Eidgenössische Technische Hochschule Zürich
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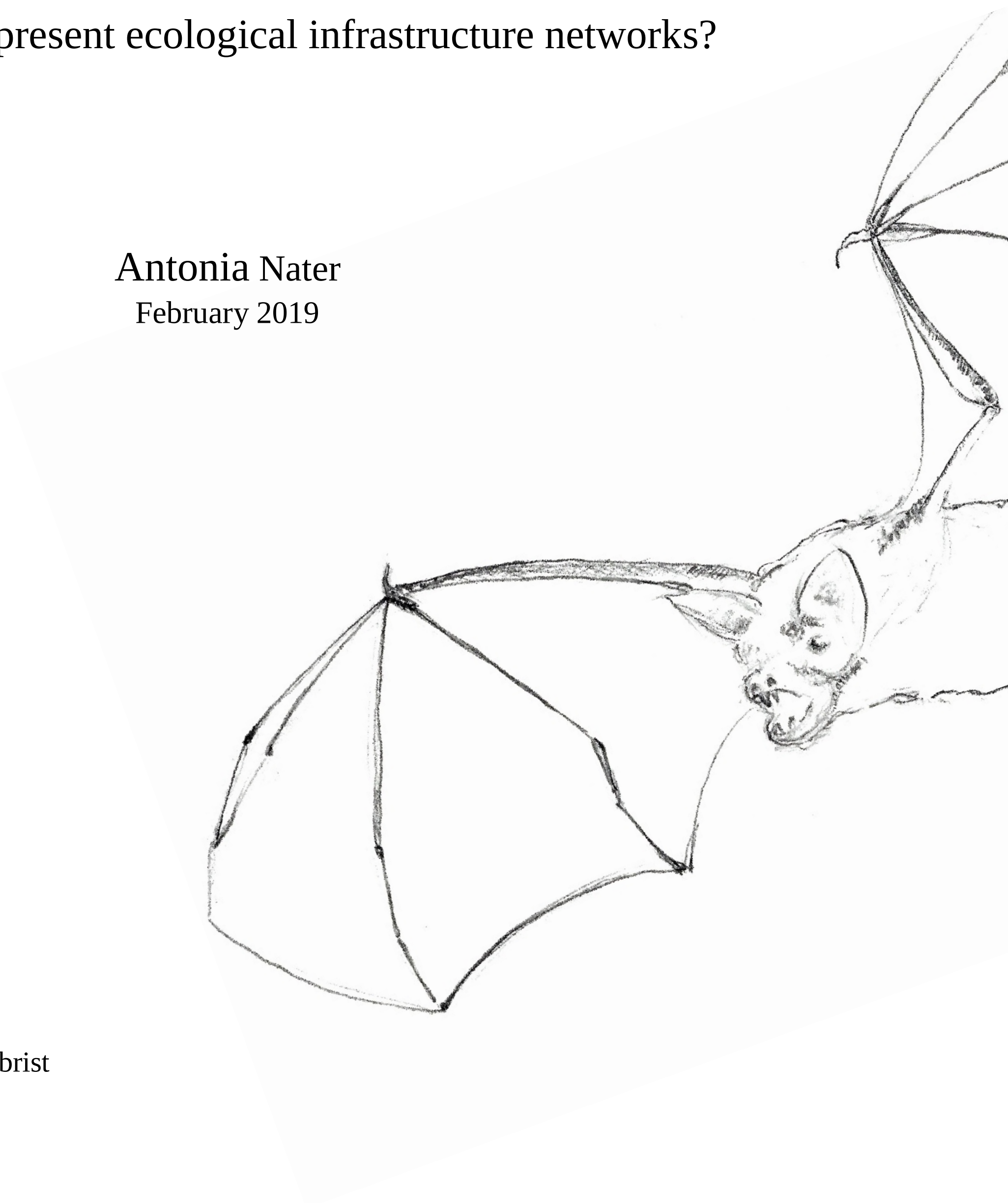
Eidg. Forschungsanstalt für Wald, Schnee und Landschaft WSL

Master thesis

Evaluating methods to predict commuting flyways of Greater mouse-eared bats (*Myotis myotis*):

Do corridors represent ecological infrastructure networks?



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Cover picture: Greater mouse-eared bat (*Myotis myotis*)

ABSTRACT

Dark corridors have been suggested as conservation tool to restore landscape connectivity and enhance species movement across fragmented and artificially illuminated landscapes. Bats are known to use dark corridors for commuting between roost and foraging habitats. Thus, bats can serve as model species to evaluate efforts in urban and land-use planning. Such plans aim at restoring connectivity and at establishing an ecological infrastructure network that links remaining habitat patches through corridors. While foraging areas and roosts have been investigated in numerous studies, state of knowledge about the bat commuting corridors is scarce. To contribute to a better understanding of how corridors are chosen by bats and to expand data basis for planners from expert opinion to a general, reproducible conservation tool, a corridor model was developed. In this study, the numeric bat corridor model has been validated by means of empirical data and expert opinions. The activity of *Myotis myotis* has been recorded at 34 locations in the community of Veltheim (Canton of Aargau, Switzerland), the church of which is home to a large maternity roost of this species. The empirical activity measures were then compared to the corridors predicted by the numeric corridor model and to corridors identified by the regional bat expert. The delineation of corridors by the expert was found to outperform the corridors by the numeric model and the strong negative influence of artificial light on the activity of *M. myotis* was confirmed. Further relations between the activity recorded and a large number of variables associated to artificial light and the ecological infrastructure network was modelled, using the two modelling approaches Multiple Linear Regression and Random Forest. Among light variables derived from ISS images and streetlight position we could not account for a variable to overcome current data gap in the extensively representation of night lighting. The activity of *M. myotis* was found to be related to landscape elements of the ecological infrastructure networks, revealing the potential of this approach.

Keywords: landscape connectivity, land-use planning, expert knowledge, light pollution, Random Forest, Multiple Linear Regression

INTRODUCTION

Massive human pressure on landscapes is seen as major threat to global biodiversity (Grimm et al., 2008; Elmqvist et al., 2013). The most severe impacts are land use changes that alter landscapes heterogeneity and composition, reduce habitat areas and lead to fragmentation (Concepción et al., 2015; Scolozzi & Geneletti, 2012; Grimm et al., 2008). The progressive fragmentation reduces connectivity of remaining habitat patches (Trakhtenbrot et al., 2005). The provision of corridors to link landscape fragments has been suggested to enhance the conservation value of landscapes (Diamond, 1975; Bennett, 2003; Bloemmen &van der Sluis, 2004).

Although corridors are important conservation tools, only recently they made their way onto the political agenda. Land-use and urban planning politics in Europe and Switzerland aim to restore human-impacted landscapes by implementing a functional network of ecological corridors to facilitate species movement (Ricketts, 2001; Bundesamt für Umwelt BAFU, 2017). The concept of ecosystems as infrastructures has evolved in the late 1980's as scientists and conservationists transferred the concept of man-made infrastructure, that provide essential goods and services, on ecosystems (Cardoso da Silva & Wheeler, 2017; Garmendia et al., 2016). The concept of the ecological infrastructure network has recently been defined as "the structural landscape network that is composed of the critical landscape elements and spatial patterns that are of strategic significance in preserving the integrity and identity of the natural and cultural landscapes […]" (Yu, 2012).

Greater mouse-eared bats (*M. myotis*) use corridors along vertical structures to commute from the roost to their foraging habitats (Bohnenstengel et al., 2014). Among other bat species, *M. myotis* use man-made structures such as large roofs and church attics as breeding roosts and well may live in urbanized areas (Zahn, 1999; Rudolph & Liegl, 1990). Living in the vicinity of humans, makes them particularly sensitive to land-use and illumination changes. Interrupted and artificially lit corridors, inappropriate renovation of buildings hosting a roost, reduced food supply due to insecticides and unsuitable forest management have led to a strong decline in bat populations in the second half of the 20^{th} century (Voigt &Kingston, 2015; Bohnenstengel et al., 2014). Many recent studies reveal an overall negative effect of artificial night lighting on bats, even if the strength of the impact differs among species (Pauwels et al., 2019; Azam et al., 2018; Hale et al., 2015; Stone, Jones &Harris, 2009). Yet, assessing the extensive impact of light pollution, first requires the ability to measure it. Pauwels et al. (2019) demonstrated the potential of remote sensing data to account for artificial light impact in cities. However, it is not assessed whether this approach is suitable for rural, less heavily light-polluted areas.

By EU (Council Directive 92/43/EEC, 1992) and Swiss (Art. 20 NHG) legislation, all bat species are protected. Since 2012 an international agreement for bat conservation (UNEP/ Eurobats) has coordinated Europe wide efforts to protect bats. Establishing and protecting corridors is a major goal in bat conservation (Hutson et al., 2015). Although different studies have been assessing the suitability of buildings as roosts (Berková et al., 2014) and potential foraging areas (Güttinger, 1997), the current knowledge about commuting corridors is scarce (Ravessoud et al., 2017). Most known bat roosts in Switzerland are looked after by a professional Bat Protection Responsible. Thus, expert knowledge mainly on the roost, yet also on corridors is available. Nevertheless, expert opinion is often seen as biased by unilateral observation (Stevenson-Holt et al., 2014). Often, quantitative models are employed to provide unbiased, reproducible information to practitioners and planners.

Ravessoud et al. (2017) developed a numeric corridor model to predict commuting corridors of *M. myotis*. The corridor model was fitted to empirical bat activity records. It can serve as helpful tool to effectively contribute to bat protection, by directly demonstrating areas in need of action. In addition, it may help to enhance knowledge on how corridors are used by bats (Ravessoud et al., 2017).

Bat conservationists and landscape planners have recognized the value of such models and have declared interest in pursuing this approach. Before applying the model to all known roosts in Switzerland, the present study evaluated the modelled outcomes by comparing them to an expert opinion and experimentally assessed bat activity on a roost independent of their prior modeling approach. The study area included the colony of *M. myotis* in the community of Veltheim (Canton of Aargau, Switzerland), the church of which is home to a maternity colony of more than 1000 individuals of this species. The aims of this master thesis were to

i) evaluate the quality of the outcomes of the numeric corridor model by means of empirical data and comparison to expert-derived prediction,
ii) assess the influence of artificial light and evaluate different methods of measurements of artificial light at night,
iii) and to investigate the potential of bats as model species for implementation into recent planning efforts for ecological infrastructure networks.

MATERIAL AND METHODS

STUDY AREA

The study was conducted in the community of Veltheim (Canton of Aargau) in northern Switzerland (Fig 1a). Since at least 50 years the church attic in the community of Veltheim (2’653’461 / 1’254’405) hosts over 1000 individuals, thus the second largest maternity roost of *M. myotis* nation-wide (Andres Beck, Bat Protection Responsible, pers. communication).The community of Veltheim is situated within the perimeter of the regional nature park of national interest ‘Jurapark Aargau’. The ‘Jurapark Aargau’ has been established in 2012, encompassing 241 km^2. The perimeter is embedded in the Jura plateau, bounded by the two rivers Rhein and Aare. It is a rural area, characterized by valuable and structured cultural landscapes. The perimeter includes four areas graded as areas of national interest (BLN) and two amphibian spawning areas of national interests, constituting an important, large-scale and coherent natural environment (Jurapark Aargau, 2017).

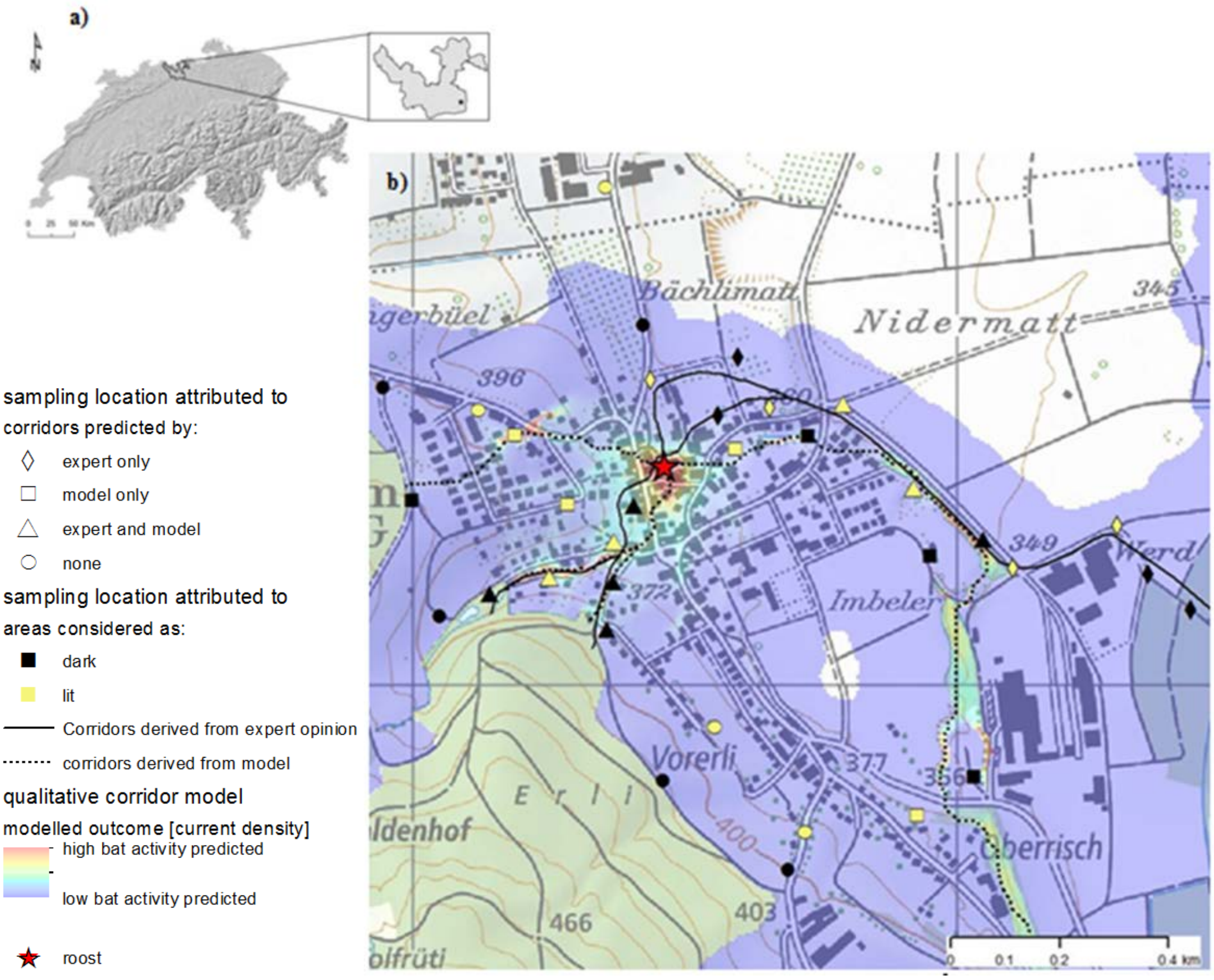

Fig. 1: Representation of the study area and the sampling design with **(a)** the location of the community of Veltheim. The church attic hosts a well-known roost of *M. myotis;* **(b)** the position of the 34 sampling locations to record bat activity with the outcome of the qualitative corridor model (colour gradient), the model (stippled lines) and expert opinion derived corridors (solid lines) and the roost.

STUDY SPECIES

M. myotis is a widespread bat species of central Europe and one of the largest of the 30 bat species in Switzerland (Güttinger et al., 2003; SFF, 2018). Due to the strong decline of the species in the 1970’s / 1980’s, it is currently still classified as a vulnerable bat species (Bohnenstengel et al., 2014) and is considered a species of highest priority (Bundesamt für Umwelt BAFU, 2011). Additionally, *M. myotis* is a target species in the context of ecological infrastructure. This bat , is representative of highly mobile, structure-dependent species (Marti, 2017). Thus, *M. myotis* is an excellent model species to assess how the concept of ecological infrastructure can be integrated into conservation management.

In April females of *M. myotis* congregate to form the nursery colonies, where each rears a single pup. At night, they leave roost shortly after sunset to commute to foraging areas. Carabid beetles (*Carabidae*) are their most important category of prey (Steck & Güttinger, 2006). Deciduous forests, freshly mown meadows, pastures and open areas with no or only low growing vegetation are the most important foraging habitats of *M .myotis* (Arlettaz, 1996; Liegl &von Helversen, 1987; Güttinger, 1997). While females congregate to form nursery colonies, males mostly live solitarily.

PREDICTING *M. myotis* COMMUTING CORRIDORS

EXPERT PREDICTION - *M. myotis* corridors as assessed by expert knowledge

Since over 30 years the colony of *M. myotis* in the community of Veltheim is monitored by Andres Beck (Bat Protection Responsible, Canton of Aargau). Based on his long-time experiences he qualitatively estimated commuting corridors of the colony on a 1:25’000 map (Fig. 1b).

NUMERIC MODEL – *M. myotis* corridors as assessed by a quantitative corridor modelling framework

The numeric corridor model includes eleven environmental variables accounting for trees, structures, terrain ruggedness, structure ruggedness and canopy ruggedness (see supplement material S2 for detail; Ravessoud et al., 2017). Variables were statistically evaluated on empirical data. The optimal set of variables was applied on every 1x1m cell within a 5x5 km frame, resulting in a Habitat Suitability Map (HSM). The HSM was then transformed into a resistance map, each resistance value calculated by the inverse of the quality values (Ravessoud et al., 2017; Stevenson-Holt et al., 2014). The resulting resistance map was used to identify cumulative costs of routes connecting roost and foraging areas. Only routes with low cumulative costs were retained. Results were visualized as current running through a ‘curcuitscape’, with high current density value representing attractive and channeling landscape features regarding commuting activity. The current density layer for the colony of *M. myotis* in the community of Veltheim already existed and was used to identify model assessed corridors of the colony. For stratification of sampling locations, corridors were visually identified.

FIELD SURVEY – *M. myotis* corridors as assessed by experimental field data

Bat activity was recorded in two sampling campaigns at the end of July and the beginning of August 2018 (27.07.-31.07. and 03.08.-07.08.). Bat echolocation calls were recorded with autonomous ultrasound recorders (BATLOGGER; Elekon AG, Lucerne, Switzerland). Along with the vocalizations, the temperature, GPS position and time were recorded in real time. Bat activity was recorded from 15 minutes before sunset to 15 minutes after sunrise. The microphones of the BATLOGGER were fixed at ~1.5 meters above ground, facing towards the church (roost) and slightly pointing towards the ground to protect it from rain damage. Weather conditions were constantly dry and hot during both sampling periods.

34 sampling locations around the roost were defined. To ensure powerful stratification of the sampling locations, landscape matrix surrounding the roost was divided in eight categories by means of two criteria; corridor predictions and artificial light pollution. Firstly, landscape was discerned in areas without corridors and areas representing assessed corridors. Areas representing a corridor were further divided by the criteria of corridor predictor, model or expert. Thus, the following four categories were constituted: [1] the area is attributed to a corridor that is equally predicted by model and expert;
the area is attributed to a corridor that is divergent predicted by model and expert and is therefore attributed to either [2] expert prediction or [3] corridor model prediction; [4] the area is not predicted to be a corridor by either method. Attribution to corridors was made visually by proximity estimates.
These four landscape categories were further divided by artificial light conditions into ‘dark [D]’ or ‘lit [L]’ locations (Fig.2). The allocation was made visually on the map indicating public street lighting. Classification was done to ensure powerful stratification of sampling locations.

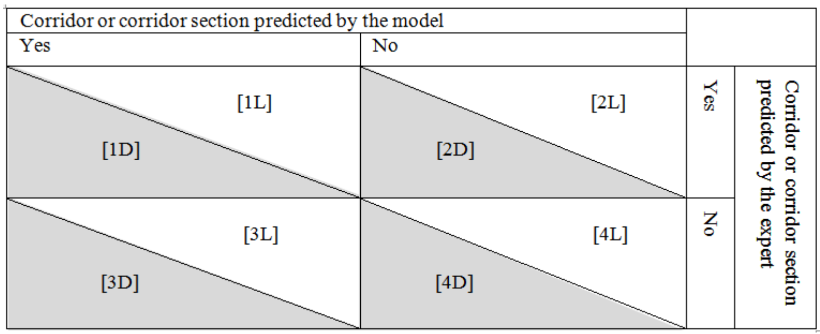

Fig.2: Representation of the sampling design. The landscape matrix was divided into eight categories by associating to corridors and light conditions. Corridors can either be predicted equally by expert and model [1], by only one of them [2], [3] or none of them [4]. Association to corridors and assessment of light conditions [L: lit, D: dark] was made visually to ensure useful stratification.

Sampling locations were selected to equally cover all eight landscape categories. In the final arrangement of the sampling location, the light regime, the ownership structure and the nearby environment was also taken into account. Locations too close to hard surfaces such as streets were avoided as resulting echoes could deteriorate the quality of the recordings. Finally, locations positioned directly underneath light sources were avoided.

ANALYSIS OF BAT ACTIVITY

Bat recordings were processed with BatScope version 4.0. BatScope is a semiautomated software to process acoustic high frequency recordings of bats used for surveys of bat activity, habitat use and monitoring (Obrist & Boesch, 2018). Records processing consists of 6 steps including import, detection and cutting of calls, inspection for parameter, classification, verification and export. While classification is an automated process relying on a reference base covering 27 EU species, verification has to be done manually by the user. Here successive filters regarding classification and characteristics of the calls were used to verify genuine calls of *M. myotis.*

EXPLANATORY VARIABLES: SELECTION AND PROCESSING

To complement the visual classification of the landscape described above, further variables related to expert and model prediction were extracted (Tab. 1). All variables were processed and calculated in ArcMap GIS 10.3 (ESRI, 2016).

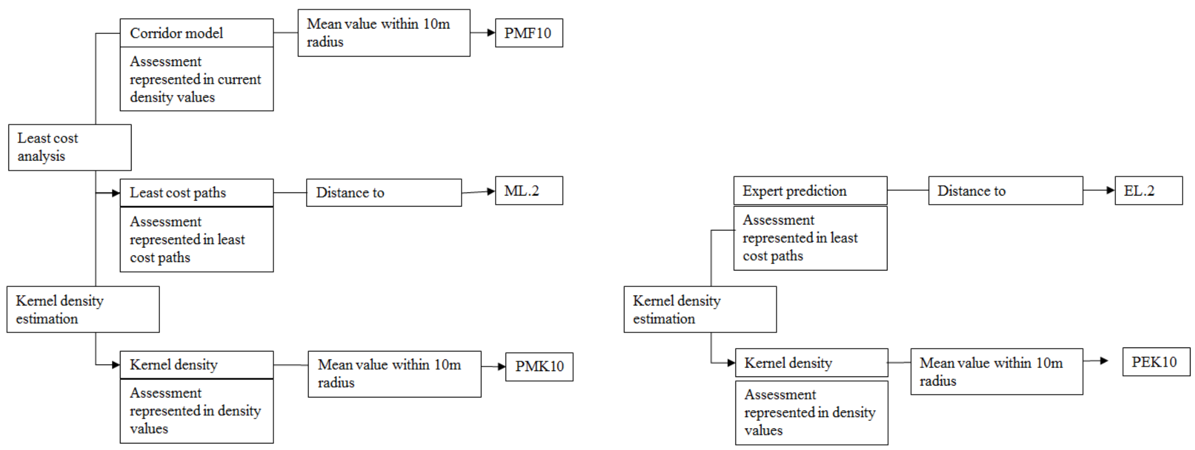

Fig.3: Workflow of model processing and variable extraction. In total five variables were extracted from model predictions (left hand side) and expert prediction (right hand side).

VARIABLES EXTRACTED FROM THE CORRIDOR MODEL

Three variables were extracted from the corridor model (Fig.3). Firstly, the mean current density value within a 10 meter buffer for each sampling location was extracted (*PMF10*), using the GIS tool *zonal statistics as table*. A 10m radius was chosen for construction of the buffer as this covers the reach of the BATLOGGER microphone. Secondly, linear paths were derived by processing the model and calculating least cost paths (see supplement material S1 for detail). Fictitious destinations had to be created to force the construction of several least cost paths, to become consistent with visually assessed corridors (Fig. 1b). Subsequently, a new raster layer was created by calculating kernel density (*Kernel density*, width: 50m) for every least cost path. Mean density value of this newly created layer within a 10m radius was calculated as a third variable (*PMK10*).

VARIABLES EXTRACTED FROM EXPERT-DERIVED PREDICTION

The analogue 1:25'000 map with indicated expert corridors was scanned and then imported in ArcMap. Manual georeferencing by means of striking landscape elements such as road crosses was performed. Corridors were then digitized by creating new line features. Consecutively, a new raster layer was created by calculating kernel density (with: 50m) for every corridor predicted by the expert. The mean value extracted within a radius of 10m around each sampling location represented the expert prediction value per sampling location. As second variable derived from expert prediction, the distance from a sampling location to the closest commuting corridor predicted by the expert was calculated (*EL.2*).

LIGHT VARIABLES

To assess the influence of artificial night lighting on bat activity, different approaches to account for light pollution were pursued. Three sources of information were used to identify four variables representing night lighting (Tab. 1). Firstly, the light intensities were measured at the sampling location once per recording period between 22:00 and 23:00h. At each location, measurements were repeated in all four compass directions in ~1.5 m distance from the microphone of the BATLOGGER and a final average was calculated. The Luxmeter used (Luxmeter testo 540; Testo AG, Mönchenaltdorf, Switzerland) was sensitive 1 lx.

The second source of information was the location of streetlights. The positions of the streetlights were determined with a GPS device (Garmin Oregon 700). The nearest distance from each sampling locations to the closest streetlight was extracted using the GIS tool *Near* (*SL.2*).
Azam et al. (2018) found that light from street lighting has an effect on low flying *M. myotis* up to 25m away from a light source. Accordingly, the number of streetlights within that distance was counted (*SL.3).*
As third information source night photographs taken by astronauts on the International Space Station (ISS) showing the study area were used. The images were corrected for linearity, optical vignetting, the camera settings, and calibrated based upon star fields (Hale & Arlettaz, 2017). The calibrated ISS images were supplied as four raster layers for each of the four colour bands Red (R), Green1(G1), Green2 (G2) and Blue (B). The value of each cell corresponds to the radiance of the cell surface (nW/cm^2/sr) (Hale & Arlettaz, 2017). In order to improve accordance of clear features such as lake boarders and crossroads between ISS images and the ortho-image, the ISS image was shifted 50 meters to the east using the GIS tool *Shift.* Then, pixel value of each of the four raster layers at each sampling location was extracted using the *Extract value to point* GIS tool. Final radiance value per sampling location (*ISS.50*) was calculated from extracted values as follow: R+ ((G1+G2)/2) +B.

VARIABLES TO REPRESENT ECOLOGICAL INFRASTRUCTURE

Based on literature research (Klaus and Pauli, 2012; Kuttner et al., 2013; Marti, 2017) we have compiled a list of ecological elements potentially important for the implementation of an ecological infrastructure network. After screening available data, some variables were skipped, as they were not present in meaningful distance to the roost. In total seven variables that describe elements to establish the ecological infrastructure network were remaining (Tab. 1). The remaining variables account for single trees (*Eb.2, Eb.4*), hedgerows (*HiK.2, GhiB.2*), open water bodies (*GewO.2*) and land management (*EgW.1a, Wa.1a*). For the analysis of the variables representing the ecological infrastructure, a buffer distance of 35 meters was chosen , thereby avoiding an overlap of buffers between sites. To investigate whether feature diversity influences bat activity, the number of elements positively associated to the ecological infrastructure network present within 35m radius was counted (*OI.6*).

Variable collection was broadened by variables representing landscape infrastructure elements not associated to the ecological infrastructure but still known to have an influence on bat activity. Roads represent barriers to commuting bats due to collision danger and noise emission (Bennett &Zurcher, 2013). Correspondingly, a variable to quantify influence of roads was built, by calculating distance from each sampling location to the closest road broader than three meters (*Str.2*). The road network from swissTLM^{3D} (Bundesamt für Landestopografie swisstopo, 2013) was used to select roads broader than 3 meters, representing illuminated roads with regular car traffic.

Background structures provide relevant information to bats for navigation. Thus, bats often fly parallel to linear landscape elements such as tree lines and hedge groves (Limpens & Kapteyn 1991). Schaub & Schnitzler (2007) showed that bat commuting corridors are similar regardless of whether edges consisted of a house wall or vegetation. In accordance, distance to the closest building was calculated by using the GIS tool *Near* (*Geb.2*). Building data was derived from swissTLM^{3D} (Bundesamt für Landestopografie swisstopo, 2013). Finally, distance to the roost was calculated (*Roost.2*), as generally activity is expected to decline with increasing distance to roost as a consequence of thinning effects.

Tab.1: Selection of variables used to model the recorded activity of *M. myotis.*

Variable type	Variable name	Code	Source and Reference	Value range
Variables extracted from corridor model	Mean value of current density within 10m radius	*PMF10*	Numeric corridor model (Ravessoud et al., 2017)	0-0.0219
	Distance to closest corridor assessed by the corridor model	*ML.2*	Numeric corridor model (Ravessoud et al., 2017)	0-0.0393
	Mean value of kernel density within 10m radius	*PMK10*	Numeric corridor model (Ravessoud et al., 2017)	0-461.75
Variables extracted expert corridor prediction	Distance to closest corridor assessed by the expert	*EL.2*	Expert corridor prediction (Andres Beck, 2018)	0-543.91
	Mean value of kernel density within 10m radius	*PEK10*	Expert corridor prediction (Andres Beck, 2018)	0-0.0209
Variables to represent ecological infrastructure	Total area of extensively used meadow within 35m	*EgW.1a*	Kanton Aargau_1669_ökologische Ausgleichsflächen	0-2807.8
	Total area of forest (unclassified) within 35m radius	*Wa.1a*	swissTLM^{3D}_BB (Bundesamt für Landestopografie swisstopo, 2013)	0-2405.1
	Distance to open streams	*GewO.2*	swissTLM^{3D}_GEWAESSER (Bundesamt für Landestopografie swisstopo, 2013)	7.5-579.2
	Count of single trees within 35 m radius	*Eb.4*	SwissTopo 1:25'000 (Bundesamt für Landestopografie swisstopo, 2019)	0-12
	Distance to closest single tree	*Eb.2*	swissTLM^{3D}_EINZELBAUM_GEBUESCHE (Bundesamt für Landestopografie swisstopo, 2013)	5.6-106.5
	Distance to hedgerows in building zones	*GHib.2*	Jurapark Aargau (Marti, 2017)	2.5-787.9
	Distance to hedgerows in cultivated land	*HiK.2*	Jurapark Aargau (Marti, 2017)	0.2-743.6
	Structural diversity of landscape (number of valuable landscape features within 35m radius)	*OI.6*	see above	0-4
	Distance to roads > 3m width	*Str.2*	swissTLM^{3D} STRASSEB_20013(Bundesamt für Landestopografie swisstopo, 2013)	0.9-135.4
	Distance to closest building	*Geb.2*	swissTLM^{3D}BUILDING3D_1_0 (Bundesamt für Landestopografie swisstopo, 2013)	3.7-298.2
	Distance to roost	*Roost.2*		92-1003.3
Light variables	Mean value of radiance	*ISS.50*	ISS Images processed (Hale & Arlettaz, 2017)	0-0.1502
	Distance to closest streetlight	*SL.2*	Field data	6.6-659.2
	Count of streetlights within 25m radius	*SL.3*	Field data	0-3
	Measured lux at sampling location	*Lux*	Field data	0-3.5

STATISTICAL ANALYSIS

The response variable 'activity' is defined as sum of sequences attributed to *M. myotis* counted within time period 21:30 to 22:40 h. We focused on the 'fly-out', the time window where most of the individuals leave the roost for commuting to foraging areas. The 'fly-out' time window covered more than 50% of total activity (Fig 4). The position and duration of the time slot (70 minutes) was selected by visual analysis of the activity distribution over time showing clearly recognizable, sudden increase and decrease of total activity identifying fly-out occurrence (Fig. 4).

Due to sporadic technical failures not all BATLOGGERs recorded during five nights. Therefore, relative bat activity was calculated by dividing per site the total of counts by the number of recorded nights. In order to obtain a normal distribution in the residuals, as required by the Multiple Linear Regression model, a log transformation was applied to relative activity values. First, variables were tested for interactions. Variables with correlation coefficients greater than 0.7 should be removed. As no interactions emerged, all variables were kept for the analysis. Prior to analysis all variables were standardized (mean=0, standard deviation=1).

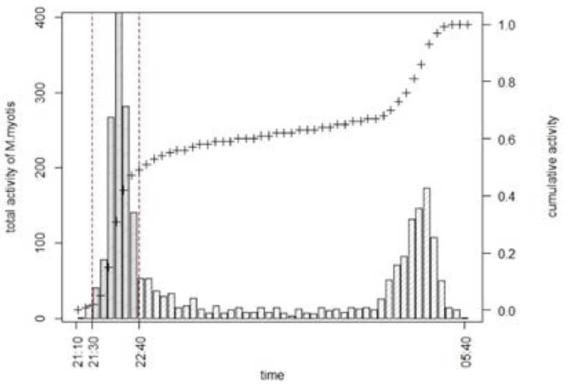

Fig. 4: Only activity of *M. myotis* measured between 21:30 and 22:40h was included in the statistical analysis. This ‘fly-out’ period, when bats leave the roost after sunset, is clearly recognizable by a sudden activity increase and decrease.

Differences in activity regarding expert and model prediction, light availability and diversity of ecological infrastructure was tested, using analysis for variance ANOVA. Subsequently, two different analyzing methods were applied; Multiple Linear Regression (MLR) and Random Forest (RF). All statistical analyses were conducted using the R Statistical Software 3.4.1 (R Development Core Team, 2019).

MLR is a classical approach that has been largely applied for the prediction of dependent variables from a set of predictor variables (Zhang et al., 2017). It is reasonably robust, if the number of observations is larger than the number of variables (Grömping, 2007). The contribution of each variable to the regression model was assessed using the R package *relaimpo* (Grömping, 2006). The metric ‘lmg’ (Lindeman et al., 1980) was used to represent the contribution of single variables in the respective models.

Random forests (RF) are nonparametric and allow nonlinearities and interactions to be learned from the data (Grömping, 2007). Random forests consist of a combination of many trees; the overall prediction value is an average of all prediction values of single trees (Grömping, 2007). In this study the number of trees was set to ntree=500. The number of variables randomly sampled as candidate at each split (mtry) was set to 14, 15 respectively (number of variables in the initial dataset-1). RF allows to assess contribution of single variables to model directly and can therefore be compared to regression techniques (Grömping, 2007). Comparison was done using the mean decrease in accuracy (%IncMSE). Random Forest was implemented using the package *randomforest* in R.

MLR and RF were applied on six different data sets (Fig.5). One dataset only included variables associated to night lighting and to ecological infrastructure. The other five, each additionally contained one specific expert or corridor model derived variable.

Akaike's information criterion procedure (Akaike, 1976) was applied to select best models in MLR. The AIC is an information-theoretic approach that is widely used in ecological data analysis (Burnham & Anderson, 2002). The algorithm constructs different candidate models ranging from a global model to a single predictor model (Tesfamichael & Beech, 2016). Single models are then compared to an unknown model that is thought to represent full reality (Burnham & Anderson, 2002). The model that minimizes information loss from full reality model is chosen as best model. Consequently, models with lowest AIC are considered the best model. All models within 2 AIC units are meant to have the same explanation power.

In the process of RF modelling, variables were selected by means of their %IncMSE values, that represent importance of variable in the model. Firstly, variables with negative %IncMSE values were removed, as they negatively influence explanation power of the model. Then variables with low %IncMSE values were removed stepwise, starting with the variable showing the lowest %IncMSE value. The removal of these variables went simultaneous with an increase in the percentage of variance explained by the model. Thus, the selection of variables was stopped, as soon as the removal of variables did not result in an improvement of the model.

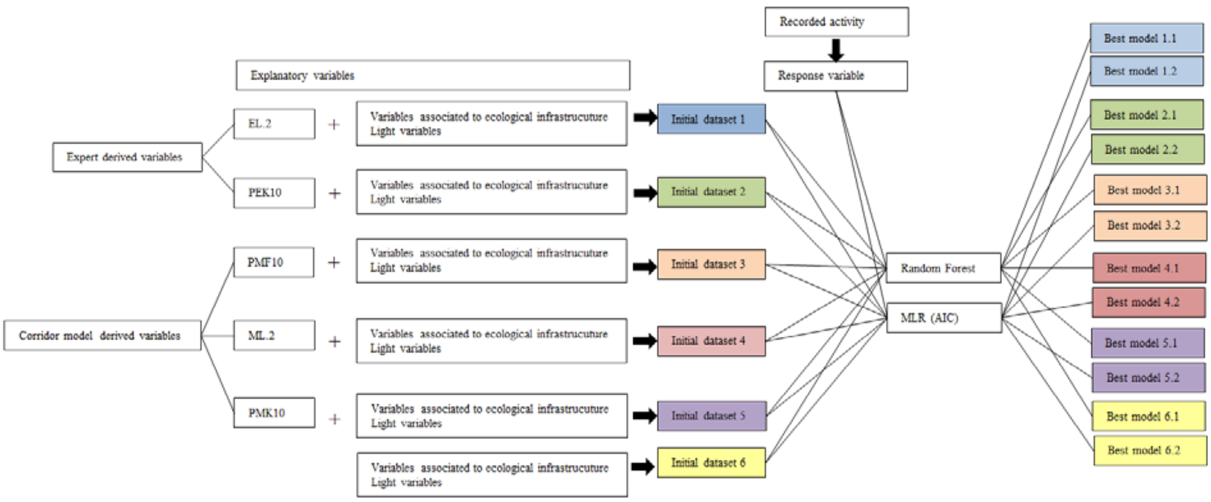

Fig. 5: Presentation of the analysis concept of this master thesis. Two different model approaches were applied on six different initial datasets, resulting in twelve best models.

RESULTS

FIELD DATA

A total of 72’100 bat passes were recorded, whereof 51’736 records contained more than one signal and were therefore classified as bats. However, only 5% of these recordings were attributed to *M. myotis*, resulting in 2’613 single sequences assigned to that species. When restricted to the ‘fly-out’ time period (Fig.4), the number of recordings amounted to 1’321 verified *M. myotis* activity sequences. Relative activity per sampling location varied between 0 to 35.4 counts per night recorded (Fig. 7). No activity was measured at location 17. At locations 7, 8, 14 and 33 less than one *M. myotis* crossed per night on average. These sampling locations are either not attributed to any predicted corridor [4] or to a corridor only predicted by the model [2] (here and following, numbers in square brackets relate to ‘treatments’ in the sampling design as detailed in Fig.2). Artificial light could be measured at all of these locations, light intensity varying between 0.25 and 1 lux.

With more than 30 *M. myotis* crossing per night, highest activities were recorded at locations 5, 20 and 27 (Fig.7). With 29.5 and 27.6 counts per night, locations 3 and 32 revealed remarkably high activity too – both being situated close to either side of a waterbody. These locations were attributed to corridors equally predicted by model and expert [1] or to corridors only predicted by the expert [3]. Surprisingly, location 32 wasn’t attributed to any corridor [4]. Fig. 7 shows the density of activity per night recorded per sampling location, highlighting activity hotspots with more than 25 *M. myotis* crossing per night. At none of these hotspots artificial light was present.

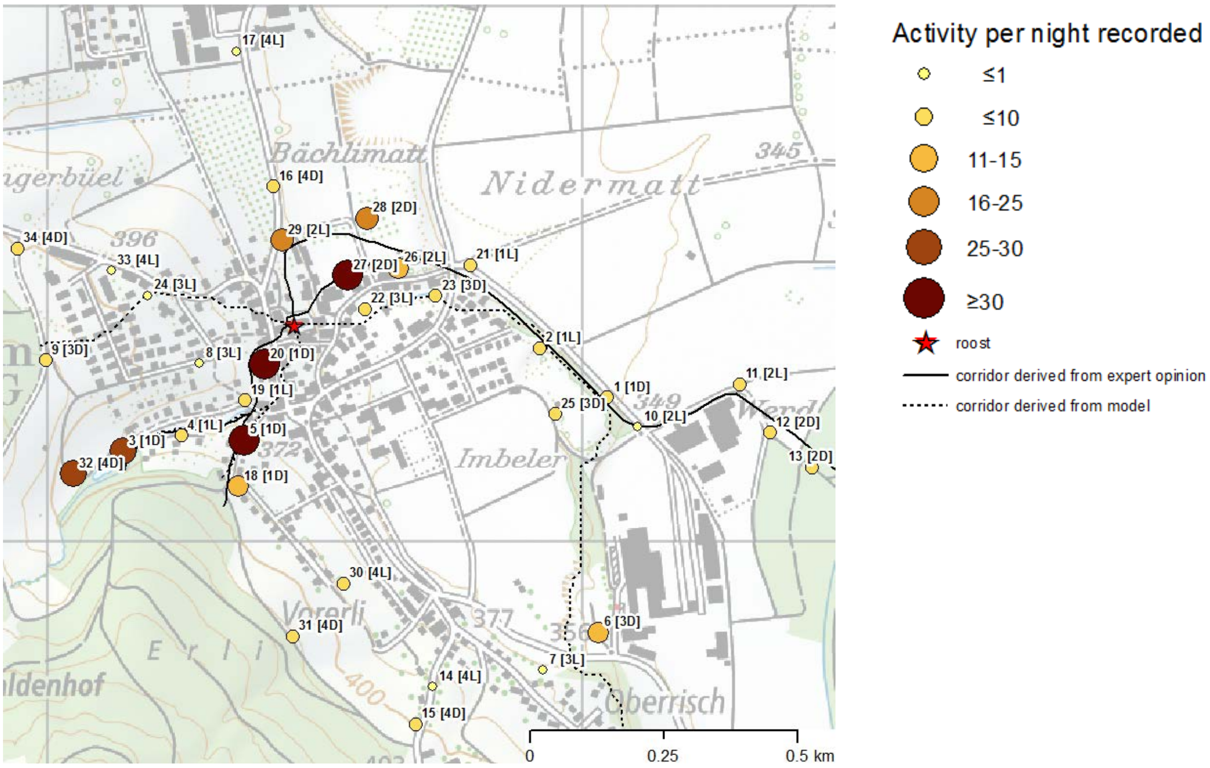

Fig. 7: Illustration of sampling locations, showing ID, sampling scheme classification (square brackets, see Fig.2) and sampled mean commuting activity of *M. myotis* per night, represented by size and color of bubble.

DIFFERENCES IN THE ACTIVITY OF *M. myotis*

Mean activity differed significantly between the four classes representing allocation to predicted corridors ($p = 0.037$, Fig.8a). With a mean of 1.25 recorded sequences per night, empirically assessed bat activity was lowest at locations attributed to corridors only predicted by the corridor model [3]. Slightly more activity (on average 1.29 sequences per night recorded) was measured at locations that weren't attributed to any corridor predictions [4]. At locations attributed to corridors only predicted by the expert [2], an average activity of 2.12 counts per night was recorded. Highest activity was counted at locations attributed to corridors, that were equally predicted by corridor model and expert [1].

Experimentally assessed activity at locations attributed to corridor predicted by the corridor model [1,3] did not differ significantly from locations not attributed to a model predicted corridor (p-value: 0.625, Fig. 8b). However, activity was significantly higher at locations attributed to an expert predicted corridor [1,2], compared to locations not attributed to an expert predicted corridor (p-value <0.001). Experimental counts at locations attributed to an expert predicted corridor were 2.92-times higher compared to locations not attributed to an expert predicted corridor.

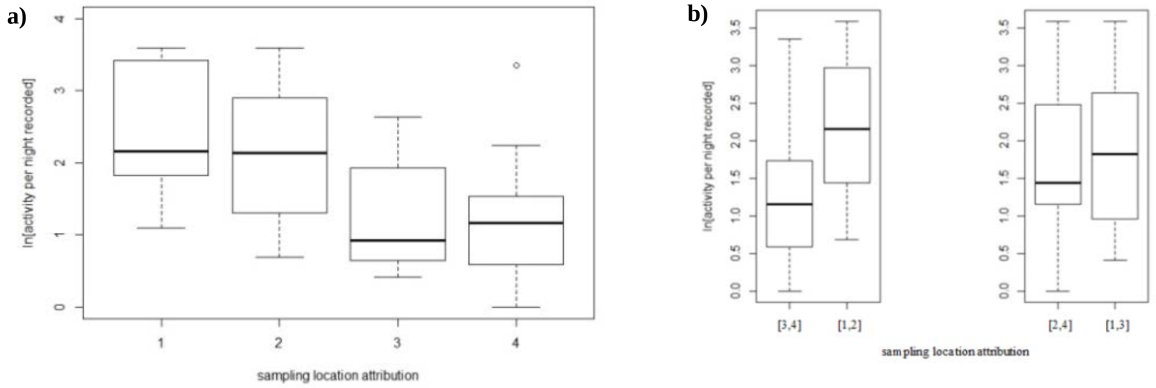

Fig. 8ab: Boxplot showing the distribution of experimentally assessed bat passes. Sampling locations were attributed to corridors as detailed in Fig. 2.

LIGHT EFFECTS

In total 244 bat passes were registered at locations influenced by artificial light (≥ 0.25 lux measured at sampling location). In contrast 1077 passes were measured at locations not influenced by artificial light (0 lux measured). Thus, activity was 4.4-fold higher at locations where no artificial light was present (Fig. 9a). Hence there is a statistically significant higher activity of bats at sampling locations not influenced by artificial light (p-values < 0.001). Artificial light had a negative influence on the activity of *M. myotis* down to an illumination threshold of 0.25 lux.

Bat activity tended to be higher at more diversely structured locations (Fig. 9b) Surprisingly, it seems less important how diverse the nearby environment (35m radius) is, as long as the environment includes at least a single ecological valuable landscape element.

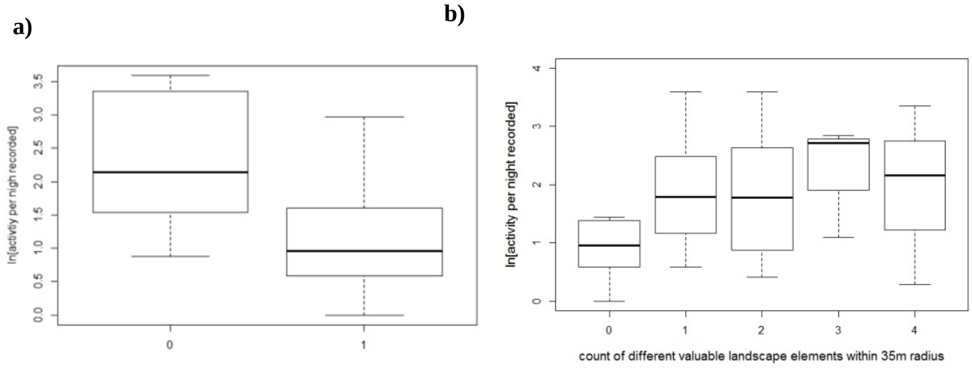

Fig. 9: Bat activity was influenced by **a)** the presence (1) of artificial light and **b)** the structural diversity. Presence of artificial light represent measured lux values ≥ 0.25 lux. In total six elements were included in the assessment of the structural diversity.

M. myotis ACTIVITY MODELLING

MULTIPLE LINEAR REGRESSION

For each of the six initial datasets one best model was developed (Fig.5). All six best models included less variables than the initial datasets, as variables with low influence on the response variable were removed in the selection process. Table 3 gives an overview on the 'lmg' metrics (in %) of the variables, that were included in at least one best model. 'Lmg' metrics represents the contribution (in%) of each variable to the model. Thus, high 'lmg' metrics indicate important variables. Explanatory variables not represented in Table 3 (*EgW.1a, ISS.50, SL.2, Eb.4, Geb.2, Str.2*), were not selected for any best model. For all three best models developed from an initial dataset, that included a corridor model derived variable, number of variables decreased to seven. The respective corridor model derived variable was not among the selected seven variables. The number of variables in the best models developed from the datasets including an expert derived variable, decreased to nine and still included the respective expert derived variable (Tab.3). Distance to expert corridor (*EL.2*) and mean value of expert prediction (*PEK10)* showed similar importance (represented by the 'lmg' metrics) in their respective best model (Tab. 3).

For the light variables the number of streetlights within 25 m radius and measured lux were retained in all best models, although according to the 'lmg' metric the measured lux was more important (*Lux*) to explain the variance in bat activity than the number of streetlights (*SL.3*). For the variables associated to the ecological infrastructure the distance to shallow streams (*GewO.2*) and to hedgerows in building zones (*Ghib.2*), as well as the variable representing the diversity of ecological valuable elements (*OI.6*) were included in all six best models.
For the exception of OI.6, all these variables had a negative influence on the activity of *M. myotis*.
Surprisingly, the variable representing distance to roost (*Roost.2*) was only of importance in some of the best models (Tab. 3).

Regarding AIC value and adjusted R^2 the model that performed best among all, was the one where the variable PEK10 was included as expert derived variable (Tab.3). PEK10 was derived from the expert prediction, describing mean prediction value based on the kernel density of indicated corridors.

Tab. 3: Overview on the 'lmg metrics (in %) representing importance of each variable in the respective best model. Explanatory variables not represented in this table were not included in any of the six best model. The best model derived from the dataset including PEK10, showed the lowest AIC value.

		Explanatory variables included in at least one best model											
		Lux	SL.3	GewO.2	HiK.2	Ghib.2	Eb.2	Wa.1a	OI.6	Roost.2	Respective corridor model or expert variable	AIC	adjusted R^2
Expert or corridor model derived variable included in the initial dataset	PMK10	22.61	11.97	26.23		6.14	4.46		12.09	16.49		-20.25	0.6749
	PMF10	22.61	11.97	26.23		6.14	4.46		12.09	16.49		-20.25	0.6749
	ML.2	22.61	11.97	26.23		6.14	4.46		12.09	16.49		-20.25	0.6749
	PEK10	22.38	9.64	25.31	2.59	10.18	2.08	1.66	6.27		19.91	-35.01	0.7607
	EL.2	21.48	8.91	20.79	2.46	12.29	2.35	1.52	8.18		21.98	-22.31	0.6949
	NONE	22.61	11.97	26.23		6.14	4.46		12.09	16.49		-20.25	0.5874

RANDOM FOREST MODEL

The %IncMSE metric represents the importance of a variable in the model, as it indicates how the predictive ability of the model chances, when the variable is replaced (Vincenzi et al., 2011). Thus, a variable with a low %IncMSE value is unimportant in the model and its removal has only marginal effects. The removal of variables with negative %IncMSE values are even positive for the prediction strength of a model.

Corridor model derived variables (*PMK10, PMF10, ML.2)* all showed negative %IncMSE values. On the contrary, expert derived variables (*EL.2, PEK10*) both showed high %IncMSE values (Fig. 10a, b). According their %IncMSE value, they were graded as second, third most important ,variable respectively, in the respective best model. Among the light variables the measured lux was by far the most important variable in all the six best models. Distance to streetlight and number of streetlights within 25m were included in some of the models but showing very low %IncMSE values. The ISS image derived variable showed strongly negative values and was excluded in all six datasets. Distance to shallow streams showed high %IncMSE values in all six best models, in most of them even representing the second most important variable. The variable representing the total area of extensively used meadow in the 35m radius (*EgW.1a*), was kept in all best models too, while structural diversity (*OI.6*) and distance to single trees (*Eb.2*) was only included in some of the best models. All other variables associated to the ecological infrastructure were removed in the variable selection process. The distance to the roost was included in all best models, but demonstrating different importance in the respective model.

The best model derived from the dataset including PEK10 as expert prediction derived variable could explain 41.63% of the variance in the recorded bat activity. In comparison to the other five best models it showed the highest explanation power. The remaining five best models could explain around 32% of variance.

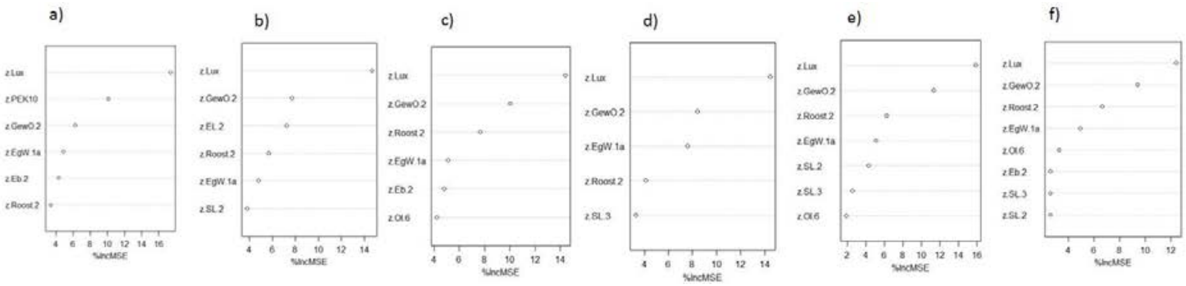

Fig. 10: Presentation of variable importance measure (%IncMSE) for the six best models: [a-b]: initial dataset included an expert derived variable, [c-e]: initial dataset included a corridor model derived variable, [f]: initial dataset did not include a corridor model or expert derived variable.

DISCUSSION

Highest commuting activity of *M. myotis* was experimentally measured at sampling locations attributed to corridors coincidently predicted by the corridor model and the expert. When comparing measured activity at locations attributed to corridors that have been either predicted by expert or model, the higher activity was observed at locations attributed to a corridor predicted only by expert.
This is not coherent with other studies investigating differences in model and expert prediction. Expert-based prediction was found to be less reliable and precise in previous studies (Stevenson-Holt et al., 2014; Clevenger et al., 2002; Seoane et al., 2005). Experts may be biased by subjective perception. This becomes obvious when looking at large-scale species movements of hardly detectable and observable species, which are irregularly distributed across the landscape. Investigation of this study was done on a rather small spatial scale (5x5km). Additionally, bat commuting activity is easy to observe, as all individuals of a bat colony leave from a known roost within a small, known time frame. Hence in this context expert knowledge seems very accurate. Thus, benefits of the model are in particular revealed, when expert knowledge is missing due to missing expert or increasing distance to roost.

Artificial night lighting has an overall negative effect on the activity of bats (Hale et al., 2015). Especially low and fast flying species, among them *M. myotis* avoid illuminated areas due to an increased predation risk (Rydell et al., 1996). Artificial light can even induce barrier effects for commuting activity (Azam et al., 2018; Stone, Jones &Harris, 2009). The results of this study confirm the adverse impact of artificial light on *M. myotis.* Night lighting has a measurably adverse effect on the activity of *M. myotis* above an illumination threshold of 0.25 lx. This result is in line with Azam et al. (2018), who showed *Myotis* spp. to avoid lux values below 1 lx. Yet, for effective use of corridors by light-sensitive bats as *M. myotis* they recommend an illumination threshold of 0.1 lx (Azam et al., 2018). The result of this thesis shows that night lighting also effects bats on a very low light level and must not only be considered in urban planning, but also on small-scale planning of rural communities.

The numeric corridor model could not account for light pollution due to data lack. This limitation could be overcome by making the spatial distribution of night light available as a GIS layer. Due to this limitation, two sources of information were tested to overcome the data gap; location of streetlights and nocturnal light imaging from ISS. Even if the streetlight density was retained in best models in Linear Regression, lmg values representing importance of variable were low. So, neither distance to closest streetlight, nor streetlight density, nor ISS images revealed potential for capturing influence of artificial night lighting on *M. myotis.* On the contrary, Pauwels et al. (2019) showed that ISS image-based variables as well as streetlight density within 200m radius both are appropriate measures to account for the influence of artificial night lighting on bat commuting activity. They conducted their studies in heavily light-polluted cities with nights up to 40 times brighter than natural conditions (Rich &Longcore, 2006), distinctively recognizable on the ISS images. This study was conducted in a more rural, less light polluted area. Moreover, ISS images did not mirror the hilly landscape of our study area. Thus, the results of this study could not confirm the potential of remote sensing data to account artificial light impact for rural areas. We therefore suggest the conduction of more research on night pictures taken by drones. These pictures could then be processed and calibrated similar to the ISS images.

For the variables associated to the ecological infrastrucuture network shallow streams were found to be the most important landscape feature interacting with commuting activity of *M. myotis*. Several studies have identified aquatic habitat as favorable habitat for bats (Rainho & Palmeirim, 2011; Russo & Jones, 2003). Due to the extraordinary high temperatures and long-lasting period of drought during the sampling period, water bodies might have been even more important as small water bodies dried up earlier. Additionally, in Liner Regression modelling distance to hedgerows was found to interact with bat commuting activity. The echolocation signal of *M. myotis* is adapted to detect background structures such as hedgerows and trees in long distances up to 25 meters (Bonnmann &Schnitzler, 2005). Thus, hedgerows serve as landmarks for their navigation. Additionally, extensively used meadows showed high interaction with measured activity of *M. myotis* independent of initial data set and modelling approach.

Freshly mown meadows are known to be suitable foraging habitat for *M. myotis* (Güttinger, 1997). In late summer they feed on scrane flies, over low meadows, where the bats can detect their prey. When bat activity was recorded in late summer, many meadows surrounding the roost were freshly cut. Thus, extensively used meadow may influence measured bat activity, as they serve as foraging habitat. Meadows were not integrated as potential foraging areas in the numeric corridor model as remotely sensed data on temporally varied agricultural management throughout the vegetation season is not yet available spatially explicit. The results of this thesis reveal which landscape elements might be integrated in the ecological infrastrucuture network to provide valuable corridors and resource areas. It furthermore demonstrates the potential of the ecological infrastructure network for bat conservation.

Enhancing the structural diversity in order to establish an ecological infrastrucuture is one of the main goals defined in the action plan for the regional nature park 'Jurapark Aargau'. The results of this study show that diversity of ecological valuable landscape element seems to be less important than the fact, that the landscape includes at least one of these elements. Furthermore, analysis of recordings reveal great differences in activity of *M. myotis* on small scales. Thus, the existing draft of the ecological infrastrucuture planning, which only relies on extensively managed areas, is not detailed enough and requires spatial refinement. Successful implementation of an ecological infrastructure network will require a combination of local, regional and national scale functional assessments, including the consideration of artificial light at night.

In comparison to the RF, which shows a weaker relationship between dependent and independent variable(proportion of variance explained: 41.63%)., the results obtained with MLR have much higher predictive values (R^2: 0.7607). Nevertheless, in both approaches the same variables revealed high importance. Surprisingly, the total area of extensively used meadow was only retained in best models obtained from Random Forest. As Random Forest also accounts for nonlinear association, the total area of extensively used meadow seems to influence bat activity in a nonlinear function – and possibly only in the late season. Differences between the two approaches have been discussed in different research fields (Oliveira et al., 2012; Smith, Ganesh &Liu, 2013; Zhang et al., 2017). The results of the comparisons are not consistent, indicating that suitability of Random Forest and Multiple Linear Regression depends on the dataset applied.

Random Forest variable importance measures might not be reliable in studies where potential independent variables vary in their scale of measurement, number of classes or data type (Strobl et al., 2007). The result obtained from variable selection then might be misleading as suboptimal independent variables may be artificially preferred (Strobl et al., 2007).

In this study variables of different scales of measurements were used, but values were standardized for statistical analysis to ensure uniform value ranges. However, variables differed in data type. While some variables showed continuous numbers, others were defined in classes. As variables represented in classes were associated to different environmental factors, number and size of classes varied between variables. This demonstrated that the dataset involved in this study might not be perfectly suitable for Random Forest analysis due to biased variable selection process.

Juvenile *M. myotis* that are born in spring, become independent in august and start commuting just like adult bats. It is not yet fully understood, how this fact changes commuting activity of the colony. It is hypothesized that juveniles need a training period to learn how to navigate. During this period the use of corridors might be less distinct and overall commuting activity pattern may alter as a function of the presence of juveniles (Ravessoud et al., 2017). Thus, recordings in early summer would be more precisely reflecting commuting activity, due to exclusion of juveniles activity.

Ravessoud et al. (2017) developed the corridor model for the two bat species Greater mouse-eared bat (*M. myotis*) and Lesser Horseshoe Bat (*R. hipposideros*). Selection of environmental parameters for the basis of the model was species specific due to species-specific echolocation and flight behavior. In the study presented here, only the corridor model for *M. myotis* was evaluated. Further steps include evaluation of the corridor model for *R. hipposideros*. This study provides a valuable approach to evaluate the corridor model outcome for both species at different roosts. The results of this study and results of further evaluations should demonstrate potential weakness of the model, that must be improved before model commuting corridors for all known roosts in Switzerland and make corridor maps available for planners or public. Moreover, the results of this thesis indicate a strongly negative impact of artificial light on the commuting activity of *M. myotis.* Thus, further steps also include investigation of an approach to make the impact of artificial light on bat commuting activity available as a GIS layer.

This study aimed at comparing bat activity assessment by a numeric bat corridor model, expert-derived corridor assessment and experimentally measured bat activity of *M. myotis.* Expert derived prediction showed higher compliance with empirically assessed bat movement and therefore outcompeted the prediction of the corridor model. In contrast to expert knowledge of nocturnal lighting, the corridor model does not account for artificial night lighting, due to data lack. The potential of remote sensing data and streetlight density to overcome this data gap that has been suggested in an earlier study (Pauwels et al., 2019), could not be confirmed in this thesis investigating bat commuting activity in a rural, less light-polluted area. We recommend further research on the approach of using a drone to capture small-scale night lighting and implementation of night lighting in the corridor model. Elements mentioned to establish the ecological infrastructure networks positively correlate with bat activity, demonstrating the potential of the concept of ecological infrastructure for practical bat conservation. However, great differences in bat activity on a small-scale were measured, the current concept of the ecological infrastructure planning must be refined to ensure functionality of established corridors on multiple scale.

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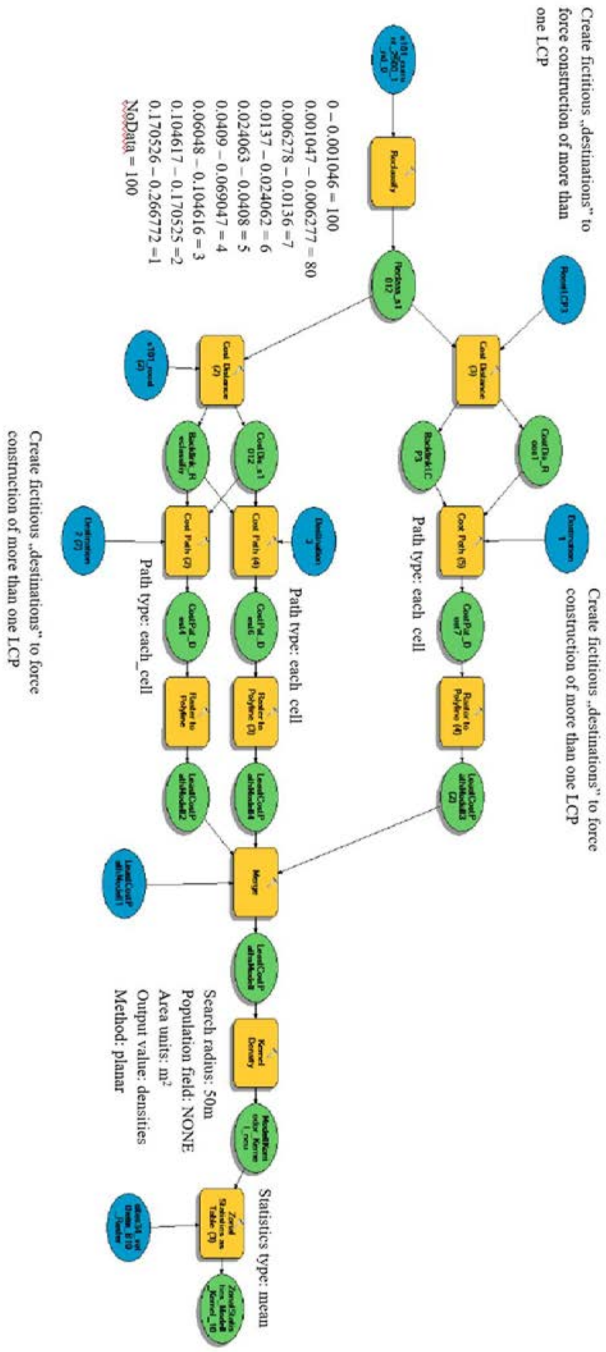
SUPPLEMENT MATERIAL

S1 – ArcGIS MODEL BUILDER: FROM NUMERIC CORRIDOR MODEL TO LEAST COST PATHS

In order to have the same initial state for analysis we derived least cost paths from the numeric corridor model. Least cost paths describe paths with lowest cumulative travelling cost for a given species in a landscape matrix.



S2 – VARIABLES IN THE NUMERIC CORRIOD MODEL

The numeric corridor model included environmental variables as explanatory variables. Landscape features may be represented in various measurement approaches.

Tab.1: Description of the environmental variables included in the numeric corridor model.

landscape feature	measurement
trees	Edge density at 25m scale
trees	Cover at 25 m scale
trees	Cover at 10m scale
structures	Edge density at 10m scale
structures	Edge density at 25m scale
Terrain ruggedness	Curvature at 10m
Terrain ruggedness	Curvature at 5m
Structure ruggedness	Vector Ruggedness Measure at 10m
Structure ruggedness	Terrain Ruggedness Index at 10m
Structure ruggedness	Vector Ruggedness Measure at 25m

ETH

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Eigenständigkeitserklärung

Die unterzeichnete Eigenständigkeitserklärung ist Bestandteil jeder während des Studiums verfassten Semester-, Bachelor- und Master-Arbeit oder anderen Abschlussarbeit (auch der jeweils elektronischen Version).

Die Dozentinnen und Dozenten können auch für andere bei ihnen verfasste schriftliche Arbeiten eine Eigenständigkeitserklärung verlangen.

Ich bestätige, die vorliegende Arbeit selbständig und in eigenen Worten verfasst zu haben. Davon ausgenommen sind sprachliche und inhaltliche Korrekturvorschläge durch die Betreuer und Betreuerinnen der Arbeit.

Titel der Arbeit (in Druckschrift):

Evaluating methods to predict commuting flyways of Greater mouse-eared bats (Myotis myotis): Do corridors represent ecological infrastructure networks?

Verfasst von (in Druckschrift):

Bei Gruppenarbeiten sind die Namen aller Verfasserinnen und Verfasser erforderlich.

Name(n):	Vorname(n):
Nater	Antonia

Ich bestätige mit meiner Unterschrift:

- Ich habe keine im Merkblatt „Zitier-Knigge" beschriebene Form des Plagiats begangen.
- Ich habe alle Methoden, Daten und Arbeitsabläufe wahrheitsgetreu dokumentiert.
- Ich habe keine Daten manipuliert.
- Ich habe alle Personen erwähnt, welche die Arbeit wesentlich unterstützt haben.

Ich nehme zur Kenntnis, dass die Arbeit mit elektronischen Hilfsmitteln auf Plagiate überprüft werden kann.

Ort, Datum	Unterschrift(en)
Zürich, 06.02.2019	Antonia Nater

Bei Gruppenarbeiten sind die Namen aller Verfasserinnen und Verfasser erforderlich. Durch die Unterschriften bürgen sie gemeinsam für den gesamten Inhalt dieser schriftlichen Arbeit.

Sampling location ID	Treatment (see Fig.2)	Recording period	Date and time of lux measurement	Coordinates of BATLOGGER	Orientation of microphone	Device number	Recorded activity total	Recorded activity per night recorded
1	1D	27.07. – 31.07.	30.07.2018, 23:03	654 047 / 254 269	W	1005	22	5.50
2	1L	27.07. – 31.07.	30.07.2018, 23:05	653 920 / 254 361	N	1008	23	7.67
3	1D	27.07. – 31.07.	30.07.2018, 22:28	653 142 / 254 169	NO	1014	118	29.50
4	1L	27.07. – 31.07.	30.07.2018, 22:30	653 251 / 254 198	O	1015	10	2.00
5	1D	27.07. – 31.07.	30.07.2018, 22:34	653 368 / 254 190	NO	1828	99	33.00
6	3D	27.07. – 31.07.	30.07.2018, 22:46	654 030 / 253 831	SW	1867	65	13.00
7	3L	27.07. – 31.07.	30.07.2018, 22:43	653 926 / 253 760	N	1865	2	0.50
8	3L	27.07. – 31.07.	30.07.2018, 22:18	653 284 / 254 333	O	1007	4	0.80
9	3D	27.07. – 31.07.	30.07.2018, 22:24	652 997 / 254 339	O	1017	22	7.33
10	2L	27.07. – 31.07.	30.07.2018, 22:53	654 103 / 254 215	N	1010	3	1.00
11	2L	27.07. – 31.07.	30.07.2018, 22:54	654 294 / 254 294	W	1004	16	3.20
12	2D	27.07. – 31.07.	30.07.2018, 22:56	654 351 / 254 204	SW	1006	15	5.00
13	2D	27.07. – 31.07.	30.07.2018, 23:00	654 429 / 254 139	NW	1011	9	2.25
14	4L	27.07. – 31.07.	30.07.2018, 22:41	653 720 / 253 729	N	1013	1	0.33
15	4D	27.07. – 31.07.	30.07.2018, 22:39	653 689 / 253 659	N	1866	13	2.60
16	4D	27.07. – 31.07.	30.07.2018, 22:15	653 422 / 254 663	S	1018	11	3.67
17	4L	27.07. – 31.07.	30.07.2018, 22:11	653 353 / 254 916	S	1020	0	0.00
18	1D	03.08. – 07.08.	06.08.2018, 22:34	653 356 /254 103	NO	1020	57	14.25
19	1L	03.08. – 07.08.	06.08.2018, 22:31	653 369 / 254 264	NO	1011	26	5.20
20	1D	03.08. – 07.08.	06.08.2018, 22:47	653 406 / 254 331	NO	1013	176	35.20
21	1L	03.08. – 07.08.	06.08.2018, 21:44	653 791 / 254 516	W	1005	6	3.00
22	3L	03.08. – 07.08.	06.08.2018, 21:55	653 593 / 254 434	SW	1018	8	1.60
23	3D	03.08. – 07.08.	06.08.2018, 21:47	653 726 / 254 459	NW	1007	14	4.67
24	3L	03.08. – 07.08.	06.08.2018, 22:14	653 188 / 254 460	SO	1004	5	1.00
25	3D	03.08. – 07.08.	06.08.2018, 22:53	653 949 / 254 238	W	1008	7	1.40
26	2L	03.08. – 07.08.	06.08.2018, 21:50	653 655 / 254 511	W	1828	33	11.00
27	2D	03.08. – 07.08.	06.08.2018, 21:59	653 561 / 254 497	SW	1014	177	35.40
28	2D	03.08. – 07.08.	06.08.2018, 22:07	653 597 / 254 604	SW	1866	81	16.20
29	2L	03.08. – 07.08.	06.08.2018, 22:11	653 438 / 254 563	S	1865	92	18.40
30	4L	03.08. – 07.08.	06.08.2018, 22:43	653 554 / 253 922	NW	1015	11	2.20
31	4D	03.08. – 07.08.	06.08.2018, 22:38	653 459 / 253 823	N	1017	42	8.40
32	4D	03.08. – 07.08.	06.08.2018, 22:29	653 048 / 254 127	NO	1010	138	27.60
33	3L	03.08. – 07.08.	06.08.2018, 22:22	653 120 / 254 506	S	1867	4	0.80
34	4D	03.08. – 07.08.	06.08.2018, 22:25	652 944 / 254 547	SO	1006	11	2.20

Sampling location ID	**PEK10**	**EL.2**	**PMF10**	**PMK10**	**ML.2**
1	0.018486	9.359642	0.001649	0.016066	14.41403
2	0.015459	14.90438	0.004327	0.01645	12.5105
3	0.014613	13.33696	0.001591	0.001728	30.60283
4	0.018497	9.553232	0.01578	0.017924	13.5005
5	0.018305	13.30255	0.008856	0.021599	0.196499
6	0	390.8772	0.001241	0	57.93466
7	0	488.2151	0.000636	0.000015	52.76894
8	0	92.69676	0.005656	0	114.3007
9	0	232.4511	0.003299	0.004019	29.09498
10	0.019938	0	0.001696	0.000071	50.49951
11	0.010787	19.05359	0.000496	0	248.2503
12	0.011752	22.08319	0.000754	0	298.51
13	0.01013	24.64771	0.002761	0	382.5025
14	0	516.4501	0.006369	0	260.9843
15	0	543.9157	0.001576	0	309.6593
16	0	113.5205	0.000815	0	230.8295
17	0	374.5312	0	0	461.7467
18	0.01297	20.57614	0.005541	0.003348	34.59241
19	0.020956	21.25131	0.010737	0.019293	25.45584
20	0.012021	28.68715	0.013781	0.00309	32.9017
21	0.011352	21.92754	0.001286	0	83.43791
22	0	73.47834	0.004201	0.015949	17.30015
23	0.000017	55.31744	0.00531	0.021946	2.829117
24	0	222.3422	0.039603	0.021074	2.63469
25	0	83.02658	0.001561	0	78.30806
26	0.019914	17.83642	0.001551	0	63.45454
27	0.019872	3.10076	0.003272	0	85.95864
28	0.002573	38.88544	0.000725	0	165.3977
29	0.011715	18.60467	0.001976	0	139.8654
30	0	267.0961	0.001171	0	302.3615
31	0	276.6046	0.001034	0	323.6891
32	0	96.10411	0.000205	0	132.2145
33	0	304.3034	0.002723	0	75.82609
34	0	429.5109	0.001347	0	183.4731

Sampling location ID	Lux	ISS.50	SL.2	SL.3
1	0	0.000681	265.5809	0
2	0	0.002754	151.7621	0
3	0	0.010164	45.73745	0
4	3.5	0.008044	7.789662	1
5	0	0.014415	7.867736	1
6	0	0.001558	165.0548	0
7	0.25	0.004	50.12962	0
8	0.75	0.012242	8.245337	2
9	0	0.008117	131.137	0
10	0.5	0.003086	330.308	0
11	0	0	511.1973	0
12	0	0.002433	575.6115	0
13	0	0.000107	659.2706	0
14	0.75	0.014569	23.00167	1
15	0	0.007143	55.80379	0
16	0	0.007394	160.6755	0
17	1	0.007929	19.26812	2
18	0.5	0.006981	21.25852	1
19	0.75	0.015023	6.627595	1
20	0	0.015028	31.09856	0
21	0.5	0.002655	30.28236	0
22	0.75	0.001039	30.43562	0
23	0	0.01118	30.11574	0
24	0.25	0.009227	24.8219	1
25	0	0.001997	176.0614	0
26	0.5	0.001271	18.7823	1
27	0	0.001402	40.22572	0
28	0	0.005327	117.8315	0
29	0.5	0.003504	64.10395	0
30	0.25	0.008978	48.37704	0
31	0	0.014956	135.1937	0
32	0	0.004671	147.2513	0
33	1	0	38.53894	0
34	0.25	0.00245	142.7574	0

Sampling ID	EgW.1a	Wa.1a	GewO.2	Eb.2	Eb.4	Ghib.2	HiK.2	OI.6	Str.2	Geb.2	Roost.2
1	0	1127.577	366.04	77.79	0	585.035	57.19221	1	7.650507	84.81457	600.98
2	2807.797	366.9229	209.63	11.21	4	613.21	24.06262	4	34.44334	35.4423	460.57
3	0	2405.05	22.07	55.94	0	42.22	119.4159	2	36.35389	32.03084	396.84
4	0	0	13.09	26.94	1	26.8	94.47409	3	36.35389	11.39647	294.79
5	0	0	43.7	28.42	1	142.77	81.62247	1	0.934985	11.97449	233.89
6	0	0	394.73	44.95	4	305.78	18.16298	2	28.96679	42.42745	807.4725
7	0	90.59934	455.05	22.33	8	197.69	47.70686	2	40.11431	23.23735	794.0577
8	0	0	116.74	60.9	0	133.18	207.7059	0	2.073024	11.71449	191.3003
9	0	1332.15	238.4	57.91	0	235.35	159.9393	1	4.341752	67.0609	469.0572
10	0	776.0971	433.23	62.81	0	575.36	6.844325	2	4.589971	49.824	668.9004
11	0	0	256.29	106.53	0	765.41	208.2712	0	11.12251	28.95925	839.8134
12	0	524.1824	202.61	101.53	0	754.18	246.0448	1	8.494717	55.86408	911.8202
13	0	3848.451	104.32	101.53	0	787.9	330.8789	1	96.10438	143.2365	1003.266
14	47.22093	0	579.18	16.86	1	2.48	3.296961	4	2.01074	21.32476	723.1906
15	0	0	521.16	32.48	1	58	20.41451	2	9.378217	41.60603	779.3546
16	0	0	259.53	33.96	1	490.72	530.5141	1	5.137106	98.83024	261.5924
17	0	0	194.41	96.88	0	714.11	734.6619	0	12.88995	298.2385	522.9705
18	0	510.6569	114.26	28.29	1	162.37	32.27423	3	5.997969	3.762256	319.3257
19	0	0	19.37	12.26	4	151.45	146.7088	2	9.761289	20.9582	168.1211
20	0	0	92.37	29.82	2	215.06	222.8189	1	29.54796	4.793424	92.00824
21	0	0	70.96	86.45	0	640.88	141.5761	0	4.894207	33.91271	347.9088
22	0	0	44.43	46.36	0	428.21	299.0495	0	21.95666	12.17326	134.8139
23	0	0	7.48	8.32	3	556.97	171.0511	2	28.27932	14.62425	270.1003
24	0	0	254.51	16.17	2	249.26	326.8202	1	25.62166	9.531407	279.0692
25	0	0	310.73	26.35	5	509.8	0.231171	2	99.67168	14.71256	515.1413
26	0	0	54.9	25.85	2	522.8	254.9061	1	24.2125	18.33203	220.9406
27	2382.914	0	79.02	26.33	12	439.08	340.3344	2	41.67383	22.19371	135.9389
28	168.7356	0	149.16	62.5	10	538.93	349.3557	3	22.44396	78.93011	241.2589
29	0	0	218.61	9.03	4	409.13	452.49	1	4.074978	18.14042	160.3247
30	0	0	368.77	6.47	4	223.85	234.0752	1	26.44282	24.00698	491.1962
31	1241.358	1262.503	412.57	100.12	0	267.84	277.8856	2	117.7086	100.2336	581.4085
32	1515.076	390.359	34.59	26.9	3	145.34	18.94308	4	135.413	66.7559	497.9098
33	0	0	279.34	5.62	2	310.04	341.0225	1	11.10491	18.92999	356.2683
34	0	0	224.69	31.67	1	424.07	373.9336	1	3.38828	51.28839	636.7628