

## PREDICTION OF WIND SPEEDS BASED ON DIGITAL ELEVATION MODELS USING BOOSTED REGRESSION TREES

Peter Fischer<sup>a,\*</sup>, Christophe Etienne<sup>b</sup>, Jiaojiao Tian<sup>a</sup>, Thomas Krauß<sup>a</sup>

<sup>a</sup> Remote Sensing Technology Institute, German Aerospace Center (DLR), Münchener Str. 20, 82234 Wessling, Germany -  
(Peter.Fischer, Jiaojiao.Tian, Thomas.Krauss)@dlr.de

<sup>b</sup> Secquaero Advisors Ltd., 8001 Zürich, Switzerland - Christophe.Etienne@secquaero.com

Commission VI, WG I/5

**KEY WORDS:** Digital Elevation Model, Wind Speed, Non-Parametric Regression

### ABSTRACT:

In this paper a new approach is presented to predict maximum wind speeds using Gradient Boosted Regression Trees (GBRT). GBRT are a non-parametric regression technique used in various applications, suitable to make predictions without having an in-depth a-priori knowledge about the functional dependancies between the predictors and the response variables. Our aim is to predict maximum wind speeds based on predictors, which are derived from a digital elevation model (DEM). The predictors describe the orography of the Area-of-Interest (AoI) by various means like first and second order derivatives of the DEM, but also higher sophisticated classifications describing exposure and shelterness of the terrain to wind flux. In order to take the different scales into account which probably influence the streams and turbulences of wind flow over complex terrain, the predictors are computed on different spatial resolutions ranging from 30 m up to 2000 m. The geographic area used for examination of the approach is Switzerland, a mountainous region in the heart of Europe, dominated by the Alps, but also covering large valleys. The full workflow is described in this paper, which consists of data preparation using image processing techniques, model training using a state-of-the-art machine learning algorithm, in-depth analysis of the trained model, validation of the model and application of the model to generate a wind speed map.

### 1. INTRODUCTION

The strong linkage between geomorphologic parameters and wind flux has been used to describe a broad range of phenomena influenced and driven by wind, like estimating the direction of an unknown air pollution source (Antonić and Legović, 1999), mapping wind erosion risk and dust emission-deposition (Reiche et al., 2012) or simulating snow redistribution and accumulation (Winstral and Marks, 2002). Besides of ecologic applications, the discrete description of wind flux and maximum wind speeds is also a key parameter to estimate the risk of damages by wind, Heneka (Heneka and Ruck, 2004) gives a detailed overview of different loss functions based on maximum wind speeds.

Estimating wind speeds over complex terrain is a challenging task, thus different methodical approaches exist to make such predictions. The domain of meteorological models deals with atmospheric boundary layers and the description of interactions in the atmosphere to model the behaviour of airflows, detailed application examples are given in (Hofherr and Kunz, 2010) and (de Rooy and Kok, 2004). Using Computational Fluid Dynamics (CFD) programs who solve the discrete Navier-Stokes equation are also suitable for simulating wind speeds, but preparing such a simulation and running it is very resource demanding from a computational point of view. The DEM needs to be transformed into a volumetric mesh which represents the surface and the boundary conditions of the simulation in a sufficient manner, otherwise the air mass transportation would give no reliable results. Garcia and Boulanger (Garcia and Boulanger, n.d.) give an example in using a CFD program for simulating low altitude wind flow, using a SRTM dataset with an spatial extent of more than 10000 km<sup>2</sup>, covering Mt. St. Helens (USA).

Besides of these strict mechanical models which aim to simulate air flow, also general statistic techniques can be adapted for making spatial predictions, different tools are found in the regression domain. The goal of regression analysis is to uncover functional dependancies between a set of independent parameters and a set of dependent variables. By using such techniques, it's possible to make quantitative predictions with a known uncertainty based on a set of random samples. As the strict functional model is quite complex for wind speed prediction, it seems beneficial to use techniques from the non-parametric regression domain. Lehmann (Lehmann et al., 2002b) developed a software package called Generalized Regression Analysis and Spatial Predictions (GRASP), which uses generalized additive models (GAMs) to model the spatial behaviour of a broad range of phenomena. It has been successfully used for different applications in ecological modelling, keywords are vegetation mapping, biodiversity and spatial species distributions (Cawsey et al., 2002, Lehmann et al., 2002a, Overton et al., 2002, Ray et al., 2002, Zaniewski et al., 2002). Besides of GAMs, also other non-parametric regression methods have been used for making spatial predictions. Leathwick (Leathwick et al., 2005) gave an example in using multivariate adaptive regression splines (MARS) to predict the occurrence and density of fish populations in New Zealand freshwater system. They used a broad range of environmental variables like stream size, temperature and distance from the sea, the probabilities of occurrence were then used to produce maps for New Zealand's entire river network. A working guide to boosted regression trees (BRTs) is given by Elith (Elith et al., 2008), the use case is deals also with the distribution of a fish species in New Zealand's river network.

In this paper we present a case study to predict wind speeds using GBRTs. Regression Trees, often simultaneously referred as Decision Trees, aim to approximate the unknown target function by iteratively partitioning the feature space in piecewise constant functions. The set of rules which defines the final model can be

\*Corresponding author. Tel.: +49 8153 281561; Fax: +49 8153 281444.

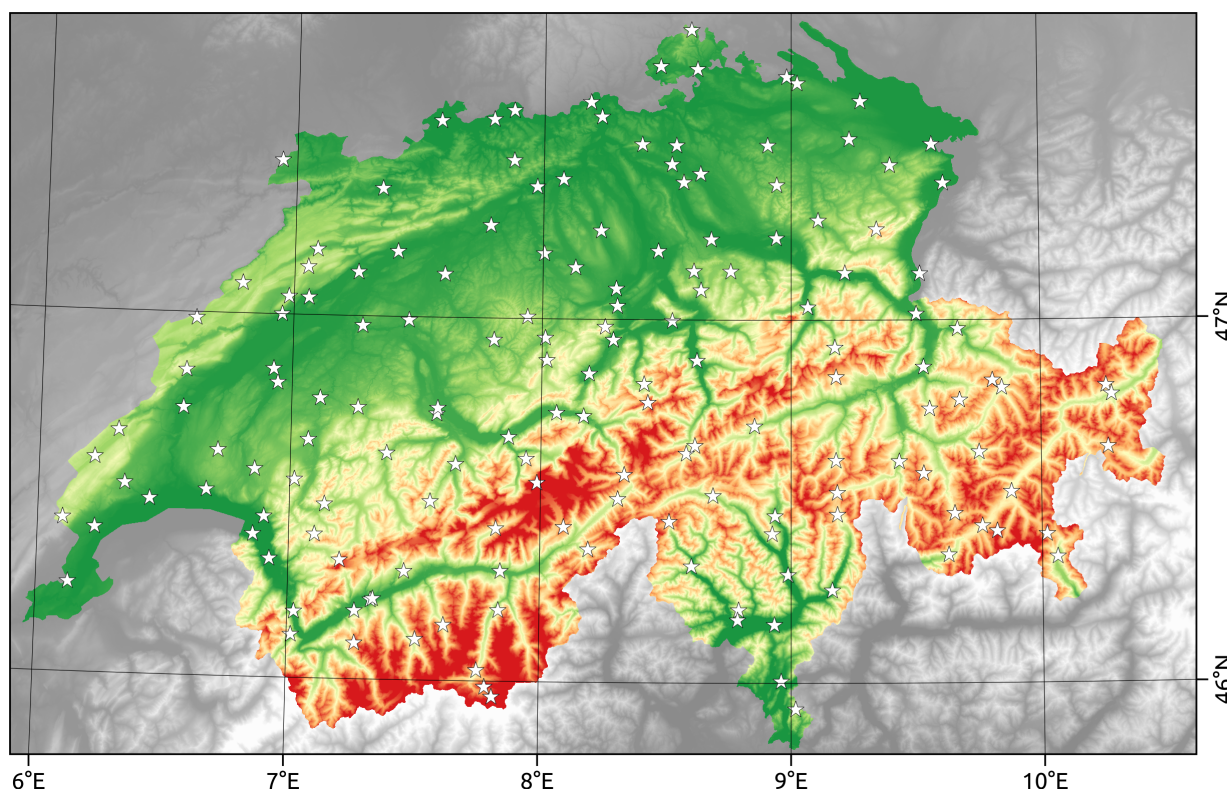


Figure 1: Weather stations of MeteoSwiss

visualized as tree, which makes the model easy to understand and interpret. Introduced by Breiman (Breiman et al., 1984), over the last decades a broad range of extensions was developed. An in-depth description of the algorithm with practical examples is given in (Hastie et al., 2001). Boosting is an extension of the initial regression tree algorithm. Instead of creating a single tree, boosting creates iteratively an ensemble of trees which aim to minimize the residuals of the initial model. The final model consists of a collection of trees, following a gradient-descent strategy, where different loss functions (Mean Square Error, Absolute Error, Huber Loss, etc.) are possible.

As the prediction of the wind speed strongly relies on the earth surface, a set of describing parameters is derived from the initial DEM. Besides of first and second order derivatives like slope, aspect and curvature, also a geomorphologic classification algorithm for landform analysis is used. Introduced by Weiss (Weiss, 2001), the Terrain Positioning Index (TPI) distinguishes between major landforms (hills, ridges, valley and others), which have an impact on the near ground air mass transportation system. An additional wind specific index based on DEM which provides a numerical measure of the degree of wind shelter, the TOPEX score, is also taken into account. A discussion of the TOPEX score and other qualitative and quantitative methods to assess topographic exposure is given by Chapman (Chapman, 2000). Both TPI and TOPEX have in common that they give freedom to the user about the maximum distance of height values to take into account, which helps to adjust the algorithm to the specific application.

## 2. AREA OF INTEREST, DATA

The study site is Switzerland, a mountainous region in the heart of Europe. The diversified landscape includes mountains higher than 4000 meters and steep canyons, but also farm land, lakes

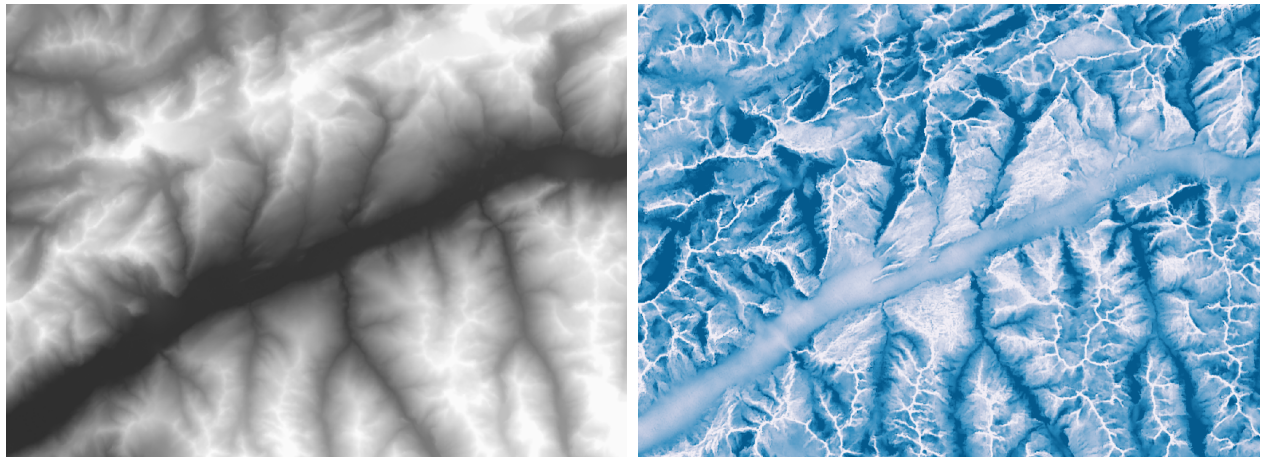
and urban areas. The southern part of Switzerland is dominated by the Alps, leading to a dynamic orography with more than 3000 mountains higher than 2000 meters. The DEM was recorded by the SRTM mission and is provided with a spatial resolution of 30 meters (Farr et al., 2007). Having a representative set of wind measurements is essential for the task. The Federal Office of Meteorology and Climatology MeteoSwiss maintains a network of more than 200 weather stations. The data are conveniently accessible via the online portal IDAweb at no charge for research. An overview of the locations of the weather stations is given in figure 1, the height of the stations ranges from 203 to 3580 meters above sea level (asl).

### 2.1 WEATHER STATIONS

The 200 weather stations used for this work are fully automatic and deliver wind speed and wind directions at an interval of 10 minutes. The station situated at the lowest altitude of 203 m asl is placed in Magadino/Cadenazzo. The place is part of the canton Tessin, and is less than 10 km from the famous lake Garda. The highest station is placed at the Jungfernjoch in the canton of Bern, at an altitude of 3580 m asl. The Jungfernjoch is a saddle between the two mountains Jungfrau and Mönch, having the famous mountain Eiger nearby. The average altitude of all stations is about 1032 m asl. The gust peak measurements (one second) are delivered in a day-wise granularity, the time span taken into account starts in January 1981 and ends in September 2015. From the listed measurements for each station the 98th percentile (W98) was derived and then used for the evaluation.

### 2.2 PREDICTOR VARIABLES

Based on the initial DEM several DEMs with a downsampled spatial resolution were generated, using bi-cubic interpolation. The spatial resolution steps are 30 m, 300 m, 600 m, 1000 m



(a) DEM, color encoding from black to white (min. to max. height) (b) TOPEX, color encoding from white to blue (min. to max. angle score)

Figure 2: Comparison of DEM (left) and derived TOPEX map (right)

and 2000 m. For each DEM, the first and second order derivatives slope, aspect, profile and plan curvature were calculated. A detailed description of the derivatives is given by Wilson and Gallant (Wilson and Gallant, 2000). The landform classification is based on the TPI using two kernel maps, one with 100 m inner radius and 500 m outer radius, one with 100 m inner radius and 2000 m outer radius. In combination with a slope map a classification into 10 major landforms is done, the classes are like suggested by Weiss (Weiss, 2001). The TOPEX score map is calculated taking the height values in a range from 100 m to 2000 m in the eight major cardinal directions into account. Figure 2 shows a subset of the DEM and the corresponding TOPEX map. An overview about the at least 7 different predictor groups and the different scales is given in table 1.

As all predictors rely on the DEM and several predictors are available at different scales, orthogonality between the single predictors becomes an issue. On the one hand, one descriptor at different scales could be useful to simulate different channelling and deflection effects of wind flow, on the other hand introducing several correlated predictors into the model building process will blow up the model without increasing the overall accuracy. To overcome this problem, minimum one and maximum two descriptors of each of the descriptor groups is used for the final modelling. In the single descriptor groups the goal is to choose the two predictors having the lowest Pearson correlation coefficient, as a restriction the correlation coefficient between variables of one group must not exceed 0.75. This approach enforces to add all relevant information to the model building process without overwhelming it with a big group of orthogonal predictors.

Descriptor Group	Resolution	Data class
Altitude	30, 300, 600, 1000, 2000	Numeric
Slope	30, 300, 600, 1000, 2000	Numeric
Aspect	30, 300, 600, 1000, 2000	Numeric
Planform Curvature	30, 300, 600, 1000, 2000	Numeric
Profile Curvature	30, 300, 600, 1000, 2000	Numeric
TOPEX	2000	Numeric
TPI	2000	Categorical

Table 1: Description of Stock Data attributes

### 3. METHODOLOGY

GBRTs is considered as an ensemble method, combining several weak learners to a strong predictor. The term regression tree names already the type of learner. Regression Trees are known

for their simplicity in interpretation, for being able to handle numerical and categorical data, and for being able to fit complex non-linear relationships and interactions between predictors. In this examination for each geo-referenced wind measurement  $y$  a set of predictor variables is derived from the DEM, denoted by  $x$ . A regression tree is then an estimate  $\hat{f}$  of the functional dependency between the predictors  $x$  and the response  $y$ .

Regression trees aim to partition the feature space into piecewise constant functions, also referred as regions. The description of such a functional model by a single tree is given in equation 1. In the final model each predictor  $x$  is linked to a region  $R$ , the limiting borders of  $R$  are defined by the interval  $I$ .  $M$  is the number of regions which corresponds to the number of split points of the tree plus one (having binary split points) and  $c$  corresponds to the constant response value predicted by the model. The building of a single tree is an iterative process, at each node the predictor variable and its value are chosen in order to minimize the overall error of the model. Depending on the nature of the problem different loss functions can be used, like sum of squares, Huber loss or others. The response value is than the average value of all response values satisfying the rule set given by the tree.

$$\hat{f}(x) = \sum_{m=1}^M c_m I(x \in R_m) \quad (1)$$

Gradient Boosting means that instead of growing one single regression tree, several trees are modelled and added to a model, where each new tree aims to minimize the residuals of the existing model. Equation 2 describes this process, where the model  $F_m(x)$  at boosting step  $m$  consists of the model  $F_{m-1}(x)$  plus the regression tree  $\hat{f}$ , which aims to minimize the residuals of  $F_{m-1}(x)$ . In most algorithm implementations the number of trees of the final model has to be specified by the user, but also a stopping criterion would be possible.

$$F_m(x) = F_{m-1}(x) + \hat{f}(x) \quad (2)$$

The additive boosting process of adding new trees  $\hat{f}(x)$  to the existing model  $F_{m-1}(x)$  is explained in detail in equation 3. In each boosting step, a new tree is appended to the present model  $F_{m-1}(x)$ . The new tree  $\hat{f}(x)$  minimizes the loss function  $L$  which is given as the sum of the residuals between the  $n$  re-

sponses  $y_i$  of the training data and the predicted response of the present model  $F_{m-1}(x_i)$  plus the new tree  $\hat{f}(x)$ .

$$F_m(x) = F_{m-1}(x) + \arg \min_{\hat{f}(x)} \sum_{i=1}^n L(y_i, F_{m-1}(x_i) + \hat{f}(x)) \quad (3)$$

#### 4. RESULTS AND DISCUSSION

As predictor for the final model, the DEM with 30 m spatial resolution was used. All down sampled versions had a correlation coefficient higher than 0.8 to each other, therefore they would not add any further information. From the slope maps the resolution combination of 30 m and 1000 m has the lowest correlation coefficient with 0.49, for the aspect maps the combination 30 m and 600 m resulted in the minimum correlation coefficient of 0.13. For both profile and plan curvature the combination of 30 m and 2000 m spatial resolution give the lowest correlation coefficient nearby zero. The TOPEX map and the TPI map are taken as is.

Figure 3(a) gives an overview of the influence of the single predictors in the final model. As expected, altitude and TOPEX are the two predictors who contribute most to the final model. As mountain peaks and ridges are in most cases not sheltered by higher topographic entities in their neighbourhood, the influence of this parameter seems obvious. Figure 4 shows the maximum Wind Speed map, here we also see the strong influence of the altitude, as the underlying landforms are clearly visible. Areas which are sheltered by surrounding entities can easily be distinguished from unsheltered areas by the TOPEX score. Areas having a high TOPEX score are less exposed to wind streams than areas in open valleys, because of this we expect the lowest wind speeds in such sheltered areas. The wind speed map proves this, as the lowest wind speeds are measured and also predicted in the submontane regions. Lakes have a TOPEX score nearby zero, the large lakes like lake Geneva, Lake Constance and others appear with a higher predicted wind speed than the bordering areas. Furthermore the wind speeds on the surface of the water are almost constant. This is not surprising, as the predictors stay constant at this places. Aspect on two different scales is the next contributing predictor. There is no clear and simple explanation of this situation, but we consider northwest as the main wind direction. Two points lead us to this assumption. First, on the northern hemisphere air masses following the pressure-gradient from the equator to the poles tend to circulate in a clockwise direction, an effect explained by the Coriolis force. Second, besides of this global phenomenon the Mediterranean area is the setting for several large scale wind systems. The Mistral is a strong, northwesterly oriented wind mainly occurring in the south of France and influencing the Mediterranean area. The contributing air mass regime affects also the western alps. A visual examination of the wind map shows that ridges oriented to the northwest in general show higher wind speeds, an observation which can be explained by the two before mentioned meteorological phenomena. Slopes and Curvatures are not the predictors having dominant influence to the final model. As TOPEX scores can be considered as an enhancement of slope measurements, probably in the final model the slope values are just overruled by TOPEX scores, being the superior predictor. The contribution of profile and plane curvature to the main model is also low, but should not be neglected. Both curvatures suite well for describing complex phenomena, perhaps the different scales at which they were introduced into the model should be reconsidered. Surprisingly the landform analysis has the lowest impact in the final model. As landforms can

also be derived to a certain degree from the TOPEX score, probably the TPI is also outvoted like the slope values by the prime predictor. Having in mind that in contrast to most other predictors the TPI is just introduced on one scale into the model, this is still to some degree implausible.

The final model consists of 1800 trees, figure 3(b) shows the decrease in deviance of the model for each added tree to the final model. 70 percent of the 200 weather stations were used for the training of the model (blue line), the remaining 30 percent were used for control purposes. By adding too many trees to the model, variance will decrease too much and over fitting will occur. In the example, after 1800 iterations no real gain can be expected from adding more trees. To prevent such a behavior during the model building process, different regularization techniques are used. We introduced the four restricting parameters maximum tree depth, number of samples per leaf, learning rate and subsampling to lead the model building into the right direction. The maximum tree depth was binded to three, building a large number of trees with low depth is a general technique to avoid over-fitting. The influence of single and not representative outliers in the set of random samples should be minimized. This can be ensured by giving a minimum number of samples per leaf for the tree growing process. We have decided to have at least ten samples per leaf, as we're convinced that making a split leading to leafs with less then ten samples would lead to an unrepresentative response function. The learning rate, which can be considered as a weighting factor for each single tree, is 0.001. As the methodology of GBRT is to some degree comparable with the method of steepest descent, this factor can be considered as a factor lowering the step length whilst not influencing the step direction. The big number of 1800 trees in combination with the low learning rate ensures a quite moderate decrease in the model error leading towards the optimal combination of regularization parameters. By introducing stochasticity into the model building process, variance and bias of the final model can also be minimized. Subsampling is a common technique to introduce stochasticity by just taking a random subsample of the training data sets per boosting iteration into account. We used just 50 percent of the available training data sets per boosting iteration. Table 2 gives an overview of the mentioned and used regularization parameters.

Attribute	Value
Maximum Tree Depth	3
Minimum Samples per Leaf	10
Learning Rate	0.001
Subsampling Rate	0.5

Table 2: Regularization Parameters

The final model has a RMSE of 3.28 and a coefficient of determination of  $R^2 = 0.78$ .

#### 5. CONCLUSIONS AND FUTURE WORK

A new approach for predicting wind speeds using GBRT is presented. We see that GBRT in conjunction with established DEM based predictors are capable to model the complex behaviour of wind streams over a large mountainous area. The results are reliable within a given accuracy.

Besides of the used predictors, more domain-related predictors could be integrated into the model. A quite simple examples is the Terrain Ruggedness Index, which quantifies topographic heterogeneity (Riley et al., 1999). Besides of the geomorphometric operators, also more sophisticated indexes inspired by ray-tracing could be added. Openness is such a parameter, which expresses



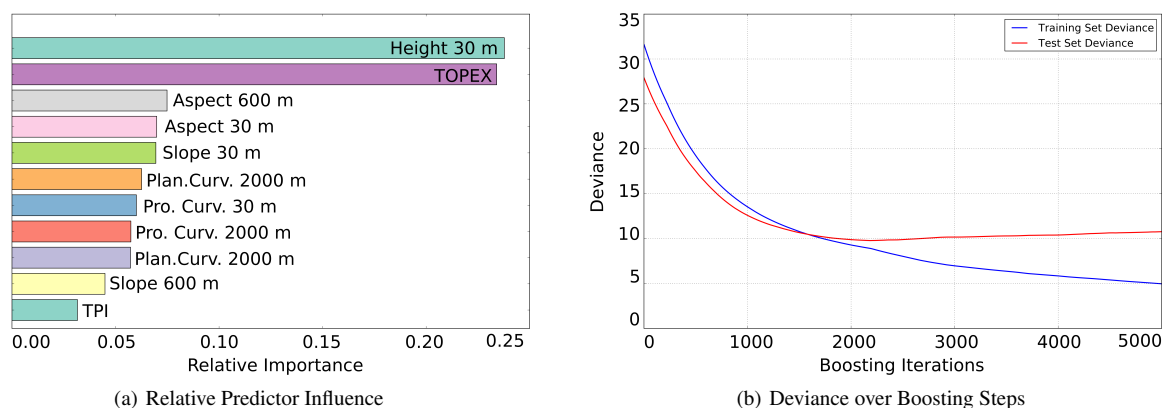


Figure 3: Model Description

the degree of dominance or enclosure of a location on an irregular surface like a DEM (Yokoyama et al., 2002). Another quite promising approach would be to add indexes which make use of flow routing algorithms. Lindsay and Rothwell (Lindsay and Rothwell, 2008) introduced the Channelling and Deflection Index (CDI), a sophisticated algorithm which leaves the ray-tracing domain and makes also usage of multiple flow direction (MFD) algorithms to simulate the complex behaviour of air streams. Different possible MFDs are named, probably the most promising for future investigations is  $D_{\infty}$  (Tarboton, 1997).

Tuning the parameters of the GBRT is a iterative and subjective task. Finding the optimal parameter set and handling the trade-offs between number of trees, learning rate, tree depth and others needs to be carried out by an experienced operator. Grid search can be adopted to test a certain number of possible combinations of different parameters, pointing to an optimal set with respect to a given loss function. Techniques like global optimization domain would probably lead to better results, for example evolutionary algorithms or genetic algorithms.

## ACKNOWLEDGEMENTS

The author wants to thank the Federal Office of Meteorology and Climatology MeteoSwiss for the provision of the gust speed measurements. Furthermore the author wants to thank Prof. Anthony Lehmann from University of Geneva for correspondance and advice.

## REFERENCES

- Antonić, O. and Legović, T., 1999. Estimating the direction of an unknown air pollution source using a digital elevation model and a sample of deposition. *Ecological Modelling* 124(1), pp. 85–95.
- Breiman, L., Friedman, J., Olshen, R. and Stone, C., 1984. *Classification and Regression Trees*. Wadsworth and Brooks, Monterey, CA.
- Cawsey, E., Austin, M. and Baker, B., 2002. Regional vegetation mapping in australia: a case study in the practical use of statistical modelling. *Biodiversity & Conservation* 11(12), pp. 2239–2274.
- Chapman, L., 2000. Assessing topographic exposure. *Meteorological Applications* 7, pp. 335–340.
- de Rooy, W. C. and Kok, K., 2004. A Combined PhysicalStatistical Approach for the Downscaling of Model Wind Speed. *Weather and Forecasting* 19(3), pp. 485 – 495.
- Elith, J., Leathwick, J. R. and Hastie, T., 2008. A working guide to boosted regression trees. *Journal of Animal Ecology* 77(4), pp. 802–813.
- Farr, T., Rosen, P., Caro, E., Crippen, R., Riley, D., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werenr, M., Oskin, M., Burbank, D. and Alsdorf, D., 2007. The shuttle radar topography mission. *Reviews of Geophysics*.
- Garcia, M. and Boulanger, P., n.d. Low Altitude Wind Simulation over Mount Saint Helens Using NASA SRTM Digital Terrain Model.
- Hastie, T., Tibshirani, R. and Friedman, J., 2001. *The Elements of Statistical Learning*. Springer Series in Statistics, Springer New York Inc., New York, NY, USA.
- Heneka, P. and Ruck, B., 2004. Development of a storm damage risk map of germany - a review of storm damage functions. In: *Proceedings of the International Conference for Disasters and Society*, Karlsruhe, 2004.
- Hofherr, T. and Kunz, M., 2010. Extreme wind climatology of winter storms in Germany. *Climate Research* 41(2), pp. 105 – 123.
- Leathwick, J., Rowe, D., Richardson, J., Elith, J. and Hastie, T., 2005. Using multivariate adaptive regression splines to predict the distributions of New Zealand's freshwater diadromous fish. *Freshwater Biology* 50(12), pp. 2034–2052.
- Lehmann, A., Leathwick, J. and Overton, J., 2002a. Assessing new zealand fern diversity from spatial predictions of species assemblages. *Biodiversity & Conservation* 11(12), pp. 2217–2238.
- Lehmann, A., Overton, J. M. and Leathwick, J. R., 2002b. GRASP: generalized regression analysis and spatial prediction. *Ecological Modelling* 160(12), pp. 165 – 183.
- Lindsay, J. and Rothwell, J., 2008. Modelling channelling and deflection of wind by topography. In: Q. Zhou, B. Lees and G.-a. Tang (eds), *Advances in Digital Terrain Analysis, Lecture Notes in Geoinformation and Cartography*, Springer Berlin Heidelberg, pp. 383–406.
- Overton, J., Theo Stephens, R., Leathwick, J. and Lehmann, A., 2002. Information pyramids for informed biodiversity conservation. *Biodiversity & Conservation* 11(12), pp. 2093–2116.
- Ray, N., Lehmann, A. and Joly, P., 2002. Modeling spatial distribution of amphibian populations: a gis approach based on habitat matrix permeability. *Biodiversity & Conservation* 11(12), pp. 2143–2165.

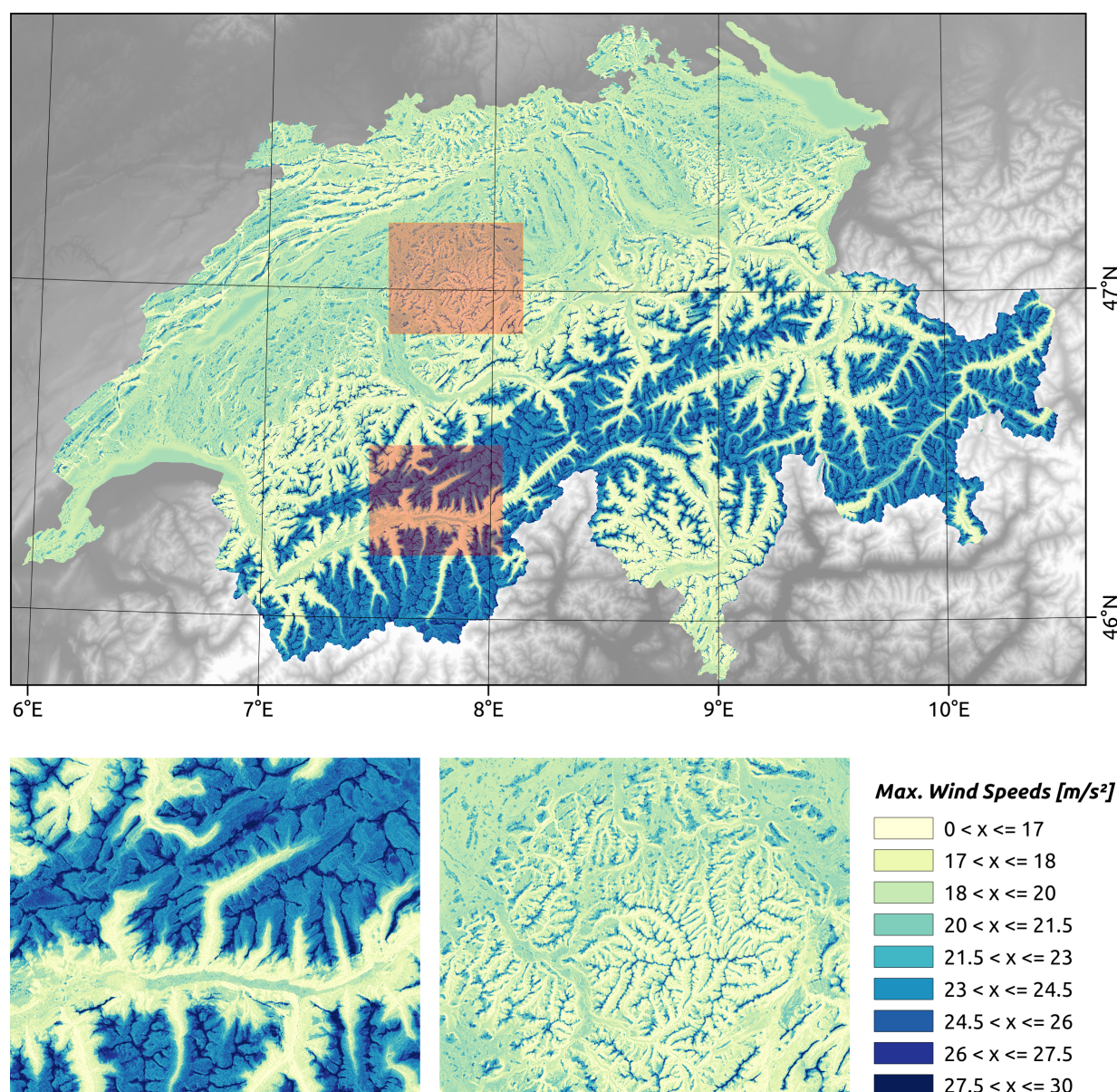


Figure 4: max. Wind Speed map

Reiche, M., Funk, R., Zhang, Z., Hoffmann, C., Reiche, J., Wehrhan, M., Li, Y. and Sommer, M., 2012. Application of satellite-remote sensing for mapping wind erosion risk and dust emission-deposition in inner mongolia grassland, china. *Grassland Science* 58(1), pp. 8–19.

Riley, S. J., Degloria, S. D. and Elliot, R., 1999. A terrain ruggedness index that quantifies topographic heterogeneity. *Intermountain Journal of Sciences* 5(1-4), pp. 23–27.

Tarboton, D. G., 1997. A new method for the determination of flow directions and upslope areas in grid digital elevation models. *Water Resources Research* 33, pp. 309–319.

Weiss, A.-D., 2001. Topographic position and landforms analysis. Poster Presentation, ESRI Users Conference, San Diego, CA.

Wilson, J. and Gallant, J., 2000. *Terrain Analysis: Principles and Applications*. Earth sciences: Geography, Wiley.

Winstral, A. and Marks, D., 2002. Simulating wind fields and snow redistribution using terrain-based parameters to model snow

accumulation and melt over a semi-arid mountain catchment. *Hydrologic Processes* 16, pp. 3585–3603.

Yokoyama, R., Shlrasawa, M. and Pike, R. J., 2002. Visualizing topography by openness: a new application of image processing to digital elevation models: Photogrammetric engineering & remote sensing, v.

Zaniewski, A. E., Lehmann, A. and Overton, J. M., 2002. Predicting species spatial distributions using presence-only data: a case study of native new zealand ferns. *Ecological modelling* 157(2), pp. 261–280.