A new method for estimating carbon dioxide emissions from transportation at fine spatial scales

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Received 1 July 2010
Accepted for publication 5 November 2010
Published 29 November 2010
Online at stacks.iop.org/ERL/5/044008

Abstract
Detailed estimates of carbon dioxide (CO2) emissions at fine spatial scales are useful to both modelers and decision makers who are faced with the problem of global warming and climate change. Globally, transport related emissions of carbon dioxide are growing. This letter presents a new method based on the volume-preserving principle in the areal interpolation literature to disaggregate transportation-related CO2 emission estimates from the county-level scale to a 1 km2 grid scale. The proposed volume-preserving interpolation (VPI) method, together with the distance-decay principle, were used to derive emission weights for each grid based on its proximity to highways, roads, railroads, waterways, and airports. The total CO2 emission value summed from the grids within a county is made to be equal to the original county-level estimate, thus enforcing the volume-preserving property. The method was applied to downscale the transportation-related CO2 emission values by county (i.e. parish) for the state of Louisiana into 1 km2 grids. The results reveal a more realistic spatial pattern of CO2 emission from transportation, which can be used to identify the emission 'hot spots'. Of the four highest transportation-related CO2 emission hotspots in Louisiana, high-emission grids literally covered the entire East Baton Rouge Parish and Orleans Parish, whereas CO2 emission in Jefferson Parish (New Orleans suburb) and Caddo Parish (city of Shreveport) were more unevenly distributed. We argue that the new method is sound in principle, flexible in practice, and the resultant estimates are more accurate than previous gridding approaches.

Keywords: volume-preserving interpolation, distance decay, carbon dioxide (CO2) emissions, transportation, geographic information systems

1. Introduction
Carbon dioxide (CO2) emissions are produced in our daily lives through burning fossil fuels to meet essential needs such as electricity, heating, and transportation. As a major component of greenhouse gas emissions, increased CO2 emissions due to anthropogenic activities have been suggested to contribute to global warming; rising global temperatures will cause sea levels to rise and threaten to alter global as well as local climate conditions, affecting forests, crop yields, water supplies, and the economy (Parry et al 2007, Rosenzweig et al 2007, Guy and Levine 2001). Many countries have already produced national-level estimates of CO2 emission. In the United States, the Department of Energy's Energy Information Administration (EIA) has been conducting an inventory of annual CO2 emissions at the national spatial scale. The
US Environmental Protection Agency has also completed an inventory of greenhouse gas emissions and sinks at the national level, as well as actively encouraging states to develop state-level inventories. However, there is an emerging need from both the science and policy-making communities for CO₂ emission data at fine spatial scales. An accurate, spatially distributed inventory of carbon dioxide emissions reported in a uniform grid will serve as a useful input to many energy and climate impact modeling efforts, enable integration of other data sources (such as world population data and energy consumption data), and provide a baseline dataset for policy development to reduce CO₂ emissions (Gurney et al 2009b, Mohan et al 2007).

There are quite a few examples in which fine-scale spatial estimates of CO₂ emission have been sorely needed for model input and policy evaluation (Osses de Eicker et al 2008). In Ohio, fine-scaled CO₂ emission data were used in conjunction with land use and other GIS (geographic information system) data to determine where to increase forest acreage for carbon sequestration so that the state’s total CO₂ budget can be reduced (Guy and Levine 2001). In the United Kingdom, it was suggested that the government should develop spatial hydrogen infrastructures and technology because of its great potential in reducing the country’s CO₂ budget. However, such effort will require data on the spatial distribution of CO₂ emissions at fine spatial scales, so that hot spots or vulnerable spots of emission can be identified (Strachan et al 2009).

This letter focuses on the estimation of CO₂ emissions from the transportation sector from coarse to fine grid scales. The spatial estimation of CO₂ emissions from the transportation sector can be derived either from a bottom-up or a top-down approach. The bottom-up approach is based on detailed street-level traffic flow data that are aggregated into cells or zones. Such detailed data are very limited and difficult to obtain, hence a top-down approach is often employed instead. The top-down approach is a disaggregation process, transforming large-size, usually irregularly shaped, emission data to small-sized uniform grid data. The approach is based on the assumption that the amount of emissions is highly correlated with some indicators such as population density, road network density, and others.

There have been a few attempts in producing fine-scale estimates of carbon emissions, and geographic information system (GIS) technology has been heavily utilized. In the United States, a project named ‘Vulcan’ has quantified fossil fuel CO₂ emissions for the contiguous US at a spatial scale of 10 × 10 km² grid and temporal scales as fine as hours (Gurney et al 2009b, 2009a). The Vulcan inventory data for the year 2002 were constructed from seven emission data sets, which come in different forms (e.g., point or area form) and at different spatial scales (e.g., facility or county level). Additional geocoded data sets, such as census, residential and industrial clusters, and roadways, were used to help downscale the emission estimates into 10 × 10 km² grids. The Vulcan approach is considered process-driven, with an underlying assumption that more emissions are expected to occur closer to the sources. The Vulcan inventory data shows excellent agreement with the national-level US Department of Energy inventories. However, significant deviations in the CO₂ emission estimates occur when compared with another 1° × 1° fossil fuel CO₂ emission inventory generated by A Brenkert; the latter inventory was generated primarily based on population distribution (Andres et al 1996, Olivier et al 1999). The Vulcan group argues that downscaling CO₂ emission based on population concentration does not reflect the emission of the industrial sector accurately, as many industrial areas, such as the Gulf Coast oil and gas industry, do not coincide with large population centers.

In Chile, a spatial disaggregation approach was used to create 1 km² grids using road density as proxy for mid-sized cities (Osses de Eicker et al 2008, Tuia et al 2007), whereas traffic counts, land use, and the major road network were used as proxies for emission intensity for large cities (Saide et al 2009). Similarly, Streets and others developed an inventory of air pollutants in Asia for the year 2000 using a top-down approach (Streets et al 2003). Line source (road networks) emission allocation is conducted by multiplying pre-generated allocation factors by regional or national emission total. The allocation factors for line sources are created by combination and transformation of geographic information, such as road network type, ship-lane information, and others.

Another notable example of large-scale gridded inventory effort is by Dalvi et al (2006). They downscaled the total carbon monoxide (CO) emissions over India for 2001 from state level (28 points) to district level (about 500 points) and then interpolated from the district points to a 1° × 1° grid mesh using a point interpolation method. Their model, called G-SMILE (GIS-based Statistical Model for Interpolation of Large Emissions), utilizes the spatial variation of CO emission source data, such as rural and urban bio-fuel uses, vehicular traffic, and coal and biomass burning emissions, to help allocate state-level estimates into district-level estimates. Then, the ‘natural neighbor local interpolation’ method was used to interpolate the irregularly spaced district points into a uniform 1° × 1° grid mesh. Their results reveal the location of emission hotspots across India and the relative contributions of various sources.

These GIS-based process-driven approaches to downsampling broad-scale estimates into fine spatial-scale estimates have proven to be effective and reasonably accurate. However, there are two shortcomings regarding the previous downsampling approaches. First, although some downsampling approaches allocate the broad-scale estimates proportionally into fine-scale estimates, the methods generally do not guarantee the volume-preserving property throughout the interpolation process. For example, the above-mentioned Indian CO emission estimation project used an approach that distributes the state-level estimates proportionally to districts, thus preserving the total value (i.e., volume) of the original state-level estimate at the district level. However, the process of gridding district-level estimates into 1° × 1° grids was based on an interpolation method (the natural neighbor local interpolation method) that does not guarantee volume preserving. In other words, if one sums all the grid values within a district, the total value may not be the same as the original district value. For the Indian CO emission estimation, the total CO emissions from 1° × 1° gridded cells were estimated to be 60 357 Gg, whereas the total
original CO emissions was 69,376 Gg, yielding a data loss of about 13%. This problem occurred because the gridding process does not guarantee volume preserving.

Figure 1 is a hypothetical example comparing the downscaling of three zone estimates into a 5 \times 5 grid mesh using two approaches, a volume-preserving interpolation (VPI) approach and a commonly used grid interpolation method (generated by an inverse distance weighting method), which does not guarantee volume preserving. As shown in figure 1(c), the resultant zone estimates from the non-volume preserving interpolation method are different from the original estimates. The volume-preserving areal interpolation property has been discussed extensively in the GIS and spatial modeling literature (Tobler 1979, Goodchild and Lam 1980, Lam 1983, 2009). The volume-preserving property is said to be an essential criterion for a more reliable areal interpolation, and estimates derived from those methods that are volume preserving are generally more accurate than those derived from methods that do not preserve volumes (Lam 1983, 2009).

The second shortcoming of most previous downscaling approaches is that they have seldom incorporated a distance-decay function explicitly in allocating the emission estimates. As already pointed out in the Vulcan study and a few other studies, the underlying assumption is that more emissions are expected to exist closer to the sources (Gurney et al 2009a, Wentz et al 2002). For emission from transportation, this distance-decay property is important, as it is expected that emissions would be higher for those cells that have or are closer to highways and other transportation routes than those cells that are farther from the transportation routes.

This letter demonstrates a new method to downscaling transportation-related CO₂ emissions using the state of Louisiana as an example. There are 64 parishes in Louisiana (counties are called parishes in Louisiana) and the resultant grid in this study is 1 km². The method is based on the principle of volume preserving, as well as the distance-decay principle, in assigning the weights of the grids, thus overcoming the two shortcomings of previous downscaling approaches.

2. Study area and data
Situated in the south of the United States, the state of Louisiana is the 10th highest carbon dioxide polluting state in the US (USEIA 2008a). CO₂ emission of Louisiana on a per capita basis is approximately 40 tons each year. CO₂ emissions are inventoried by five sectors (USEIA 2008b). The industrial sector accounts for 46% of all CO₂ emissions from combustion of fossil fuels in 2005. The next two largest sources of carbon dioxide are the transportation sector (28%) and electric utilities (23%). The combined share of residential and commercial sectors is fairly small, approximately 3%, and is largely electricity usage for water and space heating/cooling (USEIA 2008c).

CO₂ emission data from the transportation sector for the year 2002 at the county (parish) scale in Louisiana were obtained from the Vulcan inventory. The emission estimates contain three separate components: on-road emissions (mobile transport using designated roadways), non-road emissions (vessels along waterways, trains along railroads), and airport emissions associated with air travel (Gurney et al 2009a). The on-road emissions are based on the county-level vehicle miles traveled (VMT) and CO₂ emission factors. The VMT data come from the National Mobile Inventory Model (NMIM) County Database (NCD) for 2002, which quantifies the vehicle miles traveled in a county by month, specific to vehicle class and road type. The Mobile6.2 combustion emissions model is used to generate CO₂ emission factors on a per mile basis, given inputs such as fleet information, temperature, fuel type,
and vehicle speed. Non-road emissions are structured similarly to the on-road mobile emissions data and consist of mobile sources that do not travel on designated roadways. These data, retrieved from the NMIM NCD, have a space/time resolution of county/month and are reported as activity (number of hour/month vehicle runs), population, and a CO₂ emission factor specific to the vehicle class. The airport emission data include both take-off and landing, and the data are taken factor specific to the vehicle class. The airport emission data include both take-off and landing, and the data are taken from the GIS data obtained from the Louisiana Department of Transportation and Development (LDOTD, see table 1). We tabulated that in year 2000 Louisiana had a total of 60,765 miles of road, 1964,694 registered cars, and 1570,804 registered trucks. The northern part of Louisiana is easily accessible from the southern end by interstate highways 49 and 55. The eastern and western ends of Louisiana are connected by interstate highways 10, 12 and 20. Some of the prominent US highways include road routes 167, 90, 190, 71, 171, 84, 165, 79, 80 and 61 (figure 3).

As background information for on-road emissions, according to the GIS data obtained from the Louisiana Department of Transportation and Development (LDOTD, see table 1), we tabulated that in year 2000 Louisiana had a total of 60,765 miles of road, 1964,694 registered cars, and 1570,804 registered trucks. The northern part of Louisiana is easily accessible from the southern end by interstate highways 49 and 55. The eastern and western ends of Louisiana are connected by interstate highways 10, 12 and 20. Some of the prominent US highways include road routes 167, 90, 190, 71, 171, 84, 165, 79, 80 and 61 (figure 3).

The navigated waterways are defined as waterways that have been traveled by vessels transporting 10,000 gallons of oil or fuel in 1999 (Louisiana Oil Spill Coordinator’s Office LOSCO, see table 1). Louisiana lies principally along the Gulf of Mexico and the Mississippi River, which traverses from north to south for a distance of about 600 miles and empties into the Gulf of Mexico. In addition, there are several intracoastal waterways, the Red River, the Sabine, the Pearl, Calcasieu, the Mermentau, the Vermilion, Bayou Teche, the Atchafalaya, the Bofou, the Courtbale, Bayou D’Arbonne, Amite River, the Tickfaw, the Natalbany, and a number of other smaller streams, constituting a natural system of navigable waterways, aggregating over 4000 miles in length (we tabulated from the GIS data) (figure 4).

Based on the railroad dataset published by LDOTD in 2006, the following railroads operate in Louisiana, which are Acadiana Railway, Arkansas, Louisiana and Mississippi Railroad, Baton Rouge Southern Railroad, Kansas City Southern Railway, New Orleans and Gulf Coast Railway, Louisiana Southern Railroad, and others, aggregating over 2800 miles in length. Railroads are divided into four types, including Class I railroad, Regional Railroad, Local Railroad and Switching & Terminal Railroad (US Department of Transportation and Bureau of Transportation Statistics 2002).

There are many airports in Louisiana. However, not all Louisiana airports have regularly scheduled flights. Major airports in Louisiana are in Monroe, Shreveport, Ruston, Opelousas, Eunice, New Orleans, Baton Rouge, Lafayette, Lake Charles, Houma and Morgan City (figure 5).

### 3. Methods

The method is based on both the principles of volume preserving and distance decay. The distance-decay principle was used to determine the weight for each grid, and the volume-preserving principle was used to determine the corresponding emission unit. The distance-decay principle is grounded on the assumption that proximity to the source is a main determinant of emission intensity, and the principle has been utilized previously to estimate the spatial distributions of both CO₂ emissions and concentrations (Cohen et al 2005, Su et al 2009b, Wentz et al 2002, Zou et al 2009). In particular, Cohen and others utilized the distance-decay principle and a buffer zone to estimate emission contributions from each road link so that the results can be input into a regression model for estimating subsequent CO₂ concentrations (Cohen et al 2005; p 9). Similar distance-decay principles have been used to calculate a distance-weighted emissions intensity index at each target grid cell so that they can be used to generate high-resolution (1 km grid) air pollution maps across Europe (Vienneau et al 2009; p 258). Moreover, it is reasonable to assume that higher levels of traffic intensity occurs in areas closer to highways, thus higher CO₂ emissions in areas of closer proximity to highways are expected.

However, regarding the distance-decay function and the threshold, the literature did not point to a consistent model, and the choice of an appropriate distance-decay function remains to be a subject of further research. For example, Su and others found that a negative exponential curve with a gentle slope (i.e., very close to a linear form) explains the distance decay of NO₂ concentrations away from highways, but with only a small portion of variance explained ($R^2 = 0.32$) (Su et al 2009b). The distance thresholds tested in their studies ranged from 50 m to 15 km (Su et al 2009a). Vienneau and others used varying distance thresholds ranging from 1 to 25 km for NO₂ emission modeling for airports of different sizes (Vienneau et al 2009). They used an inverse distance squared distance-decay function ($1/d^2$) as a starting model for emission

### Table 1. Data description and sources.

| Data                  | Form      | Description                                      | Coordinate system          | Source               | Date   |
|-----------------------|-----------|-------------------------------------------------|----------------------------|----------------------|--------|
| CO₂ emissions         | Attribute | On-road, non-road, and airports                 | None                       | Vulcan Inventory     | 2002   |
| Parishes              | Polygon   | Boundaries of parishes                          | Geographic NAD83           | LDOTD                | 2007   |
| Roads                 | Polyline  | Intermates, US highways, and Louisia state highways | Geographic NAD83           | Census Tiger         | 2006   |
| Highways              | Polyline  | State maintained road network                   | UTM Zone 15 NAD83          | LDOTD                | 2007   |
| Railroads             | Polyline  | Railroads                                       | UTM Zone 15 NAD83          | LDOTD                | 2006   |
| Waterways             | Polyline  | Navigated waterways                             | Geographic NAD83 LOSCO     | 1999                 |
| Airports              | Point     | Airport locations                               | UTM Zone 15 NAD83          | LDOTD                | 2007   |
dispersion and found that a more gradual distance-decay form (than the $1/d^2$) was more accurate.

In light of the inconsistent results from the literature, we chose the straightforward, linear approach to estimating the CO2 emissions in our study. Moreover, we used a distance threshold of 10 km for on-road and non-road emissions because the Vulcan inventory uses a $10 \times 10 \text{ km}^2$ grid. A 10 km distance threshold for the current $1 \text{ km}^2$ grid hence would enable comparison between the two estimates, as shown below (figure 3). For airport emissions, the threshold was assumed to be bigger and was arbitrarily fixed at 20 km, which is within the ranges tested in the study by Vienneau et al (2009). Both distance thresholds were selected primarily as an example to illustrate the method. All the weights were reclassified into ten classes so that we can easily visualize and compare the results.

Once the weights were determined, the volume-preserving property was imposed for each source and for each parish. The general principle is to assign weights to each grid from each source so that the sum total of each source is equivalent to its parish total. The method can be summarized into four major steps:

1. For each emission source, compute a set of weights for each grid.
2. Sum the total weight of each parish.
3. Calculate the CO2 emission unit of each grid.
4. Use the weights and units to calculate CO2 emission of each grid.

Figure 2 outlines the steps involved in producing the final grid estimates.

The transportation-related CO2 emission data by parish have three distinct components (sources): on-road, non-road, and airport. Road length and road network density have been used in previous studies to correlate with on-road CO2 emission (Osses de Eicker et al 2008, Gurney et al 2009b, Saide et al 2009, Streets et al 2003, Tuia et al 2007). Hence, these two variables were selected for this study as allocation factors. Emissions per length of road types (e.g. urban, rural, interstate, or arterial) vary greatly. However, since most literature used only distance to major highways (not all types of roads) to determine the weight for each grid, this project also focused on using highways only for calculating the weight. In addition, the parish’s road network density for all roads was used to adjust the weight (see equation (2) below). These two variables, the road network density and highway weights, are assumed to yield a useful summary weight of on-road emission for each grid.

Therefore, on-road CO2 emission at a grid depends on two factors: (1) the distance of the grid from major highways including interstates, US, and state highways; and (2) the road network density of the parish. The highway weight of a grid is determined by equation (1):

$$a_j = 10 - \text{Int}(d_j), \quad \text{if } d_j < 10 \text{ km}, \quad \text{otherwise } a_j = 0$$

(1)

where $a_j$ is the highway weight for grid $j$, and $d_j$ is the distance of grid $j$ from the center of the nearest highway. We set 10 km as the threshold, that is, when a grid is more than 10 km away from its nearest highway, the weight is zero. When the source is within the grid, the weight is ten. As an example, if a grid is 2.3 km away from the nearest highway, then from equation (1), the highway weight will be eight.

In the second step, the road network density for each parish is determined by dividing the total road length (in km) within a parish by its area (in km$^2$). The on-road emission weight at a grid ($w_{j}$) is then adjusted by multiplying its highway weight ($a_j$) with the corresponding parish’s road density ($r_p$) (equation (2)), and the resultant weights ($w_{j}$) are reclassified into ten categories of weights, as in equation (3):

$$w_{j} = (a_j \ast r_p), \quad \text{for } j \in p$$

(2)
Figure 3. (a) Highways coverage (including all interstate, US, and state highways). (b) Road network density grids for all roads. (c) On-road emission grids (1 km²) estimated by this project. (d) Vulcan estimates mapped by dividing the emission value of each Vulcan grid (10 km²) into 100 grids to enable visual comparison between the two estimates.

Figure 4. Non-road emission grids (c) derived from railroads and waterways ((a) and (b)).

\[ w_j = \text{Int} \left( \frac{a_j}{k} + 1 \right) \]  

where \( k \) is the class interval value. In this letter, we used ten classes, hence \( k = \frac{\max(a) - \min(a)}{10} \).

The non-road emissions, which include both railroads and waterways, were determined the same way as on-road emissions, using a threshold value of 10 km. The railroad weight and the waterway weight for each grid were computed using equation (1). The two weights were then averaged and reclassified into ten categories using equation (3).

For airport emissions, as mentioned above, we used a threshold distance of 20 km instead of 10 km since the area of influence from airplanes is assumed to be wider than that of cars or trucks for highways and roads. Equation (1) was used to compute the airport weights and equation (3) was used to reclassify the weights into ten classes.

Once the on-road, non-road, and airport weights were determined for each grid, the volume-preserving property was enforced through equation (4). Given an emission source, the unit emission value for each grid within a parish (\( u_p \))
Figure 5. Airport emission grids (b) derived from airport locations (a).

Figure 6. Comparison between the original transportation-related CO2 emissions at the parish level (a) and the 1 km² grid level (b). The four highest emission parishes (labeled as A, B, C, and D) are enlarged and shown in (c).

is computed by dividing the emission value \((e_p)\) at parish \(p\) by the total weights of all grids within the parish \((t_p)\) using equation (4):

\[
u_p = \frac{e_p}{t_p}.
\]

The emission value at each grid \(j\) is then a product of its weight and the parish’s unit emission value, as in equation (5)

\[
e_j = w_j \ast u_p.
\]

The emission of each source (on-road, non-road, and airport) was then summed to produce the final transportation-related CO2 emission estimates at the grid level.

A number of GIS functions, including feature overlay, converting features to raster, calculating Euclidean distance, calculating density, and reclassification, were utilized in the analysis (figure 2). The procedures were carried out using the ArcGIS 9.2 platform. These GIS functions are critical to this study. For example, the module of calculating (Euclidean) distance is needed to determine how far each grid is from the nearest source (highways, waterways, railways, and/or airports). The module of feature overlay and converting features to raster are needed to convert the parish boundaries from vector form into raster grids. Minor errors are expected along the parish boundaries during the vector-raster conversion process.

4. Results

The results show that there are 1351,641 km² grids for the state of Louisiana. The highest grid value is 727.60 tons, and is located in Jefferson Parish (Kenner city). (The lowest grid emission value is 0.) The average grid emission value is 56.37 tons. There are 39,085 grids that are above the average grid CO2 emission, and there are 15,808 grids that have no transportation-related emissions. Compared with the parish statistics, the minimum, maximum, and average emission values were 13,587, 481,243, and 119,398 tons year\(^{-1}\), respectively.

As expected, the resultant gridded maps of transportation-related carbon emissions resemble closely the spatial distribution of major transportation routes and centers such as highways, railroads, waterways, and airports (figures 3–5). Figure 6 compares the original transportation-related CO2 emissions by parish with the final 1 km² grid estimates. The gridded map (figure 6(b)) shows more variation within a parish, especially for those parishes which are primarily rural and with low population density (shaded as yellow in figure 6(b)). The biggest contrast between the two maps lies in the southern part of Louisiana, where the original parish-level choropleth map portrays some of the parishes (such as Terrebonne Parish)
as high emission for the entire parish, whereas only a small concentrated area within the parish is attributed as the likely source in the gridded map (figures 6(a) and (b)). At the parish level, the highest emission was Jefferson Parish (New Orleans suburb), with a value of 481,243 tons per year in 2002, and the parish with the lowest emission value was Tensas (northern part of the state, along the Mississippi River), with a value of 13,587 tons per year. The five lowest emission parishes included, in addition to Tensas, La Salle, St Helena, Jackson, and Red River parishes (below 24,000 tons) (figure 6(a)). The four highest CO2 emission parishes were Jefferson, East Baton Rouge, Caddo, and Orleans parishes, which had emission values higher than 400,000 tons per year. The four parishes are shown in an enlarged map in figure 6(c). Grids that contribute high CO2 emissions basically covered the whole East Baton Rouge Parish and Orleans Parish, whereas CO2 emissions in Jefferson Parish and Caddo Parish (where city of Shreveport is located) were more unevenly distributed. These are due to uneven spatial distribution of highways and other transportation-related sources in these latter two parishes.

We also conducted a visual comparison of the spatial patterns of the emission estimates derived from this project and from the 10 km2 Vulcan grids. To make the two estimates comparable visually, we divided the Vulcan estimates by 100 so that the basis is 1 km2 grid. We then mapped the two estimates using the same color intervals, as shown in figures 3(c) and (d). As expected, the Vulcan estimates are more spatially concentrated with more grids of higher emission values, whereas the estimates from this project are more gradual. This is mainly due to the difference in grid sizes used as well as the difference in methods used to assign emission values to the grids (Gurney et al 2009a). We noted, however, that a meaningful comparison would necessitate the use of a valid third reference source in order to determine whether our model yields more accurate estimates of emissions. Also, the comparison would need to be thorough, including either all or a representative sample of locations within the state, and is beyond the scope of this letter.

As in similar previous studies, this letter has attempted to improve the spatial resolution of CO2 emission data using a GIS-based method governed by the volume-preserving interpolation and distance-decay weighting principles. Allocating transportation-related emission according to its expected activities and modeling them along the location of their activities (e.g. roads, airports), as employed in this letter, improves the characterization of the carbon emission of the transportation sector. Furthermore, by enforcing the volume-preserving property, the emission estimates are expected to be more accurate. A more accurate spatial characterization of carbon emission would serve as an important data input to many types of emission models (Kinnee et al 2004, Gregg and Andres 2008). Furthermore, the gridded estimates at 1 km2 resolution could be made to match other world data sets, such as the 1 km2 grid resolution world population data set called LandScan, as well as other satellite remote sensing data (Lam et al 2009).

5. Conclusions

This letter presents a GIS-based method to disaggregate transportation-related CO2 emissions from the parish scale to the 1 km2 grid scale, using the state of Louisiana as an example. The method improves existing approaches by enforcing the volume-preserving property throughout the interpolation process, as well as incorporating a distance-decay principle in the estimation. The volume-preserving property, which ensures that the sum total of all grid estimates within a parish is preserved, has been proven in the literature to be a useful property for improved accuracy in interpolation estimates. The distance-decay function, which was implemented in this letter in its most simplistic form (linear), is assumed to have better represented the behavior of transportation-related carbon emissions. The resultant grid estimates derived from the proposed method hence is considered more realistic, and can serve as a more accurate input to many other mathematical models.

Moreover, the method is very flexible such that different assumptions or different distance-decay functions can be incorporated in future studies. For example, more factors could be taken into account in improving transportation-related emission estimates, such as the type of highway, number of highway lanes, traffic volumes, and so on. The same volume-preserving principle can be applied to estimate other emissions.

Acknowledgments

The authors wish to thank the two anonymous referees for their valuable comments. This research was partially funded by two research grants from the US Bureau of Ocean Energy Management, Regulation, and Enforcement (BOEMRE) (formerly MMS-Minerals Management Service) (award #: M09AC15619, M09AC15620). The authors are solely responsible for the content and views contained in this letter.

References

Andres R J, Marland G, Fung I E and Matthews E 1996 A 1° × 1° distribution of carbon dioxide emissions from fossil fuel consumption and cement manufacture, 1950–1990 Glob. Biogeochem. Cycles 10 419–29

Cohen J, Cook R, Bailey C R and Carr E 2005 Relationship between motor vehicle emissions of hazardous pollutants, roadway proximity, and ambient concentrations in Portland, Oregon Environ. Modelling Softw. 20 7–12

Dalvi M, Beig G, Patil U, Kaginalkar A, Sharma C and Mitra A P 2006 A GIS based methodology for gridding of large-scale emission inventories: application to carbon-monoxide emissions over Indian region Atmos. Environ. 40 2995–3007

Goodchild M F and Lam N S N 1980 Areal interpolation: a variant of the traditional spatial problem Geo-Processing 1 297–312

Gregg J S and Andres R J 2008 A method for estimating the temporal and spatial patterns of carbon dioxide emissions from national fossil-fuel consumption Tellus Series B: Chemical and Physical Meteorology 60 1–10

Gurney K R, Mendoza D L, Geethakumar S, Zhou Y, Miller C C, Sahni N, Seib B and Ansley W 2009a Vulcan Science Methods Documentation (Version 1.1) Purdue University www.purdue.edu/cas/carbon/vulcan
Gurney K R, Mendoza D L, Zhou Y, Fischer M L, Miller C C, Geethakumar S and De La Rue Du Can S 2009b High resolution fossil fuel combustion CO₂ emission fluxes for the United States Environ. Sci. Technol. 43 5535–41
Guy E D and Levine N S 2001 GIS modeling and analysis of Ohio’s CO₂ budget: mitigating CO₂ emissions through reforestation Ohio J. Sci. 101 34–41
Kinnee E J, Touma J S, Mason R, Thurman J, Beidler A, Bailey C and Cook R 2004 Allocation of onroad mobile emissions to road segments for air toxics modeling in an urban area Transport. Res. D 9 139–50
Lam N S N 1983 Spatial interpolation methods: a review Am. Cartograph. 10 129–49
Lam N S N 2009 Spatial interpolation International Encyclopedia of Human Geography vol 10, ed R Kitchin and N Thrift (Oxford: Elsevier) pp 369–76
Lam N S N, Arenas H, Li Z and Liu K B 2009 An estimate of population impacted by climate change along the US coast J. Coast. Res. Special Issue 56 1522–6
Mohan M, Dagar L and Gurjar B R 2007 Preparation and validation of gridded emission inventory of criteria air pollutants and identification of emission hotspots for megacity Delhi Environ. Monit. Assess. 130 323–39
Olivier J G J, Bouwman A F, Berdowski J J M, Veldt C, Bloos J P J, Visschedijk A J H, van der Maas C W M and Zandveld P Y J 1999 Sectoral emission inventories of greenhouse gases for 1990 on a per country basis as well as on 1° × 1° Environ. Sci. Policy 2 241–64
Osses de Eicker M, Zah R, Trivino R and Hurni H 2008 Spatial accuracy of a simplified disaggregation method for traffic emissions applied in seven mid-sized Chilean cities Atmos. Environ. 42 1491–502
Parry M L et al 2007 Technical summary Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change ed M L Parry, O F Canziani, J P Palutikof, P J van der Linden and C E Hanson (Cambridge: Cambridge University Press) pp 79–131
Saide P, Zah R, Osses M and Osses de Eicker M 2009b Spatial disaggregation of traffic emission inventories in large cities using simplified top-down methods Atmos. Environ. 43 4914–23
Streets D G et al 2003 An inventory of gaseous and primary aerosol emissions in Asia in the year 2000 J. Geophys. Res. 108 8809
Su J G, Jerrett M and Beckerman B 2009a A distance-decay variable selection strategy for land use regression modeling of ambient air pollution exposures Sci. Total Environ. 407 3890–8
Su J G, Jerrett M, Bernardo B, Wilhelm M and Ghosh J K 2009b Predicting traffic-related air pollution in Los Angeles using a distance decay regression selection strategy Environ. Res. 109 657–70
Tobler W R 1979 Smooth pycnophylactic interpolation for geographic regions J. Am. Stat. Assoc. 74 519–36
Tuia D, Osses de Eicker M, Zah R, Osses M, Zarate E and Clappier A 2007 Evaluation of a simplified top-down model for the spatial assessment of hot traffic emissions in mid-sized cities Atmos. Environ. 41 3658–71
US Department of Transportation and Bureau of Transportation Statistics (BTS) 2002 Louisiana Transportation Profile (Washington, DC: BTS)
USEIA (US Energy Information Administration) 2008a State Emissions by Year Washington, DC
USEIA (US Energy Information Administration) 2008b State Emissions by Sector Washington, DC
USEIA (US Energy Information Administration) 2008c Louisiana Carbon Dioxide Emissions from Fossil Fuel Consumption (1980 to 2005) Washington, DC
Vienneau D, de Hoogh K and Briggs D 2009 A GIS-based method for modeling air pollution exposures across Europe Sci. Total Environ. 408 255–66
Wentz E A, Gober P, Balling R C Jr and Day T A 2002 Spatial patterns and determinants of winter atmospheric carbon dioxide concentrations in an urban environment Ann. Assoc. Am. Geogr. 92 15–28
Zou B, Wilson J G, Zhan B and Zeng Y 2009 An emission-weighted proximity model for air pollution exposure assessment Sci. Total Environ. 407 4939–45