Mapping air filtering in urban areas. A Land Use Regression model for Ecosystem Services assessment in planning

Stefano Salata [a,*], Silvia Ronchi [b], Andrea Arcidiacono [b]

[a] *Interuniversity Department of Regional and Urban Studies and Planning, Politecnico di Torino, Italy*
[b] *Department of Architecture and Urban Studies, Politecnico di Milano, Italy*

ABSTRACT

The control of air quality in urban areas is drawing attention, as it generates significant benefits. Land use planning directly affects Ecosystem Services, particularly on air quality. Nonetheless, scientific knowl-edge of the effects derived by Land Use Changes on air quality is inadequate for planning proposals.

This paper proposes an analytical application in the metropolitan area of Milan (North-west of Italy), one of the highly air-polluted areas of Europe. A spatial-based methodology to predict Particulate Matter concentration is tested using the regional emission inventory as a benchmark. The paper assumes that different dynamics cause of air pollution: (i) atmospheric emissions due to different kinds of land use sources; (ii) the rebound/ resuspension of particles caused by the impervious degree of soil, and (iii) the absorption through green areas and trees.

The methodological innovations introduced by this paper are related to (i) the small gridded distribu-tion of values, and (ii) the emissions dynamics mix up with those on resuspension and absorption.

This study experiments the upgrade of the existent Land Use Regression approach for Particulate Matters prediction and establishes a new methodology with a newer set of inputs. Compared to traditional approaches, the study can support the decision-making process for local planning.

Keywords:
Ecosystem Services Mapping
Air filtering
Land Use Regression Land use planning

1. Introduction

1.1. Ecosystem Service approach

Urban areas with artificial surfaces dominated by anthropic activities generate the concentration of pollution causing an unhealthy condition for human life (Gulia et al., 2015).

The quality of air over urban areas depends on many factors, such as the road size and transport system, the compactness of housing and density/typology of settlements, the degree of sealed and non-sealed ground surfaces such as pavements, roads, squares or green areas, and the distribution of vegetation (shrubs and trees) in urban areas. Moreover, the altitude, the meteorological variables, and the wind direction affect Particulate Matter (PM) measurements (Beelen et al., 2009; Briggs et al., 1997; Foley et al., 2005; Mazzeo and Venegas, 1991).

Nowadays, it is widely recognized that Land Use/Land Cover (LULC) has a direct effect on PM concentration and other kinds of air pollutants. The international literature concurs on the fact that different LULC emits distinct air pollutants: the human activities in anthropic sites directly generate PM concentration. That is so because all anthropic areas (houses, industry, roads and transportation) are sources of pollution, but also because other kinds dynamics affect the PM concentrations. For example, impermeable surfaces change the rebound dynamics of air pollutants (Carvacho et al., 2004; Orza et al., 2011). When the soil is sealed, the particulate cannot deposit on the ground and still re-bound in the air causing an increase in its concentration.

Particularly, in addition to direct emission, land use-related PM concentrations in the air are associated by two main dynamics, the rebound and the absorption. The former acts as a hotspot of PM concentration, and causes a significant increase in air pollutants due to rebound of PM on sealed urban surfaces. Whereas the latter acts as a sink of pollutants, since the unsealed/permeable green areas, especially those of trees with a compacted canopy have a significant effect of lowering the PM concentration (Fig. 2).

Therefore, LULC influences PM concentration both as a source as well as a sink. While sealed areas generate PM, with different degrees, green areas help capture gaseous and particulate airborne pollutants absorbing their concentrations. For these reasons, urban

Abbreviations: ES, Ecosystem Services; LULC, Land Use/Land Cover; LUR, Land Use Regression; PM, Particulate Matters.

* Corresponding author.
E-mail address: ssalata1983@gmail.com (S. Salata).

Published Journal Article available at: https://doi.org/10.1016/j.ecoser.2017.09.009

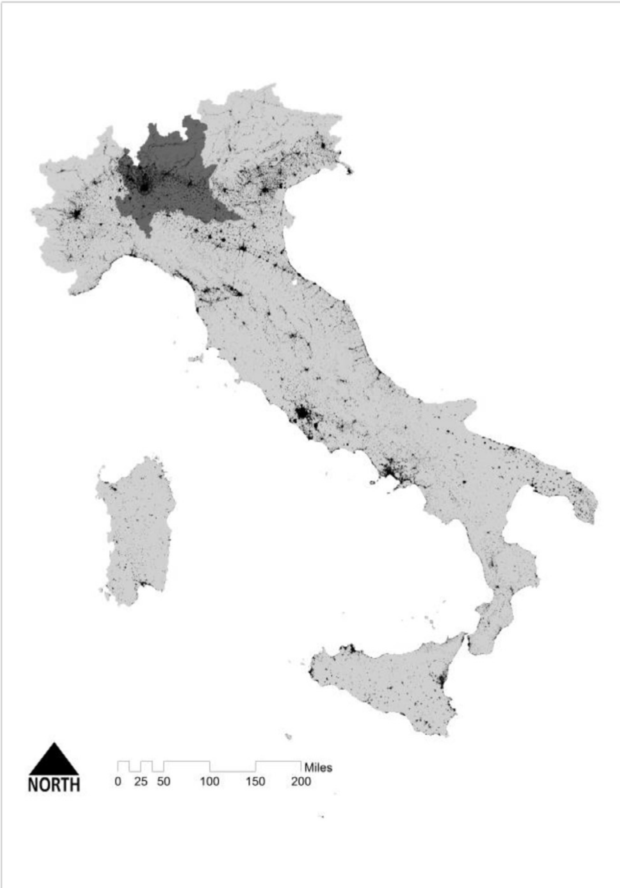

Fig. 1. The study area.

green areas play a vital role in the provision of health conditions for citizens (Calfapietra et al., 2009; Nowak, 2006; Nowak et al., 2006). Their ecological functions provide different Ecosystem Services (ES). Among others, the regulative air filtering service provided by green areas is essential for quality in the urban environment, as it reduces the level of total PM concentration in the air (Akbari, 2002; Bardelli et al., 2011; Brack, 2002).

Currently, scientific knowledge of relations between land use and air quality is broad yet fragmented. The above mentioned LULC-related dynamics (emission, resuspension, and absorption) are often studied singularly with different approaches and theoretical frameworks. This so-called "disciplinary fragmentation" is quite valuable for academic and scientific debate because it supports an in-depth knowledge of the physical dynamic of PM in urban areas. Nonetheless, the fragmentation of disciplines limits the possibility to fill the gap between theoretical knowledge on specific ES and their utilization for sustainable territorial policies. Synthetically, the knowledge of LULC related to PM spatial distribution is still inadequate to support stakeholders and decision makers in designing land use policies in urban areas.

The traditional planner's knowledge of the ES deterioration related to land use changes is quite poor. The most used software for ES mapping (e.g. Integrated Valuation of Ecosystem Services and Tradeoffs or Artificial Intelligence for Ecosystem Services) provides various models for the spatial assessment of different regulative ES, while a specific model/tool for air quality which relates the LULC characteristics to the biophysical value of PM concentration is not yet provided.

Until now however, the effect of land use changes on air quality has not been modelled by standard open-access ES mapping software, as in the case of others ES. Considering that air quality in urban areas is one of the primary drivers of adverse effects on human health, studies focusing of urban air should consider more attention.

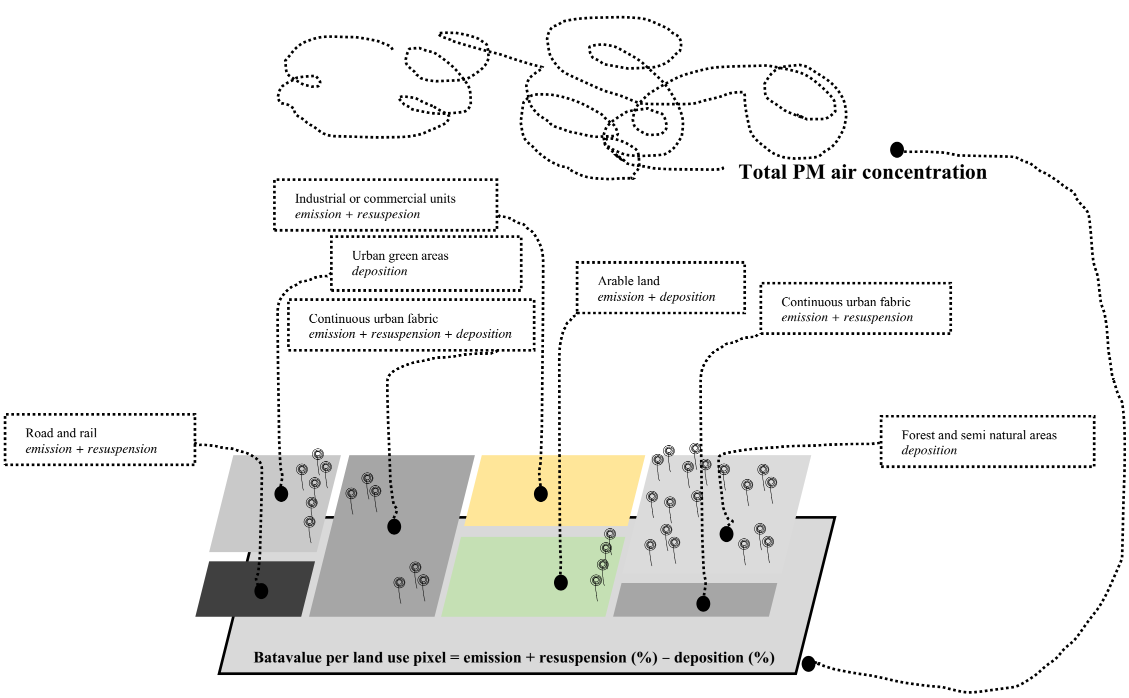

Fig. 2. Concept scheme of average PM_{10} in urban areas. PM values are predicted using land use variables: sealed surfaces generates PM (emission and resuspension) while unsealed plays for deposition.

In this paper, we propose a methodology that predict the PM spatial concentration obtained through a Land User Regression equation. Particularly, the study will consider the coarser part of PM (PM10) which is in part generated by the dust stirred up by vehicles on roads.

The study assumes that LULC data are considered as predictors of air pollution. Compared to traditional LUR models, the study uses local datasets, since it refers to local planning activity. Plan-ners are likely to design land use project using detailed maps (of a 1:10,000 scale at least), thus we employed values of PM_{10} using a fine-scale LULC dataset.

Considering that key policies of sustainable urban development are focused on "quality of life" and "livability", there is a pressing need to map and evaluate the effect of land use changes on airborne pollutant concentration in metropolitan areas. In this context, the possibility of mapping the air filtering capacity under different LULC typologies can support decision makers during the screening phase of a local Plan definition.

1.2. Mapping Particulate Matter concentration

Recently, attention to ES has risen because their connection with urban planning policies (Haase et al., 2014). Typically, when ES are considered during the planning process, sustainability indicators show an increase in value (Ahern et al., 2014; Haase et al., 2014; Li et al., 2014), and the assessment of targeted policies for environmental quality in urban areas can be achieved and monitored.

Many research activities are devoted to estimating the benefits of land use changes to some ES (Burkhard et al., 2012; Clerici et al., 2014; Langemeyer et al., 2016); still, such kind of assessment depends on knowledge of soil quality, the interaction between soil and subsoil and air, and the ecological effects and impacts of a land use transformation on other ecosystems.

Nowadays, new models for ES mapping and assessment are widely used to set environmental planning policies and share common knowledge about Natural Capital among different stakeholders (Nelson et al., 2011). The higher the knowledge of the various ES biophysical values, the greater the likelihood of reaching a sustainable target of land use efficiency (Artmann, 2014) potentially increasing public health (Carb, 2005).

Unfortunately, the air filtering capacity of urban green spaces has not been yet accounted when a multifunctional ES assessment is considered during planning phases. However, air quality seems to become one of the major indicators for better living conditions (Miranda et al., 2015; Sancho et al., 2014) because it has a direct effect on public administration costs related to diseases caused by air pollution.

The air filtering service is often associated with another significant kind of regulative services i.e. – the carbon sequestration. However, even if carbon sequestration is somehow related to air quality the service of carbon storing cannot be compared with the air filtering service since the former measure the tons of carbon stored on the soil and the latter the quantity of PM on air. Even both services are regulative, air filtering is delivered by different ecological functions that are not the ones of the carbon stored above-ground, below-ground and on soil litter.

This paper aims to connect existing field studies on LULC related PM distribution to define a preliminary methodological approach for mapping PM concentrations using emissions, resuspension, and absorption dynamics. Results should be tested for practical land use planning activities, and particularly during the Strategic Environmental Assessment (SEA), where the effects of LULC configuration on health should improve the awareness of citizens and politicians. Public health expenditure is a good proxy for air quality (Ostro and Chestnut, 1998); it is widely recognized that urban green areas play a beneficial role in PM abatement (Martínez et al., 2014).

From a methodological perspective, modeling air quality using land use variables has several limitations. International literature on PM detection (fine and coarse) (de la Paz et al., 2015; Vecchi et al., 2007) commonly argue that many variables characterize the relation between LULC and air quality. The first indicates that (i) air quality is often dependent by environmental factors (PM detection is influenced by upwind or downwind analysis positions) and, moreover, climate variables heavily influence the PM measurement and depends by site-specific conditions. Thus, it is not possible to define a linear equation between LULC emissions and local PM concentrations; unless the model aims at defining average values for long-time series; (ii) the scientific approach of physical gaseous uses to keep emission, rebound, and deposition dynamics distinct from one another because they behave distinctly under different atmospheric conditions. Such dynamics are measured with different techniques/tools: concentrations are typically detected through fiber filters (of different diameter) using an active sampler, while rebound or deposition dynamics are often detected through measurement of aerosol vertical fluxes using an optical particle counter based on a direct Eddy Covariance approach (Damay et al., 2009).

However, the importance of bridging the gap between a fragmented theoretical framework and the needs for supporting effective policies to increase the quality of urban environment demands some steps forward. In the proposed methodology, different approaches are combined to set a model that estimates the benefit derived from green urban spaces on air quality, to do so, we use a spatial interpolation method as the basis for average daily PM_{10} concentration. The methodology also promotes air-quality assessment tool able to support land use policies: the availability of an air filtering mapping model determines policies on urban green areas implementation that considers PM_{10} concentration as a proxy for sustainability. Such gain in precision is fundamental to meet the needs of land use planning decision-making process (Ahern et al., 2014; Hilde and Paterson, 2014; Primmer and Furman, 2012).

2. Material and methods

2.1. The study area

This study focuses on the City of Milan (northwest of Italy, Lombardy Region), which constitutes the core of the biggest metropolitan system in Italy (Fig. 1). The Organization for Economic Cooperation and Development (OECD) classification states the Greater Milan is the metropolitan area with the most extensive socioeconomic and settlement system (Sali et al., 2016). It encom-passes eight Lombardy Provinces, including Novara (which is a Pro-vince of Piedmont Region), with a total population of 7.4 million inhabitants (Sanesi et al., 2016). The city is one of the most densely populated in Italy, and it suffers the effects of a daily heavy commuting network from the suburbs to the inner-city, leading to all severe air pollution issues.

Particularly, the urban area of Milan is affected by a high degree of artificial covers occasioning a high concentration of noise, pollution and other anthropic threats that result in a decreased quality of life (Fattore et al., 2016).

Milan has a dry winter period (normally between December and January), which determines an increase in air pollutant concentrations above the threshold limit (50 $\mu g/m^3$ for 35 days per year) determined by the Italian National Law n. 155 of 13 August 2010.

The study uses the estimated PM concentration registered by ARPA sample sites,[1] and it simulates PM_{10} distribution over the entire urban area during the peak air pollution concentration recorded in the 2015 winter season.

2.2. Data sources

Considering the LUR methodology of Janssen et al. (2008) which estimates the averege contentration of air pollution using land use variables at national scales, two innovations were introduced: (i) a LULC dataset with a high spatial resolution and (ii) the integration of two additional dataset for a better assessment of model prediction: the Copernicus High-Resolution Layer and the city tree registry (Benini et al., 2010). The main input data are:

1. *LULC*. The datasets were derived from detailed regional databases publicly available (www.geoportale.regione.lombardia.it), dating 2012 ad called DUSAF. Information was obtained by photointerpretation of the regional territory. Digitalization was obtained at a 1:5,000 scale with a minimum detectable size of 5-meter. A total extension of 1600 m^2 for non-urban areas, and of 400 m^2 for urban areas was detected. The database adopted the same classification criteria and categories based on the Corine Land Cover dataset (http://uls.eionet.europa.eu/CLC2006/CLC_Legeng.pdf) (44 land use classes).
2. The Copernicus High-Resolution dataset – Imperviousness Degrees data (2012). Elaborated by ISPRA and European Environmental Agency, the layer provides a raster spatial distribution of sealed surfaces over the entire territory with cell values ranging from 0 (unsealed) to 1 (sealed).
   Data were collected with Fast Track Service Precursor on Land Monitoring – Degree of soil sealing with a high-detailed resolution output of 5-meter cell. Since 2009, the service has been realized for the European Commission by Planetek Italia (Geoland 2 project).
3. The Geographical Information System for urban green areas of the City of Milan which includeda digital mapping of urban green areas and trees.
   The tree registry counts more than 2780 public urban green areas (2340 hectares, 13% of the municipal territory, based on the data available in 2016) of different typologies, distributed across nine different urban zones. It counts more than 225,000 trees, of which 26,000 are of the recent plantation (last three years). The 60% of trees are located in public green areas, gardens and parks, the 29% in linear tree plantations, and the rest located in school or public building gardens. The 47% of the species are *Acer*, *Platanus* and *Tilia*.

2.3. Spatial interpolation of the model

European Commission's Air Quality Directive No. 30 of 1999 first introduced target and limit values for population exposure to fine particles. The monitoring system is traditionally composed by fixed stations distributed over a survey area. In our case study, the registered concentrations were used to set up a regression equation. The LUR methodology assumes that the relation of the registered PM_{10} concentrations and the LULC composition can be modeled by a linear equation that predict the PM_{10} distribution over the entire territory of study. The city of Milan has empowered a well-developed and capillary monitoring system consisting of three fixed detection stations (Juvara Pascal street, Verziere street and Senato street) inside the municipality of Milan, in addition to eight fixed detection stations in the metropolitan area. The abundance of a monitoring system is crucial to obtain a well-developed spatial interpolation model that predict PM concentration.

The literature that explores relations between LULC and PM concentrations use the LUR as the equation that predicts pollutant on air using LULC variables (Janssen et al., 2008; Lee et al., 2015; Lu and Wong, 2008; Vienneau et al., 2009). Different statistic interpolation models were tested to generate PM distribution (Ayers, 2001; Contreras and Ferri, 2016; de Hoogh et al., 2014; Karppinen et al., 2000; Li and Heap, 2011; Mercer et al., 2011; Ryan and LeMasters, 2007). These models directly relate the con-centration of pollutants to LULC. As introduced, spatial interpola-tion models based on regression assume that LULC is a proxy of PM concentration. Thus, it is important to find out the correct rela-tions between LULC variables and their effect on air quality (Vautard et al., 2007).

The estimation of PM concentration (Janssen et al., 2008) is an output of a spatially interpolated model based on a land use indicator (β) as a proxy of the total emission. The methodology assumes that LULC should be used as the independent variable for a regression equation of PM concentration.

Moreover, the method is integrated by other LULC variables: the sealing pattern, and the quantity and distribution of trees. The study uses the following datasets:

- DUSAF, integrated with street network dataset, and used as a LULC variable that determines emissions;
- degree of imperviousness used as a variable that determines resuspension;
- tree cadastre used as variable that determines deposition;

Compared to the methodology presented in the study of Janssen et al. (2008), the spatial interpolation of LULC variables was carried out by using a regular grid of 1 * 1 km instead of 4 * 4 km.

The analytical framework is made up of the following steps:

1. Development of RIO land use classification using the DUSAF (Janssen et al., 2008). The RIO methodology links statistical emission data of the air pollution to land use patterns at the local scale using a land use indicator. For this step, a GIS session has been launched with Esri ArcGIS 10.3 to integrate the base-map with the detailed infrastructural system, and subsequently, land use classes were grouped according to RIO ones. The scale of representation is 1:10,000 instead of the original RIO scale of 1:250,000.
2. The association of LULC classes to RIO has been used to set specific emission factors of the INEMAR-ARPA[2] (Table 2) agency that provides specific emission quantification for different sources (Table 1). This association has been possible because the sources of air pollution (first column in the Table 1) are related to the DUSAF classification (third column in the Table 2).
3. The procedures for spatial interpolation took into consideration the guess of land use indicator β by using the Regional INEMAR-ARPA sector. The β indicator is a float number that associate at a specific land use an emission factor which has been previously normalized (Table 3). Its estimation considers setting the emission of residential land uses (RCL1 and RCL2) as the benchmark for normalization (value 1). Accordingly, the β value ranges from 0.15 (RCL8) to 2.08 (RCL4).

[1] ARPA is the Regional environmental agency responsible for air quality measurements.

[2] INventary of Emission on AiR is the Regional database of emissions for typologies of land covers in Lombardy

Table 1
Emission table in the Province of Milan (2012) – (Source: INEMAR ARPA LOMBARDIA).

		SO_2	NOx	COV	CH_4	CO	CO_2	N_2O	NH_3	PM2.5	PM10	PTS	CO_2eq	Precurs. O_3	Tot. acidif. (H+)
		t/year	t/year	t/year	t/year	t/year	kt/year	t/year	t/year	t/year	t/year	t/year	kt/year	t/year	kt/year
Production and transformation energy plant	S1	12	1216	116	253	2744	1995	9.4		12	12	12	2003	1904	27
Non-industrial combustion	S2	281	3413	1121	520	6140	5258	111	8.2	534	556	583	5303	5968	83
Industrial combustion	S3	1446	1598	298	22	491	937	12	1.5	98	120	155	941	2302	80
Productive processes	S4	13	22	1766	3.9	206	48	0.8	12	59	109	154	49	1816	1.6
Extraction and distribution of fuels	S5			1968	23,530								494	2297	
Use of solvents	S6	0.1	0.5	21,275	0.0	0.2			1.7	176	200	284	350	21,276	0.1
Road transport	S7	25	14,912	4654	349	19,486	4144	142	229	885	1157	1459	4195	24,995	338
Other mobile sources and machinery	S8	56	1237	364	1.7	1125	186	3.9	0.2	43	44	44	187	1997	29
Waste treatment	S9	37	362	166	20,808	75	197	147	64	10	10	11	680	906	13
Agriculture	S10	12	135	5490	12,705	639		583	4851	71	86	178	448	5903	289
Other sources and sinks	S11	2.3	11	355	24	241	-37	0.4	0.2	228	229	229	-37	395	0.3
Total		**1885**	**22,907**	**37,572**	**58,217**	**31,148**	**12,728**	**1008**	**5168**	**2117**	**2523**	**3110**	**14,613**	**69,760**	**861**

Table 2
Conversion from INEMAR-ARPA classification to RIO classification, according to DUSAF classes.

FROM EMEP TO RIO	RIO CLASS	DESCRIPTION	DUSAF_Code
S2	RCL1	Continuous urban fabric	1111,1112,11231
S2	RCL2	Discontinuous urban fabric, green and sports	1121,1122,1123,1411,1412,1421,1422,1423
S3 + S4	RCL3	Industrial or commercial units	12111,12112,12121,12122,12123,12124,12125,12126
S7	RCL4	Road and rail networks and associated land	1221,1222
S8	RCL5	Port areas	
S8	RCL6	Airports	124
S1 + S4 + S5 + S9	RCL7	Mine, dump and construction sites	131,132,133,134
S10	RCL8	Arable land	2111,2112,2115,21131,21132,21141,21142
S10	RCL9	Agricultural areas	213,221,222,2241,2242,2311,2312,2313
S11	RCL10	Forest and semi-natural areas	314,3113,3221,3222,3223,3241,3242,31111,31112,31121,31311,31312
S11	RCL11	Wetlands and water bodies	331,411,511,5121,5122,5123

Table 3
Normalization of emission values using residential areas as proxy.

RIO CLASS	abs	norm
RCL1	556,35	1
RCL2	556,35	1
RCL3	229,29	0,41
RCL4	1.156,85	2,08
RCL5	44,4	0,08
RCL6	44,4	0,08
RCL7	130,93	0,24
RCL8	85,58	0,15
RCL9	85,58	0,15
RCL10	228,72	0,41
RCL11	228,72	0,41

Table 4
Relation of β value and PM concentration measurement for regression equation.

	Beta value	Detected values
3412	0.438061201	**70**
2743	0.774922754	**77**
2393	0.672709845	**85**
2386	1.014474459	**97**
2316	0.923878019	**81**
2249	0.928087319	**87**
2843	0.697863667	**60**
2224	0.863504783	**97**
2618	0.502080946	**82**
2682	0.706171377	**87**

4. Evaluation of the spatial distribution of β values over the study area. The distribution of β values was determined with a spatial grid of 1 * 1 km instead of 4 * 4 km. LULC classes were grouped into each cell and then the average β value has been assigned according to LULC composition using ArcGis dissolve function.
5. Implementation of initial guess of β values with auxiliary datasets such as the soil sealing dataset and the tree registry.The new β value (β1) is then a result of emission data, adding a fraction value for resuspension dynamics (that increases concentrations) and detracting the fraction of deposition (that decreases concentrations).
6. Statistical interpolation of measured values with the new guess of β1 values (Table 4). According to the RIO approach, the regression equation was calculated by using the 10 sample points where PM wasrecorded with fixed ARPA stations during a field campaign conducted on 5th December 2015 (see Sec-tion 2.1), one of the days of maximum PM concentration in the Milan metropolitan area. Thus, the linear regression outlines the predicted concentration of PM_{10} for all the grid cells using the β value as the regression coefficient.
7. Finally, the spatial distribution of predicted concentration over the study area was modelled by combining kriging using a spherical semivariogram model with a radius setting of maximum 12 β values. This operation has been carried using Esri ArcGis 10.3.

Results were used to present a metropolitan-level assessment (Nuissl et al., 2009), rather than a sub-national one (Miranda et al., 2015).

2.4. Model implementation

As the resuspension dynamics of PM_{10} in an urban environment is highly affected by pavements, roads, and other impermeable surfaces, a correction of the original β value was used to account for an increase of maximum 15% (de la Paz et al., 2015) where the sealing patterns of the grid cell were 100%. It is therefore assumed that a complete sealed land use pattern increases emission of PM_{10} at a fraction no higher than 15% (Dordević et al., 2004; Früh-Müller et al., 2016).

The implementation of the original β value was conducted by using the Copernicus High-Resolution Layer database. It consists of a raster of cell size 5 m with different sealing degrees (from 0 to 100%) whose quantification was assigned to the grid cell to mod-ify the original β values. The average sealing value cell was con-ducted usign the Esri ArcGIS 10.3 intersect function between the sealing layer and the grid cell map of β value distribution. Each cell in the first β guess value sample was interpreted and assigned to different soil sealing strata: from 0% to 100%. This procedure aimed at restituting a meta-model of land cover types for specific sealing parameters.

The first integration serves to modify the initial guess based on emission only, with a value ranging from 0 to 15% of the initial β value that accounts for local resuspension.

A second correction was applied to estimate in the model the parts of PM_{10} which are removed by absorbtion of green areas. Such correction considers that significant scientific bibliography is dedicated to assessing the influence of trees and vegetation of urban green spaces as pollutant removers (Akbari, 2002; Bardelli et al., 2011). The integration of emission models to predict the total PM_{10} concentration was performed to assess PM deposition using the urban green and tree registry. The assumption is that PM deposition due to green areas acts as a sink for pollutants. Accordingly, the traditional interpolated model based on relations between land use and emissions was incorporated with additional LULC-related datasets.

Green areas are a sink of pollution rather than a source thereof, and contribute to PM abatement (Nowak et al., 2006; Selmi et al., 2016); as a consequence, the contribution of green areas to PM concentration is not accounted for emission dynamic, but for absorption (decreasing values).

In this research, an assessment of PM_{10} absorption for the metropolitan City of Milan is set out using I-tree software (Cabaraban et al., 2013). I-Tree software estimates the deposition of air pollutants (expressed in kg for O_3, NO_2, PM_{10} and SO_2) and air pollution removal (expressed in kg for NO_2, PM_{10} and VOC) by the municipality's street tree population (USDA Forest Service, 2008).

More specifically, the software provides different opportunities for both biophysical and economic evaluations by considering:

- annual pollutant removal by urban trees (SO_2, NO_2, O_3, PM_{10});
- annual removal of carbon monoxide (CO);
- the total amount of carbon stored in the entire trees;
- the net annual amount of sequestered carbon;
- urban forest structure, including species composition, coverage, health, biomass, and ground cover (shrubs, among others);
- effect of trees on the energy balance of buildings (including the reduction of CO_2 emissions);
- susceptibility to pests;
- tree species composition (including Exotic species);
- rainwater retention
  (Nowak et al., 2006).

In this study, trees on private gardens were not accounted for. According to the manuals and inventory of I-Tree Streets (v 6.0), data inputs needs information on tree species (genus, species and varieties) plus additional information on their size (High, DBH – diameter at breast height divided into 10 classes, from less than 7.6 cm to more than 106 cm). Our data are referred to the public trees located in the city of Milan and managed by the public administration, the private ones are not included in the cadastre.

Table 5
Annual air quality benefits of public trees of Milan city.

Species	Deposition	
	kg of PM_{10}	$
White poplar	559.7	13,900
American sycamore	714.2	17,736
Broadleaf Deciduous Small	171.8	4,957
Black locust	341.3	9,323
Sweetgum	111.3	3,039
Northern red oak	287.5	7,854
Conifer Evergreen Medium	372.1	12,363
Boxelder	272.8	7,453

Each tree was linked to an "Spp_Code" related to the species, according to the "Species code table" of I-Tree. When a species was not included in the archive, it was associated to a generic identification code to distinguish the Conifer from the Broadleaf and then the Broadleaf evergreen and the Broadleaf deciduous, including information on the size of the tree (Small, Medium, Large).

The tree registry consists in a point shapefile that has been intersected with the city LULC, thus it has been possible to have another spatial dataset that supplements the ones of emission and resuspension.

Outcomes for PM_{10} values were grouped by species, and divided by assigning a share of deposition for each tree based on its characteristics and structure (Table 5). This operation was conducted using Microsoft Excel functions successively associated to the point shape file of the trees through a GIS operation (table join) to include the amount of deposition per species.

Given the input, the software automatically provides a statistical dataset for annual air quality benefits produced by public trees: the annual PM_{10} deposition on tree surface.

Furthermore, the software automatically calculates the monetary values of ES air purification established for the United States as adjusted by the producer price index (PPI) for the year 2007 (U.S. Department of Labor; Baró et al. 2014; Nowak et al. 2002).

The final step was the association of the deposition value of the trees with the above mentioned β value distribution; the procedure was performed using an Esri ArcGIS 10.3 overlay function combining first a union operation between the tree registry and the grid cell map and then a dissolve function for a visual distribution of the total deposition values per each grid cell.

The values were standardized (Prawiranegara, 2014) by scaling from 0 to 1 and divided into nine categories using Jenks natural breaks classification method; the ranking expresses the deposition action by trees depending on density and species of trees in each grid cell (Fig. 3).

According to the principle of re-suspension, deposition values were also used to decrease the original β value of maximum 15%. The procedure assumes a balanced dynamic between resuspension and deposition. The final distribution of the predicted PM_{10} concentration values was accomplished through a Land Use Regression (prediction function of Microsoft Excel) using the final interpolated β1 value in the grid cell (which was a product of the original β value, plus the re-suspension fraction minus the deposition fraction).

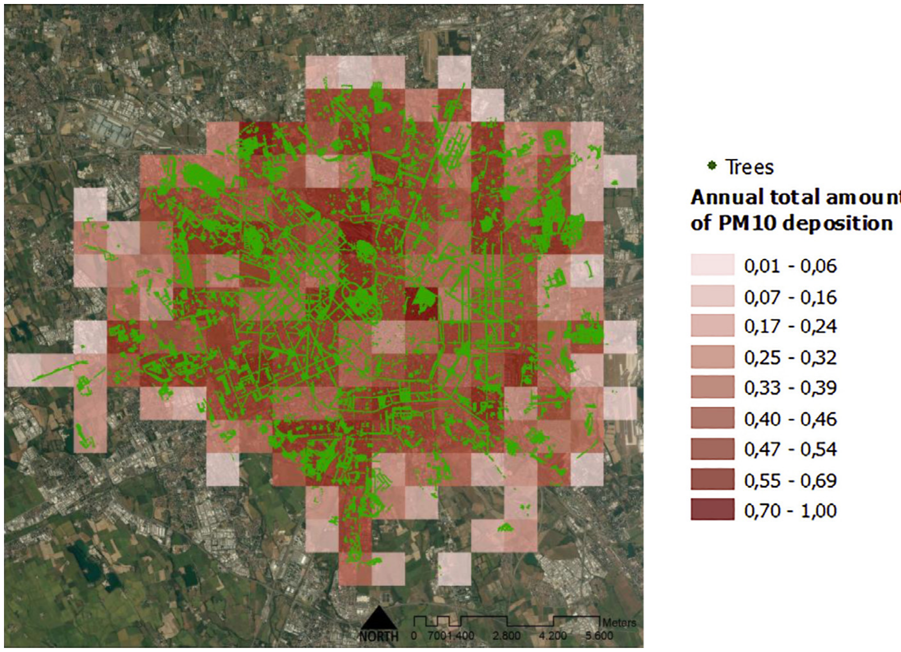

Fig. 3. Distribution of deposition values using the tree registry.

3. Results and discussion

3.1. The model output: distribution of PM_{10} concentration

With regard to the distribution of absorption values (Fig. 3), the grid cells nearest to the city centre, with a high value of deposition, correspond to an important urban park (the urban park of Porta Venezia) with a high vegetation equipment and the Monumental Cemetery of Milano that includes ancient trees governed by a specific legislation for their conservation and protection.

The cells with a low amount of PM_{10} deposition were instead characterized by a continuous urban fabric with a dense urban morphology where the tree equipment is quite scarce (Fig. 3).

The overall contribution of urban trees to PM_{10} deposition is 11,638.4 kg, which means a significant contribution to the removal of pollutants from the air.

The final output of the study is a map of PM_{10} distribution considering an average daily pollution in a period of highly PM concentration (registered values of December 2015 were used as a benchmark).

Fig. 4 shows PM_{10} values ranging from more than 89 $\mu g/m^3$ to more than 71 $\mu g/m^3$. All values are above the threshold of 50 $\mu g/m^3$ (which is the daily maximum threshold fixed by European Commission's Directive No. 30 of 1999), and the distribution of values show a higher concentrations in the core area, especially along the northeast axes (P.ta Venezia, Città Studi, Loreto and Bicocca). That is a part of Milan where central station, bus stations, and the directions to the most industrialized part of the metropolitan area are located.

Fig. 4 also shows a mixed pattern of concentrations with a few variation in the core area. In the central area of the city, PM_{10} values range from 80 $\mu g/m^3$ to 89 $\mu g/m^3$ and their distribution follows the dense and compact LULC patterns (Fig. 4). All the ancient built-up area of the city is subjected to great PM concentrations due to a high sealing degree of the soil and the presence of a dense road network. Outside of the first city ring the situation is quite heterogeneous.

The eastern part of the city is influenced by the urban motorway which runs along the border of the compact city and plays as a source of pollution. Historical quarters such as Lambrate, Città Studi or Rogoredo are affected by a high degree of PM concentration, while in the southern part the quarters of Corvetto and Gratosolio are subjected to less PM concentration due to their proximity to the Parco Agricolo Sud Milano: one of the most relevant sovra-local green zones of the city. Such mitigative effects are also visible on the west border of the compact city where the Parco delle Cave and Monte Stella and other green quarters such as the Gallaratese, San Siro and Cesano Boscone lower the PM concentration thanks to their green equipment. In these areas the results showed that vegetation and trees may effectively lower the air pollution, playing a vital function to reduce the average air concentration of PM_{10}.

3.2. Limitations and opportunities

Assuming that the RIO approach states that relations between land use information and pollution concentration could formulate accurate models, the proposed methodology represents an attempt of a better spatial interpolation model for air quality prediction. From a city planning perspective, such an attempt is of great importance, because the comparison of different LULC scenarios allows assessing the predicted impact of land use changes on air quality at the city scale and, thus, to evaluate the trade-off among different land use configurations. The model helps to address better the cost-benefit balance related to air quality increase or decrease associated with urban planning decisions. Methodologically, if a fine-scale spatial model is reliable enough to find out the relationship between land uses and PM, then it is possible to test the model against different LULC configurations and check whether or not alternative scenarios increments or deteriorate the air quality.

Further calibration of this model is fundamental to reach the standard reliability of other LULC-dependent ES models (Ho et al., 2015; Johnson et al., 2010). This consideration implies that the implementation of the model in a standalone software should potentially provide in future an open-access software that operationalizes the tested methodology and provides a new easy-to-use tool for ES mapping. Such tool will demand from a hypothetical

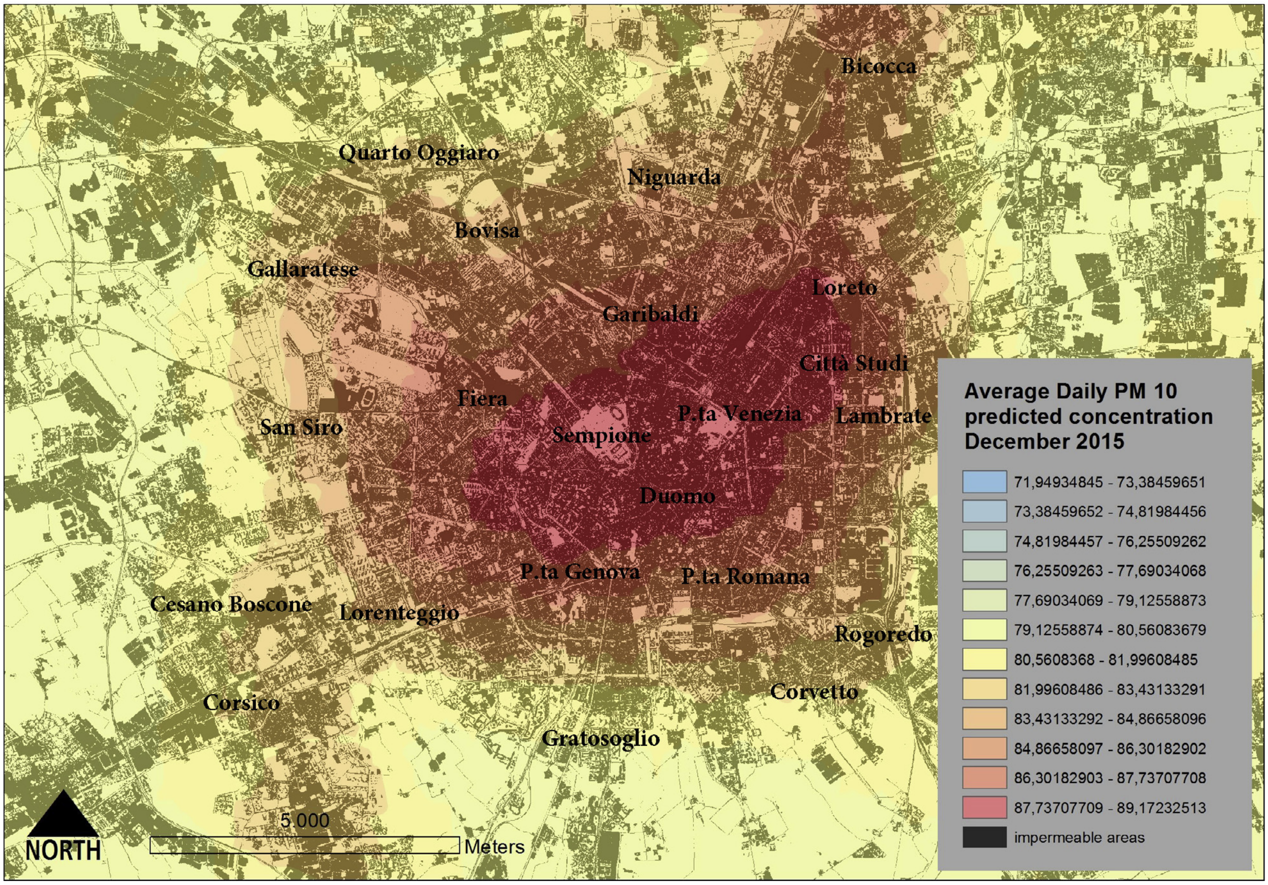

Fig. 4. Distribution of final PM_{10} prediction using kriging methodology.

user a LULC map as an input and, together with few optional variables, it generates as output a spatial map of biophysical/economic values for a context-based study area.

Air filtering services are harder to assess compared to other ES. Air is affected by turbulent dynamics and measured concentrations are not completely a product of local emission rather than a mark of the upwind source of pollution (Carvacho et al., 2004). Weather, altitude, humidity, the wind and other variables have a significant influence on PM fluxes (Bertazzon et al., 2015; Zhang et al., 2015). Nonetheless, the ES approach for land use planning is a result of a simplification of the real ecological processes and functions that generate final services.

At this stage, PM predictions obtained through LUR should be considered only as a benchmark, since this method uses only land use values as predictors of PM concentration. The proposed methodology assumes that the integration of land use with other predictors, particularly the sealing rate of the ground surfaces and the tree registry, will improve the prediction of PM concentra-tion. Nonetheless, often the risk with linear predictive models is that a refinement of input data does not correspond to better out-put reliability, because the distribution of values is sometimes chaotic, and may depend on external variables.

The limitation of the I-Tree software is that the model is specially designed for US case studies and custom adaptations are necessary. For instance, the selection of the climate region is based on US climate conditions, and if the software is used in other countries it is important to define the appropriate input dataset. Moreover, although the I-Tree database has over 5000 species, it does not include tree and shrubs typical of the Lombardy Region.

The interpolation methodology employed here also has also limitations. The dynamics of resuspension and deposition accounting for a maximum increase or decrease of 15% of the β initial guess. This is an oversimplification, but it was accepted as a tentative of model implementation to overcome the traditional model. Whether the result is well addressed or not, it should stimulate the need for future advance research in a PM_{10} field campaign measurement within the Milan metropolitan area. If detected concentrations of PM_{10} are similar to the predicted ones, then the model should be deemed reliable, otherwise, and that is more likely, it will have to be validated, adjusted and corrected with empirical data that integrate the regression equation.

Despite the above mentioned limitations, the LUR approach seems to reach a good predictive reliability and is less time consuming compared to measurement campaigns extended to large areas of investigation. Thus its utilization for planning purposes should be considered feasible.

Finally, the upgrade of the study has to account for a refinement of the grid for the guess of β value. The distribution in urban areas has to consider at least cells of 500 m by 500 m, otherwise urban historical green areas bordered by dense built-up zones such as Parco del Sempione are not visible as expected in the final PM distribution.

The need of a finer assessment has to consider also a refinement of fixed and non fixed stations for PM detection. A limit of this study is that the predictive model uses only few measured concentrations, while the efficacy of such approach request much more registered values to adjust and calibrate the regression equation.

4. Conclusions

The integration of PM_{10} emission data with other LULC-related dynamics representation increases the reliability of traditional LUR-based air quality models and aims to support and guide planners and policy makers considering the cause-effect of land use changes to air quality.

The future challenge is to integrate those models together to map the ES connected to air quality during the planning process and to use this evaluation to assess the effect of land use change scenarios.

The proposed methodology hopes to apply recent research advancements in the field of air quality and its relations with land use change, especially by integrating Land Use Regression models and vegetation. Since planners are likely to define a spatial project using detailed maps, the assessment presented here associates a visual distribution of PM concentrations to detailed Land Use resolution map. A fine-scale resolution of the spatial distribution of PM_{10} concentration is a step to consider air quality as a proxy for healthy conditions of citizens into land use decision-making process (Carb, 2005; Yu et al., 2011).

Our methodology reinforces the value of planning for sustainable air quality policy by estimating PM concentrations due to current and predicted land use scenarios. The assessment of air pollution in urban planning will help to predict the decrease of healthy conditions linked to air quality in the urban environment and to potentially determine the cost of public welfare under different scenarios.

If sustainability is a new paradigm of contemporary planning, there is an apparent need to develop air pollution models at fine scale using GIS techniques that allow a better explanation of the cause-effect mechanism of land use change. Awareness of the environmental effect of land use change on air quality might be a good way of achieving affordable results over the coming years.

References

Ahern, J., Cilliers, S., Niemelä, J., 2014. The concept of ecosystem services in adaptive urban planning and design: a framework for supporting innovation. Landsc. Urban Plan. 125, 254–259. https://doi.org/10.1016/j.landurbplan.2014.01.020.

Akbari, H., 2002. Shade trees reduce building energy use and CO2 emissions from power plants. Environ. Pollut. 116, S119–S126. https://doi.org/10.1016/S0269-7491(01)00264-0.

Artmann, M., 2014. Institutional efficiency of urban soil sealing management – from raising awareness to better implementation of sustainable development in Germany. Landsc. Urban Plan. 131, 83–95. https://doi.org/10.1016/j.landurbplan.2014.07.015.

Ayers, G.P., 2001. Comment on regression analysis of air quality data. Atmos. Environ. https://doi.org/10.1016/S1352-2310(00)00527-6.

Bardelli, T., Giovannini, G., Pecchioli, L., Pecchioli, L., 2011. Air quality impact of an urban park over time. Procedia Environ. Sci. 4, 10–16. https://doi.org/10.1016/j.proenv.2011.03.002.

Baró, F., Chaparro, L., Gómez-Baggethun, E., Langemeyer, J., Nowak, D.J., Terradas, J., 2014. Contribution of ecosystem services to air quality and climate change mitigation policies: the case of urban forests in Barcelona, Spain. Ambio 43, 466–479. https://doi.org/10.1007/s13280-014-0507-x.

Beelen, R., Hoek, G., Pebesma, E., Vienneau, D., de Hoogh, K., Briggs, D.J., 2009. Mapping of background air pollution at a fine spatial scale across the European Union. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2008.11.048.

Benini, L., Bandini, V., Marazza, D., Contin, A., 2010. Assessment of land use changes through an indicator-based approach: a case study from the Lamone river basin in Northern Italy. Ecol. Indic. 10, 4–14. https://doi.org/10.1016/j.ecolind.2009.03.016.

Bertazzon, S., Johnson, M., Eccles, K., Kaplan, G.G., 2015. Accounting for spatial effects in land use regression for urban air pollution modeling. Spat. Spatiotemporal. Epidemiol. 14–15, 9–21. https://doi.org/10.1016/j.sste.2015.06.002.

Brack, C.L., 2002. Pollution mitigation and carbon sequestration by an urban forest. Environ. Pollut. 116, S195–S200. https://doi.org/10.1016/S0269-7491(01)00251-2.

Briggs, D.J., Collins, S., Elliott, P., Fischer, P., Kingham, S., Lebret, E., Pryl, K., VanReeuwijk, H., Smallbone, K., VanderVeen, A., 1997. Mapping urban air pollution using GIS: a regression-based approach. Int. J. Geogr. Inf. Sci. 11, 699–718. https://doi.org/10.1080/136588197242158.

Burkhard, B., Kroll, F., Nedkov, S., Müller, F., 2012. Mapping ecosystem service supply, demand and budgets. Ecol. Indic. 21, 17–29. https://doi.org/10.1016/j.ecolind.2011.06.019.

Cabaraban, M.T.I., Kroll, C.N., Hirabayashi, S., Nowak, D.J., 2013. Modeling of air pollutant removal by dry deposition to urban trees using a WRF/CMAQ/i-Tree Eco coupled system. Environ. Pollut. 176, 123–133. https://doi.org/10.1016/j.envpol.2013.01.006.

Calfapietra, C., Fares, S., Loreto, F., 2009. Volatile organic compounds from Italian vegetation and their interaction with ozone. Environ. Pollut. 157, 1478–1486. https://doi.org/10.1016/j.envpol.2008.09.048.

Carb, 2005. Air quality and land use handbook: a community health perspective.

Carvacho, O.F., Ashbaugh, L.L., Brown, M.S., Flocchini, R.G., 2004. Measurement of PM2.5 emission potential from soil using the UC Davis resuspension test chamber. Geomorphology 59, 75–80. https://doi.org/10.1016/j.geomorph.2003.09.007.

Clerici, N., Paracchini, M.L., Maes, J., 2014. Land-cover change dynamics and insights into ecosystem services in European stream riparian zones. Ecohydrol. Hydrobiol. 14, 107–120. https://doi.org/10.1016/j.ecohyd.2014.01.002. Contreras, L., Ferri, C., 2016. Wind-sensitive interpolation of urban air pollution forecasts. Procedia Comput. Sci. 80, 313–323. https://doi.org/10.1016/j.procs.2016.05.343.

Damay, P.E., Maro, D., Coppalle, A., Lamaud, E., Connan, O., Hébert, D., Talbaut, M., Irvine, M., 2009. Size-resolved eddy covariance measurements of fine particle vertical fluxes. J. Aerosol Sci. 40, 1050–1058. https://doi.org/10.1016/j.jaerosci.2009.09.010.

de Hoogh, K., Korek, M., Vienneau, D., Keuken, M., Kukkonen, J., Nieuwenhuijsen, M.J., Badaloni, C., Beelen, R., Bolignano, A., Cesaroni, G., Pradas, M.C., Cyrys, J., Douros, J., Eeftens, M., Forastiere, F., Forsberg, B., Fuks, K., Gehring, U., Gryparis, A., Gulliver, J., Hansell, A.L., Hoffmann, B., Johansson, C., Jonkers, S., Kangas, L., Katsouyanni, K., Künzli, N., Lanki, T., Memmesheimer, M., Moussiopoulos, N., Modig, L., Pershagen, G., Probst-Hensch, N., Schindler, C., Schikowski, T., Sugiri, D., Teixidó, O., Tsai, M.-Y., Yli-Tuomi, T., Brunekreef, B., Hoek, G., Bellander, T., 2014. Comparing land use regression and dispersion modelling to assess residential exposure to ambient air pollution for epidemiological studies. Environ. Int. 73, 382–392. https://doi.org/10.1016/j.envint.2014.08.011.

de la Paz, D., Borge, R., Vedrenne, M., Lumbreras, J., Amato, F., Karanasiou, A., Boldo, E., Moreno, T., 2015. Implementation of Road Dust Resuspension in Air Quality Simulations of Particulate Matter in Madrid (Spain). Front. Environ. Sci. 3. https://doi.org/10.3389/fenvs.2015.00072.

Dordević, D., Vukmirović, Z., Tošić, I., Unkašević, M., 2004. Contribution of dust transport and resuspension to particulate matter levels in the Mediterranean atmosphere. Atmos. Environ. 38, 3637–3645. https://doi.org/10.1016/j.atmosenv.2004.04.001.

Fattore, E., Paiano, V., Borgini, A., 2016. Human health risk in relation to air quality in two municipalities in an industrialized area of. Environ. Res. 111, 1321–1327. https://doi.org/10.1016/j.envres.2011.06.012.

Foley, J.A., Defries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. Science 309, 570–574. https://doi.org/10.1126/science.1111772.

Früh-Müller, A., Hotes, S., Breuer, L., Wolters, V., Koellner, T., 2016. Regional patterns of ecosystem services in cultural landscapes. Land 5, 17. https://doi.org/10.3390/land5020017.

Gulia, S., Shiva Nagendra, S.M., Khare, M., Khanna, I., 2015. Urban air quality management-a review. Atmos. Pollut. Res. 6, 286–304. https://doi.org/10.5094/APR.2015.033.

Haase, D., Larondelle, N., Andersson, E., Artmann, M., Borgström, S., Breuste, J., Gomez-Baggethun, E., Gren, Å., Hamstead, Z., Hansen, R., Kabisch, N., Kremer, P., Langemeyer, J., Rall, E.L., McPhearson, T., Pauleit, S., Qureshi, S., Schwarz, N., Voigt, A., Wurster, D., Elmqvist, T., 2014. A quantitative review of urban ecosystem service assessments: concepts, models, and implementation. Ambio 43, 413–433. https://doi.org/10.1007/s13280-014-0504-0.

Hilde, T., Paterson, R., 2014. Integrating ecosystem services analysis into scenario planning practice: accounting for street tree benefits with i-Tree valuation in Central Texas. J. Environ. Manage. 146, 524–534. https://doi.org/10.1016/j.jenvman.2014.05.039.

Ho, C.-C., Chan, C.-C., Cho, C.-W., Lin, H.-I., Lee, J.-H., Wu, C.-F., 2015. Land use regression modeling with vertical distribution measurements for fine particulate matter and elements in an urban area. Atmos. Environ. https://doi.org/10.1016/j.atmosenv.2015.01.024.

Janssen, S., Dumont, G., Fierens, F., Mensink, C., 2008. Spatial interpolation of air pollution measurements using CORINE land cover data. Atmos. Environ. https://doi.org/10.1016/j.atmosenv.2008.02.043.

Johnson, M., Isakov, V., Touma, J.S., Mukerjee, S., Özkaynak, H., 2010. Evaluation of land-use regression models used to predict air quality concentrations in an urban area. Atmos. Environ. 44, 3660–3668. https://doi.org/10.1016/j.atmosenv.2010.06.041.

Karppinen, A., Kukkonen, J., Elolähde, T., Konttinen, M., Koskentalo, T., 2000. A modelling system for predicting urban air pollution: comparison of model predictions with the data of an urban measurement network in Helsinki. Atmos. Environ. 34, 3735–3743. https://doi.org/10.1016/S1352-2310(00)00073-X.

Langemeyer, J., Gómez-Baggethun, E., Haase, D., Scheuer, S., Elmqvist, T., 2016. Bridging the gap between ecosystem service assessments and land-use planning through Multi-Criteria Decision Analysis (MCDA). Environ. Sci. Policy. https://doi.org/10.1016/j.envsci.2016.02.013.

Lee, J.-H., Wu, C.-F., Hoek, G., de Hoogh, K., Beelen, R., Brunekreef, B., Chan, C.-C., 2015. LUR models for particulate matters in the Taipei metropolis with high densities of roads and strong activities of industry, commerce and construction. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2015.01.091.

Li, J., Heap, A.D., 2011. A review of comparative studies of spatial interpolation methods in environmental sciences: performance and impact factors. Ecol. Inform. 6, 228–241. https://doi.org/10.1016/j.ecoinf.2010.12.003.

Li, F., Wang, R., Hu, D., Ye, Y., Yang, W., Liu, H., 2014. Measurement methods and applications for beneficial and detrimental effects of ecological services. Ecol. Indic. 47, 102–111. https://doi.org/10.1016/j.ecolind.2014.06.032.

Lu, G.Y., Wong, D.W., 2008. An adaptive inverse-distance weighting spatial interpolation technique. Comput. Geosci. 34, 1044–1055. https://doi.org/10.1016/j.cageo.2007.07.010.

Martínez, J., Saavedra, Á., García-Nieto, P.J., Piñeiro, J.I., Iglesias, C., Taboada, J., Sancho, J., Pastor, J., 2014. Air quality parameters outliers detection using functional data analysis in the Langreo urban area (Northern Spain). Appl. Math. Comput. 241, 1–10. https://doi.org/10.1016/j.amc.2014.05.004.

Mazzeo, N.A., Venegas, L.E., 1991. Air pollution model for an urban area. Atmos. Res. 26, 165–179. https://doi.org/10.1016/0169-8095(91)90031-Q.

Mercer, L.D., Szpiro, A.A., Sheppard, L., Lindström, J., Adar, S.D., Allen, R.W., Avol, E.L., Oron, A.P., Larson, T., Liu, L.-J.S., Kaufman, J.D., 2011. Comparing universal kriging and land-use regression for predicting concentrations of gaseous oxides of nitrogen (NOx) for the Multi-Ethnic Study of Atherosclerosis and Air Pollution (MESA Air). Atmos. Environ. 45, 4412–4420. https://doi.org/10.1016/j.atmosenv.2011.05.043.

Miranda, A., Silveira, C., Ferreira, J., Monteiro, A., Lopes, D., Relvas, H., Borrego, C., Roebeling, P., 2015. Current air quality plans in Europe designed to support air quality management policies. Atmos. Pollut. Res. 6, 434–443. https://doi.org/10.5094/APR.2015.048.

Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., Pennington, D., Mendoza, G., Aukema, J., Foster, J., Forrest, J., Cameron, D., Arkema, K., Lonsdorf, E., Kennedy, C., Verutes, G., Guannel, G., Papenfus, M., Toft, J., Marsik, M., Bernhardt, J., 2011. InVEST 2. 0 Beta User ' s Guide : Integrated Valuation of Ecosystem Services and Tradeoffs, The Natural Capital Project.

Nowak, D.J., 2006. Institutionalizing urban forestry as a "biotechnology" to improve environmental quality. Urban For. Urban Green. 5, 93–100. https://doi.org/10.1016/j.ufug.2006.04.002.

Nowak, D.J., Crane, D.E., Walton, J.T., Twardus, D.B., Dwyer, J.F., 2002. Understanding and quantifying urban forest structure, functions, and value David 1–9.

Nowak, D.J., Crane, D.E., Stevens, J.C., 2006. Air pollution removal by urban trees and shrubs in the United States. Urban For. Urban Green. 4, 115–123. https://doi.org/10.1016/j.ufug.2006.01.007.

Nuissl, H., Haase, D., Lanzendorf, M., Wittmer, H., 2009. Environmental impact assessment of urban land use transitions-A context-sensitive approach. Land Use Policy 26, 414–424. https://doi.org/10.1016/j.landusepol.2008.05.006.

Orza, J.A.G., Cabello, M., Lidón, V., Martínez, J., 2011. Contribution of resuspension to particulate matter inmission levels in SE Spain. J. Arid Environ. 75, 545–554. https://doi.org/10.1016/j.jaridenv.2011.01.006.

Ostro, B., Chestnut, L., 1998. Assessing the health benefits of reducing particulate matter air pollution in the United States. Environ. Res. 76, 94–106. https://doi.org/10.1006/enrs.1997.3799.

Prawiranegara, M., 2014. Spatial Multi-criteria Analysis (SMCA) for basin-wide flood risk assessment as a tool in improving spatial planning and urban resilience policy making: a case study of Marikina River Basin, Metro Manila – Philippines. Procedia – Soc. Behav. Sci. 135, 18–24. https://doi.org/10.1016/j.sbspro.2014.07.319.

Primmer, E., Furman, E., 2012. Operationalising ecosystem service approaches for governance: do measuring, mapping and valuing integrate sector-specific knowledge systems? Ecosyst. Serv. 1, 85–92. https://doi.org/10.1016/j.ecoser.2012.07.008.

Ryan, P.H., LeMasters, G.K., 2007. A review of land-use regression models for characterizing intraurban air pollution exposure. Inhal. Toxicol. https://doi.org/10.1080/08958370701495998.

Sali, G., Mazzocchi, C., Corsi, S., 2016. Exploring land use scenarios in metropolitan areas: food balance in a local agricultural system by using a multi-objective optimization model. Agric. Agric. Sci. Procedia 8, 211–221. https://doi.org/10.1016/j.aaspro.2016.02.095.

Sancho, J., Martínez, J., Pastor, J.J., Taboada, J., Piñeiro, J.I., García-Nieto, P.J., 2014. New methodology to determine air quality in urban areas based on runs rules for functional data. Atmos. Environ. 83, 185–192. https://doi.org/10.1016/j.atmosenv.2013.11.010.

Sanesi, G., Colangelo, G., Lafortezza, R., Calvo, E., Davies, C., 2016. Urban green infrastructure and urban forests: a case study of the Metropolitan Area of Milan. Landsc. Res. 6397, 1–12. https://doi.org/10.1080/01426397.2016.1173658.

Selmi, W., Weber, C., Rivière, E., Blond, N., Mehdi, L., Nowak, D., 2016. Air pollution removal by trees in public green spaces in Strasbourg city, France. Urban For. Urban Green. 17, 192–201. https://doi.org/10.1016/j.ufug.2016.04.010.

USDA Forest Service, 2008. I-Tree vue user's manual, v. 3.0.

Vautard, R., Builtjes, P.H.J., Thunis, P., Cuvelier, C., Bedogni, M., Bessagnet, B., Honoré, C., Moussiopoulos, N., Pirovano, G., Schaap, M., Stern, R., Tarrason, L., Wind, P., 2007. Evaluation and intercomparison of Ozone and PM10 simulations by several chemistry transport models over four European cities within the CityDelta project. Atmos. Environ. 41, 173–188. https://doi.org/10.1016/j.atmosenv.2006.07.039.

Vecchi, R., Marcazzan, G., Valli, G., 2007. A study on nighttime-daytime PM10 concentration and elemental composition in relation to atmospheric dispersion in the urban area of Milan (Italy). Atmos. Environ. https://doi.org/10.1016/j.atmosenv.2006.10.069.

Vienneau, D., de Hoogh, K., Briggs, D., 2009. A GIS-based method for modelling air pollution exposures across Europe. Sci. Total Environ. 408, 255–266. https://doi.org/10.1016/j.scitotenv.2009.09.048.

Yu, H.-L., Wang, C.-H., Liu, M.-C., Kuo, Y.-M., 2011. Estimation of fine particulate matter in taipei using landuse regression and bayesian maximum entropy methods. Int. J. Environ. Res. Public Health. https://doi.org/10.3390/ijerph8062153.

Zhang, J.J.Y., Sun, L., Barrett, O., Bertazzon, S., Underwood, F.E., Johnson, M., 2015. Development of land-use regression models for metals associated with airborne particulate matter in a North American city. Atmos. Environ. 106, 165–177. https://doi.org/10.1016/j.atmosenv.2015.01.008.