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Modelling the Dependency between Visitor Numbers and Meteorological Variables via Regression Trees

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Abstract: We propose using regression trees as a flexible and intuitive tool for modelling the relationship between weather conditions and day to day changes of the visitor load in outdoor recreation areas. Regression trees offer a number of advantages when compared e.g. to linear models, specifically by outlining different seasonal and meteorological scenarios. When applied to video monitoring data from the Lobau, an Austrian nature conservation area, good regression tree models for the total number of visitors and the counts for some visitor categories (bikers, hikers, swimmers) were found, while other categories could not be adequately represented (dog walkers, joggers). The regression trees indicate a strong relationship between weather and total visitor numbers, as well as weather and the number of bikes and swimmers, respectively. The relationship to weather was found to be only slight for hikers and dog walkers, and completely absent for joggers.

In general, the use of derived meteorological quantities in form of thermic comfort indices for characterizing weather conditions results in better models than the use of directly observable meteorological quantities.

INTRODUCTION

It has been shown (Brandenburg, 2001, Brandenburg and Ploner, 2002) that the number of visitors to the Lobau can be predicted with good results by using a combination of meteorological variables and derived thermic comfort indices which are used to describe human perception of weather conditions. These predictions were based on linear regression models for the logarithmised visitor numbers.

Regression trees are an attractive alternative for prediction because they handle nonlinearity and interactions between variables implicitly. Additionally, they offer a hierarchy of importance of the predictors involved, a classification of the data based on both predictors and the predicted variable, and an intuitive graphical representation of the model.

In this article, we hope to address three basic questions:

1. the basic suitability of regression trees in modelling visitor loads,
2. the possible improvement of model quality when including meteorological information,
3. the relative merits of directly observable meteorological variables like temperature as opposed to derived comfort indices.

MATERIAL & METHODS

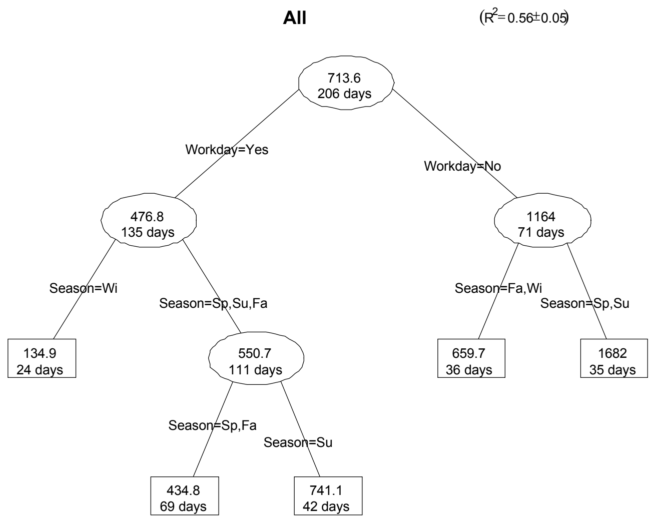
Data Collection

Visitor numbers were gathered using video material collected between August 1998 and September 1999. Cameras were located at five main entrance points to the Lobau. Visitors were counted and assigned to one of several user groups (hikers, dog walkers, joggers etc.). Due to practical problems with camera maintenance, specifically during the initial phase of the project, complete data from all five video stations was available for 206 days (out of 426) only. While we were able to interpolate missing visitors numbers quite well by using the results of the non-compromised stations, we have followed the decision of Brandenburg, 2001, to use only the 206 complete days for modelling. In order to take into account obvious fluctuations in visitor numbers, these days are classified as either 'workdays' (working days) or ''holidays' (i.e. either weekend or a public holiday).

Meteorological data were obtained from a nearby weather station. The technical details of the data collection are described in Brandenburg and Ploner, 2002.

We have modelled both total visitor numbers per day and the counts for five user categories:

Figure 1.Regression tree for the total visitor number per day, using only seasonal information.



- Bikers and hikers make up the main part of visitors to the Lobau.
- Dog walkers and joggers are comparatively smaller user groups, but with potentially high impact on the local wildlife.
- Swimmers also represent a smaller visitor group, though through the typically longer duration of their stay, they tend to have high ecological impact.

Numerous meteorological variables have been considered for their relevance in recreation behaviour (Brandenburg and Ploner, 2002). For use as independent variables in the regression trees, we have found it sufficient to work with ambient air temperature, relative humidity, wind velocity, precipitation, vapor pressure, and solar radiation, each observed at 2 pm.

The meteorological elements listed above were use to calculate a number of *comfort indices.* These indices are combinations meteorological variables that are designed to measure the subjective perception of weather on a one-dimensional scale corresponding to the everyday use of 'good' and 'bad' weather as opposites on a fairly continuos scale. For our current work, we have considered four parameters:

- Equivalent Temperature (Auer et al., 1990),
- Effective Temperature (Auer et al., 1990),
- Chill Factor (Becker, 1972),
- Physiologic Equivalent Temperature (Matzarakis et al., 2000).

Definitions and some background information on these indices is given in Brandenburg, 2001.

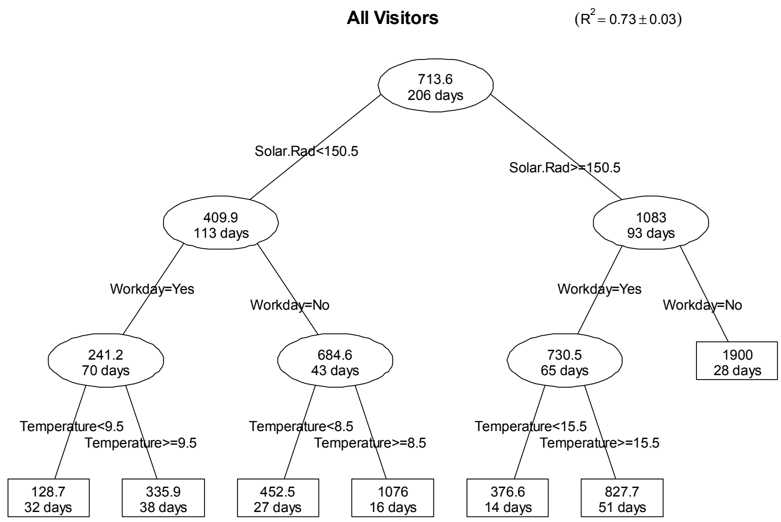
Working with regression trees, we have found the Equivalent Temperature (T_{eq}) to be the most useful comfort index: it gave persistently better results than the others, and was the only one that offered high quality models for visitor numbers on its own, without including either one of the other comfort indices or some meteorological variable.

Classification and Regression Trees (CART)

Regression trees describe the relationship between a response variable and a set of independent variables by recursively partitioning the data set at hand. The methods and terminology described in the following are due to Breiman et al., 1984.

Starting with the full set of observations, the current set is divided in two so as to make the two new subsets as homogenous as possible in regard to the response variable. This process is repeated until all subsets appear to be sufficiently homogenous. The resulting partition of the data set can be described by a binary tree, where each terminal node represents a subset of the observations, and each interior node represents one of the splitting rules. The value predicted by the model for each of the terminal nodes is then an appropriate summary function of the response variable within that node, usually the mean. Figure 1 shows the graphical representation of such a tree for the daily total number of visitors to the Lobau: internal nodes are shown as ovals, terminal nodes as rectangles, and

Figure 2. Regression tree for the total visitor number per day, using seasonal information and meteorological data.



the corresponding splitting criterion as edges; each node contains the average visitor load for the corresponding subset (first line), and the number of days in the subset (second line). Starting from the topmost (or *root*) node, which stands for the complete set of observations, we see that the set contains 206 days with 713.6 visitors on average. In the first step, these observations are split up according to whether they were made on a workday (left branch) or on a holiday (right branch). The corresponding nodes show that there are 135 workdays and 71 holidays, with average visitor loads of 476.8 and 1164 respectively. The left node is then split up again, this time according to the season the observation occurred in: winter workdays go to the right, all others to the left. The right node, with 24 observations averaging 134.9 visitors, is a rectangular terminal node that is not split up any further, unlike the 111 days in the left node. In this way, the 206 daily visitor counts are split up into five subsets (terminal nodes) according to workday and season, with visitor loads ranging from 134.9 on winter workdays to 1682 on spring and summer holidays.

In our approach, splitting rules involve only one independent variable at a time: a simple threshold value for intervalscaled or ordinal variables, and a partition of the observed values for a nominal variable. Starting from the root, all possible splits for all variables within a node are considered, and the one which produces the greatest homogeneity is chosen; the process is then repeated for both subnodes, until all nodes within the tree are sufficiently homogenous. While this stepwise procedure does not guarantee that the resulting tree is optimal overall, it assures that important splits happen before less important ones ('further up' the tree).

Regression trees that are grown only with regard to the homogeneity of the terminal nodes are well known to overfit the data badly, resulting in needless and irreproducible complexity of the model. This is avoided by balancing the size of the tree against its cross-validated predictive power: the initially grown maximally homogenous tree is cut back progressively by removing terminal branches, resulting in a sequence of trees of decreasing complexity and increasing cost (in terms of loss of predictive power). Among these trees, the most parsimonious one is chosen. This process is known as *cost-complexity pruning*.

It has the added advantage that the tree model comes together with a crossvalidated estimate of the model quality. This estimate is calculated by splitting up the data set randomly in ten subsets and refitting the tree ten times, while leaving out each one of the subsets in turn. The trees grown on ninety percent of the data are then used to predict the average for the left-out ten percent. The combined mean squared predictions errors of the crossvalidation runs, divided by the sample variance, is called *relative error* (*RE*) by Breiman et al. (1984, chapter 8.3). In this article, we use the equivalent *coefficient of determination*, which we write in a slight abuse of notation as

$$R^2 = 1 - RE \, .$$

As Breiman et al. (op.cit.) note, R^2 as defined above is not really the same as in linear regression, specifically it is neither the square of a correlation coefficient nor can it be properly interpreted as the amount of variance explained. Still, it is a measure of model quality, with values close to one implying good predictive power, and with values close to zero implying a poor model. We feel that this is not only more familiar for most researchers, it also makes comparisons with linear models as described e.g. in Brandenburg and Ploner, 2002, much easier for the reader than the relative error.

The R software package we used in our analysis (Ihaka and Gentleman, 1996) relies on the approach described in Clark and Pregibon, 1993, the specific model that we employed (Poisson deviance for counting data) on the implementation described in Therneau and Atkinson, 1997.

Modelling Strategy

We have used regression trees to model visitor numbers in several different user categories under three different assumptions:

1. that apart from the visitor numbers, only seasonal data is available, i.e. in which season a visitor count was observed, and whether on a workday or holiday,
2. that in addition to the seasonal information, we have meteorological variables like ambient air temperature, humidity,etc.,
3. that we have T_{eq} values in addition to the seasonal information.

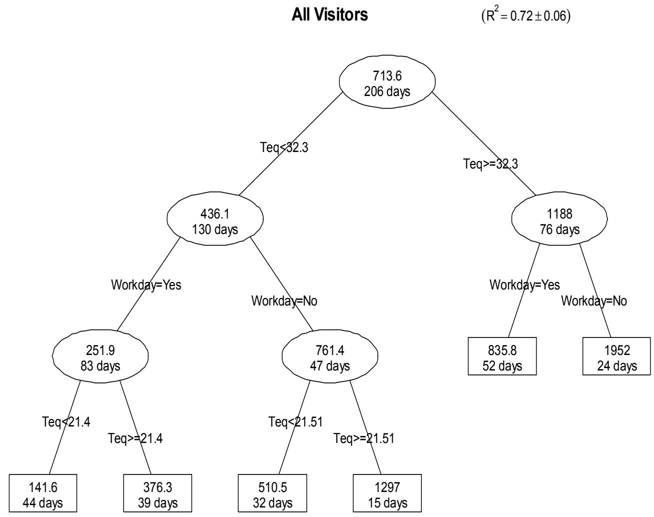
The first class of models serves as a baseline result, telling us how well we can expect to do in predicting visitor loads *without* using meteorological information at all. A comparison of these results with the second and third class hopefully shows the possible improvement in model quality and predictive power when incorporating weather information, and a comparison of the models in the second and third class highlights the respective advantages of directly observed and derived meteorological variables.

RESULTS

Total Number of Visitors

Figure 1 shows the regression tree using only seasonal information. The first split is according to whether a day is a workday or not, and the following splits are according to season: for workdays, spring and fall are grouped together, whereas for holidays, fall and winter, and summer

Figure3. Regression tree for the total visitor number per day, using seasonal informatio and Equivalent Temeprature (T_{eq}).



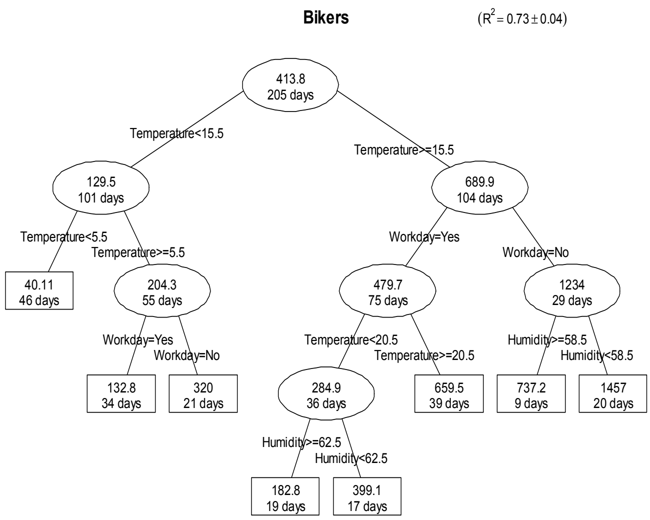
and spring end up in the same terminal nodes. Hardly surprising, the lowest average visitor load is recorded on winter workdays (leftmost terminal node), and the highest on spring and summer holidays (rightmost terminal node). Also, a summer workday has a higher average visitor load (741.1) than a holiday during the colder season (659.7). The overall model quality is quite good for such a simple model (R^2=0.56).

Figure 2 shows the regression tree that incorporates meteorological observations. Here, the main split is according to solar radiation; the next split for both nodes with high and with low solar radiation is into workdays and holidays, and the final splits are by ambient air temperature. The model partitions the observation days into seven subsets, with average visitor loads ranging from 128.7 on workdays with low solar radiation and temperatures below 9.5°C, to 1900 on holidays with high solar radiation. The model quality is quite good (R^2=0.73) and clearly higher than for the seasonal model in Figure 1. For the total number of visitors at least, using meteorological variables clearly improves the model. The resulting model is also remarkably balanced, in the sense that the second-level splits are on workday, and the third level of splits on temperature, so that the final subsets are defined by the same variables in the same order.

Figure 3 finally shows the regression tree for daily visitor counts using only seasonal information and Equivalent Temperature (T_{eq}) to characterise the different scenarios. The quality of the model is quite as good as that in Figure 2 (R^2=0.72 instead of R^2=0.73), though with a slightly higher standard error (s.e.=0.06 instead of s.e.=0.03). The root node is first split into days with T_{eq} below and above 32.3. This is quite close to the distinction between "comfortable' (35.1 to 49) and 'cool' (below 35.1) given for the T_{eq} in Auer et al., 1990, so we adapt these names here for the right and left branches of the tree, respectively. Both comfortable and cool days are then split up according to the workday, and the cool days are then split up again on T_{eq}, into workdays above and below 21.4, and holidays above and below 21.51, respectively. The splitting values for cool workdays and cool holidays are very similar, so we interpret this as a split between days that are properly 'cold' and days that are merely 'cool', where the limit is at a T_{eq} value of approximately 21.5. The final partition can therefore be read as cold workdays, cool workdays, cold holidays, cool holidays, comfortable workdays and comfortable holidays, with corresponding estimated visitor loads (terminal nodes in Figure 3 from left to right). This is a quite satisfying interpretation, and if we look back to Figure 2, we see that the categories derived using the solar radiation and the temperature can be interpreted in much the same way, though the model contains an additional split of the set of days that we have denoted as comfortable holidays above.

It should also be noted that the models in Figure 2 and 3 do not use the season to partition the observation days. Apparently, the information in both the meteorological variables and the T_{eq} make the rather artificial distinction between traditional seasons redundant in explaining visitor loads for the Lobau.

Figure 4. Regression tree for the number of bikers per day, using seasonal information and meteorological data.



Bikers

The regression tree for the number of bikers per day (not shown), based on seasonal information only, is of comparable quality to the one for the total visitor number (R^2=0.57, see also Table 1), though it is slightly more complex (six terminal nodes instead of only five in Figure 1). Figure 4 shows that again, the inclusion of meteorological information clearly improves the quality of the model (R^2=0.73). The main split here is between days with temperatures above and below 15.5°C: the right branch comprises cool days, while the left branch might properly be designated as 'coolish and above'. The cool days are then split again into outright cold days (below 5.5°C), and moderately cold to cool (between 5.5°C and 15.5°C). Note that even on the 46 cold days, we can expect an average of 40.11 bikers per day! The moderately cold to cool days are split up again into workdays and holidays, with about 2.5 times the average number of bikers on holidays than on workdays. Going back to the root node, the 'coolish and above' days are also split up into workdays and holidays. The holiday branch is then divided one more time, into days with high and low humidity (above and below 58.8%), where humid days see about half of the number of bikers than less humid days. The workdays on the other hand are again divided into coolish and 'comfortable or better' days, according to air temperature (above and below 20.5°C); on the coolish side, we have again the distinction between humid and less humid days (above and below 62.5°C), again with about half the number of bikers for the humid days. Compared to Figure 2, the tree is somewhat larger, and clearly less balanced in the relative importance of the independent variables. This might suggest a more complex relationship between weather and the number of bikers, though it should be noted that the construction of the regression tree in Figure 4 also requires only three independent variables, none of them what might be considered the most obvious meteorological parameter, i.e. precipitation. A possible explanation for this suspicious absence is offered in the Discussion.

Figure 5 shows the regression tree for the number of bikers, using only seasonal information and the T_{eq}. The model shows a clear improvement to the model in Figure 4, indeed it is the best of all our models (R^2=0.81). As in Figure 3, the first split occurs according to the T_{eq}; the splitting value is virtually the same (32.06 instead of 32.3), so again, we consider this as a split between cool and comfortable days. The cool days on the left branch are then split up into cold days (T_{eq} below 21.4) and moderately cold to cool days (T_{eq} between 21.4 and 32.06). The latter are then again divided into workdays and holidays. The comfortable days are immediately split up into workdays and holidays, and only the workdays are further subdivided on the T_{eq}, with splitting value 46.08. In the classification given by Auer et al., 1990, this is at the upper end of the comfort zone (35.1 to 49), already close to the category 'slightly humid' (49.1 to 56). In our case, workday bikers seem to prefer the more humid condition, so maybe here it stands rather for the difference between a 'nice' and a 'very nice' day.

As for the total number of visitors, both the meteorological variables and the T_{eq} make the season redundant.

Hikers

Figure 6 shows the regression tree for the average daily number of hikers, based on seasonal information only. The main split is between workdays and holidays, with workdays further divided into cold season (fall and winter) and warm season (spring and summer), whereas the distinction for holidays is between spring and the other seasons. While the quality is quite good for this simple kind of model (R^2=0.61), adding either meteorological variables or a comfort index (not shown) does not substantially improve the quality of the models (Table 1); these models also differ only slightly from the one in Figure 6, by splitting workdays according to solar radiation and T_{eq}, respectively, instead of seasons, with only minor changes in predicted average visitor loads. Specifically, the distinction between spring and the other seasons remains for holidays, so that the right subbranch is identical to the one in Figure 6.

This implies that for the number of hikers, weather is more relevant on workdays than on holidays, even though its consideration does not

Figure 5. Regression tree for the number of bikers per day, using seasonal information and Equivalent Temperature (T_{eq}).

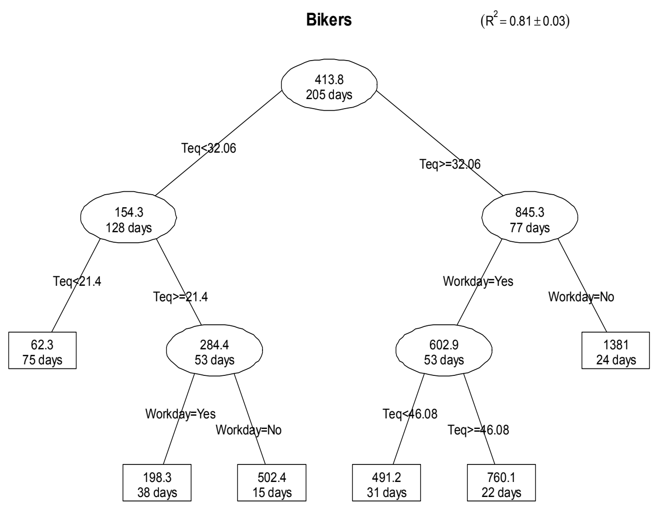
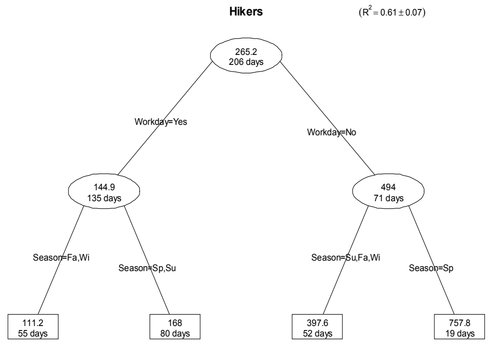


Figure 6. Regression tree for the number of hikers per day, using only seasonal information.



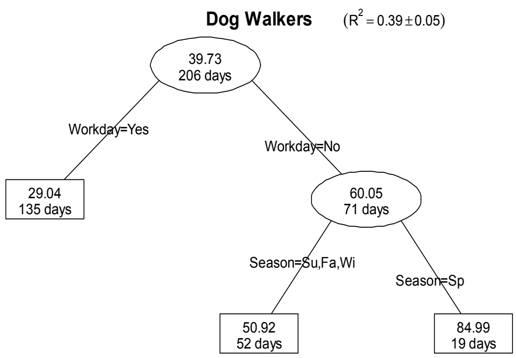
improve model quality substantially. This agrees with the fact that the largest numbers of visitors were observed on the first weekends during spring with tolerable weather conditions (Brandenburg and Ploner, 2002). This seems to indicate that there is a greater willingness for a weekend or holiday walk in the Lobau, regardless of weather.

Dog Walkers

The regression tree for dog walkers shown in Figure 7 is a simplified version of the model for hikers shown in Figure 6: days are split into workdays and holidays, and only holidays are further split into spring holidays and all others. Including either meteorological data or comfort indices did not change this model at all: apparently, the number of dog walkers is quite independent of meteorological conditions. Given the need to walk a dog daily, this is not too surprising, though it might be seen to imply that the majority of dog owners come from the residential areas within walking distance to the Lobau, as it appears improbable that dog owners would travel far under bad weather conditions.

The overall model quality is not good (R^2=0.39), so that apparently, there are factors neither seasonal nor meteorological that cause the variation in the number of dog walkers.

Figure 7. Regression tree for the number of dog walkers per day, using only seasonal information.



Joggers

The only model we were able to fit to describe the average daily number of joggers distinguishes between workdays and holidays, and is execrably bad (R^2=0.17). The model does not change when meteorological variables or comfort indices are added, so we find ourselves quite unable to make predictions about the average number of joggers.

Swimmers

The seasonal model for the number of swimmers (Figure 8) is quite what we would expect: swimmers only in summer, more on holidays than on workdays. Given the extremely simple structure, the quality of the model is quite good (R^2=0.64).

Adding meteorological variables results in the slightly more complex model shown in Figure 9: no swimmers below 20.5°C ambient air temperature, a few hardened cases between 20.5°C and 24.5°C. Serious recreational swimming starts at 24.5°C, with an average of 20.08 swimmers on workdays and of 70.58 on holidays. While this model also sounds quite plausible, it is even slightly worse than the simple seasonal model (R^2=0.59).

Adding the T_{eq} to the seasonal data, we get the model in Figure 10: no swimmers below a T_{eq} value 42.94, a lot above 42.94 on holidays, a few on workdays with T_{eq} values between 42.94 and 50.4, and an average amount on workdays above 50.4. The model quality is very good (R^2=0.79). Note that the splitting value 50.4 is already in the 'slightly humid' zone (49.1 to 56) given in Auer et al., 1990, whereas the other splitting value 42.94 is safely within the 'comfortable' zone (35.1 to 49).

	Seasonal	***Weather***	T_{eq}
Total	0.56±0.05	0.73±0.03	0.72±0.06
Bikers	0.57±0.05	0.73±0.04	0.81±0.03
Hikers	0.61±0.07	0.65±0.07	0.64±0.07
Dog Walkers	0.39±0.05	-	-
Joggers	0.17±0.08	-	-
Swimmers	0.64±0.07	0.59±0.01	0.79±0.05

Table 1. Crossvalidated measures of determination R^2 (with standard errors) for three different classes of regression tree models: using only seasonal information, i.e. season and day of the week (Seasonal), using seasonal information and meteorological variables (Weather), and using seasonal information and the Equivalent Temperature (T_{eq}). For dog walkers and joggers, these models are identical.

Figure 8. Regression tree for the number of swimmersper day, using only seasonal information.

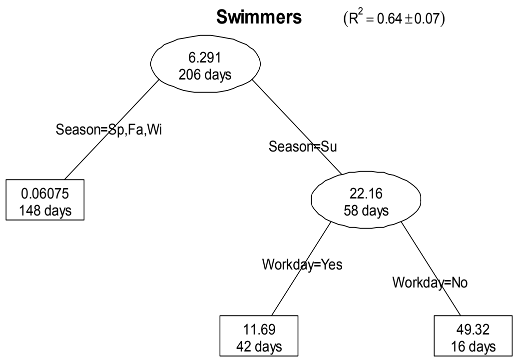


Figure 9. Regression tree for the number of swimmers per day, using seasonal information and meteorological data.

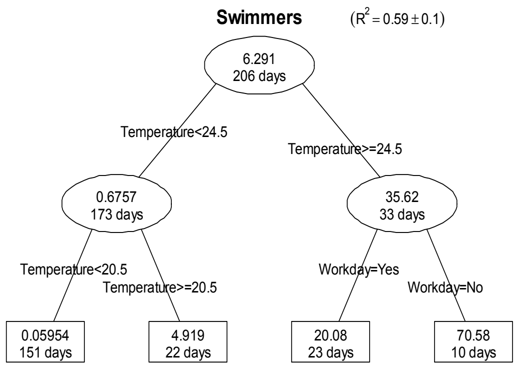
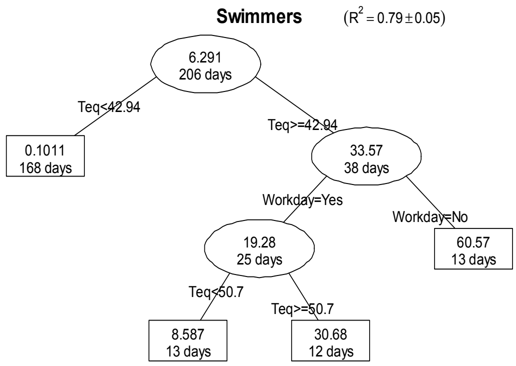


Figure 10. Regression tree for the number of swimmers per day, using seasonal information and Equivalent Temperature (T_{eq}).



DISCUSSION

Suitability

The regression trees for visitor counts exhibited mostly excellent (total count, bikers, swimmers) to acceptable (hikers) model fit, only the trees for dog walkers and joggers were of poor and very poor quality, respectively. The models partition the set of all observations into two to eight different subsets that are defined by seasonal and meteorological conditions. We feel that the interpretations we have given based on the graphical representations of the trees are persuasive, at least for the categories where we could achieve good model fit (total count, bikers, swimmers, hikers). For those categories where we failed to do so (dog walkers, joggers), we suspect that this is due to measurement error: these are comparatively small groups, so that the samples of the video material that were analysed (15 minutes out of every hour, see Brandenburg and Ploner, 2002) did capture the number of joggers accurately enough. Admittedly this is not the case for swimmers, which are not much more numerous, but this might be explained by the fact that the distribution of visitors over the day has only one pronounced peak for swimmers (slightly before noon), but two (one in the evening and one in the morning) for joggers and dog walkers, so that in fact the visitors in the last two categories are spread out more thinly over time.

Comparing these results with the linear models fitted to the logarithmised visitor numbers in Brandenburg and Ploner, 2002, we find that the overall pattern of model quality is the same for most user categories: excellent quality for the total number and the bikers, slightly worse quality for the hikers, only moderate quality for the dog walkers, and very bad quality for the joggers. The R^2 for these linear models is always higher than for the corresponding regression trees, though we do not feel that this represents a serious shortcoming: first, R^2 for the linear models is a proper proportion of variance explained, which, as pointed out above, it is *not* for the regression trees, so these values are not strictly comparable; additionally, the linear models were fitted to the logarithmised visitor counts, so while any predictions made on the log-scale can easily be transformed back to the original scale by taking the exponential function, this is not true of the error of the model. On top of this, we achieved excellent model fit for the swimmers, for who the linear model was even worse than for the joggers, so that we score much better using regression trees in at least one user category.

Using Weather Information

The best tree models are those that incorporate meteorological data as a crucial part (total number, bikers, swimmers); models that retain the season as a variable in the presence of meteorological information exhibit lower model quality (hikers), while those that ignore it are bad to very bad (dog walkers, joggers). In summary, if modelling is worthwhile, it relies on meteorological data and conversely, only through the inclusion of these data are we able to achieve satisfactory model quality.

Meteorological Variables vs. Comfort Indices (T_{eq})

Models based on the T_{eq} are never worse than those using physical meteorological variables, and distinctly better for bikers and swimmers. In case of the hikers, where the comfort index does about as well as the meteorological measurements, we found that the former was more helpful in characterising the partition suggested by the regression trees.

CONCLUSIONS

- Regression trees offer models for visitor numbers that are easily understood and can be displayed attractively. They suggest typical combinations of circumstances for different user groups which influence the decision to visit the recreation area.
- The predictive power of the tree models is comparable to the linear models given in Brandenburg, 2001, without the need to use logarithmised visitor numbers as the dependent variable.
- Using meteorological variables for the tree models improves their predictive quality and makes them more interesting as a short-term predictive management tool, at least for large user groups.
- Using comfort indices, and specifically the Equivalent Temperature, yields models that are more powerful, simpler, and more intuitive than using a combination of physical variables. It is not clear though, whether the comfort indices themselves can be predicted with a sufficient degree of precision to make their use practical.

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