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Meso-scale life-cycle impact assessment of novel technology policies: The case of renewable energy

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Abstract

Assessing the environmental risk of novel technological systems and of the European Union (EU) policies supporting them and regulating their implementation requires good understanding of (i) the pressure on the environment posed by the large-scale use of new technology, and (ii) the vulnerability of the receptor of this pressure. Generic life-cycle assessments (LCAs) provide exhaustive accounting of environmental pressure, yet they do not take into account the vulnerability of the receiving ecosystem. Generic studies of technology externalities fail to produce conclusions on the impacts in a certain area of the systems envisaged due to lack of site-specific information. The combined use of generic (LCA) and spatially referenced data offers new opportunities for comprehensively analysing the environmental impact of novel technologies. A novel information fusion methodology is suggested.

Example applications are presented herein focusing on the evaluation of renewable energy technologies as an example of the implementation of meso-scale LCA for integrated environmental risk assessment of EU technology policies. © 2000 Published by Elsevier Science B.V.

Keywords: Life-cycle assessment; Integrated environmental assessment; Information fusion; Spatial analysis; Technology policy

1. Introduction

Assessing the environmental risk of novel technological systems and of the European Union (EU) policies supporting them and regulating their implementation requires good understanding of (i) the pressure on the environment posed by the large-scale use of new technology, and (ii) the vulnerability of the receptors of this pressure. Life-cycle

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assessment (LCA) is one of the most widely accepted tools for the evaluation of the environmental burden characterising technological products and processes. Generic LCAs provide exhaustive accounting of environmental pressure, yet they do not take into account the vulnerability of the receiving ecosystem. The adverse effect of the lack of spatial differentiation in generic LCAs on the relevance of the assessed impacts was clearly demonstrated by Potting and Blok [1,2]. Owens [3] gives a good overview of the constraints imposed on life-cycle impact assessment (LCIA) by the lack of spatial and temporal differentiation in life-cycle inventory (LCI). He does not seem to believe that there are many possibilities to enhance LCIA accuracy in predicting non-global impacts. According to other LCIA experts, however, the relevance of LCIA can be greatly increased by introducing site-relevant factors into the assessment process [1,4–7]. The susceptibility of the receiving areas to an impact may, therefore, be evaluated.

Among the most prominent methodologies suggested for economy-wide sustainability (or environmental performance) assessment are material input per service unit (MIPS) accounting of national input–output (I–O) accounts [8] (otherwise known as materials flow accounting, MFA), as well as energy intensity analysis of technical–economic processes [9]. MIPS (or MFA) was developed during the 1990s principally at the Wuppertal Institute in Germany and Leiden University in the Netherlands. It aims at capturing the overall environmental burden of economic systems by considering the efficiency with which materials are converted to GDP and the impact that the mobilisation of materials has on the environment. According to Hinterberger et al. [10], MIPS is the “only measure introduced to date that can be used to compare relative environmental demands, and which can be translated directly into the realm of economics”. According to them, no reliable system exists for aggregating waste material flows according to their environmental impact.

It has been argued, however, [11] that the degree to which an aggregate indicator based on weight conveys accurate and meaningful information about the level and trend in the ecological impact of society’s waste streams, and consequently, of the environmental impact of society-wide policy initiatives is unclear. It is entirely plausible that a decline in the total mass of waste released to all environmental media (i.e. soil, water, and air) could be accompanied by no change or even an increase in ecological impact due to qualitative changes in the waste streams and increased vulnerability of the receiving ecosystem.

The meso-scale LCA methodology presented here aims to overcome the problems encountered in present generic studies of technology externalities, which, although comprehensive in the description of the possible impacts of technology on the environment and on human and ecosystem health, fail to produce conclusions on the impacts of practical applications of the systems envisaged due to lack of site-specific information.

One of the major problems stemming the applicability of LCA for policy assessment is uncertainty. Inherent uncertainty in the LCA methodology has been widely recognised and acknowledged [12,13]. The methodology itself is composed of several consecutive phases. These are, following the ISO LCA method [14]:

- goal and scope definition;
- inventory analysis;

- impact assessment; and
- interpretation and, if possible, valuation of impacts.

Each phase has its own sources of uncertainty [15]. Goal and scope definition determine the system boundaries, an essential step towards a comprehensive and practicable LCA. The inventory data set is characterised by various data elements, typically containing inherent uncertainties, which ultimately undermine the certainty of the LCA results. Important data elements are:

- data sources and age;
- geographical, temporal, and technological representativeness;
- accuracy and precision of data;
- aggregation (data for individual processes are added together rather than listed separately);
- categorisation (substances are put into substance categories rather than being reported as individual substances);
- gaps in data; and
- system boundaries, allocation methods, and other choices and assumptions made in putting together the inventory data set.

The combined use of generic LCA and spatially referenced data offers new opportunities for the generation of comprehensive analyses of the environmental impact of novel technologies. Geographically based information allows the creation of impact vulnerability zones in the geographical frame of reference be it regional, national, or international. The data synthesis methodology suggested is the following:

- perform generic LCI and impact characterisation of the technology set the policy is concerned about. System processes need to be modelled in as much disaggregation as possible in order to limit uncertainties due to data aggregation and categorisation;
- produce impact vulnerability zones according to different scenarios of policy implementation at the regional scale;
- collect geo-referenced land use/cover data in the area of interest;
- couple geo-referenced land use/cover data with impact vulnerability zones to estimate local impact; and
- re-aggregate local impact maps to obtain general impact information for the area of interest.

In this work, the evaluation of the main prerogative of the Commission’s Green Paper on renewable energy technologies (calling for essentially a doubling of the renewables’ share in the EU energy budget by 2012) serves as a key example of the implementation of meso-scale LCA for integrated environmental risk assessment of EU technology policies. Various types of adverse impacts on public health and the natural environment are shown by tracing corresponding “risk” zones. Several of these risks can be added vectorially, thus providing the overall areas of vulnerability to the adverse impacts of the renewable energy system. Spatially referenced calculation of environmental risk allows the comprehensive, yet site-relevant LCA of renewable energy systems that would need to be deployed if the EU policy as described in the Green Paper were to be readily implemented. Monetary valuation of the environmental and health impacts considered have been avoided; the information is presented in non-aggregated form instead. It was felt that a multi-dimensional representation of the externalities of renewables is more useful to policy-makers by not following a compensatory logic and thus, not confounding the results of the analysis with end-of-pipe aggregation errors.

2. Methodology

The methodology proposed in this paper for the spatial integration of externalities in the design and implementation of EU technology policies is part of a project aiming at providing a comprehensive integrated assessment of the deployment of community policy on innovative technologies. Particular attention is paid to the introduction of renewables in the EU energy system in order to assess the impacts of meeting the challenges set forth by the Green Paper on renewables. This objective poses specific requirements to the methodology developed to integrate economic and environmental analysis. In particular, generic life-cycle analysis of the related energy systems and fuel cycles such as devised in other related projects of the European Commission (e.g. ExternE [16]) and other similar efforts fail to take into account the relative vulnerability of the receptors of the adverse impacts of energy technology. Site and plant-specific environmental impact assessment on the other hand takes into account, explicitly, the state of health of the local ecosystem and population. However, it is usually costly and hardly ever affects the siting of the plants or the determination of scenarios for policy implementation at the regional level. The meso-scale approach developed in this work attempts to couple the results of detailed generic life-cycle assessment and impact pathway analysis with regional information through the use of state-of-the-art spatial analysis tools.

The meso-scale integrated LCA algorithm in its application on renewable energy policy assessment integrates:

(a) detailed economic evaluation of the total cost of renewable energy system (for power and heat production) in non-previously existent fuel and energy markets, and
(b) life-cycle environmental assessment of the impacts and potential benefits to the ecosystem and human health due to the use of renewable resources for energy generation.

This tool addresses the needs of policy-makers, energy and financial investors and other concerned stakeholders (such as farmers or NGOs) alike. It aims to assist the integration of renewables into current and future energy markets by providing a comprehensive and well-structured methodology for the evaluation of the feasibility and attractiveness of bio-energy systems to all concerned actors. The following algorithm highlights the analytical steps followed in the implementation of this methodology in the case of renewable energy technology deployment.

(1) Calculation of cost and primary resource input needed for the renewable energy plant of a target size from technical–economic analysis of the primary resource requirements.

(2) Application of resource productivity models to calculate specific yield of the renewable resource in the region of interest (e.g. tons of dry biomass/ha for a biomass-to-energy system, GJ/ha of mean annual solar irradiation for solar thermal or photovoltaic systems). Detailed alternative scenarios for the implementation of the renewables policy are devised in order to meet the top policy goals with the most resource-efficient technology mix in the area of concern. Societal compatibility of the technological innovations considered is accounted for at this stage. In the case of renewable energy, this ultimately determines the target plant size of the processes considered more appropriate for the renewable resource base of the region examined.

(3) Calculation of the actual area requirements for the renewable resource harvesting and technology implementation in the case of the target power plant size. At this step, all relevant policy initiatives affecting the renewable energy policy implementation should be considered. For instance, in the case of biomass-to-energy systems, the recently reformed Common Agricultural Policy should be taken into account with regard to its reference to the alternative uses of marginal agricultural land. In the case of, say, photovoltaics, the upcoming liberalisation of the internal electricity market in the EU would need to be considered regarding the boundary conditions it sets in the power generation and distribution system. This result is fed back into the technical–economic analysis model to update the cost of plant feedstock preparation (production, management, harvesting and transport).

(4) Generation of emissions table according to the target plant size using data from generic life-cycle analysis databases such as GEMIS [17] or Öko-bilanz [18] and other environmental information sources (e.g. ExternE or INSPIRE results). Emission factors $f_e^{s,i}$ (in the case of renewable energy, a GJ or some other equivalent energy unit can be used) for each technological process i that is used to produce product p are used to calculate emissions $E^{p,s,i}$ of substance s per functional unit according to the formula

$$E^{p,s,i} = f_e^{s,i} P^{p,i}.$$

Here, $P^{p,i}$ is the level of production of product p with process i.

(5) Application of the appropriate meso-scale pollution dispersion model(s) under worst-case atmospheric conditions to generate the worst-case envelope of pollution dispersion regional maps. In this work, Gaussian models were used; they were deemed appropriate for the level of uncertainty inherent in the other phases of the LCA. Eulerian models may be preferred if the orography of the region concerned is too complex. These, however, usually are more sensitive to imprecision and uncertainty than Gaussian plume models. They put, therefore, additional pressure to the LCA practitioner for precise, geo-referenced information, which thus far has proven to be difficult to come by.

(6) Calculation of the impact on human health, the incremental air pollution due to the policy implementation might have at the regional scale through the use of exposure–response (E–R) functions. For this calculation, spatially referenced information on the distribution of the different population classes in the territory of interest is

required. Human body response to exposure to air pollution is influenced by the age and the current individual state of health. Information about asthmatics, young children, and elderly population is therefore essential for the relevance of the analysis.

(7) Calculation of the average annual traffic increment due to the operations of the plants required to implement the policy at the regional level.

(8) Calculation of the incremental cost of road resurfacing due to the additional traffic generated by plant operations according to a road deterioration model. This one should be representative of road conditions in the region of concern.

(9) Calculation of the marginal increase in the number of traffic accidents due to the additional traffic generated by carrying primary and intermediate process materials from the appropriate road accidents models; if appropriate data exist, calculate economic cost. Here, differentiation of the several distinct types of road and vehicular traffic conditions in the areas of interest would have to be accounted for.

(10) Cross-correlation of soil vulnerability with land use maps to produce regional soil vulnerability class maps. The USDA classification of soil usability classes may be used as a starting point here. A soil vulnerability classification may be interpreted as the inverse of soil usability for agriculture. The most usable soil class has the lowest vulnerability, and the least usable one presents the highest vulnerability.

Calculation of the impacts of the policy implementation scenarios was done on freshwater quality at the regional scale. In this work, a new, flexible pollution index, FPI, was used as an indicator combining the compounded average level of any number of pollution parameters selected for water quality description, and their maximum value. The index satisfies the requirements for sensibility to pollution variations, robustness to unforeseen temporal and spatial fluctuations, flexibility, i.e. distributional stability, with regard to both missing information and indicator substitution.

In the following sections, a detailed description of the steps summarised in the above algorithm will be explained in more detail. The LCIA delineated above needs to be aggregated to represent potential impacts at the appropriate decision-making level. In modern day Europe, regional authorities are the ones who usually assume the legal responsibility of actually implementing and controlling EU-wide technology policies. That is why regional spatialisation of the LCA results is necessary for integrated policy assessment.

3. A case study: biomass to energy

3.1. Scope

Complete ‘cradle-to-grave’ analysis for technology-specific fuel cycles has been applied in this work. For power generation, the chain of processes from fuel extraction and processing, to power generation and waste disposal are taken into account.

The developed methodology could be applied to all energy systems. However, the work presented herein focused on the LCIA of EU policies and in particular, the recent Green paper on renewables. Biomass-based systems and wind energy are among the most prominent renewable energy technologies with regard to their potential for market penetration within the next decade. The upcoming liberalisation of the internal electricity market in the EU coupled with the advent of low-cost, user-friendly telecommunication technology and electronic commerce enhance the market attractiveness of decentralised power generation. Therefore, the power generation fuel cycle of biomass-to-energy conversion through the combustion of a typical energy plant, namely, Miscanthus (also known as elephant grass) in small (up to 5 MW e) power plants was taken as an example. Regional applications were envisaged in northern Italy (Piedmont) and southern Spain (Andalusia). In the application of the meso-scale LCA methodology in Piedmont, a combined heat and power generation cycle is considered, while in the case of the use of solid residues from olive oil in Andalusia, only heat production for district heating systems was considered.

3.2. Economic cost calculation

Conventional economic performance indicators such as the net internal rate of return for energy investors and other stakeholders with economic interests in renewables deployment (e.g. farmers providing the biomass feedstock for firing combined heat and power plants) can be calculated taking into account the detailed features of the technological system envisioned and its appropriate resource base. In the case of biomass-to-energy systems, the system boundaries for the economic analysis would encompass all the phases of resource exploitation including growing, management, harvesting and delivery to the plant. The Common Agricultural Policy provision of supporting the use of set-aside land for non-food agricultural use or other types of related national policy initiatives such as the UK non-fossil fuel obligation (NFFO) need to be taken into account in the costing calculations.

3.3. External costs calculation

The principle objectives of the externalities calculation presented herein included: (a) the development of a unified methodology for quantifying the environmental impacts and social costs associated with the production of energy at a regional scale; and (b) the identification of the information needs and of further critical methodological issues and research requirements for the efficient integration of the environmental and health impact of novel energy technology at the regional level.

3.4. Impact pathway analysis

The ‘impact pathway’ approach [19] is suggested for the assessment of the external impacts and associated costs resulting from the supply and use of energy. The methodology proceeds sequentially through the pathway linking a ‘pressure’ to an ‘impact’ and subsequent valuation, as shown in Fig. 1. It provides a logical and transparent way of quantifying externalities.

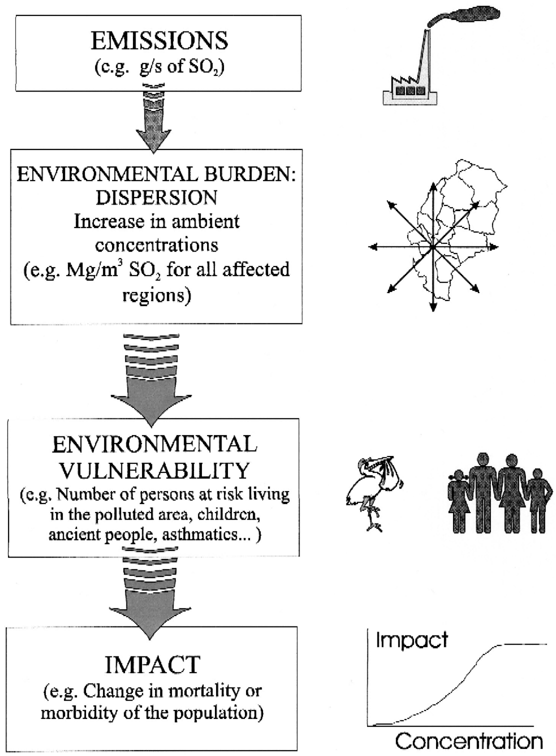


Fig. 1. Illustration of the main steps of the impact pathways methodology applied to the consequences of pollutant emissions.

In order to comply with these principles, the analysis starts from the assessment of the effects of individual renewable energy projects which are specified with respect to:

- technology used;
- location of the power generation plant;
- vulnerability of the local environment; and
- type, source, and composition of fuel used.

In order to facilitate the calculation of the effects of policy measures at the regional level, however, the results of the impact pathway analysis are accumulated and expressed in terms of regional vulnerability and impact maps. Using the software tool developed in the frame of this research work, the exact location of the power plants foreseen by the deployment of the Community renewables policy at the regional scale may vary — the user decides upon the most attractive deployment scenario by evaluating and visualising the effects of different scenarios on economic and environmental costs alike. Fig. 2 shows the information flow diagram of the policy implementation assessment procedure. The impact assessment covers all environmental media and it is coupled with calculated effects on human health.

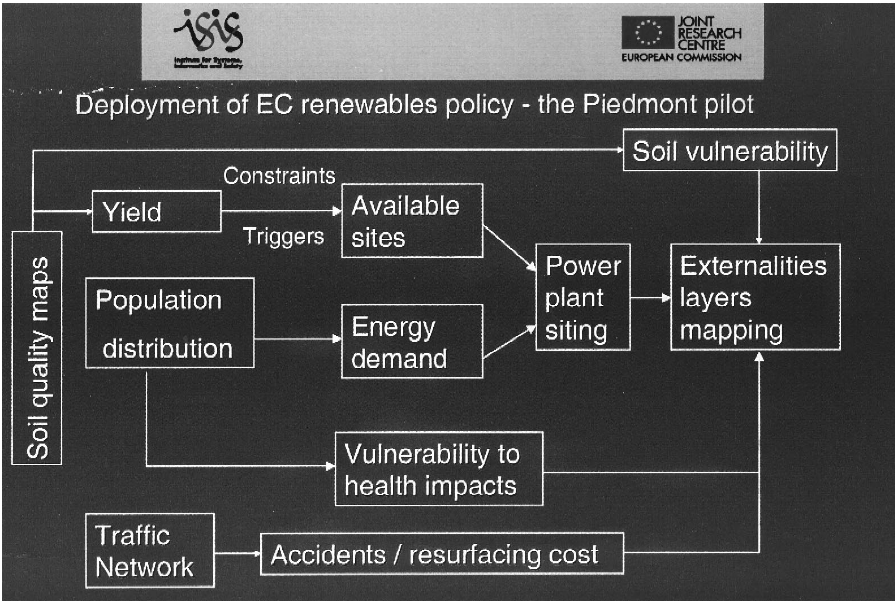


Fig. 2. Information flow diagram in the implementation of the integrated meso-scale LCA for technology policy assessment at the regional scale.

3.4.1. Air pollution

3.4.1.1. Atmospheric pollutants. Atmospheric pollutants from power stations with direct impacts on human health and ecosystems may be classified into three groups according to the atmospheric chemical and physical processes involved in their formation, and their chemical properties.

• Primary pollutants emitted directly from the stack (no atmospheric chemical reaction involved) like particulate matter, nitrogen and nitrous oxides (NO_x and N_2O) and sulphur dioxide (SO_2).

• Acidifying pollutants (e.g. sulphuric acid and nitric acid) formed from emissions of SO_2 and NO_x. Principally, these pollutants are hazardous for vegetation and materials, therefore, it is their dry and wet deposition rather their ambient concentration which is of interest. Owing to their importance on vegetation and materials, they will not be considered in the following methodology regarding human health effects.

• Photochemical oxidants, like ozone, formed in the atmosphere through chemical reactions of nitrogen oxides and hydrocarbons in the presence of sunlight.

The cumulative concentrations of primary pollutants from the policy implementation at the regional scale are calculated. Due to lack of sufficient information, no assessment of photochemical pollutants was done. It remains a priority task for future studies.

3.4.1.2. Atmospheric transport modelling. Atmospheric pollutants are transported by wind and diluted by atmospheric turbulence until they are deposited to the ground by either turbulent diffusion (dry deposition) or precipitation (wet deposition). Following emission from the stack, some of the primary pollutants react in the atmosphere to form secondary ones, but in the vicinity of the power plant (up to 10–50 km) secondary chemical reactions in the atmosphere have little influence on the concentrations of primary pollutants. Due to the emission height from the top of tall power station stacks the near surface ambient concentrations of these primary pollutants close to the stack depend heavily on the vertical exchange rate of the lower atmosphere. Vertical mixing depends on the atmospheric stability and the existence and height of inversion layers (whether below or above the plume). For these reasons a model that neglects chemical reactions but is detailed enough in the description of turbulent diffusion and vertical mixing is the most efficient means of assessing ambient air concentrations of primary pollutants on a local scale. Gaussian plume models are commonly used for these estimations of local scale pollutant dispersion from continuous emissions at point source. They assume that the concentration distribution at the surface from a continuous release into the atmosphere has Gaussian shape, as in

$$C(x,y,z) = \frac{Q}{\pi \upsilon \sigma_y \sigma_z} \exp\left[-\frac{1}{2} \left(\frac{y^2}{\sigma_y{}^2} + \frac{z^2}{\sigma_z{}^2} \right) \right]$$

where C = concentration of a pollutant at the point (x,y,z) [mg/m^3]; Q = emission rate of pollutant (g/s); υ = wind speed at the x direction (m/s); z = active height of pollutant source (m); σ_y = standard deviation across y direction (m); and σ_z = standard deviation across z direction (m).

The assumptions embodied in this type of model usually include those of flat terrain and constant meteorological conditions so that the plume travels with the wind in a straight line at a constant speed. Dynamic features that affect dispersion, for example vertical wind shear, are ignored. These assumptions generally restrict the range of validity of these models to a region within 50–100 km of the source. The straight-line assumption is most strongly justified for a statistical evaluation of long periods (1 year), where mutual changes in wind direction cancel each other out, rather than for an evaluation of short episodes. The plume standard deviation as a function of position and weather conditions are important parameters in this model, and much attention has been focused on providing parameterisations to calculate their value from available meteorological data.

The meso-scale LCA method described in the paper is open enough to accommodate any set of impact assessment tools the final users may dispose of. With regard to air pollution dispersion, the method has so far been implemented using both a simple, Gaussian plume model and the US Environmental Protection Agency models ISCT3, CTDM + and AIRMOD. The last two models are used regularly by the US EPA for regulatory purposes. They are developed to deal with industrial source emissions in a complex terrain. They are, thus, suitable for the meso-scale application described in this work.

In the specific case study in Piedmont, however, Gaussian plume models proved to be appropriate for catching the cumulative effects of air pollution emitted by all the four small power plants envisaged in order to implement the relevant EU policy in the geographical scale of the case study. If larger areas need to be covered or the terrain is complex (i.e. has complex geography), any of the regulatory models cited above should rather be used.

3.4.1.3. Public health effects of air pollution. Combustion processes cause an increase in the concentration of certain atmospheric pollutants. Several of these have been associated with adverse health effects within the general public. The magnitude of impacts is estimated following the damage function approach. For modelling purposes, the impact pathway representing a set of complex processes is broken down into the following stages [20]:

(a) emission;
(b) transport and diffusion (plus atmospheric chemistry);
(c) exposure;
(d) biological and physical impacts (irritant effects on the respiratory system, increased airway resistance, biochemical and morphological changes, increased susceptibility to infections); and
(e) health effects (mortality and morbidity).

Although the above scheme indicates some early markers of response to inhaled pollutants, at present, there is no agreed understanding of the mechanism whereby small changes in ambient air pollution may lead to increased mortality or severe morbidity (e.g. hospital usage) on the same day or soon after. In general, this seems likely to occur only against a background of severe pre-existing condition of ill-health. The precise mechanisms are however unknown.

In this work, ‘primary’ pollutants, i.e. particulate, SO_2, NO_x only have been taken into account. In general, epidemiological studies of the public health effects of these pollutants do not consider personal exposure of the study group. Rather, they examine relationships between health effects and ambient concentrations of pollutants. This simplifies implementation. Yet, it has the disadvantage that there is limited knowledge of how changes in ambient air pollution are related to changes in the various types of indoor environment, where the majority of the EU population spends most of its time.

Air pollution levels show substantial temporal and spatial variation. Concentration values are integrated over time to provide average values:

$$E = \int_{t_1}^{t_2} C(t)\mathrm{d}t.$$

A Gaussian diffusion model is used to predict the annual average concentration in the whole area of analysis. The region considered is sub-divided into smaller areas using a regular grid system of a 500×500 m spatial resolution. Each grid cell is assumed to have a homogeneous pollutant concentration calculated by the pollution transport model. The associated population at risk is the population resident in that grid cell. As in epidemiological studies, daily movements of people between grid cells are ignored. Effects are estimated separately by grid cell and then accumulated.

Most of the E–R relationships are related to a certain risk group, such as children, elderly, or asthmatics. To quantify effects within a certain risk group, the share of the risk group in the total population needs to be known. E–R functions for children are applied to the population that is less than 15 years old. The mean European estimates for the prevalence of asthma among adults is of 7%.

The population-weighted increment of the concentration is defined as

$$C_{\mathrm{pop}} = \sum_{i=1}^{n} \frac{c_i\, p_i}{p_{\mathrm{total}}}$$

with: c_i = concentration in grid cell i; p_i = population in grid cell i; and p_{total} = total population within the reference environment.

The impact assessment procedure adopted is based on E–R functions derived from a large number of epidemiological studies. For ease of implementation, the key relationships were linearised and annualised, assuming independence of background. The results of the impact analysis shown in Fig. 3 are limited to a 50 × 50 km area of Piedmont, namely, the province of Alessandria. The life-cycle impact database construed in the realm of this work, however, covers the whole region of Piedmont and even the adjacent Italian regions. The largest area, where the assumptions upon which the analysis is based, corresponds to European administrative regions.

3.4.1.4. E–R relationships. Numerous well-conducted epidemiological studies in the past 15 years state that there is a broad-based body of evidence showing small but

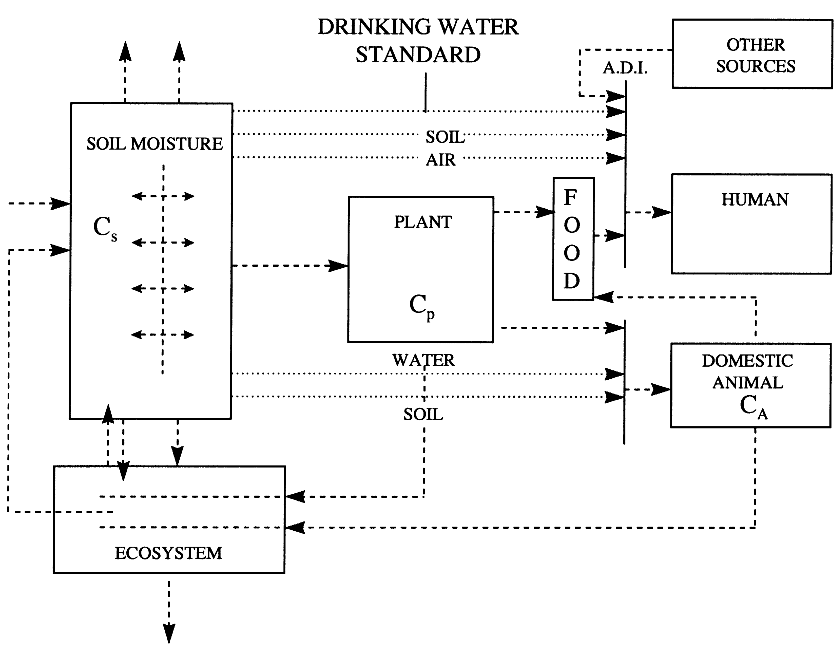


Fig. 3. Information flow diagram for the impact of technology policy implementation on soil quality and human health.

definite increases in risks associated with increases in air pollution (notably fine particles of a diameter smaller than 2.5–10 μm, ozone, and plausibly SO_2). Studies conducted in North America and in Europe have shown relationships quantitatively linking air pollution with health endpoints ranging from premature mortality through hospital admissions, emergency room visits (ERVs) and restricted activity days (RADs) to exacerbation of asthma, respiratory symptoms, and loss of lung function. Thus, the effects are not restricted to high-episode days but occur at ambient concentrations previously considered to be safe. The evidence strongly suggests that there may be adverse health effects even with the small increments in air pollution associated with modern electricity production.

Incremental air pollution that can be attributed to power generation is a mixture of pollutants emitted from a power station, and secondary pollutants formed subsequently as the emissions interact with the environment. Both background levels and pollution increments vary with time and place; incremental pollution varies also with technology and fuel source. The air pollution mixture was disaggregated and, where possible and warranted, E–R relationships were provided separately for the three (four, if O_3 is considered) principal pollutants: particles (in particular, particulate matter of diameter lower than 10 μm), NO_x, SO_2.

For each of these pollutants, where appropriate, E–R relationships were identified, describing changes in health endpoints associated with unit changes in pollutant. All the E–R relationships proposed are based on epidemiological studies of general air pollution, i.e. experimental studies which demonstrate a statistically significant relationship between pollutant and endpoint of interest, in a well-designed study using appropriate statistical methods, and adjusting suitably for the effects of possible confounding factors, including other pollutants.

The appropriate E–R relationships should be [26]:

- credible as set of functions (including the additivity or not of estimated impacts across different health endpoints and individual pollutants) against the background of what is known generally about the effect of air pollution;
- reliable individually, i.e. from well-conducted studies, of appropriate design, using appropriate statistical methods and adjusting for confounding factors such as weather and seasonal or other longer-term trends;
- transferable/generalisable, i.e. from studies in situations that are similar enough to the proposed application;
- with exposure features compatible with the dispersion modelling of incremental pollution; and
- with an E–R relationship that can easily be implemented: ideally, linearised, and independent of background levels.

Tables 1–3 show some indicative E–R relationships for the case of fine particulate matter impact on human health. These relations were applied to calculate the cumulative effects of primary air pollutants emitted due to the implementation of the Green Paper on renewables as shown in the Results section of this paper.

Table 1
E–R functions used for the assessment of *mortality effects* due to incremental *particulate* air pollution

Particulate and mortality			
References	Exposure level		
Schwartz [21]; PM-10 and acute mortality (% change)	Low Mid High	0.064 0.104 * 0.145	Change in annual PM_{10} concentration in [$\mu g/m^3$]
Dockery [22]; PM-10 and chronic mortality (% change)	Low Mid High	0.295 0.386 * 0.477	

3.4.2. Impact on soil quality and effects on humans

The assessment of the effects of the most energy efficient processes on soil quality and, through the soil, on human and animal health and the ecosystem will follow the scheme outlined in Fig. 3. According to the evaluation done following this scheme, soil vulnerability classes of the regional territory can be identified. These classes relate to the perceived usability of the soil for agricultural use after the implementation of the policy in question.

3.4.3. Impact on water quality and effects on human health

In order to globally evaluate the effects of pollution from the most energetically efficient processes, a global, yet flexible index, was sought. This index would have to be flexible enough in order to account for local differences in water use and state of the environment, as well as carrying capacity of the aquatic ecosystem affected by the technical system under consideration.

FPI is a new index for water quality rating, based on a combination of the average and the maximum value of any number of parameters. The index parameters were

Table 2
E–R functions used for the assessment of *acute effects on morbidity* due to incremental *particulate* air pollution

Particulate and morbidity			
References	Exposure level		
Schwartz [23] and Burnett et al. [24]; change in hospital admissions for respiratory infection per 10^5 persons per year	Low Mid High	0.124 0.187 * 0.251	Change in annual PM_{10} concentration in [$\mu g/m^3$]
Schwartz [23] and Burnett et al. [24]; change in hospital admissions for COPD per 10^5 persons per year	Low Mid High	0.161 0.227 * 0.293	

Table 3
E–R functions used for the assessment of *chronic effects on morbidity* due to incremental change in *particulate* air pollution

Particulate and morbidity			
References	Exposure level		
Schwartz [25] (chronic); change in prevalence of adults with chronic bronchitis per 10^5 adults at risk	Low Mid High	45 70 * 94	Change in annual PM_{10} concentration in [$\mu g/m^3$]
Schwartz [25] (chronic); change in prevalence of adults with respiratory illness per 10^5 adults at risk	Low Mid High	60 95 * 129	

estimated with the aim of measuring the quality of a freshwater stream for aquatic life and wildlife.

FPI serves as an estimator of freshwater pollution which combines the compounded average level of any number, p, of pollution parameters selected for water quality description, and their maximum value:

$$\mathrm{FPI}(j)=\sqrt{\left[\mathrm{Max}_i\left(W_{ij}^* C_{ij}^*\right)\right]^2 \frac{1}{W_{zj}^{*\,2}}+\left(\frac{1}{p}\sum_{i=1}^{p} W_{ij}^* C_{ij}^*\right)^2}$$

where C_{ij}^* $(i=1,\dots\ p)$ is a standardised measure of ith water pollution parameter, j denotes jth use of water. Pollution parameters are standardised through either calibration curves of risk of adverse effects to jth use of water, or standard levels fixed by national or international authorities. In the case of the relation between parameter value and the expected risk of environmental damage, which may be represented by a ratio, standardisation is obtained by relating the parameter value to its standard level; $C_i^* = C_i/L_i$ where L_i is the threshold (standard), level of parameter i. If C_i^* is greater than 1, the concentration of ith pollutant overcomes its threshold, and water is considered at various levels of intolerability; $W_{ij}^* = W_{ij}/\sum_i^p W_{ij}$ is the relative weight of the ith parameter selected to define the jth use of water ($\sum_i^p W_{ij}=1$); if the data on a parameter is missing, the weight of the parameter is void and the remaining relative weights still sum to 1; W_{zj}^* is the relative weight of parameter z, whose standardised and weighted values is maximum among the p representative parameters; and $\mathrm{Max}_i(.)$ denotes the operator "maximum" of standardised and weighted parameters.

The FPI: is null if water is not polluted at all, i.e. all parameters are null or in their equilibrium values, and increases as one or more parameters diverge from their standard values. Water quality is assumed to be inversely proportional to the value assumed by FPI, and precisely: $0 \le \mathrm{FPI} < 1 \Rightarrow$ water is of quality adequate for use; and $\mathrm{FPI} > 1 \Rightarrow$ water is at risk for the prospected use.

The following information is needed to parameterise the FPI index.

A selection of water pollution parameters for jth type of use: the problem is irrelevant if quality parameters are defined by law and are the only ones for which data are collected.

A weight to be attached to each parameter: if no weight is guessed, the trivial solution of equal weights is adopted. For the adequacy of FPI, weights are relevant since the linearity assumption of C_{ij}^* parameters, would give otherwise the same importance, for evaluation, to a proportional variation above the threshold, for instance, to ammonia and suspended materials, while a level of suspended materials.

To evaluate water quality for aquatic life, an EU panel of experts on environment protection interacted with the research group which developed the FPI both to order the parameters according to relevance for the stated uses of water, that of maintenance of aquatic life of the least demanding fish species, and to guess importance weights for the selected parameters. In one sense, the implemented index is aimed at evaluating the “natural quality” of water. The analysis of expert weights highlights the following.

(a) The most relevant indicators of water quality are dissolved oxygen (DO) and ammonia concentration: together, they are assumed by experts to cover more than 50% of the perceived quality dimensions.

(b) pH, mineral concentration, surface active agents and temperature almost complete the representation of water quality dimensions; it should be stressed that this group of parameters represent aspects which are additional to the ones expressed by the DO and ammonia rates.

(c) BOD, suspended solids, and other contaminant concentrations are judged of minor importance for index formulation and may be considered replaceable by the previous parameters.

(d) Experts agree on weights estimation of the relevant parameters, i.e. on DO, NH_4^+, and pH, but tend to disagree on the evaluation of temperature, surface active agents and parameters which are given weights below 2% of the total. In particular, experts tend not to agree on the role of suspended solids and nutrients for aquatic life and wildlife. Nevertheless, if weights are winsorized, i.e. the distribution of estimates is trimmed on tails, the evaluations of the experts are almost identical.

The suggested index is insensitive to seasonal variations if an annual value has to be estimated. Its time-stability is due to the unchanging relevance of the main parameters, which compose it and this property has been assessed by the authors through an accurate statistical analysis. (An unconstrained index would be, instead, much more dependent on seasonal outliers of a single water parameter. These features make FPI ideal for long-term monitoring at the local level and for cross-regional comparison.)

3.4.4. Impacts and damages from additional energy-related traffic

Primary renewable energy resource transportation may have several harmful effects on the environment, the most important of which are:

- reduction of road surface life, due to heavy traffic;
- increased number of accidents due to the higher traffic;
- increased noise, due to the truck traffic;

- higher concentration of air pollutants, which are emitted from the truck exhausts; and
- probable changes in biodiversity, due to a combination of noise and air pollutants [27].

Air pollution effects were already incorporated into the part (regarding air pollution) of the impact pathways analysis of the energy system life cycle. There is no good scientific agreement on models linking noise and threats to biodiversity to traffic, since these phenomena have a pronounced local character. Hence, our work is limited to an estimation of the impact of truck traffic on road surface durability and road accident frequency. For a very comprehensive review of modelling regarding accident increase and reduction of road surface life, the reader is referred, respectively, to the 'Revised Monograph on Traffic Flow Theory'[1] edited by the Federal Highway Administration (US Department of Transportation Research and Development), and to the final report of the study 'External Costs of Fuel Cycle' performed by the National Technical University of Athens, Chemical Engineering Department, Bio-resource Technology Unit [20].

3.4.4.1. Traffic and safety. Satterthwaite [28] has done a comprehensive review of the impacts of traffic flow on safety. According to his findings, when only one traffic stream is relevant to accident frequency determination, the power function and polynomial models have been used to link traffic flow and accident frequency.

$$m = \alpha q^{\beta}$$

$$m = \alpha q + \beta q^2 + \dots$$

where m is the accident frequency, and q is the appropriate measure of traffic flow in the road sections examined by the model. At times, the more complex power form

$$m = \alpha q^{\beta + \gamma \log q}$$

is used which is also akin to the polynomial model when expressed in logarithms.

$$\log m = \log \alpha + \beta \log q + \gamma (\log q)^2.$$

When two or more traffic streams or kinds of vehicles are relevant, the product of power functions is commonly used:

$$m = \alpha q_1^{\beta} q_2^{\gamma} \dots$$

For the purposes of this study, given the characteristics of the rural road network of the Northern Italy, a power-function model coupling incremental traffic accidents with traffic load for road sections that are more than 0.5 miles long was used. The model is an elaborated power function $m = \alpha(\mathrm{ADT})^{\beta}(\mathrm{ADT})^{\gamma \log(\mathrm{ADT})}$. Here, m is the calculated rate of road accidents (accident/year) and ADT stands for annual average daily traffic

[1] This publication is an update and expansion of the Transportation Research Board (TRB) Special Report 165, "Traffic Flow Theory", published in 1975, carried out and edited by Drs. Nathan H. Gartner, Carroll J. Messer, and Ajay Rathi under the supervision of an Advisory Committee consisting of Mr. Richard Cunard (TRB), Dr. Henry Lieu (FHWA), and Dr. Hani Mahmassani (University of Texas at Austin).

(vehicles/day). Parameters α ($\alpha = 0.0026$), β ($\beta = 0.78$), and γ ($\gamma = 0.88$) were estimated for a series of road types and geometric features to simulate road conditions in the regions of concern. Distinction between municipal and provincial roads with low traffic load on the one hand, and the provincial ones with high traffic on the other was made.

A word of caution is in order. In the present context, the focus is on how accident frequency depends on traffic flow. Accordingly, the models were written with flow (q) as the principal independent variable. However, traffic flow is but one of the many causal factors which affect accident frequency. Road geometry, time of day, vehicle fleet, norms of behaviour and the like all play a part. Therefore, what is at times lumped into a single parameter β really represents a complex multi-variate expression. In short, the modelling of accident frequency is multi-variate in nature. The inherent uncertainty in the parameter estimation procedure should not be discarded by the LCA practitioners.

3.4.4.2. Reduction of road surface life due to heavy traffic. The impact assessment is based on the wear caused on surface road by each load of truck. Road durability will then be determined by the number of loads. The following equation calculates the number of loads that a road can afford before it needs resurfacing:

$$N_j = \frac{A_0(D+1)^{A_1}(L_2)^{A_3}}{(L_1+L_2)^{A_2}}$$

L_1 = total weight of the vehicle divided by the sum of its axles;
L_2 = type of axle weight, $L_2 = 1$ for single axe, $L_2 = 2$ for tandem axles (two axles close together);
D = road durability, for rigid pavements. D equals the pavement thickness in inches for flexible pavements; D is a linear combination of pavement, base and sub-base thickness with coefficients 0.44, 0.14, and 0.11, respectively; and
A_j = structural coefficients presented in the following table.

	Rigid pavement	Flexible pavement
A_0	$e^{13.505} = 733\,033$	$e^{12.062} = 173\,165$
A_1	5.041	7.761
A_2	3.241	3.652
A_3	2.270	3.238

Once the number of necessary resource loads to feed the plants during 1 year is established, and assuming that the only traffic in the particular road system is by trucks that carry biomass, it is possible to calculate after how many years resurfacing would be needed. Then, knowing the average road life, it is possible to calculate the percentage contribution of the renewable resource transportation to the decrease in road durability. The economic evaluation comes now from the application of this percentile contribution to the total average cost of road resurfacing.

4. Results and discussion

The implementation of the meso-scale LCA methodology outlined in detail in the previous sections has shown that there is a lot to be gained from the spatial integration of technology externalities in order to evaluate the environmental and social–economic impacts of EU-wide technology policy. The application of the meso-scale LCA in the case of renewable energy deployment in southern European regions including Northern Italy and Southern Spain demonstrated the interest in coupling generic LCI tables and waste or pollution emission factors with spatially-referenced population and ecosystem distribution profiles. In the north of Italy, one of the most energy-efficient scenarios for the implementation of the Green Paper on renewables included the deployment of a small number of moderate-size power plants fuelled with biomass. The impacts of this scenario assuming optimal siting of the power plants on human health as measured by the population weighed annual average concentration are shown in Fig. 4. Siting optimisation is defined via an interactive multi-objective optimisation algorithm attempting to satisfy maximum economic gain, maximum public service, minimum primary resource requirements and minimum environmental and public health impact.

In fact, siting the biomass-fuelled power plants necessary to cover 12% of domestic energy consumption in Piedmont, Northern Italy is a decision that would ideally take into account:

(a) the service rendered to the local communities;
(b) the primary resource (i.e. biomass) availability in the vicinity of the plants;
(c) the cumulative effects on the state of the environment; and
(d) the respect of ecological vulnerability thresholds for vulnerable receptors.

The latter requires a more site-specific impact assessment. It assumes, therefore, detailed knowledge of the ecosystem state in the region. In the eventual absence of such information (currently, a very likely condition in many parts of the Union), key vulnerable receptors such as national parks, significant cultural heritage sites, etc. may be identified and considered in the close-in assessment.

The multi-objective optimisation algorithm developed in the frame of this work in principle functions in two steps/modes.

(i) “Closed-loop” optimisation —the optimisation algorithm provides a reduced set of “optimal” solutions ranked based on the degree to which they satisfy the various criteria considered.

(ii) “Open-loop” optimisation or else generation of optimal scenarios to be assessed interactively by the user. The cumulative impact of different “near-to-optimal” solutions is calculated on-line and quantified according to the indicators presented above. The user is allowed to vary parts (or the whole) of the system configuration suggested by the software in order to build complete scenarios of policy implementation. Crisp and qualitatively described information may be used to incorporate various aspects of user preferences. Impacts are calculated anew and visualised via GIS-based representations (impact and vulnerability maps) and cumulative indicators as appropriate. In Fig. 5, soil vulnerability in the region of Piedmont due to the Green Paper implementation is shown.

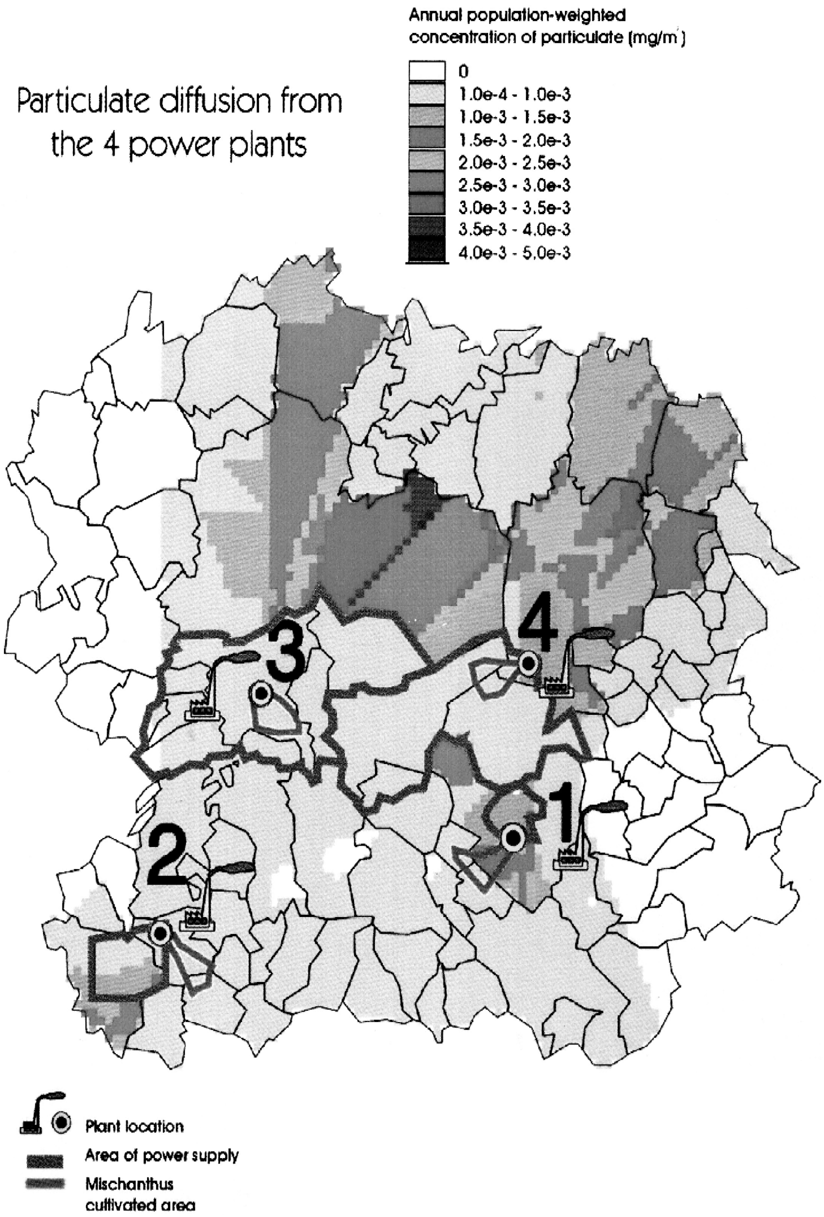


Fig. 4. Annual population-weighed concentration of particulate matter in the area of Alessandria (region of Piedmont) resulting from the implementation of the Green Paper on Renewables via biomass-to-energy systems.

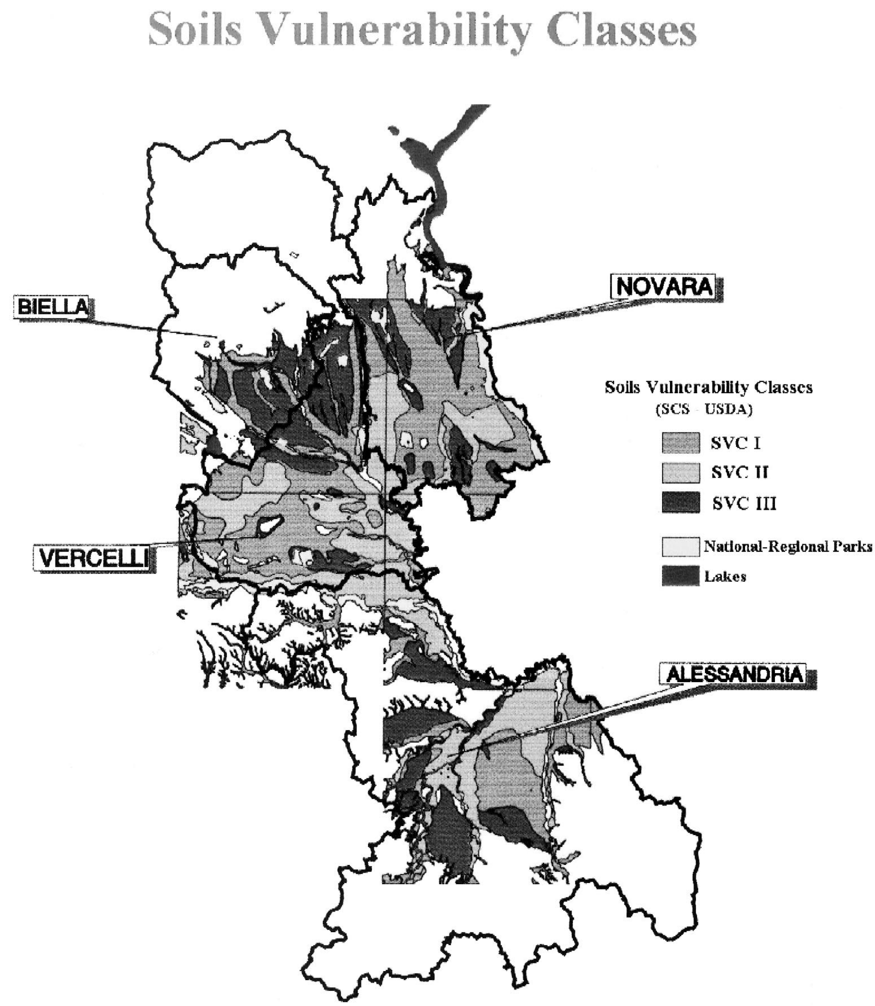


Fig. 5. Soil vulnerability classes in Piedmont due to the exploitation of biomass for energy generation.

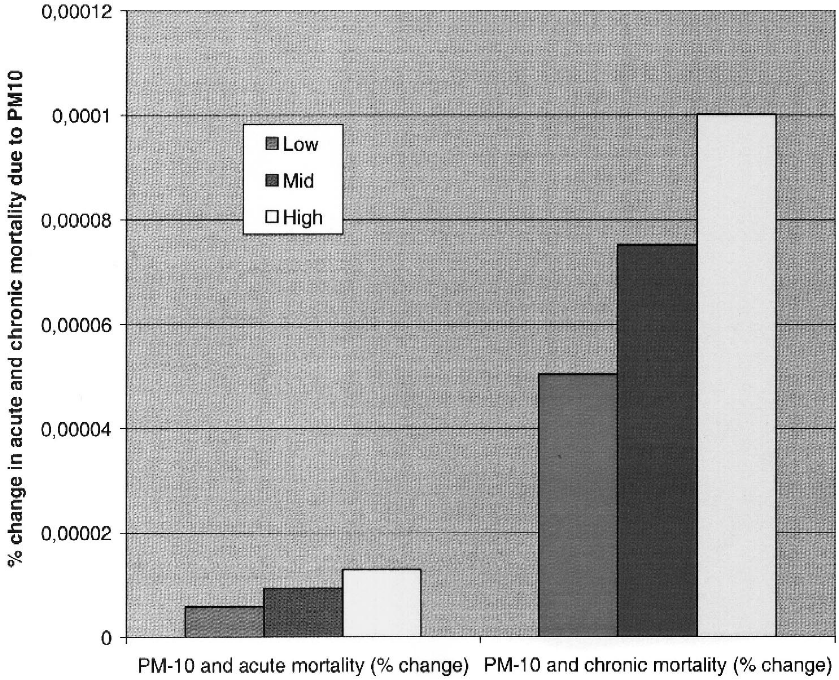
In this way, multi-criteria based comparison among various alternative scenarios is possible. The system is mathematically robust, yet flexible enough to fit the needs and interests of different decision-maker classes at the community, national, and regional levels.

In addition to the spatially referenced life-cycle impacts calculated by the meso-scale LCA, cumulative effects can be reckoned through vectorial addition of the effects. The overall impact of the production of a product or service p, is given by

$$A^p = \sum A^{p,i} = \sum_i \sum_s \left(E^{p,s,i} f_c^i \right)$$

where: $f_c^i =$ cell factor denoting the vulnerability of the receptor in cell c to the impact i.

(a)


0,00012
0,0001
0,00008
0,00006
0,00004
0,00002
0
% change in acute and chronic mortality due to PM10
Low
Mid
High
PM-10 and acute mortality (% change)
PM-10 and chronic mortality (% change)

(b)

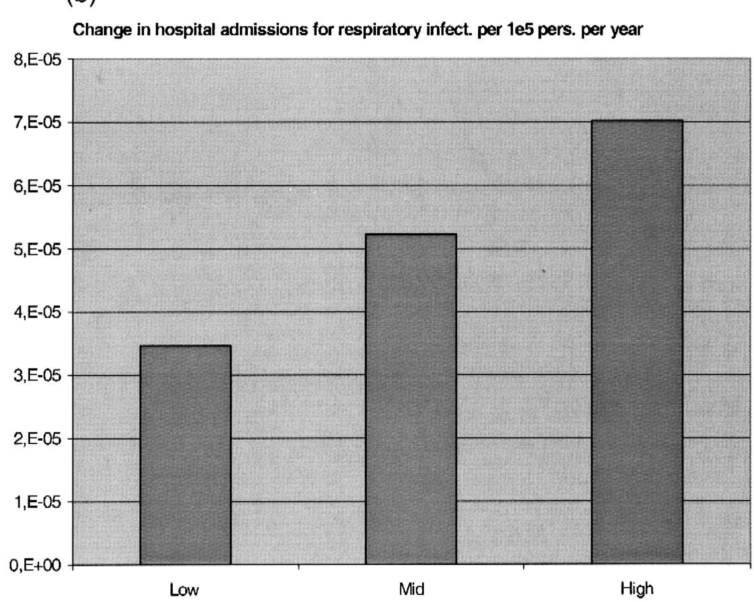

Change in hospital admissions for respiratory infect. per 1e5 pers. per year
8,E-05
7,E-05
6,E-05
5,E-05
4,E-05
3,E-05
2,E-05
1,E-05
0,E+00
Low
Mid
High

Fig. 6a and b shows the cumulative adverse effects of the community renewables policy implementation in Piedmont with regard to disturbances on human health. Adverse impacts of respective incremental traffic load (in terms of increased traffic accident rate per road type) are shown in Fig. 7. Bioenergy-related traffic has an impact on the order of 2% on total road damage. Considering the mean lifetime of road surface in northern Italy (8–9 years), the total economic impact of road maintenance due to bioenergy-related traffic is estimated to reach ca. 340 000 Euro over the 20 years of the plants' lifetime.

It should be noted that the effects presented in Figs. 6a,b and 7 and in the above discussion are all of the "cost" type, i.e. undesirable. This by no means implies that the policy should not be implemented. Climate change may very likely have both global and local (regional) effects. Enhanced morbidity due to the spread of infectious disease, modified patters of water resources and regimes, changes in rainfall and its seasonal patterns, and effects on biodiversity are among the most pronounced ones. Impacts would undoubtedly vary based on the current conditions and vulnerability of the local ecosystems. Given the uncertainty that plagues local impact assessment of global warming and the different space and time scales of its global effects, the best practicable way of action is to accept the strategic policy objectives and analyse the various alternatives of implementation.

The EU renewables policy has been devised to provide answers to the EU commitments in Kyoto, while maintaining and enhancing the competitiveness of the European industry and securing energy supply in a liberalised market. As such, it has many advantages. The claim of the authors is, however, that European policy-makers at all levels, Community, national, and regional would benefit from an evaluation of the adverse impacts of technology policies. This information would be essential for the comprehensive understanding of policy externalities. Our aim is to help policy-makers devise full scenarios of policy implementation and adapt them to regional societal, economic, and environmental conditions enhancing, thus, their cost-effectiveness. Indeed, the major merit of the approach, as shown in the case study on renewables, is that it gives policy-makers the possibility to compare among different regional technology policy options in order to attain the same level of greenhouse gas abatement.

Clearly, results reported in this paper as is the case of all large-scale policy assessments [29] and LCA in general are very sensitive to data and model uncertainties [30,31]. In the case of health impacts, large uncertainties still exist regarding the link between air pollution and human health. Although indications of direct links between air pollution and, say, respiratory disease exist, epidemiologists do not seem to agree upon an exact quantification of the impacts. In the EU, the recently completed EXPOLIS study [32] has provided the first large-scale epidemiological indications on the human health impacts of atmospheric pollution. The epidemiological models used in this paper

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Fig. 6. (a) Cumulative percentile incremental change of mortality due to the implementation of the Green Paper on Renewables in Piedmont. (b) Cumulative incremental change of morbidity due to the renewables policy implementation in Piedmont (indicator: hospital admissions for respiratory infection per 10^5 persons per year).

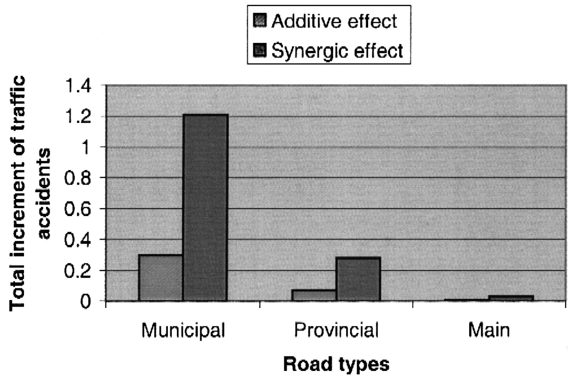

Fig. 7. Total accident rate increment due to bioenergy-generated traffic in Piedmont (over the plants lifetime).

are based on studies pursued in the US. A more appropriate approach would be to use EU data. These would represent more adequately the lifestyle differences, which influence the final impact of technology and pollution on humans. It will be one of the future work priorities of the authors.

Incremental traffic impact is calculated based on a series of statistical models developed using data from the US, Canada, Germany and other European countries, in particular, with regard to the conditions of rural roads. Region-specific data would be more appropriate to use. Still, the models developed have demonstrated mathematical robustness. A sensitivity analysis of the adverse impacts of policy implementation along the impact pathway showed that model uncertainty has not ensued large variations in the impacts reckoned by the model. Input data uncertainty was reduced as much as possible through a series of independent cross-checks among the various datasets used in the case study. Local data were further validated through consultation with local experts and competent authorities.

The emission factors calculated through the LCI part of the study were found to agree well with the ones that can be found in the best available total emission databases available in the EU to date, such as Öko-bilanz and GEMIS. Finally, the set of meteorological data employed to calculate air pollution transport and, hence, air pollution effects on public health were constructed in close collaboration with the regional meteorological centre of Lombardy. This centre maintains the most validated data sets regarding climate and weather conditions at the regional scale in northern Italy.

Integration of spatial information into LCA assisted by environmental data and model fusion is a powerful tool for going beyond the limitations of conventional LCA. The latter has often been criticised for its limited ability to cope with spatial and temporal variation. Owens [3] discusses four remedies to deal with the poor agreement between the LCIA-forecasted impact and the expected occurrence of actual impact. Model and data fusion to address the actual relevance of the assessed impact is one. Indeed, our future work will focus on the articulation of a model fusion methodology integrating the use of policy-relevant indicators and explicit treatment of the various uncertainty classes involved in policy assessment. Our objective is to support policy-making by providing scientific tools facilitating the integration of multiple governance objectives in a structured framework.

The accuracy of prediction with the resulting spatialisation of ecological impact is close to the maximum achievable with the currently available environmental information tools. Linking policy prerogatives with the vulnerability of the receptors whereupon this policy is to be applied goes far beyond the abilities of analytical tools used in risk assessment and environmental impact analysis.

5. Conclusions

The work described in this paper has provided an efficient analytical tool to assist community innovation and technology policy. The case of the implementation of the latest EU policy on renewable energy deployment (with a view to meeting the Kyoto obligations of the Union) was used as an example. Policy support can be provided by the methodology presented herein in a number of areas including those detailed below.

5.1. *Environmental impact*

- Identify the spatial distribution of primary resources (resource mapping) and the corresponding environmental impact.
- Environmentally sensitive areas (if available as a spatial dataset for GIS) can be taken into account during the analysis and considered when assessing the details of the actual implementation of the policy.

5.2. *Social impact*

• Provide basis for a decision support tool. By identifying in a transparent and user-friendly way the perceived impacts not only of one individual plant, but rather of a comprehensive policy initiative on the local population, concerned stakeholders have a sound basis for participatory decision-making and, consequently, the effectiveness of community policy is maximised.

• Assistance in rural development through identifying opportunities for technology policy deployment schemes, which in turn would help create employment.

5.3. *Economic impact*

- Identify the optimum structure for technology policy deployment.
- Aid the development of economically viable innovation and technology deployment projects at the regional scale.

In conclusion, this work has demonstrated that the spatial assessment of technology policy impact assessment (on the environment, the society, and the economy alike) can be a very useful tool for community policy implementation. Current multi-platform information technology lends itself to user-friendly integrated assessment of technology policies by allowing the functional integration of economic, environmental, and safety considerations. Future work of the authors is oriented towards the development of object-oriented multi-model information systems taking full advantage of the potential of object-oriented database management technology and model fusion techniques.

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References

[1] J. Potting, K. Blok, in: H.A. Udo de Haes, A.A. Jensen, W. Klöpffer, L.-G. Lindfors (Eds.), Integrating Impact Assessment into LCA, Brussels, Society of Environmental Toxicology and Chemistry, Europe, 1994, pp. 91–98.
[2] J. Potting, K. Blok, Journal of Cleaner Production 3 (4) (1995) 201.
[3] W. Owens, Journal of Industrial Ecology 1 (1) (1997) 37.
[4] J. Potting, M. Hauschild, Journal of Life-Cycle Assessment 2 (3) (1997) 171.
[5] J. Potting, M. Hauschild, Journal of Life-Cycle Assessment 2 (4) (1997) 209.
[6] H. Udo de Haes, Towards a Methodology for Life-Cycle Impact Assessment, Brussels, Society of Environmental Toxicology and Chemistry, Europe, 1996.
[7] H. Wenzel, M. Hauschild, L. Alting, Environmental Assessment of Products. Volume 1: Methodology, Tools, and Case Studies in Product Development, London, Chapman & Hall, 1997.
[8] F. Schmidt-Bleek, Fresenius Environmental Bulletin 2 (1994) 245.
[9] R. Constanza, S.C. Faber, J. Maxwell, Ecological Economics 1 (1989) 335.
[10] F. Hinterberger, F. Luks, F. Schmidt-Bleek, Ecological Economics 23 (1997) 1.
[11] C.J. Cleveland, M. Ruth, Journal of Industrial Ecology 2 (3) (1999) 15.
[12] E.J. Bonano, in: R. Deshotels, R.D. Zimmerman (Eds.), Cost-Effective Risk Assessment for Process Design, McGraw-Hill, New York, 1995.
[13] L. Ortolano, A. Shepherd, in: F. Vanclay, D.A. Bronstein (Eds.), Environmental and Social Impact Assessment, Wiley, New York, 1995.
[14] ISO (International Organisation for Standardisation), Environmental management — life cycle assessment — principles and framework, Draft International Standard ISO/DIS 14040, 1996.
[15] S. Schaltegger, A. Braunschweig, K. Büchel, F. Dinkel, R. Frischknecht, C. Mailefer, M. Ménard, D. Peter, C. Pohl, M. Ros, A. Sturm, B. Waldeck, P. Zimmermann, in: S. Shaltegger (Ed.), Life Cycle Assessment (LCA) — Quo Vadis? Birkhäuser Verlag, Basel, Switzerland.

[16] M. Edwards, P. Edwards, N. Mortimer, B. Briggs, B. Sorensen, B. Meir, K. Willis, S. Navrud, Externalities of Energy, 1995, European Commission, DG XII, Luxembourg.
[17] GEMIS database, Öko-Institut Darmstadt, 1998.
[18] R. Frischknecht, P. Hofstetter, I. Knoepfel, E. Walder, R. Dones, E. Zollinger, Ökoinventare für Energiesysteme (Eco-inventory for Energy Systems), Federal Office for Energy, Switzerland, 1993.
[19] W. Krewitt, P. Mayerhofer, A. Trukenmüller, R. Friedrich, International Journal of Life Cycle Analysis 3 (2) (1998) 86–94.
[20] E.G. Koukios, N. Diamantidis, S. Arvelakis, S. Theocharopoulos, D. Vokou, External costs of fuel cycles: The case of biomass in Greece, Final Report, 1995, National Technical University of Athens.
[21] J. Schwartz, American Journal of Epidemiology 137 (1993) 1136.
[22] D.V. Dockery, American Review of Respiratory Disease 139 (1989) 587.
[23] J. Schwartz, American Review of Respiratory and Critical Care Medicine 150 (1994) 648.
[24] R.T. Burnett, R.E. Dales, M.E. Raziene, D. Krewske, P.V. Summers, G.R. Roberts, M. Raad-Young, T. Dann, J. Brook, Environmental Research 65 (1994) 172.
[25] J. Schwartz, Environmental Research 62 (1993) 7.
[26] C. Winston, Journal of Economic Perspectives 5 (1) (1991) 116.
[27] ORNL, Damages and Benefits of the Biomass-to-Energy Fuel Cycle: Estimation, Methods, Impacts and values, Oak Ridge National Laboratory and Resources for the Future, 1992, Oak Ridge, TN.
[28] S.P. Satterthwaite, A Survey into Relationships between Traffic Accidents and Traffic Volumes, Transport and Road Research Laboratory Supplementary Report, SR 692, 1981.
[29] F. Campolongo, R. Braddock, Environmental Modelling and Software 14 (1999) 275.
[30] F. Campolongo, S. Tarantola, A. Saltelli, Computer Physics Communications 117 (1999) 75.
[31] A. Saltelli, S. Tarantola, K. Chan, Journal of Multi-criteria Decision Analysis 8 (1999) 139.
[32] M.J. Jantunen, K. Katsouyanni, H. Knöppel, N. Künzli, E. Lebret, M. Maroni, K. Saarela, R. Srám, D. Zmirou, Air Pollution in European Cities: the EXPOLIS Study, Kansanterveyslaitoksen julkaisuja B16, 1999 (ISBN: 951-740-3576).