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Exploitation of Calculated Local Temperature Topography Variations - a Case Study in Kenya

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Abstract: Due to the changes in the climate, more extreme weather conditions occur. Weather extremes (such as heat, drought, freeze, etc.) are limiting conditions for the cultivation of agricultural crops. Long term monitoring of particular quantities such as temperature, humidity, wind conditions and so on are essential for decision making in agriculture. Since the monitoring is an expensive process, the physical monitoring stations are usually very coarse. The common approach to combine these data with a global model. This paper presents steps which can be done further, using temperature as an example. The paper first presents a workflow, how to create a denser model of temperature distribution from a course one model of temperatures. Next, the paper outlines a method of how to analyze the temperature spatial distribution in time. The aim is to use historical meteorological series (e.g. of temperatures) to help farmers and producers of agriculture's products with decision making.

Keywords: meteorology, model, local, temperatures, spatial, distribution, digital elevation model

1. Introduction

While modeling of weather conditions for the future is not a simple task (see e.g. [1], [2], [3]), analysis of weather conditions from historical meteorological data can be done easily. Since the data measurements are related to irregular and sparse network of points complemented by a coarse weather model, there has to be used some kind of interpolation method together with a knowledge of such data distribution over space and time. For our purposes, a temperature is chosen as an essential variable for crop planting and monitoring.

The spatiotemporal distribution of temperature is affected by many factors, such as topography, hydrology, wind conditions, air humidity, air pollution, cloudiness and so on. Particularly a distribution of day temperatures above a certain value (35°C) was selected as a test bed for this paper. The aim is to detect hot days which could have a destructive impact on crops. Specifically, the temperatures in Kenya, July 2018 were examined while taking topography as a crucial factor influencing the spatial distribution of temperature into account.

The structure of the paper is as follows. The next chapter deals with the objectives of the paper and is followed by the main part of this paper in chapter Methodology. Such a chapter describes data and technology used, together with a description of workflow for calculation of local temperature distribution. After that, results of local temperature distribution is depicted from a point of view of extreme conditions occurrences, especially heat over 35°C, which can lead to occurrences of draught, when combined with low precipitation. Last, but not least, the benefits of such a local temperature distribution calculation is outlined and finally the conclusions are set in the last chapter.

2. Objectives

The goal of this paper is to calculate local temperature variations based on available topography data (terrain) in combination with global-ish weather-related data. The intended end result for this paper is to have a locally represented data about a particular weather condition, a temperature for this case, respecting the local varieties of such condition, unlike the coarse weather data distribution.

Such a result should help better understand local weather conditions, mostly for the occurrences of extreme conditions such as drought, freeze, floods and so on, especially in a long-term period of time. Particularly a workflow for recognition of a long-term high-temperature occurrence situation in an area of Kenya is outlined in this paper. This situation can lead, in combination with low precipitation, to a draught occurrence. This is one of the threats reported during surveys performed in [4] Such information can serve for better local-oriented agriculture management of both breeding and/or planting kind.

There are two main influences of terrain to temperature. First is the elevation ~ the temperature drops as the elevation rise - under normal weather conditions. The second factor is the slope orientation (aspect) to the cardinal directions ~ the slope orientation influences the exposition to solar radiation. Even when our research activities head beyond, only the influence of elevation is described in this paper. The aim is to demonstrate methods to elaborate weather data.

Following experiment described in the Methodology chapter shows a way, how the temperature distribution can be estimated by a mathematical model applied on geographic data. The following work and other influencing factors incorporated are a part of affiliated projects (see chapter 7 Acknowledgements).

A disclaimer has to be noted here: to use such a methodology for producing relevant advice and warning to agriculture - a calibration to local conditions has to be made.

3. Methodology

This chapter is dealing with a description of input data, analysis of the data, mining information from the data and with a short description of the technology used for the data treatment. Therefore, it is divided into four subchapters.

3.1 Pilot Area and Used Data Description

Kenya, as a hosting country of the IST-Africa 2019 conference, was chosen as a pilot area for this paper. Nevertheless, thanks to the input data used, almost any region of the planet could be used for the workflow described further, with respect to the local extreme occurrences (draught vs. frost etc.).

The pilot area of Kenya is presented in Figure 1, the input data used for the local temperature distribution modeling are depicted in Figure 2 and in Figure 3. Figure 2 shows a digital elevation model created by NASA Shuttle Radar Topography Mission (SRTM) Version 3.0. The resolution of the data is 30 seconds (C. 1 km x 1 km) [5]. The data was downloaded via the USGS EarthExplorer [6], particularly GTOPO30 product was used [7].

In Figure 3, there is a grid of points with spacing about 0,25-degree x 0,25-degree, which is in Kenya about 28 km x 28 km. Such a grid of points contains an attribute of temperatures (in Kelvins) at 2 m above the surface in each grid cell in a particular time, acquired from ERA5 dataset [8]. Note that all input data use EPSG 4326 (WGS-84) as a coordinate system.

Figure 1: Kenya - an area of interest delimitation (background map - World Topo Map by ESRI).

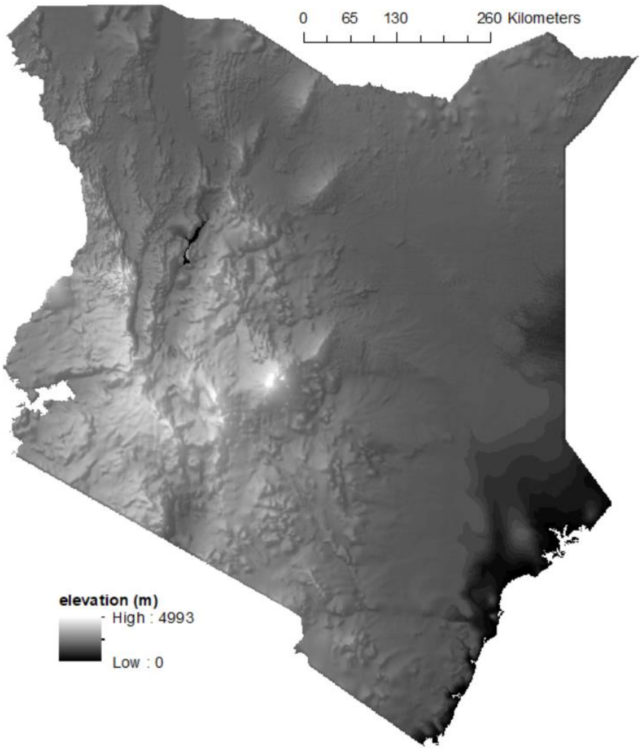

Figure 2: Digital elevation model derived from the SRTM used (whiter cell means higher altitude).

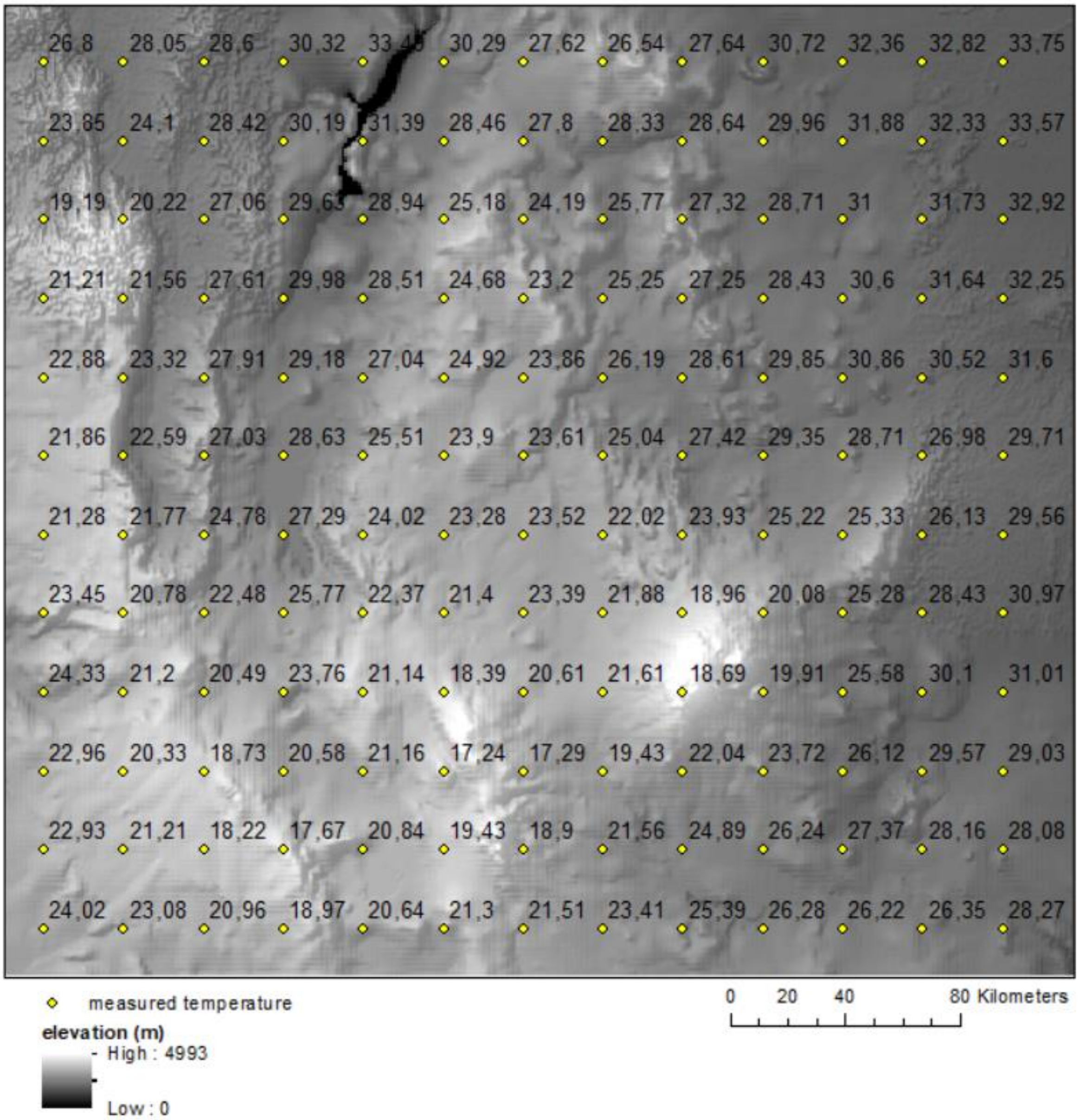

Figure 3: A detail of input temperatures grid related to elevation 2 m over the surface (SRTM in the background).

3.2 Calculation of Topography Factor

This chapter describes a methodology used for the local temperature distribution modeling using a factor of local topography. There is a well-known fact (see e.g. [9]) that under normal weather circumstances a temperature on Earth's surface decreases averagely by 0.65 °C for every 100 meters of elevation. Next, temperatures provided by global meteorological models (see input data) are related to a lattice of particular geographic positions with elevation defined as an elevation 2 m above Earth's surface.

But a digital elevation model used by contemporary meteorological models is sparse, e.g. like DEM on the left side and red profile in Figure 4, inspired by [10]. Therefore, the experiment depicted below converts the surface temperatures from such a sparse DEM to more granular DEM (e.g. the SRTM DEM on the right side and the blue profile in figure 5) aiming to show local temperature changes caused by elevation.

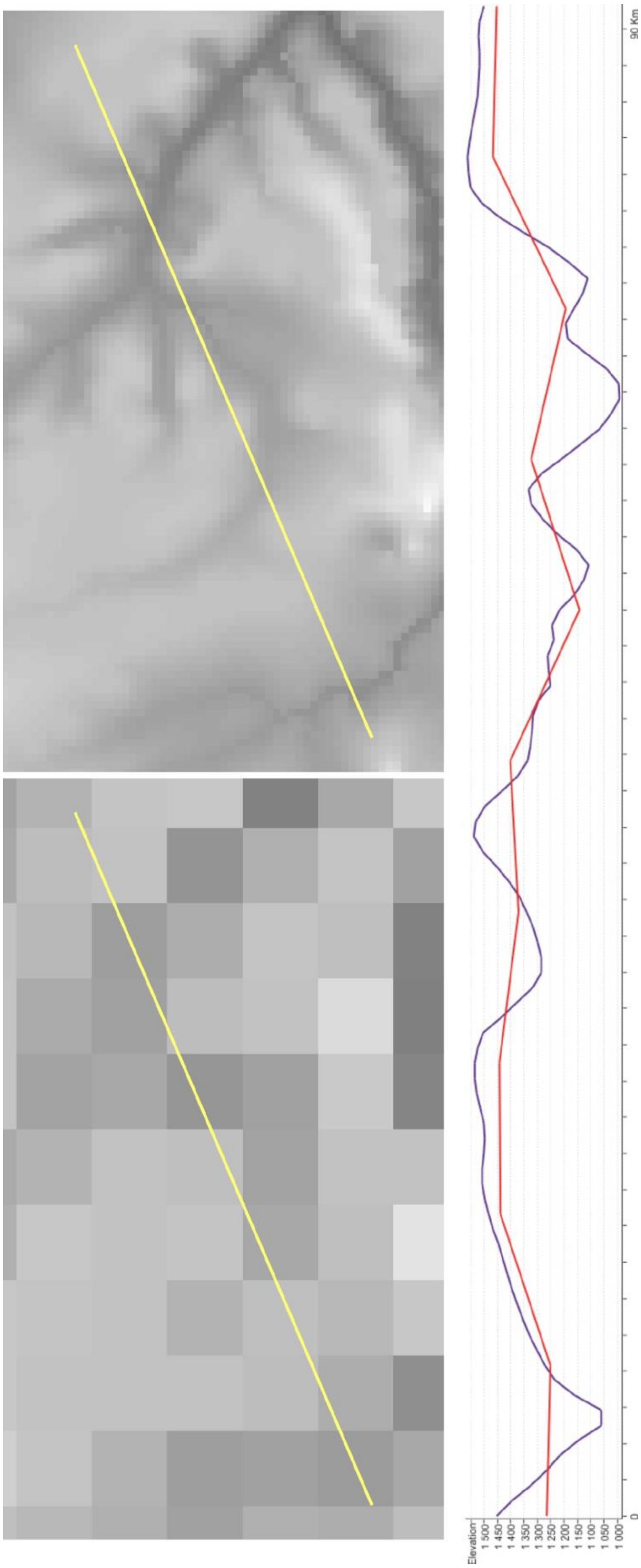

Figure 4: Influence of different cell size to the accuracy of the resultant DEM. Coarse DEM used for 2 m above surface elevations in ERA5 meteorological data (left side of the figure and the red profile) versus the more granular SRTM DEM (right side of the figure and the blue profile).

There are initial lattice of temperatures on surface ($T_{s(x,y)}$), where *(x,y)* are coordinates for each particular lattice point, where *x ~ [1 .. n]*, *y ~ [1 .. m]* and the distance among lattice points is *NxN* km, where *NxN* ~ approx. 28 x 28 km for Kenya (based on the meteorological data from ERA5 [8]).

$$\begin{matrix} T_{s(x1y1)} & T_{s(x2,y1)} \,..\, T_{s(xn,y1)} \\ T_{s(x1y2)} & T_{s(x2,y2)} \,..\, T_{s(xn,y1)} \\ .. & .. \quad .. \\ T_{s(x1ym)} & T_{s(x2,ym)} \,..\, T_{s(xn,ym)} \end{matrix} \qquad (1)$$

Our goal in this step is to have this lattice of temperatures on a surface much more granular. Therefore, we propose an algorithm which consists of the following steps:

1. Recalculate surface temperature T_s to temperature at sea level (T_0) to remove an elevation factor which influences the temperature.
2. Densify the *NxN* T_0 temperature lattice to more granular resolution (1x1 km spacing in this case).
3. Apply the elevation factor to calculate temperatures back on the surface, but on more granular temperature lattice with distances among points 1x1 km.

The steps are described in detail in the chapters below.

3.2.1 Temperature Reduction to Sea Level

Recalculate surface temperature T_s to temperature at sea level (T_0) for each particular lattice point by applying the vertical temperature elevation factor (gradient) (see [9]), which says that under normal circumstances, the temperature decreases averagely:

1. by k = 0.0065 °C by each 1 meter for elevations between 0 and 2000 m above sea level
2. by k = 0.005 °C by each 1 meter for elevations above 2000 m above sea level

$$T_0 = T_s + k * E_s \qquad (2)$$

where E_s is the elevation of the lattice point representing the T_s.

E_s is derived from the SRTM terrain model [6], covering the area of interest by 1x1 km lattice of elevations ~ therefore, the 1x1 km resolution can be of this granularity maximally (if it makes sense to have it that granular).

3.2.2 Densification of the Temperature Lattice at Sea Level

Having the T_0 lattice with *NxN* spacing, the next step is to run an interpolation (spline or other) to densify T_0 lattice to 1x1 km SRTM spacing, see Figure 5.

A spline function for the interpolation of temperature lattice at the sea level was used, because it creates a smooth distribution of the interpolated values and it preserves the values of temperatures, where the temperature was measured (see the input data - lattice *NxN*).

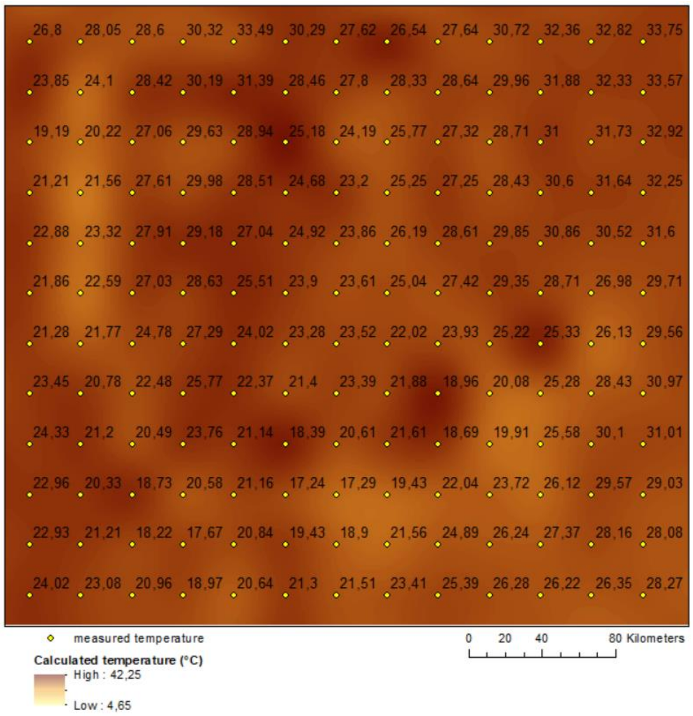

Figure 5: Densified temperature field at the sea level (lattice 1x1 km).

3.2.3 Application of Elevation Factor to Calculate Temperatures on Earth's Surface

Reversing the formula (2) to formula (3):

$$T_s = T_0 - k * \frac{E_s}{100} \qquad (3)$$

and applying it to T_0 lattice with 1x1 km spacing, the temperature on terrain represented by lattice T_s with 1x1 km spacing now also has the desired granularity, see Figure 6.

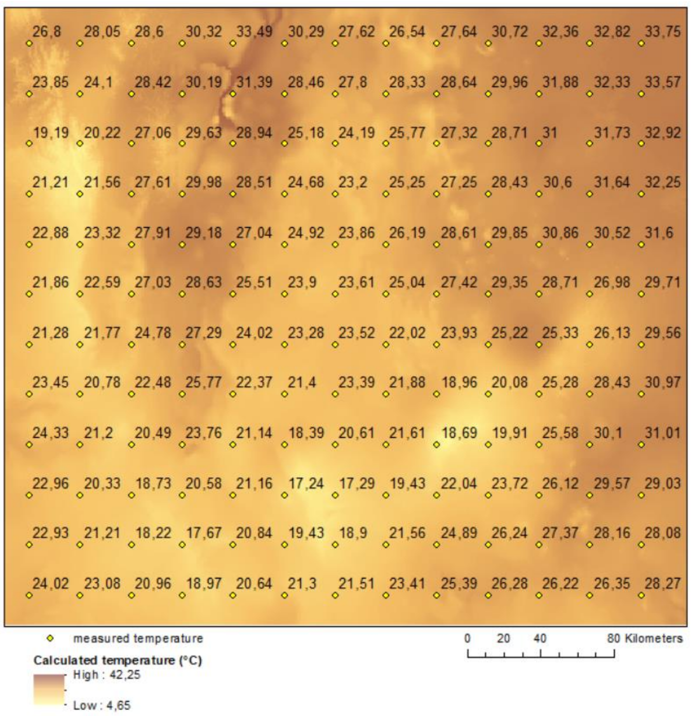

Figure 6: Densified temperature field on the surface (lattice 1x1 km).

3.3 Detection of Heat and Drought Areas

An example of a use of the workflow described in the previous subchapter, a detection of heat and drought areas can be useful output. Such detection is based on two crucial variables: temperature and soil moisture, especially on high temperature and low soil moisture, which can lead to a potentially high risk of soil dryness. While this paper deals with temperature variable only, this kind of variable is outlined further, with respect to the detection of high temperature during a period of time.

A high temperature can be perceived as a kind of a threshold enabling high evaporation of soil moisture. Together with a time period when the temperature above a certain threshold occurred, is the combination of factors, which can lead to dryness of land and decreasing yield of crop and livestock production at the area, where high temperature and low soil moisture occurred.

A time-period examined can be distinguished in two levels of complexity:

- Count of days over threshold during a certain period of time.
- Count of consecutive days, when the situation occurred during a certain period of time.

For the purposes of the first experiments which are described in this paper, the first complexity option was selected. A temperature threshold was set on 35°C and a month of July 2018 (temperatures at 12 a.m. for each day of the month) were chosen. The reason is that the dry period of the mid-March ~ July cropping season [11] starts in July [12]. And high temperatures during dry period can cause damage to crops by drying the land too much. An example of an intermediate result, areas of temperature over 35°C (red color) for the date of 1st July 2018 at 12 a.m. is depicted in Figure 7. The cumulative results are described in chapter 4 Results.

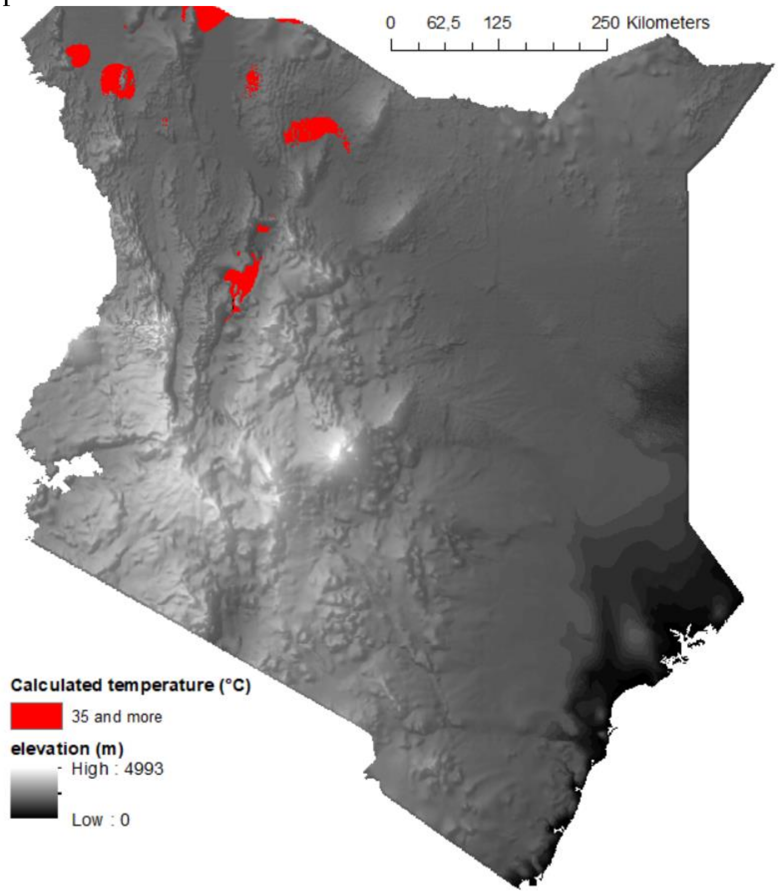

*Figure 7: High-temperature occurrences at 12 a.m. 1st July 2018.
Red areas have temperatures over the threshold.*

3.4 Used Technology

This chapter describes particular calculations of temperature distribution modeling based on the previously described factors. ArcGIS Desktop software was used for the calculations. As a desktop environment, it was convenient for rapid development and validation toward a proof of concept. After a discussion with experts and validation of the concept, the plan is to implement the solution in a cloud-based environment using open source geographical information software deployed on the server side (such as gdal/ogr libraries [13] and GRASS GIS tools [14]) and an option to use smartphone or even a dumbphone (non-smartphone) at the client side.

4. Results

This chapter describes the particular results of temperature distribution modeling using the input data described in subchapter 3.1, according to the workflow described in subchapter 3.2, especially showing results from detection of areas with a high risk of potential soil dryness depicted in subchapter 3.3. The results depicted in Figure 8 and 9 are calculated for temperatures at 12 a.m. of each day in July 2018.

For each of the following figures a number of days with temperature over 35°C is displayed, while Figure 8 shows such information derived from the course source temperature data, Figure 9 shows such information derived from more granular local temperature distribution model calculated according to the workflow described in chapter 3 Methodology.

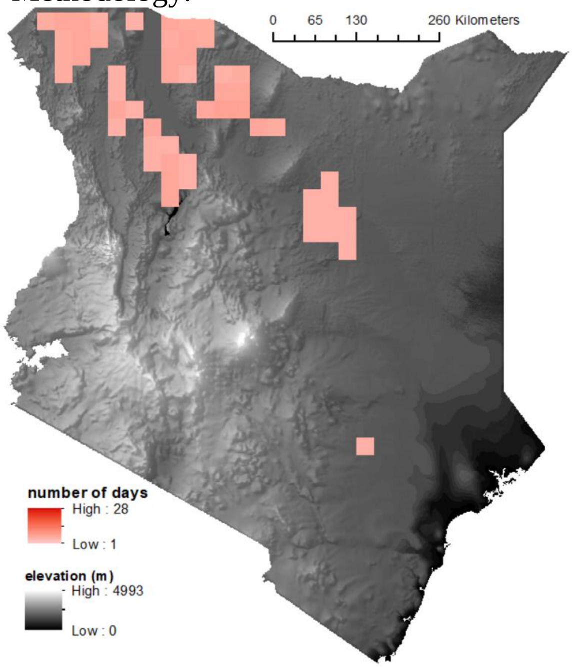

Figure 8: The number of high-temperature middays based on weather data from [8].

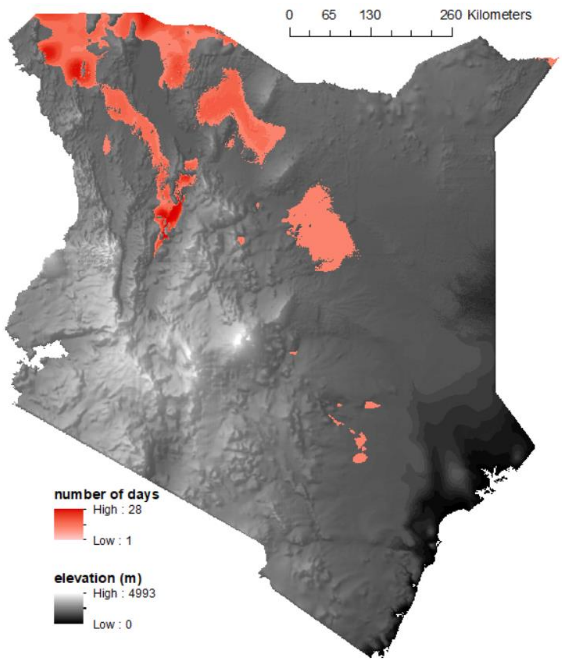

Figure 9: The number of high-temperature middays based on calculated detailed temperature distribution model.

Comparing information from Figure 8 and Figure 9, it can be seen that there is a huge difference in a number of days, when a temperature over the chosen threshold occurred, which is caused by the resolution of the input, resp. calculated data.

Moreover, using more dense information about weather condition instead of global-ish one can help in retrieving better, more local-relevant information about the climate. Such information about a potential risk of soil dryness, when the high temperature is combined with low soil moisture, is crucial information for local agriculture management.

Even though the local temperature distribution calculation is based on real measured weather data, a comparison with (or ideally calibration to) local ground weather stations or generally sensors recording the local temperature should be taken into consideration in further experiments. That's because there is plenty of side effects affecting temperature distribution such as air humidity, wind speed, and direction, which can change the expected or calculated temperature distribution. Nevertheless, we didn't have such information provided during the deploying of the initial experiment.

5. Business Benefits

The workflow presented in this paper could provide beneficial information to a farmer at a micro-scale level. While the local temperature distribution is calculated for critical days within a year for a long period of time, it can provide information, which areas are endangered by high temperature and potential soil dryness over a period of time. It can thus help to a farmer with decision making, crop protection and therefore with yield productivity. Mainly where to plant which kind of a crop, which areas need to be protected somehow if there is a need for irrigation and so on.

A disclaimer has to be noted here: the paper is focused on the introduction and presentation of the methodology. Therefore, the results presented on pictures have to be taken as illustrative only. When the methodology is tested validated and calibrated, then it can be deployed in a cloud environment, allowing usage of both smart and non-smartphones at the clients' side.

6. Conclusions

This paper presented a workflow for local temperature distribution modeling. We made an initial step of the complex local temperature distribution calculation by considering topography as an underlying factor influencing the local distribution of temperature. The results seem promising in a way of temperature distribution, but a meteorological expert's estimation and/or real data from sensors within the used grid of temperatures should be taken into consideration and the local model should be verified and rectified by such information. The future version of the workflow for local temperature distribution modeling will incorporate also the influence of land use/land cover, hydrology, cloudiness and so on, potentially even urban areas as hot spots increasing temperature.

Based on the workflow presented, an example of outcomes for agriculture decision makers is outlined, presenting areas endangered by long-term high temperatures occurrence over a period of time. For further deployment of such a workflow, a server-side tool will be provided and it will serve demanded information based on an extent of chosen locality. The activities resulting in this paper and the next planned development is supported by projects mentioned below.

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- Data-Driven Bioeconomy (DataBio). H2020: ICT-15-2016-2017, no.: 732064. www.databio.eu
- Research and development of intelligent components of advanced technologies for the Pilsen metropolitan area (InteCom), by the Czech Ministry of Education, Youth and Sports CZ.02.1.01/0.0/0.0/17_048/0007267 [CZE: Výzkum a vývoj inteligentních komponent pokročilých technologií pro plzeňskou metropolitní oblast (InteCom). EU,

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