

PROSEMINAR PROPOSAL

A Temperature Map of the City of Bern by Using Machine Learning Approaches

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Abstract

The urban heat island (UHI) effect significantly impacts urban residents through thermal stress. This project aims to create a map of temperature distribution to address this issue in Bern by calculating different models (multivariate linear regression, KNN, Random Forest) of temperature distribution. The models contains two meteorologic variables (temperature and precipitation) from a automated weather station in Zollikofen (WMO Standard), nine land use classes and temperature for the climate network of the city of Bern. All models are classified according to bias (precision) and MAE (accuracy). The best model will be used used to create a map.

1 Background and Motivation

Anthropogenic climate change is expected to increase the amount, intensity, and duration of heat waves. The urban heat island (UHI) effect further amplifies this trend in urban environments (Burger et al., 2021; Gubler et al., 2021; Wicki et al., 2018). The UHI effect is expressed by higher air temperatures in urban areas compared to rural areas in the region (Oke, 2006). The effect is highest during night, as the emission of longwave radiation in urban environments is impaired and sensible heat fluxes are enhanced, whilst latent fluxes are reduced (Burger et al., 2021; Gubler et al., 2021). People living in urban areas are thus highly affected by the UHI effect via thermal stress (Burger et al., 2021; Wicki et al., 2018). Given that more than 75 % of the Central European population lives in urban areas, the increasing trend poses one of the major weather threats to people in urban environments (Wicki et al., 2018). Studying spatial temperature variabilities in urban areas is therefore crucial to implement adaptation measures to minimize effects on human health and the environment (Burger et al., 2021).

To capture small-scale temperature changes in these climatically complex areas, high spatial resolution measurement networks are needed. However, automated weather stations (AWS) are scarce due to their high costs. To tackle this problem, Gubler et al. (2021) developed a new type of low-cost measurement devices (LCDs). The LCD consists of a temperature logger and a custom-made radiation shield that is naturally ventilated. 79 LCDs were installed in the city of Bern, Switzerland in 2018 (Gubler et al., 2021). Gubler et al. (2021) reported an overestimation of hourly mean temperature measurements by the LCDs (0.61°C to 0.93°C) compared to the reference station (AWS) during daytime (06:00 – 22:00). During night-time (22:00 – 06:00), differences were much lower or even negative (-0.12°C to 0.23°C). But not only the LCD temperature and the anomaly between the LCDs and the AWS is interesting, but also the temperature distribution of the entire region of Bern, shown on a map.

Tinner et al. (2023) created a map of the distribution of temperatures in Bern for the current logger temperatures. This predicts the local temperature based on land use data as demonstrated by Burger et al. (2021). The approach used by Burger et al. (2021) is a multivariate linear regression Model. As the model only knows the current temperature distribution, its scope and statistical power are limited.

2 Objective

This project aims to compare machine learning techniques (random forest and KNN) to a multivariate linear regression model with land use classes and meteorologic data, thus using collected data from the past four years (2019-2022) of meteorological and logger

measurements to train the models. The model then predicts the local temperature as measured by the loggers based on meteorology and land use classes. Furthermore, we want to explore if machine learning is superior to multivariate linear regression. To quantify the quality of the models, we calculate the bias (for accuracy) and the MSE (for precision) for each model. We use the coefficient of determination R^2 to quantify what percentage of the total variance our models explain. The model will then also be used to show temperature distributions for a possible day as a map. All of this will be implemented in with respect to best open science practices and reproducibility.

3 Implementation

3.1 Data

First, we want to introduce the source of the data that will be use in this project. We use temperature data for the years 2019-2022 from the network of the city of Bern. This is a numerical data set of the 3 m temperature in about 110 locations, with a temporal resolution of 10 minutes for all LCDs. This data is publicly available on BORIS. We use additional data from the AWS at Zollikofen, as it is the official meteorologic station of Bern. The two meteorological variables (2m temperature, precipitation) with a temporal resolution of 10 minutes for the years 2019-2022 will be used as well as the timestamp. Data of the previous one, three and five days will also be fed into the model. This data will presumably be uploaded to a repository to ensure availability since the IDAWEB-data service is open for scientific use but not completely open access. To show small scale urban patterns of temperature distributions, land use data as shown in Burger et al. (2021) is used. These are cantonal land use classes. The land use classes are then spatially averaged to obtain the layers most effective as shown in Burger et al. (2021) . The land use data from the canton data will presumably also be uploaded to a repository since the data has to be downloaded manually from the webpage of the canton. Table 1 provides a brief overview of the data we will use.

Table 1: The table shows all the data which will be used in this project. Click on the source to get access to the raw data of this project

Source	Type	Kind of data	Resolution	Period
BORIS	Numeric	3m temperature, coordinates	15 min	2019-2022
IDAWEB	Numeric	Meteorological Variable and coordinates	10 min	2019-2022
Canton of Bern	Raster	8 different Land Use Classes	different	-

3.2 Methodology

The data of the LCDs of the years 2019 until 2022 is read in and combined with metadata to locate the measurements. This data is combined with the appropriate land use values according to the loggers location. Then meteorologic values are added to each measurement according to its timestamp. Now, the models are trained on the years 2019 to 2022. The models have as the predictor variable therefore the land use classes (9 classes; table 2) and the meteorologic data of the current and the past one, three and five days to predict the temperature of a given logger which is the target variable. This will be done for a multivariate linear regression model, a KNN model and a random forest model. Separate LCD-locations will be used as validation data so that complete independence is guaranteed. Evaluation will be done by determining the R^2 , bias, and MAE for each model and use them to compare the models.

Table 2: The table shows all the 9 land use classes from (Burger et al., 2021) with their optimal zonal average distance which will be used.

Class	File Name	Resolution [m]
Land cover buildings	Bul_Raster_51	250
Open space sealed	SE_Raster_101	500
Open space forest	FO_Raster_51	250
Open space garden	GA_Raster_5	25
Open space water	WA_Raster_21	100
Open space agriculture	AC_Raster_101	500
Slope	SLO_21	100
Vegetation height	VH_WSL_21_21	100
Mean building height	BH_21	100

As a visualization of the model, a map is then rendered by combining the land use layers with meteorologic data. The model uses the locations of LCDs as reference values. Therefore, the temperature of a arbitrary point between two LDCs depends on the numerical values of the land use layers and meteorology in general. This meteorologic information can be chosen freely and may give insight into different possible heat distributions. Based on the land use layers and the meteorology the model calculates the temperature distribution for the city of Bern. This will be done for hypothetical days to explore the heat distribution on varying conditions.

All of the workflow will be done in R and be uploaded to github.com on a public repository with a GNU Affero General Public License. The workflow aims at full transparency and reproducibility.

4 Responsibilities and Timeline

For our project, we split the responsibility for each task. But this does not mean that the responsible person works alone. All decisions are based on a collaborative exchange. Table 2 shows the tasks and who is responsible for them.

Table 3: The table shows the distribution of tasks. The listed person has the leadership for the respective task. However, the result is based on an equal professional exchange

Who	Task	Deadline
Both	Exchange so that both are on the same level of knowledge	Week 42
Both	Write the proposal	Week 42
Staff	Meeting with the staff to discuss the proposal	Week 43
Both	Revise the proposal	Week 44
Nils	Data wrangling	Week 44
Nils	Making data available for open science	Week 45-46
Patrick	Regression and linear Regression model	Week 45-47
Patrick	KNN	Week 45-47
Nils	Random Forest	Week 46-47
Both	Buffer	Week 48
Both	Test the reproducible workflow	Week 49

5 Risks and Contingency

- Data loss and technical issues: To minimize the chance of data loss or technical issues all code and implementations as well as all data is backed up to github. If the data becomes too large there should either be an R-Script that generates the file or the file should be backed up onto external sources.
- Issues with coding: In case we face severe issues with the implementation, the staff panel will be consulted.

6 Impact

The generated model will be able to calculate the temperature of a given site based on land use and meteorologic data. This could be used for three things: One can calculate the temperature of the past, the present or the future. Therefore, one could look at the heat of Bern during the last 100 years or use the predictions of MeteoSwiss to predict the urban heat island in the future if all variables are available. This could be of societal relevance since heat is a concern in cities especially with climate change. Second, a warning system could be implemented and warn people in affected areas. Third, one could also assess the

excess deaths during the summer months of the past few decades by calculating the heat distribution of past summer nights and so better the understanding of heat deaths. These are just some of the possibilities a new model would offer.

7 Bibliography

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