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Estimating daily PM_{2.5} and PM₁₀ across the complex geo-climate region of Israel using MAIAC satellite-based AOD data

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Abstract

Estimates of exposure to PM_{2.5} are often derived from geographic characteristics based on land-use regression or from a limited number of fixed ground monitors. Remote sensing advances have integrated these approaches with satellite-based measures of aerosol optical depth (AOD), which is spatially and temporally resolved, allowing greater coverage for PM_{2.5} estimations. Israel is situated in a complex geo-climatic region with contrasting geographic and weather patterns, including both dark and bright surfaces within a relatively small area. Our goal was to examine the use of MODIS-based MAIAC data in Israel, and to explore the reliability of predicted PM_{2.5} and PM₁₀ at a high spatiotemporal resolution. We applied a three stage process, including a daily calibration method based on a mixed effects model, to predict ground PM_{2.5} and PM₁₀ over Israel. We later constructed daily predictions across Israel for 2003–2013 using spatial and temporal smoothing, to estimate AOD when satellite data were missing. Good model performance was achieved, with out-of-sample cross validation R² values of 0.79 and 0.72 for PM₁₀ and PM_{2.5}, respectively. Model predictions had little bias, with cross-validated slopes (predicted vs. observed) of 0.99 for both the PM_{2.5} and PM₁₀ models. To our knowledge, this is the first study that utilizes high resolution 1km MAIAC AOD retrievals for PM prediction while accounting for geo-climate complexities, such as experienced in Israel. This novel model allowed the reconstruction of long- and short-term spatially resolved exposure to PM_{2.5} and PM₁₀ in Israel, which could be used in the future for epidemiological studies.

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Keywords

Air pollution; Aerosol Optical Depth (AOD); Epidemiology; PM₁₀; PM_{2.5}; Exposure error; High particulate levels; MAIAC

1. Introduction

Satellite data have been frequently used in recent years to predict both coarse and fine particulate matter (PM) (Emili et al. 2010, Chang et al. 2013; Chudnovsky et al. 2014; Hoff and Christopher 2009; Kloog et al. 2014a; Lee et al. 2011; Sorek-Hamer et al. 2013b). Aerosol Optical Depth (AOD) from the Moderate Resolution Imaging Spectroradiometer (MODIS) is a commonly used satellite product for predicting PM concentrations as it measures light extinction at given wavelengths due to scattering and absorption along the measured atmospheric column. AOD has been used globally over areas with different characteristics showing a range of results, e.g. Northeast USA (Kloog et al. 2011, 2012) - a relatively dark and vegetated area; Lombardy, Italy (Nordio et al. 2013); and Israel - a Mediterranean region characterized by a high percentage of bright surfaces, e.g. desert (Sorek-Hamer et al. 2015).

In particular, Israel experiences a complex geo-climatic variation, with different geographic and weather patterns within a relatively small area, e.g. desert conditions in the south, snow-capped mountains in the north, coastal environment, densely populated metropolitan areas, vegetated regions, and large differences in height above the sea level that range from -417m to 1204m (Erell et al. 2003; Kafle and Bruins 2009). The coastal region holds a large part of the population along with pollution sources. The latter, combined with varying meteorological conditions, affects the region air quality (Levy et al. 2008). Dust, transported to the region from the Sahara desert and the Arabian peninsula during the winter and the transition seasons contributes significantly to the total PM load in Israel (Ganor et al. 2009; Sorek-Hamer et al. 2013a). Similarly, transboundary transport of anthropogenic sulphates and nitrates from southern and eastern Europe is a main source of PM_{2.5} loading.

In Israel, the PM_{2.5}/PM₁₀ ratio demonstrates clearly that the PM_{2.5-10} fraction dominates the ambient particulate matter in days affected by dust, with ratios of about 0.3. In contrast, in days not affected by dust this ratio equals ~0.5 (Sorek-Hamer et al. 2013a), which is nevertheless smaller than ratios that are observed in the Eastern US or Europe, 0.7–0.8. The Israeli PM_{2.5} monitoring network is distributed very heterogeneously. To overcome the relatively sparse surface monitoring network available in Israel, Sorek-Hamer et al. (2015) have used AOD products from MODIS with a fairly coarse spatial resolution (10 km) to estimate PM across Israel. Both the Dark Target (DT) and the Deep Blue (DB) algorithms for AOD retrieval were used to predict ground PM_{2.5} using mixed effects models. The best PM_{2.5} prediction was obtained using the AODDB product, presenting a R² of 0.45. Using the AODDB product significantly increased the spatiotemporal availability of the AOD over the Israeli bright surface area and improved PM_{2.5} prediction relative to using the more common AODDT retrievals.

The varying daily relationship between MODIS based AOD and ground PM_{2.5} have been shown in many studies (Kloog et al. 2014a; Lee et al. 2011). This daily varying relationship can be attributed to differences in particle composition, daily variability of the planetary boundary layer (PBL) structure and height, and changing relative humidity and the aerosol vertical concentration profile. A single calibration slope between PM_{2.5} and AOD is not well suited for capturing these daily changing relationships. We thus make use of a mixed model approach which allows for the regression intercepts and slopes to vary daily to control for this inherent day-to-day variability in the AOD-PM_{2.5} relationship caused by time-varying parameters. Mixed model regressions are powerful tools that incorporate both spatial and temporal predictors as well as day-specific random-effects. The mixed model approach was used successfully in different geo-climatic regions.

Previous studies that used the recently developed Multi Angle Implementation of Atmospheric Correction (MAIAC) retrieval algorithm (1 km spatial resolution) revealed improved PM predictions and large spatiotemporal availability (Kloog et al. 2011; Lee et al. 2011, Chudnovsky et al. 2014; Nordio et al. 2013)). Similar results were obtained also when using MODIS/MAIAC retrievals within different regression models (Chang et al. 2014; Hu et al. 2014). Nonetheless, although MAIAC AOD was successfully used for estimating PM_{2.5} concentrations in North America, it has rarely been tested for estimating PM₁₀ concentrations nor in more complex geographic and climatic regions as Israel (e.g. Emili et al. 2011).

In this study we examined the use of the highly spatiotemporal resolved MAIAC data in Israel, a complex area with diverse topography and climate conditions, exploring its PM_{2.5} and PM₁₀ predictions reliability. We applied all the three stages of the daily calibration method, based on a mixed effects model, to predict ground PM_{2.5} and PM₁₀ over Israel. To our knowledge, this is the first study that utilizes MAIAC data for PM prediction while accounting for geo-climatic complexity such as experienced in Israel.

2. Material and Methods

2.1 Study domain

The study region included the entire state of Israel (Figure 1) apart from its most southern region, where population is very scarce and monitoring data is unavailable. Since our model is aimed for use in environmental epidemiology we choose to limit already computationally intensive model runs to populated regions in Israel. Israel is located along the eastern Mediterranean coast, between 29.5° and 33.5°N. Climatically, Israel is situated in the subtropical dry-lands and is characterized by a hot and dry summer and a single rain season (November – March). In spite of its small area (~420 km from north to south and a maximum width of ~110 km), it experiences sharp climatic and geographic gradients, both in the north-south and the east-west directions. Hence, the study region includes very diverse geographic and climatic regions, including large rural areas, large forested regions, water bodies, mountains and the Mediterranean coastal plains.

2.2 Satellite Data

One of the main MODIS aerosol products is spectral AOD. This level 2 MODIS product is available daily across the entire globe. The product has been utilized in many studies, mainly using the “Dark Target” (DT) MODIS algorithm over land that provides a 10 km resolution AOD. Recent studies evaluated the Deep Blue algorithm and found that it performs better over bright surfaces both with respect to retrievals availability as well as for $PM_{2.5}$ and PM_{10} estimation. MAIAC, developed by Lyapustin and colleagues, is a new processing algorithm that provides a high 1 km resolution AOD product. The MAIAC algorithm begins with gridding the data to a fixed 1 km grid and accumulating of up to 16 days of measurements. The algorithm uses a time series analysis and processes groups of pixels to derive the surface bidirectional reflectance distribution function (BRDF) and aerosol parameters over both dark vegetated surfaces and bright surfaces, without the assumptions typically used by the current MODIS operational processing algorithms. The spatio-temporal analysis also helps MAIAC’s cloud mask in augmenting traditional pixel-level cloud detection techniques. MAIAC’s high resolution, which is important in many applications such as air pollution studies, may bring new information about aerosol sources and, potentially, their strength. Validation against AOT obtained at Aerosol Robotic Network (AERONET) stations in several U.S. West Coast sites showed that the MAIAC and MODIS algorithms have very similar accuracy over dark and vegetated surfaces but that MAIAC shows, in general, better accuracy over brighter surfaces as a result of its spectral retrieval of the regression coefficients and the explicit BRDF characterization. Due to its generic nature and developed angular correction, MAIAC can retrieve AOD over bright deserts, as demonstrated for the Solar Village AERONET site in Saudi Arabia. This ability of MAIAC is crucial in areas such as Israel, where large regions are characterized as desert. In this work we used MAIAC AOD over Israel based on MODIS Aqua L1B data for the years 2003–2013 (generated on 01/10/2014). The correlation between MAIAC (Aqua) AOD and AERONET AOD has been locally evaluated with data from the Nes Ziona AERONET station located in the central-southern part of the country, in an urban area (long:34.78917, lat:31.92250). The data from both AOD sources are for the years 2003–2013.

The Pearson correlation ($r=0.85$) was calculated with hourly MAIAC and AERONET AOD data, relative to the Aqua overpass time, from the closest grid cell (long:34.792, lat:31.926) (Figure 2). The raw MAIAC data went through additional screening. We applied thresholds based on MAIAC guidelines which use quality assurance (QA) flags and uncertainty values (UN) to then exclude pixels with erroneous AOD values. The QA and UN data allows us to better filter out pixels that are cloud contaminated, have issues with surface brightness, snow etc. The mean retrieval per pixel across the study area for all years was 2682. The first quartile (Q1) had 2513 observations while the third quartile (Q3) had 2984 observations.

2.3 Ground Monitoring data

Israel’s PM ground monitor network is distributed heterogeneously mainly around four urban areas in the coastal plain: Tel Aviv, Jerusalem, Haifa, and Ashdod (Figure 1). Daily $PM_{2.5}$ and PM_{10} concentrations across Israel for the years 2003–2013 were obtained from the Technion Center of Excellence in Exposure Science and Environmental Health (TCEEH) air pollution monitoring database (TAPMD). Monitoring in Israel is conducted by different

local Municipalities Associations for the Environment (MAE) and regulated by the Ministry of Environmental Protection (MoEP). The measurements are performed using TEOM™ continuous monitoring instruments that are operated and maintained according to the US-EPA guidelines, with a typical accuracy of $\pm 5\%$. Since data in some stations were not collected continuously throughout the study period, we only used monitors with at least 20% yearly data availability. Overall, we used data from 45 PM_{2.5} monitoring stations and 41 PM₁₀ monitoring stations with unique locations, which operated during the study period.

2.4 Spatial and Temporal Predictors of PM_{2.5}

Because the relationship between PM_{2.5} and AOD depends on the optical properties, size distribution, and vertical profile of the aerosol, which change daily and vary spatially, we fit a calibration regression that incorporates predictors of these properties. Since available covariates do not capture all of these attributes, we allowed the calibration coefficients to vary on a daily and regionally basis, as described below. Spatial and temporal covariates were generated using Qgis ver. 2.6, ArcMap ver. 10.2 and R statistical software ver. 3.12.

The spatial predictors used in this work are: population density, elevation, traffic density, distance from major roads, distance from the shoreline and the percent of open space. These variables were chosen because they can serve as surrogates for emissions of particles with different optical properties. Specifically:

Population Density—Population density data were obtained from the Israeli Central Bureau of Statistics. We calculated the weight-averaged population for each 1 km grid cell based on the tracts intersecting these grid cells.

Elevation—Elevation data were obtained from the ASTER global digital elevation model (GDEM) data. ASTER GDEM coverage spans from 83 degrees north latitude to 83 degrees south, encompassing 99 percent of Earth's landmass. The spatial resolution is 30m. Since there are elevation contrasts across the entire country we used elevation as a spatial predictor.

Traffic Density—Road data were obtained from the Israel Survey Bureau mapping service (MAPI) and included all the roads across Israel, from one lane to the country major roads. We calculated the total road density using the line density tool, which is part of the ArcGIS spatial analyst toolbox. It calculates the magnitude (density) per unit area (1 km) of polyline features (all the roads) that pass within 1 km radius around each 1 km cell centroid throughout the study area. The road density was then intersected with the 1 km grids resulting in an attribute table containing the road density in each 1 km grid cell.

Distance from major roads/shoreline—We calculated distances from the centroids of our grid to both the Israel shoreline and major roads across Israel using Qgis. These distances (in meters) were attributed to each centroid across the study area.

Percent of open space—We used the ICBS land use dataset to calculate the percentage of open space in each 1 km grid cell across the study area. The percent of open space

included all the following areas: large-lot single-family housing units, parks, forestry, and vegetated areas used for recreation, soil erosion control, or aesthetic purposes.

The temporal predictors used in this work are:

Meteorological data—All meteorological variables used in the analysis were obtained through the TAPMD. Grid cells were matched to the closest weather station with available meteorological variables (24 h means). We used the following daily mean meteorological variables: air temperature, relative humidity and rainfall.

Dust event classification—In order to capture the presence of dust events in the region, all observations throughout the study period were classified as affected by dust (dust flag=1) or as not affected by dust (dust flag=0). The daily dust flag was assigned according to an extended scheme of Sorek Hamer et al. (2013a).

NDVI—We used the publicly available monthly MODIS NDVI (Normalized Difference Vegetation Index) product (MOD13A3) at 1 km spatial resolution. The monthly resolution was chosen under the assumption that NDVI values do not change considerably within a month period except for the periods of spring green-up and fall senescence.

PBL—Daily mixing height of the planetary boundary layer (PBL) were obtained from modeled data of the National Center for Scientific Research (CNRS) at a 50 km spatial resolution. PBL can vary with the wind speed and can influence the concentration and the pollutant vertical profile.

2.6 Statistical Methods

All modeling was done using the R statistical software version 3.12 and SAS version 9.3. Our aim was to generate spatio-temporally resolved daily PM_{10} and $PM_{2.5}$ predictions in each 1 km grid cell for the entire 2003–2013 period. For this, we developed a series of processes (Figure 3).

First, calibration of the gridded AOD data was performed against PM_{10} and $PM_{2.5}$ monitoring data that were collected within 1 km of the AOD value. The calibration stage adjusted for all the spatio-temporal predictors similar to classic land use regressions (LUR). Second, using this model daily PM_{10} and $PM_{2.5}$ concentrations were calculated in grid cells with AOD data but without available monitoring data. Third, daily PM_{10} and $PM_{2.5}$ in grid cells with no AOD data for that day were estimated, taking into account the region-specific association between grid-cell AOD and PM levels as well as the association between PM_{10} and $PM_{2.5}$ levels in any given grid with that in neighboring grid cells. Missing MAIAC AOD data are not random, possible reasons for the missing AOD retrievals that may be associated with ground level PM include dust storms, snow, and heavy cloud coverage. Thus, in the calibration process we incorporated inverse probability weighting (IPW) to potentially avoid bias in the regression coefficient estimates, and thus in the resulting predictions. The IPW approach up-weights observed grid cell-day combinations with covariate patterns that are more often missing AOD data. To obtain these weights, we fitted the following logistic

regression model for the probability (p) of observing an AOD value in cell i on day j for each year:

$$\ln\left(\frac{\hat{p}}{1-\hat{p}}\right) = \beta_0 + \beta_1 \text{Elevation}_i + \beta_2 \text{PBL}_{ij} + \beta_3 \text{Temperature}_{ij} + \text{Month} \quad (\text{Eq. 1})$$

$$IPW = \left(\frac{1}{\hat{p}}\right) \quad (\text{Eq. 2})$$

where (p) is the probability for availability of AOD in each day in each grid cell in each year. It should be noted that there were no IPW observations which had a disproportionate influence in the yearly models. Since the daily PM-AOD calibration factors can vary spatially across the complex Israeli area, we divided Israel into 5 regions based on geography and climate. The day-specific intercept and AOD random effects in the model are nested within the geographical regions of the study. The mixed model calibration process was performed using the lme4 package in R:

$$\begin{aligned} \text{PM}_{ij} = & (\alpha + u_j + g_{j(\text{reg})}) + (\beta_1 + v_j + h_{j(\text{reg})}) \text{AOD}_{ij} + \sum_{m=1}^6 \gamma_{1m} X_{1mi} + \sum_{m=1}^6 \gamma_{2m} X_{2mj} + \varepsilon_{ij} \\ & (u_j, v_j, k_j) \sim N[(0, 0), \sigma] \\ & (g_{j(\text{reg})}, h_{j(\text{reg})}) \sim N[(0, 0), \sigma_{\text{reg}}] \end{aligned} \quad (\text{Eq. 3})$$

3)

where PM_{ij} is the measured PM_{10} or $\text{PM}_{2.5}$ concentration at spatial site i on day j ; α and u_j are the fixed and random (day-specific) intercepts, respectively, AOD_{ij} is the AOD value in the grid cell corresponding to site i on day j ; β_1 and v_j are the fixed and day-specific random slopes, respectively. X_{1mi} is the value of the m -th spatial predictor at site i (i.e. population density, percent of open space, distance to main roads, elevation, and traffic density). X_{2mj} is the value of the m -th temporal predictor on day j (i.e. PBL height, NDVI, temperature, relative humidity and dust classification). The terms $g_{j(\text{reg})}$ and $h_{j(\text{reg})}$ are the daily random intercepts and AOD slopes specific to each study area region, nested within the overall random effects u_j and v_j . We assume that σ is a 3 x 3 diagonal matrix with diagonal elements σ_u^2 , σ_v^2 , σ_k^2 , and σ_{reg} is a 2 x 2 diagonal matrix with diagonal elements σ_g^2 , σ_h^2 .

In the second stage, the above model is used to predict PM_{10} and $\text{PM}_{2.5}$ in each day and grid cell for which MAIAC AOD is available. In the third stage, we used the AOD- PM_x relationships to estimate daily PM_{10} or $\text{PM}_{2.5}$ in all the grid cells across Israel, i.e. even in those where MAIAC AOD data were missing. This was achieved by fitting a generalized additive mixed model (GAMM) with a thin plate spline, which is a smooth function of latitude and longitude (using the grid cell centroids) and a random intercept. Moreover, we created discrete 30 km buffers around each AOD cell and calculated the daily mean PM_{10} and $\text{PM}_{2.5}$ from the stations in the 30 km buffer around each grid cell, as a predictor of PM_{10}

and $PM_{2.5}$ on that day in that grid cell. To allow for temporal variations in the spatial correlation, we fitted a separate spatial surface for each bi-monthly period in each year. Using this method provides additional information about the concentrations in the missing grid cells that classic interpolation does not provide. Specifically, we fitted the following semiparametric regression model:

$$\begin{aligned} \text{Pred}PM_{ij} = & (\alpha + u_i) + (\beta_1 + v_i) MPM_{ij} + s(X_i, Y_i)_{k(j)} + \varepsilon_{ij}, \\ (u_i, v_i) \sim & [(\mathbf{0}, \mathbf{0}), \Omega_\beta] \end{aligned} \quad (\text{Eq. 4})$$

where $\text{Pred}PM_{ij}$ is the predicted PM_{10} or $PM_{2.5}$ concentration at a grid cell i on a day j based on the calibrated model (predicted PM at available AOD points); MPM_{ij} is the mean PM in the relevant 30 km buffer for site i on a day j ; α and u_i are the fixed and grid-cell specific random intercepts, respectively; β_1 and v_i are the fixed and random slopes, respectively. X_i and Y_i are the longitude and latitude of the centroid of grid cell i , respectively, and $s(X_i, Y_i)_{k(j)}$ is a smooth function of the location (modeled by thin plate splines) specific to the bi-monthly period $k(j)$ in which day j falls (that is, a separate spatial smooth was fitted for each bi-monthly period).

Running a calibration model with a large number of parameters runs the risk of over fitting. We used two approaches to avoid this. First, we used a mixed model to estimate the region and day specific slopes. Hence, the only parameters we are estimating are the covariances of the random effects, Σ and Σ_{REG} . Second we validated our models using ten-folds out-of-sample cross validation (CV) techniques. We randomly divide our data into 90% training and 10% evaluation datasets ten independent times, using for the evaluation the model that has been fitted for the training set. Only terms that increased the CV R^2 were kept in the model. To test our results for bias we regressed the measured PM value for a given site and day against the corresponding predicted value from the 90% sample that excluded that monitor. Model prediction accuracy is estimated by calculating the square root of the mean squared prediction errors (RMSPE). In addition, we calculated a spatial RMSPE using a model that contained only the spatial components, to make it more comparable to the commonly used monthly/yearly LUR models. As a sensitivity analysis, we also tested whether our models were improved, by using the local spatial and temporal predictors, as compared to a simple AOD calibration model in which AOD is regressed only against $PM_{2.5}$. Thus, in addition to our main model, we also report fits for an AOD-only model, a Land use and Met model, an AOD and land use model, and an AOD and temporal predictors model. Finally, we explored the model performance for the cold season (winter months) and warm season (summer months) separately.

4. Results

Table 1 presents descriptive statistics on the PM_{10} and $PM_{2.5}$ ground monitoring data. The mean PM across Israel from all the monitoring stations during the entire study period (2003–2013) was 23.13 and 53.05 $\mu\text{g}/\text{m}^3$ for $PM_{2.5}$ and PM_{10} , respectively. Table 2 presents the overall spatial and temporal model fits (R^2) for 2003–2013 for all the sensitivity analyses. Model fits were better using the full model following the calibration process, improving the

prediction accuracy both temporally and spatially (temporal R^2 of 0.84 and spatial R^2 of 0.89). Table 3 summarizes the results from the calibration stage (process 1) for both the $PM_{2.5}$ and PM_{10} models. The models presented relatively high cross-validated (CV) fits across the challenging study area for both $PM_{2.5}$ and PM_{10} . For PM_{10} , the model presents a mean CV R^2 of 0.79 and a CV slope of almost one (slope of observed vs. predicted of 0.99), suggesting little bias of the PM_{10} model. The models also perform well when looking at the spatial and temporal components: for the temporal model the CV R^2 was 0.79 and for the spatial model the CV R^2 was 0.76. The CV RMSPE of the calibration was $25.10 \mu\text{g}/\text{m}^3$ while the spatial RMSPE (which is a RMSPE similar to traditional LUR RMSPE) was $0.78 \mu\text{g}/\text{m}^3$. This is considerably less than the observed variability in PM_{10} concentrations across Israel, which ranged in the study period from $1 \mu\text{g}/\text{m}^3$ to $3,222 \mu\text{g}/\text{m}^3$ (mean of $53.05 \mu\text{g}/\text{m}^3$). The final model also performed well, with a mean R^2 of 0.82 - a rather high value considering that the model predicted concentrations even when satellite AOD data were unavailable.

For $PM_{2.5}$ the model presented a mean CV R^2 of 0.72 and a CV slope of, again, almost one (slope of observed vs. predicted of 0.99), showing little bias of the CV models. The CV R^2 of the temporal model was 0.71 and the CV R^2 of the spatial model was 0.84. The CV RMSPE of the calibration was $8.53 \mu\text{g}/\text{m}^3$ while the spatial RMSPE was $1.31 \mu\text{g}/\text{m}^3$ ($PM_{2.5}$ ranged from $1 \mu\text{g}/\text{m}^3$ to $793 \mu\text{g}/\text{m}^3$). The performance of the final model was, again, very good, with a mean R^2 of 0.81.

The season-specific models revealed that the model performed slightly better during the summer period: for PM_{10} the CV R^2 was 0.82 and 0.73 for the summer and winter, respectively, whereas for $PM_{2.5}$ the CV R^2 was 0.72 and 0.64 for the summer and winter, respectively. Figure 4 shows the spatial pattern of the predicted $PM_{2.5}$ and PM_{10} , averaged over the entire study period. Mean predicted $PM_{2.5}$ concentrations range between $16.63 \mu\text{g}/\text{m}^3$ and $30.60 \mu\text{g}/\text{m}^3$. Mean predicted PM_{10} concentrations range between $43.50 \mu\text{g}/\text{m}^3$ and $71.27 \mu\text{g}/\text{m}^3$.

Table 4 demonstrates the differences between the mean measured and predicted $PM_{2.5}$ concentrations in three main metropolitan areas- Haifa, Tel-Aviv, and Jerusalem.

4. Discussion

To our knowledge, this is the first study that uses high resolution daily $PM_{2.5}$ and PM_{10} models in Israel. We developed and validated models to predict daily $PM_{2.5}$ and PM_{10} concentrations at a 1 km resolution across Israel, allowing us to better estimate long-term daily PM exposure both at urban and rural areas. A good model performance has been shown across the extremely challenging geo-climatic characteristics of Israel, incorporating many different climatic zones (e.g. coastal, mountain, urban, desert) in a relatively small area ($\sim 20,000 \text{ km}^2$). The models developed in this study perform significantly better than any other model available to-date for Israel (Table 3).

Several other regions with complex conditions have been studied previously in relation to using satellite aerosol products for PM prediction, in particular the San Joaquin Valley

(SJV), central California, which experiences similar geo-climate conditions as in Israel apart from major dust outbreaks. Yet, these previous studies estimated hourly/daily PM concentrations in SJV based on MODIS AOD (10 km). In particular, Rosen et al. demonstrated an improved simple linear agreement between hourly PM_{2.5} concentrations at two monitoring sites and MODIS AOD at a 5 km resolution relative to the standard operational MODIS 10 km AOD product ($R^2=0.59$ and $R^2=0.05$, respectively). In China, another area with intricate characterization, a geographic weighted regression (GWR) model has been recently used, showing a reasonable and representative spatial pattern of regional variability of PM_{2.5}, similar to that from ground measurements. Although the GWR model offers promise for accurate large scale PM_{2.5} monitoring, Song and colleagues recommend further research on the integration of more model predictors (e.g. land use, season) and the use of higher satellite spatial resolution.

Our results show that PM₁₀ calibrated better with MAIAC compared to PM_{2.5}. This could be due to (a) the daily PM concentrations in Israel show a major coarse fraction (PM_{2.5-10}), with mineral dust and sea salt the major sources of naturally occurring coarse-mode aerosols. The contribution of the coarse mode is evident from the ratio of PM_{2.5} to PM₁₀ concentrations in stations that monitor both PM fractions. The annual average ratio is about 50%, and during dust storms it decreases to 30%. These ratios are much smaller than those evident in north Europe and USA, i.e. in regions for which most of the AOD-PM studies have been performed to date. (b) There are many more PM₁₀ monitoring stations than PM_{2.5} monitoring stations in Israel (and they also started to report earlier), which may affect the model performance. (c) Finally, the TEOM™ monitoring devices used for PM_{2.5} and PM₁₀ monitoring in Israel require conditioning of the aerosol before the measurement takes place. This conditioning may affect the particulate content of adsorbed semi volatile compounds, VOCs, which are normally found in larger amounts in the fine fraction. This may lead to underestimation of the true PM concentrations, especially for PM_{2.5}, which may explain why we got better agreement for PM₁₀.

Our model can be used in various disciplines for estimating PM, and may be particularly useful for environmental epidemiology studies. Robust and validated air pollution exposure data are missing in Israel and our PM_{2.5} and PM₁₀ predictions could allow studying both acute and chronic effects in the entire population, rather than in a small sample as commonly done in current epidemiological studies.

However, there are several limitations to our models that should be noted. First, although our 1 km resolution predictions are the finest resolution of AOD data available from MODIS/MAIAC, it may still not capture the effects of the very local sources, such as busy highways (which scale is much smaller than 1 km). Another limitation is the lack of data on the composition of the PM estimates. Future analyses may allow us to develop models to estimate exposure to specific PM components. Moreover, because our model uses satellite measurements, it cannot forecast future concentrations. Thus, the benefit for environmental policy may be primarily through understanding past and current exposure patterns, quantifying the impacts of previous interventions, and for studying PM-related acute and chronic health effects. Future improvement of this model may benefit from further

developments of the MAIAC algorithm and combine other AOD measures from the two MODIS sensors on Aqua and Terra satellites.

In summary, this is the first study that utilizes MAIAC AOD for PM_{2.5} and PM₁₀ prediction while controlling for the geo-climatic complexities of Israel. The new model allowed us to reconstruct spatially resolved long-term daily average concentrations of PM_{2.5} and PM₁₀ in Israel.

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Research highlights

- We estimated daily $PM_{2.5}$ and PM_{10} using Novel MAIAC satellite-based AOD data
- Our Models performed very well with fits of 0.79 and 0.72 for PM_{10} and $PM_{2.5}$, respectively
- Our results revealed very little bias (Slope of predictions versus withheld observations = 0.99)
- Our model enables reconstruction of long/short term resolved exposure to $PM_{2.5}$ and PM_{10} in Israel

Figure 1.
Map of the study area showing all PM_{2.5} and PM₁₀ monitoring stations across the study area.

Figure 2. Correlation between MAIAC (Aqua) AOD and hourly AERONET AOD, relative to the Aqua overpass time, from the Nes Ziona station. Both AOD datasets are for the period 2003–2013. There are only 1470 days (~36%) with both available AOD sources at the Aqua overpass time, while 25 of them observe AOD above 0.5.

Fit daily calibration using data from pixels with
collocated PM and AOD:
 $PM_{2.5} \sim AOD + \text{other spatio-temporal predictors}$
(fit with mixed effects model)

Use the calibration models fits to predict $PM_{2.5}$
in grid cells with AOD but without monitors

Estimate $PM_{2.5}$ in cells with *no available AOD*
data using spatial smoothing of nearby AOD and
daily regional patterns

Figure 3.

Flowchart illustrating the model steps for obtaining a complete cover of $PM_{2.5}$ prediction over the study area.

Figure 4.
AOD-based predictions of the 2003–2013 mean $\text{PM}_{2.5}$ and PM_{10} concentrations in each 1x1 km grid cell across Israel.

Table 1

Descriptive statistics of the PM₁₀ and PM_{2.5} records across the study area in the years of 2003–2013.

Station	Mean	Min	Max	Median	SD	IQR	Q1	Q3	Days of data available (all stations)
PM10 (µg/m³)	53.05	0.01	3222.73	38.62	65.76	25.40	28.60	54.00	72,778
PM2.5 (µg/m³)	23.13	0.01	1676.01	19.46	25.27	11.87	14.33	26.20	94,094

Note: Q1 and Q3 are quartiles

Table 2

Coefficient of determination (R^2) of the various models developed in this study for predicting $PM_{2.5}$.

Model	Overall R^2	Spatial R^2	Temporal R^2
LU+MET	0.75	0.61	0.76
AOD	0.77	0.76	0.78
AOD+MET	0.77	0.74	0.77
AOD+LU	0.77	0.77	0.70
AOD+MET+LU	0.84	0.89	0.84

Cross -validated (CV) PM_{2.5} and PM₁₀ model performances of the calibrated models (using the training datasets) for the entire study period of 2003–2013.

Table 3

Model	R ²	Intercept ^a	Slope ^a	Spatial R ²	Temporal R ²	RMSPE ^b	Spatial RMSPE ^b
PM ₁₀	0.79	0.11±0.25	0.99±0.01	0.76	0.79	25.10 µg/m ³	0.78 µg/m ³
PM _{2.5}	0.72	0.24±0.12	0.99±0.01	0.84	0.71	8.53 µg/m ³	1.31 µg/m ³
* PM ₁₀	0.69					27.92 µg/m ³	
* PM _{2.5}	0.45					12.06 µg/m ³	

^a Presented as parameter estimate ± SE from a linear regression of observations versus predictions.

^b Root of the mean squared prediction error.

* Sorek-Hamer et al (2015)

Table 4

Comparing the measured mean PM_{2.5} concentrations to the predicted PM_{2.5} concentrations in the Tel-Aviv, Jerusalem, and Haifa areas for the whole study period (2003–2013).

	Tel-Aviv	Haifa	Jerusalem
Mean measured PM _{2.5}	23.38 µg/m ³	19.36 µg/m ³	23.71 µg/m ³
Mean predicted PM _{2.5}	21.80 µg/m ³	18.8 µg/m ³	22.58 µg/m ³