy of small-scale yield forecasts varies considerably from year to year. Also direct impact like unreliable yield or electric conductivity recording influences the quality of input data. To improve the quality of results, it may be necessary to manipulate existing input and target variables. It has to be tested whether a classification of the input and target variables, in comparison to the metric scaled input and target variables, offer improvement in accuracy. Therefore, different classification systems are examined in this study. Equal intervals as a classical scheme are tested at first by varying the width of intervals. A further focus lies on quantile classification and at least on a standard deviation classification scheme. Initial studies implementing ANN with focus on soil parameters actually show positive effects, regarding to classification. The paper provides information on the extent to which improvements in the small-scale yield forecast results occur and whether the results found can be generalized. The results found in this paper are essential for further work with ANN in site-specific nitrogen application.*

Keywords. *Precision Farming, Knowledge Discovery in Databases, Artificial Neural Networks, Nitrogen fertilization, Big Data, Data Mining and Deep Learning.*

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Introduction

Precision farming includes a wide range of technology targeting a more precise agricultural production. These technologies have different acceptance in agricultural practice. While adoption rates of seed genetics and precision steering have exceeded 50 percent in several geographic markets, grower adoption of site-specific seed and fertilizer management continues to lag behind. As O'CONNOR (2018) describes, the reasons are quiet simple: Genetically improvements or precise steering technology have more visible and compelling value. Also WEIGERT (2006) elucidated a constant increase of installed systems for yield mapping, but only a weak implementation in the management process. The assumption is that farmers could not achieve economic benefits from this technology.

In the economic year 2015/2016 1,44 billion euros were spent on nitrogen (N) fertilizers only in Germany. Expenditures on potash came on second place with only 268 million €, followed by phosphate fertilizers with 252 million € and lime with 245 million € (STATISTISCHES BUNDESAMT, n.d.). Thus nitrogen accounts by far for most of the fertilizer expenses in German agriculture. Further the thematic is not only relevant from an economic standpoint, but also in questions of environmental impact. According to data of the FAO (2017) worldwide fertilizer application will steadily grow in the next years. O'CONNOR (2018) mentioned that oxygen depletion triggered by excessive nitrogen and phosphorus levels, primarily caused by fertilizer runoff, is becoming a serious problem in several major waterways. "The U.S. National Academy of Engineering has listed "Managing the Nitrogen Cycle" as one of its 14 grand engineering challenges for de 21st century", so O'CONNOR (2018). Politicians in the European Union and Germany recognized the problem and reacted with stricter laws. In 2017 the new German ordinance of fertilization was realized and pretend a legal limit for fertilization (DÜV, 2017). This is a third point why farmers are forced to use their resources even more sparingly and efficiently in the future.

Site-specific management generates enormous amounts of very cost-efficient data. In a sense that farmers could benefit from these data, the application of data mining techniques in precision agriculture could prove to be a viable tool. WAGNER (2012) proves in many field trials between 2005 and 2011, that the application of data-mining techniques (especially ANN) for site-specific nitrogen fertilization in average reveals a positive result of 22,26 €/ha in comparison to a uniform treatment variant. Although these models are promising they are not applicable consistently. The replication of models with variables from other fields was not possible in every case. There are many assumptions which could explain these circumstance. At first measuring soil parameters, e.g. electrical conductivity or electrical resistance depends heavily on water saturation of soils. So not in every year and not on every field a reliable dataset could be produced. Weather conditions are the second important factor which influence the accuracy of models. Particularly the historical yield has proven as a good predictor variable. But large yield fluctuations from year to year show different results in prediction accuracy. There are furthermore influence factors, for example the circumstance that plant growth is a dynamic biological process, which has intrinsic balancing abilities in order to plant nutrition.

For generating adequate decision rules for nitrogen fertilization, no model with hundred percent accuracy is necessary, because at least natural disturbance factors and intrinsic biological abilities are definitely not possible to predict. So the question is how to generate a sufficient accurate decision model, that is stable over years and possibly later across regions. The first step of building a model is the preparation of the data in use. In previous models metric scaled, absolute numbers were used. To improve the quality of results, it may be necessary to manipulate existing input and target variables. It has to be tested whether a classification of the input and target variables, in comparison to the metric scaled input and target variables, offer improvement in accuracy. Therefore, different classification systems are examined in this study. This initial information on the extent to which improvements in the small-scale yield forecast results occur and whether the results found can be generalized.

Materials and Methods

Field location and trial design

The data used in this study was collected from a 65 ha field which hosts a long-term field trial which started in 2003. The field is part of the “experimental farm Görzig” of the Martin-Luther-Universität Halle-Wittenberg. The field which is numbered as 550, is located near Görzig in Sachsen-Anhalt (Germany). The average precipitation of 475 mm per year, frequently leads to a negative water balance in the growing season. The average annual temperature is 9 °C. The flat terrain lies between 90 and 100 meters above sea level. The predominant soil type is Chernozem and the texture class is silt loam. In general, the field trial is designed for a long-term basic fertilization trial. Therefore, the field is divided into a 36 x 36 meters’ grid, which is adapted on the technical equipment of the farm. All variables which are used in this study are fitted and averaged on the grid cell scheme. Figure 1 depicts the yield of winter wheat of field 550 in 2015. The yield varied between 26 and 131 decitonnes (dt) per hectare (ha) with an average of 86 dt/ha.

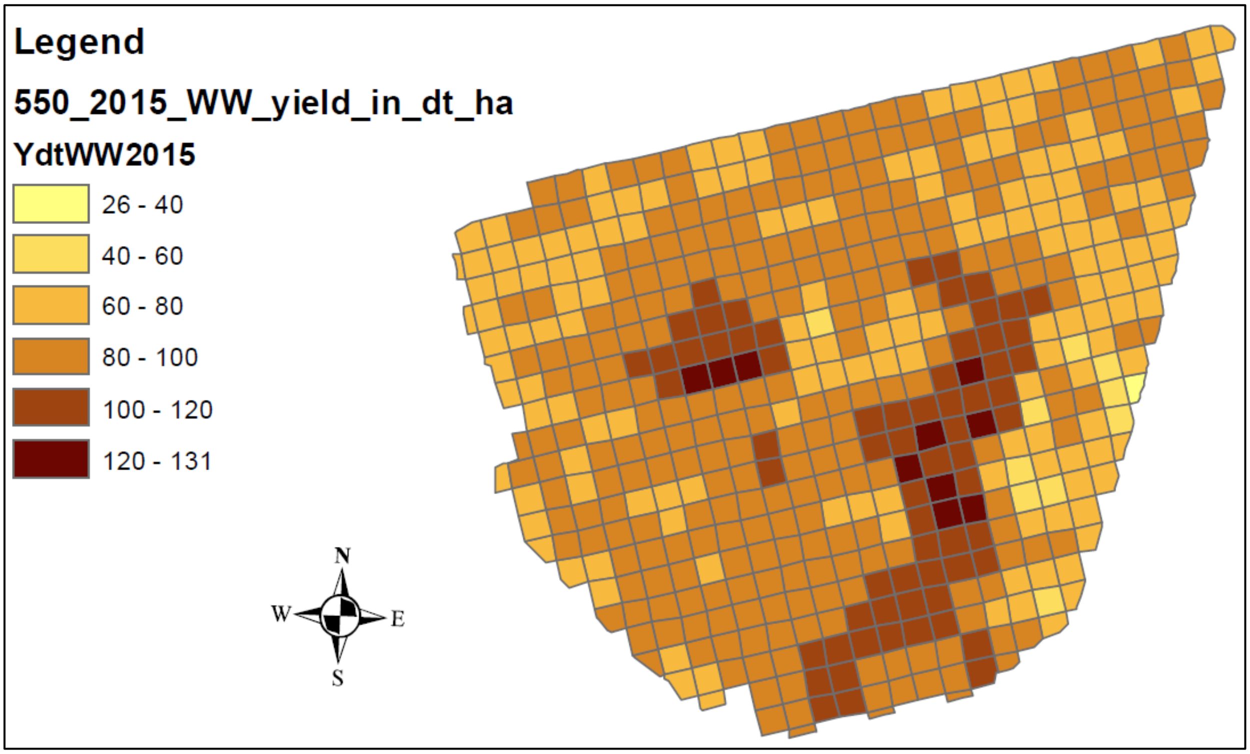

Figure 1: Trial design of field 550 combined with the yield map of winter wheat 2015

Database

The grids in the outer boundary zone of the field (36m) are not included in the dataset. Many confounding factors, e.g. soil compaction, overlapping of farming activities or incomplete yield recording disturbs the acquisition of a reliable dataset in this zone. So in total 448 grid cells are included in the analysis which results at least in 58 ha of trial area. Several measurements were carried out between 2003 and 2015. The variables which are used as predictors for ANN modelling are shown in table 1 (next side). In some years no yield record was possible. So in total there are 8 years of historical yield data which can be used for the prediction of the yield of 2015. The electrical conductivity was measured in three years which are all included. The descriptive statistics for each variable used in this paper shows figure 3 in the appendix.

Table 1: Variables used for yield prediction with ANNs

Variable	Labeling	Crop	Input form	Year
Historical yield	YdtKM2003	Corn	Absolute & relative[1]	2003
	YdtWW2004	Winter wheat	Absolute & relative	2004
	YdtWW2007	Winter wheat	Absolute & relative	2007
	YdtWW2010	Winter wheat	Absolute & relative	2010
	YdtWR2011	Winter rape	Absolute & relative	2011
	YdtWW2012	Winter wheat	Absolute & relative	2012
	YdtWG2013	Winter barley	Absolute & relative	2013
	YdtWR2014	Winter rape	Absolute & relative	2014
	YdtWW2015	Winter wheat	Absolute & relative	2015
Electrical conductivity	EC03	-	Absolute	2003
	EC09	-	Absolute	2009
	EC15	-	Absolute	2015
Electrical resistance	Avg_Rho_1, 2, 3, 4, 5, 6 & 1-6	-	Absolute	2017
Mass balance index	MBI	-	Absolute	-
Topographical wetness index	TWI	-	Absolute	-
Clay content	Ton	-	Absolute	-
Silt content	Schluff	-	Absolute	-
Sand content	Sand	-	Absolute	-
Fine content	Feinanteil	-	Absolute	-

[1] The average yield of a grid cell is also included as a relative value to the average yield of the field.

Yield prediction with ANNs

Artificial neural networks try to mimic the way a human brain works and they try to "learn" how to classify data using knowledge embedded in training sets. Neural network describes a set of virtual neurons connected by weighted links. Each neuron performs easy tasks, but the network can perform complex tasks when all its neurons work together. "Commonly, the neurons in networks are organized in layers, and these kinds of networks are referred to as multilayer perceptrons. Such networks are composed by layers of neurons: the input layer, one or more "hidden" layers and finally the output layer. A training set is used for setting the network parameters so that a predetermined output is obtained when a certain input signal is provided. The hope is that the network is able to generalize from the samples in the training set and to provide good classification accuracy" (MUCHERINO et. al., 2009).

There exists much literature about how to use data mining technologies and how to interpret the results. For instance, MUCHERINO et. al. (2009) and WEIGERT (2006) give good examples for possible applications of ANNs in agriculture. But all authors are unison that for every issue, respectively optimization problem at least, it has to be tested whether and how a positive result is reachable. A standard solution for application is not available yet.

For developing ANN models for yield prediction, in this study the software SPSS Modeler® from IBM (version 17.1) is used. All combinations of ANN models are based on the multi-layer-perceptron algorithm. For every training cycle 30 % of the dataset was separated for validation to prevent overfitting. The software is adjusted to calculate the best network topology automatically. So for every single combination the seemingly best network topology is computed. As target variable always the yield of winter wheat in 2015 (YdtWW2015) is used.

Model combinations

In this study three combinations of models with classified variables are tested in comparison to a model with only metric scaled variables (standard model). The following table 2 shows the possible combinations of input and target variables with its abbreviations.

Table 2: Combination of Input and Target variables in the tested ANNs.

Input variable	Target variable	Abbreviation
Metric	Metric	ImTm
Classified	Metric	IcTm
Metric	Classified	ImTc
Classified	Classified	IcTc

Classification types

There are many possibilities to classify a dataset. In this study the allegedly most important are applied. The used classification types are depicted in table 3. At first intervals are set to a fix number of equal classes. Therefore, the number of classes is varied in two-staged intervals from 6 to 12. The second type used in this paper is a classification scheme based on standard deviation. For this the mean value is calculated and then class breaks are placed above and below the mean at intervals of either 1, 2 or 3 standard deviations. The third method used is the quantile classification. Quantile classification assigns the same number of data values to each class. There are no empty classes or classes with too few or too many values. Each class contains an equal number of predictors, for example 20 % of the data in each group in a quintile classification. For detailed information see the IBM User's Guide (n.d.).

Table 3: Classification types, number of classes and its abbreviations

Classification type	Number of classes	Abbreviation
Equal intervals	12	EI 12
	10	EI 10
	8	EI 8
	6	EI 6
Standard deviation	3	SD 1
	5	SD 2
	7	SD 3
Quintile	5	Quintile
Decile	10	Decile

Results and Discussion

The results of the model with metric scaled input and target variables (ImTm) are shown in table 4. With a coefficient of determination (R^2) of nearly 82 % respectively a linear correlation (r) of 0,9 the model has a pretty high yield prediction accuracy in comparison to ANNs trained for other yield-years. According to a nitrogen efficiency of 20,4 kg N/t yield, for winter wheat in this region with an ANN approach (between 2005 and 2011 on 15 field trials - for details look at results of WAGNER (2012)), the standard deviation (SD) of 6 dt/ha is acceptable. This means that a fertilization recommendation leads to an over- or undersupply of a bit beyond 12 kg N/ha. For agricultural practice this is absolutely satisfactory. But there are outliers which could not be predicted optimal. In the sample the maximum error of nearly 22 dt/ha and the minimum error of over -24 dt/ha would lead in extreme cases to an over- or undersupply of round about 45 kg N/ha respectively -50 kg N/ha. On a small-scale basis this is too inaccurate. The average absolute error is also pretty good with 4,72 dt/ha in comparison to other models in other years. n indicates the total number of observations respectively cases which are computed in the model.

Table 4: Statistical summary for the "ImTm" ANN model

Input data	R^2	SD	r	Min. error	Max. error	Avg. error	Avg. abs. error	n
metric	81,6	6,08	0,90	-24,28	21,90	-0,22	4,72	448

Figure 2 (next side) illustrates the ANN output of the "ImTm" model according to the total number of accurate prediction values. As one can see, ANNs operate with an intrinsic classification scheme. Therefore, little value groups (bins) are created to compare afterwards the accuracy of observed and predicted values.

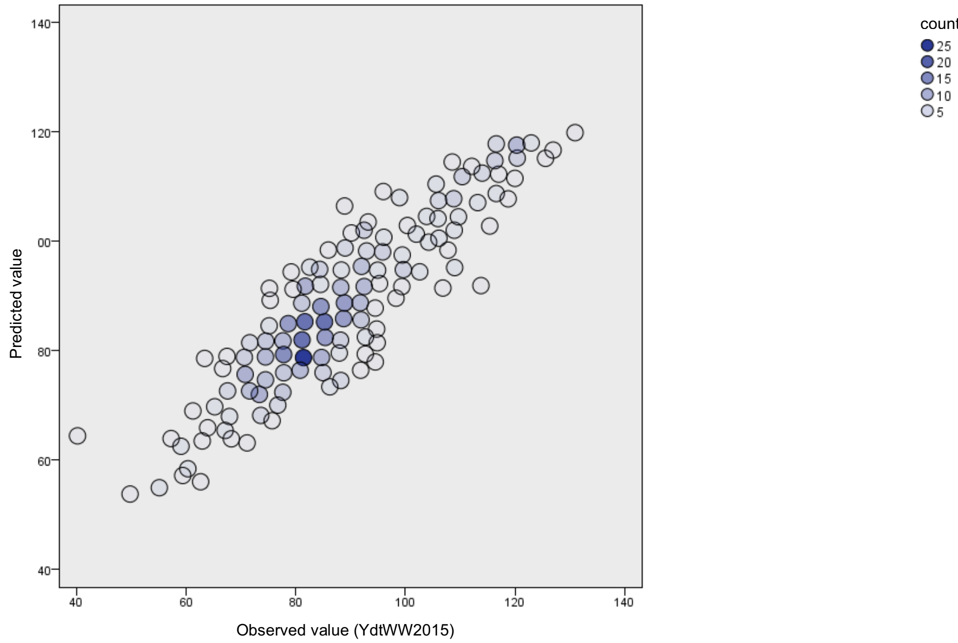

Figure 2: Matching of predicted to observed value groups in total count

The first model with classified input variables and metric target variables (IcTm) is depicted in table 5. The highest accuracy is reached by the classification types EI 12, EI 6 and decile. With values from 82 to 85 % they perform slightly better than the pure metric model “ImTm”. The SD and average absolute error could be clearly improved in the case of EI 12 and decile classification. All other models are definitely worse than “ImTm”.

Table 5: Statistical summary for the “IcTm” model

Classification type	R²	SD	r	Min. error	Max. error	Avg. error	Avg. abs. error	n
EI 12	85	5,39	0,92	-24,12	20,75	0,49	3,95	448
EI 10	75	7,04	0,86	-26,40	22,45	-0,17	5,26	448
EI 8	67	7,99	0,82	-28,36	25,06	-0,14	6,09	448
EI 6	82	6,02	0,91	-25,43	24,42	0,00	4,52	448
SD 1	76	7,00	0,87	-24,65	20,35	0,15	5,37	448
SD 2	70	7,77	0,84	-25,00	28,25	0,05	6,05	448
SD 3	73	7,32	0,86	-26,56	24,23	-0,44	5,68	448
Quintile	63	8,65	0,79	-39,80	21,74	-0,13	6,55	448
Decile	84	5,64	0,92	-26,67	19,21	0,62	4,18	448

The next model is based on classification of input and target variables. Table 6 shows the statistical summary. Now all classification types show worse results except the standard deviation classification. With a steadily rising coefficient of determination from 82 (SD 3) to 89 % (SD 1) the model looks even better than in a metric based form. But there are some limitations according to SD 1. In this case the model only predicts a low yield (below -1 SD), average yield (-1 to +1 SD) and a high yield (over +1 SD). This means a classification of only 3 classes which is logically easier to predict. The more classes the model has, the worse it performs. There is a gradient from SD 1 to SD 3. But even with 7 classes (SD 3) the model seems to perform sufficient accurate in comparison to “ImTm”.

Table 6: Statistical summary for the “IcTc” model

Classification type	R²	Correct n	False n	Correct %	False %	n
EI 12	55	246	202	55	45	448
EI 10	53	237	211	53	47	448
EI 8	61	270	178	61	40	448
EI 6	66	295	153	66	34	448
SD 1	89	398	50	89	11	448
SD 2	88	396	52	88	12	448
SD 3	82	369	79	82	18	448
Quintile	64	287	161	64	36	448
Decile	43	192	256	43	57	448

The last model is tested with metric input and classified target variables (ImTc). The results here are similar to the model above. The SD method performs sufficient accurate and even better than in “IcTc” with an R^2 of 89 % (SD 3) up to 95 % (SD 1). Also here the SD 1 is less interesting than the SD 3 classification model.

Table 7: Statistical summary for the “ImTc” model

Classification type	R^2	Correct n	False n	Correct %	False %	n
EI 12	55	246	202	55	45	448
EI 10	57	256	192	57	43	448
EI 8	61	273	175	61	39	448
EI 6	75	335	113	75	25	448
SD 1	95	426	22	95	5	448
SD 2	90	401	47	90	10	448
SD 3	89	400	48	89	11	448
Quintile	61	273	175	61	39	448
Decile	42	190	258	42	58	448

Conclusion

The attempt to reach better accuracy in yield prediction with ANNs, via classified input and/or target variables, is basically interesting and showed positive results in this work. Therefore, in this study three combinations of ANNs with three different classification types in nine variations are tested. The model with metric scaled input and target variables, as a standard model, is compared to the other combinations of models. The main focus lies on the accuracy of a model, which is expressed through the coefficient of determination.

The results are largely promising in some cases. So the model “IcTm” with the classification type EI 12, EI 6 and decile classification, showed a slightly better accuracy than the standard version. Also standard deviation and the average absolute error could be visibly improved. The model with classified input and target variables showed a very different result: Except from the standard deviation classification type, all classification types performed worse than the standard model. The R^2 of SD 3 with 82 % could be improved up to 89 % in the case of SD 1. But the limitations of a three class scheme like SD 1 must be considered. The range of one standard deviation means a yield span from over 1,2 tons in this case. According to a nitrogen efficiency of 20,4 kg N/t yield, only the middle class around the mean value could be fertilized acceptable (~12 kg N/ha over- or undersupply). But the question is how accurate the lower and upper class could be addressed under these circumstances. The last model with metric input and classified target variables showed similar results compared to the previous mentioned model. Only the models with standard deviation classification schemes performed sufficiently. The accuracy in this model is even better with an R^2 of 89 % (SD 3) up to 95 % (SD 1).

To sum up, it has shown that classification schemes can improve the results of ANN models for yield prediction. To give a final summary of findings in this paper:

- Classification of input variables leads to a better performance of models with a higher number of classes (in this case 12 classes in equal weight and decile classification)
- Classification of input and target variables leads to a good performance of standard deviation classification schemes. All other models perform worse.
- The best accuracy was reached by classifying only the target variable. Here also standard deviation schemes are unrivaled.
- Looking at standard deviation classification, schemes with a higher number of classes (SD 3) should be preferred to guarantee a higher accuracy in high and low yield zones.

This paper was developed to give a first overview of how ANNs for yield prediction react on different classification methods. Further aspects have to be integrated, like the usage of data from other fields and other years or even other variables. Further it has to be tested how accurate the models perform in a field application. At least, for generalizing the mentioned results, further research is necessary.

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Appendix

Feld	Diagramm	Messung	Min	Max	Mittelwert	Std.Abw.	Schiefe
Avg_Rho_1		Stetig	34.914	91.914	52.022	7.009	0.938
Avg_Rho_2		Stetig	33.278	130.000	58.273	10.916	1.191
Avg_Rho_3		Stetig	28.871	160.543	67.210	17.985	0.977
Avg_Rho_4		Stetig	17.806	184.200	72.203	27.150	0.763
Avg_Rho_5		Stetig	31.581	226.829	76.445	28.022	1.315
Avg_Rho_6		Stetig	31.278	264.000	77.908	32.080	1.571
Avg_Rho_1-6		Stetig	31.801	176.248	67.343	19.456	1.255
EC03		Stetig	21.530	57.760	34.091	4.512	0.347
EC09		Stetig	31.630	42.240	36.947	1.754	0.082
EC15		Stetig	54.690	68.310	60.141	2.820	0.647
MBI		Stetig	-0.147	0.164	0.005	0.038	0.439
TWI		Stetig	5.433	12.113	7.953	1.362	0.546
Ton		Stetig	3.770	10.940	8.284	0.933	-0.749
Schluff		Stetig	35.875	80.085	74.236	4.247	-3.748
Sand		Stetig	11.510	60.330	17.480	4.766	3.856
Feinanteil		Stetig	11.585	29.995	24.678	2.227	-1.413
YdtKM2003		Stetig	27.159	109.553	61.270	13.321	0.730
YdtKM2003		Stetig	27.159	109.553	61.270	13.321	0.730
YdtKM2003_relativ		Stetig	0.444	1.792	1.000	0.217	0.775
YdtWW2004		Stetig	60.542	118.771	95.099	9.533	-0.825
YdtWW2004_rel...		Stetig	0.650	1.244	1.000	0.098	-0.826
YdtWW2007		Stetig	62.427	113.230	96.677	8.535	-0.655
Ydt2007_relativ		Stetig	0.639	1.177	1.000	0.087	-0.599
YdtWW2010		Stetig	59.184	105.818	88.598	8.271	-0.781
Ydt2010_relativ		Stetig	0.670	1.187	1.000	0.093	-0.793
YdtWR2011		Stetig	9.000	78.553	44.132	14.951	0.278
Ydt2011_relativ		Stetig	0.222	1.816	1.000	0.333	0.249
YdtWW2012		Stetig	54.862	123.554	106.985	9.272	-1.715
Ydt2012_relativ		Stetig	0.522	1.138	1.000	0.086	-1.731
YdtWG2013		Stetig	73.907	120.009	88.505	5.649	0.404
Ydt2013_relativ		Stetig	0.856	1.316	1.000	0.059	0.319
YdtWR2014		Stetig	22.844	75.713	60.682	5.910	-1.330
Ydt2014_relativ		Stetig	0.384	1.213	1.000	0.095	-1.459
YdtWW2015		Stetig	40.155	130.972	86.726	14.175	0.669

Figure 3: Descriptive statistics of variables in use