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forecAstring
System
for urban
heaT Island
effect

“Implementation of a forecAstring System for urban heaT Island effect for the development of urban adaptation strategies” (LIFE ASTI)

Action C.7

Report on the local pilot actions for Thessaloniki and Rome

Thessaloniki January 2022



Table of contents

ASTI Project introduction	4
ACTION C.7: “Local pilot actions.”	4
Report on ACTION C.7	5
Introduction	5
The WRF weather forecasting system.	5
Observational weather data.	5
Support-vector machine model.	6
Methods.....	7
Preparation, training and validation of the downscaling method.....	7
Evaluation methods of Local Pilot actions.	9
Results.....	10
SVM algorithm training and evaluation for 2015.	10
Local Pilot Actions scenarios evaluation for Rome.	10
Scenario 1.....	10
Scenarios 2 and 3.	12
Local Pilot Actions evaluation for Thessaloniki.....	17
Conclusions	20
Technical remarks.	20
Summary	21

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LIFE ASTI Project introduction

The LIFE ASTI project focuses on addressing the impact of Urban Heat Island (UHI) effect on human mortality, by developing and evaluating a pilot system of numerical models that will result to the short-term forecasting and future projection of the UHI phenomenon in two Mediterranean cities: Thessaloniki (Greece) and Rome (Italy).

The phenomenon of UHI has an impact on human health, which becomes more intense, as the duration of the heat wave episodes is expected to increase due to climate change. The spread of urban areas has become alarming in recent years; almost 73% of Europe's population lives in cities, a rate which is expected to reach 80% by 2050. Extensive urbanization is triggering significant changes to the composition of the atmosphere and the soil, which result to the modification of the thermal climate and the temperature rise in urban areas, compared to neighboring non-urban ones.

ACTION C.7: "Local pilot actions."

This action aims to develop and evaluate pilot actions on local level which will serve as case studies for future reference. The modeling systems of UHI forecasting that have been implemented during action C.2, were put again in use in action C.7. The current action is also linked to action C.5, as it assists in future adaptation action plans, and provides a more complete perspective, necessary to further develop and operate the heat health warning systems (action C.6)

The Municipality of Thessaloniki has already landformed the yards of four (4) schools based on bioclimatic criteria. It is foreseen, that higher-level green interventions will take place in parks and nodal areas in the city. The above-mentioned interventions will provide a good opportunity, to be utilized as a case studies for modelling systems. In particular, the models will be adapted according to the land use changes in the specific areas of interest in Thessaloniki, in order to assess their impact on air temperatures, the heat health warnings and the energy demand based on HDD/CDD at local level.

This case study will also be supported by observational data in the framework of the installation of supplementary urban weather stations (action A.2). Similar green activities will be identified in Rome in order to perform a similar case study. The aforementioned pilot actions, will form the basis for a sensitivity analysis at city scale, where the impact of larger scale future interventions (i.e.involving all public schools in Thessaloniki) will be assessed.

Report on ACTION C.7

In order to evaluate the effect of UHI on local scale within the cities, we introduced an algorithm that uses the weather forecasts of a well known forecasting model/system, the Weather Research and Forecasting (WRF), and we adjusted those, with statistical methods derived from actual observational data. This was done in order to reconstruct a higher resolution forecast, that includes the effects of the local climatic variability and conditions, and it is not practical to be implemented with a wide area weather forecasting system. On the statistical methods we used, we identified and introduced some variables that characterize the local conditions, in order to be able to make prediction while modifying the effect of land use in each city. The resulting algorithm, gave us a temperature and relative humidity response, in correlation to changes and scenarios proposed for each city.

Introduction

This action contributes to other actions of the project (Actions C.1, C.2, C.3 and C.4). In this section, we will describe the key components and methodologies that this work depends on. To estimate the results for the Local Pilot Actions scenarios, we combined the weather forecasts of the WRF model with weather observational data from the cities. We used the observational data to create statistical and computational methods for adjusting and correcting the large area forecast, in order to represent better the local condition on smaller scales. In general, we call this procedure “downscaling,” and it describes the resolution increase of the forecast, and any transformation of the data that this includes.

The WRF weather forecasting system.

This work uses the results of a weather forecasting system, developed for LIFE-ASTI project. The meteorological forecasting model WRF, coupled with the Single Layer Urban Canopy Model, was used for the weather prediction at high resolution for Thessaloniki and Rome. An extended description of the system can be found on the Action C.1 LIFE-ASTI report (Kontos et al. 2019).

Observational weather data.

For both Thessaloniki and Rome, we acquire time series of weather data. The data are a product of this project partners and cover the year 2015 (Parliari et al. 2022). After some quality control, screening and validation, we were able to create a combined data set of observations and WRF forecast, with one to one match for temperature and relative humidity. The geographical location and the amount of available data are summarized in Table 1.

Table 1: Valid hourly observational data of 2015, used in model training.

Station	Domain	Data points	Longitude	Latitude
Al001	Rome	7722	12.65	41.84
Al003	Rome	8604	12.66	41.93
Al004	Rome	8520	12.27	41.89
Al007	Rome	8643	12.50	41.91
MI-01	Rome	8370	12.48	41.83
MI-04	Rome	8760	12.44	41.79
MI-11	Rome	8158	12.40	41.96
MI-13	Rome	8738	12.53	41.93
Airport	Thessaloniki	8251	22.97	40.53
Eptapurgio	Thessaloniki	8757	22.96	40.64
Malakopi	Thessaloniki	8684	22.98	40.62
Martiou	Thessaloniki	8409	22.96	40.60
Paparrigopoulou	Thessaloniki	7213	22.94	40.64
Pedio Arews	Thessaloniki	8756	22.96	40.62
Rooftop Zanis	Thessaloniki	8796	22.96	40.63

Support-vector machine model.

The statistical tool we used for combining the available observational data and the WRF weather forecast is a Support-vector machine (SVM). A brief description of the SVM algorithm, as taken from Wikipedia (2022) states:

Support-vector machines or support-vector networks, are a class of machine learning algorithms. Which use supervised learning and associated learning algorithms, that analyze data for classification and regression analysis. Developed at AT&T Bell Laboratories by Vladimir Vapnik with colleagues (Boser, Guyon, and Vapnik 1992; Guyon, Boser, and Vapnik 1993; Cortes and Vapnik 1995; Drucker et al. 1997).

Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling

exist to use SVM in a probabilistic classification setting). SVM maps training examples to points in space so as to maximise the width of the gap between the two categories. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

In this project we used the SVM implementation of the software library “e1071” (Meyer et al. 2021) for the “R” programming language (R Core Team 2020). Specifically, after some initial testing we choose the “nu-regression” type of SVM with a “linear” kernel.

Methods.

Here we describe the applied methodologies for the proposes of this Action. The first major part, is the preparation, training and validation of the downscaling method. The second part, is the application of the resulting tools, on scenarios for Thessaloniki and Rome. The results of the first part were incorporated in the current LIFE-ASTI computational scheme as the ‘revised’ forecasting algorithm.

Preparation, training and validation of the downscaling method.

The weather forecast obtained by the WRF (Kontos et al. 2019) has a spacial resolution of $2000m \times 2000m$. We re-grid the data in a new $250m \times 250m$ mesh, where each original WRF tile is splited in 84 new tiles with the same attributes as the original. We used the same data processing for the training of the algorithm and for the application of the resulting trained algorithm. While training, we matched the $250m \times 250m$ tiles to the corresponding observational station. Each tile, is a small subarea of the forecasting domain, and it is described with the same physical properties.

Moreover, we were able to characterize each of the available observation station with an albedo and emissivity value, obtained from satellite data. The values were calculated as the mean of emissivity or albedo, within an area of $100m$ radius around the location of each station. Also, we retrieve the altitude of the station location, using data from the SRTM 90m Digital Elevation Database (Farr et al. 2007). The whole data set was aggregated with the same time step as the WRF, so all observations were matched with the corresponding data of the WRF forecasts.

For each data point we computed some extra variables, to act as a statistical characterization signal for the training of the SVM algorithm. These are: albedo signal, emissivity signal and elevation signal. All were computed as the difference of the values at the station locations (or the new $250m \times 250m$ tile when applying for forecasting) and the value of the original $2000m \times 2000m$ WRF forecast tile. Also, we introduce a yearly periodic signal and a daily periodic signal, in order to describe any time dependent conditions. The whole algorithm was applied only on urban areas within the two domains. For locations outside the city environment the original WRF data were used.

Before the training procedure or the use of the SVM algorithm for forecasting, we applied two more adjustments on the WRF data. The first was to adjust the temperature values of WRF, to those of the observation stations elevation, by using the dry adiabatic vertical temperature gradient and subsequently the corresponding relative humidity.

The other adjustment, was a statistical correction for the temperature and the relative humidity. Due to some limitations on the implementation of the WRF forecasting scheme, we observed a constant diversion between the WRF forecast and observations. In order to mitigate this behavior, we used an appropriate multivariable linear model, which was selected to reduce this behavior. For each domain, a linear model was created separately, based on the comparison to the available observational data. Two variables (temperature and relative humidity) were corrected. The selection of the appropriate model was based on the minimization of the RMSE value. This procedure reduced the bias between the WRF forecast and observational data as shown on Table 2 and 3.

Table 2: Validation statistics for the chosen SVM models, with 2015 observational data.

City	Variable	RMSE	Bias	MAE	IOA	Pearson Cor.
Rome	Rel. Humidity	13.87	-4.65	11.30	0.77	0.65
Rome	Temperature	2.12	-0.37	1.64	0.98	0.96
Thessaloniki	Rel. Humidity	17.76	-9.81	14.11	0.71	0.59
Thessaloniki	Temperature	3.10	0.57	1.87	0.96	0.93

Table 3: Validation statistics for WRF and 2015 observational data.

City	Variable	RMSE	Bias	MAE	IOA	Pearson Cor.
Rome	Rel. Humidity	14.66	-5.74	11.24	0.83	0.73
Rome	Temperature	2.10	-0.57	1.57	0.98	0.97
Thessaloniki	Rel. Humidity	17.67	-10.64	13.73	0.76	0.66
Thessaloniki	Temperature	3.06	0.61	1.81	0.97	0.94

The above procedure, created the data set of the year 2015 and was used for the “training” of the SVM model. During training, we tested different combinations of the available variables, and as an optimization factor, we choose the minimization of the RMSE value. While training, we used 70% of the data set for training and the rest 30% for validation.

After the validating the chosen SVM model, we utilized the whole data set again, searching for a combination of variables that minimize RMSE. This was done to make available data spanning through a whole year. In the training we always included temperature, relative humidity, albedo signal, emissivity signal and elevation signal as factors of the SVM model prediction. This was a requirement, in order to create a model in which will be able to manipulate the local characteristic. These changes will reflect to hypothetical scenarios of land use changes or changes of the surfaces characteristics.

The implementation of the SVM, there are some spatial and physical constraints, in order to protect the final results of possible erroneous data. First, the SVM correction was applied only for the location with a Corine land use index that corresponds to urban areas (i.e. Corine land use indexes 1 to 11). Secondary, if the new values of temperature deviate more than 3°C from the original WRF values, they are excluded, and the initial values are used instead. Similar, for the relative humidity, that limit was set to 30%.

Evaluation methods of Local Pilot actions.

Two different approaches were used to estimate the results of the three local pilot actions scenarios. On both we applied the statistical correction on the WRF forecast, using the results of the SVM model we have created.

On the first one, we estimate the results of the land use change, by modifying the land use on the initial input data of the WRF model ("modWRF"). Thus, we used the revised algorithm to produce a forecast for a hot time period for each city, with different land use values. The altered data, were applied on one WRF forecasting tile, in the center of an urban area. Once with a land use of urban environment and then with more "green" environmental cases. From those forecasts, we calculate a diurnal difference between cases, that is relevant for each city.

The other method, was to manipulate the input parameters of the SVM model ("dirSVM"). Hence, we iterated over different modification factors of albedo and emissivity for the typical hot period of the year (July to August) for the city. Albedo and emissivity, were always input parameters on the SVM model and can be altered at will at the final forecasting stage.

The two different methods were necessary, due to the emerged constraints of the input data we encounter. Due to the availability of the observational data and their variability, the SVM algorithm was able to produce a response of temperature and relative humidity, in relation to the WRF forecasts, only for the conditions of Rome. The input data for Thessaloniki, lacked the needed variation, so the SVM algorithm, although it can provide us with improved results (Table 2) on the local scale, it was found insensitive to the modification of the emissivity and albedo. As a result, we adopted an alternative method to approximate the expected effects of the pilot action, by modifying the initial Land Use Index on the WRF model.

The underlying assumption here, was that there is a relation between the land use typing by Corine and some general characteristic like emissivity and albedo that corresponds to different materials and structure within the cities. The two main descriptors (emissivity and albedo) were chosen because both can be measured by instruments on satellites, and that data are available for large areas in fine resolutions.

We can describe **Albedo** as a measure of the diffuse reflection of solar radiation, over the total solar radiation. So an albedo value of 0 means that the body surface absorbs completely the incoming solar radiation, and a value of 1, that it is perfectly reflective and doesn't absorb any energy.

On the other hand, **emissivity** is the effectiveness of a surface to emit energy as thermal radiation. For the temperature range of the materials within the city, the emitted radiation is on the infrared part of the electromagnetic spectrum. It is defined as the ratio of the thermal radiation from a surface to the radiation from an ideal black surface at the same temperature as given by the Stefan–Boltzmann law. The surface of a perfect black body (with an emissivity of 1) emits thermal radiation at the rate of approximately 448 W/m^2 at temperature of 25°C .

Results.

SVM algorithm training and evaluation for 2015.

With the described training procedure, we created four SVM models, one for each city and for each variable (i.e. temperature and relative humidity). The criteria for choosing the “best” model was the minimization of the RMSE value between the model forecasts and the observational data of 2015. Summary of the validations statistics are on Table 2 and 3. Each of those four model will be used for the final adjustments of the raw WRF forecast, and thus the resulting forecast will have a finer resolution and will take into account the observational data available.

Local Pilot Actions scenarios evaluation for Rome.

Scenario 1.

The description of the scenario is “Reducing green areas by replacing specific current planted areas in the city with urban structures.” This is case of worsening the UHI effect, by increasing the density of the buildings and urbanization, and reducing the free green areas (Figure 1). For that we used the “modWRF” method described above. The evaluation was done using the diurnal change produced by the land use input of WRF model.

As shown in Figure 2, in this case we expect a temperature increase on those areas, of about 0.2°C to 1.5°C , for the major part of the day, compared to the previously green areas. Accordingly, there was a decrease in relative humidity between 0.5% and 7%. This is affecting the regions which are characterized by Corine Index 10 and 11 (“Green urban areas” and “Sport and leisure facilities”) (Table 4), which have been converted to the equivalent of Corine Index 1 (“Continuous urban fabric”), for this scenario evaluation.

Table 4: Affected area by land use for Rome scenario 1.

Corine Land Use	Area [m^2]	Rome area %
10	13250000	1.1
11	15414542	1.2
Totals	28664542	2.3

12

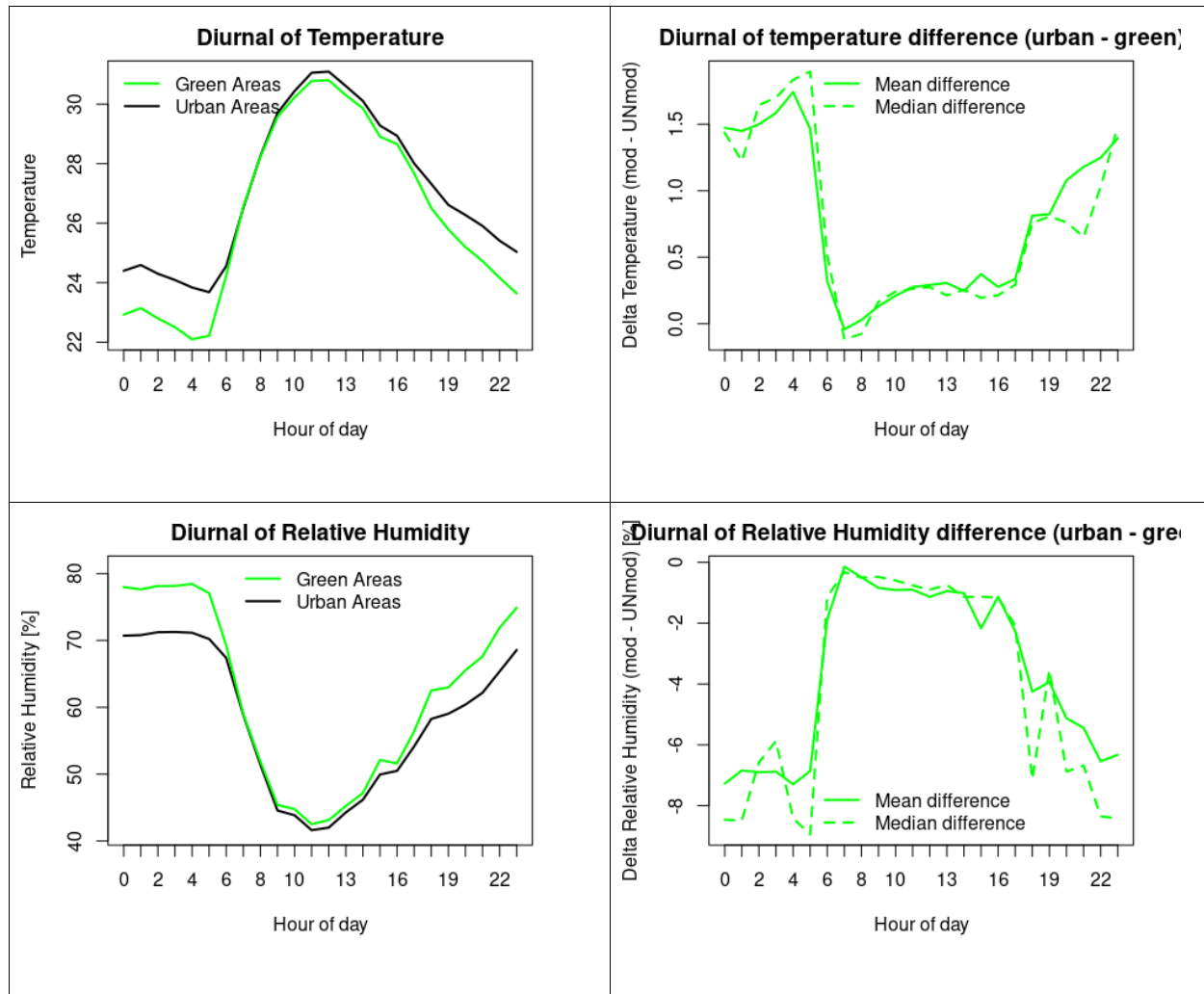


Figure 2: Effect on temperature and humidity for first scenario. Land use change from green to urban.

Scenarios 2 and 3.

For both these scenarios we are using the “dirSVM” method by applying the described changes of albedo, directly to the SVM inputs. The descriptions of the two scenarios are: “2. Reduce the albedo of continuous and discontinuous urban areas by 10%, 25% and 50%” (Figure 3) and “3. Reduce the albedo of Industrial, commercial, road and rail network areas by 10%, 25%, 50%” (Figure 4). Both scenarios are describing conditions, that are directed towards the mitigation of the UHI phenomenon. The application was done on different areas within the city of Rome, with different levels of intensity.

The results of the “dirSVM” method are aggregated on the Table 5 and Figure 5. Due to the nature of the scenarios, here we present the proposed changes in albedo, along with a variety of changes in emissivity. It is expected that changes of the surface albedo are accompanied by changes in emissivity (Figure 3.8), depending on the materials and the structures physical properties. As a result, the proposed cases, imply, that a selection of materials with better characteristics can have an impact on lowering the mean temperature on those areas.

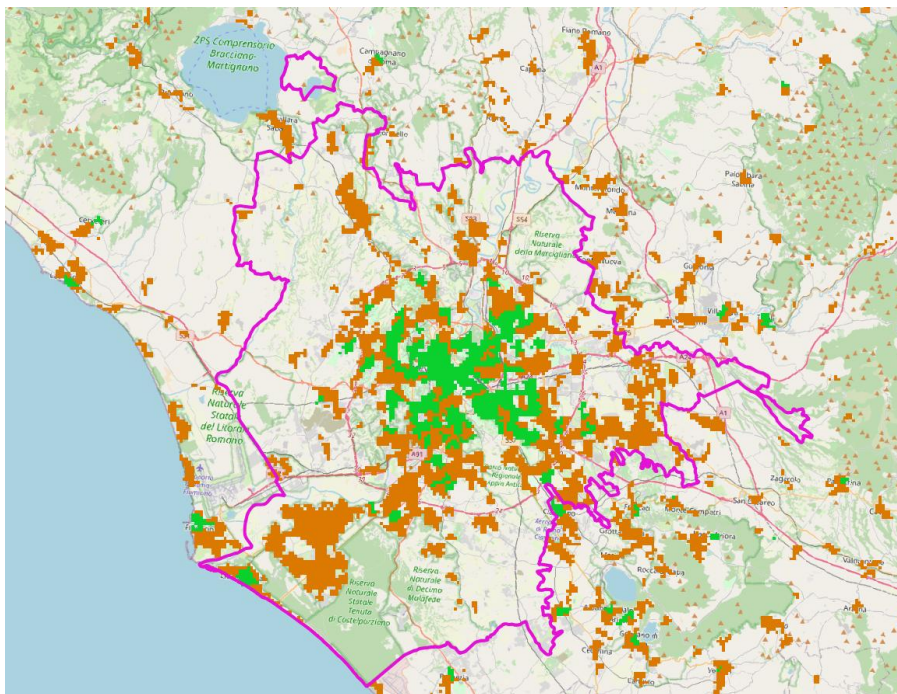


Figure 3: Rome affected areas on scenario 2. Land use index 1 green and 2 orange.

Figure 4: Rome affected areas on scenario 3. Land use index 3 yellow, 4 red, 5 green and 6 cyan.

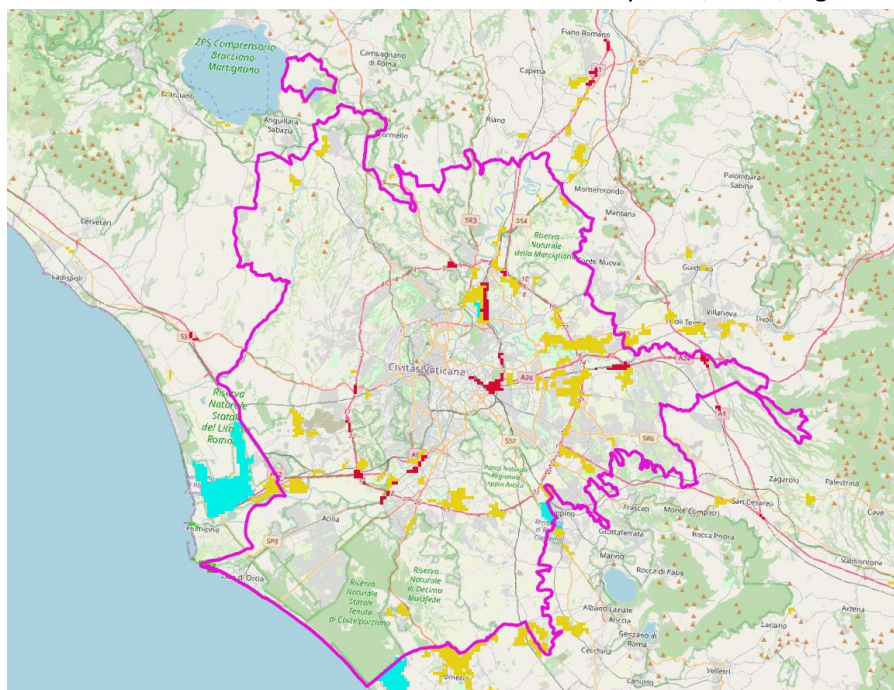


Table 5: Differences on temperature and relative humidity from the case with default Albedo and emissivity.

Albedo Modification [%]	Emissivity Modification [%]	Temperature Difference [C]	Relative Humidity Difference [%]
-50	-10	-0.54	11.17
-50	-5	-0.35	9.43
-50	0	-0.16	2.88
-50	5	-0.03	-1.94
-25	-10	-0.46	10.88
-25	-5	-0.27	8.23
-25	0	-0.08	1.48
-25	5	0.05	-3.36
-10	-10	-0.41	10.64
-10	-5	-0.22	7.47
-10	0	-0.03	0.60
-10	5	0.09	-4.24

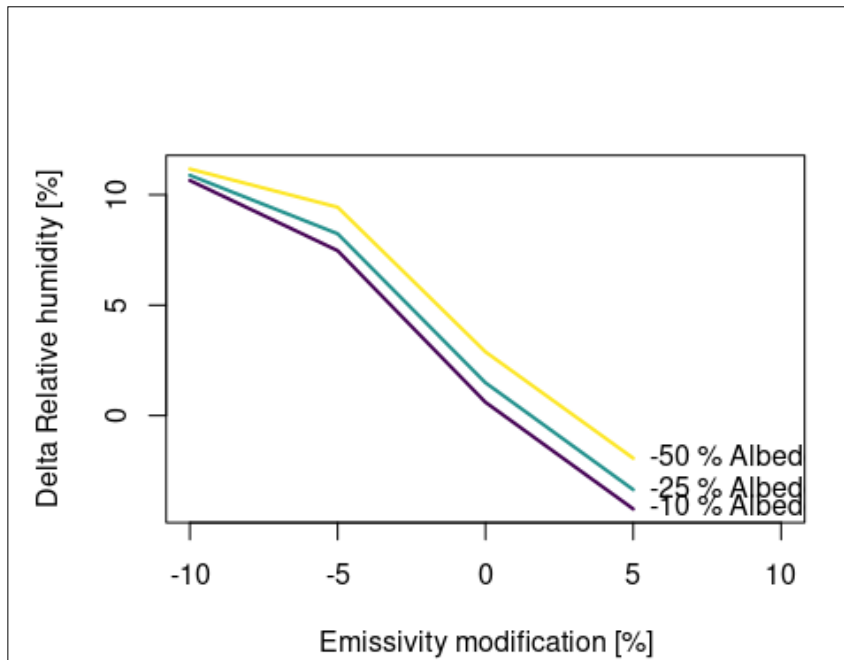
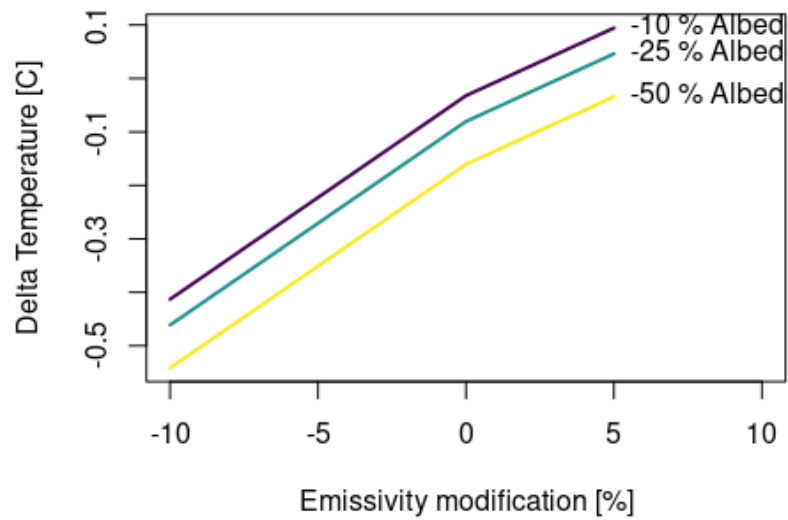


Figure 5: Differences on temperature and relative humidity from the case with default Albedo and emissivity.

Additionally, we investigated another approach, similar to the one for the first scenario. Which is, to consider the effect of changing the land use input in the WRF model (“modWRF” method). In that respect, we can also produce an approximation of the diurnal cycle on those areas (Figure 6), that also shows a decrease in mean temperature and especially at nighttime. This behavior is in favor of mitigating the results of UHI.

Using the Corine land use database we can estimate the corresponding area of the affected regions within the city of Rome. For the second scenario, the affected areas of the city, are described by Corine index 1 and 2 (“Continuous urban fabric” and “Discontinuous urban fabric”) are on Table 6. For the third scenario, the affected areas are described by Corine index 3, 4, 5 and 6 (“Industrial or commercial units,” “Roads and rail networks and associated land,” “Port areas,” “Airports”) and can be found on Table 7.

Table 6: Affected area on scenario 2 with Corine land use index 1 and 2.

Corine Land Use	Area [m^2]	Rome area %
1	82467908	6.6
2	229737218	18.4
Totals	312205127	25.0

Table 7: Affected area on scenario 3 with Corine land use index 3, 4, 5 and 6.

Corine Land Use	Area [m^2]	Rome area %
3	43911399	3.51
4	7744633	0.62
5	291338	0.02
6	2007209	0.16
Totals	53954579	4.32

All the above cases, although are data driven, depend on multiple variables, not easily available or described. The complex structure and physical properties of a city, can create a high variability of the final outcome. With this assessment tools, we can create some guidelines on the expected effects, of changes in the urban structure or Rome, using the current status and function of the city. In general, the ‘greening’ of urban and industrial areas can result of cooler nights on those regions, and the choice of the material used, can further effect that result.

Local Pilot Actions evaluation for Thessaloniki.

As discussed in the introduction and the description of the Action C.7, there are some interventions, planned or completed by the Municipality of Thessaloniki, for which we accessed their impact on the local temperature and humidity. On those, we have included some other discussed plans, that are of special interest for the city.

The interventions in brief are:

1. Landscape redesign of green space at the crossroads of Papanastasiou and Voulgari Streets. Implementation includes planting 79 trees, 431 shrubs. Creation of water canal and walkways with water permeable materials.
2. Redevelopment of the park at the crossroads of M. Mpotsari and Helectra streets. Implementation includes planting 24 trees, landscaping with water-permeable materials and greenery and a new playground.
3. Construction of planted roof at the 26th Thessaloniki Gymnasium. 15922 perennial, herbaceous and annual plants will be planted, and pebble paths will be paved.
4. Mavili Square reconstruction with bioclimatic design elements. Redesigning the area as recreational area with low traffic, using environmentally friendly paving materials and enriching the greenery with 72 trees, 1062 bushes and 177 perennial herbs.
5. Modification of 1st High School and 18th Gel Toumpa school yard with bioclimatic criteria. Reduce the size of the bare surface of asphalt, increase and maintain the planted surfaces.

The forecasting algorithm for Thessaloniki was able to function for downscaling the weather forecast to the fine resolution of 250 m. Thus, it can be used for the current forecast and for the future projections. Although, due to the homogeneity of the Thessaloniki urban region and the location of the stations, there wasn't enough variability for the albedo and emissivity parameters within the training data. As a result, we had to use the "modWRF" method for Thessaloniki.

In this method, we utilize the whole forecasting scheme (WRF and SVM), and change the land use characterization of a specific WRF $2000m \times 2000m$ tile within the urban domain. We tested for two land use types (2 and 10), that correspond to typical "greening" of urban areas, and are relevant for Thessaloniki. Corine Land Use index 2 refers to "Urban fabric / Discontinuous urban fabric" and Corine Land Use index 10 to "Artificial, non-agricultural vegetated areas / Green urban areas." The urban area of Thessaloniki was initially characterized, in its entirety, as Corine Land Use index 1 (Urban fabric / Continuous urban fabric.)

So we separated the location in two scenario cases. “Case 1”: A change of Corine Land Use from 1 to 2, which represents, changes on existing urban structures, with “greener” surfaces and material. And “Case 2” A change of Corine Land Use from 1 to 10 corresponding to even more intense greening, with new park areas and large scale interventions. The corresponding diurnal changes in temperature and relative humidity are shown on Figure 7.

Concluding, for the first two location on the Table 8 (Papanastasiou - Voulgari and Mpotsari - Helectras) we applied the results of the “Case 2” conditions. For the rest of the locations we expected conditions similar to those of “Case 1.” Those conditions are expected to occur, in the center of each location, as a cumulative effect of the above interventions. On both cases, the daily drop in temperature is about 0.5°C and during the night more than 1.5°C. This further indicates that the changes undertaken by the municipality can have significant effects on the mitigation of the UHI phenomenon, and similar changes will reduce the impact of the UHI phenomenon.

Table 8: Characteristics of Municipality of Thessaloniki areas of concern.

Location	Area [m ²]	Mean emissivity	Mean albedo	Case
Papanastasiou - Voulgari	4618	0.9673	0.2209	1
Mpotsari - Helectras	2832	0.9687	0.1939	1
Green roof, 26th Middle school	1389	0.9660	0.1966	2
1st Middle school and 18 High school of Toumpa	6290	0.9673	0.2271	2
Mavili square	3453	0.9660	0.2025	2
Thessaloniki Interanational Fair	170976	0.9663	0.2527	2
Aristotle Square	22089	0.9662	0.2186	2

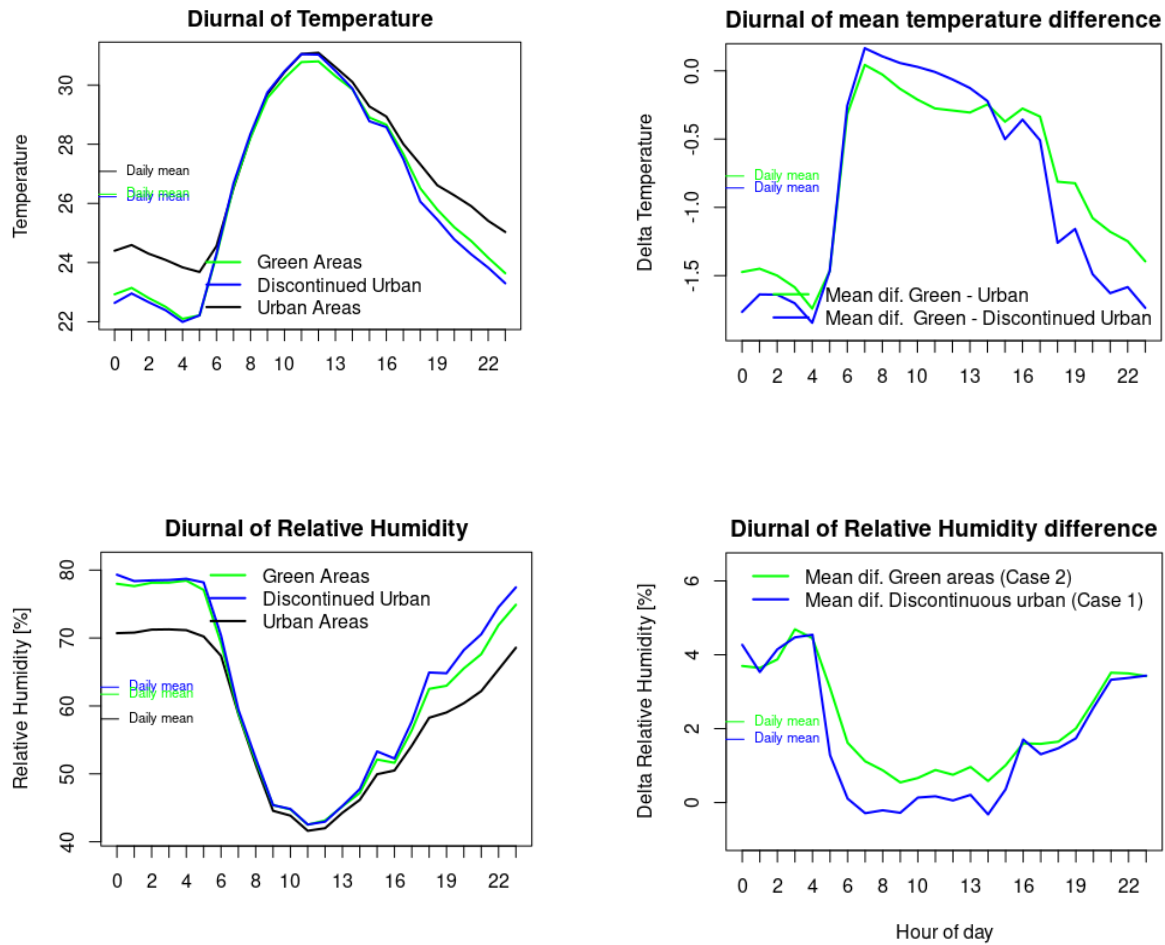


Figure 7: Effect on temperature and humidity on land use change from urban to green and from Discontinuous urban to green areas, in Thessaloniki. Where, green color describes location of 'Case 1' and blue for 'Case 2' locations.

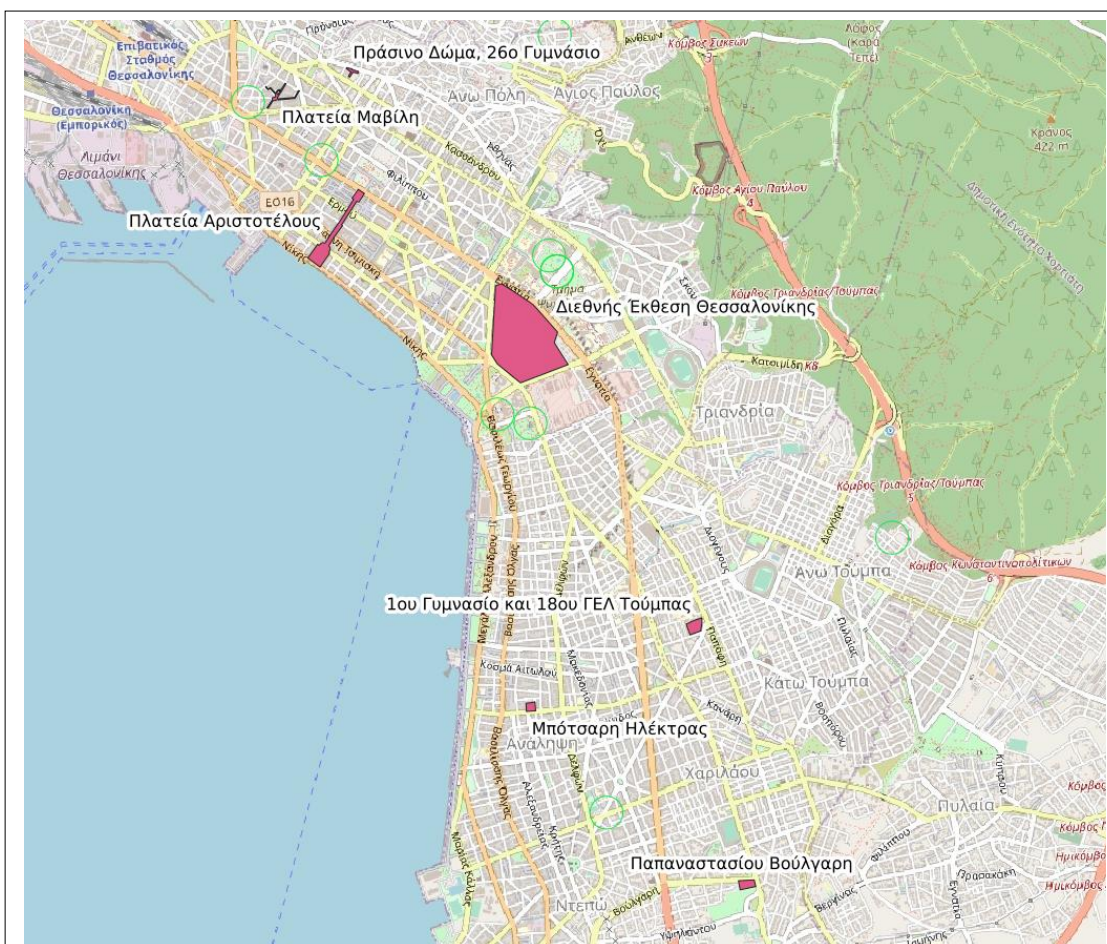


Figure 8: Map of the locations of the local pilot actions for Thessaloniki.

Conclusions

Technical remarks.

Due to the availability of the initial condition data for the WRF model, the training data for 2015 and the operational data for the model, are from different sources. This has the potential to decrease the effectiveness of the SVM, as there are inherent differences between the two.

The time span of one year for the observational data, can be considered small. Although the observational data and the WRF, display an adequate correlation, the SVM algorithm should be provided with more data. Larger variation of input data from different years, would be favorable in training for forecasting for more extreme weather conditions.

More recent data could be used for the training of the SVM model. The weather patterns and the city response to them, change constantly. Near-real time data could be utilized both in the improvement of the algorithm and the constant evaluation and development.

The locations of the observational stations, could have more variety, in order to represent better the different land use types and conditions within the cities. Also, the observational data, had some data quality issues, and some had to be rejected from usage for the training of the SVM. This increased the uncertainty of the relation between the WRF model and the observational data, for some periods of the year and some combinations of conditions.

Overall, the SVM algorithm, gave as results with the expected behavior in respect to the Urban Heat Island phenomenon, and was able to reduce some discrepancies between the WRF and the observational data. Future implementations would be improved, by now having better understanding of the technical aspects and requirements.

Summary

The goal of action C.7 was to establish the appropriate input parameterization of environmental variables for the UHI model, in accordance with the proposed land use scenarios for Thessaloniki and Rome. We created the tools, and applied them in order to investigate changes in vegetation area and covering materials of different surfaces. Produced valuable data for the UHI phenomenon, by a model that was developed to cope with the characteristic conditions of Mediterranean urban environments, and can be used on plans and action to mitigate and study the UHI phenomenon on both cities.

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