PERFORMANCE AND VERIFICATION OF A DOWNSCALING APPROACH FOR METEOROLOGY AND LAND USE, USING A MESOSCALE MODEL IN A COMPLEX TERRAIN INDUSTRIAL AREA IN GREECE.

V. MATTHAIOS¹, A.G. TRIANTAFYLLOU¹ AND T. ALBANIS²

(1) Laboratory of Atmospheric Pollution and Environmental Physics
Department of Geotechnology and Environmental Engineering
Technological Education Institute of Western Macedonia, 50100 Kozani, Greece
(2) Laboratory of Environmental Technology, Department of Chemistry, University of Ioannina, Greece
E-mail address: atria@airlab.teikoz.gr

EXTENDED ABSTRACT
Meteorological and air quality forecasting models are important tools in several applications, such as, prediction of air pollution levels, air quality management, environmental impact assessments, decision support systems in cases of pollution episodes and/or accidents in industrial or other facilities. Meteorological input data and land use changes are key factors as input for these models, which affect their results and consequently the field of their applicability. In this work, the examination of a models’ behavior is attempted, running under different configuration circumstances in a complex terrain area. For this purpose, The Air Pollution Model (TAPM), which is a mesoscale, nestable, prognostic meteorological and air pollution model was used, configured and ran for Western Macedonia, a heavy industrialized complex terrain area in NW Greece. In this occasion, three different runs were applied, for a two years period (2010-2011). First, default configuration of the model, second with data assimilation in winds and finally with changes in land use. The area that was covered from those runs is approximately 810x810 km² spacing for the outer grid, focusing inside the region of interest with spacing 45x45 km². The results from the simulations’ performance show that default configuration defers from the one with land use changes but not significantly, while a perfect agreement between the predicted and the measurement values in the configuration with data assimilation is occurred.

Keywords: Meteorological Modeling, long-year simulations, Data assimilation, TAPM, land use

1. INTRODUCTION
Simulation-forecasting models are an important tool for researchers, in order to understand the behavior of meteorological parameters for avoiding or limiting pollution episodes. These models are applicable in air quality management situations, environmental impact assessment studies, as well as weather and pollution prediction. Forecast becomes more difficult when the area of interest is characterized as complex for the terms of the simulation (e.g tall mountains, land mines, lakes, industrial activities, urban and rural locations). This consist an interesting case, for both the researcher and the developer of the model because, on the one hand the forecaster needs an accurate prediction and, on the other hand the modeler needs to know the field of application of the model. Another point of interest in those models is data assimilation and updated land use changes, which are significant factors-parameters in prediction models that influence their results and therefore a more accurate prediction (Hurley et al 2005, Femeli et al 2013).
In the basin of Amyntaio-Ptolemais-Kozani, a heavy industrialized activity is taking place over the last decades, due to the lignite power stations and open pit mines that exist and operate there. In such case, meteorological and air quality management tools including forecasting models are very important. Several studies have been made over the past years referring to the basin, investigating the applicability of forecasting models as an air quality management tool. Triantafyllou et al.2002 studied the pollutants transport conditions and the atmospheric conditions that favors pollutant concentrations, by using a coupled atmospheric mesoscale model and a Lagrangian dispersion model. Laboratory of Atmospheric Pollution and Environmental Physics (LAP-EP) with Zoras et al.2008 operate and validate a forecasting system in West Macedonia based on the combination of TAPM and SKIRON, to give the next day weather forecast, while Sfetsos and Bartzis, 2008 developed a regional weather and air quality forecasting system for the area by using the MM5-SMOKE/CMAQ modeling system. The last attempt was also made by LAP-EP from Triantafyllou et al.2011 by developing a local scale meteorological and air pollution forecasting system in West Macedonia (WMac/FOS), combining two models CCAM and TAPM for a seven days weather forecast and a four days pollution prediction. This study attempts to verify the implementation of the dispersion model TAPM and its operation in the WMac/FOS system in weather forecast. For this case, TAPM was configured under different conditions in the basin, for a two years period to a downscaling approach for a more accurate prediction. For this performance, data assimilation and land use changes in the model were used.

2. DATA AND METHODOLOGY

2.1 Study Area

The area of interest that simulated in this study, covered the geographically axis of Amyntaio-Ptolemais-Kozani, which is located in the center of West Macedonia in Greece. The topography is characterized complex, because of the surrounding tall mountains located NE and SW from the basin, with heights 600 to more than 2000m above mean sea level. Moreover, the basin sides are covered with wooded and isolated trees, scrubs and sparse hummock. In the center and NE of the basin there are several heavy industrial activities, including lignite power stations with lignite mined in the nearby open pit mines. Furthermore, S from the valley an artificial lake of Polifitos is located. This lake together with the four natural lakes of Petron, Vegoritida (NE), Ximaditida and Zazari (NW) are also showed in the Figure 1. The climate of the area is continental Mediterranean with low temperatures during winter and high ones during summer. The winds in the center of the basin blow mostly along the NW/SE axis due to channelling of the synoptic wind, since the NW/SE axis coincides with the major geographical axis of the basin. More information about the basin can be found in (Trantafyllou et al 2013a, Triantafyllou et al 2013b)
2.2 The dispersion model TAPM

TAPM is a PC-based, 3D, non-hydrostatic, nestable, prognostic meteorological and air pollution model that solves fundamental fluid dynamics and scalar transport equations to predict meteorology and pollutant concentration. For computational efficiency, it includes a nested approach for meteorology and air pollution, which allows a user to zoom-in to a local region of interest quite rapidly. It uses global input datasets of terrain height, land use, sea-surface temperature and synoptic meteorological analyses. More information can be found in (Luhar et al 2003, Hurley et al 2005).

2.3 Models configuration and performance

The models default configuration (TAPM_NAS), version 4.0.5, run for a two years period (2010-2011) using 25 vertical models levels at 10m, 25m, 50m, 100m, 150m, 200m, 250m, 300m, 400m, 500m, 600m, 750m, 1km, 1.25km, 1.5km, 1.75km, 2km, 2.5km, 3km, 3.5km, 4km, 5km, 6km, 7km and 8km and three nested domains of 45x45 horizontal grid points at 18, 6, 2-km spacing for meteorology. Synoptic scale meteorological data sets in TAPM were provided by the American Bureau of Meteorology, while topography and
land-use are derived from the United States Geological Survey (USGS). Five places were selected as output, namely, Pontokomi (PNT), Pentabrysos (PENT), K.Komi (K.K), Amyntaio (AMY), Kolinda (KOIL), in order to validate the meteorological parameters of wind speed (WS), components U (west east component) and V (south-north component) from wind direction, temperature (TEMP) and relative humidity (RH). For this model configuration, 68h were required for the integration of the run on an Intel(R) Core(TM) 2 Duo CPU E8400@3.00GHz, 1.96GB RAM. The second configuration (TAPM_AS) performed by using an additional parameter (assimilation in winds) for four places (PNT, PENT, K.K, AMY), while keeping all the other parameters (vertical levels, domains, grid spacing, synoptic datasets, topography and land-use) unchanged. It should be noted that although, KOIL was selected as output in this run, no assimilation was used for that place. This was made by purpose, as the intention was to see the influence of data assimilation in the prediction of winds. This model configuration, took 75h of simulation in the same hardware. Finally, a third run (TAPM_LU) was performed, applying changes in the land use, made from user edit mode in the highest resolution 2km (Figure 2, 3). These changes were considered necessary, since industrial activity is not included in land use database. The same vertical and horizontal grids, with the same synoptic scale datasets were used as the default configuration. For the completion of this configuration 68h of simulation was required for the output results.

![Figure 2. Vegetation and land use in TAPM, data from USGS in default configuration.](image)

![Figure 3. Vegetation and Land use changes edited by user.](image)


### 2.4 Verification indices

For each monitoring station, six performance indices, as proposed by Willmott (1981) and Pielke (1984) were calculated for hourly data for a two years period. The Index of Agreement (IOA), Root-Mean Square Error (RMSE), Pearson Correlation Coefficient (CORR), SkillR, SkillV, Arithmetic Mean for observed-predicted values (Mean_Obs, Mean_Pred) and Standard Deviation for observed-predicted values (STD_Obs, STD_Pred) where, O_mean and P_mean are the averages of observation (Oi) and predicted (Pi) values respectively. Especially the IOA is a measure of how well the predicted variations around the mean observations are represented, with ranges from 0 to 1, as reported in the literature a number greater than 0.5 generally indicates a good prediction (Hurley et al.2001, P.Zawar-Reza et al.2005,).
3. RESULTS AND DISCUSSION

TAPM was configured and ran for meteorology covering a period of two years, from 1 January 2010 to 31 December 2011. The output files were selected at the nearest inner grid (2km resolution) to the monitoring station at 10m above ground level (AGL).

Table 1 presents the performance statistics for the meteorological parameters of each monitoring site (PNT, PENT, K.K, AMY, KOIL). The statistics are based on hourly data values for each site (see Figure 1 for location). The IOA between the observed and the modeled values for temperature remained almost unchanged for all monitoring stations and much higher than the benchmark 0.5. A high score of IOA for temperature is a typical result of the model (P.Zawar-Reza et al.2005, Hurley, 2002, Hurley et al.,2003). Pearson correlation coefficient gave the same high score with IOA, with values above 0.94 for all three runs, in all monitoring stations where the RMSE index remained lower than the STD. In a study of Hurley et al. 2005 applied in a coastal terrain, the prediction of mean and standard deviations of observations for temperature showed skill, with Skill_V remaining near to 1 and Skill_R remaining close to 0.4. The same statistics were confirmed in the current verification, were TAPM was applied in a mountainous complex terrain. In addition, the results showed that relative humidity is predicted very well, with IOA values for all simulations and for all stations, being higher than 0.7. Pearson correlation coefficient remained the same for all stations and for all three model configurations. Moreover, the RMSE also stayed lower than the STD values, excluding PENT in TAPM_AS and in TAPM_LU, affecting a little the Skill_R. Therefore, the model predicts well the relative humidity for all monitoring stations. It is important to mention that, Syrakos et al. 2008, in a study concerning the area under investigation, operated and evaluated the meteorological model MM5 for eleven selected days running during the period 04-09/2007. In their study two indices were used (mean bias, root mean square error) for both wind direction and speed, resulting in some cases, in relatively large mean bias for wind direction. The authors suggest that an improvement of these results can be done with the use of data assimilation.

In our work, a two years period is covered, using six verification indices (IOA, RMSE, CORR, Skill_R, Skill_V, and STD). More specifically, the highest IOA is presented in TAPM_AS for the stations of PNT, PENT, K.K and AMY with values ranging from 0.83 to 0.91. In TAPM_NAS the IOA for the aforementioned stations was 0.62 for PNT, 0.7 for PENT and 0.55 for K.K and AMY. The IOA corresponding to KOIL station remained unchanged and equal to 0.57, for both TAPM_AS and TAPM_NAS runs. The configuration of TAPM_LU, resulted in a slight reduction of IOA corresponding to PNT and AMY stations, however the index remained above benchmark. No changes were recorded for IOA of PENT and K.K.

In the performance of TAPM_AS, the RMSE was less than STD and Pearson correlation was near to 1, while the model showed skill in all stations apart from the station of KOIL, where no assimilation was included. The TAPM_NAS illustrates lower correlation comparing to the TAPM_AS, which is also true for the monitoring station of KOIL. In the same configuration, the model showed skill to the monitoring stations of PNT and PENT. Finally, in the third run TAPM_LU the model had the same performance with TAPM_NAS, with indices like Pearson correlation, RMSE, STD, skill_R and V being almost unaffected.

The Variables for component U and V reveal better IOA and Pearson correlation coefficient for the TAPM_AS configuration, with IOA higher than 0.85 and correlation coefficient higher than 0.74 for the stations with data assimilation, a fact that is also evident from skills R and V. Default configuration TAPM_NAS showed a good prediction
for PNT with IOA 0.64 and 0.77 for U and V components, respectively. For K.K station the model under-predicts V component, which is also verified by the same indices, while in AMY the results showed an under-prediction for both components, substantiated by skills R and V among with Pearson correlation coefficient. For PENT a slightly under-prediction in the U component was applied, which is confirmed by correlation coefficient and Skill R. When changing land use, the corresponding configuration (TAPM_LU), resulted in U and V components demonstrating a good IOA and skill for K.K, better than those in TAPM_NAS configuration. Referring to KOIL station, variables for U and V remained almost unchanged for all indices, showing a somewhat under-prediction in all three runs. The rest components in all the other stations scored almost the same values with default configuration.

To sum up, the best prediction was simulated by TAPM_AS, as shown in Table 1, which seems to be performing better for all stations inside (PNT, PENT) and in the boundaries of the basin (K.K, AMY), for all wind variables. The simulation showed good skill in predicting the mean and standard deviations of observations, with the RMSE being lower than STD. The IOA is above benchmark 0.5 (>0.7) indicating a very good prediction. TAPM_NAS showed skill in predicting winds for the stations inside the basin (PNT, PENT) with IOA above 0.5. For the stations located in the boundaries (K.K and AMY), a slightly under-prediction seems to occur for the same variables. TAPM_LU simulation had the same behavior with TAPM_NAS, giving better prediction for the winds to the inner stations, than those in the border of the simulation domain. More specifically, TAPM_LU predicted the wind speed variable better to PNT and PENT, with IOA values being higher than 0.58. As far as the monitoring stations of K.K and AMY are concerned, the IOA was near the benchmark. For components U and V, in the same simulation, the model had good prediction in PNT, PENT and K.K for both components. More particularly, in K.K the TAPM_LU configuration simulated better the U and V components than the default configuration, result that was also verified by all indices, while in AMY values remained the same.

4. CONCLUSIONS

The current study, presented the performance and verification of a mesoscale model TAPM in a complex terrain industrial area in Greece. For this verification, three runs were applied, each one with different configuration, for a two years period (2010-2011). The three different experimental conditions include 1) Default configuration of the model with five selected output stations (PNT, PENT, AMY, K.K and KOIL), 2) Configuration with data assimilation in winds for the five aforementioned outputs, inputting data assimilation for four stations (PNT, PENT, AMY, K.K) and 3) Configuration for the same outputs but with changes in land use. All meteorological variables were extracted at the highest resolution of the simulation 2km and at the lowest vertical level 10m. The analysis showed:

Configuration 1: Default configuration statistics, revealed an almost perfect agreement for temperature, a very good agreement for relative humidity and a good agreement in winds, depending on the station location.

Configuration 2: Configuration with data assimilation in winds, suggested a very good agreement of for all monitoring stations in winds, while the agreement for temperature and relative humidity remained the same as in Configuration 1. Exception was the KOIL station, where no assimilation was included and all indices score remained equal to those in the default configuration.

Configuration 3: Configuration with changes in land use statistics, illustrated the same score in the agreement of variables with the default configuration, apart from the station of K.K where indices in components U and V had a higher score.
Finally, the model showed a good prediction for all three different configurations. Data assimilation configuration (Config.2) has almost perfect agreement to the measurement values (>0.83). Default and land use simulations (Config1,3) have also a good agreement above benchmark or at the benchmark (0.5), with almost the same score. It should be noted that the changes in land use were in a small percentage referring to the grid domain.

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**REFERENCES**

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Table 1  
Statistics from TAPM simulation, hourly averaged values for 10m wind speed AGL (WS), the west-east component of wind for 10m AGL (U), the south-north component of wind for 10m AGL(V), Temperature (TEMP) and relative humidity (RH).

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<td>1.0</td>
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<td>0.47</td>
<td>0.82</td>
<td>0.3</td>
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<td>0.61</td>
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<td>0.82</td>
<td>0.3</td>
<td>1.7</td>
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<tr>
<td></td>
<td>RX</td>
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<td>0.1</td>
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<td>1.50</td>
<td>1.16</td>
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<td>2.5</td>
</tr>
</tbody>
</table>

Obs, observations; Size, Number of hourly averaged values used for the statistics; Mean, arithmetic mean; STD, standard deviation; CORR, Pearson correlation coefficient (0=no correlation, 1=exact correlation); RMSE, root mean square error; IOA, index of agreement (0=no agreement, 1=perfect agreement); Skill_R, (RMSE)/(STD_OBS) (<1 shows skill); Skill_V, (STD_PRED)/(STD_OBS) (near to 1 shows skill).