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A comparative study of soil temperature models, including machine learning models

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Forword

Jeg vil takke alle som var rundt meg under skrivingen, for uten dere så ville jeg ikke ha klart å fullføre.

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Abstract

This study focuses on 3 models that have been used in the literature to predict soil temperatures. The depths chosen as targets are 10cm, and 20cm in 4 regions; Innlandet, Østfold, Vestfold, and Trøndelag. In each region there are 4 stations spread along the region to get the most coverage of area to be the most representative of the local area. The models chosen had been used in the literature to predict soil temperatures. The data used in this study was collected from Kilden with the features; hourly air temperature from 2m height, soil temperature from 10cm depth, soil temperature from 20cm depth.

The models chosen are LSTM, BiLSTM, GRU, linear regression, and linear regression model modified by Plauborg. All the models performed within 2°C RMSE and an absolutt bias of 1.5|°C| except linear regression that had an RMSE of 4.5°C RMSE and absolutt bias of

Oppsumering

Denne studien ser på modeler som predikerer jordtemperaturer

Keywords: LSTM, GRU, RNN, Soil temperature, Machine learning, regression,hourly, weather forecasting data

1 Introduction

In agriculture soil temperature is one of the important parameters to put into consideration when thinking about pest prevention, conservation, and yield prediction. The reasoning for this is that knowing the soil temperature is gaining useful insight into gain important info for water management [2], potential yields [3], calculation of plant-growth [4], and predicting hatching insect eggs[5, 6]. Being able to predict the soil temperature a few days in advance does give insight into potential flooding and erosions[7], when seeds start to sprout [4], nitrogen processes [8] in the soil. Due to climate change it is more important to know soil temperatures at given

If it's important, why don't institutions measure it everywhere? There are several reasons for this, but a common reason is that it's expensive to install new equipment on old weather stations. Furthermore it is unfeasible to install sensors absolutely everywhere at any depth, however it is not nessesery with full coverage of an area as it is sufficient to have a few samples here and there to get an overview of the current state of the soil. Another thing is that it might be impractical to install sensors in some areas due to climate, soil quality (or lack there of), or the misrepresentation of the area if its an geographical or meteorological special case.

Sometimes the weather station do have the sensors in the fields reading soil temperature at given levels, but due to technical misadventures and unforeseen phenomenons there might be gaps or misreadings that need to be replaced with approximations or NULL values[1]. ~~However the absolute necessity to messure soil temperature everywhere is not critical since the usefulness of the soil temperature is to give an overview of the area and how it would develop in the future.~~

Previous research has investigated soil heat conductivity, leading to the formulation of differential equations [10]. However, these mathematical statements, which involve heat transfer, are computationally demanding and challenging to simulate or calculate [10, 11]. Numerical solutions are not the only obstacle; the dynamic nature of heat within the soil also plays a crucial role. For instance, frost in Scandinavian countries significantly alters soil heat conductivity [7],

[1]These values are different from 0 as they represent "no data" and can't be used to do calculations.

further complicating accurate calculations. As part of this study, data will be collected from Norway, situated within the Scandinavian region.

Deeplearning models

A beneficial model would be one using the fewest number of parameters as possible while returning results within acceptable tolerances. This study will consider models that can use only time and air temperature as those two features are the most common measurements measured at weather stations, since soil temperature is not necessarily calculated as stated earlier. A good metric in this study will be considered to be a combination of Root Mean Square Error and Explained Variance (see section 3.5).

This study aims to address the following key questions:

- Achieving Good Results with Minimal Parameters: Can satisfactory predictions be obtained using a limited set of meteorological and chronological parameters?
- Deep Learning Models for Soil Temperature Prediction: Is it feasible to employ deep learning models for predicting soil temperatures?
- Complexity of Deep Learning Models: Is it necessary to utilize complex deep learning architectures when predicting soil temperatures?
- Suitable model for northic climate: Is there a model that fits for the Scandinavian climate?

Regarding deep learning models, this study primarily focuses on Recurent Neural Network networks and explores various compositions of this technology. The definition of a "good result" will be relative to the performance of other models in the field and to similar studies that employ comparable architectures. Additionally, the Gated Recurent Unit (GRU) has been considered as an alternative to LSTM in this context due to its simplicity, and yet mechanically similar to the LSTM.

2 Theory

This section discusses the theory behind the models used in the study, there are a few base models (section 2.2, and 2.4) based on the interpretation of the papers hand picked for this study

2.1 Soil temperature

THe difficulti in predicting the soil tempearatutre comes from that the enviroment is highly variant and radicaly diffenrent from each other. A farmer in Sunndal in Middle-Norway would have to do different considerations than a farmer in Karasjok in Nord-Norge or a farmer in Bergen in Sør-Norge simple due to differn climat and soil profile. There exist methods to help farmers get an local estiamte of current soil state; Methods such as soil texture, soil smell, soil feel, and colour. These methods works to make on-the-spot desition to when plant crops, water the crops, or when to harvest. A better approch is to have a model to predict the upcoming tempartues so farmers have a window of time to prepere for crop harvest or planting.

A simple naive way to predict soil temperature would be to use the equation found by [17]

$$\text{daily soil temperature} \approx \widetilde{T}_{\text{soil,year}} + e^{-z/D}\sin(\omega t - z/D + \phi) \tag{1}$$

This analytical formula has its limitations as it does not take into account rain fall, snow melt, freezing, and re-freezing. Futher more, the formula does not incoporate the importance of the surface temperature and its inpact on the soil layers over time. An ideal formula would incorporate all of these elements and possibly more, but that would require more computation power than currently available.

An expantion of this soultion was expanded by [18] by including the solar movement to predict daily soil temperatures. The sun does heat up the soil differently depending on it angle over horizon and the cloud blocking or not hiding the sun. It is commented by the author of [18] that this simple model does not describe the soil temperature the effect of snow cover or precipitations effekts..

From current understanding of soil physics a modern model researches in cooperate the saturated hydraulic conductivity and the unfrozen water content to their equations[7]. Some of these formulas contains nested exponentials[7]. This formulation introduces numerical limitations as the estimation at the center of the formula would be amplified as the computation continues. A commonly used approch is Finite Difference Method (FDM) where a differntial equation gets decomposed to several equation that gets mapped to a grid with boundry conditions[8, 19, 20].

Discuss the problem with predicting soil temeprature

2.2 Linear regression

Air temperature has a direct connection to soil temperature as the main source of thermal energy next to solar radiation. A primitiv relation between air temperature and soil temperature at a given depth would be

$$T_{\text{Soil, n cm}} \approx \beta_{\text{n cm}} T_{\text{Air}} + \vec{varepsilon} \tag{2}$$

The $\beta_{\text{n cm}}$ represent the scaling factor for the air-soil relation. The regression model will be for the sake of convenience be expressed as the following expression

$$\vec{F}(\mathbf{A})\vec{\beta} = \vec{y} + \vec{\varepsilon} \tag{3}$$

Where $\vec{F}$ is a vector function with following domain $\vec{F} : \mathbb{R}^{n\times m} \to \mathbb{R}^{n\times p}$ where $m, n, p \in \mathbb{N}$, $\mathbf{A}$ is the data in matrix form with dimensions $\mathbb{R}^{n\times m}$, $\vec{\beta}$ is the regression terms with shape $\mathbb{R}^{p\times 1}$,

$\vec{y}$ is the target (TJM10 or TJM20) with shape $\mathbb{R}^{n\times 1}$, and $\vec{\varepsilon}$ is the residual error with the same shape as$\vec{y}$.

This basic model to express the linearity of the components to soil temperature. This will function as the base model for regression models.

2.3 Plauborg linear regression model with Fourier terms

An improvement over an time independent linear regression model would be a time dependent linear regression model that takes not only current time into account of the calculations but also previus messurments. It is current knowlage that soil temperatures depends on previous temperatures and meteorological phenomenons. In the paper Plauborg [1] extend the features from only air temperature at current time to include also previus days of year and the air temperature from those days as an extention of [18]. This means the following F function that Plauborg used would be

$$\vec{F} := [air_t, air_{t-1}, air_{t-2}, air_{t-3}, \sin(\omega t), \cos(\omega t), \sin(2 * \omega t), \cos(2 * \omega t)]^T$$

Where air_t is the air temperature at time t expressed in day of the year (0-365), ω is the angular frequency in radians per hour or radians per day, depending on the time unit. The sine/cosine elements in the F function represent the variations through the day by fitting $\vec{\beta}$ to the yearly variation. To adapt the authors model to an hourly time unit would be to either

1. Extend the F function to include a larger ω coefficient to reflect hourly oscillations in conjunction with daily fluctuation
2. Refit the Fourier terms with a larger ω coefficient to make the oscillations more representative of daily temperature changes.

The larger coefficient could be expressed as $\pi/12$ while the smaller ω for daily values would be rescaled to $2\pi/365$.

The problem with this approach would be Fouriers Sine-Cosine series approximation which would suggest that Plauborg's method could be subject to overfitting with addition of more terms. On the other hand it gives us a way to compute the coefficients α_i and γ_i for sine and cosine terms respectively, though it would be more numerically stable with a pseudo-inverse computation or a max log likelihood approach.

2.4 Long Short Term-Memory (LSTM) model

When modeling soil temperature it is important to know the previus hours or days to predict the next timestep, for this a natural selection for a data driven model is a recurrent network. This type of network makes prediction based on previus timesteps in the data, however the longer timespan the model takse into account the less important are the earlier time-steps in the data.

To combat this there was developed an improved model called Long-Short Term Memory model[22] that deploys a memory cell that feeds information from earlier timesteps to the late ones. To make sure that redundant information or unimportant features don't get feed forward there is forgetting gates that removes some of the newly learned patterns and integrates it into the memory cell.

Write more

The most common problem in Neural networks is the vanishing gradient problem where updating the first few layers of a large network becomes exponentially more difficult since the adjustments gets smaller and smaller for each layer towards the start rather than the reverse. Long Short Term-Memory changes this by caring information from the previous cells forward

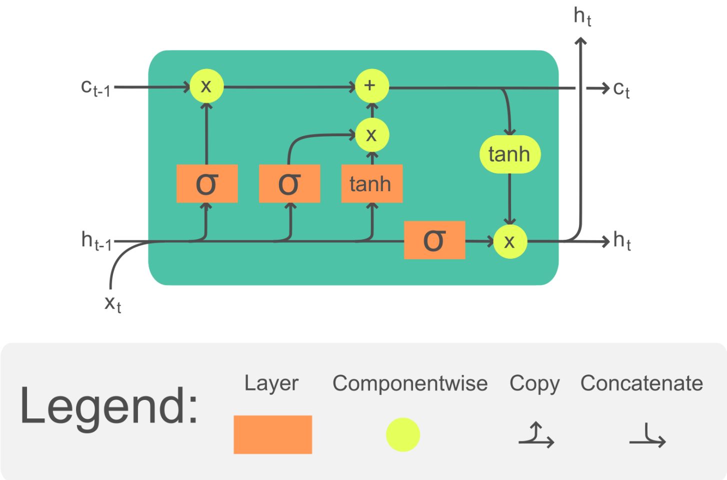

Figure 1: LSTM cell, From: Chevalier [21]

thereby allowing updating earlier cells with bigger impact than the standard approach[22]. LSTM is part of a family of Recurent Neural Network's that passes information to other cells in the same layer.

2.5 Gated Recurent Unit (GRU)

The comlexaty of soil temperatures and its dependensy of previus time-steps make Recurent Neural Network's a natural chose of a deep learning model, but the intricasy of an LSTM makes it difficult to fine tune. An alternative to LSTM is the GRU model[23] that has fewer parameters to adjust however it has a memory mechanism that allows it to forget and remember information that is passes to other cells in the model.

Figure 2: The GRU model where the memory cell gets more efficiently adjusted by the update gate (z) and appended information via the reset gate (r).

The GRU model has the advantage over LSTM to be smaller, and more efficiently convergence due to the integration of memory and prediction layer.

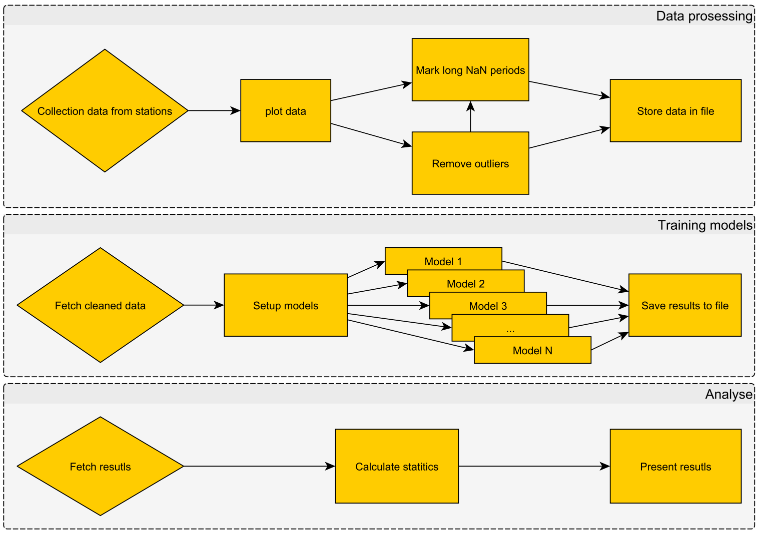

Figure 3: A surface level diagram of the methodology.

3 Method

Complete diagram

3.1 Source of data

For this comparative study the following data sources will be used

1. Norwegian Institute of Bioeconomy Research LandbruksMeteorologisk service (LMT) 2. Norwegian Institute of Bioeconomy Research Kilden (Kilden) 3. The Norwegian Meteorological Institute (MET)

3.2 Dataset

The dataset is chosen from four regions in Norway; Innlandet, Vestfold, Trøndelag, and Østfold. From each region are four stations picked:

All stations are sampled from the date[2] 03-01 to 10-31 from 2016 to 2020. The features mean hourly soil temperature at 10cm (TJM10), mean hourly soil temperature at 20cm (TJM20), and mean hourly air temperature at 2m (TM) are sampled from the LMT database.

3.2.1 Selection process

An array of stations was provided by LMT based on their possession of the necessary data. All stations were reviewed, checked for missing data, and those with excessive gaps were removed from the list or replace with another station. After compiling a list of stations, each one was re-examined to identify outliers present in the data and eliminate them accordingly. If certain stations had an excessive number of missing values after the outlier check, nearby stations were sought, and the affected station was replaced and the outlier check was re-done. Table 4 is showing station 17 (Apelsvoll, Innlandet) before treatment, and table 5 shows the same station cleaned and ready for being used as training/testing data.

[2] Format month-day

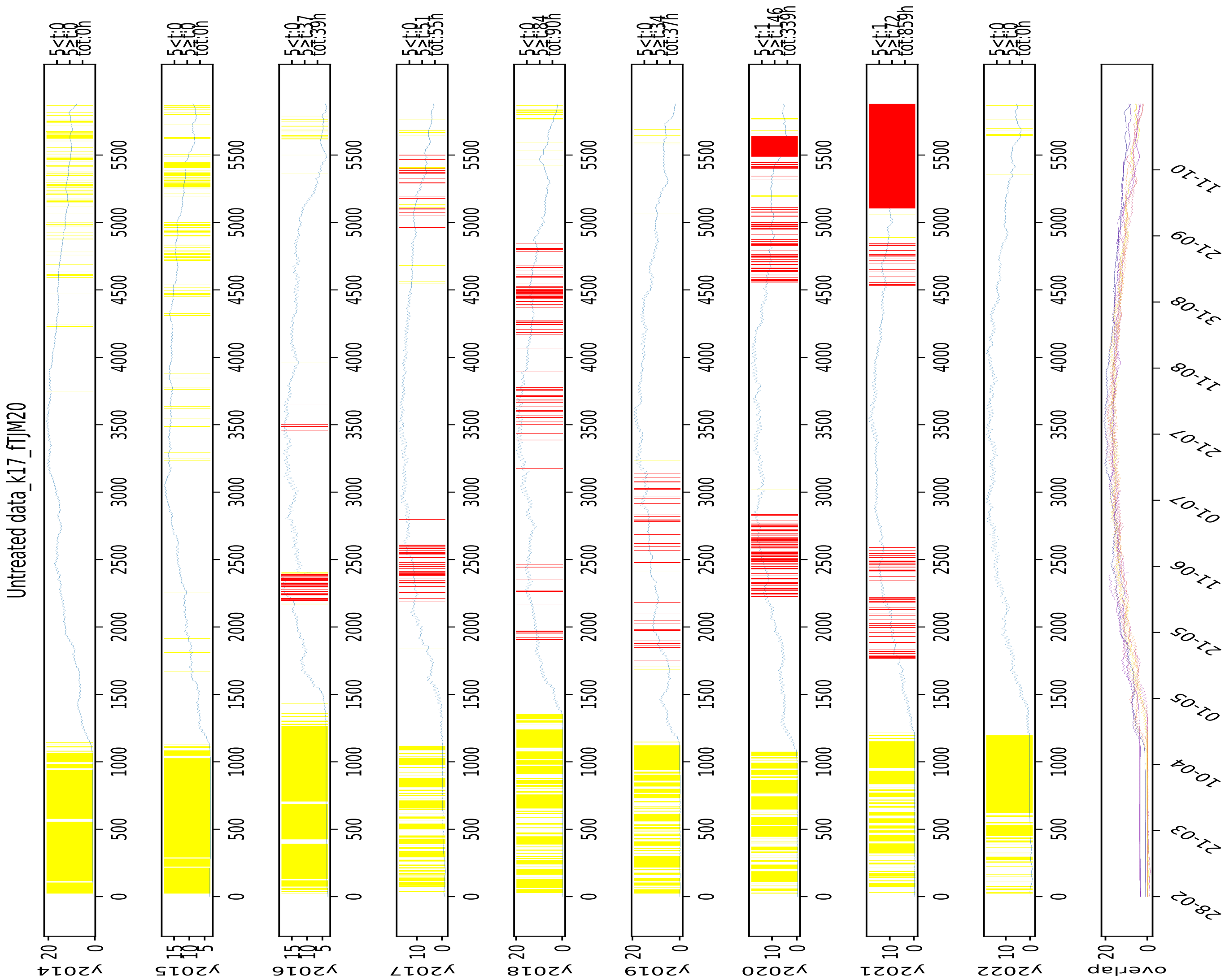

Figure 4: Visual representation of missing values at station 17 from 2014 to 2022 at the parameter "TJM20". The left numbers indicated how many hours that are missing and how many of them are shorter than or longer than 5 hours. The yellow markings indicate possible outliers based on the given year, all markings was checked if they were actual outliers. The red colouring indicate missing values in the data (represented in the data with code "NULL").

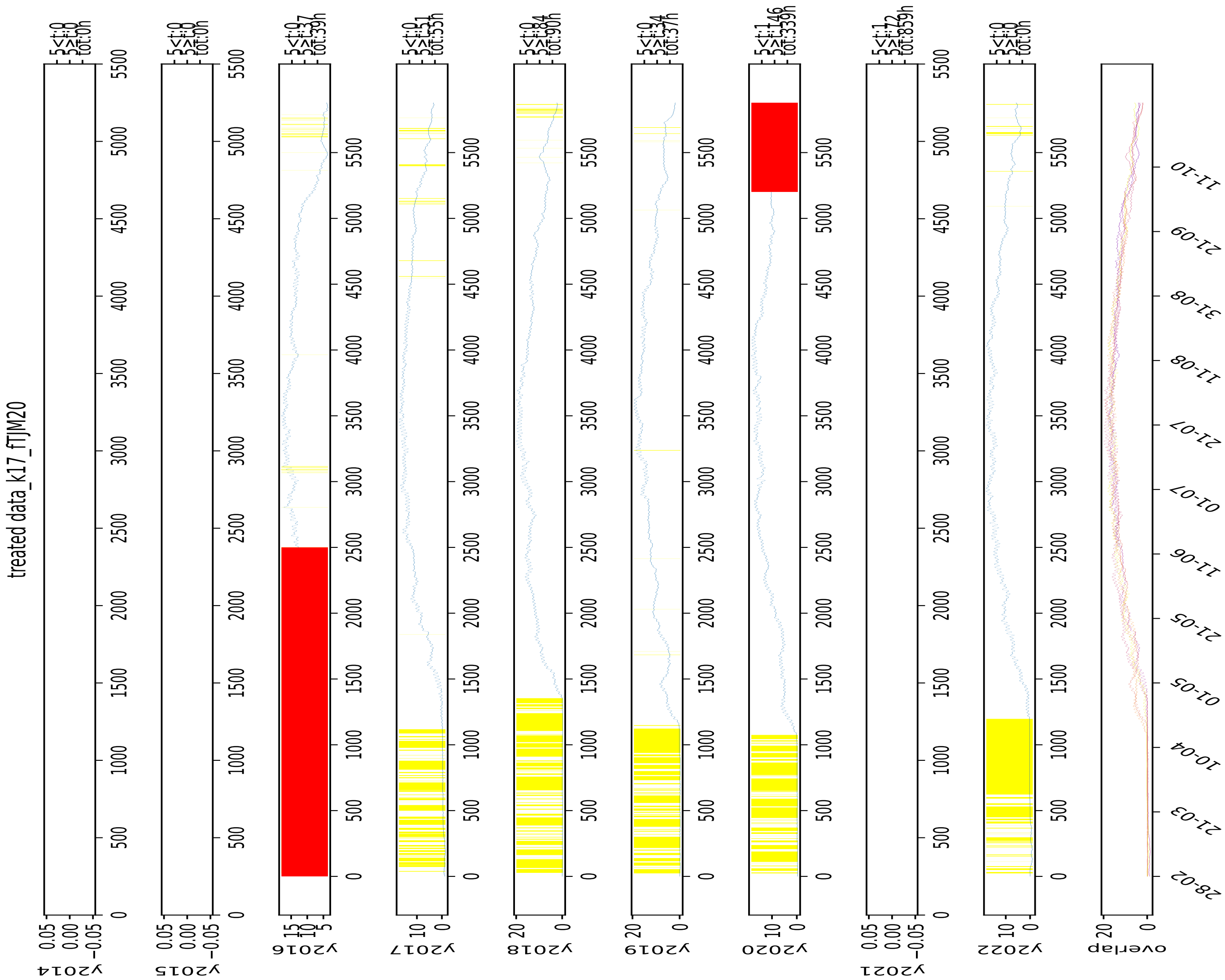

Figure 5: Visual representation of missing values at station 17 from 2014 to 2022 at the parameter ”TJM20” after treating for outliers. The left numbers indicated how many hours that are missing and how many of them are shorter than or longer than 5 hours, however for this visualisation they indicate the untreated version of the data. The yellow markings indicate possible outliers based on the given year, all markings was checked if they were actual outliers. The red colouring indicate missing values in the data (represented in the data with code ”NULL”). The years 2014 and 2015 was removed from the dataset but not coloured in due to technical limitations of reusable code, and furthermore half of 2016 was removed due to suspicion of misreading from sensor at this station.

Region	Name	ID	Drain type	MET name	Latitude	Longdetude
Innlandet	Apelsvoll	11	Selvdrenert	SN11500	60,70024	10,86952
Innlandet	Fåvang	17	Selvdrenert	SN13150	61,45822	10,18720
Innlandet	Ilseng	26	Selvdrenert	SN12180	60,80264	11,20298
Innlandet	Kise	27	Vannmettet	SN12550	60,77324	10,80569
Trøndelag	Kvithamar	57	Vannmettet	SN69150	63,48795	10,87994
Trøndelag	Frosta	15	Selvdrenert	SN69655	63,56502	10,69298
Trøndelag	Mære	34	Selvdrenert	SN71320	63,94244	11,42527
Trøndelag	Rissa	39	Vannmettet	SN71320	63,58569	9,97007
Vestfold	Lier	30	Vannmettet	SN19940	59,79084	10,25962
Vestfold	Sande	42	Vannmettet	SN26990	59,61620	10,22339
Vestfold	Tjølling	50	Selvdrenert	SN27780	59,04641	10,12513
Vestfold	Ramnes	38	Vannmettet	SN27315	59,38081	10,23970
Østfold	Rakkestad	37	Vannmettet	SN3290	59,38824	11,39042
Østfold	Rygge	41	Selvdrenert	SN17380	59,39805	10,75427
Østfold	Tomb	52	Vannmettet	SN17050	59,31893	10,81449
Østfold	Øsaker	118	Vannmettet	SN3370	59,31936	11,04221

Table 1: Station information from stations used in this study. The MET names was found by looking at the coordinates of the station and finding the closest MET station coordinates.

Name	version	description
Powershell	7.3.11	Windows native scripting language
Curl	8.4.0 (windows) libcurl/8.4.0 Schannel WinIDN	Commandline tool to communicate with servers usi
python	3.9.11	popular Scripting language

Table 2: The description the software used in this study

The data plots (see figure 4 and 5 as example) shows all the raw data plotted as a blue line from 03-01 to 10-31. The yellow markings is placed there by computer algorithmns (see section 3.3.1 for in-depth explanation of the outlier detection methods) as potential outliers in the data. These markings have been looked over and verified weather or not they are genuine outliers or not. Further more the red lines are indicators of missing values, the number of missing values longer or shorter than 5 hours[3] are noted on the side bare with the total number of missing values regardless of length. The bottom bar are all the years laid on top of each other to highlight any years or periods that deviates for a particulate year compared to all the other years. There will be two versions of these plots, one for the untreated data and one for the treated data to show the difference the interpolation does to the data (see seciotn 3.3.2 for further details.).

3.2.2 Collection of data

In the tabel 2 are the softwares used in this study and in the collection and treatment of the data. The program used in the collection of meteorological messurements is Powershell in combination with Curl. Using hyperlinks gathered from inspecting Kilden's web page using the browser (Microsoft edge) built-in inspector tool to get the relevant links to send data requests. The presise URL's can be reviewed on GitHub in the studies GitHub repository[4]. For a more surfac

[3]The threshold for rain is 3 hours due to the high variance.
[4]Link: https://github.com/ConAltDelete/MT24CS

FROST	Description
Station ID	Sendt a request to LMT for station information using their remote API.
LMT	Description
Meteorological data	Requested soil temperature from 10cm depth, and 20cm depth and air temperature (2m), from 2014-03-01 to 2022-10-31.

Table 3: Description of what was requested from each server (MET, LMT).

level description on what was requested of the servers see table 3.

3.2.3 Storage of data

The storage of the data is done through two data structures; Hashmap and DataFrame from the package pandas. The transformation of data is done with a customized data-type called ”DataFileHandler” which is converted to a module for convenience. The keys for the hashmap is chosen by the naming of the data files and the pattern given to the class. To escalate the loading of the data it will also be exported to a binary file for faster retrieval.

Technical overview of custom data structure The data structure used to store the data from the different stations is called ”DataFileHandler” and stores the data in a nested dictionary which can be inpreted as the data structure ”tree”. The main features of ”DataFileHandler” is

1. Simple syntax for partitioning the data
2. Grouping the data after loading
3. Transforming all the data with the same function
4. loading and unloading of a large collection of data

3.3 Data cleaning and treatment

To use the data in this study it must be cleaned and treated for training. Though the data has been examined by the supplier, however it still had outliers that needed to be treated before modelling. For this reason several steps and methods is utilized in the prepossessing steps. The selection process for finding these station can be compiled into these steps

1. Recommendation from Norwegian Institute of Bio-economy Research
2. Compute the missing values in the data
3. Missing values analyse
4. Searching LMT database for alternative station candidates if current data is insufficient
5. If some station was replaced the repeat step 2

3.3.1 Outlier detection and removal

Though the data fetched from LMT is treated and controlled the external data from MET might not be, and this research project incorporated raw, untreated data from LMT to fill inn missing values.

Revise so it reflects what you actually do

The method to quickly find obvious outliers was to look at the following condition

$$|z(|\Delta T|)| = \left| \frac{|\Delta T| - E(|\Delta T|)}{Var(|\Delta T|)} \right| > 4°C \tag{4}$$

Make more clear

Where the $E()$ is the expected value, and $Var()$ is the variance. This condition looks at the absolute difference between consecutive measurements and calculates the z-score for each observation. It is expected that the change in temperature can't be too rapid. Further methods used to highlight potential outliers is

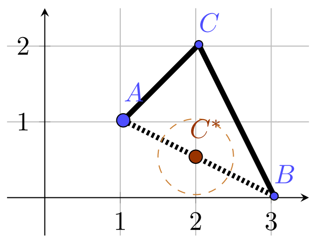

Figure 6: An simple outlier detection method utilizing a simple line to estimate where the expected point (C^*,red dotted circle) is supposed to be. If observed point C falls outside the tolerance level (green circle) then it is marked as an outlier.

3.3.2 Missing value imputation

The data has missing values, in particular during early Autumn when there were sub-zero temperatures meaning any rain measurements done during this period would have unpredictable fluctuations since at negative temperatures water can freeze, get clogged up with residual biomaterial from the surrounding area . When interpolating values the method chosen is a linear interpolation with a maximum period of 5 consecutive hours for soil temperatures, and 3 consecutive hours for air temperatures. The reasoning for this is that the soil temperatures are more reliable makeing it safer to interpolate without loosing too much information, while air temperatures has a higher variance making it more difficult to interpolate without cutting values.

Rewrite this part to reflect what is going on

3.3.3 Summary of data

After going to the prosedure the current form of the station are

3.4 Setup of models

In general, write more on all subsections

The models are set up in according to the relevant paper the model is fetched from, alternatively reuse the code made by the author. When importing the data to the model there will be modifying to the original code to facilitate for the model as far as it goes. Any modifications will be in the appendix under section ??. For the convenience of the reader all code is using the sklearn estimator class to make all the models discuses in this study more user friendly and

mean std	max min	38	11	57	41	27
	2014	μ:11.711 max:31.8 σ:6.4 min:-4.0	μ:10.66 max:30.0 σ:6.472 min:-4.5	μ:10.922 max:31.2 σ:6.59 min:-11.9	μ:12.203 max:33.0 σ:6.63 min:-4.5	μ:10.988 σ:6.564
	2015	μ:10.385 max:25.0 σ:5.693 min:-5.7	μ:9.121 max:28.6 σ:5.764 min:-7.1	μ:9.567 max:27.5 σ:5.366 min:-6.7	μ:10.608 max:26.4 σ:5.676 min:-5.1	μ:9.416 σ:5.906
	2016	μ:11.343 max:27.4 σ:5.919 min:-5.2	μ:9.842 max:26.4 σ:6.49 min:-7.4	μ:9.54 max:28.6 σ:6.016 min:-8.1	μ:11.218 max:28.8 σ:6.406 min:-5.5	μ:10.104 σ:6.508
	2017	μ:10.346 max:25.2 σ:6.095 min:-9.2	μ:9.049 max:28.5 σ:6.171 min:-8.7	μ:9.412 max:27.1 σ:5.896 min:-8.0	μ:10.708 max:27.3 σ:6.077 min:-6.4	μ:9.322 σ:6.339
	2018	μ:11.026 max:32.3 σ:8.809 min:-19.7	μ:10.166 max:30.2 σ:9.322 min:-21.4	μ:9.588 max:32.0 σ:7.611 min:-21.4	μ:11.554 max:33.7 σ:8.628 min:-19.2	μ:9.694 σ:9.471
	2019	μ:10.944 max:31.6 σ:6.832 min:-12.0	μ:9.275 max:29.4 σ:7.081 min:-13.2	μ:9.306 max:32.4 σ:6.983 min:-13.0	μ:10.843 max:30.4 σ:6.679 min:-12.8	μ:9.556 σ:7.083
	2020	μ:11.281 max:29.7 σ:7.453 min:-6.8	μ:9.918 max:28.5 σ:6.662 min:-9.0	μ:9.625 max:32.8 σ:6.619 min:-6.2	μ:11.323 max:30.2 σ:6.324 min:-6.6	μ:10.328 σ:6.639
	2021	μ:11.722 max:30.3 σ:6.793 min:-6.1	μ:10.181 max:27.7 σ:6.762 min:-8.8	μ:9.889 max:29.9 σ:6.375 min:-8.3	μ:11.519 max:29.8 σ:6.553 min:-7.1	μ:10.459 σ:6.827
	2022	μ:11.327 max:29.1 σ:6.786 min:-6.9	μ:9.644 max:26.8 σ:6.652 min:-10.3	μ:9.722 max:28.4 σ:5.791 min:-8.2	μ:11.192 max:28.5 σ:6.625 min:-7.5	μ:9.869 σ:6.89

Table 4: Every cell of the table has the

mean std	max min	38	11	57	41	27
	2014	μ:12.793 max:22.8 σ:5.559 min:1.5	μ:11.146 max:23.3 σ:5.983 min:0.1	μ:10.603 max:22.2 σ:5.696 min:0.0	μ:13.38 max:24.8 σ:5.721 min:2.4	μ:12.241 σ:5.92
	2015	μ:10.99 max:18.7 σ:5.321 min:0.4	μ:8.035 max:19.7 σ:5.148 min:-0.2	μ:9.554 max:16.7 σ:4.382 min:0.1	μ:11.099 max:20.6 σ:4.949 min:0.8	μ:10.498 σ:5.579
	2016	μ:11.667 max:19.9 σ:6.074 min:0.1	μ:10.028 max:20.0 σ:6.286 min:-1.3	μ:9.152 max:17.4 σ:5.249 min:-0.2	μ:11.169 max:21.9 σ:5.782 min:-0.1	μ:10.576 σ:6.462
	2017	μ:10.545 max:17.6 σ:5.467 min:0.1	μ:9.306 max:18.3 σ:6.13 min:-1.4	μ:9.038 max:16.3 σ:4.871 min:-0.1	μ:11.002 max:18.5 σ:4.957 min:0.3	μ:9.842 σ:6.066
	2018	μ:11.123 max:21.2 σ:6.316 min:0.5	μ:10.312 max:21.9 σ:6.95 min:0.0	μ:8.456 max:17.1 σ:5.599 min:-1.3	μ:12.439 max:25.9 σ:7.815 min:-0.8	μ:10.03 σ:6.856
	2019	μ:10.961 max:21.0 σ:5.668 min:0.4	μ:9.727 max:22.0 σ:6.264 min:-0.1	μ:9.204 max:19.4 σ:5.274 min:0.1	μ:10.491 max:20.3 σ:5.405 min:0.2	μ:10.502 σ:6.145
	2020	μ:9.965 max:19.5 σ:5.872 min:0.8	μ:9.927 max:22.4 σ:6.387 min:-1.6	μ:9.551 max:18.0 σ:5.288 min:0.1	μ:12.209 max:23.9 σ:6.329 min:0.6	μ:10.567 σ:6.098
	2021	μ:11.013 max:19.5 σ:6.182 min:0.1	μ:10.106 max:20.4 σ:6.248 min:-0.3	μ:9.214 max:17.8 σ:5.324 min:-0.3	μ:11.891 max:23.5 σ:6.341 min:0.0	μ:10.417 σ:6.443
	2022	μ:10.615 max:18.1 σ:6.127 min:0.3	μ:13.182 max:21.3 σ:3.953 min:3.9	μ:9.711 max:18.1 σ:4.965 min:0.3	μ:11.318 max:21.8 σ:6.12 min:-0.2	μ:10.305 σ:6.311

Table 5: Every cell of the table has the

mean std	max min	38	11	57	41	27
	2014	μ:12.524 max:21.7 σ:5.424 min:1.7	μ:10.922 max:21.6 σ:5.761 min:0.3	μ:10.149 max:19.1 σ:5.364 min:-0.1	μ:12.91 max:22.2 σ:5.34 min:2.6	μ:11.865 σ:5.593
	2015	μ:10.849 max:17.9 σ:5.136 min:0.6	μ:7.92 max:17.9 σ:4.912 min:0.0	μ:9.335 max:15.5 σ:4.32 min:0.2	μ:10.826 max:18.2 σ:4.705 min:1.4	μ:10.197 σ:5.33
	2016	μ:11.562 max:19.4 σ:5.923 min:0.3	μ:9.842 max:18.5 σ:6.064 min:-0.7	μ:8.946 max:16.2 σ:5.12 min:0.0	μ:10.834 max:19.7 σ:5.511 min:0.0	μ:10.205 σ:6.219
	2017	μ:10.371 max:16.9 σ:5.432 min:0.3	μ:9.102 max:16.8 σ:5.993 min:-1.1	μ:8.805 max:15.2 σ:4.74 min:0.1	μ:10.626 max:16.4 σ:4.751 min:0.4	μ:9.489 σ:5.871
	2018	μ:11.093 max:20.5 σ:6.146 min:0.6	μ:10.149 max:20.3 σ:6.539 min:0.2	μ:8.108 max:15.6 σ:5.415 min:-0.9	μ:11.758 max:22.2 σ:7.332 min:-0.3	μ:9.664 σ:6.439
	2019	μ:10.873 max:20.4 σ:5.554 min:0.8	μ:9.672 max:20.4 σ:5.961 min:0.3	μ:9.017 max:18.3 σ:5.122 min:0.2	μ:10.366 max:18.5 σ:5.125 min:0.7	μ:10.186 σ:5.838
	2020	μ:9.764 max:18.7 σ:5.746 min:0.8	μ:9.817 max:20.5 σ:6.134 min:-0.7	μ:9.368 max:16.8 σ:5.173 min:0.1	μ:11.804 max:21.2 σ:6.003 min:1.0	μ:10.21 σ:5.826
	2021	μ:10.773 max:19.2 σ:6.007 min:0.3	μ:10.014 max:19.1 σ:5.995 min:0.1	μ:8.963 max:16.6 σ:5.177 min:-0.3	μ:11.7 max:21.4 σ:6.083 min:0.2	μ:10.032 σ:6.194
	2022	μ:10.387 max:17.6 σ:5.6 min:0.5	μ:12.987 max:19.2 σ:3.605 min:5.1	μ:9.478 max:16.8 σ:4.844 min:0.4	μ:11.15 max:19.5 σ:5.83 min:0.1	μ:9.988 σ:6.024

Table 6: Every cell of the table has the

mean std	max min	42	118	52	37	30
	2014	μ:12.0 max:32.2 σ:6.459 min:-3.1	μ:11.792 max:31.5 σ:6.384 min:-3.5	μ:11.961 max:31.9 σ:6.684 min:-4.0	μ:10.8 max:30.7 σ:6.437 min:-4.6	μ:11.486 σ:6.473
	2015	μ:10.417 max:25.4 σ:5.871 min:-4.8	μ:10.283 max:24.6 σ:5.477 min:-4.9	μ:10.447 max:25.8 σ:5.932 min:-6.4	μ:9.361 max:26.2 σ:5.738 min:-6.0	μ:10.151 σ:5.807
	2016	μ:11.037 max:29.4 σ:6.476 min:-4.2	μ:10.993 max:27.3 σ:6.22 min:-5.8	μ:11.096 max:28.4 σ:6.457 min:-5.7	μ:10.161 max:26.9 σ:6.444 min:-9.8	μ:12.434 σ:6.282
	2017	μ:10.558 max:26.8 σ:6.214 min:-8.5	μ:10.425 max:25.2 σ:5.9 min:-6.4	μ:10.373 max:25.6 σ:6.159 min:-6.7	μ:9.48 max:24.6 σ:6.112 min:-7.0	μ:10.693 σ:6.371
	2018	μ:11.399 max:33.0 σ:8.932 min:-14.5	μ:11.338 max:33.1 σ:8.456 min:-16.6	μ:11.451 max:32.6 σ:8.545 min:-18.0	μ:10.513 max:31.3 σ:8.762 min:-20.1	μ:11.321 σ:9.113
	2019	μ:10.47 max:30.9 σ:6.822 min:-9.8	μ:11.057 max:31.5 σ:6.716 min:-11.3	μ:10.705 max:30.6 σ:6.754 min:-13.2	μ:9.97 max:31.6 σ:7.077 min:-16.6	μ:10.596 σ:6.99
	2020	μ:11.027 max:29.4 σ:6.673 min:-7.5	μ:11.439 max:30.2 σ:6.453 min:-6.6	μ:11.072 max:28.9 σ:6.496 min:-7.1	μ:10.403 max:29.7 σ:6.697 min:-7.4	μ:11.019 σ:6.703
	2021	μ:11.351 max:29.2 σ:6.746 min:-5.8	μ:11.586 max:29.4 σ:6.595 min:-5.5	μ:11.059 max:27.7 σ:6.618 min:-7.6	μ:10.51 max:28.2 σ:6.807 min:-8.1	μ:11.417 σ:6.888
	2022	μ:11.094 max:28.6 σ:6.682 min:-6.3	μ:11.405 max:29.4 σ:6.714 min:-7.3	μ:10.878 max:28.0 σ:6.85 min:-8.7	μ:10.162 max:30.5 σ:6.92 min:-9.7	μ:11.135 σ:6.841

Table 7: Every cell of the table has the

mean std	max min	42	118	52	37	30
	2014	μ:12.296 max:21.8 σ:4.887 min:2.7	μ:11.901 max:21.8 σ:5.262 min:1.9	μ:12.462 max:23.2 σ:5.157 min:2.6	μ:11.237 max:21.6 σ:5.153 min:2.0	μ:10.76 σ:4.841
	2015	μ:10.957 max:20.3 σ:5.29 min:0.1	μ:10.506 max:19.5 σ:5.022 min:0.5	μ:11.307 max:19.4 σ:4.865 min:1.1	μ:9.761 max:17.8 σ:4.506 min:0.5	μ:9.371 σ:4.52
	2016	μ:11.293 max:20.7 σ:6.044 min:-0.1	μ:10.866 max:19.6 σ:5.599 min:-0.4	μ:11.951 max:20.2 σ:5.67 min:0.1	μ:10.593 max:19.8 σ:5.565 min:-0.4	μ:13.312 σ:5.304
	2017	μ:10.46 max:19.0 σ:5.741 min:-0.3	μ:10.099 max:16.9 σ:4.974 min:-0.2	μ:10.887 max:19.7 σ:5.337 min:0.1	μ:10.147 max:18.5 σ:5.147 min:-0.2	μ:11.175 σ:5.969
	2018	μ:11.048 max:22.0 σ:6.59 min:0.0	μ:10.154 max:19.4 σ:6.354 min:-0.9	μ:11.39 max:21.2 σ:6.804 min:-1.0	μ:11.104 max:21.2 σ:6.219 min:-1.5	μ:11.53 σ:6.856
	2019	μ:10.672 max:21.4 σ:6.061 min:0.1	μ:10.666 max:20.9 σ:5.485 min:0.1	μ:11.665 max:21.7 σ:5.495 min:0.3	μ:10.772 max:21.4 σ:5.612 min:-0.2	μ:11.156 σ:6.38
	2020	μ:13.184 max:22.8 σ:4.763 min:1.6	μ:10.823 max:19.6 σ:5.071 min:0.4	μ:12.331 max:21.7 σ:4.968 min:0.8	μ:10.809 max:21.0 σ:5.292 min:0.0	μ:11.59 σ:6.166
	2021	μ:10.999 max:23.2 σ:6.997 min:-0.4	μ:10.277 max:19.6 σ:5.911 min:-0.7	μ:6.954 max:22.1 σ:5.746 min:0.0	μ:10.592 max:22.0 σ:6.4 min:-0.5	μ:11.455 σ:6.647
	2022	μ:10.835 max:20.6 σ:5.968 min:-0.1	μ:10.22 max:17.4 σ:5.147 min:0.2	μ:13.996 max:19.4 σ:3.069 min:7.4	μ:10.336 max:19.9 σ:5.99 min:-0.3	μ:11.188 σ:5.964

Table 8: Every cell of the table has the

mean std	max min	42	118	52	37	30
	2014	μ:12.967 max:20.6 σ:4.05 min:4.6	μ:11.672 max:20.3 σ:5.003 min:2.4	μ:12.146 max:20.9 σ:4.928 min:3.3	μ:11.153 max:19.7 σ:4.936 min:2.3	μ:11.023 σ:4.889
	2015	μ:10.765 max:18.6 σ:5.038 min:0.4	μ:10.395 max:18.0 σ:4.73 min:0.9	μ:11.079 max:17.8 σ:4.704 min:1.6	μ:9.719 max:16.6 σ:4.527 min:0.6	μ:9.661 σ:4.49
	2016	μ:11.107 max:19.3 σ:5.776 min:0.2	μ:10.772 max:18.3 σ:5.258 min:-0.1	μ:11.672 max:18.7 σ:5.442 min:0.4	μ:10.385 max:18.3 σ:5.425 min:-0.4	μ:13.167 σ:4.825
	2017	μ:10.317 max:17.3 σ:5.501 min:0.1	μ:9.993 max:16.0 σ:4.768 min:0.2	μ:10.64 max:18.0 σ:5.151 min:0.2	μ:10.118 max:16.9 σ:5.043 min:0.0	μ:10.919 σ:5.686
	2018	μ:10.863 max:19.9 σ:6.187 min:0.3	μ:9.931 max:18.3 σ:6.071 min:-0.6	μ:11.079 max:20.0 σ:6.518 min:-0.6	μ:10.889 max:20.0 σ:6.133 min:-0.7	μ:11.36 σ:6.404
	2019	μ:10.517 max:19.9 σ:5.775 min:0.5	μ:10.45 max:19.4 σ:5.272 min:0.3	μ:11.375 max:20.4 σ:5.302 min:0.5	μ:10.458 max:19.3 σ:5.432 min:-0.3	μ:11.026 σ:5.874
	2020	μ:12.791 max:20.1 σ:4.488 min:2.5	μ:10.61 max:18.3 σ:4.837 min:0.8	μ:12.258 max:20.4 σ:4.773 min:1.2	μ:10.827 max:19.4 σ:5.16 min:0.5	μ:11.365 σ:5.725
	2021	μ:10.749 max:20.6 σ:6.743 min:-0.1	μ:9.995 max:18.1 σ:5.67 min:-0.7	μ:12.573 max:24.2 σ:6.025 min:0.0	μ:10.524 max:20.5 σ:6.311 min:-0.3	μ:11.118 σ:6.41
	2022	μ:10.601 max:18.5 σ:5.692 min:0.3	μ:9.926 max:16.5 σ:4.949 min:0.5	μ:12.151 max:22.4 σ:5.246 min:0.9	μ:10.379 max:18.7 σ:5.867 min:0.0	μ:10.98 σ:5.679

Table 9: Every cell of the table has the

compatible with sklearns other functions. The details of the models will be discussed in section 2, this section discusses the setup and implementation of the models.[5]

3.4.1 Basic Linear model

The linear model (section 2.2) utilises in the study is created from the python model sklearn (or scikit-learn according to pythons package manager). The model is setup with standard parameters, and the data is fed into the model without scaling with fitted intercept coefficient.

3.4.2 Plauborg

The Plauborg regression will be formulated as a linear regression problem so that the Linear-Regression function in the Sci-kit module can be used. For the parameters used in the paper[1] the F function defined in section 2.3 will be formulated with loops to give rise 3 more parameters for fine-tuning the model. Nan-values generated from the procedure get replaced with 0, since the data fed to the model is significantly larger than 10h (the minimum for the training is 24h).

3.4.3 LSTM

rewrite or possibaly move

LSTM[22] was developed in the field of Economy to predict the rise and fall of stocks, but has shown to be applicable to other problems that relies on time-series. It has been used to predict soil temperatures[4, 16, 24–30]

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network (RNN) designed to handle long-term dependencies in sequential data. Unlike regular RNNs, which often suffer from vanishing gradient problems, LSTMs utilize a more complex cell structure that allows them to capture long-term dependencies more effectively.

- **Input Gate (it)**: $a_i = \sigma(W_{xi} \cdot X_t + W_{hi} \cdot H_{t-1} + b_i)$
- **Forget Gate (f_t)**: $a_f = \sigma(W_{xf} \cdot X_t + W_{hf} \cdot H_{t-1} + b_f)$
- **Cell State Update ($\tilde{C}_t$)**: $\tilde{C}_t = \tanh(W_{xc} \cdot X_t + W_{hc} \cdot H_{t-1} + b_c)$
- **New Cell State (C_t)**: $C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$
- **Output Gate (o_t)**: $a_o = \sigma(W_{xo} \cdot X_t + W_{ho} \cdot H_{t-1} + b_o)$
- **Hidden State (H_t)**: $H_t = o_t \cdot \tanh(C_t)$

Where:

X_t represents the input at time step (t).

H_{t-1} is the hidden state from the previous time step.

W and b are weight matrices and bias terms.

σ denotes the sigmoid activation function

tanh represents the hyperbolic tangent activation function.

LSTMs have proven effective in various tasks such as natural language processing, speech recognition, and time series prediction. They provide a powerful mechanism for modeling sequential data while mitigating the vanishing gradient problem commonly encountered in vanilla RNNs.

[5] Caution to the reader; The code used was run on the Linux subsystem (Debian) on windows due to the fact that the current version of tensorflow can't run on Windows.

3.4.4 BiLSTM

rewrite

Bidirectional Long Short-Term Memory (BiLSTM) networks enhance traditional LSTMs by considering context from both forward and backward directions. Here's how they work:

BiLSTMs consist of two LSTM layers operating simultaneously:

- The forward LSTM processes the input sequence from the beginning to the end. - The backward LSTM processes the input sequence from the end to the beginning. By combining the outputs of these two LSTMs, BiLSTMs effectively capture information from both past and future context. - This context expansion is particularly useful in tasks where context matters in both directions:

Natural Language Processing (NLP): BiLSTMs excel in tasks like part-of-speech tagging, named entity recognition, and sentiment analysis. - Speech Recognition: Capturing context from both sides of an audio sequence improves accuracy. - Time Series Prediction: BiLSTMs enhance predictions by leveraging past and future data points. - Mathematically, the final hidden state of the BiLSTM at time step (t) is the concatenation of the forward and backward LSTM hidden states:

$$H_t = [H_t^{(f)}, H_t^{(b)}]$$

The resulting output can be used for downstream tasks such as classification, regression, or sequence labeling.

Information from earlier timesteps is important to say something about current timesteps, same can be said about the other time direction. To get the best of both direction one can use a bidirectional LSTM (BiLSTM) to combine the information from both approches. To make one of the models read the data backwards the model pipeline reverses the data and trains on that. A visualiation of this can be shown in the first layer in figure 7.

3.4.5 Modified BiLSTM

To investigate the posssibility of RNN a more complex model was developed to see if the introduction of more layers would improve the accuratsy of the base model.

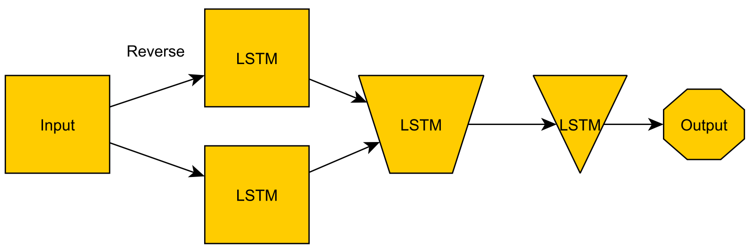

Figure 7: Simple diagram of the structure of the BiLSTM. The data from the input layer gets duplicated and passed to two LSTM's where one of them get the data in reverse. When both models have trained on the data they gets concatenated and passed to another LSTM that has half of the units as output. The final LSTM has a single cell as output leaving a single value as the prediction.

Complete caption, and improve figure

Soil temperatures depend on earlier timestamps, so to make accurate predictions, it's essential to include temperature data from $t, t-1, \ldots, t-k$. Evaluating the data both forwards and backwards helps identify features that are noticeable in specific directions. The BiLSTM model, implemented using TensorFlow's Keras module, consists of three layers:

EXPAND

Parameter name	Range
Epochs	[4,8]
Units	$\{2^6, 2^7, 2^8\}$
Lag time	$12i$ for $i \in [1, 14]$

(a) The search space for the modified BiLSTM model. The units define the number of LSTM cells used in the LSTM output. The lag time specifies how many hours the model will take into account when predicting soil temperature. The square brackets indicate an interval including endpoints, while the curly brackets indicate a list of elements.

Parameter name	Range
Sine terms	[1,10]
Cosine terms	[1,10]
Lag time	[1,14]

(b) The search space for the Plauborg model. The square brackets indicate an interval including endpoints. The "Lag time" indicated the number of time-steps before current time-steps do the model include $(t_{-1}, t_{-2}, \dots)$

Parameter name	Range
Epochs	[4,10]
Lead time	$\{24 * n \mid n \in [1, 7]\}$

(c) Parameter space for both LSTM and BiLSTM. The square brackets indicate an interval including endpoints. The "Lag time" indicated the number of time-steps before current time-steps do the model include $(t_{-1}, t_{-2}, \dots)$

Table 10: Parameter search space for the different deep learning models

- A Bidirectional LSTM layer for feature extraction.
- A regular LSTM layer to condense information with a tanh activation function
- An LSTM layer for prediction with a tanh activation function

The activation functions used are hyperbolic tangent and sigmoid. The output layer employs the identity function ($f(x) = x$). The hidden layer has half as many recurrent cells as the input layer, and the output layer condenses the hidden layer's output to a single value. For more details, refer to Figure 7 and Table 10a.

This model is an extention of "Modeling Hourly Soil Temperature Using Deep BiLSTM Neural Network"[4] written by Li *et al.*

3.4.6 GRU

The Gated Recurent Unit (GRU) is a simplification of the LSTM cell with fewer total gates, and no output gate. This makes it quicker to train and better for memory deficient computers/servers. The model used in this study is the Keras defult GRU layer.

GRU shares similarities with LSTM networks but simplifies the architecture by using two gates: the update gate and the reset gate. These gates allow GRU to selectively retain relevant information from previous time steps while avoiding unnecessary washing of information. The update gate determines how much past information should be passed to the future, while the reset gate controls how much past information to forget. GRU has been effective in various sequence modelling tasks.

EXPAND, and add formulas

3.5 Metrics

The metrics used in this study are

• Root Mean Square Error (RMSE) • Mean Absolut Error (MAE) • Explained Variance (R^2) • bias • Log Condition number ($\log(\kappa)$) • digit sensitivity

Soil temperatur as a different behaviour than air temperature since energy (temperature) though the soil gets dampen and delayed. Since the data used in this study has outliers that was not cought during data treatment, which has been addresed, the author of this study desided to include two more metrics that are not usually included in the evaluation; The log condition number, and digit sensitivity. Both metrics are based on the calculation of the condition number defined as

$$\kappa = \lim_{\varepsilon \to 0^+} \sup_{|\partial x| \leq \varepsilon} \frac{|f(x+\partial x) - f(x)|}{|f(x)|} * \frac{|x|}{|\partial x|} \tag{5}$$

Calculating this directly is impossible due to the limitations of handling infinitesimally small numbers in simulations. However, this paper uses a specific algorithm (referred to as κ) to estimate this value for all the models.

Algorithm 1: Method for calculating κ. $\mathcal{U}$ is a uniform random distrebution in a range.

Data: Data
Result: $\log(\kappa)$
Let κ_f be the function 5;
$\kappa \leftarrow 0$;
for $i \in 1 \ldots |Data|$ **do**
    $\partial x \leftarrow \mathcal{U}_{[-\sqrt{\varepsilon/|Data|}, \sqrt{\varepsilon/|Data|}]}$;
    $k \leftarrow$ calculate with κ_f from x and $x + \partial x$;
    if $k > \kappa$ **then**
        $\kappa \leftarrow k$;
    end if
end for
return κ

The digit sensitivity is included to give an intuitive understanding of κ and is computed simply as $\log_e(\kappa)+1$. This number tells us the significant digit generated from the model. If the number is less than 0 then its the ith digit after the decimal point.

For the rest of the metrics, they are defined as follows

- RMSE $= \sqrt{\frac{\sum(y_{\text{pred}} - y_{\text{truth}})^2}{n}}$
- MAE $= \frac{\sum|y_{\text{pred}} - y_{\text{truth}}|}{n}$
- bias $= \frac{\sum(y_{\text{pred}} - y_{\text{truth}})}{n}$
- $R^2 = 1 - \frac{\sum(y_{\text{pred}} - y_{\text{truth}})^2}{\sum(y_{\text{pred}} - \vec{y})^2}$

Where $\vec{y}$ is the mean of the target, y_{pred} is the predicted data, and y_{truth} is the observed soil temperature.

3.5.1 Model training

The models get trained on air temperature, however the precise input for each model is not the same for all. The features used for each model are described in table 10 and their transformation in table 11.

The models get a sample of the training data at the time due to the size and the amount for missing data (for example figure 4) The algorithm used to fetch reliable indexes are demonstrated at algorithm 2.

Algorithm 2: Find Non-NULL Ranges (Abstract)

Input : Input data data
Output: List of tuples: ranges

```
FindNonNaNRanges(data) ranges ← empty list;
start ← None;
for item in data do
    if item is not NULL then
        if start is None then
            start ← item;
        end if
    end if
    else
        if start is not None then
            Add (start, item index - 1) to ranges;
            start ← None;
        end if
    end if
end for
if start is not None then
    Add (start, Last index) to ranges;
end if
return ranges;
```

model name	features	transformations
Linear regression	TM	Time get translated to hours by taking the day since new year and multiplying by 24 for then add the hour part.
Plauborg	Time, TM	Time get translated in two way; the current day since new year if looking at daily values, and hours since new year if looking at hourly predictions. When converting TM to daily values the hourly data get averaged.
BiLSTM	Time, TM	Time get translated to hours since new year.

Table 11: Parameters used for predicting soil temperatures at depth 10cm and 20cm.

3.6 Use of Artificial Intelligence in this paper

In this paper there has been used Artificial Intelligence (AI), specifically Bing Chat / Copilot hosted by Microsoft Cooperation according to the current guidelines for use of artificial intelligence at the faculty of The Norwegian University of Life Science (NMBU), for the following purposes:

1. Formalising sentences and rephrasing sentences.
2. Spellchecking
3. Code generation of basic consepts and structures (tree traversal, template for generic classes)

It is important to emphasize that my engagement with AI have been actively curated and verified with known sources. All code underwent rigorous manual inspection within a dedicated testing environment. Furthermore, no confidential or sensitive information was shared with the AI; my interactions focused solely on broad topics and general inquiries. To validate the accuracy of AI-generated responses, I cross-checked them with established research papers and textbooks.

model		52	37	50	38	57	34	27	17	average
Linear model 10cm	R^2	0.221	0.473	0.584	0.388	0.295	-1.386	0.551	0.501	0.423
	MAE	2.889	3.503	2.702	3.741	3.356	3.415	3.236	3.432	3.267
	RMSE	3.679	4.501	3.611	4.815	4.293	4.262	4.272	4.518	4.231
	bias	1.226	2.07	1.766	2.502	2.775	3.176	2.078	2.506	2.303
Plauborg model (daily values) 10cm	R^2	0.664	0.873	0.938	0.845	0.85	0.397	0.895	0.875	0.861
	MAE	1.837	1.755	1.105	1.908	1.547	1.687	1.627	1.78	1.621
	RMSE	2.418	2.206	1.395	2.42	1.978	2.143	2.063	2.26	2.074
	bias	-0.636	0.373	-0.046	0.667	1.108	1.535	0.396	0.921	0.608
Plauborg model (hourly values) 10cm	R^2	0.636	0.857	0.884	0.754	0.677	-0.193	0.872	0.828	0.794
	MAE	1.964	1.804	1.472	2.368	2.263	2.306	1.724	1.979	1.926
	RMSE	2.514	2.344	1.908	3.055	2.906	3.013	2.277	2.649	2.529
	bias	-0.349	0.237	0.558	1.363	0.677	0.845	0.163	0.065	0.597
BiLSTM 10cm	R^2	0.699	0.929	0.948	0.919	0.898	0.64	0.924	0.927	0.906
	MAE	1.706	1.37	1.048	1.315	1.274	1.262	1.482	1.39	1.355
	RMSE	2.276	1.65	1.267	1.748	1.631	1.666	1.757	1.724	1.706
	bias	-1.077	-0.198	-0.376	0.221	0.302	0.654	-0.18	0.334	0.038
LSTM 10cm	R^2	0.703	0.917	0.936	0.891	0.859	0.508	0.91	0.917	0.884
	MAE	1.712	1.496	1.129	1.501	1.48	1.491	1.575	1.443	1.491
	RMSE	2.264	1.778	1.413	2.029	1.915	1.946	1.905	1.839	1.892
	bias	-0.77	0.082	-0.067	0.562	0.537	0.868	0.05	0.502	0.31
GRU 10cm	R^2	0.723	0.931	0.946	0.903	0.86	0.497	0.923	0.926	0.894
	MAE	1.577	1.331	1.001	1.387	1.485	1.52	1.396	1.308	1.396
	RMSE	2.183	1.618	1.291	1.91	1.909	1.996	1.762	1.734	1.807
	bias	-0.77	0.04	0.043	0.628	0.527	0.844	0.053	0.392	0.329

4 Results

Summerize results

Make sections

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4.1 Linear regression vs Plauborg

The global measure for the linear regression has an average error of $2.3°C \pm 4.23°C$ while the global messure of the Plauborg daily model has an average error of $0.6°C \pm 1.96°C$. Further more Plauborg has an hight R^2 value indicating that it follows the temperature changes in the soil better than just scaling the air temperature by a scaling factor.

The linear model shows subpar predictive capabilities compared to Plauborg's model who uses the same technics but interoperate time dependence.

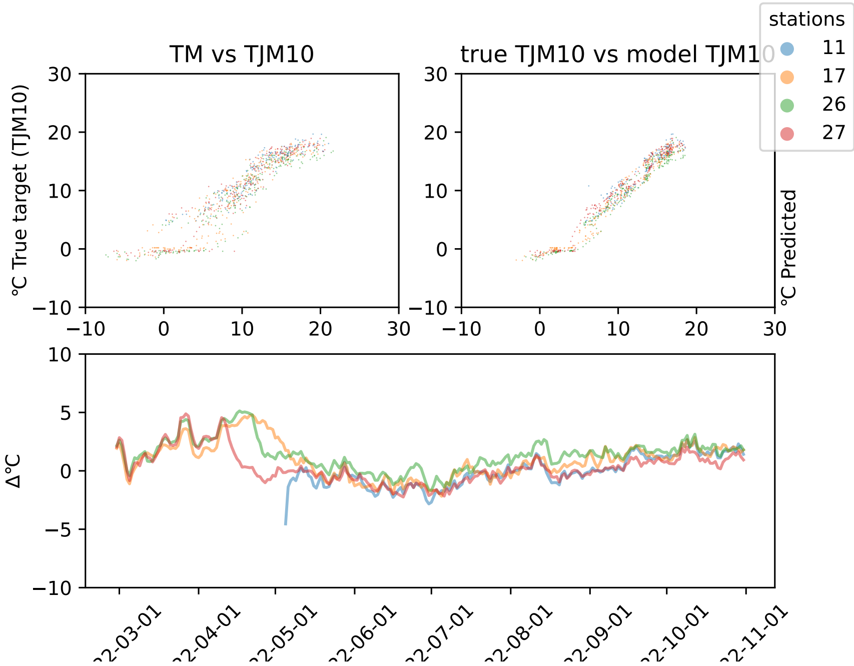
4.2 Modification of Plauborg

The Plauborg model trained in Norway was found to only need 3 days (t_0, t_{-1}, t_{-2}) compared to [1] that needed 4 days $(t_0, t_{-1}, t_{-2}, t_{-3})$. However for the Fourier terms both models (Danish model and the Norwegian model) required 2 sine and cosine terms. For the 20cm target the models diverge in the sense of quantity of terms. It was found that the 20cm model needs 14 sine terms and 2 cosine terms, however only needs 2 days.

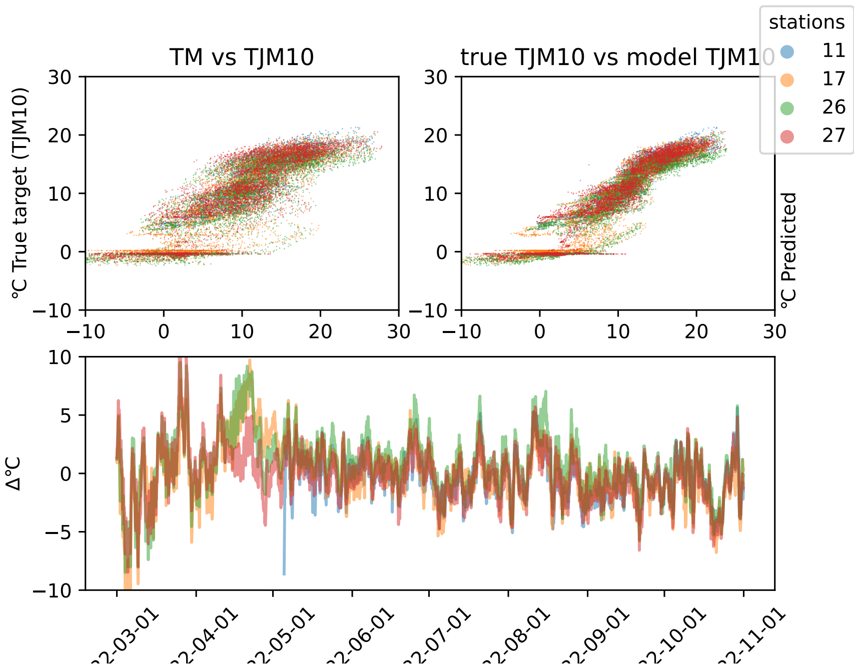
model		41	118	42	30	39	15	26	11	average
Linear model 10cm	R^2	0.593	0.306	0.506	0.588	0.213	-0.003	0.456	0.51	0.423
	MAE	3.07	3.486	3.525	3.106	3.193	3.141	3.651	2.713	3.267
	RMSE	3.976	4.5	4.571	4.053	4.057	3.918	4.714	3.567	4.231
	bias	1.494	2.93	2.109	1.733	2.835	2.799	2.902	1.529	2.303
Plauborg model (daily values) 10cm	R^2	0.9	0.839	0.881	0.908	0.828	0.787	0.855	0.864	0.861
	MAE	1.587	1.697	1.75	1.519	1.455	1.428	1.937	1.504	1.621
	RMSE	1.975	2.165	2.239	1.914	1.896	1.806	2.43	1.879	2.074
	bias	-0.293	1.137	0.333	-0.046	1.193	1.114	1.251	0.339	0.608
Plauborg model (hourly values) 10cm	R^2	0.903	0.706	0.852	0.892	0.633	0.562	0.843	0.823	0.794
	MAE	1.519	2.322	1.885	1.555	2.151	1.991	1.918	1.666	1.926
	RMSE	1.938	2.928	2.501	2.072	2.77	2.589	2.532	2.146	2.529
	bias	0.151	1.639	0.703	0.354	0.701	0.903	0.821	0.038	0.597
BiLSTM 10cm	R^2	0.913	0.914	0.921	0.922	0.87	0.848	0.919	0.883	0.906
	MAE	1.525	1.224	1.464	1.439	1.252	1.188	1.474	1.437	1.355
	RMSE	1.828	1.575	1.827	1.759	1.643	1.518	1.81	1.743	1.706
	bias	-0.676	0.723	-0.108	-0.484	0.366	0.378	0.669	-0.257	0.038
LSTM 10cm	R^2	0.909	0.876	0.903	0.908	0.832	0.789	0.901	0.863	0.884
	MAE	1.557	1.446	1.604	1.544	1.412	1.403	1.617	1.523	1.491
	RMSE	1.872	1.895	2.016	1.906	1.866	1.788	2.002	1.885	1.892
	bias	-0.364	1.059	0.214	-0.153	0.588	0.635	0.896	-0.048	0.31
GRU 10cm	R^2	0.926	0.885	0.919	0.924	0.828	0.779	0.913	0.872	0.894
	MAE	1.381	1.411	1.41	1.367	1.443	1.452	1.487	1.431	1.396
	RMSE	1.691	1.844	1.846	1.73	1.887	1.831	1.883	1.82	1.807
	bias	-0.295	1.124	0.266	-0.102	0.587	0.665	0.853	-0.005	0.329

model		52	37	50	38	57	34	27	17	average
Linear model 20cm	R^2	0.604	0.391	0.434	0.308	0.125	-2.248	0.415	0.336	0.308
	MAE	2.841	3.675	3.025	3.682	3.636	3.675	3.547	3.84	3.474
	RMSE	3.556	4.754	4.048	4.832	4.655	4.583	4.672	5.049	4.504
	bias	0.559	2.174	2.207	2.601	3.153	3.471	2.535	2.939	2.487
Plauborg model (daily values) 20cm	R^2	0.83	0.905	0.946	0.912	0.863	0.316	0.901	0.844	0.876
	MAE	1.873	1.496	0.985	1.367	1.538	1.836	1.534	1.911	1.536
	RMSE	2.33	1.877	1.251	1.721	1.841	2.104	1.924	2.448	1.91
	bias	-1.402	0.353	0.096	0.515	1.427	1.816	0.753	1.401	0.644
Plauborg model (hourly values) 20cm	R^2	0.803	0.83	0.836	0.736	0.617	-0.547	0.839	0.762	0.756
	MAE	1.976	1.938	1.7	2.323	2.419	2.427	1.885	2.265	2.06
	RMSE	2.504	2.513	2.176	2.983	3.079	3.163	2.455	3.023	2.676
	bias	-1.2	0.067	0.815	1.149	0.744	0.797	0.335	0.137	0.528
Multi layer Bi/LSTM 20cm	R^2	0.776	0.873	0.869	0.844	0.795	0.195	0.862	0.871	0.825
	MAE	2.132	1.829	1.5	1.736	1.722	1.86	1.864	1.732	1.798
	RMSE	2.615	2.138	1.904	2.258	2.229	2.301	2.234	2.2	2.233
	bias	-1.297	0.257	0.334	0.667	1.05	1.297	0.437	0.867	0.523
BiLSTM 20cm	R^2	0.799	0.934	0.962	0.946	0.922	0.654	0.942	0.921	0.918
	MAE	2.093	1.268	0.833	1.072	1.106	1.18	1.163	1.319	1.213
	RMSE	2.52	1.555	1.04	1.342	1.386	1.505	1.464	1.733	1.543
	bias	-1.864	-0.282	-0.214	0.095	0.633	0.907	0.13	0.594	0.056
LSTM 20cm	R^2	0.803	0.904	0.932	0.901	0.848	0.432	0.903	0.893	0.874
	MAE	2.069	1.58	1.108	1.389	1.5	1.482	1.571	1.584	1.516
	RMSE	2.494	1.881	1.395	1.818	1.935	1.927	1.9	2.024	1.913
	bias	-1.628	-0.109	0.058	0.421	0.654	0.919	0.235	0.652	0.226
GRU 20cm	R^2	0.81	0.957	0.981	0.96	0.941	0.695	0.961	0.933	0.937
	MAE	2.029	1.016	0.573	0.883	0.948	1.112	0.898	1.088	1.026
	RMSE	2.435	1.25	0.725	1.147	1.204	1.432	1.194	1.592	1.349
	bias	-1.907	-0.351	-0.207	0.087	0.638	0.913	0.106	0.566	0.048

model		41	118	42	30	39	15	26	11	average
Linear model 20cm	R^2	0.491	0.162	0.393	0.456	0.081	-0.241	0.302	0.35	0.308
	MAE	3.286	3.654	3.741	3.433	3.39	3.342	4.009	2.924	3.474
	RMSE	4.248	4.726	4.863	4.465	4.31	4.198	5.17	3.821	4.504
	bias	1.677	3.208	2.364	2.015	3.083	3.006	3.282	1.692	2.487
Plauborg model (daily values) 20cm	R^2	0.914	0.886	0.901	0.91	0.852	0.801	0.833	0.866	0.876
	MAE	1.409	1.384	1.54	1.471	1.468	1.411	2.101	1.443	1.536
	RMSE	1.748	1.742	1.966	1.817	1.729	1.681	2.528	1.735	1.91
	bias	-0.371	1.139	0.346	-0.014	1.402	1.215	1.578	0.463	0.644
Plauborg model (hourly values) 20cm	R^2	0.872	0.656	0.807	0.859	0.615	0.484	0.801	0.755	0.756
	MAE	1.665	2.422	2.099	1.708	2.186	2.094	2.105	1.847	2.06
	RMSE	2.135	3.029	2.739	2.276	2.79	2.706	2.757	2.346	2.676
	bias	0.13	1.722	0.746	0.428	0.633	0.827	0.892	-0.023	0.528
Multi layer Bi/LSTM 20cm	R^2	0.857	0.787	0.854	0.859	0.768	0.683	0.848	0.82	0.825
	MAE	1.862	1.829	1.935	1.887	1.642	1.617	1.932	1.627	1.798
	RMSE	2.202	2.351	2.349	2.234	2.128	2.07	2.385	1.992	2.233
	bias	-0.21	1.355	0.407	0.045	0.976	0.979	1.258	0.172	0.523
BiLSTM 20cm	R^2	0.929	0.935	0.937	0.933	0.911	0.896	0.919	0.916	0.918
	MAE	1.291	1.07	1.254	1.269	1.055	0.953	1.408	1.111	1.213
	RMSE	1.581	1.315	1.562	1.559	1.337	1.211	1.753	1.369	1.543
	bias	-0.767	0.735	-0.112	-0.483	0.603	0.512	0.875	-0.145	0.056
LSTM 20cm	R^2	0.9	0.878	0.897	0.904	0.843	0.781	0.882	0.838	0.874
	MAE	1.553	1.368	1.595	1.538	1.337	1.369	1.699	1.547	1.516
	RMSE	1.874	1.795	1.996	1.872	1.772	1.757	2.12	1.907	1.913
	bias	-0.487	1.029	0.174	-0.17	0.57	0.582	1.009	-0.066	0.226
GRU 20cm	R^2	0.954	0.951	0.952	0.957	0.927	0.915	0.937	0.944	0.937
	MAE	1.049	0.917	1.059	0.995	0.94	0.862	1.179	0.892	1.026
	RMSE	1.264	1.143	1.362	1.24	1.206	1.089	1.547	1.122	1.349
	bias	-0.775	0.735	-0.105	-0.471	0.607	0.548	0.853	-0.119	0.048



(a) The daily model of Plauborg model. The model uses daily avergae tempratures to predict soil temperatures.



(b) The hourly model of Plauborg model. The model uses hourly temperature data.

Figure 8: Comperasion of daily versus hourly predictions

scope	spesific scope	RMSE °C	MAE°C	bias °C	log(κ(model))	digit sensitivity	R^2
global	—	2.529	1.926	0.597	-0.44	-1	0.794
region	Østfold	2.448	1.894	0.512	-0.446	-1	0.816
region	Vestfold	2.412	1.81	0.733	-0.44	-1	0.846
region	Trøndelag	2.822	2.176	0.781	-0.445	-1	0.547
region	Innlandet	2.382	1.805	0.312	-0.432	-1	0.847
local	52	2.514	1.964	-0.349	-0.44	-1	0.636
local	41	1.938	1.519	0.151	-0.448	-1	0.903
local	37	2.344	1.804	0.237	-0.443	-1	0.857
local	118	2.928	2.322	1.639	-0.446	-1	0.706
local	50	1.908	1.472	0.558	-0.443	-1	0.884
local	42	2.501	1.885	0.703	-0.437	-1	0.852
local	38	3.055	2.368	1.363	-0.442	-1	0.754
local	30	2.072	1.555	0.354	-0.449	-1	0.892
local	57	2.906	2.263	0.677	-0.441	-1	0.677
local	39	2.77	2.151	0.701	-0.446	-1	0.633
local	34	3.013	2.306	0.845	-0.447	-1	-0.193
local	15	2.589	1.991	0.903	-0.444	-1	0.562
local	27	2.277	1.724	0.163	-0.444	-1	0.872
local	26	2.532	1.918	0.821	-0.438	-1	0.843
local	17	2.649	1.979	0.065	-0.442	-1	0.828
local	11	2.146	1.666	0.038	-0.444	-1	0.823

Table 12: Hourly Plauborg model results.

The modification to Plauborg's model is minor, by replacing the ω with a larger coefficient it can be used with hourly data. As seen in figure 8b the variation is stronger than 8a however the overall performance is comparable as seen in table 17 and table 15.

With modification to the model to accept hourly data it still preforms approximately as well as the daily data version. With a average error of $0.597°C \pm 2.529°C$ for TJM10 and $0.528°C \pm 2.676°C$ for TJM20. It was found that the modified Plauborg model only needs 2 sine terms to make a good prediction and 12h of air temperature which would translate to half a day instead of 3 days.

4.3 Deep learning models

LSTM based models has a higher RMSE than the GRU model that performs similary to the Plauborg models in its performance while the rest (BiLSTM, and LSTM) inhibits a Autumm descrepensy, see section 5.1.

scope	spesific scope	RMSE °C	MAE°C	bias °C	log(κ(model))	digit sensitivity	R^2
global	—	2.074	1.621	0.608	-1.264	-2	0.861
region	Østfold	2.168	1.704	0.24	-1.27	-2	0.856
region	Vestfold	2.022	1.564	0.219	-1.246	-2	0.892
region	Trøndelag	1.957	1.528	1.235	-1.261	-2	0.782
region	Innlandet	2.165	1.71	0.714	-1.261	-2	0.873
local	52	2.418	1.837	-0.636	-1.265	-2	0.664
local	41	1.975	1.587	-0.293	-1.264	-2	0.9
local	37	2.206	1.755	0.373	-1.264	-2	0.873
local	118	2.165	1.697	1.137	-1.267	-2	0.839
local	50	1.395	1.105	-0.046	-1.265	-2	0.938
local	42	2.239	1.75	0.333	-1.261	-2	0.881
local	38	2.42	1.908	0.667	-1.266	-2	0.845
local	30	1.914	1.519	-0.046	-1.264	-2	0.908
local	57	1.978	1.547	1.108	-1.262	-2	0.85
local	39	1.896	1.455	1.193	-1.268	-2	0.828
local	34	2.143	1.687	1.535	-1.27	-2	0.397
local	15	1.806	1.428	1.114	-1.258	-2	0.787
local	27	2.063	1.627	0.396	-1.267	-2	0.895
local	26	2.43	1.937	1.251	-1.267	-2	0.855
local	17	2.26	1.78	0.921	-1.267	-2	0.875
local	11	1.879	1.504	0.339	-1.269	-2	0.864

Table 13: Daily Plauborg model results.

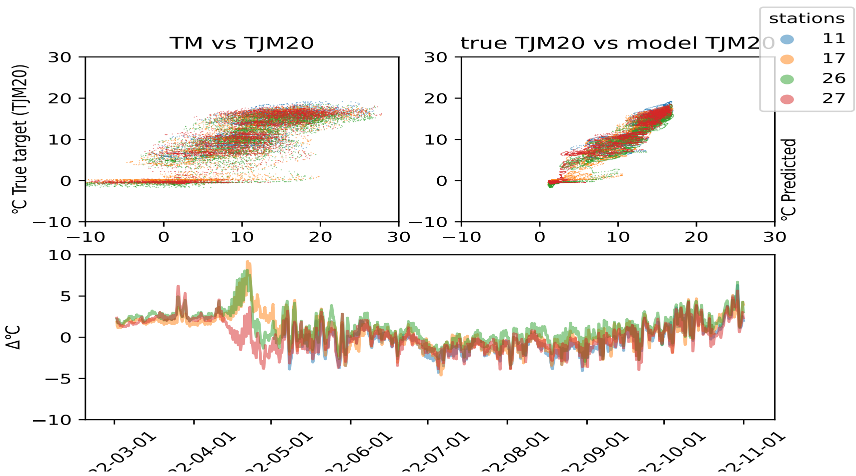


Figure 9: LSTM model applied at stations in the region Innlandet in 2022 with 10cm soil temperature as target.

The number of epochs was fixed at 10, however the performance grafs shows that after

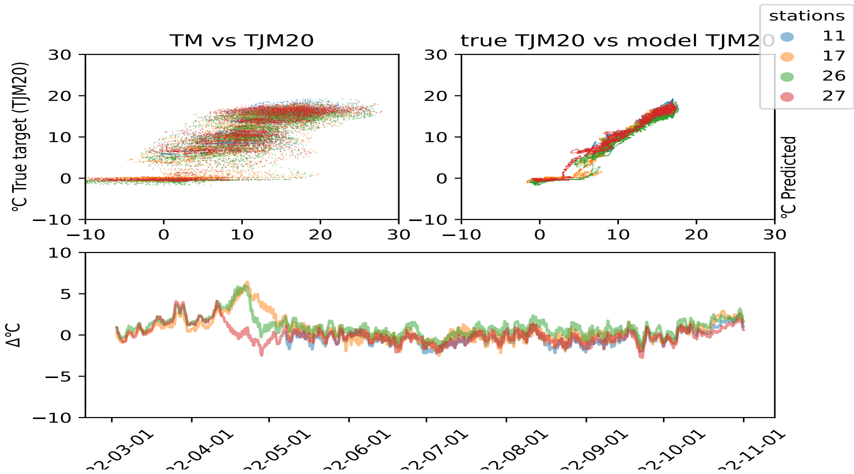


Figure 10: GRU model applied at staions in the region Innladet in 2022 with 10cm soil temperature as target.

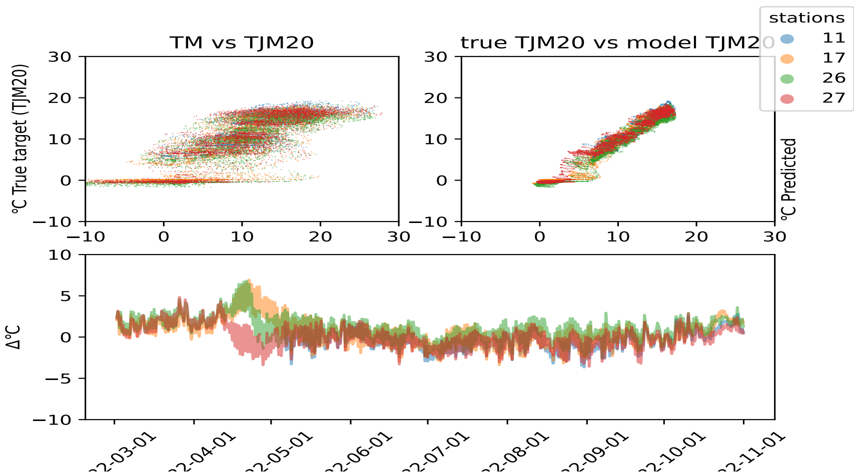
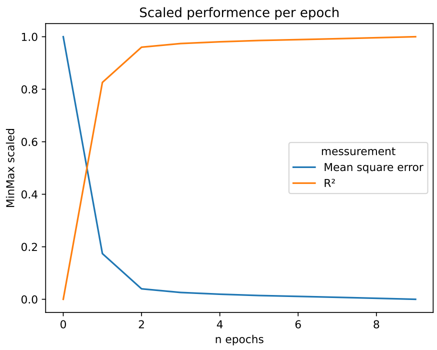
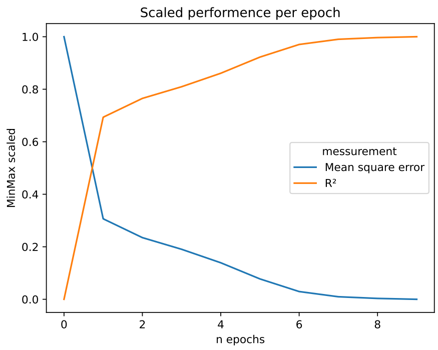


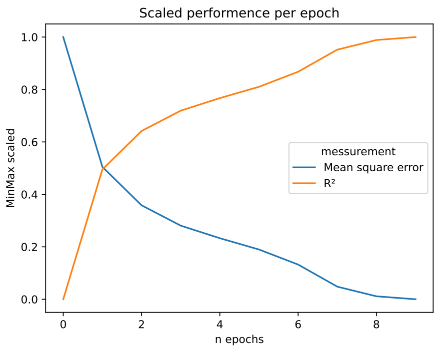
Figure 11: BiLSTM applied at stations in the region Innlandet in 2022 with 10cm soil temperature as target.



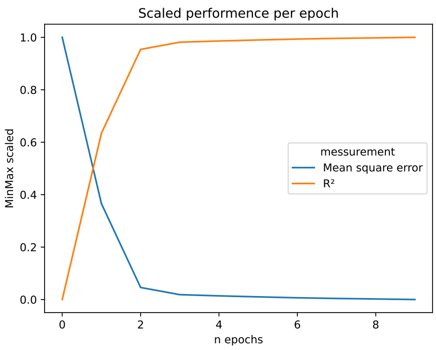
(a) Graf of BiLSTM 10cm performance per epoch.



(b) Graf of BiLSTM 20cm performance per epoch.



(c) Graf of LSTM 10cm performance per epoch.



(d) Graf of LSTM 20cm performance per epoch.

Figure 12: Performance graphs displaying the developments of Mean Square Error and Explained Variance (R^2) for each epoch.

5 Discussion

Write a discussion

5.1 The Autumn discrepancy

A phenomenon that arose during performance evaluations was that the linear models struggles with the Autumn season. The difference graphs showed a clear over or under estimation that are larger than 10σ. When investigating the coeffisents to the model this discrepancy can be contributed to the intercept that during low temperature ($< 5°C$) giving either an over estimation or an under approximation. Further more when removing the calculation of the intersept the same phenomenon is still precent possibility due to the adaptation to Summer season.

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Show table of parameters

If one looks at the deep learning models shown at figure 11 to figure 9 this effect can be observed. The GRU model is affected similarly, but to a lesser exstent where it overestimates at a few periods during the Mars month. This can be due to snow covering the soil forming an thermal isolator keeping the soil temperature constant while the air temperature is fluxiating at relative normal rates giving the models a false sense of generality when predicting this period, however the GRU model seems to interoperate a sense of season awareness allowing it to have a more constant temperature prediction in the autumn and return to "normal" operation during Summer and Spring.

5.1.1 Temperature seasons

It can be observed in the raw data and in the diff plots (see figure 11 as an example) that the seasons can be shown though the temperatures and stable periods. The flat areas is explained by snow covers that creates an thermal isolation layer that dampens the effekt of the air temperature. There excist models in the literature that takes this effect into account[8, 31] to make a more accurate prediction of soil temperature when there is snow present or frozen soil.

5.2 Plauborg

The result of the modelling (table 16 to 19) show that modelig soil temperature without the inclusion of time is an inefficient, and inaccurate method of predicting soil temperatures.

In this study the original model, that was trained for daily values was converted to predict hourly data to see if the same formulation could be used to make predictions. When comparing the results shown in table 15 and table 14 to their daily counterpart it shows similar values showing that the model proposed in Plauborg can be extended to hourliy timeseries.

5.3 Discussion of good results of Plauborg

The inclusion of previous temperatures gives an improved estimation, even on hourly basis. The coefficents for both daily and hourly are observed to be <1 making it a mean temperature and the fourier terms would estimate the soil function(6)[32].

$$E_{\text{soil,year}}(T) + e^{-z/D}\sin(\omega t - z/D + \phi) \tag{6}$$

Since the term $exp(z/D)$ is constant we would be estimating $\sin(\omega t - Q) = \sin(\omega t)\cos(Q) - \sin(Q)\cos(\omega t)$, where Q is $z/D - \phi$ and is considered constant. This will be extrapolated to a simple sum of sines and cosines as the model does. Together the Plauborg model would estimate the approximation (8). The extra terms are nessesery to include external factors that affects the temperature (rain, soil type, atmosphere, etc).

$$E_{\text{soil,year}}(T) + e^{-z/D}\sin(\omega t - z/D + \phi) \tag{7}$$
$$\approx E_{\text{air,period}}(T) + \sum \alpha_i e^{z/D}\sin(-Q_i)\cos(i\omega t_i) + \sum \beta_j e^{z/D}\cos(-Q_j)\sin(i\omega t_j) \tag{8}$$

The differences between actual and predicted values could be due to the varying soil types at different stations. To create a more accurate model, one might need to consider additional weather-related measurements (such as air pressure, humidity, soil type, and texture) or incorporate non-linear features (such as the square root of temperature or the temperature change ratio over time)

5.3.1 RNN results compared to other studies

The BiLSTM is an improvement over LSTM and the modified BiLSTM with layers is a clear indication that added complexity to a deep learning model is the way to go for . This progression of improvements has been shown in other studies[16, 24, 26, 28, 29]. None of the deep learning models has been optimised, however in according to earlier studies that focused on these types of model the authors did find that adding layers to the models does improve the model performance.

5.4 Model comperison

The Plauborg has a clear advantage over linear regression.

5.5 Future work

The models chosen in this study is not a representative sample of current knowledge of soil temperature modelling, and this study did not aim for optimizing the models beyond what the original authors have already done with the exception for base models used for comparison pouposus. A more comprehensive is needed of more complex models that utelises cutting edge technologies, techniques, and theory. One of which is logic based models, for instance ASPER[12] that tries to incorporate logical descriptions of the problem and limits the model for better or equal results based on fewer samples[13]. Another approch is to use the newest deep learning method of the attention mechanism[33] combined with recurrent neural networks to elevate the accuracy and speed of the model. As the author of the paper [16] has show great promise with that approch.

Furthermore, the models presented in this study are not optimised as far as they can as there are more parameters one can include in the model, and Hyper-Parameter one can fine tune to improve the predictive capability of the models such as

- The type of loss function
- the learning rate
- the optimizer
- the activation function used
- weight regulation
- adding a dropout rate

This are a small collection of techniques that can be utilised to furter optimize the models for better predictive performance.

There have been significant developments in model types, including Answer Set Programming-enhanced Entity-Relation (ASPER). ASPER combines logical statements[6] with deep learning models to achieve results comparable to or better than ”non-logical” deep learning models, but with fewer samples [12]. A study demonstrated that the ASPER model can reduce the required number of samples/observations by a factor of 1/1000 [13] and studies that uses this knowledge based approach shows to improve the predictive ability of the model to predict soil temperatures[2, 14]. In an interview with the study researcher [15], it was found that while the model requires strict rules, it is possible to incorporate Bayesian statistics to enhance its generality for various applications. By relaxing the ruleset and acknowledging that the given rules may not be 100% accurate, the model can be adapted to other applications using approximation rule-sets. Its the belife of the author of current study that this model can be adapted to soil temperature prediction when incorporating Bayesian statistics.

Additionally, attention-awareness, a method developed by the Google cooperation [33] also used in ChatGPT and other modern AI technologies, has been employed to predict soil temperatures and soil moisture[16] and has shown promising results in predicting soil temperatures by dynamically putting emphases on some of the features, particular days, and combinations of these when predicting.

[6] Statements can be thought of as formulas, natural laws, or knowledge about the solution

6 Conclusion

Soil temperature significantly impacts agriculture, influencing pest prevention, conservation, yield prediction, and more. Despite its importance, widespread measurement remains challenging due to cost limitations and technical issues. Interpolating missing data using methods like global mean approximation is common but has drawbacks including requiring a previus measurements of the soil temperature. Incorporating exogenous features can improve soil temperature estimation. Advancements in prediction and measurement are crucial for sustainable agriculture and accurate climate models.

Method used in this study are

1. Fetch avalible data to use as training and testing set
2. Compile the data and treat it to be used in the modelig
3. Train all the models on the same traning data (2014 to 2020)
4. calculate and plot relavent statitics (2021 to 2022)
5. compile the results

The results of this study show that promising results can be achieved with few parameters, however further studies need to be done to see the effekt of adding more parameters or making the models more complex by adding more structure[7]. As for regression modeling; Adding time to a regression model does improve the model predictive power over a time independent model.

There is a clear advantage to data-driven modeling to further the investigation into deep learning models as the models shows comparable results to analytical models, as is show in other studies[4, 16, 26].

6.1 Limitations

This study faced a multitude of technical difficulties including,

- Trying to get the models to run properly
- Finding proper parameters to limit memory usage and time
- Insufficient computing power for some parameters
- Getting TensorFlow to work on Windows 10/11[8]

This study would be more comprehensive if these unforseen difficulties did not occure, and it is recommended that it would be done a new study going more in depth into other type of deep learning models suitable for time-series data.

7 Acknowledgements

The progenitor of this study presently partakes in an interval of non-occupational repose, traditionally associated with restorative diversion from vocational pursuits as of immediate effect of thesis submission.

[7]Sturcture as in more layers, augmentations of input and features from feature extraction.

[8]This has later in the study that was futile as the project had moved from being Windows compatible to being exclusively runnable on Linux unless choosing an outdated version of Tensorflow.

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Glossary

D | H | L | R

D

DataFrame

A table of values. The name is from the python library Pandas used in this study.. 10

H

Hashmap

A list of items where their unique placmnt in the list is detemend by their unique refrence key using a function that maps the key to a placement in the list.. 10

L

Long Short Term-Memory

A Recurent Neural Network with a memory cell to distribute information along the other RNN cells.. 4

R

Recurent Neural Network

A Neural network that passes information between cells in the same layers.. 2, 4, 5, E

Acronyms

Symbols | F | G | K | L | M | N | R

Symbols

R^2

Explained Variance. 15

$\log(\kappa)$

Log Condition number. 15

F

FDM

Finite Difference Method. 3

G

GRU

Gated Recurent Unit. 2, 5, 14, 23, III

K

Kilden

Norwegian Institute of Bioeconomy Research Kilden. 1, 6, 9

L

LMT

Norwegian Institute of Bioeconomy Research LandbruksMeteorologisk service. 6, 10, 11

LSTM

Long Short Term-Memory. 4, 5, 14, III

M

MAE

Mean Absolut Error. 15

MET

The Norwegian Meteorological Institute. 6, 10, 11

N

NMBU

The Norwegian University of Life Science. 17

R

RMSE

Root Mean Square Error. 15, 23

A Plots

B Tables

scope	spesific scope	RMSE °C	MAE°C	bias °C	log(κ(model))	digit sensitivity	R^2
global	—	2.676	2.06	0.528	-0.328	-1	0.756
region	Østfold	2.564	2	0.176	-0.324	-1	0.8
region	Vestfold	2.565	1.958	0.785	-0.317	-1	0.81
region	Trøndelag	2.938	2.279	0.75	-0.321	-1	0.477
region	Innlandet	2.612	1.997	0.379	-0.32	-1	0.799
local	52	2.504	1.976	-1.2	-0.327	-1	0.803
local	41	2.135	1.665	0.13	-0.322	-1	0.872
local	37	2.513	1.938	0.067	-0.322	-1	0.83
local	118	3.029	2.422	1.722	-0.323	-1	0.656
local	50	2.176	1.7	0.815	-0.327	-1	0.836
local	42	2.739	2.099	0.746	-0.323	-1	0.807
local	38	2.983	2.323	1.149	-0.333	-1	0.736
local	30	2.276	1.708	0.428	-0.328	-1	0.859
local	57	3.079	2.419	0.744	-0.33	-1	0.617
local	39	2.79	2.186	0.633	-0.322	-1	0.615
local	34	3.163	2.427	0.797	-0.329	-1	-0.547
local	15	2.706	2.094	0.827	-0.329	-1	0.484
local	27	2.455	1.885	0.335	-0.328	-1	0.839
local	26	2.757	2.105	0.892	-0.324	-1	0.801
local	17	3.023	2.265	0.137	-0.33	-1	0.762
local	11	2.346	1.847	-0.023	-0.33	-1	0.755

Table 14: Results from hourly version of the Plauborg model for 20cm depth.

scope	spesific scope	RMSE °C	MAE°C	bias °C	$\log(\kappa(\text{model}))$	digit sensitivity	R^2
global	—	2.529	1.926	0.597	-0.449	-1	0.794
region	Østfold	2.448	1.894	0.512	-0.45	-1	0.816
region	Vestfold	2.412	1.81	0.733	-0.43	-1	0.846
region	Trøndelag	2.822	2.176	0.781	-0.439	-1	0.547
region	Innlandet	2.382	1.805	0.312	-0.448	-1	0.847
local	52	2.514	1.964	-0.349	-0.446	-1	0.636
local	41	1.938	1.519	0.151	-0.445	-1	0.903
local	37	2.344	1.804	0.237	-0.446	-1	0.857
local	118	2.928	2.322	1.639	-0.442	-1	0.706
local	50	1.908	1.472	0.558	-0.442	-1	0.884
local	42	2.501	1.885	0.703	-0.447	-1	0.852
local	38	3.055	2.368	1.363	-0.447	-1	0.754
local	30	2.072	1.555	0.354	-0.441	-1	0.892
local	57	2.906	2.263	0.677	-0.443	-1	0.677
local	39	2.77	2.151	0.701	-0.44	-1	0.633
local	34	3.013	2.306	0.845	-0.446	-1	-0.193
local	15	2.589	1.991	0.903	-0.444	-1	0.562
local	27	2.277	1.724	0.163	-0.444	-1	0.872
local	26	2.532	1.918	0.821	-0.442	-1	0.843
local	17	2.649	1.979	0.065	-0.44	-1	0.828
local	11	2.146	1.666	0.038	-0.443	-1	0.823

Table 15: Results from hourly version of the Plauborg model for 10cm depth.

scope	spesific scope	RMSE °C	MAE°C	bias °C	log(κ(model))	digit sensitivity	R^2
global	—	1.91	1.536	0.644	-1.918	-2	0.876
region	Østfold	1.94	1.541	-0.073	-1.917	-2	0.885
region	Vestfold	1.71	1.341	0.236	-1.899	-2	0.915
region	Trøndelag	1.843	1.56	1.461	-1.913	-2	0.794
region	Innlandet	2.16	1.735	1.02	-1.909	-2	0.863
local	52	2.33	1.873	-1.402	-1.908	-2	0.83
local	41	1.748	1.409	-0.371	-1.902	-2	0.914
local	37	1.877	1.496	0.353	-1.913	-2	0.905
local	118	1.742	1.384	1.139	-1.917	-2	0.886
local	50	1.251	0.985	0.096	-1.912	-2	0.946
local	42	1.966	1.54	0.346	-1.917	-2	0.901
local	38	1.721	1.367	0.515	-1.906	-2	0.912
local	30	1.817	1.471	-0.014	-1.918	-2	0.91
local	57	1.841	1.538	1.427	-1.919	-2	0.863
local	39	1.729	1.468	1.402	-1.912	-2	0.852
local	34	2.104	1.836	1.816	-1.91	-2	0.316
local	15	1.681	1.411	1.215	-1.903	-2	0.801
local	27	1.924	1.534	0.753	-1.905	-2	0.901
local	26	2.528	2.101	1.578	-1.912	-2	0.833
local	17	2.448	1.911	1.401	-1.912	-2	0.844
local	11	1.735	1.443	0.463	-1.91	-2	0.866

Table 16: Results from daily version of the Plauborg model for 20cm depth.

scope	spesific scope	RMSE °C	MAE°C	bias °C	log(κ(model))	digit sensitivity	R^2
global	—	2.074	1.621	0.608	-1.261	-2	0.861
region	Østfold	2.168	1.704	0.24	-1.27	-2	0.856
region	Vestfold	2.022	1.564	0.219	-1.263	-2	0.892
region	Trøndelag	1.957	1.528	1.235	-1.257	-2	0.782
region	Innlandet	2.165	1.71	0.714	-1.269	-2	0.873
local	52	2.418	1.837	-0.636	-1.265	-2	0.664
local	41	1.975	1.587	-0.293	-1.266	-2	0.9
local	37	2.206	1.755	0.373	-1.26	-2	0.873
local	118	2.165	1.697	1.137	-1.263	-2	0.839
local	50	1.395	1.105	-0.046	-1.265	-2	0.938
local	42	2.239	1.75	0.333	-1.266	-2	0.881
local	38	2.42	1.908	0.667	-1.261	-2	0.845
local	30	1.914	1.519	-0.046	-1.271	-2	0.908
local	57	1.978	1.547	1.108	-1.266	-2	0.85
local	39	1.896	1.455	1.193	-1.266	-2	0.828
local	34	2.143	1.687	1.535	-1.261	-2	0.397
local	15	1.806	1.428	1.114	-1.262	-2	0.787
local	27	2.063	1.627	0.396	-1.266	-2	0.895
local	26	2.43	1.937	1.251	-1.267	-2	0.855
local	17	2.26	1.78	0.921	-1.263	-2	0.875
local	11	1.879	1.504	0.339	-1.262	-2	0.864

Table 17: Results from daily version of the Plauborg model for 10cm depth.

scope	spesific scope	RMSE °C	MAE°C	bias °C	log(κ(model))	digit sensitivity	R^2
global	—	4.504	3.474	2.487	-0.796	-1	0.308
region	Østfold	4.348	3.363	1.901	-0.796	-1	0.424
region	Vestfold	4.564	3.47	2.297	-0.796	-1	0.397
region	Trøndelag	4.438	3.508	3.175	-0.796	-1	-0.194
region	Innlandet	4.688	3.568	2.601	-0.796	-1	0.353
local	52	3.556	2.841	0.559	-0.796	-1	0.604
local	41	4.248	3.286	1.677	-0.796	-1	0.491
local	37	4.754	3.675	2.174	-0.796	-1	0.391
local	118	4.726	3.654	3.208	-0.796	-1	0.162
local	50	4.048	3.025	2.207	-0.796	-1	0.434
local	42	4.863	3.741	2.364	-0.796	-1	0.393
local	38	4.832	3.682	2.601	-0.796	-1	0.308
local	30	4.465	3.433	2.015	-0.796	-1	0.456
local	57	4.655	3.636	3.153	-0.796	-1	0.125
local	39	4.31	3.39	3.083	-0.796	-1	0.081
local	34	4.583	3.675	3.471	-0.796	-1	-2.248
local	15	4.198	3.342	3.006	-0.796	-1	-0.241
local	27	4.672	3.547	2.535	-0.796	-1	0.415
local	26	5.17	4.009	3.282	-0.796	-1	0.302
local	17	5.049	3.84	2.939	-0.796	-1	0.336
local	11	3.821	2.924	1.692	-0.796	-1	0.35

Table 18: Results from the linear regression model for 20cm depth.

scope	spesific scope	RMSE °C	MAE°C	bias °C	log(κ(model))	digit sensitivity	R^2
global	—	4.231	3.267	2.303	-0.638	-1	0.423
region	Østfold	4.236	3.28	2.015	-0.638	-1	0.45
region	Vestfold	4.277	3.26	2.019	-0.638	-1	0.517
region	Trøndelag	4.133	3.274	2.893	-0.638	-1	0.028
region	Innlandet	4.282	3.254	2.246	-0.638	-1	0.504
local	52	3.679	2.889	1.226	-0.638	-1	0.221
local	41	3.976	3.07	1.494	-0.638	-1	0.593
local	37	4.501	3.503	2.07	-0.638	-1	0.473
local	118	4.5	3.486	2.93	-0.638	-1	0.306
local	50	3.611	2.702	1.766	-0.638	-1	0.584
local	42	4.571	3.525	2.109	-0.638	-1	0.506
local	38	4.815	3.741	2.502	-0.638	-1	0.388
local	30	4.053	3.106	1.733	-0.638	-1	0.588
local	57	4.293	3.356	2.775	-0.638	-1	0.295
local	39	4.057	3.193	2.835	-0.638	-1	0.213
local	34	4.262	3.415	3.176	-0.638	-1	-1.386
local	15	3.918	3.141	2.799	-0.638	-1	-0.003
local	27	4.272	3.236	2.078	-0.638	-1	0.551
local	26	4.714	3.651	2.902	-0.638	-1	0.456
local	17	4.518	3.432	2.506	-0.638	-1	0.501
local	11	3.567	2.713	1.529	-0.638	-1	0.51

Table 19: Results from the linear regression model for 10cm depth.

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