Final Report

DEVELOPMENT AND IMPLEMENTATION OF A HOMOLOGY MAPPING TECHNIQUE TO AID THE SELECTION OF CITIES FOR MODELING OF THE EFFECTS OF URBAN HEAT ISLAND MITIGATION MEASURES ON OZONE AIR QUALITY

SYSAPP-01-008

31 January 2001

Prepared for

Mr. Edgar Mercado
Global Programs Division
U.S. Environmental Protection Agency
Ariel Rios Building (6205J)
1200 Pennsylvania Avenue, NW
Washington, D.C. 20460

Prepared by

Sharon G. Douglas
A. Belle Hudischewskyj
Jeffrey R. Lundgren
ICF Consulting/
Systems Applications International, Inc.
101 Lucas Valley Road
San Rafael, California 94903

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1 INTRODUCTION

This report summarizes the application of a homology mapping technique to aid the selection of cities for photochemical modeling – the purpose of which is to assess the effects of Heat Island Reduction Initiative (HIRI) measures on ozone air quality.

An urban heat island occurs when the temperature within a city is warmer than the surrounding area. It is an example of inadvertent climate modification (Oke, 1978). Higher temperatures within an urban area have the potential to adversely influence ozone air quality through higher temperatures, faster photochemical reaction rates, and greater emissions. Thus, EPA is investigating the effectiveness of urban heat island reduction as an ozone mitigation strategy. Two measures that have been identified as part of the EPA program to be potentially effective in reducing the high temperatures associated with an urban heat island are (1) use of reflective roof and paving material to increase the reflectivity or "albedo" of an urban area and (2) increased vegetation cover (e.g., tree planting).

Before such measures can be reliably implemented, however, it is necessary to carefully examine both the direct and indirect effects that may influence or alter the complex interactions among the various meteorological, emissions, and air quality parameters participating in the formation and transport of ozone. These effects may be beneficial or disbenficial to ozone concentration levels, and thus the combined total effects (including "side effects") must be considered. For example, by altering the surface energy budget, a higher albedo will affect other meteorological parameters such as wind speed, effective mixing height, and specific humidity. Lower mixing heights resulting from the lower temperatures may offset air quality benefits derived from the reduced chemical reaction rates. Conversely, increased vegetation cover (shading) will also result in lower surface temperatures, and increased roughness lengths associated with the vegetation may enhance the atmospheric mixing processes. Lower temperatures will reduce the production of biogenic hydrocarbon emissions from existing vegetation and enhance the deposition of ozone and other pollutant species, but the addition of vegetation may offset this effect. Lower surface temperatures may also reduce emissions from motor vehicles (in particular, evaporative emissions) and power plants (due to reduced energy demand for cooling).

Meteorological and air quality models can be used to represent the complex interactions between land-use, meteorology, emissions, and ozone formation and transport processes, and to estimate the effects of the HIRI measures on temperature and other meteorological parameters as well as ozone air quality. As part of an ongoing study sponsored by the Global Programs Division, EPA is conducting modeling to examine the potential air quality benefits from HIRI measures for selected cites throughout the U.S.

A detailed modeling analysis to assess the effectiveness of HIRI measures involves the compilation of meteorological and air quality data and preparation of a variety of modeling inputs, as well as the application of urban-/or regional scale meteorological and photochemical modeling tools. The modeling process is time and resource intensive and, thus, a detailed modeling analysis for every U.S. city that could potentially benefit from implementing HIRI measures is not likely. Thus, EPA has elected to conduct detailed, state-of-the-science modeling of selected cites and to examine the feasibility of using the results from these selected cities to represent (either qualitatively or quantitatively) the meteorological and/or ozone air quality response to HIRI measures for other not-modeled cities.

To this end, selection of cities that are "prototypical" and might best be used to represent other cities may enhance or extend the utility of the modeling exercise/results. An approach to city selection that is based on a homology mapping technique is presented in this report.

Homology mapping is a technique in which similarities in the geographical, land-use, and meteorological characteristics of a monitoring site or, in this case, urban area are used to identify a homologue or best match (from a list of surrogates) for that site or area. This technique was developed to map observed ozone data (for actual monitoring sites) to unmonitored areas (or pseudo monitoring sites) as part of the EPA-sponsored Section 812 prospective modeling analysis (designed to examine the costs and benefits of the Clean Air Act Amendments of 1990) – to provide the basis for health effects calculations throughout the U.S. (in both monitored and unmonitored areas). This application of the technique is described by Iwamiya and Douglas, 1999).

Homology mapping was used in this study to identify urban areas that could be used to represent other urban areas with respect to (1) meteorological response and (2) ozone air quality response to implementing HIRI measures. The idea is that if detailed modeling can only be done for a limited number of areas, choosing areas for modeling that are representative of other areas may extend the utility of the modeling results.

The remainder of this report summarizes the methods and results of the homology mapping based city selection analysis. Recommendations for approximately 25, 15, and 10 cities or combined urban areas representing various distributions of severity of ozone air quality problem are provided. Design of modeling domains that would capture the ten cities option is also discussed.

2 HOMOLOGY MAPPING TECHNIQUE

In this section, we present an overview of the homology mapping concept/technique and then present the application procedures used for the HIRI analysis.

OVERVIEW

Homology mapping is based on the assumption that urban areas with similar characteristics (e.g., geographical, land-use, emissions, and population) will also share other characteristics (e.g., meteorological conditions, air quality) – provided that the latter set is determined by the former and the controlling characteristics can be identified and represented quantitatively. Homology mapping can be used to map or assign “data” from one area to another (where “data” can take the form of observed values or modeling results). Mapping for each area of interest is determined by finding the best match among a set of selected areas, of the factors believed to influence the local conditions. With respect to meteorological and ozone air quality conditions, such factors may include the proximity and size of nearby cities, distance to nearest body of water, land use characteristics, and latitude. For each area of interest these factors are combined to form a geographical information system or “GIS” vector. Comparison of the vector quantities is then used to determine the best match. In general, the homology mapping approach includes four steps:

- Identifying the areas of interest
- Identifying the factors expected to influence the conditions to be represented (e.g. local meteorology, ozone concentration level, response to changing conditions)
- Creating the GIS vectors
- Finding the best match

The first two steps are specific to the application and are discussed in more detail in the following section. A general description of the mathematical components of the vector creation and comparison (finding the best match) steps is given here.

Once the GIS elements are established and requisite data are compiled, each GIS vector (representing a particular urban area) will include numerous components. In addition, some of the vector components may also have subcomponents. Each of these may have different units and/or ranges – so the final step in creating the GIS vectors is to standardize the components. The individual components of the vectors are standardized based upon the mean and standard deviation for the components of the GIS vectors.

$$\mathrm{X}_i = \left(\frac{1}{N_i}\right) \bullet \left((x_i - mean_i) / std_i \right)$$

where

X_i - Standardized value for vector component i
N_i - Number of components in sub-vector group for component i
x_i - Actual value for vector component i
$mean_i$ - Mean of vector component i for monitor GIS vectors only
std_i - Standard deviation of vector component i for monitor GIS vectors only

In essence, a z score is calculated for each of the individual components of the GIS vectors. Each standardized component for the GIS vectors now has a mean of zero and a standard deviation of one. The value for each of the standardized components is then divided by the number of subcomponents for the corresponding vector component. This procedure is necessary because of the differing units and scales of the components. Without standardization, certain components would have more weight than others.

Once the vectors are standardized, suitable matches are identified by calculating and comparing the Euclidean distance between each area under consideration. The Euclidean distance is defined as follows:

$$DistEuclidean(area1, area2) = \sqrt{\sum_i (X_{area1,i} - X_{area2,i})^2}$$

$\{X_{area1,i}\}$ - Standardized GIS vector for a given area
$\{X_{area2,i}\}$ - Standardized GIS vector for another area

This method for associating two urban areas minimizes the Euclidean distance between the GIS vectors, not the physical distance between the two areas. The smaller the value of Euclidean distance, the better the match. The best, second, and third best possible pairings are identified.

APPLICATION PROCEDURES

For the HIRI analysis, homology mapping was used in two ways. First to identify urban areas that are expected to have similar meteorological features and second to identify areas that are expected to have similar ozone air quality characteristics. By determining the matches based on the controlling or influencing factors, rather than simply the observed characteristics (e.g., temperature, ozone design value[1]) it is expected that the matches can be used to estimate the effects of changes due to implementation of HIRI measures (a causal relationship can be established).

The approach generally follows the methodology developed for the 812 project but was modified to accommodate cities rather than monitoring sites. Overall, however, the idea is the same – to use simulation results for modeled cities to represent the same for cities that are not modeled. In this case, simulation results could refer to one of two things: 1) simulated changes in meteorological parameters (e.g., temperature, effective mixing height, moisture, etc.) from a

[1] Ozone design value is a multi-year representation of ozone concentration levels within an urban area.

meteorological model (e.g., MM5[2]) due to incorporation of HIRI measures or 2) simulated ozone concentration changes from a photochemical model (e.g., UAM-V[3]) due to incorporation of HIRI measures. These correspond to different levels in EPA's proposed streamlining approach (to accounting for the effects of heat island reduction).

Step 1: Select Urban Areas

In determining which areas to include in this analysis, we obtained the current (1997-1999) 8-hour ozone design values for all areas in the U.S. from "The Green Book" on the EPA web site and selected all areas for which the design value is equal to or greater than the expected 8-hour ozone standard of 85 ppb. In addition, other areas with somewhat lower design values that represent large population centers were also included. The 8-hour design value is currently defined as the three-year average of the fourth highest annual ozone concentration. It is calculated for each monitoring site and the maximum among all monitoring sites within an urban area is used to characterize the area. The list of urban areas used for this analysis and their design values are given in Table 2-1.

Step 2: Determine "GIS" Vector Elements

The next step in setting up a homology map is to identify important geographical, population, emissions, and air quality related values that can be represented quantitatively and used to describe features that are important to or are likely to influence 1) and 2) above. For this analysis, we included:

1. Latitude
2. Elevation
3. Distance to the nearest body of water
4. Land use
5. Population
6. Area (areal extent)
7. Population density
8. Population distance of nearby cities
9. Emissions-based VOC/NO_x ratio
10. 8-hour ozone design value

We also considered other parameters such as amount of solar insolation (annual or seasonal), average temperature, number of heating degree days, and amount of urban biogenic emissions. However, these should be represented by those on the list above (i.e., latitude, distance to the nearest body of water, and elevation will largely determine the amount of solar insolation and temperature; land-use will determine the amount of biogenic emissions, etc.).

The vector components were designed to capture the basic geophysical features that can be used as surrogates for the physical and chemical processes that govern the formation, transport, and

[2] The Pennsylvania State University/National Center for Atmospheric Research (PSU/NCAR) Mesoscale Model, Version 5
[3] The variable-grid Urban Airshed Model developed by Systems Applications International, Inc.

deposition of ozone, and result in geographical differences in ozone concentration. The design and construction of the vectors is described in the following paragraphs.

The latitude component is simply the latitude of the urban area. Similarly elevation is elevation above sea level. The latitude and elevation vector components are important in determining meteorology and surrogates for both photolysis rate and temperature, important determinants of ozone production and precursor emission rates.

The distance to nearest body of water was calculated using gridded land-use data (described in more detail below). It is the distance from the center of the urban area to the nearest large body of water. Proximity to water will influence the temperature and horizontal and vertical dispersion characteristics of an area.

The land-use vector component provides information related to processes that influence both the production and the deposition of ozone. Land use influences (or in some cases is influenced by) both the meteorology of an area and the amount and density of anthropogenic and biogenic emissions. Deposition velocities (which determine the rate at which ozone and precursor pollutants are taken out of the atmosphere through deposition onto the surface) are also land-use dependent. For example, deposition of ozone is much more rapid over forested areas than water surfaces. This is also likely an important determinant in the effectiveness of HIRI measures.

The land-use components were estimated using gridded U.S. Geological Survey (USGS) land-use data. Eleven components describe the percentage of area that is urban, agricultural, range, deciduous forest, coniferous forest (including wetlands), mixed forest, water, barren land, non-forest wetlands, mixed agricultural and range, and rocky (low shrubs).

Population, area, and population density were based on 1990 U.S. Census Bureau information and may help to characterize both the amount and distribution of anthropogenic emissions (e.g., from motor vehicles) as well as the existence and magnitude of an urban heat island.

The population-distance vector component was designed to capture the influence of neighboring population centers upon the ambient concentrations of ozone. Both the size and proximity of these population centers have the potential to influence ambient concentrations. Larger population centers will generally produce more precursor pollutants to ozone formation. Due to the limiting effects of pollutant transport and diffusion, the proximity to such population centers is a primary consideration. To accommodate the prevailing westerly wind directions, only westward population distance was considered.

The westward population-distance components were constructed by first compiling a list of 23,655 cities, towns, military bases, etc. and dividing these into deciles, based on population. Again population estimates were based on 1990 U.S. Census data. Those places with populations greater than the first decile were retained and counted if they were within 50, 100, or 200 km of an urban area. In this manner, 27 components of the westward population-distance sub-vector were constructed. Only those places lying to the west of the urban area. The directional determination was based on longitude and therefore includes the southwest, west, and northwest directions.

The VOC-to-NO_x ratio was based on a national-scale emissions inventory (ca. 2000) developed for photochemical modeling under another EPA work assignment. The emissions were extracted for the grid-cell or grid-cells encompassing the urban area and the ratio was calculated. This ratio determines the response of ozone to changes in emissions.

A subset of these components (1 through 4) was used to find homologues for meteorological modeling. All of the components listed above were used for the companion analysis for photochemical modeling.

Step 2: Set Up GIS Vectors

The next step was to prepare the electronic files that contain the GIS vector element information. This GIS vector elements were standardized using the procedures outlined earlier in this section.

Step 3: Testing and Application of the Homology Mapping Technique

After standardization of the vectors – the homology mapping program/algorithm was designed to match each city in a list of not-modeled cities with a corresponding city from a list of the modeled cities. It does this by calculating the Euclidean distance (difference) between the vector elements and identifies the best match as corresponding to the pair with the smallest distance value (difference). It provides a list of the best three matches.

For the HIRI project, we don't yet know the list of not-modeled and modeled cities. Indeed the objective of the task is to identify appropriate "prototype" cities for modeling. Accordingly, the approach was as follows:

1. Select a handful of cities and make sure that they are their own best match (for testing purposes only)

2. Remove each city one at a time from the "all cities" list and find the best match for each. From the list of three best matches for each city, see if there are any cities that are good matches for a number of others (i.e., count the number of times each appears in the top three list).

These steps were applied twice – once for use with meteorological modeling and once for use with photochemical modeling – using different sets of GIS vectors (as specified above).

Table 2-1. Urban areas used for homology mapping.

City	State	MSA/CMSA/AREA	8-hr Ozone Design value
Allentown	PA	Allentown-Bethlehem-Easton	100
Altoona	PA	Altoona	95
Asheville	NC	Asheville	94
Atlanta	GA	Atlanta,	118
Augusta	GA	Augusta-Aiken	92
Austin	TX	Austin-San Marcos	88
Baltimore	MD	Baltimore	109
Baton Rouge	LA	Baton Rouge	92
Beaumont-Port Arthur	TX	Beaumont-Port Arthur	88
Benton Harbor	MI	Benton Harbor	96
Birmingham	AL	Birmingham	97
Boston	MA	Boston-Worcester-Lawrence	95
Buffalo	NY	Buffalo-Niagara Falls	86
Canton	OH	Canton-Massillon	91
Charleston	WV	Charleston	90
Charlotte	NC	Charlotte-Gastonia-Rock Hill	104
Chattanooga	TN	Chattanooga	94
Chicago	IL-IN	Chicago-Gary-Lake Co	93
Cincinnati-Hamilton	OH	Cincinnati	95
Clarksville	KY	Clarksville-Hopkinsville	86
Cleveland	OH	Cleveland-Lorain-Elyria-Akron	99
Columbia	SC	Columbia	92
Columbus	OH	Columbus	97
Dallas	TX	Dallas-Fort Worth	101
Dayton	OH	Dayton-Springfield	94
Detroit	MI	Detroit-Ann Arbor	95
Erie	PA	Erie	93
Evansville	IN	Evansville-Henderson	94
Fayetteville	NC	Fayetteville	92
Fort Wayne	IN	Fort Wayne	88
Goldsboro	NC	Goldsboro	85
Grand Rapids	MI	Grand Rapids-Muskegon-Holland	94
Green Bay	WI	Green Bay	97
Greensboro	NC	Greensboro-Winston-Salem	98
Greenville	SC	Greenville-Spartanburg-Anderson	95
Hancock	ME	Hancock	89
Harrisburg	PA	Harrisburg-Lebanon-Carlisle	97
Hartford	CT	Greater Connecticut	103
Hickory	NC	Hickory-Morganton-Lenoir	90
Houston/GAL/Braz.	TX	Houston/GAL/Braz.	118
Huntington-Ashland	WV	Huntington-Ashland	95
Huntsville	AL	Huntsville	90
Indianapolis	IN	Indianapolis	97
Johnson City	TN	Johnson City-Kingsport-Bristol	91
Johnstown	PA	Johnstown	93
Kansas City	MO	Kansas City	91

Knoxville	TN	Knoxville	104
Lake Charles	LA	Lake Charles	88
Lancaster	PA	Lancaster	101
Lexington	KY	Lexington	87
Lima	OH	Lima	88
Little Rock	AR	Little Rock-North Little Rock	83
Longview	TX	Longview-Marshall	100
Los Angeles	CA	So. Coast AQMD	147
Louisville	KY	Louisville	96
Macon	GA-SC	Macon	104
Memphis	TN-AR-MS	Memphis	95
Milwaukee	WI	Milwaukee-Racine	97
Mobile	AL	Mobile	88
Modesto	CA	Modesto	95
Nashville	TN	Nashville	102
New Orleans	LA	New Orleans	85
New York	NY-NJ-CT	New York-N.New Jersey-Long Island	107
Norfolk	VA	Norfolk-Virginia Beach-Newport News	94
Oklahoma City	OK	Oklahoma City	86
Orlando	FL		83
Owensboro	KY	Owensboro	87
Paducah	KY	Paducah	95
Parkersburg	WV-OH	Parkersburg-Marietta	91
Pascagoula	MS	Biloxi-Gulfport-Pascagoula	93
Pensacola	FL	Pensacola	91
Philadelphia	PA-NJ-DE-MD	Philadelphia-Wilmington-Trenton	110
Phoenix	AZ	Pheonix	88
Pittsburgh	PA	Pitsburgh-Beaver Valley	101
Portland	ME	Portland	92
Portland-Vancouver	OR-WA	Portland	71
Provo	UT	Provo-Orem	82
Raleigh/Durham	NC	Raleigh-Durham-Chapel Hill	101
Reading	PA	Reading	96
Redding	CA	Redding	95
Richmond	VA	Richmond-Petersburg	99
Roanoke	VA	Roanoke	90
Rochester	NY	Rochester	86
Rocky Mount	NC	Rocky Mount	90
Sacramento	CA	Sacramento Metro	102
Salt Lake City	UT	Salt Lake City-Ogden	84
San Antonio	TX	San Antonio	88
San Diego	CA	San Diego	99
San Francisco	CA	SF Bay Area	85
San Joaquin	CA	San Joaquin (Fresno)	113
Santa Barbara	CA	Santa Barbara-Santa Maria-Lompoc	82
Scranton	PA	Scranton-Wilkes-Barre-Hazelton	97
Seattle	WA	Seattle-Bellevue-Everett	81

Sheboygan	WI	Sheboygan	93
Shreveport, La	LA	Shreveport-Bossier City	88
South Bend	IN	South Bend	91
Springfield	MA	Springfield	99
St. Louis	MO	St. Louis	95
Tampa-St.Petersberg-Clearwater	FL	Tampa-St.Petersberg-Clearwater	87
Tulsa	OK	Tulsa	88
Tyler	TX	Tyler	91
Ventura	CA	Ventura	106
Washington DC	DC	DC/MD/VA	106
York	PA	York	94
Youngstown	OH	Youngstown-Warren-Sharon	96
Yuma	AZ	Yuma	82

3 RESULTS FOR METEOROLOGICAL MODELING

Results of the application of the homology mapping technique to identify urban areas that are most similar to the greatest number of other urban areas with respect to the meteorological drivers are presented in Table 3-1. For each urban area, the three best matches are given. The Euclidean distance associated with each match is also provided. While this number has little or no physical meaning, the value can be used to indicate and contrast the relative fidelity of each match.

Urban areas that most frequently appear as matches for other areas include Springfield, IL; Allentown, PA; Beaumont-Port Arthur, TX; Clarksville, WV; Johnson City, TN; Pensacola, FL; Reading, PA; Santa Barbara, CA; Canton, OH; and Chicago, IL. These are the top ten most frequent "best-match" areas. They also seem to represent a fairly broad range of geographic areas relative to coastal vs. inland location, latitude, and elevation.

Rather than guide the selection of urban areas for modeling, the meteorological homologues may provide the basis for mapping the HIRI meteorological modeling results (in terms of response of the meteorological parameters to the HIRI measures). Thus this information is simply presented here for possible use later in the HIRI study.

TABLE 3-1. Homology mapping results for meteorological modeling. ED is Euclidian distance.

City	Best Match	2nd Best	3rd Best	1st ED	2nd ED	3rd ED
Allentown	Reading	Lancaster	York	0.2005	0.2036	0.2796
Altoona	Harrisburg	Reading	Canton	0.3395	0.4633	0.5275
Asheville	Hickory	Macon	Shreveport, La	0.3501	0.401	0.4461
Atlanta	Dallas	St. Louis	Houston/GAL/Braz.	0.5967	0.6384	0.6901
Augusta	Raleigh-Durham	Shreveport, La	Longview	0.3759	0.412	0.4138
Austin	Macon	Columbia	Raleigh-Durham	0.4205	0.566	0.5945
Baltimore	Washington DC	Norfolk	Allentown	0.3583	0.5935	0.6011
Baton Rouge	Beaumont-Port Arthur	Lake Charles	Pensacola	0.1599	0.2718	0.3407
Beaumont-Port Arthur	Baton Rouge	Lake Charles	Pensacola	0.1599	0.2455	0.274
Benton Harbor	Erie	Rochester	Green Bay	0.3296	0.3803	0.4008
Birmingham	Longview	Greensboro	Huntsville	0.4449	0.4469	0.5323
Boston	Hartford	Philadelphia	San Francisco	0.6932	0.8528	0.9039
Buffalo	Milwaukee	South Bend	Rochester	0.2139	0.5101	0.5329
Canton	Reading	Allentown	Modesto	0.2115	0.3158	0.3643
Charleston	Huntington-Ashland	Parkersburg	Johnson City	0.1597	0.3078	0.3314
Charlotte	Greenville	Indianapolis	Roanoke	0.4444	0.4462	0.4745
Chattanooga	Johnson City	Knoxville	Nashville	0.3105	0.3461	0.4153
Chicago	Detroit	San Francisco	Philadelphia	0.7936	0.9262	0.9526
Cincinnati-Hamilton	Dayton	Louisville	Columbus	0.4093	0.4726	0.4807
Clarksville	Paducah	Owensboro	Evansville	0.2069	0.3253	0.3446
Cleveland	Milwaukee	Buffalo	Erie	0.4062	0.5665	0.6508
Columbia	Macon	Raleigh-Durham	Fayetteville	0.3613	0.3925	0.4461
Columbus	Dayton	Fort Wayne	Youngstown	0.261	0.3557	0.4009
Dallas	Atlanta	St. Louis	Charlotte	0.5967	0.5973	0.7697
Dayton	Columbus	Cincinnati-Hamilton	South Bend	0.261	0.4093	0.4136
Detroit	Milwaukee	Buffalo	Pittsburgh	0.6195	0.6272	0.7266
Erie	Benton Harbor	Rochester	Cleveland	0.3296	0.558	0.6508
Evansville	Owensboro	Paducah	Clarksville	0.1142	0.2571	0.3446
Fayetteville	Richmond	Rocky Mount	Goldsboro	0.3529	0.387	0.4008
Fort Wayne	Lima	Columbus	Grand Rapids	0.1964	0.3557	0.376
Goldsboro	Rocky Mount	Richmond	Fayetteville	0.0914	0.3863	0.4008
Grand Rapids	Green Bay	Sheboygan	South Bend	0.2492	0.2673	0.3378
Green Bay	Sheboygan	Grand Rapids	Benton Harbor	0.0972	0.2492	0.4008
Greensboro	Roanoke	Birmingham	Greenville	0.4442	0.4469	0.5176
Greenville	Knoxville	Roanoke	Charlotte	0.3643	0.3672	0.4444
Hancock	Springfield	Altoona	Evansville	0.7909	0.9309	0.9445
Harrisburg	Altoona	Johnstown	Reading	0.3395	0.3562	0.3675
Hartford	Boston	Salt Lake City	Baltimore	0.6932	0.7243	0.7671
Hickory	Shreveport, La	Asheville	Rocky Mount	0.3317	0.3501	0.3769
Houston/GAL/Braz.	San Diego	Atlanta	Orlando	0.4859	0.6901	0.7157

Huntington-Ashland	Charleston	Parkersburg	Johnson City	0.1597	0.2996	0.3131
Huntsville	Clarksville	Johnson City	Tyler	0.3835	0.417	0.4317
Indianapolis	Youngstown	Columbus	Charlotte	0.3654	0.4378	0.4462
Johnson City	Chattanooga	Huntington-Ashland	Charleston	0.3105	0.3131	0.3314
Johnstown	Parkersburg	Harrisburg	Redding	0.3073	0.3562	0.3622
Kansas City	Tulsa	St. Louis	Knoxville	0.5601	0.5937	0.7457
Knoxville	Johnson City	Chattanooga	Greenville	0.3454	0.3461	0.3643
Lake Charles	Beaumont-Port Arthur	Baton Rouge	Pensacola	0.2455	0.2718	0.3476
Lancaster	York	Allentown	Reading	0.1091	0.2036	0.215
Lexington	Knoxville	Cincinnati-Hamilton	Greenville	0.3765	0.4859	0.486
Lima	Fort Wayne	Columbus	Youngstown	0.1964	0.4085	0.439
Little Rock	Longview	Shreveport, La	Birmingham	0.4512	0.5343	0.553
Longview	Shreveport, La	Augusta	Tyler	0.2559	0.4138	0.4417
Los Angeles	San Joaquin	Phoenix	San Francisco	1.6393	2.2534	2.3362
Louisville	Evansville	Owensboro	Cincinnati-Hamilton	0.3756	0.4305	0.4726
Macon	Columbia	Asheville	Austin	0.3613	0.401	0.4205
Memphis	Oklahoma City	Paducah	Evansville	0.3202	0.361	0.3941
Milwaukee	Buffalo	Cleveland	Detroit	0.2139	0.4062	0.6195
Mobile	Pensacola	Beaumont-Port Arthur	Orlando	0.2829	0.317	0.401
Modesto	Canton	Reading	Goldsboro	0.3643	0.3646	0.4159
Nashville	Chattanooga	Johnson City	Clarksville	0.4153	0.4995	0.544
New Orleans	Pascagoula	Orlando	Mobile	0.9856	1.244	1.259
New York	Chicago	Philadelphia	San Francisco	1.7805	2.104	2.179
Norfolk	Ventura	San Diego	Baltimore	0.4308	0.574	0.5935
Oklahoma City	Memphis	Paducah	Clarksville	0.3202	0.4592	0.483
Orlando	Pensacola	Baton Rouge	Beaumont-Port Arthur	0.3396	0.3426	0.3704
Owensboro	Evansville	Paducah	Clarksville	0.1142	0.2078	0.3253
Paducah	Clarksville	Owensboro	Evansville	0.2069	0.2078	0.2571
Parkersburg	Huntington-Ashland	Johnstown	Charleston	0.2996	0.3073	0.3078
Pascagoula	Pensacola	Lake Charles	Beaumont-Port Arthur	0.5538	0.5644	0.6528
Pensacola	Beaumont-Port Arthur	Mobile	Orlando	0.274	0.2829	0.3396
Philadelphia	San Francisco	Washington DC	Baltimore	0.5333	0.5497	0.6927
Phoenix	Sacramento	Santa Barbara	Dallas	1.0085	1.065	1.0708
Pittsburgh	Scranton	Columbus	Youngstown	0.4175	0.4419	0.5243
Portland	Springfield	Salt Lake City	Modesto	0.9159	0.9825	1.0914
Portland-Vancouver	Seattle	Springfield	Canton	0.4324	0.5063	0.6008
Provo	Redding	Johnstown	Rochester	0.3652	0.4756	0.5013
Raleigh-Durham	Augusta	Columbia	Macon	0.3759	0.3925	0.4542
Reading	Allentown	Canton	Lancaster	0.2005	0.2115	0.215

Redding	Johnstown	Provo	Scranton	0.3622	0.3652	0.4128
Richmond	Fayetteville	Rocky Mount	Goldsboro	0.3529	0.3822	0.3863
Roanoke	Greenville	Charleston	Knoxville	0.3672	0.4183	0.4283
Rochester	Benton Harbor	Grand Rapids	Scranton	0.3803	0.3842	0.4124
Rocky Mount	Goldsboro	Hickory	Richmond	0.0914	0.3769	0.3822
Sacramento	Modesto	Richmond	Canton	0.5154	0.5482	0.565
Salt Lake City	Allentown	Springfield	Baltimore	0.5638	0.5998	0.6214
San Antonio	Tyler	Charlotte	Austin	0.5241	0.6476	0.6623
San Diego	Houston/GAL/Braz.	Tampa	Norfolk	0.4859	0.5732	0.574
San Francisco	Philadelphia	Washington DC	Baltimore	0.5333	0.5976	0.6931
San Joaquin	Phoenix	Dallas	Los Angeles	1.2559	1.5791	1.6393
Santa Barbara	Ventura	Pensacola	Goldsboro	0.3076	0.4805	0.5169
Scranton	Youngstown	Rochester	Redding	0.3109	0.4124	0.4128
Seattle	Portland-Vancouver	Springfield	Rochester	0.4324	0.7191	0.7329
Sheboygan	Green Bay	Grand Rapids	Fort Wayne	0.0972	0.2673	0.4154
Shreveport, La	Longview	Hickory	Rocky Mount	0.2559	0.3317	0.411
South Bend	Grand Rapids	Dayton	Columbus	0.3378	0.4136	0.4239
Springfield	Portland-Vancouver	Canton	Reading	0.5063	0.5166	0.5379
St. Louis	Louisville	Kansas City	Dallas	0.5105	0.5937	0.5973
Tampa	San Diego	Orlando	Pensacola	0.5732	0.5783	0.7542
Tulsa	Clarksville	Knoxville	Kansas City	0.4485	0.5587	0.5601
Tyler	Shreveport, La	Huntsville	Longview	0.4278	0.4317	0.4417
Ventura	Santa Barbara	Norfolk	Pensacola	0.3076	0.4308	0.5696
Washington DC	Baltimore	Philadelphia	San Francisco	0.3583	0.5497	0.5976
York	Lancaster	Reading	Allentown	0.1091	0.2233	0.2796
Youngstown	Scranton	Indianapolis	Columbus	0.3109	0.3654	0.4009
Yuma	Santa Barbara	Modesto	Beaumont-Port Arthur	0.6154	0.7234	0.747

4 RESULTS FOR PHOTOCHEMICAL MODELING

Results of the application of the homology mapping technique using the full set of vector components (to identify "prototypical" urban areas for photochemical modeling) are presented in Table 4-1. For each urban area, the three best matches are given. The Euclidean distance associated with each match is also provided. While this number has little or no physical meaning, the relative value can be used to indicate and contrast the relative fidelity of each match. Note that the results are not listed alphabetically but instead have been ordered according to 8-hour ozone design value. In recommending areas for photochemical modeling, we attempt to include not only those areas that are good surrogates for as many other areas a possible, but also areas represent the range of severity that characterizes ozone problems within the U.S. Specific consideration was also given to representing different regions of the country.

The ozone homologues presented in Table 3-1 may provide the basis for mapping future HIRI photochemical modeling results (in terms of the change in ozone concentration due to implementing HIRI measures). They also provide the basis for recommending urban areas for modeling (to provide the best basis for future use of homology mapping to extend the utility of the modeling results).

The three set of recommendations (corresponding to different numbers and geographical groupings of urban areas) as well as the stepwise procedure that was followed to arrive at the recommendations is presented in the remainder of this section.

DISCUSSION OF METHODOLOGY

We first identified (similar to for the meteorological modeling application) those areas that most frequently were among the best three matches for the greatest number of other areas. We then looked at different ranges of 8-hour ozone design value (including less than 85 ppb, 85 to less than 90 ppb, 90 to less than 95 ppb, etc.) and identified the same for each of these categories. We discounted those areas that had a large number of matches but for which the majority of these were small urban areas that were similar and nearby to one another. One such example is Evansville, IL; Owensville, KY; and Paducah, KY. These areas are very similar and very close and are good surrogates for one another. However, they were not good general surrogates for many other areas. Similar examples occurred for smaller cities in North Carolina, Pennsylvania, and Ohio.

We also attempted to ensure that many of the larger urban areas were represented – either directly or by reasonable surrogates. This was somewhat subjective both in terms of identifying the key/larger urban areas as well as the degree to which a good match was found. Those areas that were just not accommodated by the frequent match surrogates were added to the list and thus directly represented.

Two of our largest cities deserve special mention. No good match was found for either Los Angeles or New York. Since Los Angeles has been the subject of much study with respect urban heat island mitigation, we have opted to not include it as part of our recommendations. It is important to note, however, that our results indicate that modeling results for Los Angeles should not be used to quantify or draw conclusions about the effects of HIRI measures in other urban areas. This is an important finding – given the amount of information that has been generated for Los Angeles. There were also no good matches found for New York – again a very unique city in many respects. However, as discussed later, New York would likely be included in a modeling domain that includes other important surrogate cities and thus could be modeled directly.

Finally, from a practical perspective (given expected cost and schedule considerations) we attempted to limit our recommendations to ten different areas or modeling domains. By taking advantage of geographical proximity of some areas to one another, we also attempted to maximize the number of "best match" urban areas within these ten areas.

RECOMMENDATIONS

The following 23 urban areas include the most frequent best matches and, where important urban areas were not represented, the areas themselves:

1. Grand Rapids, MI
2. Chattanooga, TN
3. Baton Rouge, LA
4. Memphis, TN
5. Mobile, AL
6. Augusta, GA
7. Columbia, SC
8. Orlando, FL
9. Raleigh-Durham, NC
10. Indianapolis, IN
11. Tyler, TX
12. Louisville, KY
13. Charlotte, NC
14. Springfield, MA
15. San Diego, CA
16. St. Louis, MO
17. Sacramento, CA
18. Seattle, WA
19. Salt Lake City, UT
20. Detroit, MI
21. Philadelphia, PA
22. Atlanta, GA
23. Boston, MA

Based on the homology mapping results, these 23 areas could be used to represent a total of 74 of the 106 urban areas considered in this analysis – using any of the three best matches and without considering the fidelity of the match. Using only the best match, 51 urban areas could be represented.

Many of these areas are near enough to one another that they could be placed within a single regional-/urban-scale modeling domain. In defining these domains, other urban areas may also be included just based on proximity. For the list of cites above, possible domain groupings are given in Table 4-2. In addition to the key areas, other nearby areas that would also likely fall within a domain are listed. Please note that some of these domains (e.g., 2 and 3) may overlap. Similarly, depending upon the size of the modeling domain some of the additional areas may be too far away to be treated with sufficient detail (i.e., to be located within the high-resolution portion of the modeling domain).

Finally, this list is shortened in Table 4-3 to ten areas comprising modeling domains. To reduce the number of domains, areas with low 8-hour design values (less than 85 were omitted). In addition, areas that provide the least amount of benefit (matches) for homology mapping were given lower priority and some were omitted. These domains include 36 urban areas from our original list (refer to Table 2-1). Based on the homology mapping results, these 36 urban areas could be used to represent a total of 69 of the 106 urban areas considered in this analysis – using any of the three best matches and without considering the fidelity of the match. Using only the best match, 40 urban areas could be represented. Thus, while we increase the number of area that are directly represented by adding nearby areas, the overall representation of the cities is less than with the 23 best-match urban areas.

Each modeling domain would consist of a one or more coarse-resolution grids to capture the regional-scale effects on meteorology and pollutant transport and one or more high-resolution nested grids (with approximately 4 km horizontal resolution) to enable simulation of the urban-scale effects. For combined areas that include cities that are some distance apart (e.g., Grand Rapids and Detroit, MI or Tyler/Longview and Dallas, TX) multiple high resolution grids may be used. Some recent model applications (e.g., the Gulf Coast Ozone Study), however, have used extended high resolution grids.

As a final note on the use of homology mapping results, once the modeling domains and cities are selected the homology mapping algorithm should be rerun using only modeled cites as possible homologues for the not-modeled cities. Other suitable matches or mappings may exist – all results should be used with care and the fidelity of the match should be examined.

TABLE 4-1. Homology mapping results for photochemical modeling. ED is Euclidean distance.

City	Best Match	2nd Best	3rd Best	1st ED	2nd ED	3rd ED
Los Angeles	San Joaquin	Houston.	Atlanta	2.0558	2.6173	2.8421
Atlanta	Houston.	Dallas	Sacramento	0.7597	0.8723	1.0251
Houston.	Atlanta	San Diego	Sacramento	0.7597	0.8852	1.0367
San Joaquin	Phoenix	Dallas	Sacramento	1.5525	1.6835	1.7303
Philadelphia	Washington DC	Baltimore	Hartford	0.7366	0.7903	1.1089
Baltimore	Washington DC	Allentown	Philadelphia	0.4356	0.7851	0.7903
New York	Chicago	Philadelphia	Boston	1.8871	2.1494	2.4033
Ventura	Norfolk	San Diego	Modesto	0.6701	0.6873	0.76
Washington DC	Baltimore	Philadelphia	Hartford	0.4356	0.7366	0.912
Knoxville	Greenville	Chattanooga	Johnson City	0.5087	0.5234	0.6024
Macon	Raleigh-Durham	Asheville	Huntington-Ashland	0.5109	0.5792	0.6628
Charlotte	Indianapolis	Greenville	Raleigh-Durham	0.5851	0.5874	0.5892
Hartford	Boston	Springfield	Baltimore	0.795	0.8111	0.8663
Nashville	Chattanooga	Memphis	Knoxville	0.5785	0.6421	0.669
Sacramento	Modesto	San Diego	Norfolk	0.6254	0.722	0.7532
Raleigh-Durham	Macon	Huntington-Ashland	Longview	0.5109	0.5465	0.5591
Pittsburgh	Scranton	Charlotte	Harrisburg	0.5279	0.7303	0.754
Dallas	St. Louis	Charlotte	Memphis	0.7107	0.8029	0.8613
Lancaster	Allentown	York	Reading	0.2788	0.3063	0.3265
Longview	Birmingham	Augusta	Shreveport, La	0.5321	0.5328	0.5346
Allentown	Lancaster	Reading	York	0.2788	0.315	0.4177
Springfield	Richmond	Reading	Canton	0.6482	0.6938	0.6954
San Diego	Norfolk	Ventura	Sacramento	0.6423	0.6873	0.722
Cleveland	Erie	Buffalo	Benton Harbor	0.7309	0.7983	0.8271
Richmond	Fayetteville	Rocky Mount	Raleigh-Durham	0.4622	0.5367	0.6192
Greensboro	Louisville	Tulsa	Cincinnati-Hamilton	1.0626	1.0703	1.0921
Scranton	Pittsburgh	Johnstown	Parkersburg	0.5279	0.5348	0.5606
Indianapolis	Youngstown	Columbus	Charlotte	0.516	0.5396	0.5851
Birmingham	Longview	Tyler	Augusta	0.5321	0.6717	0.7023
Milwaukee	Cleveland	Louisville	Salt Lake City	0.9846	1.0726	1.0765
Columbus	Dayton	Youngstown	Grand Rapids	0.3095	0.4184	0.484
Harrisburg	Altoona	Johnstown	York	0.4319	0.4771	0.5038
Green Bay	Sheboygan	Grand Rapids	Benton Harbor	0.2441	0.3012	0.4486
Louisville	Evansville	Cincinnati-Hamilton	Indianapolis	0.5144	0.5221	0.6675
Benton Harbor	Erie	Green Bay	Sheboygan	0.3708	0.4486	0.4697
Youngstown	Columbus	Indianapolis	Lima	0.4184	0.516	0.5397
Reading	Allentown	Lancaster	York	0.315	0.3265	0.3397
Huntington-Ashland	Charleston	Johnson City	Parkersburg	0.284	0.3593	0.3631
Greenville	Roanoke	Johnson City	Knoxville	0.4348	0.5071	0.5087
Cincinnati-Hamilton	Louisville	Lexington	Dayton	0.5221	0.5769	0.6027
Redding	Indianapolis	Provo	Youngstown	0.601	0.6218	0.6458

St. Louis	Kansas City	Dallas	Indianapolis	0.6688	0.7107	0.7136
Detroit	Buffalo	Pittsburgh	Rochester	0.7799	0.9108	0.9411
Boston	Hartford	Washington DC	San Francisco	0.795	1.0746	1.1051
Altoona	Harrisburg	Reading	Johnstown	0.4319	0.5662	0.6715
Modesto	Sacramento	Canton	Santa Barbara	0.6254	0.7077	0.7185
Paducah	Memphis	Evansville	Owensboro	0.4171	0.4248	0.4339
Memphis	Paducah	Evansville	Owensboro	0.4171	0.4597	0.5072
Norfolk	San Diego	Ventura	Fayetteville	0.6423	0.6701	0.7035
Grand Rapids	Green Bay	Sheboygan	South Bend	0.3012	0.3429	0.4327
Chattanooga	Johnson City	Huntington-Ashland	Charleston	0.3501	0.4485	0.4651
Dayton	Columbus	South Bend	Grand Rapids	0.3095	0.5162	0.5519
Asheville	Hickory	Shreveport, La	Memphis	0.4068	0.5134	0.5509
Evansville	Owensboro	Paducah	Memphis	0.3244	0.4248	0.4597
York	Lancaster	Reading	Allentown	0.3063	0.3397	0.4177
Johnstown	Parkersburg	Fort Wayne	York	0.3711	0.4605	0.4643
Erie	Benton Harbor	Rochester	Green Bay	0.3708	0.6296	0.7199
Chicago	Detroit	San Francisco	Washington DC	1.0375	1.1419	1.1664
Pascagoula	New Orleans	Lake Charles	Santa Barbara	1.0949	1.1292	1.1435
Sheboygan	Green Bay	Grand Rapids	Benton Harbor	0.2441	0.3429	0.4697
Augusta	Tyler	Rocky Mount	Shreveport, La	0.4963	0.5017	0.5319
Columbia	Fayetteville	Rocky Mount	Augusta	0.4753	0.5219	0.5528
Portland	Springfield	Hancock	Canton	1.016	1.1203	1.2174
Baton Rouge	Beaumont-Port Arthur	Mobile	Lake Charles	0.4345	0.4428	0.4429
Fayetteville	Rocky Mount	Richmond	Columbia	0.4076	0.4622	0.4753
Parkersburg	Charleston	Huntington-Ashland	Johnstown	0.335	0.3631	0.3711
Johnson City	Chattanooga	Huntington-Ashland	Charleston	0.3501	0.3593	0.3684
Pensacola	Beaumont-Port Arthur	Baton Rouge	Mobile	0.3141	0.4944	0.5072
South Bend	Grand Rapids	Sheboygan	Dayton	0.4327	0.4909	0.5162
Tyler	Augusta	Evansville	Shreveport, La	0.4963	0.5756	0.5959
Kansas City	St. Louis	Clarksville	Chattanooga	0.6688	0.8686	0.874
Canton	York	Fayetteville	Rocky Mount	0.6241	0.6371	0.6432
Charleston	Huntington-Ashland	Parkersburg	Johnson City	0.284	0.335	0.3684
Roanoke	Greenville	Charleston	Parkersburg	0.4348	0.4642	0.4905
Huntsville	Clarksville	Johnson City	Paducah	0.4713	0.4777	0.5836
Hickory	Shreveport, La	Asheville	Rocky Mount	0.3887	0.4068	0.4495
Rocky Mount	Goldsboro	Fayetteville	Hickory	0.2318	0.4076	0.4495
Hancock	Springfield	Hickory	Asheville	0.9963	1.0317	1.0466
Beaumont-Port Arthur	Pensacola	Baton Rouge	Goldsboro	0.3141	0.4345	0.5326
Fort Wayne	Lima	Johnstown	Grand Rapids	0.3542	0.4605	0.4899
Mobile	Baton Rouge	Orlando	Pensacola	0.4428	0.4853	0.5072
Lima	Fort Wayne	Youngstown	Grand Rapids	0.3542	0.5397	0.5542
Lake Charles	Baton Rouge	Mobile	Orlando	0.4429	0.5714	0.6252
Tulsa	Oklahoma City	Lexington	Louisville	0.6824	0.8922	0.9353

Phoenix	Sacramento	Yuma	Santa Barbara	1.1503	1.1648	1.1717
San Antonio	Tyler	Austin	Augusta	0.6567	0.6729	0.8422
Austin	San Antonio	Tyler	Columbia	0.6729	0.7435	0.7752
Shreveport, La	Hickory	Rocky Mount	Goldsboro	0.3887	0.4726	0.4793
Lexington	Cincinnati-Hamilton	Roanoke	Evansville	0.5769	0.7638	0.7648
Tampa	Orlando	Baton Rouge	San Diego	0.6152	0.7914	0.8141
Owensboro	Evansville	Clarksville	Paducah	0.3244	0.4158	0.4339
Buffalo	Rochester	South Bend	Grand Rapids	0.5396	0.6587	0.7067
Oklahoma City	Tulsa	Memphis	Owensboro	0.6824	0.7478	0.7891
Clarksville	Owensboro	Paducah	Huntsville	0.4158	0.4401	0.4713
Rochester	Grand Rapids	Buffalo	Benton Harbor	0.5042	0.5396	0.5735
San Francisco	Norfolk	San Diego	Salt Lake City	0.9045	0.9248	0.9603
New Orleans	Pascagoula	Santa Barbara	Lake Charles	1.0949	1.4161	1.447
Goldsboro	Rocky Mount	Shreveport, La	Fayetteville	0.2318	0.4793	0.4841
Salt Lake City	Provo	Norfolk	Canton	0.7755	0.82	0.8296
Little Rock	Shreveport, La	Clarksville	Owensboro	0.5916	0.6793	0.6859
Orlando	Mobile	Baton Rouge	Beaumont-Port Arthur	0.4853	0.4961	0.5754
Santa Barbara	Lake Charles	Yuma	Modesto	0.6484	0.7029	0.7185
Provo	Redding	Rochester	Salt Lake City	0.6218	0.7553	0.7755
Yuma	Santa Barbara	Lake Charles	Mobile	0.7029	0.8353	0.8386
Seattle	Portland-Vancouver	Rochester	Canton	0.5749	0.7907	0.8571
Portland-Vancouver	Seattle	Rochester	Canton	0.5749	0.9103	0.9655

Table 4-2. Combined urban-area modeling domains using 23 best-match homologues.

Combined Urban Areas	Key Homologue Areas	Other Nearby Areas
1	Philadelphia, PA Springfield, MA Boston, MA	Richmond, VA Washington, D.C. Baltimore, MD Allentown, PA Lancaster, PA Harrisburg, PA Scranton, PA New York, NY Hartford, CT Portland, ME Hancock, ME
2	Atlanta, GA Augusta, GA Columbia, SC	Macon, GA Greenville/Spartenburg, SC
3	Raleigh-Durham, NC Charlotte, NC	Greensboro, NC Greenville/Spartenburg, SC
4	Orlando, FL	
5	Detroit, MI Grand Rapids, MI	
6	Indianapolis, IN Louisville, KY	Cincinnati, OH
7	Chattanooga, TN Memphis, TN	Nashville, TN Knoxville, TN Little Rock, AR
8	Mobile, AL Baton Rouge, LA	Pensacola, FL Pascagoula, MS New Orleans, LA
9	Tyler, TX	Longview, TX Dallas, TX
10	St. Louis, MO	
11	Salt Lake City, UT	Provo, UT
12	Sacramento, CA	
13	San Diego, CA	
14	Seattle, WA	

Table 4-3. Reduced list of combined urban-area modeling domains using best-match homologues with emphasis on potential 8-hour ozone exceedance areas.

Combined Urban Areas	Key Homologue Areas	Other Nearby Areas
1	Philadelphia, PA Springfield, MA Boston, MA	Richmond, VA Washington, D.C. Baltimore, MD Allentown, PA Lancaster, PA Harrisburg, PA Scranton, PA New York, NY Hartford, CT Portland, ME Hancock, ME
2	Atlanta, GA Augusta, GA Columbia, SC	Macon, GA Greenville/Spartenburg, SC
3	Raleigh-Durham, NC Charlotte, NC	Greensboro, NC Greenville/Spartenburg, SC
4	Detroit, MI Grand Rapids, MI	
5	Indianapolis, IN Louisville, KY	Cincinnati, OH
6	Chattanooga, TN Memphis, TN	Nashville, TN Knoxville, TN Little Rock, AR
7	Tyler, TX	Longview, TX Dallas, TX
8	St. Louis, MO	
9	Sacramento, CA	
10	San Diego, CA	

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