Estimating Exposure by Loose-Coupling an Air Dispersion Model and a Geospatial Information System

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ABSTRACT. The regulation of air quality is important for ensuring the health of a population. Current air quality decision support systems are very useful if the user possesses sufficient data to operate them and the necessary expertise to interpret their results. In general, these systems suffer as a result of their excessive complexity. The present study describes the development of a scalable air quality decision support system using the CALPUFF air dispersion model and a Geospatial Information System (GIS). This system uses receptor level exposure modeling and outputs from CALPUFF to estimate the relative impacts on human populations from multiple air pollution sources by calculating intake, defined as the amount of pollution that is inhaled by a population and intake fraction, defined as the fraction of pollutant emitted by a pollution source that is inhaled by a population. Unlike ground level pollution concentration, intake and intake fraction consider receptors and offer a more valuable estimate of pollution exposure, especially when faced with limited input data. The system also leverages the inherent strength of GIS to improve accessibility of geospatial data by generating maps of ground level pollutant concentration, intake, and intake fraction using graduated color schemes. This enables any user to identify potentially hazardous pollution sources and prioritize decisions such as development, maintenance, and decommission.

Keywords: air dispersion modeling, intake, intake fraction, human receptor, CALPUFF, decision support system, geographic information system

1. Introduction

Air quality policy is an important societal consideration, since proper air pollution regulation is critical to the well-being of a population. Recently, air quality policy makers have relied on air quality decision support tools to reinforce their decision making process. The development of these tools is a constantly evolving process that is dependent on scientific theory, technological advancement, software development, and data availability. The most significant recent improvements to air quality decision making are based on two different basic principles. The first principle is *more is better*. The techniques associated to this principle focus on the improvement of the accuracy of air quality estimation, measurement, and analysis. This is accomplished through an increase in the sophistication of air dispersion models which has led to significant accuracy improvements.

The methods for analyzing the results from air dispersion models have also improved considerably. Geospatial Informa-

tion Systems (GIS) have become the most common tool for analyzing spatial data. Many air dispersion models include a rudimentary GIS in their software, whereas some air dispersion models facilitate the conversion of their output to data formats readily accepted by popular GIS platforms. This technique, called loose-coupling, is now commonly used for detailed air quality analysis.

An application of this method is provided by Elbir (2004), who 'loosely coupled' CALPUFF and ArcGIS to model the air pollution concentrations in the city of Izmir, in Turkey using CALPUFF. The results were converted and displayed in Arc-Map where pollution concentrations were compared with air quality standards and visually inspected. Zou et al. (2009) integrated AERMOD with ArcGIS to identify the population exposure contribution from different pollution sources (namely vehicles and industries). Though not mentioned explicitly, a loose-coupling approach was used. The outputs from AERMOD were converted and imported into ArcGIS where they were interpolated and overlaid with population density. ArcGIS was then used to estimate the population exposure before estimating the source type contribution.

There is one major limitation with this technique: it is not temporally or spatially scalable. Any air quality study conducted using this technique is limited to a small area and/or a short run time because it would require an unreasonable

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amount of time and effort to complete this sort of study over a long time period and a large study area. This technique is also not scalable in terms of available data. The general assumeption is made that all emissions are included in the model. If this is not true, and it seldom is, the results will be inaccurate.

At present, there are several high level air quality decision support systems in continued development that demonstrate the *more is better* philosophy. These systems are all very similar in their design and intended use. Systems like BenMAP (EPA, 2009), AirQUIS (NILU, 2009), Airware (ESS, 2009), and EnviMan (ECOTECH, 2009) focus on modeling current air quality and, in some cases, forecasting it. Generally, each of these systems has three main purposes: estimating current air quality and comparing the results with air quality standards, forecasting air quality to provide warnings, and estimating the results of proposed air quality regulation. Since the success of these systems is dependent on accurately modeling real world air dispersion, any results are heavily dependent on the quality and completeness of input data.

These systems also suffer from a second limitation. They do not explicitly model the exposure contributions from each individual pollution source. This implies that they can be useful for evaluating proposed changes to pollution sources, but they are not very useful for screening these pollution sources to determine the best candidates for changes. For example, if an air quality regulator decides that a universal 5% reduction in benzene emission is necessary to protect the population of a nearby settlement they can use an existing air quality decision support system to estimate the results of this decision, but they cannot determine if it is the optimal decision. Perhaps there is one particular benzene-emitting source that contributes the majority of the exposure and regulating or decommissioning this source alone would be a better decision. This deficiency is addressed in this paper through the development of a system that focuses on estimating the pollutant exposure contribution from several sources.

The second basic principle driving improvement of air quality decision making is *less is more*. Logically, the more information that is included in a decision making process, the more likely it is that some information, important or not, will be overlooked. This problem is especially concerning if some of the information included is inaccurate because it is calculated using incomplete data. The techniques that are based on this principle strive to achieve reliable results with limited and incomplete datasets. The best way to achieve these results is using a relative measure of exposure, such as a comparison of source specific intakes, or the intake fraction, which is the ratio of the source specific intake to the source's emission.

Marshall et al. (2006) provided estimates of inhalation intake of five pollutants for a large group of people in California presenting different social and economic characteristics. Intake fraction was used to evaluate the uncertainty in health risks due to anthropogenic primary fine particulate matter from different source types in Finland (Tainio et al., 2010) and to study the relationship between mobile source emissions and fine particulate matter exposure across the USA (Greco et al., 2007). Recently, Du et al. (2012) reported individual intake fraction of

particulate matter and NO_x from vehicle emissions based on personal exposure data in China.

Intake fraction is defined as the fraction of the mass released into the environment from a particular pollution source that is absorbed by the population (Bennett et al., 2002). One of his advantages is that rather than relying on complete data sets for accurate results, it gives optimal results for the available data. For instance, if an air dispersion model is used to model ground level concentrations in an area with several air pollution sources and no emission data are available for one or more of the sources in that area, inaccurate results will likely be obtained. If the intake fraction is used instead of ground level concentrations, meaningful results will be obtained for all of the sources that were included in the modeling. This technique is useful in areas where complete datasets do not exist.

To estimate population exposure to power plant emissions in Beijing using CALPUFF, Zhou et al. (2003) used intake fraction to overcome a lack of data in the study area. According to the authors "the main advantage of intake fraction is in its ability to model limited sources (where data are available) and extrapolate to other sources". Basically, there was not enough emission data available in their study area to model real world concentrations without drastic underestimation. Using intake fraction, this study was able to provide recommendations despite a lack of data. More recently Carella and Mudu (2009) completed a study that focused on critically evaluating the intake fraction as an exposure measure. The study suggests the advantages of using intake fraction, especially when working with limited data. The major disadvantage they identified was the difficulty of validating intake fraction measurements.

At the time of preparing this paper, and to the best of our knowledge, there are no air pollution decision support systems focusing on estimating the relative exposure contributions of individual air pollution sources. Most air pollution decision support systems that are capable of scenario modeling can be leveraged to determine relative exposure contributions. However, the procedure for accomplishing this is less than ideal since the system must be run once for each pollution source and the results from each run must then be compiled for analysis. This may not seem too inconvenient, but the number of scenarios grows exponentially as pollution sources are added. This makes this method of screening impractical for large areas with numerous air pollution sources. This paper describes an air pollution decision support system that was developed to address this deficiency.
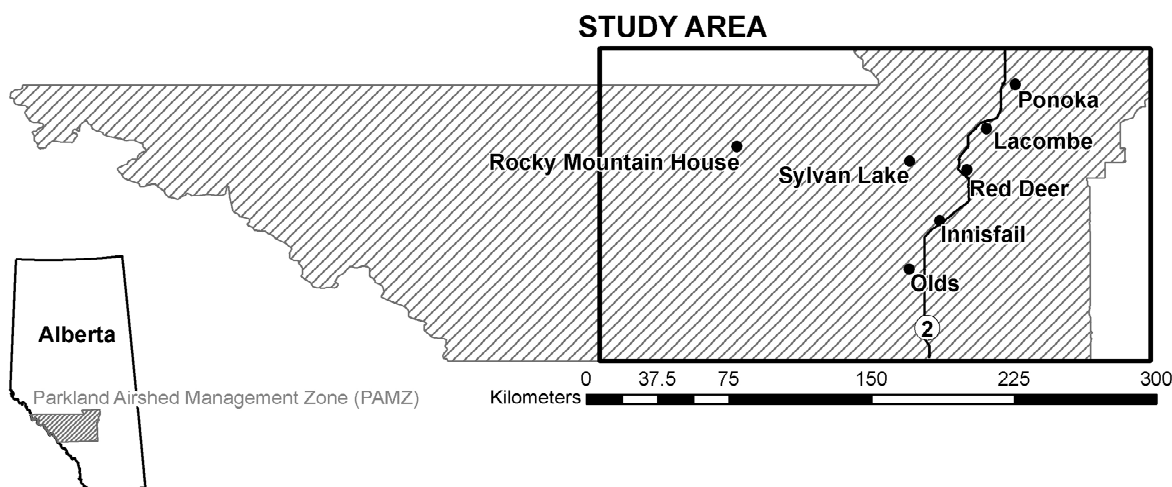
2. Objective

The proposed air quality decision support system was designed to meet four conditions. It must:

- be suitable for a range of applications including different pollutants, emission sources, and populations,
- focus on individual emission source contributions,
- complement existing scenario-focused decision support systems (such as BenMAP), by screening emission sour-

Table 1. Description of the Data Used in the Study

Description	Source	Spatial Resolution	Temporal Resolution	Date
MM5 modeled upper air data	Alberta Environment	12 km	hourly	2002
Surface Meteorological Observation data (Wind, Precipitation, Temperature, Pressure)	National Climate Data and Information Archive, Government of Canada, monitoring stations	6 discrete points	hourly	2002
Digital Elevation Model	USGS, derived from NASA's Shuttle Radar Topography Mission (SRTM)	90 m		2002
Land Cover	USGS North America Land Cover Database	1 km		1992
Pollution Emission (stacks only)	Environment Canada's National Pollutant Release Inventory (NPRI)	13 discrete points	monthly	2002
Population (including Age and Gender)	Census Canada, Dissemination Areas (DA)	416 discrete polygons		2001

Figure 1. Location of the study area.

ces to determine the best candidates for changes, and

- streamline the loose-coupling integration technique.

It will be demonstrated that this system could be used to make recommendations regarding the improvement of air quality in the study area by identifying the air pollution sources with the highest intake and intake fraction contributions. This will be done by integrating ground level air pollutant concentrations from CALPUFF with population data. These recommendations will then lead to scenarios that could be tested using a scenario-focused decision support system (such as BenMAP). Before the development of this system, users were tasked with identifying scenarios before they could be evaluated using an air quality decision support system. The system developed in this project focuses on assisting users in identifying such scenarios.

3. Methodology

Achieving the objectives of this project did not endorse the creation of an entirely new air quality decision support system. Instead it required a loose-coupling and augmentation of many existing systems and data sets. The details of these systems and data sets, as well as their interactions and the reasons they were selected for use in this project are presented in the

next sections, followed by a description of the custom software solution that was implemented for loose-coupling and augmenting them.

3.1. Study Area

The study area is a 165×180 km section of the Parkland Airshed Management Zone (PAMZ) in central Alberta, Canada (Figure 1). The PAMZ Airshed includes a portion of the Rocky Mountains on its western edge. Due to the unreasonable complexity of modeling air dispersion in mountainous regions with very limited meteorological observations, this portion of the Airshed has been excluded from the study area.

The study area was chosen to illustrate the versatility of the proposed air quality decision support tool. Covering approximately 30,000 km^2, it is uncharacteristically large when compared to most spatial extents used in air dispersion modeling projects. It includes grassland, deciduous forest, and mixed forest and contains both rural and urban areas. The total population is 227,280 inhabitants with 67,705 of them residing in Red Deer (the only city in the study area), while the remaining live in the 18 towns, 14 villages, 4 hamlets, or other rural areas within the study area. The study area also contains approximately 170 km of the Queen Elizabeth II highway, which is the

busiest roadway in Alberta (Government of Alberta Ministry of Transportation, 2009).

3.2. Data

This project requires a substantial amount of data including meteorology, air pollution emission, and population density. It focuses on the year 2002 due to the relatively high availability of the necessary data. A description of these datasets is provided in Table 1.

CALMET (the meteorological pre-processor for CALPUFF) is designed to accommodate Mesoscale Model 5 (MM5) modeled upper air data so no preprocessing of this dataset was required. The resolution of these data is much coarser than the recommended resolution for air dispersion modeling (1 km^2 or finer). However, since upper air wind patterns are not as complex as surface wind patterns, we assume that the wind did not change drastically over 12 km.

The surface meteorological observation data that were obtained from Alberta Environment required a format conversion from comma-separated value (CSV) into Station for Atmospheric Measurements (SAM). This was done using a conversion program obtained from the USGS website. SAM is a CALMET compatible format. The only problem with this dataset is its poor coverage. Although six stations are adequate to run CALPUFF on relatively flat and consistent terrain, the accuracy of the air dispersion modeling results would improve with more stations.

The Digital Elevation Model (DEM) needed only very simple preprocessing. Over 200 tiles were obtained and mosaicked into a continuous surface using ArcMap. These data have a much finer resolution than the modeling grid of 1 km. However, since this does not drastically affect the processing speed of CALMET, there was no need to use a coarser DEM.

The land-cover raster map was obtained in a CALMET compatible format and required no preprocessing. The most current land-cover map that could be obtained was created from aerial imagery captured in 1992, which is ten years earlier than would be ideal. While some land-cover changes have likely taken place during those ten years, it was unlikely that these changes were drastic enough to greatly alter the air dispersion modeling results at such a coarse spatial resolution.

The pollution emission data were obtained from the NPRI database (http://www.ec.gc.ca/inrp-npri/). This dataset was used to create a unique element for each pollutant for each pollution stack. For example, if one stack had four pollutant species, four unique elements were created. Each of these elements contained the necessary emission parameters and geographic coordinates for use as input into CALPUFF.

There are two problems with this dataset that should be mentioned. First, the stack location is based only on the facility location. This means that if a facility has several stacks they are all geocoded to be located in the center of the facility. This could result in a stack location error of up to 200 m. Given the size of the study area and the model grid of 1 km, this error was tolerable, but not ideal. Second, the emission quantities are aggregated into months. CALPUFF requires an emission rate in mass per second. To obtain this number the monthly totals were interpolated into mass per second values based on the operation times of the facility. This forces the assumption to be made that the pollutant was emitted at a constant rate whenever the facility was in operation, which may be incorrect. However, it can be expected that the impact of this approximation on the intake will be smaller than the impact on the pollutant concentration.

The population data were obtained in two files. The first one was a table containing population information based on the unique ID of each census dissemination area in the study area. The second file was a shapefile containing polygon boundaries of the census dissemination areas. A simple join was made between the table and the shapefile based on the unique identifier. Since these data were used for the GIS analysis and not for the air dispersion modeling, no consideration was given to their CALPUFF compatibility.

3.3. CALPUFF

CALPUFF is listed as the preferred air dispersion model for long range transport over complex terrain by the US Environmental Protection Agency (US EPA, 2012). It includes two main components. The first one is a comprehensive meteorological model called CALMET. CALMET produces 3D wind fields and various other air dispersion parameters required by CALPUFF (such as surface friction velocity, mixing height, and Monin-Obukhov length) from surface meteorological observations, modeled upper air, elevation, and land cover data. The second component is the non-steady-state puff air dispersion model called CALPUFF. CALPUFF produces gridded estimates of ground level pollution concentrations from the air dispersion parameters produced by CALMET and pollution emission characteristics (including stack height, stack diameter, exit velocity, exit temperature, and emission rate).

For this project, CALPUFF was run with default settings using the data described in the previous section. Air quality monitoring data were available and could be used to calibrate CALPUFF for this study. However, since several pollution sources were missing, including vehicle emissions, a calibration would not have made sense. Without modeling vehicle emissions, calibrating the model with air quality measurements would have resulted in an overestimation of the contribution of point source air pollution. After running CALPUFF, the resulting gridded ground level pollution concentrations were used as inputs for the GIS analysis.

3.4. ArcGIS

ArcGIS is a complete GIS software package. ArcMap 10.0 included all of the tools required for this project. Using ArcGIS libraries in Microsoft Visual Studio VB.NET 2010, a custom toolbar was developed for ArcMap that contains all of the tools necessary for importing and analyzing the CALPUFF results. The details of the GIS analysis will be discussed through the description of the Import, Analyze, and Evaluate tools in the next section.
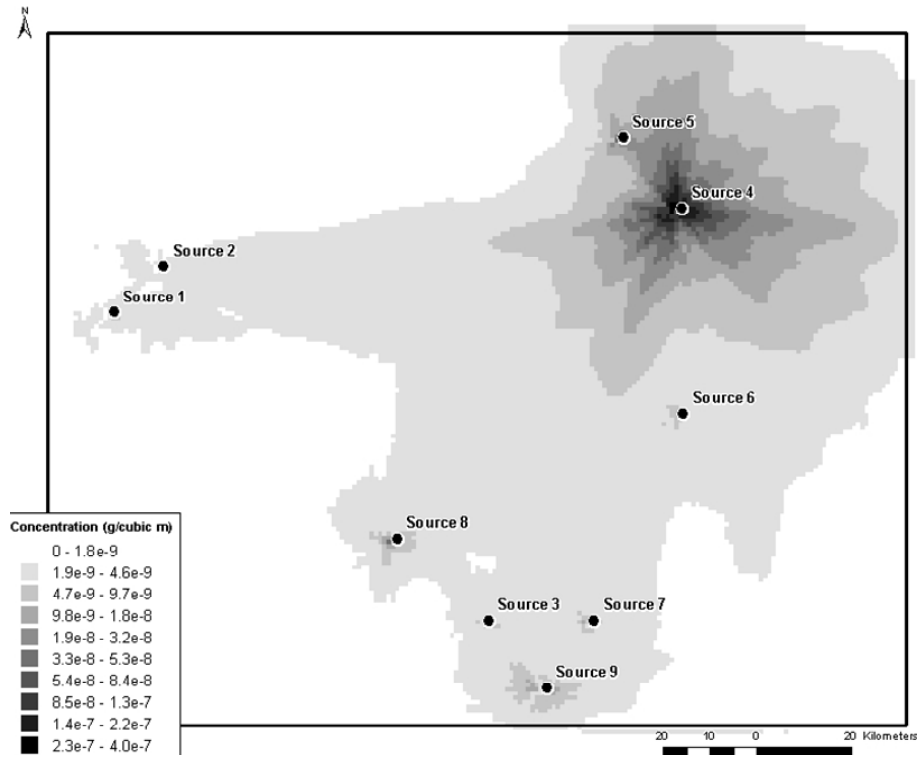
Figure 2. Average ground level PM2.5 concentration from all modeled emission sources.

3.5. Loose-Coupling CALPUFF with ArcGIS

The loose-coupling technique implemented in this project consisted of using CALPUFF to produce gridded ground level pollution concentrations and using the custom toolbar in Arc-Map for post processing and analysis. There was no need to use ArcGIS as a preprocessor since CALPUFF has built-in pre-processors for converting and importing input data.

The development of the custom toolbar in ArcMap was the most important step in the loose-coupling process of this project. Currently, loose-coupling of an air dispersion model and GIS involves several intermediate steps that require a detailed understanding of GIS. These steps can include data conversion, joining, mosaicking, merging, geocoding, and symbolization. The custom toolbar in ArcMap eliminates the need for any intermediate steps and opens the analysis procedure to researchers unfamiliar with GIS. This custom toolbar includes three tools: Import, Analyze, and Evaluate.

3.5.1. Import Tool

The Import tool reads CALPUFF outputs and creates shapefiles containing pollutant concentration information for use in the intake and intake fraction calculations.

The output from CALPUFF contains x, y coordinates and hourly concentration values. The maximum and average of these hourly concentrations are calculated and added to point features that are geocoded using the x, y coordinates. Each point feature is populated with concentration statistics representing each contributing pollutant source and the sum of all pollutant sources. Once the point shapefiles are created, their concentration statistic values are averaged based on which census dissemination area (DA) they lie within. Then a copy of the DA shapefile is created and populated with these averaged concentration statistics. The final result is a copy of the DA polygon shapefile populated with average and maximum concentrations. These polygons can then be used in the Analyze tool to calculate several types of intake and intake fraction.

3.5.2. Analyze Tool

The Analyze tool uses the results from the Import tool to calculate intake (Equation 1) and intake fraction (Equation 2) for each Dissemination Area:

$$i = P \times C \times IR \tag{1}$$

$$iF = i / Q \tag{2}$$

i = intake (g/day)
P = population
C = ground level concentration (g/m^3)
IR = weighted average inhalation rate (m^3/day)
iF = intake fraction
Q = emission rate (g/day)

A separate intake and intake fraction for each contributing source is calculated, as well as the total intake and intake fraction (i.e., from all contributing sources combined). These values are added as attributes to the DA polygon shapefile created by the Import tool.

The Analyze tool also allows the user to specify a sub-population, which will alter the population (P) and weighted average inhalation rate (IR) in Equation 1.

3.5.3. Evaluate Tool

The Evaluate tool identifies the concentration, intake, and intake fraction contribution from each of the modeled pollution sources. This is accomplished by summing these values from each concentration grid point and Dissemination Area for each contributing source. These sums are then added to the source shapefile as attributes, allowing the attribute table to be used to sort the emission sources based on their contribution to the total concentration, intake, or intake fraction.

4. Results

For the purpose of demonstrating the capabilities of the system, ground level pollutant concentrations of < 2.5 micron Particulate Matter (PM2.5) were generated for the entire study area for the month of June 2002. The resulting 1 km^2 hourly ground level PM2.5 concentration grids were used as inputs for the toolbar.

4.1. Concentration

The Import tool was used to calculate the average ground level PM2.5 concentrations from the CALPUFF output file and symbolize them using a ten class, grey scale gradient with relatively high average concentrations of PM2.5 displayed in black and relatively low average PM2.5 concentrations shown in white. Consequently, black areas indicate a greater probability of health impacts for the inhabitants than the white areas. Figure 2 illustrates the Import tool user interface displaying the average ground level PM2.5 concentration from all modeled emissions combined.

Upon visual inspection of Figure 2, emission source 4 contributes the majority of the ground level pollutant concentration to the study area. Source 4 is followed, in order of concentration contribution, by sources 9, 8, 7, and 6. It becomes difficult to order the remaining sources, which illustrates the limitation of concentration distributions alone for the purpose of screening emission sources.

The Import tool was also used to calculate the average ground level PM2.5 concentrations resulting from the emissions of each modeled emission source individually. These resulting concentration distributions were averaged over the entire study area using the Evaluate tool. Table 2 lists the contribution of each modeled emission source to the total average PM2.5 concentration for the entire study area, indicating a highest contribution from source 4.

The emission sources are ranked based on their contributions to the overall average ground level concentration of PM2.5 in the study area. If it is determined that average concentrations in the study area are higher than desired, ranking the emission sources according to this criterion will help a user to identify the emission source(s) that are mostly responsible

Table 2. Emission Source Contributions to Average Ground Level PM2.5 Concentration

Source	Concentration Contribution (ng/m^3)
4	2.69
2	2.20
3	0.477
9	0.166
5	0.0979
8	0.0855
1	0.0731
6	0.0302
7	0.0284

Table 3. Emission Source Contributions to Average PM2.5 Intake

Source	Total Intake Contribution (g/day)	Children's Intake Contribution (g/day)	Senior's Intake Contribution (g/day)
4	0.020	0.0035	0.0017
5	0.0020	0.00036	0.00027
2	0.00068	0.00012	0.000067
9	0.00068	0.00013	0.000064
8	0.00027	0.000048	0.000031
1	0.00019	0.000035	0.000020
3	0.00019	0.000033	0.000020
7	0.000083	0.000015	0.0000089
6	0.000083	0.000015	0.0000087

for the exceedance. However, no consideration is given to the exposure experienced by receptors.
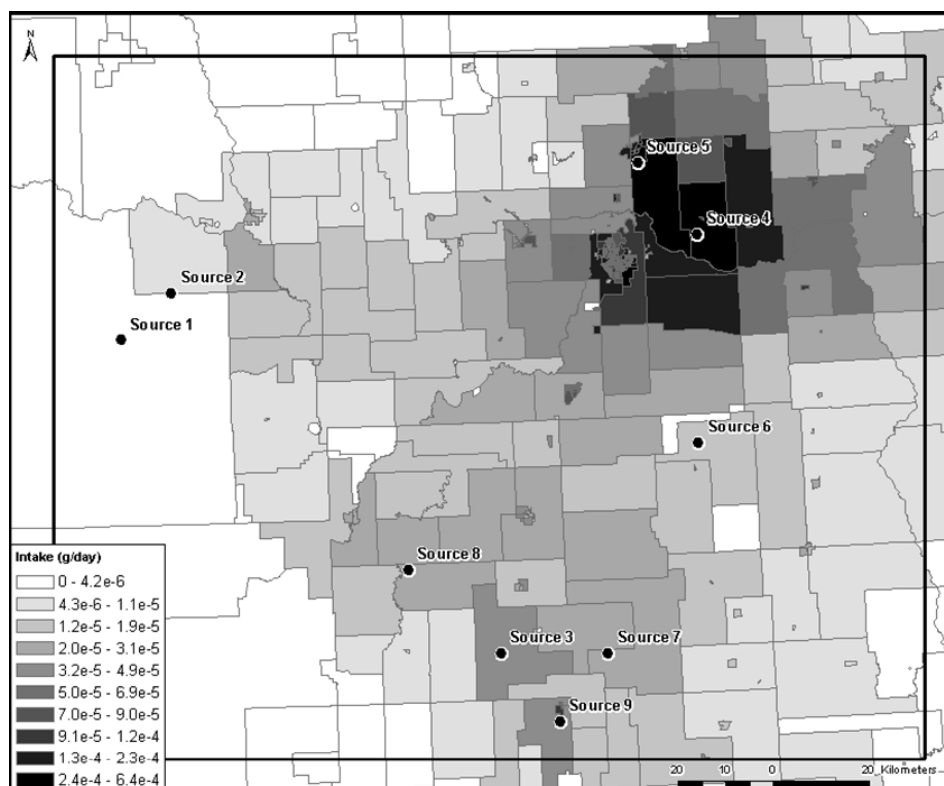
4.2. Intake

The Analyze tool was used to calculate the total intake from all emission sources combined for the total population and sub-populations of persons 14 years of age and younger (children) and persons 65 years of age or older (seniors). This represents an estimate of exposure to the concentration distribution created by the Import tool. Figure 3 illustrates the total average PM2.5 intake for the total population displayed with the Analyze tool user interface.

It allows the user to visualize the relative total intake of the population in each Dissemination Area and draw meaningful conclusions about exposure. For example, roughly 100 times as much air pollution is absorbed by the total population in the black areas compared to the white areas. Since intake is an estimate of the probability of human health effects resulting from the modeled emission in each of the Dissemination Areas, these results are useful for identifying the areas with a higher probability of negative health effects.

Table 3 presents the intake contributions of each emission source to the total population, children, and seniors calculated using the Evaluate tool. The emission sources are ranked based on their contributions to the overall average PM2.5 intake in the study area. Again, emissions from source 4 result in higher average PM2.5 intake in the study area than the other

Table 4. Emission Source Contributions to Average PM2.5 Intake Fraction

Source	Total Intake Fraction Contribution (10^{-8})	Children's Intake Fraction Contribution (10^{-9})	Senior's Intake Fraction Contribution (10^{-9})
5	28	52	38
4	9.5	17	8.3
8	5.1	9.0	5.8
3	4.5	8.1	4.9
7	4.4	8.1	4.6
9	3.7	6.8	3.5
6	3.6	6.7	3.8
2	2.6	4.6	2.5
1	2.4	4.3	2.5

Figure 3. Average intake of PM2.5 from all modeled emission sources.

modeled emission sources. From a decision support perspective, these results indicate that decreasing emissions from a higher ranked source, such as source 4 by a given fraction of the total emission would result in a more substantial drop in pollution inhaled by the population than decreasing the emissions of a lower ranked source (e.g., source 7) by the same fraction.

The intake varies when a sub-population is considered. For example, source 9 has a higher intake contribution to children than source 2 while source 2 has a higher intake contribution to seniors than source 9. From a decision support perspective, the selection of a sub-population introduces susceptibility into the air quality analysis. If a decision maker has information indicating that children are more sensitive to higher average concentrations of PM2.5 than the rest of the population,

the modeled emission sources can be ranked according to their intake contribution to children alone.

Comparing Table 3 with Table 2 reveals that considering exposure alters the priority of the modeled emission sources. For example, when considering only contribution to concentration source 5 is ranked as the fifth most significant source, but it is ranked second when considering contribution to intake.

4.3. Intake Fraction

The Analyze tool was used to calculate the total intake fraction from all emission sources combined for the total population, children, and seniors. Figure 4 illustrates the total average PM2.5 intake fraction for the total population displayed the Analyze tool user interface.
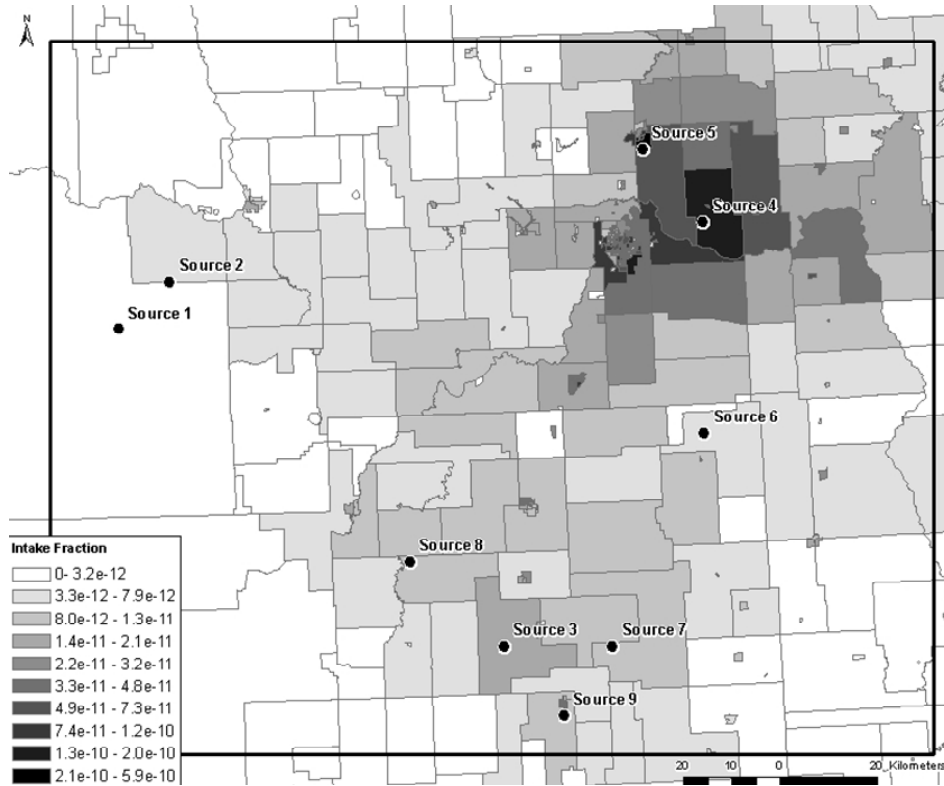
Figure 4. Average intake fraction of PM2.5 from all emission sources.

It allows the user to visualize the relative intake fraction of the population in each Dissemination Area and reveals that roughly 100 times the proportion of the air pollution emitted in the study area is absorbed in the black areas compared to the white areas. Since intake fraction is an estimate of the probability of human health effects resulting from the proportionate changes to emission rates from modeled emission sources, these results are useful for identifying the areas that are most sensitive to changes in the emission rates of sources in the study area.

Table 4 presents the intake fraction contributions of each emission source to the total population and the sub-populations of children and seniors calculated with the Evaluate tool. The emission sources are ranked based on their contributions to the overall average PM2.5 intake fraction in the study area. Emissions from source 5 result in higher average PM2.5 intake fraction in the study area than the other modeled emission sources. From a decision support perspective, these results indicate that decreasing emissions from a higher ranked source (e.g., source 5) by a given amount would result in a more substantial drop in pollution inhaled by the population than decreasing the emissions of a lower ranked source (e.g., source 1) by the same amount.

The difference between intake and intake fraction as estimates of exposure is illustrated when comparing the emission source rankings listed in Tables 3 and 4. For example, when considering contribution to intake, source 4 is the most significant source, but source 5 becomes the most significant source when contribution to intake fraction is considered.

The intake fraction also varies with the sub-population. For example, source 6 has a higher intake fraction contribution to seniors than source 9 while source 9 has a higher intake fraction contribution to children and the total population than source 6.

5. Conclusions

The objective of this research was to create an improved air quality decision support system. To avoid overlap with existing work in this area, the created system had to focus on individual air pollution source contributions and support emission source screening while streamlining the loose-coupling integration of an air dispersion model with a GIS. The capabilities of the developed air quality decision support system were then demonstrated using PM2.5 emission data and meteorological data for June 2002 in central Alberta.

The results demonstrate that the objectives of this research were met. While several previous studies have highlighted the usefulness of intake and intake fraction to assess population exposure to pollutants and the potential risks to human health, the developed air quality decision support system estimates emission source concentration, intake, and intake fraction contributions and uses them to prioritize emission sources. This may allow a decision maker to identify the sources which pose the greatest risk to the population and thus justify a reduction in emission from these sources. The opposite is also true. If an increase in emissions is necessary, the sources identified as lowest risk will make the best candidates. This offers decision

makers a starting point for investigating more detailed emission regulation or mitigation options and to screen these options, streamlining the decision making process. Rather than developing an emission regulation scenario from a template (or even intuition) and then testing it, decision makers can develop these scenarios by focusing on sources that are prioritized based on their concentration, intake, or intake fraction contributions.

The loose-coupling technique used in the developed decision support system has been effectively streamlined to the point that it requires no intermediate steps. Through the development of a custom toolbar in ArcMap, the outputs from CALPUFF can be read into an ArcMap document simply by clicking a button. The analysis on the imported CALPUFF ground level concentrations can be completed just as easily.

There are, however, some enhancements that would improve the usefulness of the developed air quality decision support tool. When importing CALPUFF concentrations from a one month modeling period, the run-time of the Import tool can be as high as twenty minutes; loading data for an entire year took two hours. A first enhancement would involve some algorithm changes, specifically concerning variable handling and memory management that would improve the processing speed of the Import tool.

A second, and more ambitious, enhancement involves exchanging the desktop GIS for a web-based GIS. This decision support system is built as an add-in to ArcMap software, which requires a very expensive annual license. Offering this system on a web-based GIS platform (such as ArcGIS Server) would increase availability to decision makers and even the general population at no cost to the user. Data could be loader and processed server-side. The Analysis and Evaluate tools would operate client-side and provide visualizations.

In summary, the air quality decision support system presented in this paper is a useful tool for prioritizing point sources of air pollution. In a further step, the location of public and private institutions, such as schools, hospitals and senior homes could be considered to evaluate more precisely the potential impact of emissions on sub-populations concentrated in specific areas. The system provides support for often ignored air quality option screening, allowing it to complement existing air quality decision support systems (such as BenMAP). This software can be installed and run on any desktop computer with an operational ArcGIS desktop license.

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