**Deep learning model to estimate land-surface temperature in Israel**

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**Project Description**

The goal of this project is to build a deep-learning model to estimate land surface temperature in Israel at a 1x1 km resolution. The Land Surface Temperature (LST) is the radiative skin temperature of the land surface, as measured in the direction of the remote sensor. Historical LST data is available at a 1x1 km resolution, however we would like to see if we can use this data as a target for a deep learning model to learn to downscale temperature data to a finer resolution.

Available Data (For Israel):

* Historical Hourly LST data for the past 20 years. Data includes:
  + lat, long of observation
  + Date & Hour in day
  + LST temperature
* Topography:
  + lat, long
  + height (above sea level)
* Vegetation index from satellite imaging (NDVI) - at a 1x1 resolution
* Additional information (e.g. 9x9 Air temperature, land use, …) may be also available - to be possibly used in the project

[shilo.shiff(at)biu.ac.il](mailto:shilo.shiff@biu.ac.il) - will provide the data for this project.

Learning Task:

The goal of the deep learning model is to estimate the 1x1 km resolution land surface temperature given the surrounding topography.

For every such 1x1 km pixel, a 9x9 ‘patch’ surrounding the pixel as in the following illustration:

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The overall LST of the 9x9 grid at a given time will be calculated as the average of the 81 LST observations at the same time. Similarly, the average height of the 9x9 grid will be calculated.

The difference between the 9x9 LST and center pixel 1x1 LST will be the target value to predict. Evaluation of the regression problem will be measured via RMSE.

For every such observation, the input to the model will include:

* The Average height of the 9x9 grid
* The average LST of the 9x9 grid
* 81 height diffs (difference between pixel height to the average height for every 1x1 pixel in the grid)
* The day in the the year (0-365, consider transform via sine and cosine)
* The time in the day (0-24, consider transform via sine and cosine)
* lat, long of center pixel
* We may add additional features as we progress (e.g. NDVI

Project work includes finding the optimal feature representation and deep learning neural net architecture (# layers etc, ) as well as analysis of the results.

It is important to test the model on unseen (held out) pixels and dates.

**Research Questions:**

1. Can you improve RMSE predictions results over the simple baseline of always predicting 0 (temp of 1x1 center pixel identical to the 9x9 average).
2. What is the optimal DL model
3. How the various features impact the prediction

**Intro**

- All of the project's code, documents, and files is located at my public git repository at:   
<https://github.com/itaybarkai/Deep-learning-land-surface-temperature-in-Israel/tree/develop>

- Code is written in Python 3.8.8 with Tensorflow 2.13

- Libraries requirements are elaborated in the "requirements.txt" file.

- MLOps – use "MLFlow" for automated experiment logging (params and metrics), experiment reviewing and graphs displays.

- Running on DSI servers, using **self-made Docker image** as the environment.

- Data sources are:

1. LST dataset - <https://zenodo.org/record/4533677#.ZFDyHHZBwuX>

2. Topography data – From "Google Earth Engine" with this short script I wrote: (…Git/Data/Topography/ Topography\_Israel\_earth\_engine.txt)

// lat,long taken from min/max of lst dataset

var israel = ee.Geometry.BBox(33.20034536095077, 34.00777509644337, 36.59654466075468, 28.996716325654262)

var dataset = ee.Image('USGS/SRTMGL1\_003');

var i\_data = dataset.clipToBoundsAndScale(israel, 409, 603)

Export.image.toDrive({

'image': i\_data,

'fileFormat': 'GeoTIFF',

'folder': 'MasterProject',

'fileNamePrefix': 'my\_topo',

'description': 'my\_topo',

'dimensions': '409x603'

});

**The LST data**

Consists of NetCDFs for each year between 2002-2020.

Each one should have 2 samples per day of the LST on each 1X1 block in Israel.

Practically each NetCDF has 5 variables:

**1. "y"** = latitude, **603** points between 28.996716325654262 and 34.00777509644337

**2. "x"** = longitude, **409** points between 33.20034536095077 and 36.59654466075468

**3. "band"** = 4 values (channels):

NIGHT\_LST = 0

DAY\_LST = 1

DAILY\_LST = 2 (average of 2 previous ones)

QA = 3

QA means if there were clouds that interrupted the actual sample and the data is generated from a previous model: (<https://zenodo.org/record/4533677#.ZFkQRHZBwuX>).  
The values in the QA band represents:

NO\_DATA\_BOTH\_DAY\_NIGHT = 0

NO\_DATA\_DAY = 1

NO\_DATA\_NIGHT = 2

BOTH\_VALID = 3

**4. "time"** = day in the year for the sample – from 0 to 365 (366 in leap years).

There might be skips in time in days that for some reason did not have a sample.

**5. "\_\_xarray\_dataarray\_variable\_\_"** = The actual LST value for each combination of the above variables.

Has shape of (364, 4, 603, 409)

\* Notice the time variable has 364 instead of 366 (leap year in 2020) because 2 days samples are missing.

This is a **numpy masked array** which means it may have invalid data (like NaN).

For example in a single specific day there were 170k out of 240k valid values.

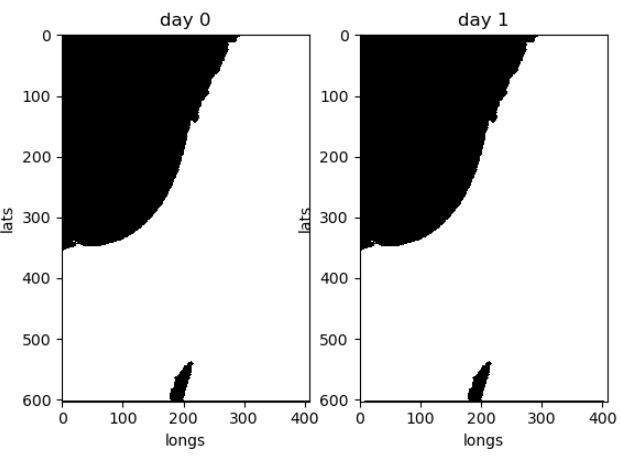
The units of the LST are 0.02 Kelvin, with values in range 7500-65535.

**LST data Invalidity**

As said, the data might be invalid/missing in some 1x1 spots on the grid.

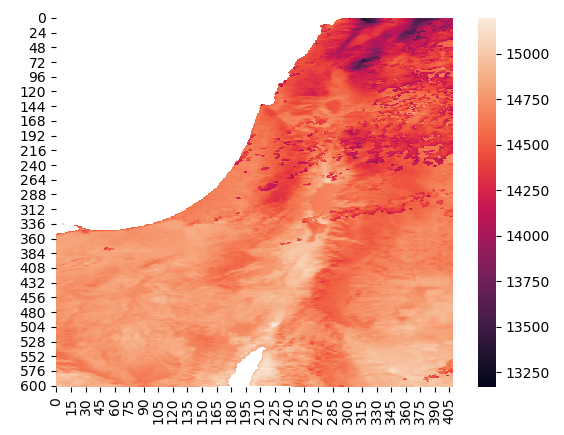
We need to decide how to treat such data points, while we want to make samples out of each 1x1 spot and its 9x9 surrounding cell.

After printing the validity of the masked array's values of "True/False" as White/Black I got:



Aside from about 10-30 points the validity map is the same between days and it looks like a ground-sea map of Israel.

Overall it means we can use only 1x1 spots with a valid 9x9 surrounding and it should work fine.

Example day temp (0.02 Kelvin units)  


**The topography data**

Queried and exported from "google earth engine", in .tiff format that has a numpy array. Can be read with python's tifffile.imread.

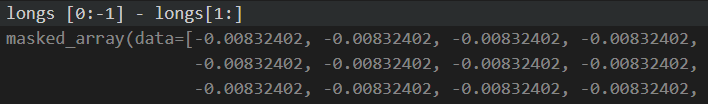
The dataset I received had the wrong resolution, as its shape was 379x559, when the LST's shape was 409x603. That would make it impossible to align the correct elevation to a sample.

In order to generate a correct resolution topography dataset I had to figure exactly how the LST dataset was made to recreate it in the google earth engine query.

In the LST data:  
latitude, 603 points between 28.996716325654262 and 34.00777509644337  
longitude, 409 points between 33.20034536095077 and 36.59654466075468

Found the length of the north and south borders to be 313km and 330km respectively, meaning the distance between each LST sample is changing.

After checking the difference between each longitude/latitude (in degrees), they were all equal ~1/120 of a degree :

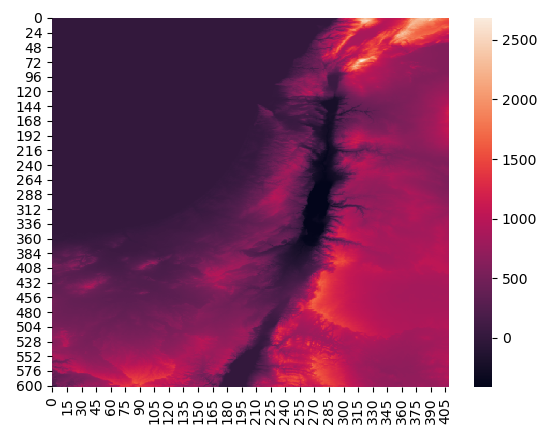
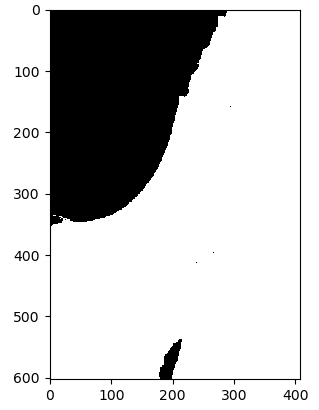


From the commonly used NASA topography dataset "USGS/SRTMGL1\_003" it is documented to have resolution of arc-seconds (1/3600 of a degree), so rescaling 30x30 pixels to each output pixel is about right and possible.

I confirmed it by clipping the dataset to a rectangle within the bounding degrees of the LST data, and received shape (12228,18041), that matches: (max\_degree-min-digree)/pixels ~= 1/3600.

I wrote a script in Earth Engine to scale this rectangle topography to dimensions of 409x603 just like the LST shape and exported a good looking .tiff file. (Script is saved near the data file)

Its min height is -415 and max height is 2687, which correctly describe the Dead Sea and the Hermon heights.

Topography binary image (left, sea values are 0) and heat map (right)  
ax.imshow(image==0, cmap=plt.cm.binary, interpolation='nearest')  
sns.heatmap(image\_f)

**Data Normalization and Feature Scaling**

After parsing the raw data, and forming a dataset with each sample having the model inputs as described in the projects description. We have the following columns:

- day of the year  
- longitude  
- latitude  
- LST average on 9x9 grid  
- height average on 9x9 grid  
- 81 columns of each cell's height diff from the average of its 9x9 grid

The question is how to tackle normalization without ruining the relations between the features (ex. different height diffs features getting differently normalized might affect the "grid" they should from)

**1. "Day of the year"** has a problem with not being cyclic – day 0 and day 364 should be close. We could use a cyclic function like sin() but it would create repeats (intermediate value theorem proves there are 2 different values that would map to the same output).  
Therefor we must split the day to 2 cyclic columns, such as sin(day), cos(day), representing the day of the year as a **Unit Circle**, thus cyclic without repeating outputs.

**2. "long" and "lat"** are evenly spaced in a segment. Intuitively it is common to use Normalization [(x – x\_min) / (x\_max – x\_min)] for this data type.

**3. "Height Diffs" –** since each one of the 81 columns represents the same data type and units, it is essential to scale them the same way, thus fitting the scaler on all these columns and then transforming them with the same parameters.

The specific Scaling method is left to experiment and is configurable.

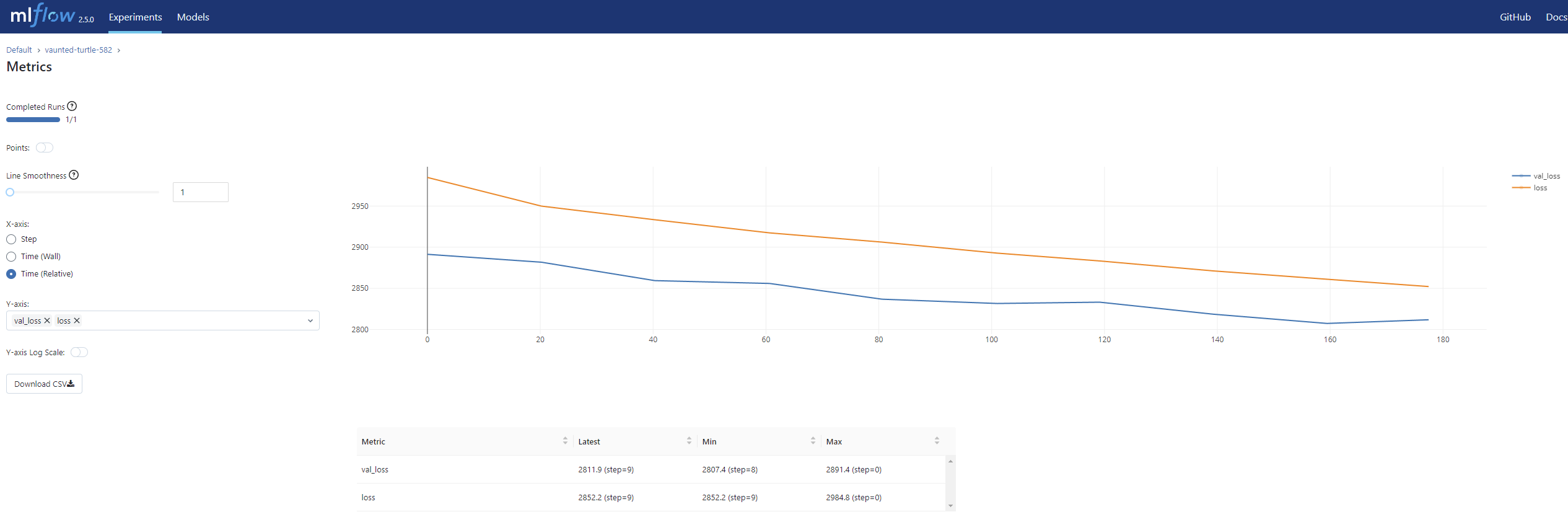
**Config**

**Code Structure**

**Processed Data Caching**

**Infrastructure + Docker**

**MLFlow**



**Models and Learning**

days space split , write also in intro bullet

**Results**

**Conclusion**

# TODO

- Auto download of data (not sure if needed, data is huge)

- MLflow copying path fix script

- MLflow graphs and pictures