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ENERGY-EFFICIENT COMMUNITY DEVELOPMENT IN CALIFORNIA: CHULA VISTA RESEARCH PROJECT

ATTACHMENT III: THE URBAN HEAT ISLAND MITIGATION IMPACT SCREENING TOOL (MIST)

PIER FINAL PROJECT REPORT

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The Urban Heat Island Mitigation Impact Screening Tool (MIST)

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Abstract

A web-based screening tool has been developed to assist urban planners and air quality management officials in assessing the potential of urban heat island mitigation strategies to affect the urban climate, ozone air quality, and energy consumption within their cities. The user of the screening tool can select from any of over 200 US cities for which to conduct the analysis. The mitigation strategies investigated include highly reflective (high albedo) construction and paving materials and urban vegetation. The user can test a range of albedo scenarios, vegetation scenarios, or combined scenarios. In addition users can simply specify a nominal urban air temperature reduction associated with some undetermined set of mitigation actions. The mitigation impact screening tool (MIST) then extrapolates results from a set of detailed meteorological model simulations for 20 cities across the US. These meteorological impacts are combined with energy and ozone impact models to estimate the impact that the specified mitigation action may have on the selected city. The results presented by MIST include a high degree of uncertainty and are intended only as a first-order estimate that urban planners can use to assess the viability of heat island mitigation strategies for their city.

Keywords: air quality, urban heat islands, atmospheric modeling, urban climate

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1. BACKGROUND

The urban climate is driven by the input of short-wave solar energy at the surface of the earth. Since urban areas tend to have relatively low reflectivity to solar radiation (low albedo) much of the solar energy is absorbed by the urban substrate. Of the energy absorbed at the surface some is convected away as sensible heat flux. The sensible heat flux depends on the temperature difference between the surface and the air and in a complex manner on the wind profile, vertical mixing characteristics above the urban surface, and wind channeling effects of the city. Surfaces also lose heat through evaporation and transpiration processes that convert water from liquid to vapor phase. The resulting latent heat flux depends on the moisture availability of the substrate as well as the underlying humidity in the air near the surface. In contrast to the natural landscape cities tend to have little vegetation and due to a large fractional cover of impervious surfaces there also tends to be less surface moisture in urban areas (Oke 1982; Owen *et al.* 1998). Another unique component of the urban energy balance is the presence of waste heat that is emitted from a range of human activities - automobiles, air conditioning equipment, industrial facilities, and a variety of other sources, including human metabolism.

The result of the complex urban surface energy balance is that cities tend to be warmer than their rural surroundings. This “urban heat island” (UHI) is typically largest in winter and during the evening hours (Oke 1981; Travis *et al.* 1987; Yoshikado *et al.* 1996; Morris and Simmonds 2001). Nevertheless, the summertime UHI is of particular importance due to the consequences for urban air quality, air conditioning energy consumption, and heat related illness and mortality (Tarleton and Katz 1995; Santamouris *et al.* 1999; Bornstein and Lin 2000; Nielsen-Gammon 2000; Lemonsu and Masson 2002). Mitigation strategies have been proposed to alleviate the negative effects of the summertime UHI (Rosenfeld *et al.* 1995; Estes 2000; Akbari *et al.* 2001; Sailor *et al.* 2002). In particular these strategies take advantage of insights gained from study of the urban energy balance. Specifically, they seek to reduce the solar radiation absorbed by the surface or increase the latent heat flux away from the surface. The physical implementation of these strategies involves use of highly reflective (high albedo) roofing and paving materials and extensive planting of urban vegetation. For example, high albedo alternatives such as white elastomeric coatings can increase the albedo of typical commercial roofs from approximately 10% to nearly 70% (Rosenfeld *et al.* 1995). In detailed analyses of surfaces that comprise the urban fabric Bretz *et al.* (1998) noted that there is significant potential in the US to increase pavement and rooftop albedos. For example, it is estimated that the surface of Sacramento, California is composed of 20% dark rooftops and 10% dark pavement. The authors suggest that the albedo of Sacramento could be increased by 0.18 using readily available materials. Similar analyses have been conducted to explore the potential urban climate impacts of increasing urban vegetation and planting shade trees (e.g., Sailor 1998; Akbari 2002). The impacts that shade trees or high albedo rooftops have on individual buildings can be estimated using building energy simulation software or estimated through the direct monitoring of building energy consumption before and after modification of the building envelope (e.g., before and after re-roofing with a high albedo alternative). Mitigation strategies, however, may also have a city-wide impact associated with the combined effect of many modified surfaces. For example, a vegetated rooftop (ecoroof) installed on one building can reduce the surface temperature of that building, and in turn, cool the adjacent air that influences the thermal environment of the entire city through advection. In order to project the potential magnitude of this indirect atmospheric effect of mitigation strategies it is necessary to use regional (or mesoscale) atmospheric models. The atmospheric effect of mitigation strategies can, in turn, affect ambient air quality, human health, and city-scale energy consumption patterns. These effects can be estimated using atmospheric model output to drive corresponding end point impact models (Sailor *et al.* 2002). Quantification of these effects can provide crucial input to urban planning and public policy decisions, but is typically a costly and time consuming process. Traditionally this sort of analysis is carried out independently for any city of interest and must be repeated for a variety of representative atmospheric conditions in order to develop a good understanding of the potential costs and benefits of such strategies over time (e.g., cooling the urban climate generally saves energy in summer, but can increase energy consumption for heating in winter).

2. MOTIVATION

As discussed above, research conducted to date suggests that albedo and vegetation strategies can reduce peak summertime urban air temperatures with concomitant impacts on air quality and energy use. The magnitude of potential impacts, however, depends on a number of factors such as the size of the city and its underlying climate. Hence, there is a need to develop a useful screening tool to provide urban planners with qualitatively accurate assessments of various mitigation options. The challenge is to develop a tool that can easily be applied to any major U.S. city. Given the level of resources and computational effort required to model the effects of a specific mitigation strategy in detail for any one city, a streamlined modeling approach is needed. As a result the U.S. Environmental Protection Agency (EPA) commissioned a series of streamlined modeling studies (Taha and Sailor 1997; Akbari and Konopacki 2003; Sailor 2003) that laid the foundation for the development of this tool.

3. OVERVIEW OF METHODS

The Mitigation Impact Screening Tool (MIST) was developed to balance the need for a cost-effective and quick means of estimating performance of mitigation strategies in a wide range of cities and the requirement that the results from the tool be based on sound scientific methods. The general approach behind MIST involved first developing a full suite of detailed meteorological model simulations for a set of test cities. These 20 cities are listed in Table 1 along with descriptive data. The suite of simulations consisted of control runs for existing historical episodes as well as mitigation scenario runs for several different levels of albedo and/or vegetation mitigation. The atmospheric effects of mitigation strategies were then extrapolated to other cities through regression analysis. This process involved identifying the key characteristics that determine the magnitude of impact on the urban climate (e.g., population, urban area extent, latitude). The estimated local climatic effects of mitigation were then used as input to other models relating atmospheric conditions to the end points of interest – in this case, tropospheric ozone air quality and building energy consumption. The MIST tool automates the process of selecting a city and mitigation strategy for the investigation, extrapolates the impacts from the existing database of results from modeled cities, and summarizes the results for interpretation.

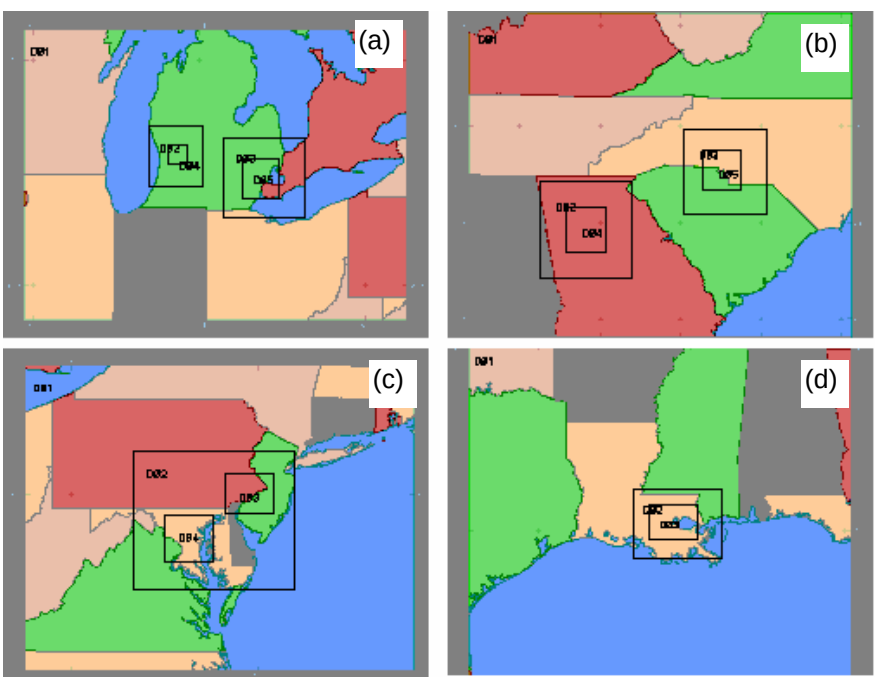


Figure 1. Example MM5 modeling domains with fine-grid nests centered over various cites: (a) Detroit and Grand Rapids MI; (b) Atlanta GA and Charlotte NC; (c) Washington DC and Baltimore MD; and (d) New Orleans and Baton Rouge LA (both within same inner nest).

Table 1. List of cities for which detailed meteorological modeling and subsequent statistical air quality modeling was performed. Results from these 20 cites form the basis of MIST.

City	State	Latitude	Longitude	Population (2000)	Area of MSA (km^2)
Atlanta	GA	33.65	84.42	4112198	16072
Bakersfield	CA	35.43	119.05	661645	21129
Baltimore	MD	39.18	76.67	2552994	8037
Baton Rouge	LA	30.53	91.15	602894	4349
Charlotte	NC	35.22	80.93	1499293	8908
Dallas	TX	32.90	97.03	5221801	24515
Detroit	MI	42.42	83.02	4441551	11209
Fresno	CA	36.77	119.72	922516	21153
Grand Rapids	MI	42.88	85.52	1088514	15007
Houston	TX	29.97	95.35	4177646	16329
Los Angeles	CA	33.93	118.40	16373645	91431
Louisville	KY	38.23	85.67	1025598	5435
New Orleans	LA	29.98	90.25	1337726	19041
Philadelphia	PA	39.88	75.25	5100931	10250
Phoenix	AZ	33.43	112.02	3251876	37793
Sacramento	CA	38.52	121.50	1628197	11097
San Diego	CA	32.73	117.17	2813833	11716
San Francisco	CA	37.62	122.38	1731183	4663
Tucson	AZ	32.12	110.93	843746	23789
Washington	DC	38.85	77.04	4923153	17914

Table 2. Default MM5 model parameters used in all atmospheric model simulations

Model Parameter	**Value(units)**	**Description and Notes**
Surface albedo	17, 15, 13 (%)	Residential, commercial/industrial, urban core
Surface roughness	35, 50, 125 (cm)	Residential, commercial/industrial, urban core
Surface moisture	10, 8, 5 (%)	Residential, commercial/industrial, urban core
Thermal inertia	2.5, 3.3, 2.4 (cal cm^{-2} K^{-1} $s^{-0.5}$)	Residential, commercial/industrial, urban core
Vertical levels	30	Variable vertical spacing with lowest level at approximately 20m, highest level extending to 10 km
Horizontal domains	3 nests	18km 6km, and 2km resolution, Mercator projection.
Boundary Layer Scheme	Blackadar	Determines exchange processes at surface
Cumulous scheme	Grell	Determines cloud formation and related processes
Radiation frequency	30 (min)	Frequency with which model evaluates radiation
Time step	45 (sec)	Time step for coarse domain. Scales with resolution for finer domains
FDDA	False	Four dimensional data assimilation turned off
IMPHYS	Simple ice model	Explicit moisture scheme
ICUPA	Grell	Grell cumulus scheme
Soil model (ISOIL)	1	5-layer soil model

4. ATMOSPHERIC MODELING

4.1. THE METEOROLOGICAL MODEL

The mesoscale atmospheric model used to assess city-scale atmospheric effects of mitigation strategies is version 3.4 of the MM5 model from the National Center for Atmospheric Research (Guo and Chen 1994; Civerolo *et al.* 2000; Grell *et al.* 2000). The MM5 is a prognostic model useful for multi-day simulations of domains with horizontal extent ranging from tens to thousands of kilometers. It allows for nesting of higher resolution domains, and uses a uniform horizontal grid structure with a terrain-following vertical coordinate. As implemented in this work the MM5 model consists of 4 preprocessor steps, a model integration (forecast) step, and post-processing analyses. The MM5 model and its preprocessors each have control files that specify a large number of simulation options, ranging from parameterization of exchange processes at the surface to parameterization of cloud processes. While it is common practice to optimize the selection and combination of physics options for the particular geographic location and weather pattern under investigation, the underlying goal of this work dictated the standardization of model options across all cities and episodes modeled.

4.2. DOMAIN DEFINITIONS

In all simulations we defined three levels of nests with resolutions of 18km, 6km, and 2km. The finest scale nests were centered over urban areas and in some cases a single simulation would include multiple 2km nests covering multiple cities within general proximity to one another. Figure 1 illustrates the typical nested domain structure. The land use data used to specify surface characteristics in all domains were from the MM5's default USGS land use data base. The spatial resolution of these data is 30 second (~0.9 km). Recent aerial photos were used to make modest refinements to the default land cover data to account for changes in physical extent of the urban areas. Furthermore, the original "urban" land use category from the USGS categorization scheme was refined to allow for three urban subcategories – residential, commercial/industrial, and urban core. Surface characteristics for these land uses were modified from the default USGS values to better reflect surface characteristic variation within urban areas.

As noted above, in running the MM5 there are a large number of simulation parameters that need to be defined. These include the time step, definition of vertical model levels, parameters defining how observations are used in defining boundary/initial conditions, frequency of radiation update, choice of boundary-layer scheme, cloud physics, and other parameters. To ensure uniform application of the MM5 for all domains we adopted a fixed set of default options. The most significant of these parameters are summarized in Table 2 along with the associated default values for the control simulations.

4.3. CONTROL SIMULATIONS

Baseline and mitigation scenarios were based on the fundamental set of model parameters discussed above. For the baseline simulation all runs were initialized at midnight GMT (00Z) of the first day. The simulations were integrated forward in time for at least 30 simulation hours, and results were analyzed after a 6 hour spin-up period. Initial simulations with longer spin-up periods did not significantly alter the analysis results. Most modeled episodes were two to four days in length. For these simulation domains (in the continental US), the initialization of 00Z (midnight GMT) corresponds to early evening of the previous day. A streamlined validation was performed where hourly temperature data from the nearest major airport weather station were compared with the near-surface air temperature predicted by the MM5 control simulations. Figure 2 illustrates typical model performance for multi-day simulations. As can be seen in this figure, the MM5 is capable of capturing general diurnal characteristics as well as multi-day warming or cooling periods. In general, predictions of maximum temperatures are more accurate than those of minimum temperatures. In an effort to capture key weather patterns contributing to poor air quality, multiple episodes (typically 2-4) were modeled for each of the 20 test cities. Figure 3 is a scatter plot of measured versus predicted air temperatures for all simulation hours for the Philadelphia domain. This figure represents 547 simulation hours over 9 separate simulation episodes averaging 60 hours each. The correlation exhibited in this figure is 0.89 and the root mean square error is 1.9 ^{o}C. These results are typical of all simulations conducted for all 20 test cities.

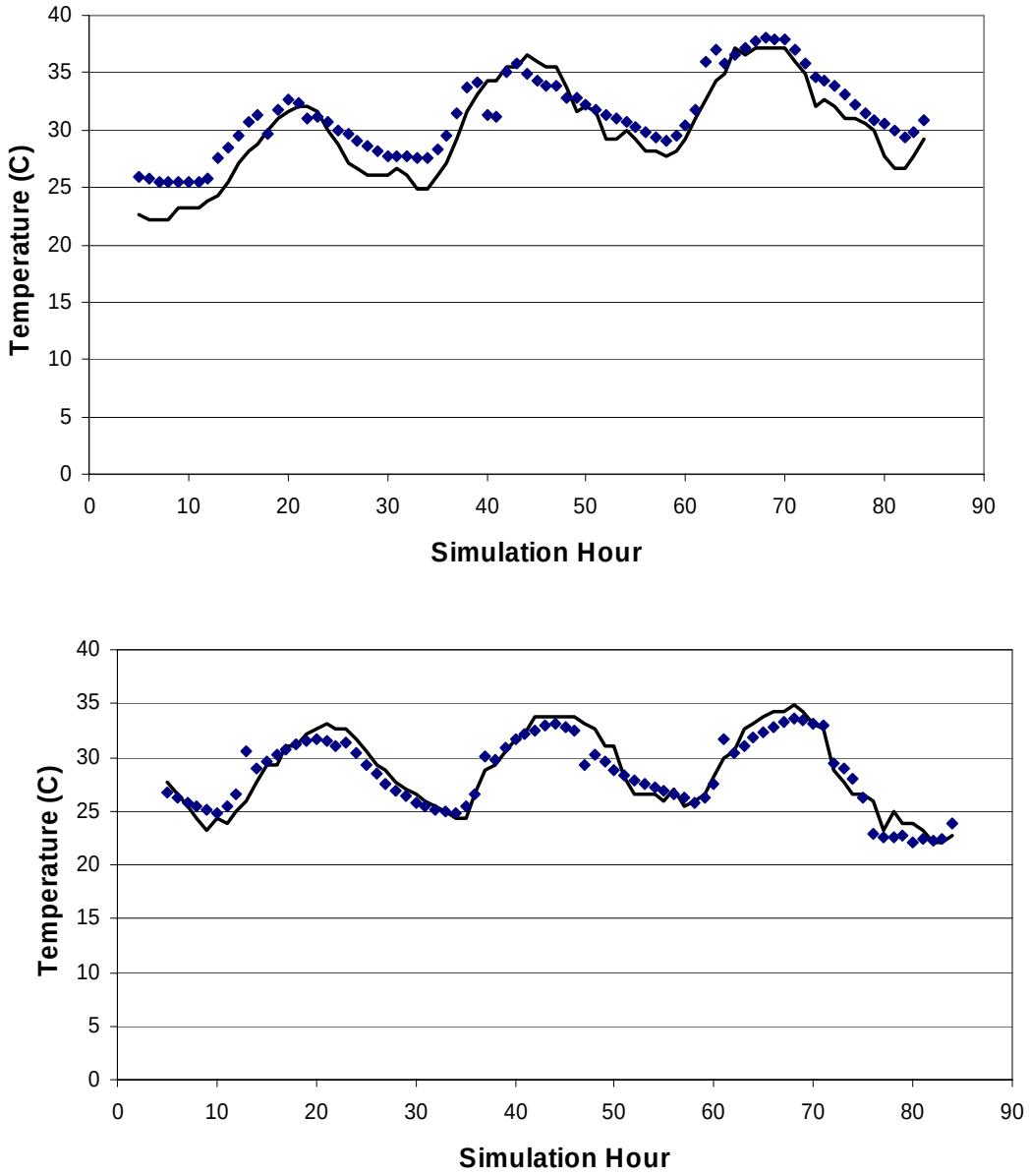


Figure 2. Typical meteorological model performance for multi-day simulations for Philadelphia. Simulations are initiated at 00 GMT on (a) July 3, 1999 and (b) July 26, 1999. Solid line is observed air temperature at Philadelphia International Airport (PHL) and symbols are the MM5 model predictions averaged over the urban grid cells corresponding to the city of Philadelphia.

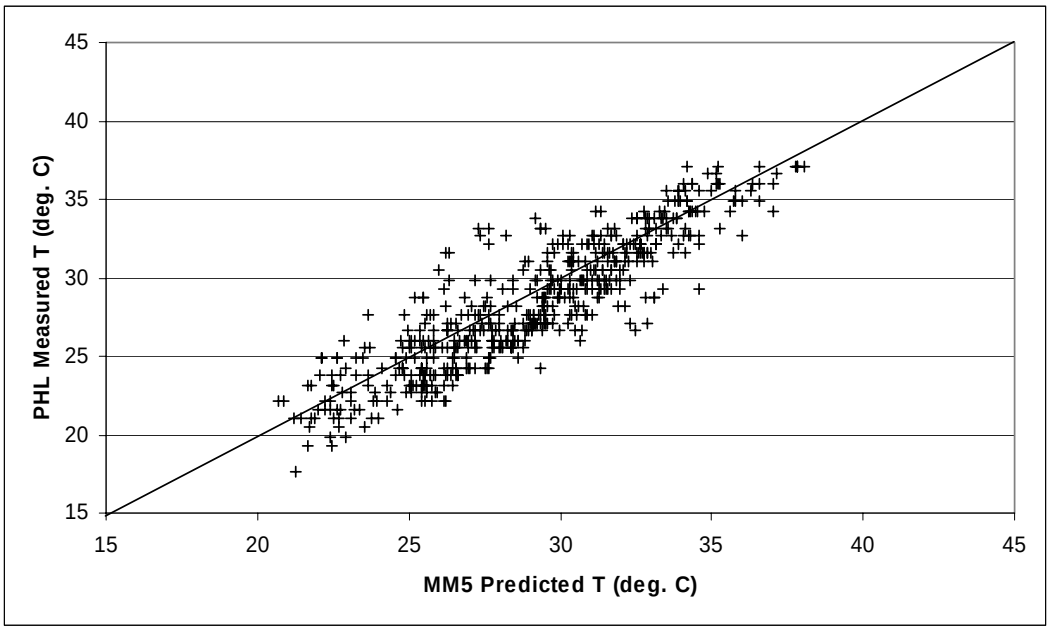


Figure 3. Scatter plot illustrating correlation between meteorological model output and corresponding airport weather station. Philadelphia as an example.

4.4. MITIGATION SIMULATIONS

After running the baseline simulations we modeled surface changes to represent various mitigation scenarios. To implement these strategies in the MM5 we altered the land use definition file to modify all urban cells. Mitigation scenarios were based on simple and uniform perturbations of surface characteristics for all urban (residential, commercial/industrial, urban core) grid cells. Mitigation scenarios included cases of 0.1 and 0.2 increase in vegetative cover and albedo (separately and simultaneously). This level of modification is consistent with estimates of achievable potential for modification from several urban fabric studies (Bretz *et al.* 1998; Akbari *et al.* 2001).

The albedo modification was implemented by directly modifying the albedo of each urban grid cell. This is possible because albedo is a fundamental parameter in the model. Vegetation, on the other hand, is not a fundamental parameter in the MM5 model. So it must be modeled through changes to other surrogate parameters. The approach we took was to assume that adding vegetative cover to an urban grid cell is equivalent to replacing part of the urban land in that grid cell by a vegetative land cover class considered to be representative of urban vegetation. The surface characteristics of the urban land use were then modified to reflect an appropriate weighting between those corresponding to an urban cell and those corresponding to a completely vegetated cell. The USGS land use category used as a surrogate for urban vegetation is the Deciduous Broadleaf category. This land use differs from the urban land use categories primarily in terms of albedo, moisture availability, roughness, and thermal inertia, with values of 0.16, 0.30, 0.5m, and 4.0 cal*cm^{-2}K^{-1}s$^{-0.5}$, respectively.

For any surface characteristic, P, the effect of a fractional increase in vegetative cover (f_{veg}) was modeled according to:

$$P_{new} = P_{urban} \cdot \left(1 - f_{veg}\right) + f_{veg} \cdot P_{veg} \,. \qquad (1)$$

Accordingly, for f_{veg}=0 the grid cell is assigned purely urban characteristics (P_{urban}), and as f_{veg} approaches 1.0 the surface characteristics become those of completely vegetated land (P_{veg}). As an example, consider an urban grid cell for which we wish to represent a 0.20 increase in vegetative cover. The initial urban moisture availability for this cell would be 0.10. The moisture availability of a completely vegetated cell

would be 0.30. The moisture availability for the cell after an increase of 0.2 in vegetative cover would correspond to:

$$M_{new} = 0.10 \cdot (1 - 0.20) + 0.20 \cdot 0.30 = 0.14 \quad (2)$$

Upon completion of all meteorological model simulations the near-surface hourly air temperature averaged over each city was extracted from each control and mitigation run. The corresponding air temperature perturbation was then calculated for use in estimating air quality and energy impacts of the mitigation strategies.

4.5. LINKING METEOROLOGY TO OZONE AIR QUALITY IMPACTS

The traditional approach to modeling the impact of mitigation measures on ozone is to select one or several historical episodes for which ambient air quality standards were violated and model these episodes using the historical land use/cover and then using a set of modified surface characteristics (e.g., (Taha and Sailor 1997; Taha *et al.* 1998). The modeling includes both a mesoscale meteorological component and a photochemical component. The use of physically-based models in such a situation is generally desirable and under ideal circumstances should result in good predictive power. Furthermore, this approach has the support of the regulatory community. At the same time, there is concern that these models (with their numerous input parameters) can easily be overfit for a particular simulation domain and episode, or even for several episodes. This approach is also prohibitively resource intensive to implement for such a large number of test cities and episodes. For the purposes of this study a sophisticated but easily implemented statistical approach was needed. This streamlined air quality modeling approach is intended to identify the order-of-magnitude air quality impacts associated with a particular mitigation strategy.

The Tree Structured Regression (TSR) classification method represents a suitable compromise between accuracy and simplicity. TSR builds a binary-tree-like model with nodes (Breiman, 1984). Originally all the data points in the learning sample reside in a single root node. So if there are 500 historical days for use in model training the root node would contain the corresponding set of 500 data vectors. Each data vector consists of the dependent variable (e.g., ozone concentration), and a number of weather-related independent predictor variables. By continuously posing and answering classification questions, every data point flows from the root node down to the next level of nodes. The classification questions are binary and are constructed to maximize the difference of predicted ozone in the two descendant nodes (e.g. one node contains data vectors for days with relatively high ozone and the other has days with relatively low ozone). It is important to note, however, that this partitioning of the data vectors is based on values of the weather-related parameters, not the actual values of ozone. Finally each data vector (day of data) attaches to a terminal node. All the nodes are formed automatically during the process. The key elements of TSR involve developing the questions (splitting rule), determining when the tree is large enough (stopping rule), and deciding how to characterize data points that reside in any terminal node (assigning rule).

Within each terminal node a multiple linear regression (MLR) was used to predict peak ozone concentrations for the corresponding weather pattern. The EPA has two metrics of ozone air quality. First they consider maximum ozone concentrations in any single hour (1-hr ozone). They also consider the maximum average ozone concentrations over any consecutive 8-hour period (8-hr ozone). Ozone air quality is considered to be unhealthy when the 1-hr and 8-hr values exceed 120 ppb and 80 ppb, respectively. Hence, our analysis developed TSR Ozone models for both the 1-hr and 8-hr standards.

The predictor variables we chose are largely based on the recommendations from existing EPA guidelines. Our models generally started with 10 predictors– day type, precipitation, pressure, previous day ozone, average relative humidity, average temperature, maximum temperature, average wind speed, temperature at 850 hpa level (T850), and geopotential height at 500 hpa level (HT500). All average variables were hourly observations averaged over the day time period from 8:00 am to 7:00 pm (local time) to correspond to the time frame during which ozone precursors are emitted and converted to ozone via the complex photochemical reaction chain. Cloud cover data for many of the cities are incomplete and so were not included in our final analysis. Our “day type” variable replaced the day of week variable suggested in EPA guidelines for ozone modeling. The day type variable has 2 possible values, work day or non-workday. The main point of this parameter is to separate out days that may have more substantial emissions (weekdays). As it

turns out the TSR methodology consistently resulted in models for which temperature and humidity variables dominated the tree structure. Temperature is important as it is highly correlated to emissions rates from biogenic and anthropogenic sources. Temperature is also an important parameter due to its role in determining rate constants for many important atmospheric chemistry reactions that are part of the complex ozone formation/destruction cycle. Humidity is important in affecting ozone in part due to its role in pollutant removal by vegetation and also the way in which water vapor affects several important reactions in the photochemical cycle. Commercial software (Cubist – www.rulequest.com) and 5 years of historical data were used to generate ozone models for each of the study cities. As the ozone season in the U.S. is generally considered to occur within the months of April to October we restricted our model development to use training data from only this portion of the year. The required ozone concentration data were obtained from the EPA AIRS database (www.epa.gov/air/data). The weather data were obtained from the National Climatic Data Center's Surface Airways database (www.ncdc.noaa.gov). A sample tree is illustrated in Figure 4. In this figure there are 1127 training points (days of data) in the root node. The first binary question that resulted from the optimization process is "Is RH_avg < 68.7%?" As indicated in the figure 848 days satisfied this criterion. Of these only 123 days also had average temperatures above 26.7 ^{o}C and RH less than 51.6%. In this TSR model for Atlanta the two weather patterns that are most important for ozone are the bottom two nodes in this figure. The corresponding average 1hour peak ozone values in these weather patterns (shown in bold under the corresponding node) are 92.1 ppb and 76.9 ppb respectively. Within each of these terminal nodes an additional multiple linear regression was performed to generate a model of how ozone responds to changes in weather parameters. With TSR models of ozone concentrations established for any city it is relatively straightforward to replace the original training data with perturbed weather corresponding to any mitigation strategy. The result is a rough estimate of the changes in ozone concentrations that could be expected for various levels of urban heat island mitigation. As temperature perturbations are the dominant factor affecting the response of ozone concentrations to mitigation strategies we defined two sensitivity parameters relating changes in ozone concentration to changes in mean air temperature. One factor (B_1hr) was calculated for the 1-hour ozone models and a second factor (B_8hr) for the 8-hour ozone models. Each factor has units of ppb per degree C. Since ozone concentrations generally increase with temperature these factors are positive and are generally in the range of 1 to 4 ppb per degree C.

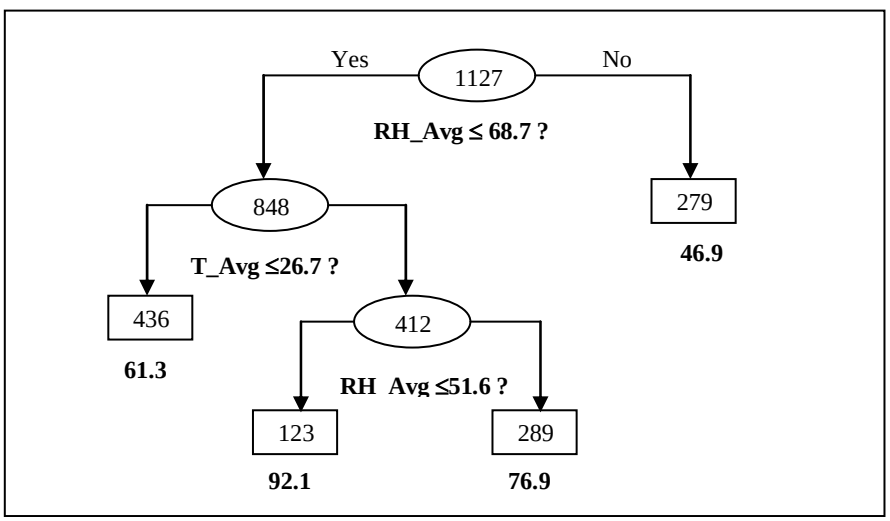


Figure 4. Sample tree for 1hour ozone in Atlanta (avg. over 12 stations). Ovals and boxes represent intermediate and terminal nodes, respectively. Numbers within ovals/boxes indicate number of data points satisfying a particular set of conditions. Numbers below terminal nodes indicate the corresponding mean ozone concentrations.

4.6. LINKING METEOROLOGY TO ENERGY IMPACTS

While all ozone impact modeling is temperature-based, energy models are typically developed in terms of the relationship between consumption and the derived parameters of Cooling Degree Days (CDD) and Heating Degree Days (HDD). These parameters reflect the demand for air conditioning and heating, respectively. In a plot of temperature vs. time CDD is the area that is both below the observed air temperature and above a threshold constant (usually 65 F). HDD is the corresponding area below the threshold constant. Using actual hourly meteteorological data from the 20 focus cities we calculated the nominal impact of a 1 ^{0}C temperature reduction (assumed uniform throughout the day) on both CDD and HDD. The results were regressed against CDD and HDD to determine functional relationshis of the form:

$$\Delta CDD = -0.4699 + 1.06E\text{-}04 * CDD + 3.39E\text{-}05 * HDD \quad (R=0.91) \qquad (3)$$

$$\Delta HDD = 0.3041 - 3.74E\text{-}05 * CDD - 3.31E\text{-}05 * HDD \quad (R=0.92) \qquad (4)$$

The values of ΔCDD and ΔHDD then represent the fractional change in degree days associated with a 1.0 ^{o}C reduction in air temperature. For example, a value of ΔCDD= - 0.15 implies that a 1.0 ^{0}C reduction in air temperature will reduce cooling degree days by 15%. For the purposes of MIST it was assumed that for temperature perturbations near 1.0 ^{o}C the impact on degree days is approximately linear. That is, ΔCDD and ΔHDD obtained from the above regressions can simply be multiplied by ΔT. Scatter plots for these regressions are given in Figure 5.

The energy models themselves were obtained from an analysis conducted by Lawrence Berkeley National Laboratory (Akbari and Konopacki 2003). For each city of their analysis specific building archetypes were modeled using the DoE-2 building energy analysis software. As building codes and insulation levels have evolved over time, LBNL presents results for both "pre-1980" and "post-1980" buildings". By modifying both the building envelope definition and the "typical meteorological year" weather data LBNL was able to simulate both the direct and the indirect effects of increasing building albedo and vegetative cover. By combining results from meteorological simulations and building energy simulations they developed estimates of how a particular mitigation strategy would impact energy consumption and peak power for residential, office, and retail space on a per 1000 sq. ft roof area basis. The LBNL meteorological simulations were developed using the same MM5 model and similar modeling techniques to those presented here. The LBNL modeling focused on buildings in a small set of cities. To apply these results across a wider range of cities they conducted two classification analyses to relate energy impacts to either CDD or HDD. They defined 11 CDD groups and 15 HDD groups to represent the impacts across different climates. Thus, the energy impacts can be estimated using either the CDD similarity or the HDD similarity approach. In all cases the energy modeling of mitigation strategies took into account both the energy savings in summer and the increased energy usage in winter.

5. SOFTWARE IMPLEMENTATION

5.1. MIST STRUCTURE

The Mitigation Impact Screening Tool (MIST) is intended to provide qualitatively accurate assessments of the likely impacts of heat island mitigation strategies averaged at the city-scale. All results presented in this tool were obtained using the state-of-the-science modeling approaches discussed above. Nevertheless, the required assumptions and approximations dictate that the results presented by MIST are qualitative in nature.

The mitigation strategies investigated include increasing urban albedo and/or increasing urban vegetative cover. MIST also allows investigation of a user-defined average temperature reduction and produces estimates of the resulting impacts on ozone and energy consumption.

There are three basic steps involved in running MIST: (1) Select the city to model; (2) define the mitigation strategy to test; and (3) estimate impacts on meteorology, air quality, and energy. The software interface is organized around these steps with corresponding user-selectable tabs.

5.2. CITY SELECTION

Data necessary to run the MIST code are available for approximately 240 major cities throughout the US. For a subset of 20 cities the input data are complete. For the remaining cities the MIST code must make some form of

interpolation/curve-fit as discussed in the corresponding sections on modeling of impacts. Figure 6 shows a screenshot of the city selection portion of MIST. The user simply scrolls down the list of states and corresponding cities and clicks on the city of interest. The advanced user has the option of editing any or all of the city-specific model input parameters. When the city selection and any parameter edits are complete the user clicks on the “Next” button to move onto the mitigation strategy component of MIST.

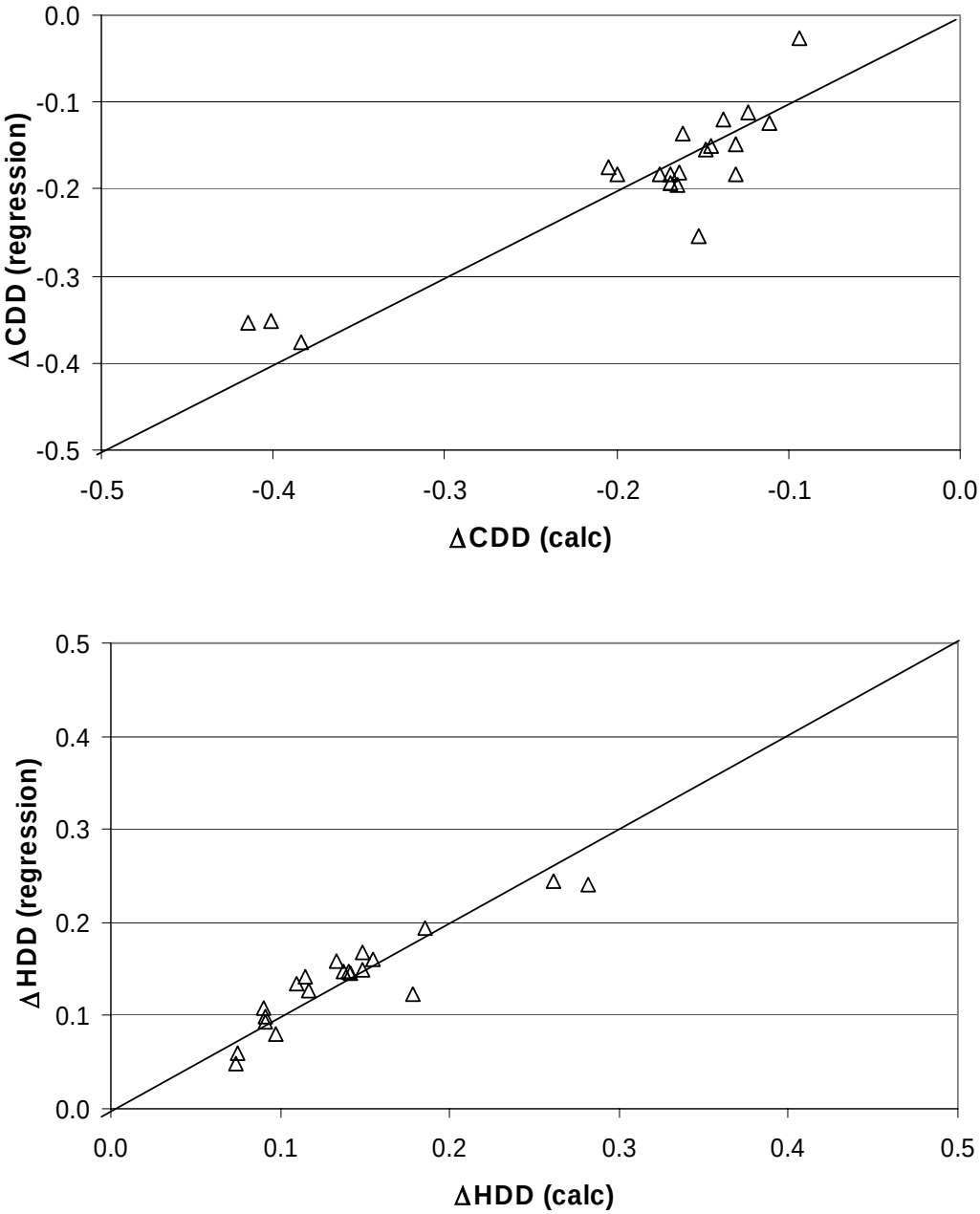


Figure 5. Scatter plots for sensitivity of annual CDD and HDD to a 1 degree C reduction in air temperature. Regression results plotted against sensitivity calculated directly from hourly temperature data.

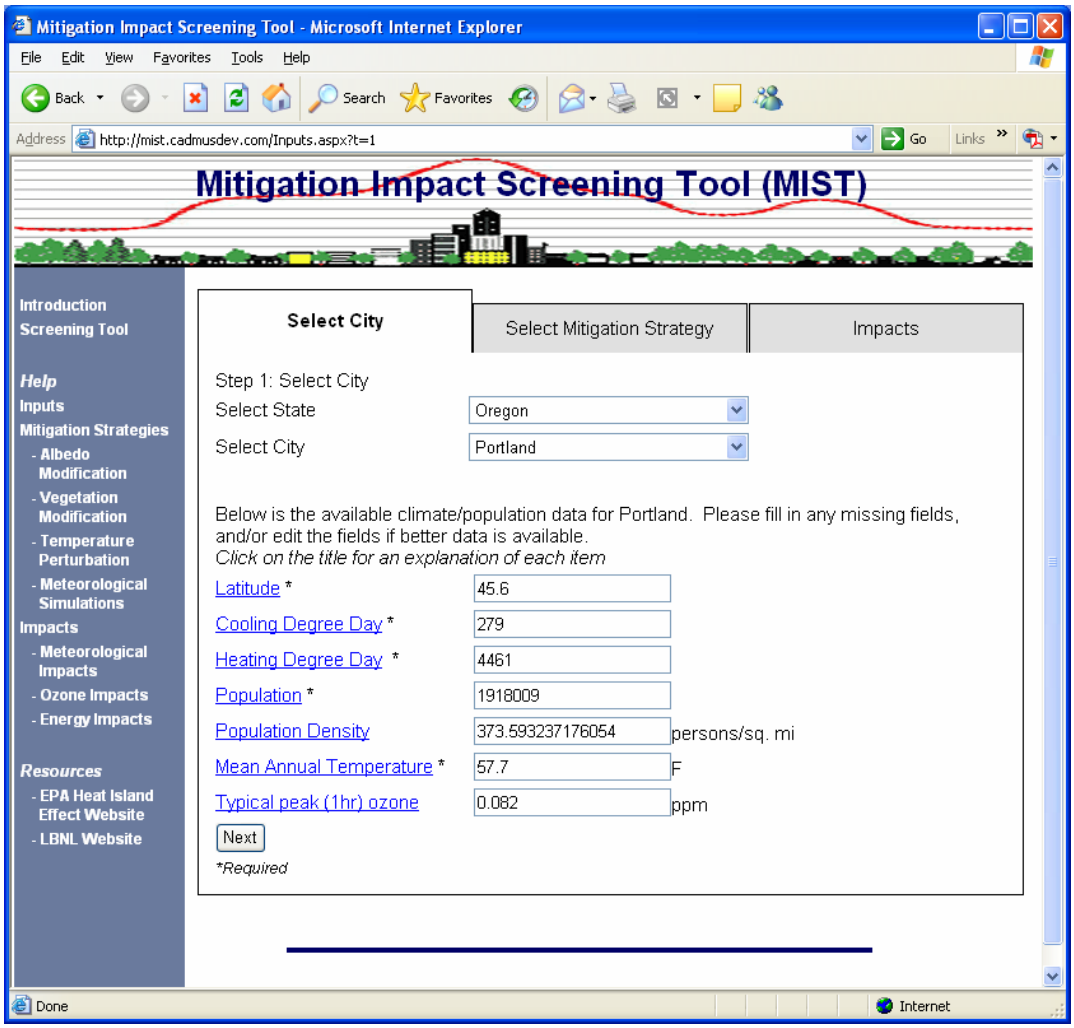


Figure 6. Screenshot of the city-selection portion of MIST.

5.3. MITIGATION STRATEGY

The user may select a vegetation, albedo, or combined mitigation strategy to model (Fig. 7). In all cases the mitigation level represents a fractional increase over the entire city, and the distribution of the change is assumed to be uniform over all urban areas. For example, suppose the city surface is 40% rooftop, 25% paved surface, and 35% vegetated surface. If the user specifies an increase of 0.1 in vegetative fraction, this corresponds to the assumption that the total vegetative cover of the city increases uniformly from 35% to 45%. Likewise a specified increase of 0.10 in city albedo is assumed to be applied uniformly over the entire city. In practice, of course, this could be accomplished in many ways. For example, consider the case where the urban albedo is increased by 0.10 by modifying *only* rooftops. Since rooftops account for only 40% of the surface area in this example one would need to increase rooftop albedo by 0.25 to affect a city-wide average increase of albedo of 0.10 (ie., 0.25*0.40= 0.10). The MIST code is not capable of discerning spatial differences in application of either mitigation strategy, however, so all mitigation is assumed uniform over the city. The MIST code limits the range to $-0.5 < \Delta < 0.5$ for changes in either albedo or vegetation. This is primarily to limit the chance of entry errors (e.g., 10 rather than 0.10). In either case the level of mitigation specified by the user is converted directly to projected changes in near-

surface air temperatures using results from mesoscale atmospheric modeling studies, as discussed in section 5.4.1. Alternatively the user may simply input a uniform temperature perturbation. This option directly implements a change in near-surface air temperature, which is assumed uniform in space and time.

In this component of MIST the advanced user is again able to modify model parameters. After selecting a mitigation strategy the user clicks on the "Next" button to move onto the impacts component of MIST.

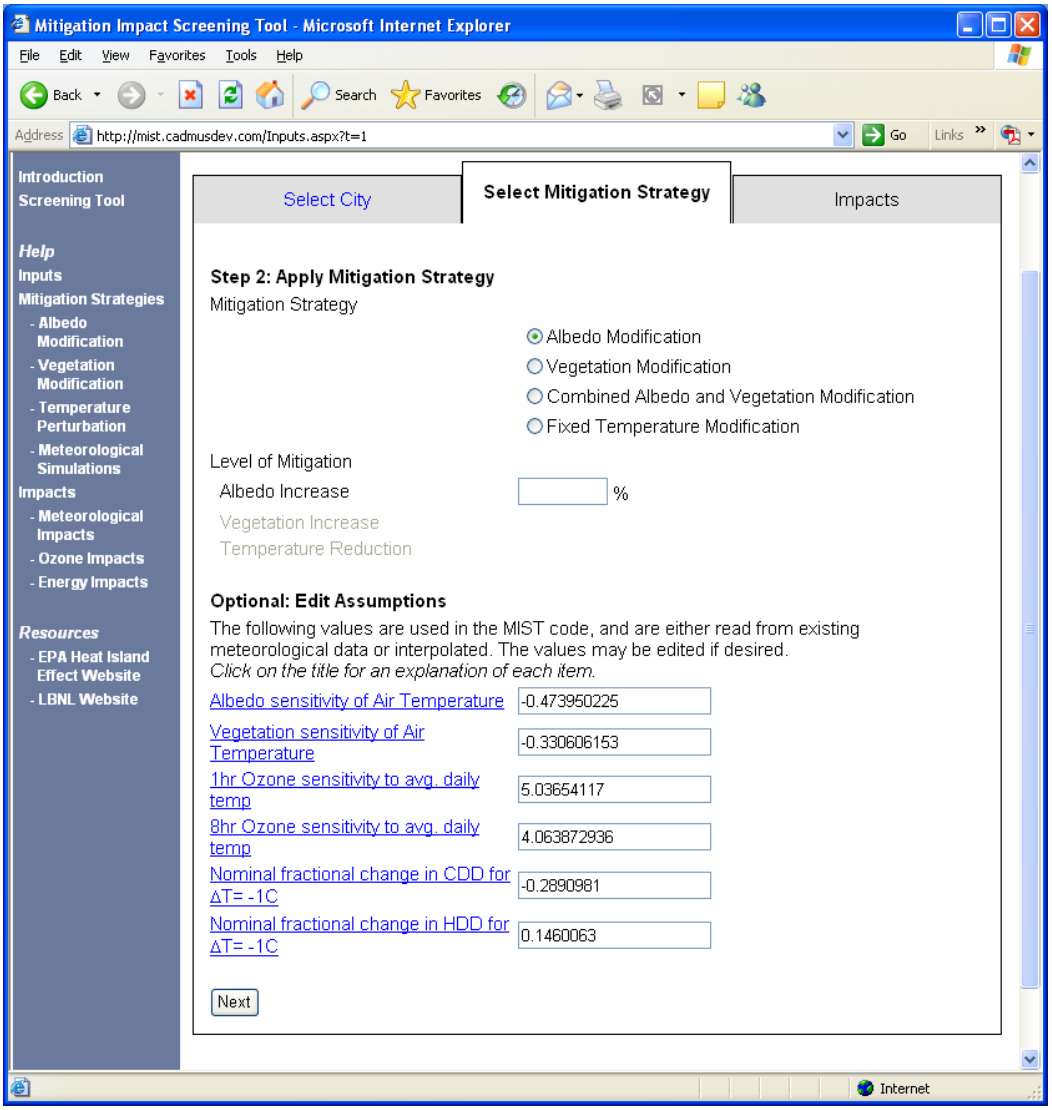


Figure 7. Mitigation strategy options in MIST

5.4. IMPACTS ESTIMATION

Urban heat island mitigation strategies can impact the urban environment in two distinct ways: directly and indirectly. The direct impacts of mitigation strategies are those that result from direct modification of the surface energy balance of buildings. For example, when a rooftop reflectivity (albedo) is increased the roof remains cooler under the hot summer sun and as a result the building's cooling load (and air conditioning energy consumption) is reduced. In addition, the implementation of heat island mitigation strategies can have an indirect impact on the entire city. For example, when rooftops are cooled through the implementation of a high albedo strategy they convect less heat to the air that flows over them. The result is a city-scale cooling of near-surface air temperatures. If the mitigation strategy has sufficient spatial extent

this indirect cooling can impact city-scale temperatures, air quality, and energy consumption. This effect has been demonstrated in regional scale simulations of various mitigation strategies (Sailor 2003; Taha 2003). In MIST the indirect impacts on ozone and the total (direct plus indirect) impacts on energy consumption are estimated using the methods presented above. These estimates are summarized in the impacts estimation section of MIST (shown in Fig. 8). More detailed output is written to a results file that the user can download or print by clicking a single button. A sample of this detailed output file for a 0.2 increase in albedo is given in fig. 9 for the city of Akron, Ohio.

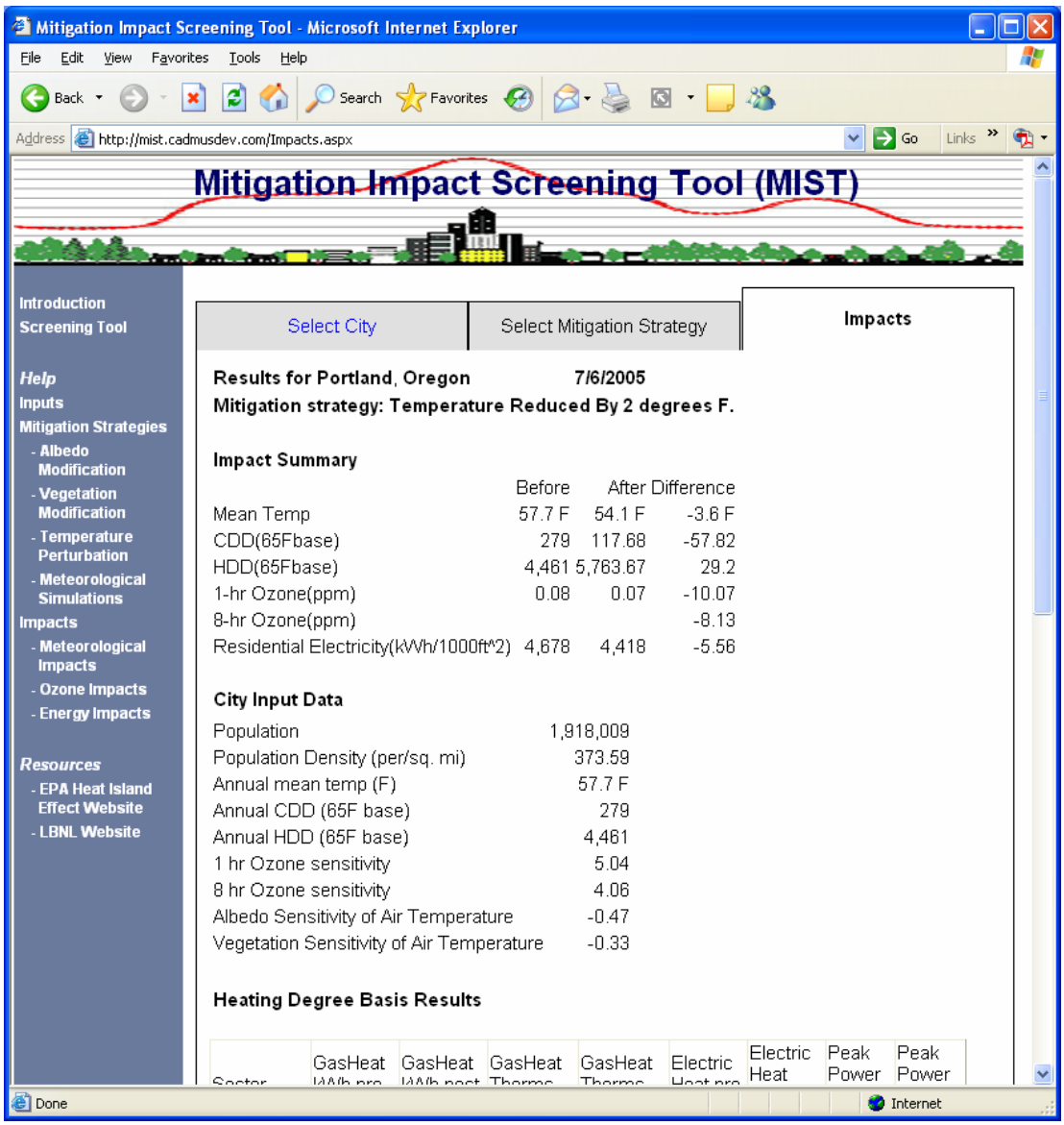


Figure 8. Impact summary section of MIST.

5.4.1. METEOROLOGICAL IMPACTS

Results from meteorological simulations in which the albedo and/or vegetation of cities was modified were used to explicitly provide estimates of the temperature impacts of surface characteristic perturbations (S_alb and S_veg) for the study cities. Each sensitivity parameter represents the change in temperature in degrees C for a 0.1 increase in albedo or vegetative cover. Results for other cities are extrapolated from this set. Six city-specific variables – population, physical area, population

density (population/area), latitude, and underlying climate as measured by cooling and heating degree days – were considered for this extrapolation process. The population of the Metropolitan Statistical Area (MSA) was found to be the single most statistically significant determinant of S_alb and S_veg for the modeled cities. Figure 10 shows the resulting regressions which are of the form:

S_alb = - 2.8E-8 * Population - 0.389 (R=0.67) (5)

S_veg = - 1.6E-8 * Population - 0.279 (R=0.69) (6)

The uncertainty in the S_alb and S_veg coefficients is estimated (using +/- 2σ) to be 0.24 and 0.13, respectively.
As weather patterns corresponding to representative bad air quality days were the focus of all meteorological modeling, the impacts on meteorology are inherently biased toward summertime impacts. The impacts for the small suite of simulations conducted for any individual city are then assumed to be uniform spatially and throughout the year. For the ozone impacts analysis this assumption is reasonable as peak ozone occurs during summer months. For the energy impacts analysis, however, the wintertime heating costs of mitigation strategies are likely to be overestimated by the present analysis. This is because albedo or vegetation modifications have the greatest impact in summer months when the solar forcing is the highest. So, assuming that the mitigation strategy will have a constant year-round impact on air temperature will lead to a conservative estimate of energy savings. In either case, however, it must be stressed that all simulations were conducted using a streamlined modeling approach, where the goal was to obtain rough estimates of the implications of heat island mitigation for urban air temperatures.

5.4.2. OZONE IMPACTS

The ozone sensitivity factors introduced above, B_1hr and B_8hr are different for different cities. While it is reasonable to suspect that their values will be influenced by city size and underlying climate a multiple linear regression analysis for the 20 test cities revealed the best two parameter models are those involving latitude and MSA population:

B_1hr = -6.02 + 0.237 * Latitude + 1.30E-7 * Population (R=0.76) (7)

B_8hr = -5.21 + 0.199 * Latitude + 1.04E-7 * Population (R=0.74) (8)

Scatter plots comparing this regression to the actual TSR model results for the 20 cities are given in Fig. 11. The estimated uncertainties in B_1hr and B_8hr (based on 2σ) are 0.4 and 0.3 ppb per degree C, respectively.
MIST estimates ozone impacts of mitigation strategies by combining the estimated air temperature impacts with the ozone sensitivity factors. As an example, Akron, Ohio (latitude 40.92 degrees, MSA population 694,960) is not among the cities directly modeled for this study. So, the temperature impact of a 0.2 increase in albedo for Akron would be estimated as -0.82 ^{o}C using eqn. 5. The corresponding 1-hr ozone sensitivity would be 3.8 ppb per degree C (using eqn. 7). Hence MIST would project that a 0.2 increase in the albedo of Akron would reduce 1-hr ozone peaks by an average of 3.2 ppb.

5.4.3. ENERGY IMPACTS

As noted above a detailed description of the energy models implemented in MIST can be found in (Akbari and Konopacki 2003). The energy portion of the MIST output file summarizes current and estimated changes in energy consumption (and peak consumption) for prototypical residential (res), office (off), and retail (ret) buildings for both pre 1980 and post 1980 construction. Natural gas (Therms) and Electricity (kWh) data are presented in terms of consumption per 1000 sq. ft of roof area. The energy results presented in the summary portion of the impacts section of MIST summarize just the residential (post 1980 construction) results before and after the implementation of a mitigation strategy as a general indicator of the magnitude of energy impacts.
All meteorological simulations were conducted with a focus on summertime impacts of mitigation strategies. As a result, the analysis of winter-time impacts of mitigation strategies on energy (heating demand) are likely to be less accurate. Specifically, we anticipate that MIST overestimates the wintertime air temperature reductions associated with mitigation strategies. The result of this is an overestimate of the wintertime heating penalty associated with mitigation strategies. Hence, this assumption leads to a conservative estimate of the annualized energy savings.

MIST (v1.1) for Akron, OH. Latitude: 40.92, Population: 694960

Heat Island mitigation analysis performed: 9/26/2005, 2:29:53 PM

MODEL PARAMETERS (see detailed help file for description)

B_1hr = 3.77 B_8hr = 3.01

S_alb = -0.41 S_veg = -0.29

MITIGATION OPTIONS

Albedo Increased by 0.2

SUMMARY WEATHER DATA:	Before Mitigation	After Mitigation
Typical Annual CDD (65F base)	614	489 +/- 24.
Typical Annual HDD (65F base)	6201	6694 +/- 335.
Annual Mean Temperature (F)	55.2	53.3 +/- 0.9

ENERGY RESULTS

Estimated impacts are in terms of energy (kWh) per 1000 sq. ft. of roof area.

BASELINE and SAVINGS data are presented for both OLDER and NEWER buildings.

ESTIMATED BASELINE ENERGY CONSUMPTION FOR OLDER (pre 1980) BUILDINGS

SECTOR	GAS HEATED BLDGS.		ELECTRIC-HEAT BLDGS.	PEAK POWER
	Elect(kWh)	Gas(Therms)	(kWh)	(Watts)
Res.	1990 to 2045	978 to 1025	17665 to 18006	3444 to 3454
Office	7796 to 8069	418 to 434	13832 to 13963	6878 to 6966
Retail	7918 to 8192	247 to 255	11493 to 11716	4836 to 4861

ESTIMATED BASELINE ENERGY CONSUMPTION FOR NEWER (post 1980) BUILDINGS

SECTOR	GAS HEATED BLDGS.		ELECTRIC-HEAT BLDGS.	PEAK POWER
	Elect(kWh)	Gas(Therms)	(kWh)	(Watts)
Res.	945 to 978	436 to 456	7819 to 7952	1829 to 1844
Office	3963 to 4075	174 to 181	6455 to 6532	3800 to 3839
Retail	3492 to 3601	58 to 59	4353 to 4500	2395 to 2401

Figure 9. Sample detailed output file for a 0.2 increase in albedo for the city of Akron, Ohio.

ESTIMATED TYPICAL ENERGY SAVINGS FOR OLDER (pre 1980) BUILDINGS

(negative values represent increase in consumption)

SECTOR	GAS HEATED BLDGS.		ELECTRIC-HEAT BLDGS.	PEAK POWER
	Elect(kWh)	Gas(Therms)	(kWh)	(Watts)
Res.	313 to 329	-27 to -27	-49 to 10	380 to 401
Office	698 to 698	-8 to -8	591 to 593	443 to 445
Retail	677 to 687	-5 to -5	626 to 637	296 to 298
Res.	~ 16 %	~ -3 %	~ 0 %	~ 11 %
Office	~ 9 %	~ -2 %	~ 4 %	~ 6 %
Retail	~ 8 %	~ -2 %	~ 5 %	~ 6 %

ESTIMATED TYPICAL ENERGY SAVINGS FOR NEWER (post 1980) BUILDINGS

(negative values represent increase in consumption)

SECTOR	GAS HEATED BLDGS.		ELECTRIC-HEAT BLDGS.	PEAK POWER
	Elect(kWh)	Gas(Therms)	(kWh)	(Watts)
Res.	135 to 145	-13 to -12	26 to 39	186 to 197
Office	251 to 254	-6 to -5	175 to 184	195 to 201
Retail	222 to 228	-3 to -3	176 to 182	109 to 112
Res.	~ 15 %	~ -3 %	~ 0 %	~ 10 %
Office	~ 6 %	~ -3 %	~ 3 %	~ 5 %
Retail	~ 6 %	~ -5 %	~ 4 %	~ 5 %

OZONE RESULTS

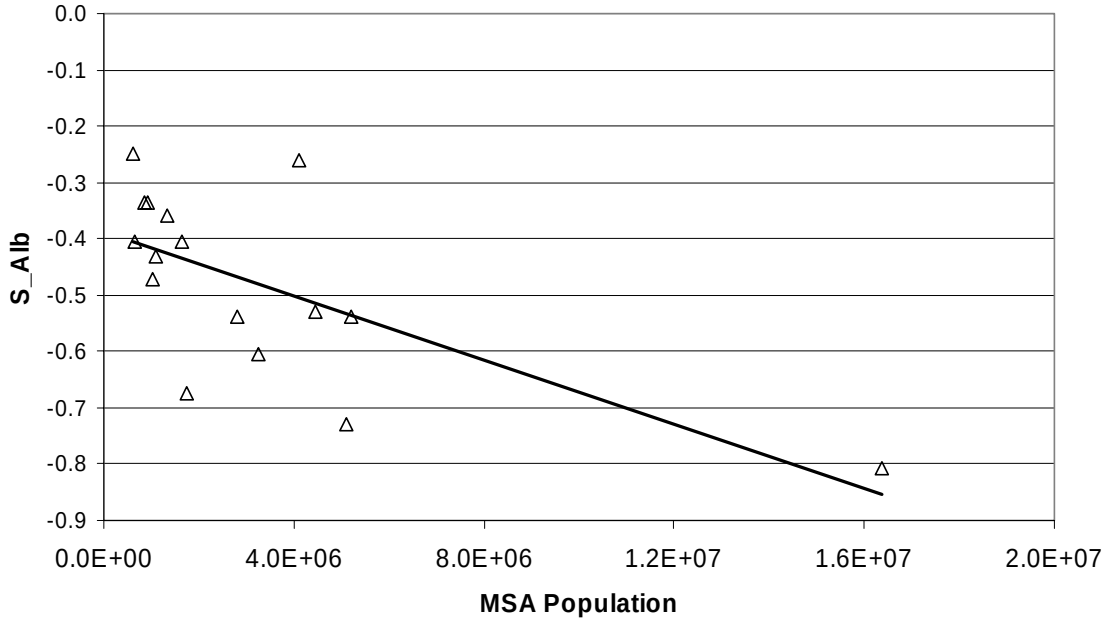
Typical maximum (1-hour) ozone concentrations: 119. (ppb)

Projected change in maximum 1-hour ozone concentrations: -5.8 to -2.1 (ppb)

Projected change in maximum 8-hour ozone concentrations: -4.6 to -1.7 (ppb)

Figure 9 continued.

(a)



(b)

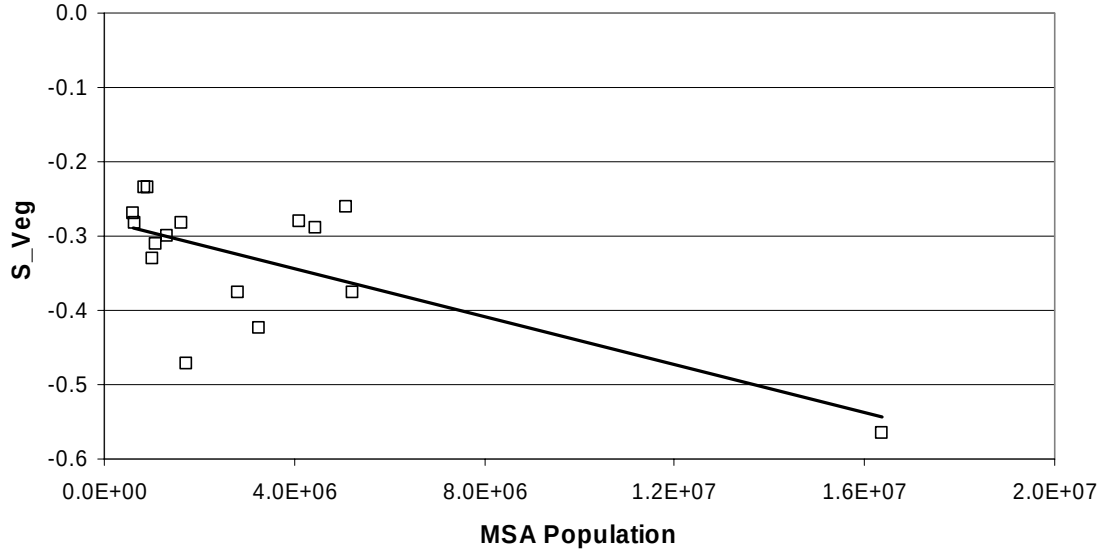
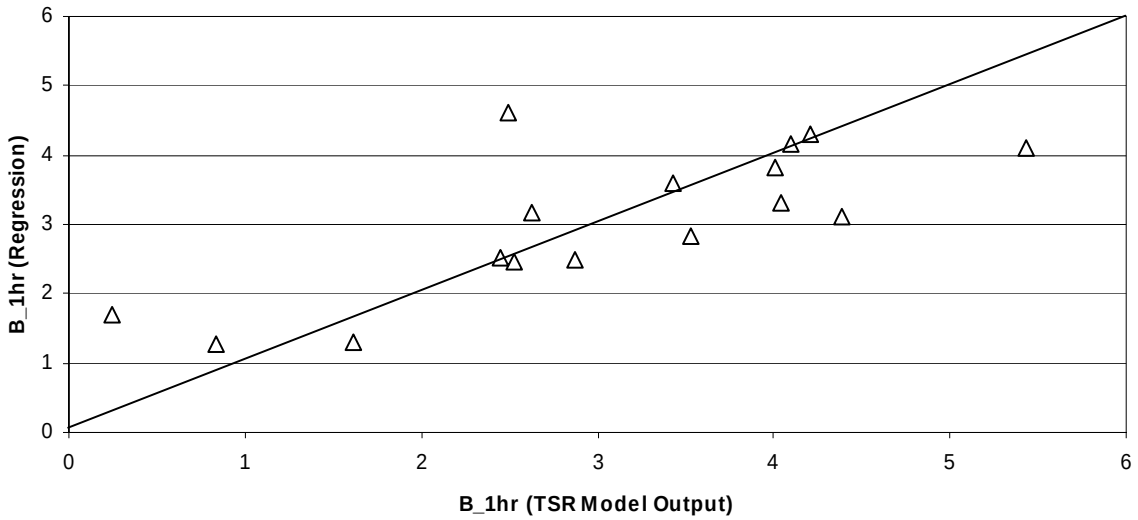


Figure 10. Scatter plots of mitigation strategy sensitivity parameters (a) S_alb and (b) S_veg plotted against metropolitan population. Solid lines represent regressions through the data (eqns. 5 and 6). Units of S_alb and S_veg are degrees C per 0.1 change in albedo and vegetation, respectively.

(a)



(b)

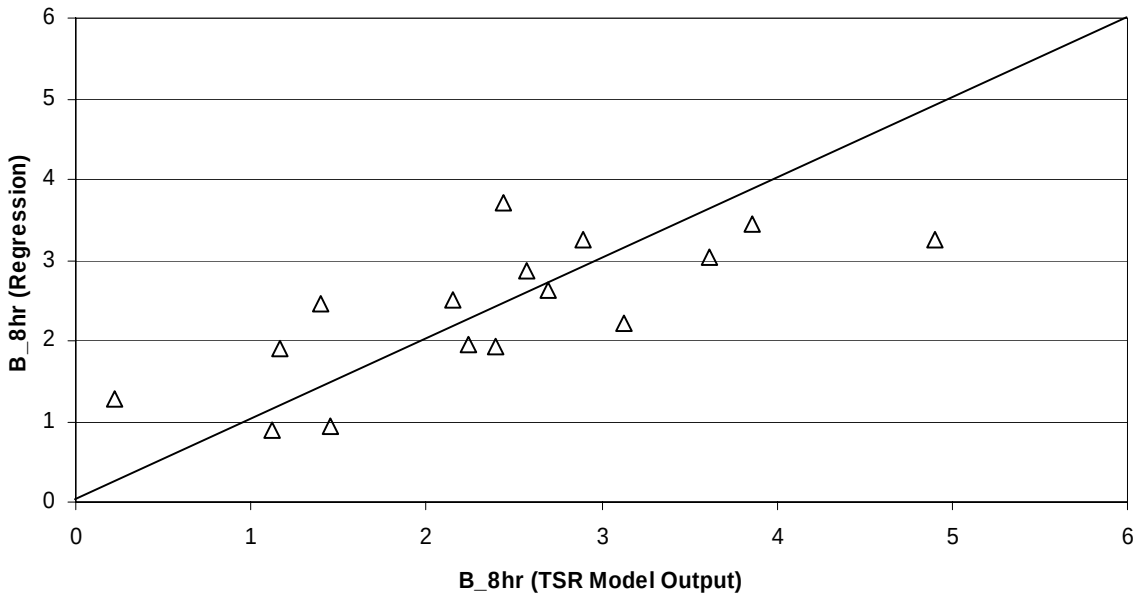


Figure 11. Scatter plots comparing TSR-predicted ozone sensitivity factors to results from multiple linear regression curve fits (see eqns. 7 and 8). Units are ppb per degree C.

6. CONCLUSIONS

In response to the need of urban planners for an easy-to-use screening tool to estimate the potential impacts of urban heat island mitigation strategies on their cities we have developed the Mitigation Impact Screening Tool (MIST). This software tool is based on streamlined mesoscale atmospheric modeling for the test cities combined with statistical models relating weather parameters to ozone and physically-based computer models of building energy consumption. MIST allows for a reasonably accurate extrapolation of these results to a wide range of cities. The end result is a screening tool that can be used as an initial quantification of the possible benefits of heat island mitigation. Given the significant number of assumptions, approximations, and extrapolations used in the software development and implementation process, MIST should not be used as the basis for regulatory decision-making. We also recommend that any initial screening be followed by a more detailed analysis using traditional methods (e.g., detailed meteorological and photochemical modeling).

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