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1. Abstract

Agricultural practices have potentially important and wide-ranging impacts on health. Nevertheless, while many studies have investigated specific risk factors, such as exposures to pesticides or endotoxins associated with livestock, few attempts have previously been made to assess health impacts of agricultural policies or land use decisions in any comprehensive way. Doing so poses clear challenges. These arise firstly from the scale of these impacts, which are generally characterised by small relative risks at individual levels but large population-level effects. Secondly, they derive from the difficulties in data acquisition and exposure modelling and uncertainties in exposure-response functions. For these very reasons, the issue of agricultural land use represents an informative and valuable context within which to explore and test methods of integrated environmental health impact assessment.

Mainly for reasons of data availability, assessments were carried out via two separate studies, one focusing on Central Macedonia and Thessaly of Greece, the other on the East Anglia and north-western areas of England. Initial scoping was done jointly, so that both studies worked to a common conceptual model of the issue, adopted broadly similar scenarios and considered the same exposures and health impacts (pesticides and cancers, and particulates and endotoxins and respiratory illness) and pathways (inhalation only). Likewise, for most pollutants the same exposure-response functions and health impact calculations were used in the two areas. Details of the scenarios and exposure assessment methods varied, however, depending on local data considerations.

In England, scenarios were developed using the Regional Impact Simulator (RegIS), which gives indications of land use change in response to climate change under the IPCC scenarios and provided data for rural land use and cropping at a spatial resolution of 5x5km for the baseline and year 2020 for low (L2020) and high (H2020) emission scenarios. For pesticides, emissions were estimated on the basis of county-level usage statistics for each active substance (AS). Aggregated source data were spatially disaggregated to finer grids (i.e. 250m), informed by agricultural census data and land cover information, using GIS methods including mask area weighting. Change ratios, derived from RegIS, were applied to the baseline source activity grids to generate grids for the L2020 and H2020 scenarios. Emission factors for individual pesticide active substances (AS) were compiled and applied to transform the source activity grids into grids of emissions (μg/m^2/year). Particulate emissions were modelled in a similar way, using emission factors for each crop type; endotoxin emissions were based on livestock numbers. The ADMS dispersion model was used to model regional dispersion profiles, taking account of local meteorology for one year, for one unit emissions of each pollutant type. Distance-weighted kernel functions were then imputed from the dispersion profiles, and applied to the 250x250m emissions grids to convert emissions into concentrations (μg/m^3/year) using GIS-based Focal sum model. Health impacts were modelled for a business-as-usual scenario and two climate-change scenarios for the year 2020. Analysis was done for a 250m grid covering each area. Exposures were modelled as the population-weighted atmospheric concentration of each agent in each grid cell.

In Greece, land use change scenarios were adopted from the ATEAM (Advanced Terrestrial Ecosystem Analysis and Modelling) project in which the primary object was to assess the vulnerability (to global climate change) of humans relying on ecosystem services. Based on these, exposures and health impacts were modelled for a business-as-usual (BAU) scenario and a climate-change (Mitigation) scenario for the baseline year (2000) and the years 2020 and 2050, at a spatial resolution of 4x4km. These data were enhanced by using supplementary land use data. In general, the same methodology used in the England case study was followed for Greece case study as well. For pesticides, sales data (by active substance and crop) were spatially disaggregated using a stochastic allocation algorithm. Then emissions were estimated for each AS by using appropriate emission factors. Differences in crop area in future scenarios are reflected in differences in pesticides data. As in the England case study, particulate emissions from crops and animal husbandry were modelled using emission factors for each crop type and animal category, while endotoxin emissions were based on livestock numbers. Furthermore, pollen emission factors were used to estimate pollen emissions from specific crops. The Focal sum model and a box volume model were used to estimate concentrations for both base year and scenarios. The CALPUFF dispersion model was run in each Region of study using a single area source (4

x 4 km) emitting 1 μg/m^2/sec (unit emission) of a typical gas. Yearly average meteorological data (wind speed and direction, temperature, relative humidity) from local meteorological stations were used to generate a 4 x 4 km kernel file corresponding to the emissions grid resolution. Risk estimation was carried out for pesticides to investigate changes in exposure, while concentration of particulates was directly used to exposure estimations.

In both study areas, exposure-response functions were derived by a combination of methods. In the absence of reliable estimates for crustal particles, the function for traffic-related PM was taken from the ERF database for England case study, while for Greece, appropriate ERFs (for both PM_{10} and $PM_{2.5}$) for local conditions were used. These ERFs were further refined with local information on hospital admissions. For endotoxins, some ERFs were obtained from a systematic literature review. However, no health impact assessment was conducted for endotoxins because these ERFs were inappropriate and there was lack of adequate background rate data for diseases related to this kind of pollutants. Efforts were made to retrieve suitable ERFs for pollen, also with no success. For pesticides, ERFs were derived for each active substance on the basis of toxicological evidence. In England, a risk analysis using the Rapid Inquire Facility (RIF) developed at the Small Area Health Statistics Unit (SAHSU), Imperial College was conducted to derive England specific RRs for cancers.

Health impacts for pesticides are computed according to an epidemiological and a toxicological approach. The former is based on RRs and the portion of exposed population and the latter on ERF from those active substances with positive carcinogenic effect. The health impact indicators for pesticides included risk and attributable burden of disease, while for particulates only the latter. The case studies in England and Greece have taken different methodological approaches to quantifying health impact from the agricultural practices.

For the England case study, differences in attributable burden between the BAU and change scenarios (L2020 and H2020) gave an estimate of the impacts attributable to the projected land use changes. Health risks due to pesticides were assessed at the ward level while risks due to particulates were assessed at the county level. Little difference between L2020 and H2020 was detected, thus results for H2020 are reported. Only a slight increase in mortality due to particulates was detected (0.5 per year for PM10) due to the land use change across both study areas, i.e. East Anglia and north west England combined. In terms of pesticides, the toxicological risk analysis for six carcinogenic herbicides estimated two attributable cases per year across both study areas. Of the seven adult cancers explored in the RIF risk analysis, risk was only detected for breast and prostate cancer in areas with total pesticide concentrations exceeding 3.6 and 0.04 ng/m^3, respectively. In terms of attributable burden due to land use change, an estimated 5 and 9 cases of breast and prostate cancer, respectively were estimated in the north west England, while the estimate in East Anglia was 2 breast cancer and 3 prostate cancer cases per year. The marginally larger increase in the north west results from a greater proportion of the population shifting between exposure categories e.g., wards shift from lower categories in the BAU to higher categories in the change scenarios.

For the Greece case study, comparisons in attributable burden between the BAU and mitigation scenarios show very small differences both for pesticides and particulates. Health risks from pesticides were carried out only for farmers who are exposed to pesticides due to their proximity to the emitting sources, whereas exposure estimates to particulates is based on the general population. It should be noted that aggregated risk estimates from pesticides, for each scenario, were found to be below the 10^{-6} value, commonly considered to be an indicator of significant risk. For the pesticides, the difference in the number of cases attributed to cancer is estimated to be 2E-5 and 1E-5, for the years 2020 and 2050, respectively, based on analysis involving 20 carcinogenic active substances. These small differences are in accord with the estimated small concentration in air (maximum at 2.2 ng/m^3) and the concomitant very low risk (approx. 3E-8). Moreover, the results show that the effect of increased cultivation of energy crops (in the context of mitigation scenarios) on health impact is almost negligible, since the total quantity of pesticides used in the energy crops considered is small, in comparison to that used in edible crops. For the particulates (PM_{10}), the changes in the number of cases between the BAU and the mitigation scenarios with respect to various health effects are also very small. For example, the difference in the number of cases for the cardiovascular diseases is 4.6E-2 (for year 2020) and 8E-2 (for year 2050). Similarly, the difference in cases attributed to respiratory health effects is 1.8E-2 (for year 2020) and 3E-2 (for year 2050).

The integrated health impact assessment due to agricultural land use changes has provided very useful insights at both the methodological and the practical level; it is noted, however, that under the assumptions made in the case studies, the calculated health impact due to agricultural activities appears to be small, in general. Moreover, a qualitative assessment of the results in conjunction with the main factors involved, indicates some interesting trends. In particular, foreseen changes in crop cultivation patterns (concerning both edible and energy crops), as a result of policies (for adaptation to, or mitigation of, climate changes), appear to have a small impact on human health; a similar effect is indicated for foreseen changes in animal husbandry. Additionally, these case studies clearly suggest topics that need to be addressed in future studies, notably patterns and duration of human exposure to agriculture-related pollutants and suitable dose response functions of all pollutants involved.

2. The issue

2.1 Rationale

Agriculture can be a significant source of environmental contamination and thus of human exposure to pollutants. Risks are often greatest for those in close proximity to agriculture (e.g. farm-workers, their families and bystanders in the local community). Nevertheless, exposures may also occur more widely as a result of long-distance transport of pollutants by air, water and the food distribution system.

Rightly or wrongly, public concern about these risks has also been inflated in recent years. In part this has been a result of well-publicised food contamination events, such as the BSE crisis in the UK or the dioxin scare in Belgium. Increased food allergies (especially in children) have likewise contributed to concerns, and (unsubstantiated) claims have been made that people living near intensively farmed land have been affected by a range of unexplained health symptoms.

Changes in agricultural land use and practice may therefore have significant implications for human health, and may raise public anxiety about food safety. In the European Union, we can expect substantial changes in coming years, as farmers react to changing economic circumstances (e.g. world food and energy prices), environmental conditions (e.g. climate change), and to government policies.

The key question here, therefore, is:

> *What are the likely health impacts for the general public of changes in agricultural land use (due to environmental, economic and policy developments) in Greece and England over the foreseeable future?*

2.2 Issue Framing

Initial scoping of the agricultural case study assessments revealed extensive evidence that agriculture can influence human health through a wide variety of mechanisms and pathways. The most powerful and important effects operate via food, and in particular in terms of the nutritional quality and safety of food. Indeed, almost every decision made by the farmer can ultimately affect food quality and safety, including all the choices made about crop variety and livestock breed, tillage practice, sowing and harvesting times, and chemical technologies (e.g. fertilisers, hormones, pesticides).

At the same time, agriculture can be a significant source of environmental contamination and of pollutants to which humans may be exposed (Figure 1, Annex 1). Pollutants produced by agriculture include pesticide and fertiliser residues, livestock wastes and animal pathogens, dust, spores and gaseous emissions. Levels of these emissions are dependent on many different aspects of land use practice, including soil tillage and drainage, crop choice, fertiliser practice, pest control regime, grazing practice, harvesting practice and waste management. Important pathways for exposure thus include:

- direct dermal contact with pathogens, pesticides and other chemicals
- inhalation of particulates, spores, pesticide residues, bacteria and endotoxins

- drinking and ingestion of pesticides, fertilisers and pathogens.

The likelihood and magnitude of these exposures is obviously greatest for those in close proximity to agriculture – i.e. farm-workers, their families and bystanders in the local community. Rural populations are therefore most at risk – though in the case of exposures via food, modern processing and distribution systems mean that there is almost no geographic limit to the exposure pathway. Exposures can also occur far more widely, however, as a result of long-distance transport of contaminants by air and water.

The range of known and suspected adverse health effects to which agriculture may contribute in this context is large, though firm evidence for some of these effects remains elusive. It is also important to remember that many aspects of farming can have benefits for health. Pesticides, for example, help to reduce contamination of food, and thus diminish the risks of a wide range of infectious diseases. Early life exposure to animals has also been shown to confer some protection against allergies in some cases. In addition, the contribution agriculture makes in maintaining the countryside provides psycho-social benefits – and the physiological benefits of exercise – to those who can access it for leisure.

The pathways, vulnerable groups and effects mentioned above reflect those that evolved through scoping this assessment. This study, however, cannot consider all of these – though a comprehensive analysis of the health risks associated with agricultural land use should certainly attempt to take account of most of them.

The next step therefore involved framing the problem in a clear and concise way. This was done through a series of consultations between the scientists involved in the England and Greece case studies, by brain storming to develop initial mind maps, and with representatives from a long list of stakeholder groups and data providers (Table 1, annex 1). It was not possible to carry out a full stakeholder consultation, nor was it necessary as this assessment was aimed at testing methods of assessment. Instead, only narrowly focused consultations were possible, mainly about pesticides and, in England, included discussions with the Pesticides Safety Directorate and Department of Food, Environmental and Regional Affairs to direct the original scoping of the case study, and to obtain relevant data.

This combined effort resulted in a mind map (Figure 2, annex 1) which was refined and revised, to provide a more structured view of the problem, in the form of a systems diagram (Figure 3 and 4 annex 1). Throughout the process, reviews were also carried out of the relevant scientific studies, to help identify which potential risk factors might be most important in affecting human health. As a consequence, three key risk factors emerged: pesticides, endotoxins and aerosols. Others that were initially considered for inclusion (e.g. health effects of nitrates) were omitted because of lack of sufficient evidence for significant health effects. In the same way, possible health outcomes of interest were defined and, informed through discussions with epidemiologists and toxicologists, the most important risk factors and exposure pathways identified. These focused on respiratory effects (from all three agents), all cause mortality for PM and cancers (from pesticide exposures).

2.3 Causal Diagram

The systems diagram was ultimately revised and specified to provide a firm basis for assessment as reflected in the causal diagram. Through several iterations, this gradually evolved into a more 'analytical' form, identifying the data and models that would be needed at each stage in the assessment.

The final causal diagram, illustrated in Figure 1, was developed in Analytica software. This is a non-working model due to the spatial nature of this assessment (i.e. concentration and exposure modelling was undertaken at a high spatial resolution in GIS). In practice, however, those elements could be modelled in GIS and inputted into the Analytica model as indexed tables such that a skilled Analytica user could transform this into an operational model of the agricultural causal chain.

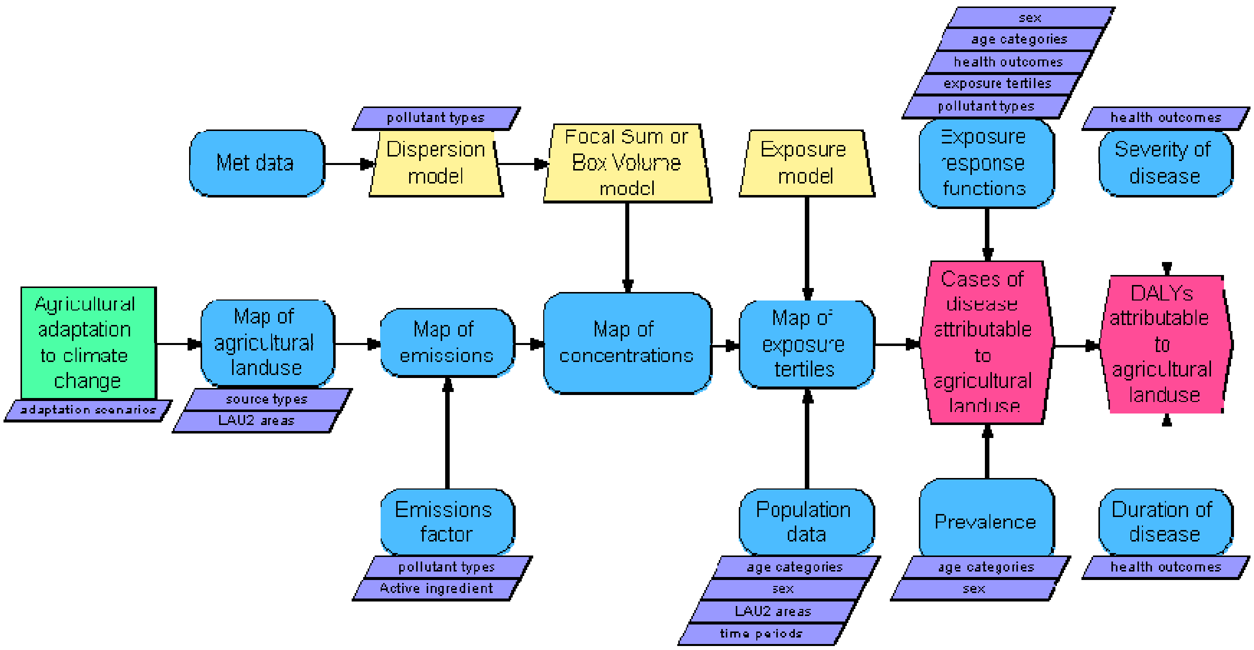


Figure 1. Causal chain customised for agricultural assessment

Issue framing identified the main agricultural pollutants as pesticides, endotoxins and aerosols for which the sources include both livestock and cropping systems and practices. Agricultural emissions are directly linked to land use (i.e. crop areas and livestock counts). Taking account of meteorological conditions and dispersion in the environment, the emissions are translated into concentrations through a GIS-based modelling approach or box volume model. Combined with the spatial distribution of the static residential population, the concentration of each pollutant is used as a proxy for exposure. Where known exposure response functions exist, the cases of respiratory disease, mortality and cancer attributable to agricultural land use scenarios may be computed. With additional information on disease duration and severity, the aggregated health impact could be presented as DALYs. Further details on implementation of the models and data used in this assessment are presented in the subsequent sections.

2.4 Exclusions and Assumptions

Several exclusions and assumptions were identified at the beginning of this assessment, while others were made as the assessment progressed in response to unforeseen challenges in implementing the causal chain. The former are described here and the latter are described throughout the remainder of this report.

The main exclusions and assumptions are as follows:

- The overall assessment is carried out in two countries, assumed to be generally representative of conditions in the north (England) and south (Greece) of Europe.
- Agricultural impacts on health operate mainly via exposures to pesticides, endotoxins and aerosols. Other important exposures are recognised (including nitrates, veterinarian and pharmaceutical products such as hormones, and animal-borne diseases) but have been excluded due to limitations in resources and expertise. A full assessment of the health impacts from agriculture would need to include these sources as well.
- This assessment focuses on inhalation exposures, though both dermal and ingestion exposures are also relevant. Food in particular is recognised as a very important pathway but is excluded from this assessment.

- Information about the key exposures and health outcomes is obtained from previous research and monitoring activities, by purpose-designed modelling, or through expert elicitation. Where this is not feasible, the assessment may proceed as far as possible though not necessarily through the entire causal chain.
- Uncertainties are likely to occur in the assessment process. These are characterized qualitatively at all stages in the assessment. It is anticipated that the level of uncertainty may, in some instances, prevent completion of a meaningful assessment. In such cases, attempts are made to quantify uncertainties to explore particular methodological concerns.
- External data is likely not available for robust validation of models used in the exposure assessment. Related existing studies on environmental concentration, fate and transport of agriculture-related pollutants will therefore be used to assess model validity.

3. Assessment methodology

3.1 Scenarios

Geographical and temporal scope

The geographical scope included major agricultural areas: Regions of Central Macedonia and Thessaly in Greece, and two regions of England (East Anglia and the northwest). Available data on land use for baseline year (2000 England, 2004 Greece) were employed for enhancing scenario maps. The temporal scope of the scenarios was 2020 and 2050, for which annual average exposure and health impact were computed.

The study population comprises the entire population within these study regions, with specific sub-populations (i.e. farmers, vulnerable groups) identified as appropriate for specific health outcomes. Population data for England derived from census 2001, available as 5 year age/sex stratified dataset at Ward level (i.e. LAU2). Change rates derived from the Office of National Statistics (ONS 2008) official sub-national projections, also age/sex stratified, were applied to compute an equivalent Ward dataset of future populations in the year 2031 (Annex 4, Table 1).

Scenario Development

For this assessment scenarios were required, describing how land use might change under different policy assumptions in the two case study areas. A prognostic assessment was carried out, aimed at answering 'what if' questions, about future impacts.

Various scenarios have been developed in Europe, each focusing on different driving forces (e.g. climate change, land use policy). The Model to Assess the Global Environment (IMAGE3), for example, is an ecological-environmental model that simulates the environmental consequences of human activities worldwide, taking into account the IPCC scenarios. For the agricultural sector of study, the model estimates changes in land use and crop area (e.g. cereals, maize, oil crops and rice) at a 50x50km resolution, up to 2100 at 5 year time slices. A clear advantage of the IMAGE model is the rather comprehensive crop list, which is useful for carrying out a detailed integrated assessment. Nevertheless, its relatively coarse resolution meant that it was not ideal for this assessment.

In Greece, therefore, the assessment built on the scenarios developed as part of the ATEAM (Advanced Terrestrial Ecosystem Analysis and Modelling) project (Schröter et al. 2004). The primary object of this was to assess the vulnerability (to global climate change) of humans relying on ecosystem services. Land use change projections in Europe are based on socio-economic and climatic scenarios, and are represented as maps at 10’x10’ resolution (ca.16x16 km) for the decade 1990-2000 (average data) (baseline) and for the years 2020 and 2050.

To provide a basis for the assessment of health impacts of agricultural land use change in Greece, scenarios had to be developed describing the likely distribution of cropping and livestock systems across the country under different possible 'futures'. Two scenarios were defined for this purpose: a 'business-as-usual' scenario and a 'climate mitigation' scenario. Each of these required some further development of the baseline information provided by the ATEAM model.

(i) Baseline 16x16km dataset from National Statistical Service of Greece (ESYE)

Arable land data at LAU-2 level (General Secretariat of the National Statistical Service of Greece – ESYE) were aggregated to 16x16km and compared to the arable land estimates from the ATEAM model. Differences between the two were normalised with respect to the ESYE data. In addition, crop data (including cereals, cotton, maize and sugar beet) from ESYE LAU-2 level were aggregated to 16x16km, in order to generate a crop distribution for each grid cell. A subset of livestock data (including cows, pigs, sheep and goats) was regressed against grassland area, available from the ATEAM. The remaining animals (including pigs and poultry) are estimated from the GAINS model and are included in the baseline data.

(ii) Business-as-usual scenario

The Business-as-usual (BAU) scenario was derived by projecting current land use estimates forward, under the IPCC A1 Scenario for 2020 and 2050. Changes in arable land in years 2020 and 2050 (from ATEAM) are utilised to project the baseline crop distributions into the future. In addition, three energy crops are included in the future data-set: sunflowers (33.3%), sorghum (33.3%) and cardoon (33.3%). Animal numbers are projected to 2020 and 2050 proportional to the estimated changes in grassland area, as indicated by the ATEAM model.

(iii) Mitigation scenario

The mitigation scenario was derived by taking account of climate change mitigation policies and future CAP developments, within the context of the IPCC B1 scenario. The baseline (2004) crop distribution is modified by reducing the proportion of (water consuming) cotton by 40% in 2020 and by 75% in 2050. The land released as a result is allocated to cereals (25% in 2020, 45% in 2050) and maize (15% in 2020, 30% in 2050). Energy crop and animal data are included in the analysis in a similar manner as in the IPCC A1 scenario (see Annexes 5.1, 5.2 and 5.3).

In England, scenarios were taken from the Regional Impact Simulator (RegIS), developed as part of the UK Climate Impacts Programme (UKCIP) to simulate the effects of climate and socio-economic change in East Anglia and northwest England (Holman et al., 2007). Impacts on rural land use and cropping are available under low and high emissions scenarios, for years 2020 and 2050, at a spatial resolution of 5x5km (Annex 4.2). This assessment only made use of the ‘so-called’ 2020 projections, as agricultural practice and pesticides were assumed to differ too much from the base year by 2050. Further rationale for this decision is that the RegIS 2020 scenario, in fact representative of the time period 2011 – 2040, is comparable to reliable population estimates available up to year 2031 (ONS 2008).

In Greece ESYE population data (census 2001) per LAU-2, their projections (country level) and the CORINE land cover map are used in an algorithm, with the objective to generate the 4x4km population numbers (total and rural), seen in Annex 5.8.

In both areas, assessments were done for a baseline year (2004) and for two future years (2020 and/or 2050). Business-as-usual scenarios were run to estimate potential impacts under current land use conditions (assumes that agricultural practices (e.g. application rates), productivity (crop and livestock densities), and emission rates remain unchanged), and change scenarios run using the land use projections provided from these sources. Differences between the two gave an estimate of the impacts attributable to the projected land use changes.

<u>Pesticides usage data</u>

In England, a national database of pesticide usage is maintained, based on sample surveys of farms (the FERA Pesticide Usage Survey). Data are collated at the regional level, though provided for use in this assessment at county (NUTS 3) level in the form of the total area and amount applied, by crop and pesticide type. Pesticide types are categorised on the basis both of functional and chemical group and active substance (ca. 350). Because of the coarse scale of these data, modelling was done to disaggregate the statistics to a more local (ward = LAU2) level, using GIS techniques (see Annex 4.1, Spatial disaggregation).

In the study regions in Greece (Thessaly and Central Macedonia), there is no legal requirement or systematic procedure for reporting of pesticide use. Purpose-designed data were therefore collected for the assessment. For the Region of C. Macedonia, pesticide sales data for the years 2000 and 2004 were obtained from relevant sale points. The data were checked and adjusted against related data obtained from the Directorate of Agricultural Development and the Directorate of Production and Development of Tobacco and Cotton of Thessaloniki (local government authorities), and advice was also taken from expert agronomists to verify and interpret the information. A similar approach was taken for the Region of Thessaly, where pesticide sales data for the Prefecture of Larisa were collected from local sale points; these were checked and enhanced with data from the Directorate of Agricultural Development of Larisa for the reference year 2000. Data comprise the amount (kg) of each active substance (AS) that was applied to the major crops, the application rate (kg/km^2 or l/km^2) and the number of applications. Data for approximately 60 active substances were collected for Thessaly and 50 for C. Macedonia. For the purpose of the assessment, the active substances were classified on the basis of their action (herbicides, fungicides, insecticides and plant growth regulators), chemical class (e.g. carbamates, organophosphorus compounds etc.) and carcinogenicity (e.g. unlikely, likely, possible etc.). A stochastic disaggregation method was used to determine probabilistic estimates of pesticide quantity, as seen in Annex 5.4.

In both cases, estimation of future pesticide usage involved the application of models. These had to take account not only of how land use might change under the different scenarios, but also changes in regulation of pesticides, and their effects on pesticide practice. At present, two general categories of active substances can be recognised - those approved for use and those under evaluation (pending approval), as discussed in Karabelas et al. (2009). For the purpose of the Greek case study, a list was developed for the major crops (for 2020 and 2050), identifying the active substances likely still to be used under these restrictions, based on the list of marketed pesticides in the Prefecture of Thessaloniki for the year 2004. A database of active substances for energy crops has also been developed. The England pesticide database was also reduced to ca. 125 active substances, reflecting those likely to remain in use in the future.

<u>Animal husbandry data</u>

In England, annual data on farming activities are reported as part of an annual census of agriculture (the so-called 'June Returns'). The data include information on a wide range of agricultural activities, including details of employment, crop areas and livestock numbers. Livestock data are defined to a high level of specification (e.g. breed, function and age of animals). Data are collated and made available at agricultural ward-level, and spatial aggregations thereof (e.g. county). Ward-level data are in some cases suppressed, however, to maintain confidentiality. Where data suppression created gaps in the data required for the case study, therefore, livestock numbers were estimated by disaggregating data from the next available level by area-weighting.

In Greece, data on livestock numbers (including dairy cows, beef cattle, fattening pigs, sows, laying hens and other poultry, horses, sheep and goats) are provided by the National Statistical Service of Greece (ESYE) at NUTS 3 level. These were disaggregated to LAU-2 level by area-weighting.

As with pesticides, future livestock numbers had to be modelled to provide estimates for the two policy scenarios in the years 2020 and 2050. Since ruminant animals (dairy cows, beef cattle, horses, sheep and goats) spend time on pastures grazing, it was assumed that numbers are strongly dependent on pasture area. Modelling was, therefore, done on the assumption that grazing intensities (per unit area of pasture) remained the same, but the spatial distribution changed with land use. In Greece, granivore (pigs and poultry) numbers also had to be modelled. These are more-or-less independent of cropping systems, so trends had to be estimated by alternative methods; in this case, using the GAINS Model (Greenhouse Gas and Air Pollution Interactions and Synergies Model) (IIASA: GAINS model, 2010).

Specifics for each study area are provided below.

Greece

For the Greece case study, databases are available for the time slices 2020 and 2050 for both business as usual and mitigation scenarios. For each scenario, the 4x4km database compromised:

- Land use data: utilized agricultural area, arable and pasture land
- Area for edible crops in 3 categories: cereals; maize; cotton
- Area for energy crop in 4 categories: sunflower; sorghum; cardoon; sugarbeets
- 5 types of livestock: cows, goats, sheep, pigs and poultry
- Population data stratified by age and profession

Figure 2 depicts the spatial distribution of arable land and cereals for the Baseline year 2000 in Thessaly and C. Macedonia. Data for arable land, main crops and energy crops for all the scenarios are presented in Table 1.

Table 1. Area for arable land, main crops and energy crops.

Year	Arable land	Cereals	Cotton	Maize	Sugar beets	Sorghum	Cardoon	Sunflower
Baseline 2000	9547	4986	2164	938	192	-	-	-
A1_2020	7096	3546	1743	699	151	194	194	194
B1_2020	8025	4563	1146	1075	167	368	368	368
A1_2050	5610	2727	1437	548	120	110	110	110
B1_2050	7448	4377	711	1192	155	138	138	138

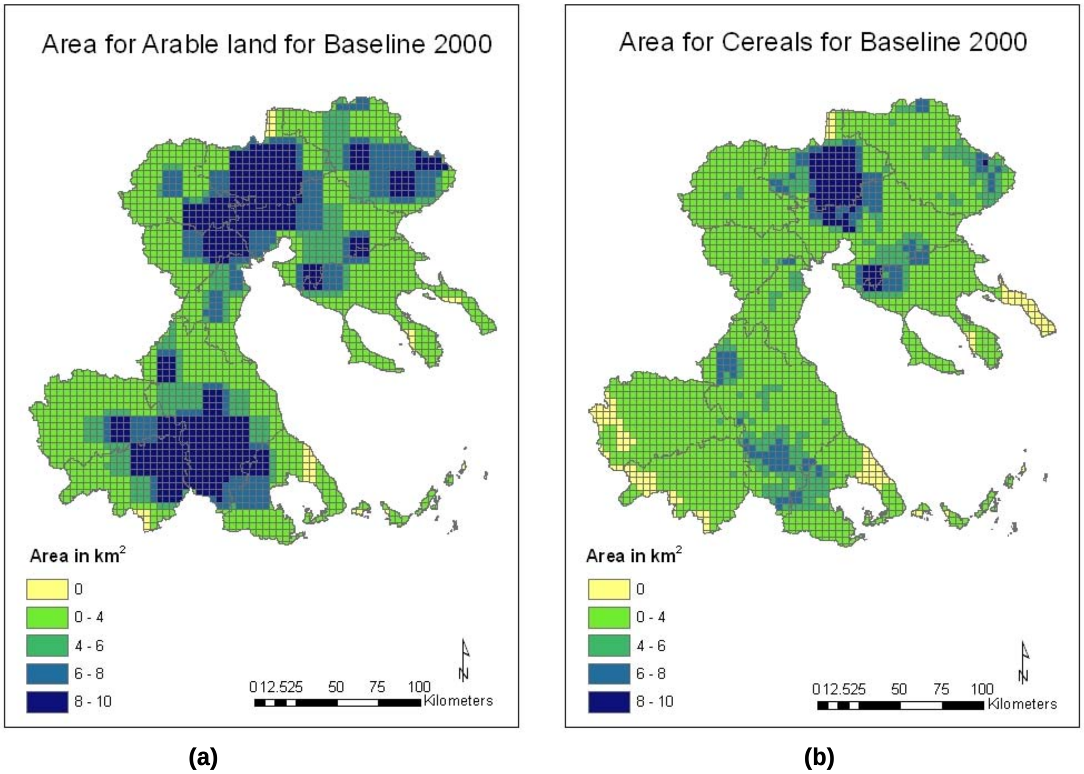


Figure 2. a) Area for arable land and b) area for cereals for the baseline year 2000, in Thessaly and C. Macedonia

England

As illustrated in Figure 3, a 5x5km land use database was created for scenarios including: 2000 JAR baseline, 2020 business as usual (BAU) (i.e. B2020), and two 2020 land use change scenarios with low (L2020) or high (H2020) emissions, respectively. For each scenario, the final 5x5km database comprised:

- Area of crop in 11 categories: cereals; set aside; peas and beans; beets; potato; grassland; soft fruit; oilseed; top fruit; lettuce and salad; and fodder.
- Amount of pesticide active substance for each of the 11 crop categories.
- 4 types of livestock: goats, cows, pigs and sheep.

Within the 5x5km grid, emissions were attributed to a finer grid (i.e. 250x250m) on the basis of Corine land cover prior to concentration modelling.

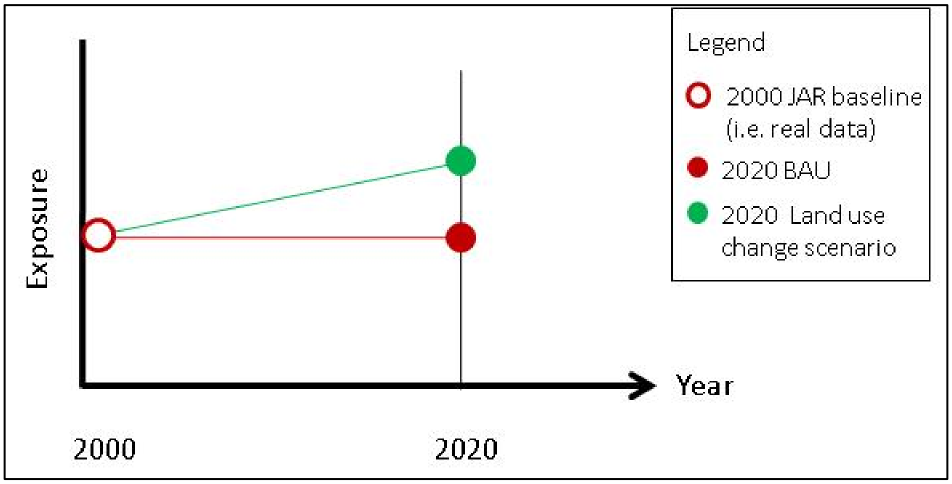


Figure 3. Land use scenarios for England

Further details are provided in Annex 4.1 on scenario development. Also included in the annex are example modelled pesticide usage maps for East Anglia at the 2000 baseline.

3.2 Exposure Assessment

3.2.1 Sources

As described in Section 3.1, the main agricultural sources, including cropping, pesticide usage and animal husbandry were incorporated in scenario development to produce a spatial database with which further emission and concentration modelling could be facilitated.

3.2.2 Emission Factors

Details on the emission factors (including actual EFs, where available) are included in the annex 2. In addition to those pollutants listed below, pollen was also evaluated. For England case study, pollen results were not reported because the EFs were considered too specific to conditions in southern Europe.

Pesticides

Emission factors for pesticides were derived from information available for the Netherlands (Linden van der et al., 2008). In this report, the emission factor for each pesticide was calculated as the ratio between the total emission of the active substance to the atmosphere and the amount used in the Netherlands (private communication J. Duyzer, TNO).

Not all active substances in the case study areas were represented within the Dutch report. Data gaps for emission factors were filled by interpolating on the basis of vapour pressure of other similar active ingredients.

Particulates

Agriculture PM emissions originate from animal husbandry with poultry and pig production being the major polluters. Main sources are animal feed and bedding materials like straw, but also animal plumage and skin. PM emission from arable agriculture mainly stem from harvest operations. Additionally, depending on soil moisture content, soil cultivation can also contribute to PM emissions.

Emission factors for atmospheric particulates have been compiled from a range of sources, including IIASA's GAINS online database. PM emission factors for Greece and Great Britain are available in Tables 1 to 4, Annex 2.

Endotoxin emission factors

Endotoxin emissions can be estimated by multiplying the endotoxin emission factors by the number of animals. For these estimates, housing periods and lengths of production cycles as well as periods when the animal house is empty for cleaning can be taken into account according to local conditions.

Available emission factors for inhalable and respirable endotoxins are summarised in Table 5 in Annex 2. The emission factors are expressed per Livestock Unit or per animal.

Pollen emission factors

Pollen is a fine to coarse powder consisting of distinct grains. Pollen grains are produced by the male parts of the flowers and are the reproductive bodies of plants and, for the purpose of fertilization, they are transported by wind to female flowers. Most pollen species are associated with some level of allergenicity, but some are particularly notorious for symptoms of hay fever.

A large amount of pollen, originating from various plants and orchards, is produced each year, usually during spring and summer. Information on release rates is sparse, and actual rates of pollen formation and release vary greatly depending on local conditions (vegetation structure and composition, soil, meteorology).

The methodology proposed here provides emission factors for agricultural crops. Pollen emission factor (EF) for a specific crop can be estimated using the following simple equation:

$$EF = aYN \tag{1}$$

Here:

EF: emission factor (pollen grains/km^2)

a : percentage (%) of pollen production that is shed

Y: pollen yield (pollen grains/plant)

N: number of plants per km^2

Example of estimation of emission factor for maize pollen is available in Annex 2.

3.2.3. Emission Modelling

Agricultural releases needed to be estimated for each pollutant as a basis for exposure estimation. Endotoxins derive mainly from livestock rearing while the others are also produced by arable farming.

Estimates of emissions were modelled for the baseline and scenarios for a regular grid covering each study area. Grids were constructed for all the relevant source activities, including area of specific crops, number of animals (i.e. head or livestock unit), and amount of pesticide active ingredients per grid cell.

For each grid cell, the emissions are calculated as the product of the agricultural activity and the source-specific emission factor, using the basic formula:

$$R = S * F \tag{2}$$

where, R is the release rate (volume/time), S is the level of source activity (/time) and F is the emission factor (volume/unit of activity).

Endotoxin

Annual emission grids for respirable and inhalable endotoxin were computed on the basis of specific livestock units and endotoxin emission factors.

In this case:

•S is the livestock count in grid cell (e.g. head/ cell)

•F is the EF for specific livestock units (e.g. µg/head)

Particulates

Annual particulate emission grids were computed as the sum of emissions from individual crop and livestock sources for which PM emission factors were compiled.

For crops:

•S is the area of specific crop in grid cell (e.g. ha/ cell)

•F is the EF for specific crops (e.g. kg/ha)

For livestock:

•S is the livestock count in grid cell (e.g. head/ cell)

•F is the EF for specific livestock units (e.g. kg/head)

Pesticides

Annual emission grids were computed for each active substance (AS) using pesticide eission factors taken from a Dutch study.

Here:

•S is amount of individual pesticide active substance in grid cell (e.g. kg/ cell)

•F is the EF for individual ASs (e.g. g /g air)

Pollen

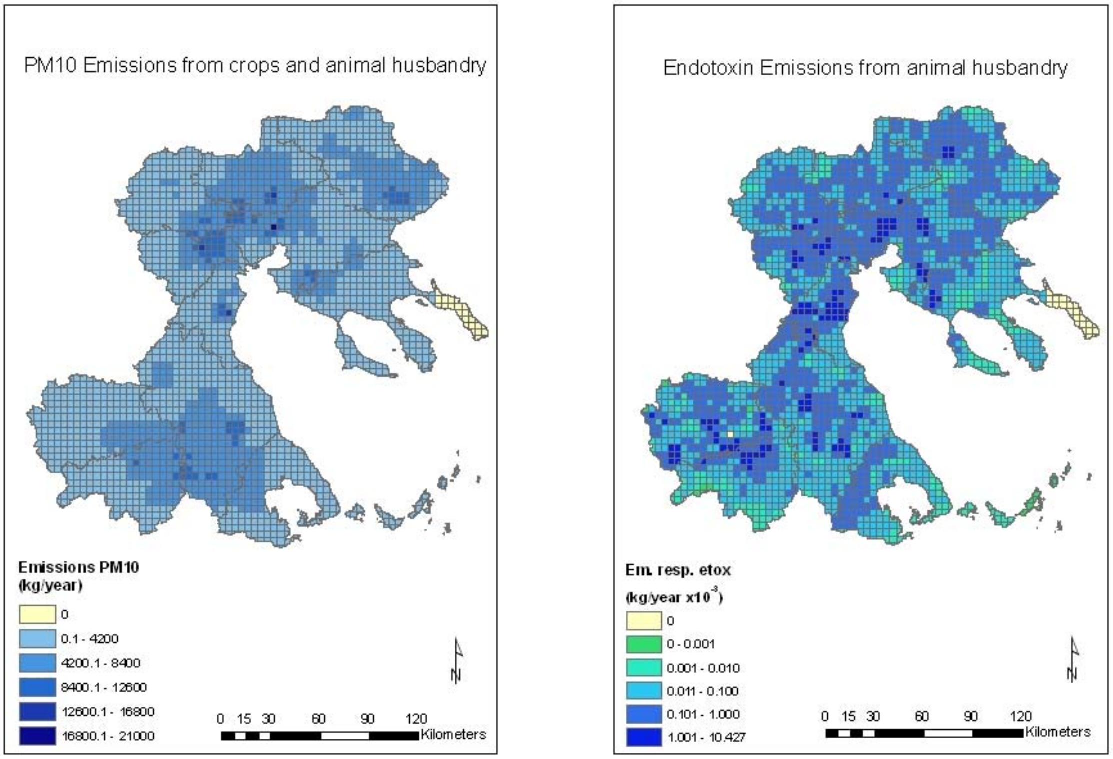
Pollen emission grids were computed as the sum of emissions from individual crops using modelled pollen emission factors. The pollen EFs are representative of the duration for typical pollen shedding (e.g one month for maize).

Here:

• S is the area of specific crop in grid cell (e.g. km^2/ cell)

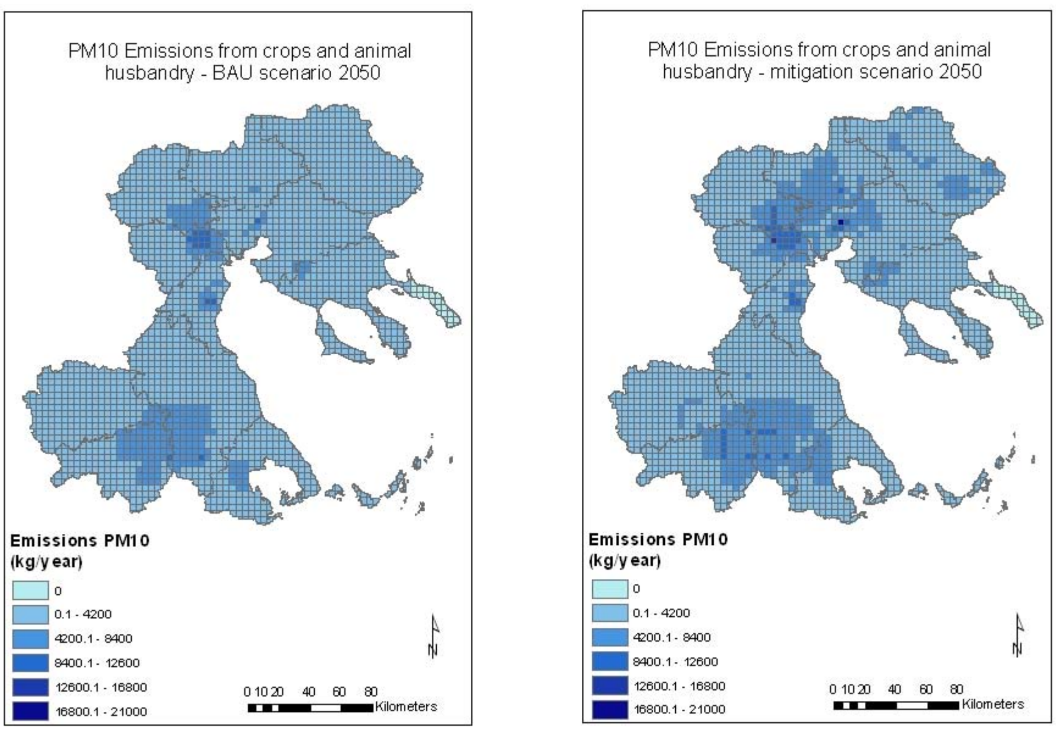
• F is the EF for specific crops (e.g. grains/km^2/year)

Figure 4 illustrates PM10 Emissions (in kg/year) from crops and animal husbandry and Endotoxin Emissions (in kg/year x 10^{-3}) from animal husbandry, respectively for the baseline year 2000 in Thessaly and C. Macedonia. PM10 Emissions (in kg/year) from crops and animal husbandry for BAU and mitigation scenarios for year 2050, respectively in Thessaly and C. Macedonia are presented in Figure 5.



(a) **(b)**

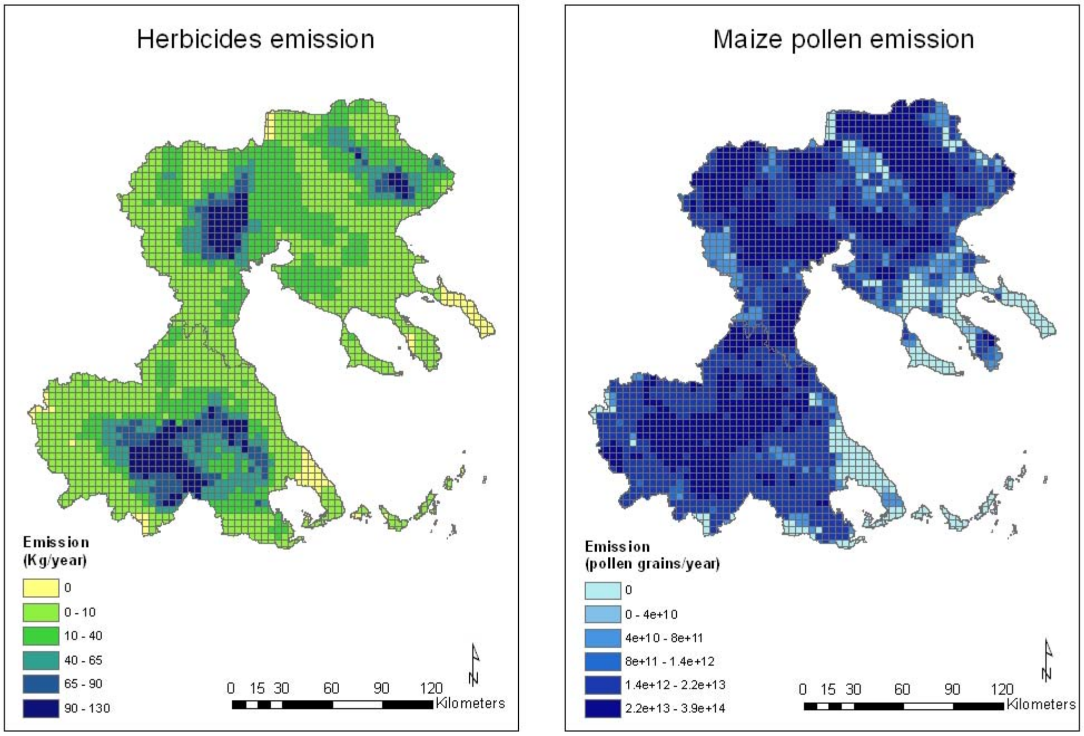
Figure 4. a) PM10 Emissions (in kg/year) from crops and animal husbandry b) Endotoxin Emissions (in kg/year x 10^{-3}) from animal husbandry for the baseline year 2000 in Thessaly and C. Macedonia.



(a) **(b)**

Figure 5. PM10 Emissions (in kg/year) from crops and animal husbandry for a) BAU and b) mitigation scenarios for year 2050 in Thessaly and C. Macedonia.

Figure 6 illustrates herbicides emission (in kg/year) and pollen emission (in pollen grains/year) from maize in Thessaly and C. Macedonia for the baseline year 2000.



(a) **(b)**

Figure 6. a) Herbicides emission (in kg/year) b) Pollen emission (in pollen grains/year) from maize for the baseline year 2000 in Thessaly and C. Macedonia.

3.2.4. Concentration Modelling

While sophisticated dispersion or propagation models are available for air pollution, these cannot always be applied in integrated assessments for a number of reasons. The necessary input may not be available; the computer processing requirements needed to handle large data sets may be excessive; and the models themselves may not be well adapted to, or validated for, the specific pollutants and settings of interest. In these situations a simpler and more generic approach to modelling is required. Here, therefore, the GIS-based focal sum method developed by Imperial College (Vienneau 2009) was used to model atmospheric concentrations of the agricultural pollutants of interest.

Box volume model

For Greece, yearly average meteorological data (wind speed and direction, temperature, relative humidity) from 6 meteorological stations (see Annex 5.5) were used as input to CALMET meteorological model (CALPUFF modeling system, 2010) to estimate the mixing layer height, H, and the magnitude of wind velocity, U, at 4 x 4 km spatial resolution, in the geographic region of interest (Thessaly and Central Macedonia, Greece). The box volume model is implemented to estimate pesticides concentration at 4 x 4 km “cells”, for the entire area of study, using the simple formula:

$$C = \frac{E}{uHL} \quad (3)$$

Here

C = pollutant concentration in air (g/m^3)

E = emission of pollutant (g/sec)

U = wind velocity (m/s)

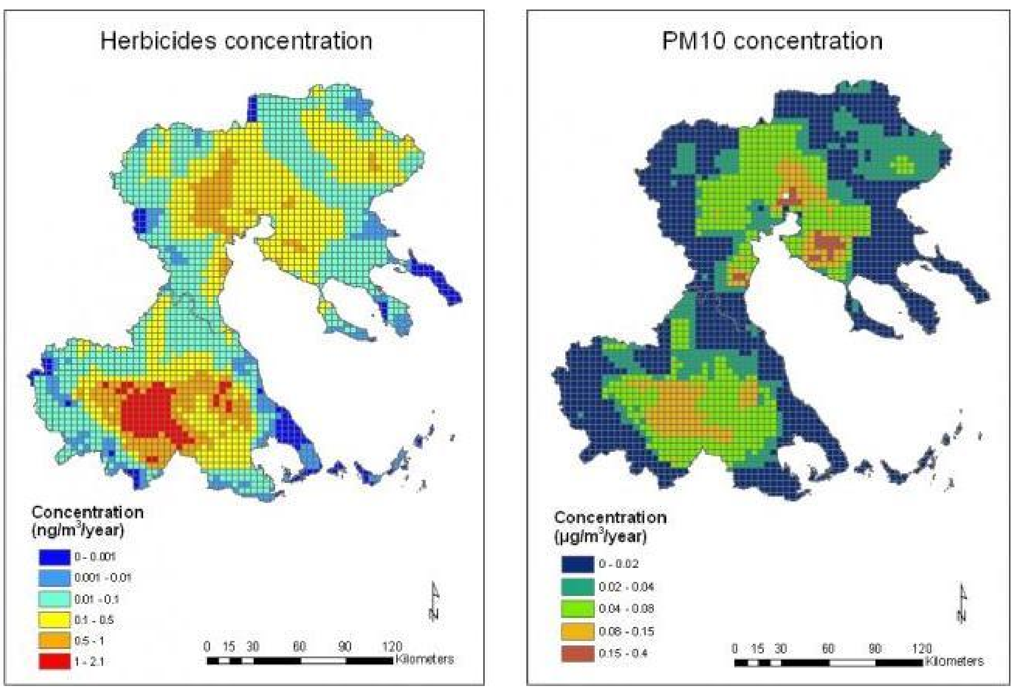
H = mixing layer height (m)

L = lateral “box” dimension (m)

This simple method provides first reasonable estimates, useful for comparison with the following more elaborate concentration calculations (see Focalsum function).

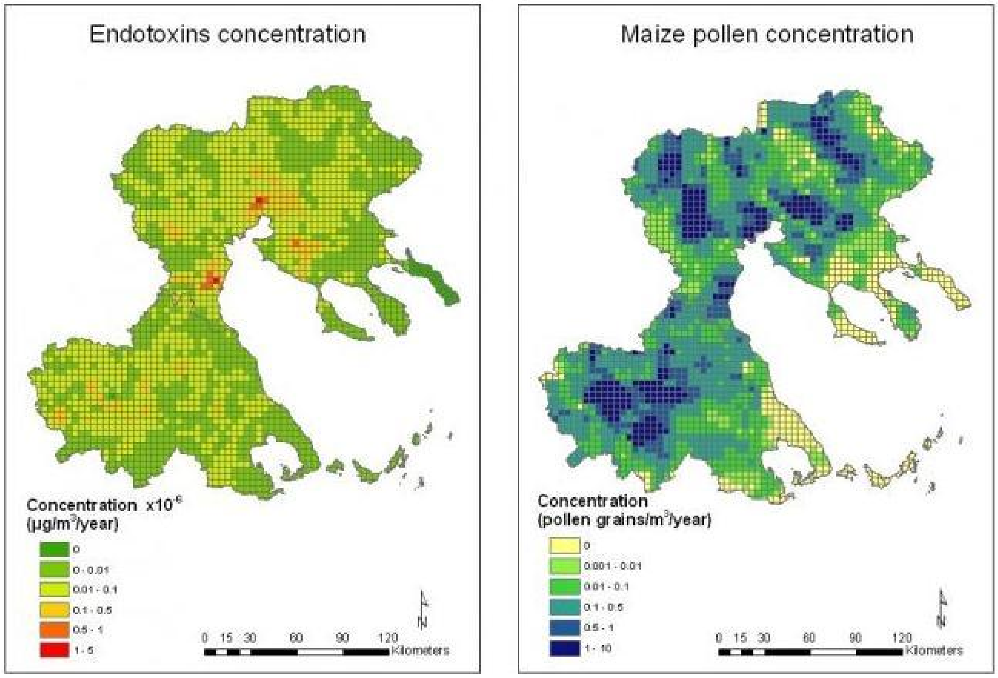
Concentration of other pollutants (i.e. PM10, PM2.5, endotoxines and pollen) were also estimated using this box volume model.

Modelled concentrations of herbicides, PM10, endotoxins and pollen (from maize) for the baseline year 2000 in Thessaly and C. Macedonia are illustrated in Figures 7 and 8.



(a) **(b)**

Figure 7. Concentration of a) herbicides (in ng/m³/year) and b) PM10 (in µg/m³/year) for the baseline year 2000, in Thessaly and C. Macedonia



(a) **(b)**

Figure 8. Concentration of endotoxins (in ($\mu g/m^3$/year) x 10^{-6}) and pollen (for maize) (in pollen grains/m^3/year) for the baseline year 2000, in Thessaly and C. Macedonia.

The Focal sum Method

Focal sum modelling requires, first, the specification of a kernel file, defining the search window and distance-based weights that will be applied applied to the gridcells it contains. This can be defined on the basis of prior knowledge or expectation, but specification is likely to be more reliable if it is derived from real-world data or independent modelling of the processes involved. In this case, a proprietary dispersion model was run in each England and Greece using area-specific meteorological data to derive the kernel files. For each study area, the area-specific kernel file was then used in an ArcGIS focalsum function to produce a grid of annual mean pesticide concentrations. This procedure is shown in Figure 9.

For England, a Gaussian dispersion model (ADMS) was used, with hourly wind speed, wind direction, cloud cover and temperature data for one meteorological station in each study area to represent typical weather conditions. Meteorological data from the British Atmospheric Data Centre were for the Wattisham station (#440) in East Anglia and Ringway (#1135) in the Northwest. Hourly data for one calendar year, 2001, were used as inputs into ADMS. The source cell was assigned 1 $\mu g/m^2$/sec emissions of an inert, gaseous pollutant species. Predicted values were obtained for a fine resolution receptor lattice (62.5 x 62.5m), and these then averaged to a 250 x 250m grid to create the weighted kernel file, matching the resolution of the available emission grids. Figures 10a-b illustrate the emission grids, kernel files and resultant concentration grids for East Anglia and the northwest, respectively.

For Greece the CALPUFF dispersion model (CALPUFF dispersion model, 2010) was run in each Region of study (Thessaly, C. Macedonia) using a single area source (4 x 4 km) emitting 1 $\mu g/m^2$/sec (unit emission) of a typical gas. Yearly average meteorological data (wind speed and direction, temperature, relative humidity) from six meteorological stations (three for each region) were used to generate a 4 x 4 km kernel file corresponding to the emissions grid resolution. Example emission data, the kernel files and the estimated concentration for the baseline year 2000 in Thessaly and C.

Macedonia are presented in the Figures 10c-d, below. Detailed parameters and assumptions for CALPUFF model can be found in the Annex 5.5.

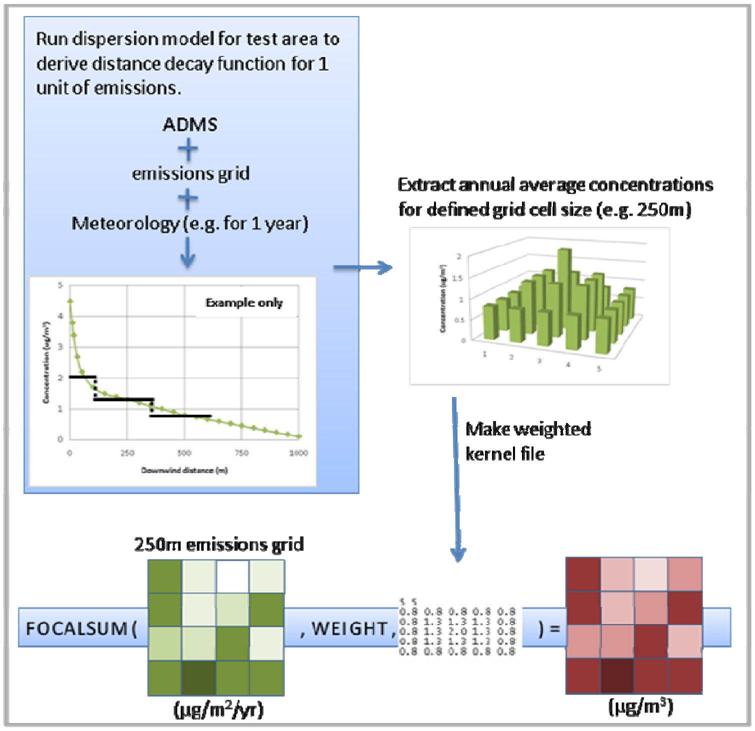


Figure 9. Focal sum procedure using dispersion model output

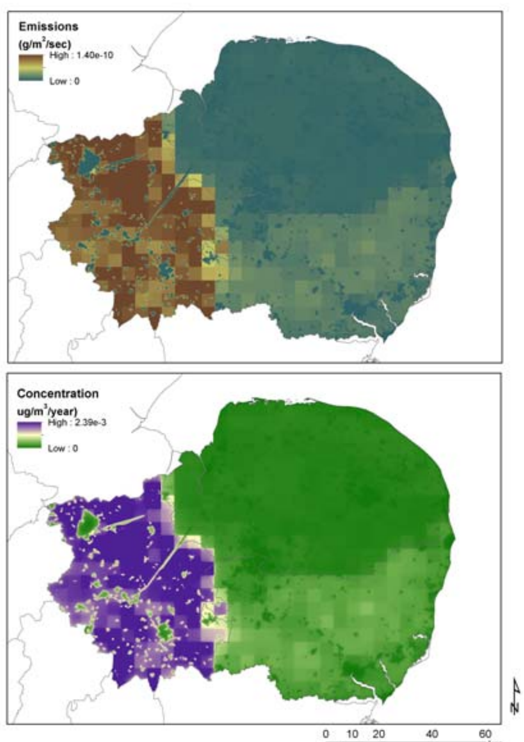


Figure 10a. Modelled concentrations: 250 x 250 m pesticide concentration East Anglia

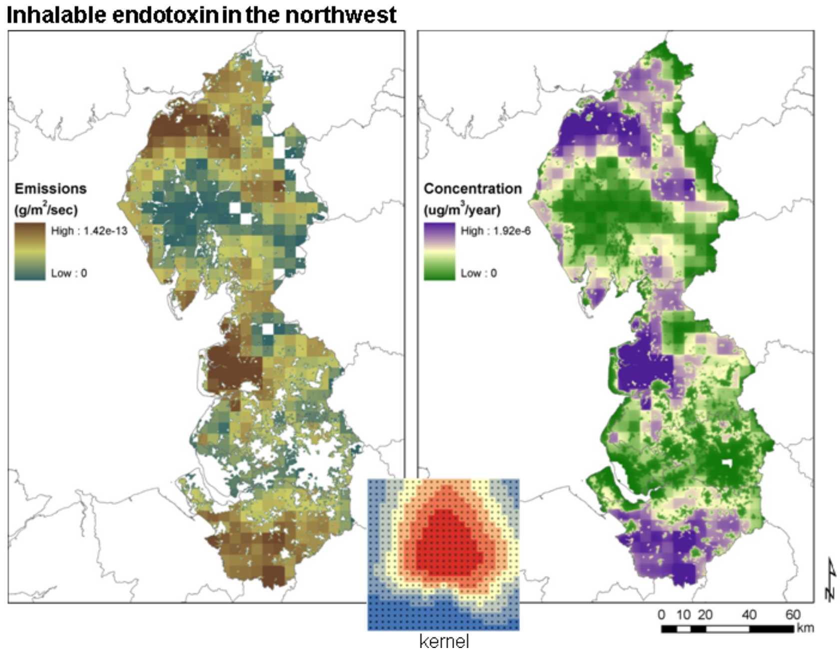


Figure 10b. Modelled concentrations: 250 x 250 m endotoxin concentration northwest England

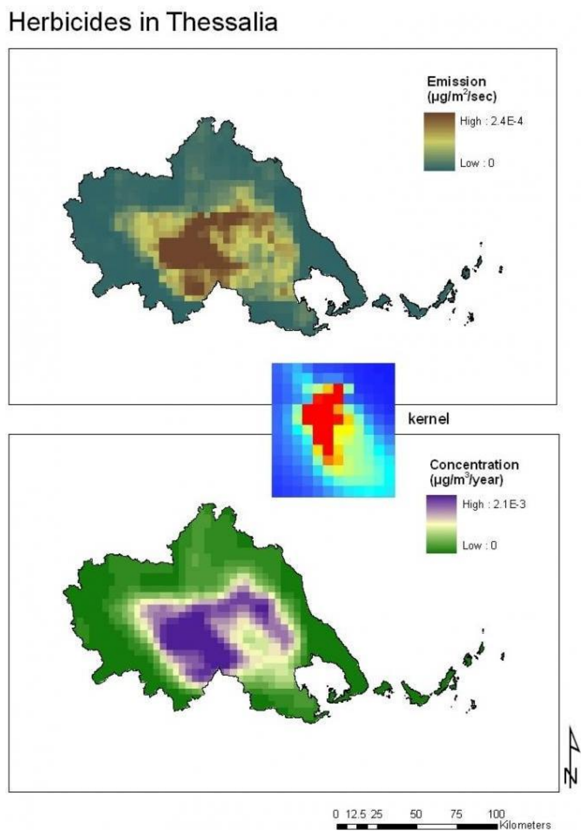


Figure 10c. Modelled herbicides concentration: 4x4 km in Thessaly for the baseline year 2000.

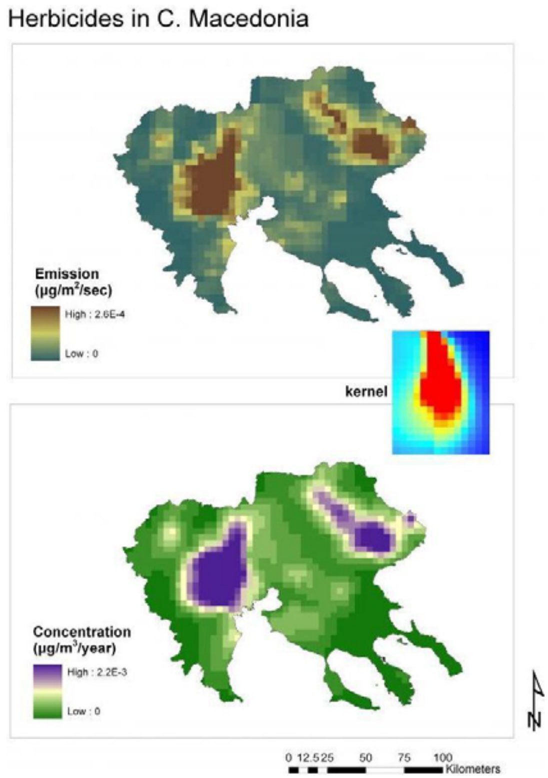


Figure 10d. Modelled herbicides concentration: 4x4 km in C. Macedonia for the baseline year 2000.

3.2.5. Estimating Exposure

Population weighted exposures were computed on the basis of the concentration grids. The UK postcode headcount data were used to estimate exposures at wards and county level, on the basis of the 250x250m grids. (Descriptive statistics for the population weighted exposures for the different scenarios are presented in Annex 4.3).

There was little difference in exposures between the future emission scenarios (L2020 and H2020) reflecting the small underlying change in land use between these two scenarios (Figures in Annex 4.2).

Population weighted exposures for pollutants in both East Anglia and the northwest were typically higher under scenario conditions compared to the BAU. The difference, however, was very marginal. Ward level exposure due to the L2020 and H2020 scenarios – after differencing the BAU – were in the order of ±1 $\mu g/m^3$. This may have implications for the following health impact assessment, because the potential risks attributable to changes in land use under low and high emission scenarios is small.

In Greece, population census data (at LAU-2 level) disaggregated to the 4x4km grid (see annex 5.8), were used to estimate exposure, to the stressor considered. Exposure to pesticides was limited to the famer population only, where as for the particulates the general population was used. Small variation in population numbers between scenarios (see annex 5.8), thus similar changes in exposure, explain the small changes in the health impact.

<u>3.3 Exposure Response Functions</u>

Relatively few exposure response functions (ERFs) were available for the exposures and health outcomes explored in this assessment. Several approaches were therefore used to obtain or derive ERFs, and these are described in the sections below.

3.3.1 Pesticides

For pesticides, evidence from both epidemiological and toxicological studies was used as a basis for deriving exposure-response functions.

Epidemiological evidence

In the absence of an authoritative and comprehensive systematic review providing ERFs for pesticides, the initial intention was to conduct a purpose-designed review for the case study. In the 1st pass of this case study assessment, an extensive literature review was therefore undertaken to identify candidate studies. This showed that existing studies of pesticides were extremely diverse; i.e. many related to specific active substances and to occupational exposures, and many had limitations not allowing a generalisation necessary for application to this study. As a consequence, the validity of a systematic review was considered to be limited. Instead two approaches were taken:

The first was involved devising an approximation procedure which drew on a previous systematic review in Canada (Bassil et al. 2007, Sanborn et al. 2007) to identify relevant health outcomes. Using this as a guide, a subset of studies with relatively general health outcomes and exposure measures was then selected. From these, hypothetical relative risks (RRs) were derived for each health outcome for assumed low, medium and high exposure categories (with the low and high category defined as 10% lower and higher, respectively, than the medium). These were then used to represent indicative exposure-response functions for the broad pesticide groups. The results of this analysis are presented in Annex 4.6.

The second approach involved a risk analysis for the England study areas using the Rapid Inquire Facility (RIF) developed at the Small Area Health Statistics Unit (SAHSU), Imperial College (Beale 2008). The RIF software integrates advanced statistics, spatial analysis and spatial epidemiology to enable assessment of environmental exposure for the purpose of disease mapping or risk analysis. Within the risk analysis, rates and relative risks can be calculated for user-defined areas around point sources or for exposure bands based, for example on concentrations of ambient pollutants such as pesticides.

The purpose of this RIF analysis was thus to derive, where they exist, appropriate relative risks for the England case study areas. The above mentioned systematic review was used to guide selection of the cancer outcomes and sub-populations to investigate in the RIF risk analysis.

The ONS Cancer Registry and Carstairs 2001 index of deprivation for the UK held by SAHSU, combined with the 250x250m exposure maps, were used to explore cancer risk, in East Anglia and the northwest, due to pesticide exposure while adjusting for socio-economic status. Risks were computed relative to the whole of England (i.e. reference area). Health data for years 2001-2005 were used both to obtain sufficient numbers and to account as far as possible for cancer latency. The RIF risk analysis was done for adults aged >25 years as there were insufficient numbers of childhood cases to achieve statistically significant results. To avoid bias, the exposure bands were arbitrarily defined based on percentiles of exposure for the combined East Anglia and Northwest study areas. It was assumed that larger urban populations would reside in the lower range, while wider bands would be needed to get sufficient numbers of cases in the medium and high exposure bands given the skewed distribution of exposures. The following bands were thus defined using Table 1 in Annex 4.3 to categorise the 250x250m exposure grid:

- Low = bottom 5th percentile
- Medium = 5th – 60th percentile
- High = Above 60th percentile

Toxicological evidence

A wide range of studies have been conducted to assess the toxicology of pesticide. By their nature, these focus on individual active substances (ASs), mainly associated with carcinogenic health effects.

Results from these studies were used to develop toxicological exposure-response relationships for specific ASs.

Data were sought on 84 ASs, identified as potentially toxic (carcinogenic or reproductive/ developmental according to US EPA) by Karabelas et al. (2009). In each case, ideally, slope factors for measured relationships between exposure and health outcome were sought. The slope factor is defined as “an upper bound, approximating a 95% confidence limit, on the increased cancer risk from lifetime exposure to an agent” (US EPA Glossary 2008a). This estimate is usually expressed in units of proportion (of a population) affected per mg/kg/day. As an alternative, however, data on 'reference doses' could be used. These represent estimates of the daily oral exposure to the human population (including sensitive subgroups) that is likely to be without an appreciable risk of deleterious effects. Reference doses derive from no-observed or lowest observed adverse effect levels (NOAEL or LOAEL) through the application of relevant uncertainty factors, and typically have an uncertainty spanning perhaps an order of magnitude.

Two main sources of information (both from the US Environmental Protection Agency) were used for these data: the IRIS database (IRIS database, USEPA 2008b) and The Reference Dose Tracking Report (Rowland, 2006). Both databases provide data mainly relating to oral exposure routes, rather than inhalation or dermal routes, and the reference doses, for example, thus refer to Chronic Oral Exposure. For 16 of the target ASs in Greece, linear exposure–response relationships were available (Table 2, Annex 5.6), thus providing ERFS for carcinogenicity; for 42 of the remainder ASs in Greece only reference doses were available, so explicit exposure-response functions could not be derived. Equivalent data for the full GB pesticide database was not sourced, thus only those ASs common with Greece were available for GB.

3.3.2 Particulate matter

A large number of studies have been conducted on health effects of atmospheric particulates, and a number of systematic reviews and large multi-centre studies have been completed. In general, however, the focus has been on particulates derived from combustion sources (especially traffic), and the extent to which these are equally applicable to particles released by agricultural activities (much of which are probably crustal in origin) is uncertain.

In the absence of ERFs for agricultural, however, existing ERFs for traffic-related PM10 and PM2.5 from the IEHIAS toolkit were used for England (e.g. mortality: 1.058 per 10µg/m^3 PM10). Link to ERF database:http://www.integrated-ssessment.eu/resource_centre/exposure_response_functions_dataset

ERFs more appropriate for local conditions were used for Greece. Following an extensive literature review, ERFs were obtained for PM10 and PM2.5 and respiratory and cardiovascular hospital admissions from three main sources (Le Tertre et al. 2002; Medina et al. 2005; Dominici et al. 2005). Although relative risks for PM10 are available for all ages, those for PM2.5 relate specifically to the elderly (>65 years old). The latter provide different relationships for COPD and respiratory tract infection hospital admissions. Particulate exposure-response functions are summarised in Table 3 of Annex 5.6

3.3.3 Endotoxins

Emissions from animal husbandry include a variety of biological, microbial and inorganic particulates. The health effects of exposure to these materials is variable: while exposures to bioaerosols (endotoxin, bacteria, fungi, parasites, pollen etc) can have adverse health effects, several studies have indicated that exposure to endotoxin may have be protective, especially for children (Braun-Fahrlander et al. 2002, Downs et al. 2001, von Ehrenstein et al. 2000, Rennie et al. 2008). A literature review has been carried out in order to retrieve appropriate endotoxin ERFs. According to Braun-Fahrlander et al. 2002, there is a strong inverse relationship between endotoxin exposure and sensitisation to common allergens and atopic diseases in school-age children. Moreover, farmers' children have lower prevalence of hay fever (adjusted odds ratio = 0.52, 95% CI 0.28–0.99), asthma (0.65, 0.39–1.09), and wheeze (0.55, 0.36–0.86) (von Ehrenstein et al. 2000). A significant nonlinear relationship between endotoxin exposure and sensitization has been also observed in adult farmers, where risk of sensitization strongly decreased with increasing exposure (Portengen et al. 2005). Tables 1 – 2 in Annex 3 summarise the endotoxin exposure response relationships.

3.4 Impact Indicators

Health impact indicators are used in order to relate cause (concentrations) to effects (human health effects) from various pollutants emitted from specific sources. The health impact indicators developed for the agriculture case study were: Risk (R), and Attributable burden of disease (AB). During scoping disability-adjusted life years (DALYs) were considered, however, DALYs were not computed due to the small risks detected or lack of good data on duration and severity.

Risk is an expression of the likelihood (statistical probability) that harm will occur when a receptor (e.g. human or a part of an ecosystem) is exposed to a hazard. An example of a risk indicator is the likelihood that a certain population will have a certain level of cancer incidence after being exposed to a certain pollutant (e.g. pesticides). The burden of disease provides a comprehensive assessment of the health status of people and gives policy makers the information need to make decisions about health.

Risk from pesticides

Active Substances (AS) based on toxicological data is given in the following equation:

$$AB = R \times P \qquad (4)$$

where:

- AB is the number of cases attributable to agricultural contaminants
- P is the exposed population and
- R is the risk from pesticides to human health that is calculated using equation 4a:

$$R = IR \times (ERF_{ASi}) \qquad (4a)$$

where:

- ERF_{ASi} is the Exposure Response Function for each AS i (in $(mg/kg/day)^{-1}$), and
- IR is a yearly averaged intake rate (in µg/kg/day), defined in equation 4b

$$IR = (C_i \times Q_{inh} \times t_{exp}) \; / \; BW \qquad (4b)$$

where:

- C_i is the average pesticide concentration in the exposure medium (in µg AS/m^3) over the exposure period (t_{exp}),
- Q_{inh} is the daily average inhalation rate (in m^3 air/d) for humans (assumed 25 m^3/d) and
- BW is the average body weight (assumed 75 kg)
- T_{exp} is a full year

Attributable Burden

AB is the number of cases attributable to agricultural contaminants under land use change scenarios, and is computed using the following basic formula (equation 5).

$$AB = \frac{(RR-1)}{RR} \times 1 \times P_e \qquad (5)$$

where:

- RR is the relative risk
- I is the background rate of disease (incidence or prevalence)
- P_e is the exposed population

Baseline prevalence and incidence rates for health outcome and mortality rates were obtained from the Office of National Statistics in the UK (see Annex 4.6).

Where exposure groups were defined (e.g. non-exposed vs exposed; or low, medium and high exposure tertiles for pesticides) equation 5 was computed once for each exposure category, then AB summed.

For particulates, a non-threshold linear relation was assumed between air pollution and all health outcomes, changing slightly the AB formula (equation 5) to that shown in equation 6. Here, for example it is assumed a RR mortality: 1.06 per 10µg/m^{3}agricultural-related PM_{10}. The entire population comprises P_e.

$$AB = \frac{(RR-1)}{RR} \times 1 \times P_e = \frac{\exp(C \times \beta) - 1}{\exp(C \times \beta)} \times 1 \times P_e \quad (6)$$

where:

- C is the concentration (e.g. µg/m^3 agricultural-related PM10)
- ß is defined in Equation 6a (e.g. ß per 1 µg/m^3= 0.0058)

$$\beta = \left(\frac{ln(RR)}{10} \right) \quad (6a)$$

AB from particulate matter can also be calculated from the following equation, as has been done for Greece:

$$AB = \frac{\exp(\beta \cdot (C_i - C_0)) - 1}{\exp(\beta \cdot (C_i - C_0))} \times I \times P_t \quad (7)$$

where:

- I is the background rate of disease (incidence rate),
- P_t is the total population
- C_0 is the background concentration (in µg/m^3) (10 µg/m^3 for PM10),
- C_i is the current concentration (in µg/m^3) and ß is a parameter that is defined in Equation 7a

$$\beta = \frac{RR - 1}{C_0} \quad (7a)$$

where:

- RR is the relative risk - i.e. the ratio of the probability of the event occurring in the exposed group versus a non-exposed group.

The incidence rates used in the Greece case study are calculated by estimating the age-specific rates and then these rates are applied to reference population (the standard world population) (WHO methodology) (Table 4, Annex 5.7).

3.5 Uncertainty Analysis

Recognition of the uncertainties in an integrated assessment is an important part of the process, even if they can't be quantified. The following describes the qualitative uncertainty approach in which uncertainty evaluation is organized in two steps:

Step 1. Identification of all uncertainty sources, grouped according to the following classification:

Scenario uncertainty refers to the description of the context (scenario setting) as a prerequisite for either modelling or measuring experimental data. It includes descriptive errors, aggregation errors, errors in selection of the assessment tier and errors due to incomplete analysis. It often includes the purpose of the environmental health impact assessment and consistency between the scenario definition and the scope and purpose of the assessment.

Model uncertainty reflects the limited ability of mathematical models to represent the real world accurately and may also reflect lack of sufficient knowledge. It is principally associated to model boundaries, extrapolation limits, modelling errors and correlation (dependency) errors. It also includes errors due to the implementation of tools and software.

Parameter uncertainty refers to data values that are not known with precision due to measurement error or limited observations (sampling error). Sometimes it consists of variability as an inherent property of the heterogeneity or diversity in the parameter, such as parameters expressed as a function of the entire population. Usually, variability cannot be reducible through further investigation. It is also possible for the uncertainty and variability of parameters to be combined.

Step 2. Qualitative/semi-quantitative characterization of uncertainty sources in three dimensions:

a) **direction** of the influence of the uncertainty source on the results

O/U: Over/Under (denoting the direction of the influence of the specific uncertainty source on the output of the estimation)

b) **level** of uncertainty

L/M/H: Low/Medium/High (denoting the level of the influence of the specific uncertainty source to the output of the estimation)

c) **appraisal** of knowledge base of the uncertainty source

L/M/H: Low/Medium/High (denoting the scientific consistency of the knowledge base underlying the assessment)

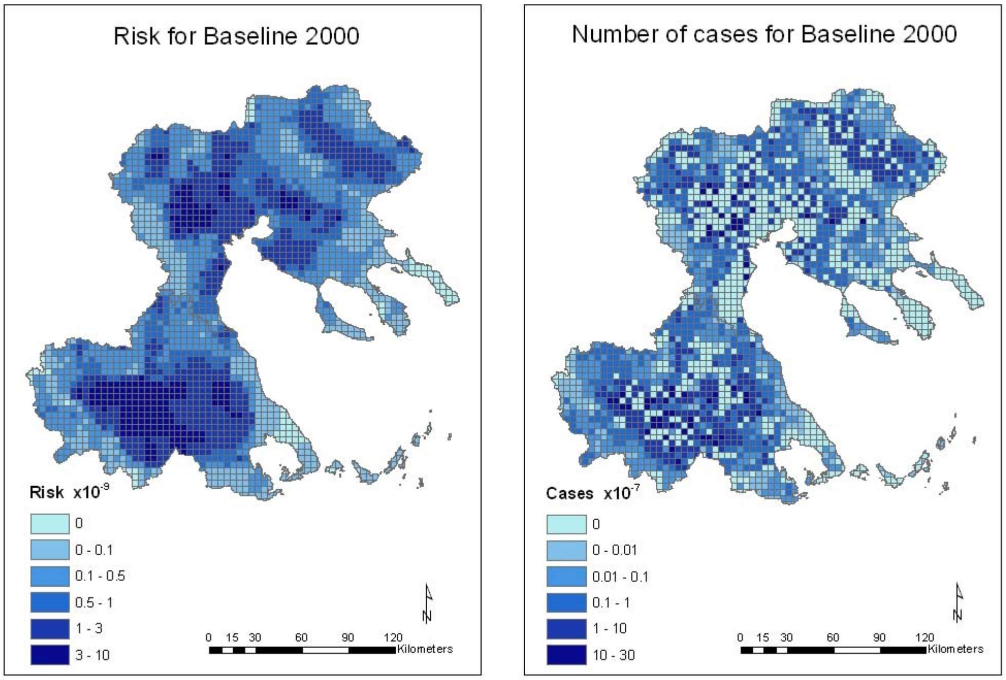
4. Results

4.1 Pesticides

4.1.1 Toxicological Risk Analysis

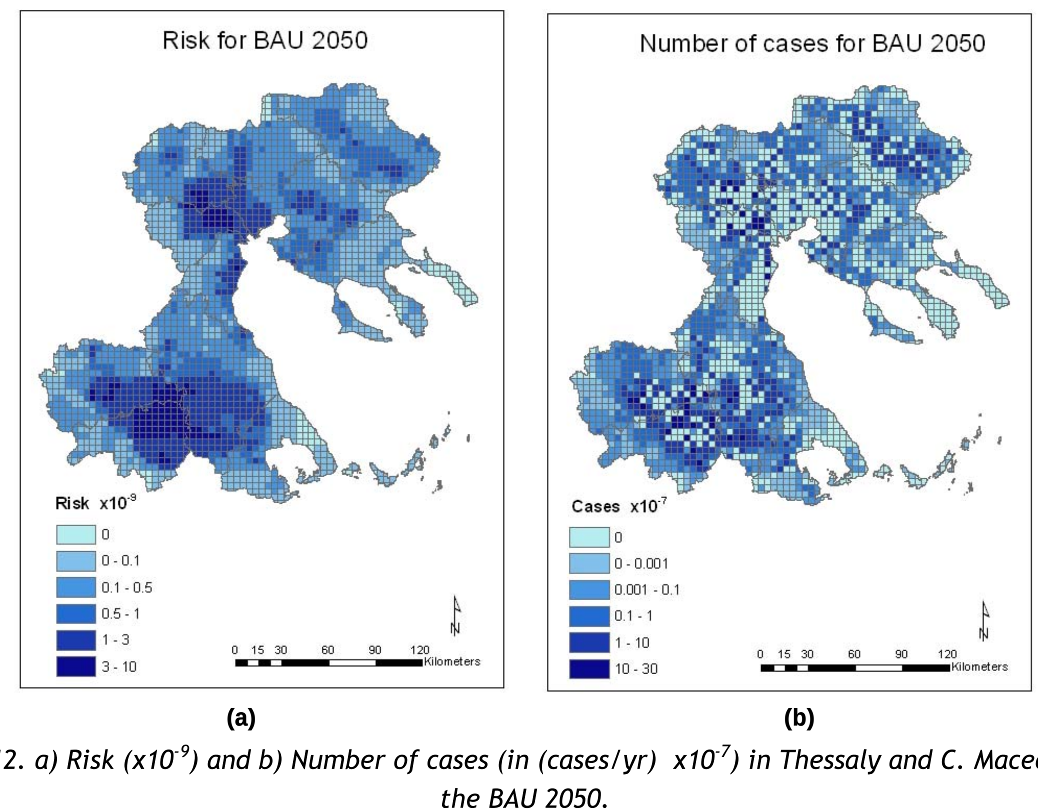
Greece

For two areas in Greece (Thessaly and C. Macedonia), risk and number of cases per cell (4x4km) due to exposure to pesticides are calculated, as described in Section 3.3.4 (Equations 4, 4a, 4b). It should be noted that only farmers who work in those areas as considered as the exposed population (Equation 4). Figures 11-13 depict the spatial distribution at 4x4 cell of risk and number of cases due to exposure to pesticides for the baseline year 2000, for BAU 2050 and MIT 2050, in Thessaly and C. Macedonia.



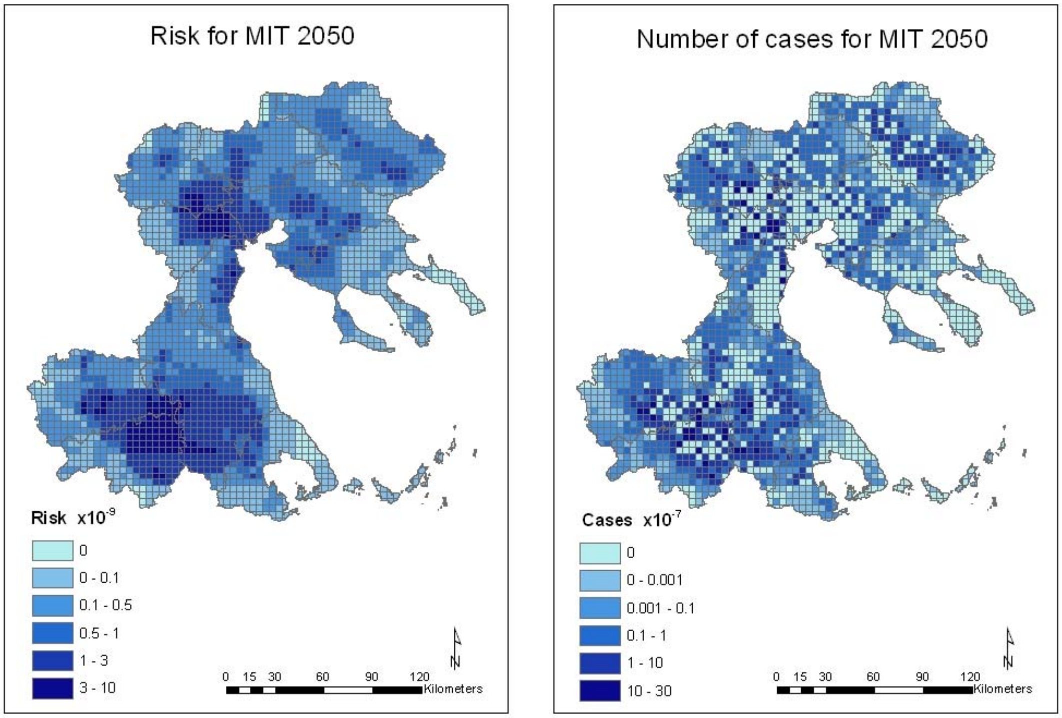
(a) **(b)**

Figure 11. a) Risk ($x10^{-9}$) and b) Incidence rate (in (cases/yr) $x10^{-7}$) in Thessaly and C. Macedonia for the baseline year 2000.



(a) **(b)**

Figure 12. a) Risk ($x10^{-9}$) and b) Number of cases (in (cases/yr) $x10^{-7}$) in Thessaly and C. Macedonia for the BAU 2050.



(a) (b)

Figure 13. a) Risk (x10^{-9}) and b) Number of cases (in (cases/yr) x10^{-7}) in Thessaly and C. Macedonia for the MIT 2050.

Risk and incidence rate for all the scenarios, for both Regions of interest, are listed in Table 2. Risk and number of cases for all scenarios per prefecture are depicted in Figure 14.

Table 2. Number of cases (cases/yr) for the Baseline year and the scenarios in Thessaly and C. Macedonia.

	Cases/yr
Baseline	2.4E-04
A1_2020	1.9E-04
B1_2020	2.1E-04
A1_2050	1.7E-04
B1_2050	1.8E-04

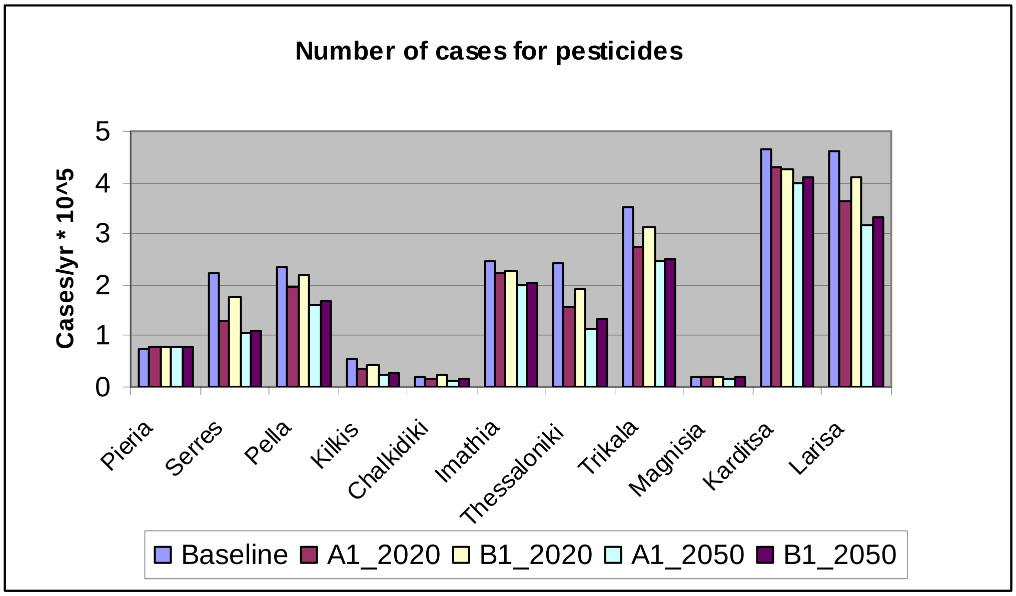


Figure 14. Number of cases for pesticides per prefecture for the baseline year and the scenarios.

England

The assessment of health risk of carcinogenic pesticides in England was trialled on herbicides, limited to those also used in the Greek case study area. This represented only six ASs for which exposure response functions (i.e. cancer slope factors) were available. The potential health impact for adults >25 years was computed on the basis of population weighted ward exposures for each of the ASs (Table 2, Annex 4.3). The assumed daily average inhalation rate and body weight for adults was 25 m^3 air/d and 75 kg, respectively. Equation 4, section 3.4 was used.

Table 3 shows the attributable cases due pesticide exposure under the different scenarios: B2020 business as usual; L2020 low emissions; H2020 high emissions. When differenced from the BAU, approximately two cases of cancer were estimated to be attributable to exposure to these six herbicides. This equated to approximately 1 case of cancer per year in each of the East Anglia and northwest England with slightly higher risk in East Anglia.

Table 3. Annual cancer cases attributable to usage of six herbicides under land use change scenarios

Scenario	**Attributable cases per year**		
	EA (n= 527)	**NW (n=1005)**	**Combined (n=1532)**
B2020	6.4	0.7	7.0
H2020	7.5	1.5	9.0
L2020	7.6	1.5	9.1
H2020 diff	1.1	0.9	2.0
L2020 diff	1.2	0.9	2.1

Note: diff indicates Scenario minus B2020

4.1.2 Geographical Risk Analysis

England

Hypothetical RRs

For this analysis, attributable cancer cases were derived using equation 5 (Section 3.4) on the basis of the population weighted ward exposures (Table 2, Annex 4.3). To apply the hypothetical RR derived in the 1st pass assessment (Table 3, Annex 4.6), the wards were first divided into non-exposed (pesticide < 1 ng/m^3) with the remaining representing exposed. The relevant subpopulation within the exposed subset of wards were then ranked by pesticide exposure, and divided into categories representing low, medium and high exposures.

For all cancer outcomes, the exposure categories were assumed to be equal tertiles (i.e. 33.3% of the population within each category). Exposure classes were defined based on the baseline population (B2020), and the exposure cut point (µg/m^3) extracted and applied to the scenario. The results, presented in Table 2, show little excess cancer attributable to land use change in East Anglia. This is an unexpected result given the higher exposures in East Anglia compared to the northwest, and is explored in more detail in subsequent sections. When study areas are combined, the greatest excess in cancer is for breast and prostate cancer as reflected by the high background incidence rates for these outcomes (Annex 4.6, Table 3).

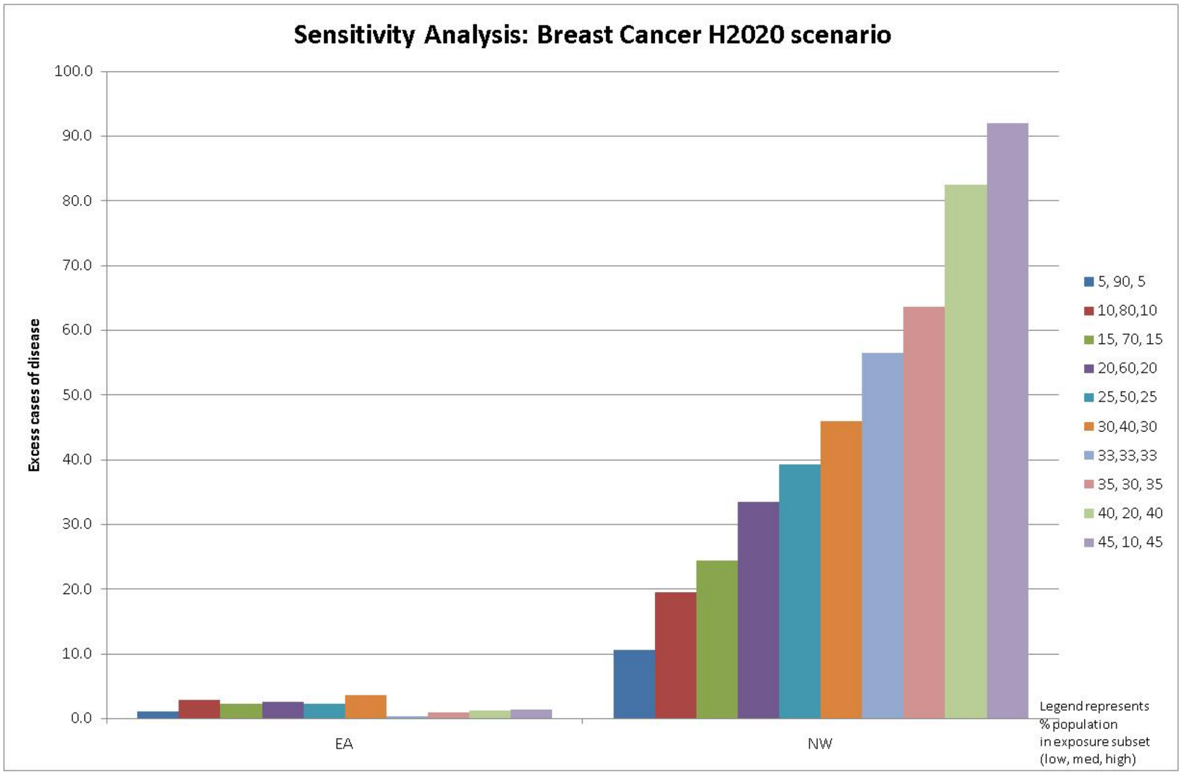
Table 4. Attributable cancer cases by study area, per year: H2020 difference

Cancer outcome	% population H2020			Attributable Cases		
	Low	Med	High	EA	NW	Combined
Breast	20.1	37.8	42.1	0.3	56.6	56.9
Pancreas	26.2	27.2	46.6	0.8	10.1	10.9
Non-Hodgkin's lymphoma	27.5	28.7	43.8	0.9	5.9	6.8
Leukaemia: adult	25.4	28.0	46.6	0.9	13.1	14.0
Leukemia: child	18.7	35.8	45.5	0.0	2.2	2.3
Brain	18.5	35.4	46.1	0.0	1.2	1.2
Prostate	19.9	36.9	43.2	1.4	66.7	68.0
Kidney	20.0	37.3	42.6	0.1	7.5	7.6

Note: Attributable cases for H2020 minus B2020

Given that the RRs were hypothetical, and that an arbitrary ±10% used to estimate RRs for the low and high categories, the sensitivity of definition of the exposure categories needed to be explored. In a follow-up sensitivity analysis, therefore, the definition of the exposure categories was modified. The hypothetical RRs were still averaged over the population to equal that of the medium exposure category (i.e. the value extracted from the literature). This was conducted by ensuring equal population in the low and high category. For example: 15% in the low and high with the remainder 70% in the medium. The sensitivity analysis was done for breast and prostate cancer, for which the greatest number of attributable cases was estimated based on tertiles.

The results of the sensitivity analysis, after differencing the BAU from the H2020 scenario, are shown in Figure 15. The pattern for both cancer outcomes is the same. For both study areas combined, the number of cases ranges from 11 to 93 (mean 48, std dev 26) for breast cancer and 11-110 (mean 56, std dev 32) for prostate cancer. The percent difference between the lowest and highest estimate is 7% and 8.8% for breast and prostate cancer, respectively.



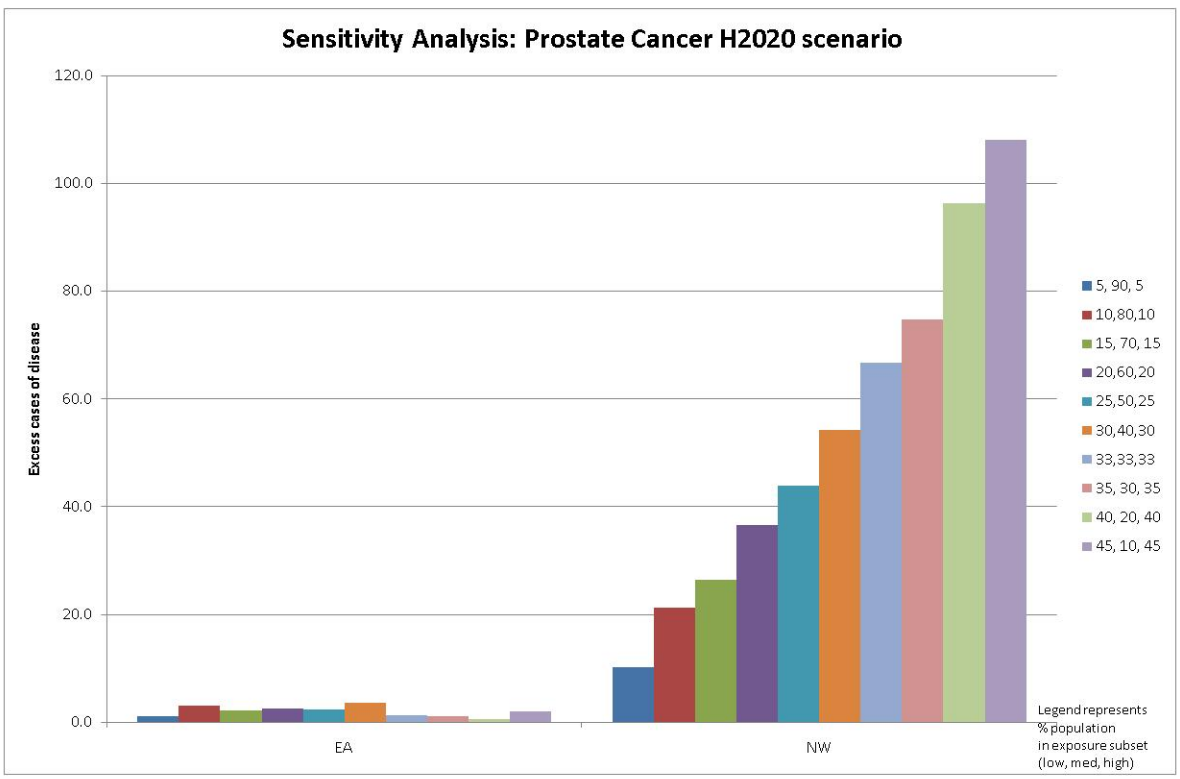


Figure 15. Sensitivity of exposure category definition: breast cancer (top) and prostate cancer (bottom)

RIF Analysis

To get around the issues related to use of non-specific RRs for the study population, a RIF analysis was undertaken to directly explore the potential cancer risk due to exposure to pesticides in the England study areas. Unadjusted and adjusted RRs were derived for each combination of pesticide group (herbicides, insecticides and fungicides, and total pesticides) and cancer outcome identified in Table 3, Annex 4.6.

No risk was identified for non-Hodgkin's lymphomia, leukemia or cancer of the pancreas, brain or kidney. The unadjusted RRs for breast and prostate cancer (Figure 16a and 16b, respectively) suggest a linear dose response relationship for total pesticides and herbicides only. These plots might also suggest that the medium exposure category is poorly defined in that the RR would need to be shifted upward to better reflect a linear relationship. To avoid influencing the results, however, the analysis was not rerun specifying different exposure bands.

It should also be noted that after adjusting for socio-economic status (SES) the pattern is RR somewhat flattened, with the adjusted RR increasing in the lowest exposure category and decreasing in the highest. While this can be explained for breast cancer, which is inversely correlated with SES, this effect was seen across all the cancer outcomes explored in the RIF risk analysis. This suggests that the two study areas are markedly different in terms of socio-economic status, and that separate analysis would have to be run to acquire sensible adjusted RRs for each study area. As a result, only the unadjusted RRs were used in subsequent calculations.

Compared with the hypothetical RR, those obtained from the RIF analysis employing exposures modelled specifically for the study areas of interest were much nearer to 1.0. This is as expected given that the hypothetical RR mainly derived from occupational studies, and were further modified to provide hypothetical RRs for exposure tertiles.

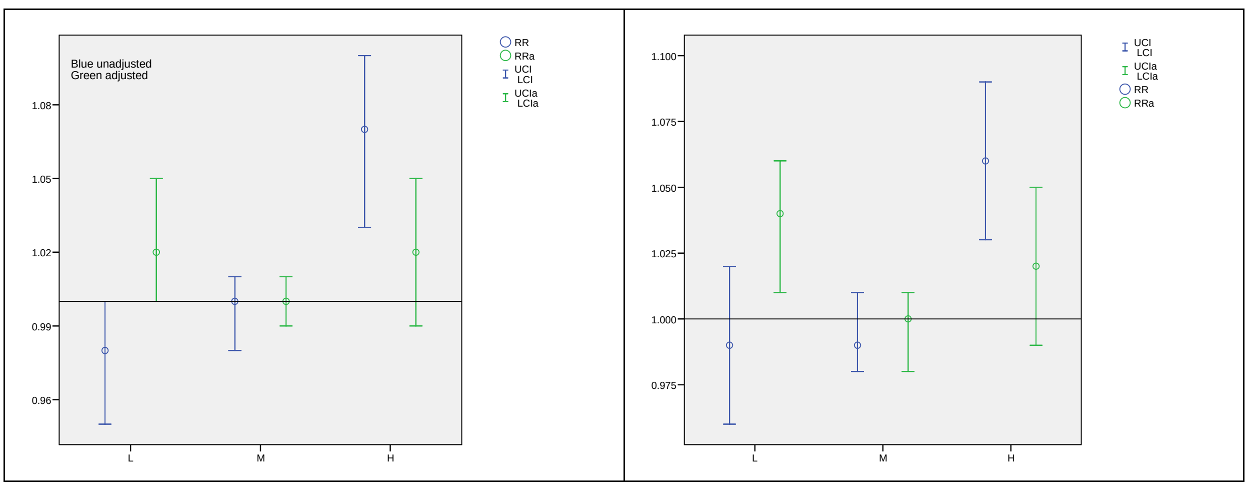


Figure 16a. Breast Cancer: total pesticides (left), herbicides (right)

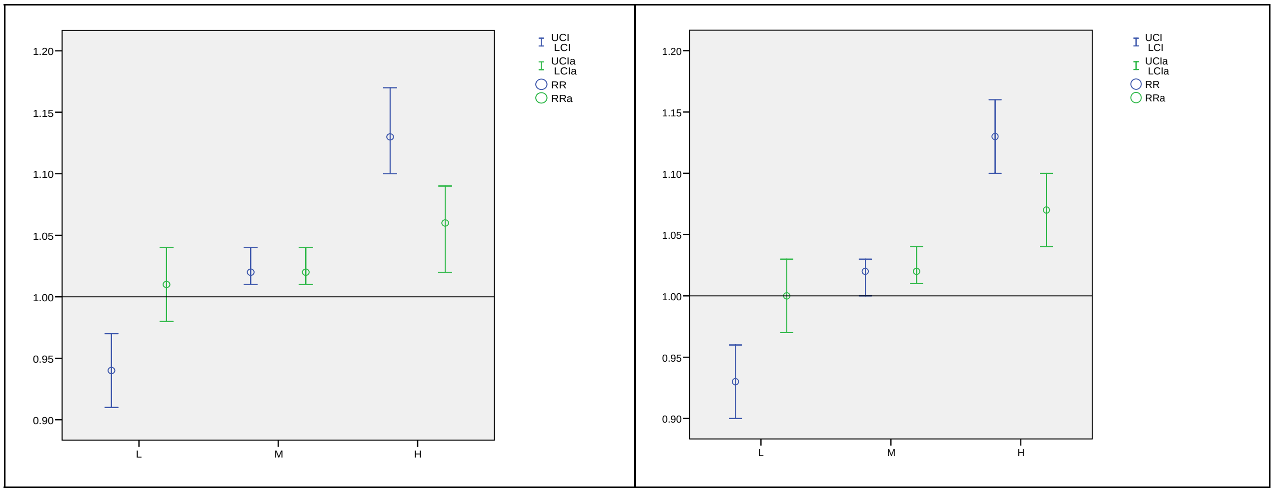


Figure 16b. Prostate Cancer: total pesticides (left), herbicides (right)

For breast and prostate cancer only, for which dose response relationships could be inferred from the unadjusted RR, the number of attributable cases was computed at the ward level for total pesticides. Although the RR were derived from the 250x250m categorised exposure grid, health impacts were assessed at ward level because this was the smallest geography for which population projections for year 2031 were available. There was no difference in attributable burden for H2020 and L2020 at this level, therefore, only H2020 results are reported.

With equation 5 (section 3.4) attributable burden was computed twice, with the results shown in Table 5:

- Run 1: used the RRs shown in Figure 16 for each exposure category. In the case of breast cancer this includes borderline and non-significant RRs in the lower categories. For both cancers, the lowest category has a RR <1 indicating the exposure was protective.
- Run 2: using only the significant RRs > 1 with the risk in other categories set to nil. Here the assumption is that exposure is not protective, rather that there is no exposure in the lower categories.

Table 5. Attributable cancer cases by study area, per year based on RIF analysis

Pollutant	Cancer	Scenario	EA	NW	Combined
Total pesticides Run 1	**Breast**	B2020	30.5 (-3.3, 50.5)	-11.7 (-85.5,27.6)	18.8 (-88.7, 78.1)
		H2020	32.7 (-1.6, 53.3)	-1.0 (-73.0, 36.8)	31.7 (-74.6, 90.1)
		H2020 diff	2.2 (1.7, 2.8)	10.7 (12.5, 9.2)	12.9 (14.2, 12.0)
	Pancreas	B2020	52.7 (38.3, 74.8)	6.4 (-31.8, 61.2)	59.1 (6.5, 136.0)
		H2020	55.3 (40.1, 77.3)	28.6 (-4.3, 82.1)	83.9 (35.8, 159.4)
		H2020 diff	2.6 (1.8, 2.4)	22.2 (27.5, 20.9)	24.8 (29.3, 23.3)
Total pesticides Run 2	**Breast**	B2020	30.5 (13.6, 42.4)	2.1 (1.0, 3.0)	32.6 (14.5, 45.3)
		H2020	32.7 (14.6, 45.5)	7.5 (3.3, 10.4)	40.2 (17.9, 55.8)
		H2020 diff	2.2 (1.0, 3.1)	5.3 (2.4, 7.4)	7.6 (3.4, 10.5)
	Pancreas	B2020	52.7 (38.3, 74.8)	40.7 (21.4, 77.8)	93.5 (59.7, 152.7)
		H2020	55.3 (40.5, 77.8)	50.0 (27.9, 91.5)	105.3 (68.4, 169.2)
		H2020 diff	2.6 (2.2, 2.9)	9.2 (6.4, 13.7)	11.8 (8.7, 16.6)

Note: diff indicates Scenario minus B2020

4.2 Particulates

Greece

For the Greece case study, the number of cases attributable to PM10 and PM2.5 from agricultural activities were estimated by using equation 7, section 3.4 per grid cell. Then the number of cases were summarized at Prefecture level. The estimation has been done for both cardiovascular and respiratory health effects for the baseline and the scenarios. Contrary to pesticides estimation, the number of cases for PM10 were estimated for the whole population, while for PM2.5 males and females older than 65 years old were used. Tables 6 and 7 summarize the number of cases from PM10 and PM2.5, respectively for the study Region (baseline year and scenarios).

Table 6. Number of cases from PM10 (cases/yr) for the baseline year and the scenarios in both Thessaly and C. Macedonia.

	Number of cases per year	
	Cardiovascular health effects	Respiratory health effects
Baseline	3.59E-01	1.38E-01
A1_2020	2.86E-01	1.10E-01
B1_2020	3.32E-01	1.28E-01
A1_2050	2.15E-01	8.30E-02
B1_2050	2.95E-01	1.14E-01

Table 7. Number of cases from PM2.5 (cases/yr) for the baseline year and the scenarios in both Thessaly and C. Macedonia.

	Number of cases per year	
	Cardiovascular health effects	Respiratory health effects
Baseline	1.68E-03	1.65E-03
A1_2020	1.55E-03	1.52E-03
B1_2020	1.84E-03	1.80E-03
A1_2050	1.95E-03	1.91E-03
B1_2050	2.68E-03	2.63E-03

Figures 17 to 20 present the number of cases due to PM10 and PM2.5 exposure per Prefecture (in Thessaly and C. Macedonia) for the baseline year and the four different scenarios. As expected, the number of cases attributable to PM10 and PM2.5 from agricultural activities are very small, while the cases for PM2.5 are much smaller because they refer only to elderly people.

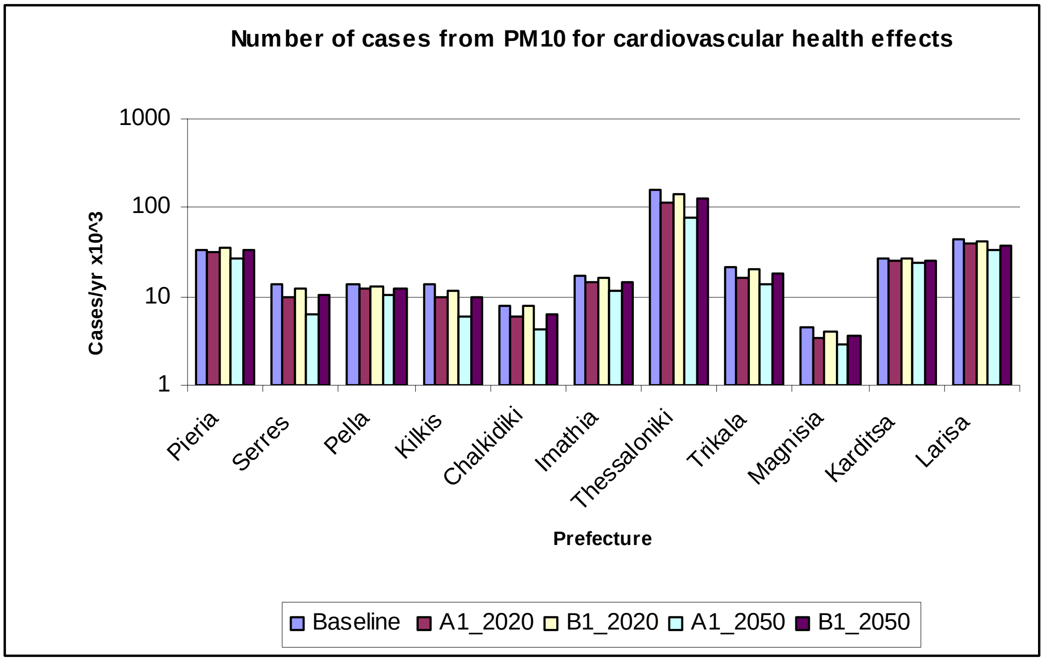


Figure 17. Number of cases attributable to PM10 from agricultural activities for cardiovascular health effects for the baseline year and the scenarios per Prefecture in Thessaly and C. Macedonia.

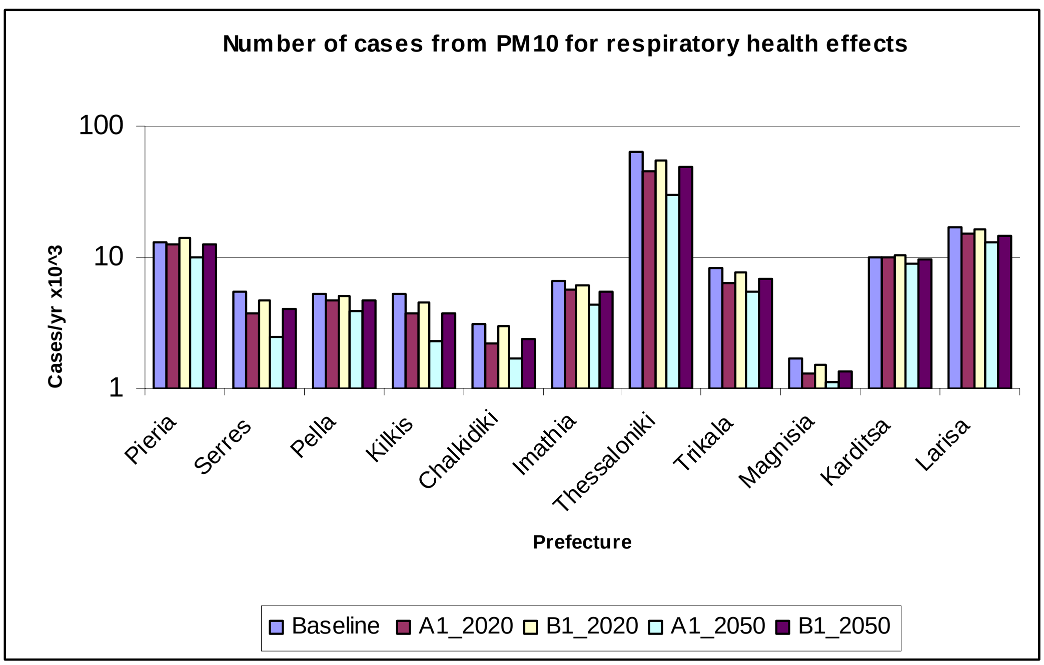


Figure 18. Number of cases attributable to PM10 from agricultural activities for respiratory health effects for the baseline year and the scenarios per Prefecture in Thessaly and C. Macedonia.

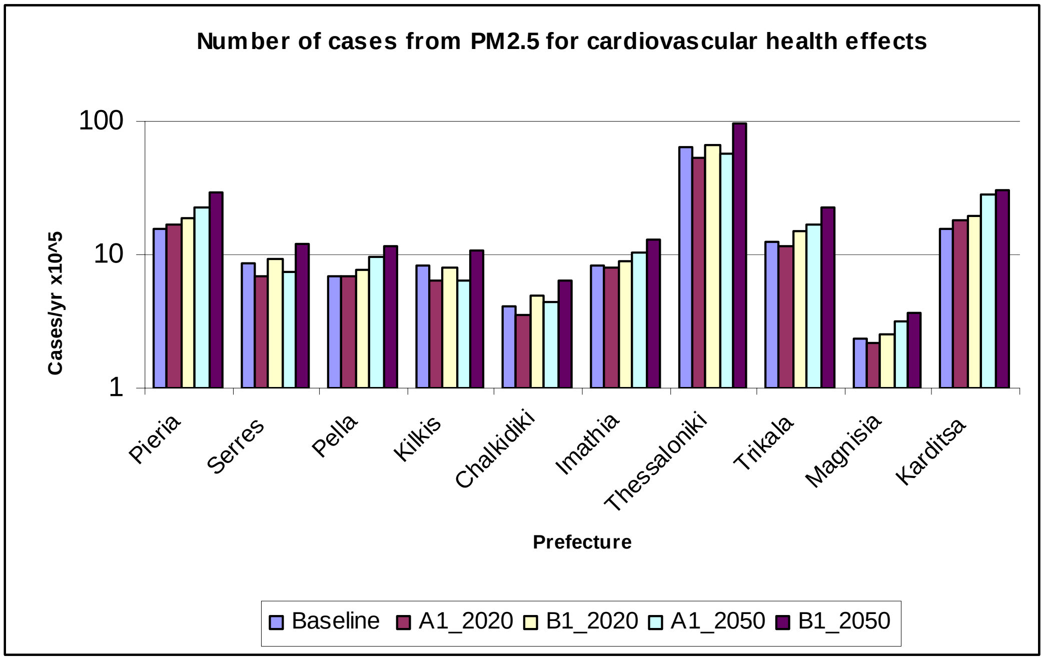


Figure 19. Number of cases attributable to PM2.5 from agricultural activities for cardiovascular health effects for the baseline year and the scenarios per Prefecture in Thessaly and C. Macedonia.

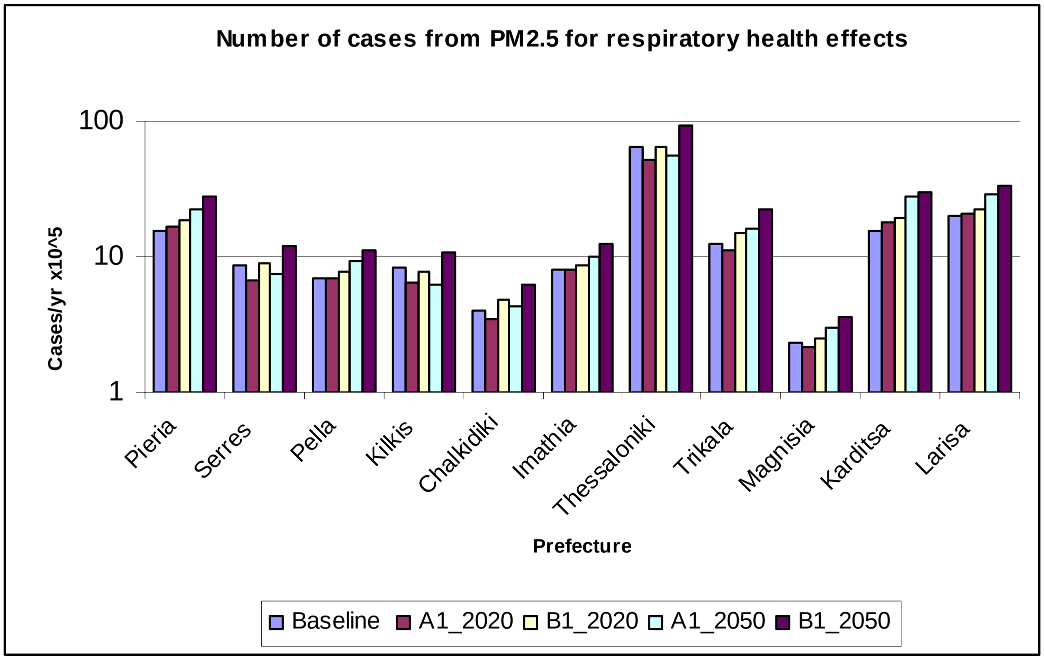


Figure 20. Number of cases attributable to PM2.5 from agricultural activities for respiratory health effects for the baseline year and the scenarios per Prefecture in Thessaly and C. Macedonia.

England

The number of deaths in the England case study areas attributable to agricultural change were computed using equation 6, section 3.4 for a linear dose response relationship. This was done at the county level using Analytica software (see Annex 4.5). The population weighted county exposures mentioned in Section 3.2.5 were computed for this analysis (presented in Table 5, Annex 4.3).

Figure 21 below shows the total number of deaths due to PM_{10} and $PM_{2.5}$ exposure in counties in both study areas under the different scenarios. Due the similarity patterns in source and in ERFs, the AB for both pollutants exhibit similar pattern across counties. The number of deaths, however, is less for $PM_{2.5}$ which is the fine component of PM_{10}. When explored by sex, the AB is greater for men due to the generally higher mortality rates for men (Table 2, Annex 4.6 – population distributions are essentially equal with 49-51% men in each counties).

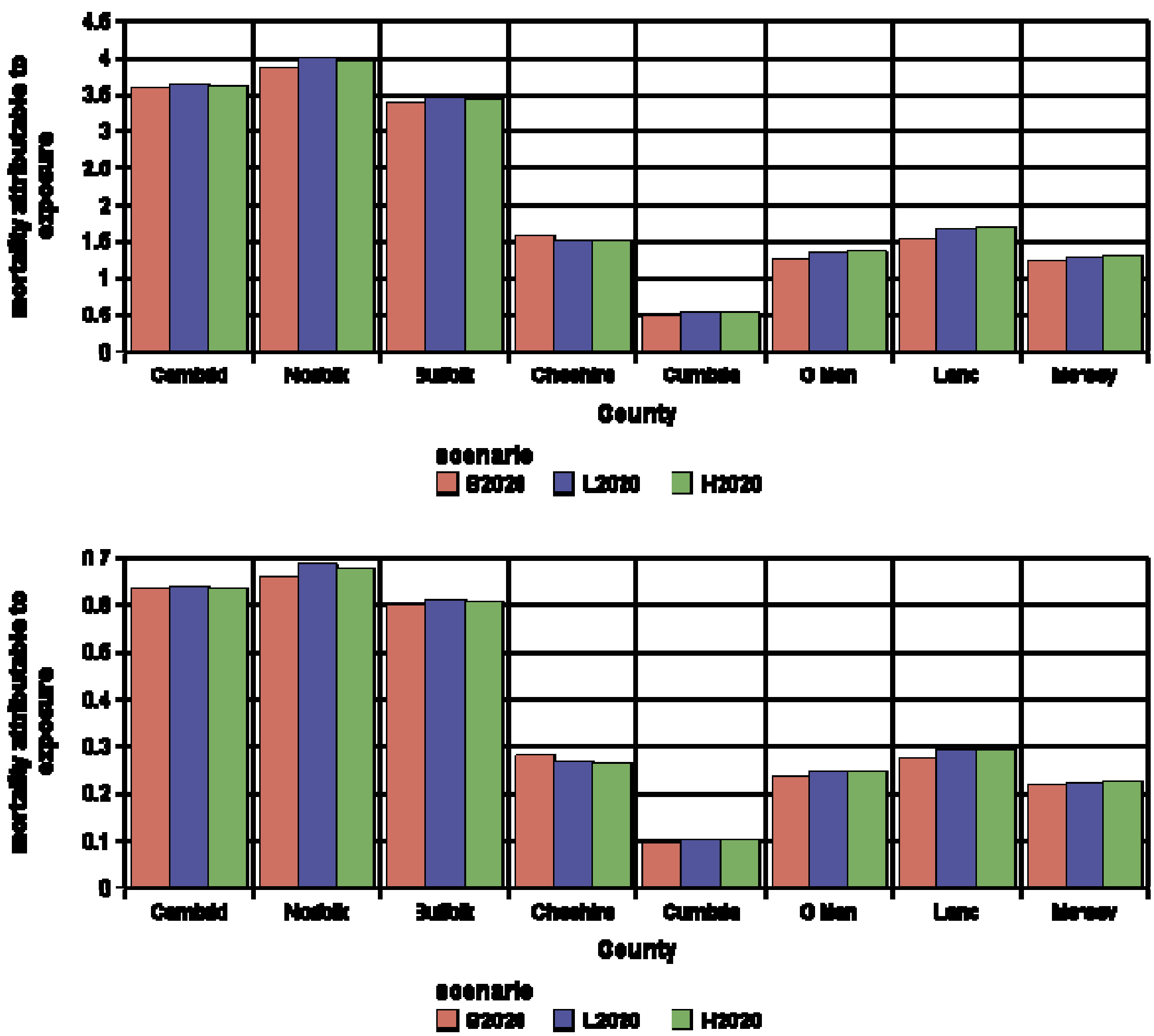


Figure 21. Deaths attributable to particulate exposure under different land use change scenarios: PM_{10} top, $PM_{2.5}$ bottom

Table 8 shows the mortality results for the low and high emission scenarios after differencing the baseline from each. Most results show a slight increase in deaths due to land use change, except for the H2020 scenario in East Anglia where deaths are slightly reduced. Focusing on the L2020 scenario for PM_{10}, across both study areas the number of deaths attributable to the land use change scenario are less than 0.5 per year. Due to the small effect, DALYs were not computed. Also, given that the ERFs for respiratory and cardiovascular hospital admissions were lower than those for mortality, health impact for these endpoints was not computed.

Table 8. Attributable deaths by study area and pollutant, per year

Pollutant	Scenario	EA	NW	Combined
PM_{10}	L2020 diff	0.25 (0.14, 0.35)	0.25 (0.14, 0.36)	0.50 (0.29, 0.71)
	H2020 diff	-0.10 (0.08, -0.14)	0.03 (0.16, 0.04)	-0.07 (0.25, -0.10)
$PM_{2.5}$	L2020 diff	0.04 (0.03, 0.06)	0.03 (0.02, 0.05)	0.08 (0.05, 0.11)
	H2020 diff	-0.02 (-0.01, -0.03)	0.0008 (0.0005, 0.001)	-0.02 (-0.01, -0.03)

Note: diff indicates Scenario minus B2020

<u>4.3 Other Pollutants</u>

Several other agricultural-related pollutants, including endotoxin and pollen, were identified during the scoping phase. As indicated above, effort was made to acquire source data and emission factors for these pollutants. For pollen, modelled exposures were not reported because the emission factors were considered too specific to conditions in Greece. Endotoxin exposure was modelled; however, due to the lack of adequate ERFs health impacts are not reported.

<u>4.4 Uncertainty</u>

This section describes the results of the qualitative uncertainty analysis for England and Greece. The Uncertainty matrix for both case study is presented in Table 9.

Greece Case Study: Source - Exposure

- The spatial resolution of the analysis (4x4km grid) is finer than that of available key data (i.e. pesticides sales, ATEAM scenario maps, population), which introduces parameter uncertainties:
  - Baseline crop data from LAU-2 level (ESYE estimates) to 4x4km grid is accomplished via area weighting. This method introduces parameter uncertainty, due to the limitations of the algorithm and the lack of any surrogate (auxiliary data).
  - Main crop projections for the scenario years introduces model uncertainty, due to the lack of information on crop variations from the ATEAM model (focuses only on land use).
  - Energy crop projections for the scenario years, introduce parametric uncertainty. The ATEAM (16x16km) makes projections for the energy crops; any uncertainty introduced is from the spatial distribution of energy crops (ATEAM) and the change in resolution.
  - Population data, available from ESYE, are at LAU-2 level and disaggregated to a high resolution grid.
- Pesticide type and usage rates for various crops were estimated mainly by collecting sales data and soliciting expert advice. Thus, there are model uncertainties regarding total pesticide quantity, the computed pesticide applications (mainly the rates) as compared to the actual ones. It should be noted, however, that the input data thus derived were deemed as being much closer to real application rate.
- The pesticides AS employed for the years 2020 and 2050 scenarios are associated with significant model uncertainty, despite efforts made to prepare a realistic list by excluding the already, or soon to be, withdrawn AS, and to include appropriate AS –approved or pending

approval- for each major crop. Means to reduce this uncertainty include direct contact with pesticide manufacturers and importers and consultation with the relevant competent authorities at the national and European level (Ministry of Agriculture, European Commission – DG Environment, DG Entreprise).

- The dispersion calculations introduce parameter uncertainty for the following reasons:
    - Using the box-volume model, the wind speed and mixing height were calculated using the CALMET model. Uncertainty is introduced because of the limited number of meteorological stations and data in the area and the method used to interpolate.
    - Use of the focal sum model, introduces parameter uncertainty due to assumption made that all meteorological conditions are similar.
- The Emission factors (EF) were derived from pesticides usage data from the Netherlands. As a result, significant parameter uncertainty is introduced in the study. Moreover, EFs for AS that were not available from Netherlands data were derived by interpolating on the basis of vapour pressures of other similar AS.
- It should be stressed that PM Emission factors refer to whole of Greece and they are not representative of local conditions; this introduces parameter uncertainty.
- Emission factors for pollen. Since no appropriate data for pollen emission factors were available in literature, a methodology was proposed for the estimation. This methodology is based on information on release rates of pollen which may vary depending on local conditions, thereby introducing model uncertainty in calculations.

Greek Case study: Exposure - health effects

- Modelled exposure is another source of parameter uncertainty:
    - For instance, an average AS ambient air concentration is estimated from the annual AS usage, using the box volume model, without considering the physical properties of the different AS and local meteorological conditions (wind speed/direction and mixing height). Thus, computed human intake, by assuming a fixed period of exposure to this concentration, for all AS, involves significant uncertainty; for example, AS physical properties (e.g. volatility, half life) differ significantly, and it is uncertain to what extent these assumptions represent reality.
    - The assumed uniform exposure (for each grid cell and averaged year) of the entire population, in the area considered (4x4km grid) introduces scenario uncertainty, since with this method we are neglecting individual exposure patterns.
    - Assessment of health impact is affected by the aforementioned scenario uncertainties related to human intake by inhalation (in various population groups), and the deficiencies caused by neglecting significant exposure pathways as well as the effect of population behavioural patterns.
- PM Exposure response functions: PM ERFs estimations have been based on average measures of PM concentrations. Average concentrations are measured in large cities and are an important source of error. Moreover, extrapolating ERFs that have been derived from a particular population to other populations for impact assessment may reduce the validity of results as many factors, including climatic conditions, age, different lifestyles, housing etc., introduce bias.
- The fact that endotoxin exposure response functions have been derived from a small population size (i.e. only few farmers) creates difficulties in extrapolating these functions in whole rural population. Different climatic conditions and animal husbandry practices introduce a kind of uncertainty. Furthermore, as the amount and duration of exposure play an important role in protection against asthma, these ERFs may not be appropriate for every cases. Another point that should be mentioned is that the majority of studies assess exposure either for first years of life or for a particular occupation.
- A major source of uncertainty in this assessment method is related to the application of toxicological data:
    - The limitations and uncertainties are well-known; i.e. extrapolation of dose response functions from animals to humans and from large to small doses, experimental

conditions in toxicological studies that do not resemble actual conditions of human exposure to pollutants, etc.

- For carcinogenic health outcomes, the assumed life-time exposure to an estimated constant concentration is another source of model uncertainty. In this case, the estimation is biased towards the more conservative side, in order to make sure that latent effects can be appropriately captured by the analysis.

England Case Study: Source - Exposure

- There is parameter uncertainty in some of the raw data sets used for this assessment and, in most instances simple methods were used to address these data deficiencies.
  - The ward agricultural census data (i.e. June agricultural returns (JAR)) contains data gaps due to data suppression to protect anonymity of small holdings. For example, if few farms are within a particular ward, information for those farms will only be displayed at the district level. If there are too few at the district, they will be recorded in the county total. Thus gaps in crop area and livestock counts were filled using an iterative area-weighting process from the next highest known level aggregation. While the total area of crop (or number livestock) within counties was maintained, the allocation of crop/livestock to specific ward known to be suppressed is subject to error which cannot be quantified.
  - Given the large number of pesticide active substances remaining in the England database (ca. 125 ASs), the pesticide usage (PU) data were broadly aggregated into herbicides, insecticides, fungicides and total pesticides. As this grouping is based only on pesticide function, and the pesticides within each of these broad groups do differ in their toxicity, this aggregation will have introduced uncertainty into the overall toxic effects of these groups.
  - There is also parameter in the PU survey data, in that no distinction between missing and no data is available for the county-level estimates. The methodology for the survey requires visiting a statistically valid number of farms at a regional level. As a result not every county may have a representative farm visited. This does not mean, however, that a particular crop is not grown in that county or that certain pesticides normally applied to that crop were not used.
  - Corine land cover 2000 was used as the primary dataset by which to delineate agricultural areas to facilitate disaggregation of the pesticide usage and agricultural survey data to a finer resolution for concentration modelling (250x250m). While the categories in Corine broadly distinguish between types of agriculture, it does not provide accurate field boundaries nor information on particular crops grown in each area. Uncertainties in this context may have been reduced by using higher resolution Land Cover Map for England, however, cost prohibited its use in this assessment.
- A minimum spatial resolution of 250x250m was selected to ensure that modelling was not attempted at a resolution below that of the input data sets (i.e. 1:100,000 vector Corine has a notional accuracy of ca. 100m). All other input data, however, are at larger spatial scales including: county-level pesticide usage, ward agricultural census (JAR), 5x5km REGIS scenarios. Correlation analysis was thus used to assess associations before disaggregating these data to finer spatial scales.
  - Mask area weighing was used to disaggregate the PU and JAR. This method introduces parameter uncertainty, due to the limitations of the algorithm and inaccuracy of the auxillary data used as the mask. While the overall pesticide usage at the county level is assured, error in pesticide usage assigned to each ward is expected. This error is difficult to quantify without ground truthing or validation with independent data. Crop correlations were 0.36–0.91 and 0.02-0.96 while livestock correlations ranged from 0.38-0.61 and 0.41-0.93 for East Anglia and the northwest, respectively.
- The definitions of crop categories within the various data sets (i.e. JAR, PU, and REGIS) were not exactly the same leading to scenario uncertainty. To overcome this issue, a concordance table between the JAR and PU was first generated giving 11 common categories. These were

then matched with combinations of the categories in RegIS, for the purpose of computing the scenario data sets, on the basis of correlation analysis. Correlations ranged from 0.19-0.58 and 0.30-0.08 for crops in East Anglia and the northwest, respectively. Correlations for livestock for both study areas were 0.29-0.76.

- It is assumed that the pesticides represented in the PU survey (ca. year 2000) are representative of those used in the future. The available pesticides, however, are rapidly changing causing significant model uncertainty. Even in the ten years since this PU survey, ca. 45% of the active substances have been withdrawn. To minimize error in the future scenarios, those AS known to be withdrawn have been excluded from this assessment.
- Focal Sum - A single, centrally located meteorological station was selected for each study area. This was done to simplify modelling, however, introduces potential parameter uncertainty in assuming weather conditions are consistent across each study area. Sub-study area model runs could have been done using additional meteorological stations however, sites with appropriate measurements for the full time series were difficult to obtain.
- As with the Greece case study, parameter uncertainty is introduced in the various emissions factors (EFs):
    - Pesticide EFs were derived from pesticide usage in the Netherlands. As a result, significant parameter uncertainty is introduced in the study. Moreover, EFs for AS that were not available from the Dutch study were derived by interpolating on the basis of vapour pressures of other similar AS.
    - PM EFs refer to the whole country, and are not necessarily representative of local conditions. Furthermore, if no emission factors were available, EFs from highly matching country-specific conditions were applied.
    - General EFs for endotoxin were derived from the literature. These were not country specific to England, thus do not take account of different modes of feeding and ventilation systems in animal housing.

England Case Study: Exposure – health effects

- Parameter uncertainty also occurs in modelling exposures
    - Although agricultural activity tends to be seasonal, concentrations were calculated as annual averages using the Focal Sum model. Whilst the Focal Sum model can allow for sub-annual modelling, simply by changing the timeframe of the input meteorological data, annual modelling was preferred to correspond to the emission factors calculated on a yearly basis.
    - Furthermore, concentration is used as a proxy for exposure in computing attributable burden.
    - Assigning exposure via postcode location assumes individuals remain within the 250x250m grid cell in which their residence is located. This is an unrealistic assumption, however, time-activity was outside the scope of this assessment.
- Exposure misclassification is another major source of parameter uncertainty in this assessment.
    - This assessment was undertaken at the ward (or higher) level, in which it was assumed that all persons in a particular ward have the same level of exposure. This is an assumption as we expect significant within-ward area variation in agricultural exposures, as indicated by the varying land use within wards apparent in Corine land cover. To take account of this issue, postcodes were used to compute population weighted exposures at the ward level on the basis of concentrations modelled at a much finer resolution (i.e. 250x250m).
    - Uniform exposure is assumed for each 250x250m grid cell. Population data attached to postcode point locations were then used to compute weighted exposures for different geographies (e.g. population weighted ward exposure). Postcodes, however, typically represent 15 households (but can reach up to 100 in some cases) and range in size between urban and rural areas. In some rural areas, therefore, many postcodes in

rural areas are likely greater than 250x250m leading to potential exposure misclassification.

- As with the Greece case study, there is uncertainty in the ERFs that were selected:
  - Most epidemiological studies related to pesticide exposure are based on specific occupational groups, where the exposure is expected to be higher than for local residents. Existing meta-analyses for relevant pesticide groups and health outcomes were difficult to find. A literature review was thus undertaken, though our own meta-analysis was not possible, given the wide range of pesticide AS (often focused on AS no longer in use), particular occupational groups, and specific disease outcomes. Several existing systematic reviews were used as a basis to derive hypothetical relative risks for exposure categories (e.g. non-exposed, exposed and/or non-exposed, low, medium, high) to represent indicative ERFs for the broad pesticide groups. Exposure misclassification was also noted in this stage of the assessment, as parameter uncertainty, where sensitivity analysis illustrated that the definition of exposure categories had a large effect on the computation of attributable burden. The implication of using hypothetical RRs was contrasted with a RIF risk analysis with which RRs were derived using the modelled exposures and health data for the study areas.
  - In the absence of specific ERFs for agricultural, existing ERFs for traffic-related PM_{10} and $PM_{2.5}$ (available within the toolkit) were used. This is a likely source of parameter uncertainty.
  - One underlying assumption of the RIF risk analysis, or any use of RRs, is that the RRs derived from real population and health data for current years can be applied to populations projected into the future.
- Exposures were computed for a populations projected to the year 2031 which approximately corresponds to the timeframe for the RegIS 2020 scenario (i.e. representative of the time period 2011 – 2040). Official trend-based population projections (including assumptions about births, deaths and migration) were taken from the UK Office for National Statistics. A simple linear model of the county change rates was applied to compute ward (and greater) level estimates for age/sex strata. These projected population data potentially include scenario, model and parameter uncertainty.
- For cancers, national background rates of disease were used rather than regional or county level estimates. Furthermore, incidence rates for cancers were taken from the baseline year and not projected to 2020.

Common uncertainties to both case studies

On the basis of the results from the two case studies for pesticides, the following brief comments may be made regarding various aspects of the methodology:

- Selected Scenario. There are certainly many driving forces expected to shape the future in agricultural land use; thus, developing credible scenarios is very complicated. Nevertheless, it appears that for the type of environmental health impact assessment considered in this study, an appropriate scenario should possess the following two main attributes: a) It should involve, or allow the introduction of, policy issues, relevant to agriculture, preferably in a transparent way. This kind of transparency and flexibility would facilitate evaluation of policy alternatives. b) It should be characterised by a sufficient level of detail, thus, requiring a minimum of labour (for enhancement) to adapt it to the needs of the health impact assessment.
- Pesticide data. Various types of problems have been identified in relation to pesticide data. In addition to lack of reliable data for most of the European countries, there are problems of data spatial resolution and specificity (in relation to crops) even in countries where records are kept (e.g. GB). Other problems due to the large number of AS in the market and the incomplete characterisation of their various properties (physical, chemical, toxicological, etc) are outlined above. It is important to stress here the difficulties created in the present study by the ever

changing (especially after year 2000) list of AS approved by the EC, as a result of the PPP Directive implementation. This variability, very difficult to predict in the long run, tends to introduce a great uncertainty, and constitutes an additional factor to be considered in this assessment.

- Dose response functions. As outlined above, this is a critical issue for the study at hand. Relevant data from epidemiological studies are very limited, and toxicological dose response functions, although available for many (but not all) AS, are characterised by significant limitations and uncertainties.
- Scale of analysis. This study is carried out at different resolutions in England and Greece respectively. It appears that selection of different resolutions does not affect the health impact estimates.

Table 9. Uncertainty matrix showing both Greece and England case study

Sources of uncertainty	Dimensions of uncertainty				
	Direction of uncertainty	Level of uncertainty	Appraisal of knowledge base	Justification - Greece	Justification – Great Britain
Scenarios considered & Assumptions made					
One pathway considered: exposure via inhalation	Not applicable	Not applicable	Not applicable	For simplicity we selected only this pathway	Same
Current and future agricultural practices are kept the same	U	L	L	We did not take into account changes to the future agriculture practices	Same
Enhancement of ATEAM land use maps with the ESYE crops	U	L	L	Based on LAU2 estimates from ESYE we aggregated data to the 16x16km grid (ATEAM native) where we made the correction at cell by cell level	
Future land use scenarios based on ATEAM 16x16km & disaggregation to the 4x4km grid	U	L	L	Uncertainty from the ATEAM and from the disaggregation of data from 16x16km grid to 4x4km (smoothing)	
Spatial variability in crop cultivation (main crop and energy crops) at 4x4km	U	L	L	Uncertainty introduced via the disaggregation of data from 16x16km grid to 4x4km	
CAP policy: changes in crop projections	U	L	L	Based on the historic trends and taking into account past CAP policies and any changes in weather conditions we decided upon the crop projections	
Scenario land use database based on REGIS 5x5km	U	L	L		Uncertainty in matching REGIS crop groups with those in JAR and PU. Attribute values (i.e. percent crop area) from REGIS also available only as categorical data with 10 categories.
Source & Exposure					
Data suppression in agricultural census data	U	L	L		Iterative area-weighting process from the next highest known level aggregation
Prefecture pesticide sales data	U	L	L	Data collected from local survey after expert elicitation	
County pesticide usage data	U	M	M		Survey is representative of regional usage, though provided at county level. Parameter uncertainty in that cannot distinguish between missing and no data (i.e. unreported ASs were assumed to mean no data)

Active substance (AS) typology (list) is kept the same in all prefectures for the regions of study	U	L	L	The survey was localized to the Thessaloniki and Larisa prefecture: it is likely that some pesticides may be area dependent (e.g. insecticides)	
AS usage rates for the baseline year	O	M	M	Model uncertainties regarding the computed pesticide applications (mainly the rates) as compared to the actual ones.	
Future Pesticide AS list – same AS and application rates as baseline year	H	H	L	Scenario /Model Uncertainty: we are not in a position to know what the future AS would be	Same
Pesticide disaggreagation: areal – weighting method	U	M	H	The assumption made that depending on the area of crop all AS (list) will be used. Equal probability of AS per crop for baseline and future	
Pesticide disaggreagation: stochastic method	U	M	M	This method, tries to identifies usage patterns based on the objective function supplied by the user	
Crop, livestock and pesticide disaggregation – mask area weighting (proportioning sources to 250m grid)	U	L	L		Assume agricultural land cover classes in Corine accurately depict size and location of agricultural parcels used as the mask in weighting JAR (ward) or PU (county) to REGIS (5km)
Lack of toxicity characterization for some pesticides	U	H	L	For some AS toxicity characterization was unknown based on U.S. EPA Carcinogens list	Same
Box-volume model	U	L	L	The wind speed and mixing height are calculated using the CALMET model, introduced parameter uncertainty.	
Focal sum model	U	L	L	Introduces parameter uncertainty due to assumption made that all weather conditions are similar	Same
Time invariant (yearly average) estimates of concentration and uniform distribution of concentration across grid cell	U	M	L	Simplifications made to the estimation of concentration. Pesticides are used during specific months and not the entire year.	Same
PM emission factors	U	L	L	EFs for whole of Greece rather than representative of local conditions	Specific country-based emission factors were used where possible. If no emission factors were available, emission factors that highly match country-specific conditions were applied.

Endotoxin Emission factors	U	M	L	Not country specific Different types of feeding and ventilation systems in animal housing Mean animal body weight	Same
Pesticide Emission factors	U	M	L	Use of the Dutch emission factors, generalization made (different climatic conditions, agricultural practices etc)	Same
Gap filling in pesticide emission factor database				EFs for AS not available were derived by interpolating on basis of vapour pressures of other similar AS	Same
Exposure – health effects					
Modelled exposure	U	M	L	Computed human intake, for all AS, involves significant uncertainty: AS physical properties (e.g. volatility, half life) differ significantly, and it is uncertain to what extent these assumptions represents reality.	Same; in addition: annual exposures computed to correspond to annual EFs for pesticides, PM and endotoxin; concentrations used as proxy for exposure
Duration of exposure	U	M	L	The duration of exposure is unique for each person any generalizations made introduce high uncertainty.	Same
Generalizations made to the human intake by inhalation	U	M	L	Deficiencies caused by neglecting significant exposure pathways as well as the effect of population behavioural patterns	Same
application of toxicological data	U	L	M	uncertainties due to the extrapolation of dose response functions from animals to humans and from large to small doses, experimental conditions in toxicological studies that do not resemble actual conditions of human exposure to pollutants, etc	Same
Potential exposure misclassification - grid resolution	U/O	L	L		Modelling on a fine (250m) grid with postcode point locations used to assign exposures. Some postcode areas in rural areas are likely greater than 250x250m.
Exposure misclassification - definition	O	H	H		Definition of exposed and non-exposed groups for pesticide attributable burden calculations (absence of valid ERFs)
ERFs for PM	U	L	L	Average measures of PM concentrations Extrapolation from different population and from different source (i.e. mainly traffic related)	Same

Endotoxin ERFs	U	L	L	Small size population Different climatic conditions and animal husbandry practices Exposure to early life Occupational exposure	Same
Intake rates	U	H	L	No adequate data to establish individual exposure profile; intake fraction is assumed to be constant between people	Same
Population data disaggregated from LAU-2 level to 4x4km grid	O	L	L	Population data are redistributed to a 4x4km grid using mask areal weighting method which generates parameter uncertainty	
Future population projections for the scenarios	O	L	L	Based on ESYE estimates we took the median scenario, country average stratified by age and gender	Linear model to apply county trend-based projections, with assumptions about births, deaths and migration from ONS
Uniform distribution of population in a grid cell	O	L	L	Simplification made for the needs of the 4x4km grid	
Estimation of farmers at the 4x4km grid	U	L	L	Simplification made, estimated via area weighting from prefecture data at 4x4km grid	
Risk estimates based on intake rates: pesticides	U	M	L	Based on calculation from intake rates and dose response: there is an identified variability	Same; limited slope factors were available
Attributable health impact from PM and pesticides	O	L	L	Variability in calculations of concentration and estimates of relative risk	exposure misclassification due to lack of valid ERFs
Background rates of disease	U/O	L	L		Use of national rates instead of regional for some health outcomes

5. Discussion

England Case study

When looking at changes in crops due to the low and high emission scenarios, neither study area stood out as having greater change (42.2, northwest England maps also examined but not included here). Given that the exposures were typically higher in East Anglia, the finding of a greater number cancer cases attributable to land use change in the northwest begs questioning. In fact, both the RIF-based analysis and that using hypothetical RR showed a greater excess in the northwest after differencing the BAU from the scenario. The full RIF risk analysis results in Table 5, however, show a more complete picture. When focusing on the scenarios themselves (B2020 and H2020), the number of attributable cases is in fact greater in East Anglia compared to the Northwest.

In both analyses the exposure categories were similarly defined, based on the distribution of combined population in both study areas. The larger increase in cases in the Northwest simply relates to the fact that greater population is changing between exposure categories e.g., people are moving from lower categories in the BAU to higher categories in the change scenarios. The exposure distribution for both areas is given in Figure 22 below.

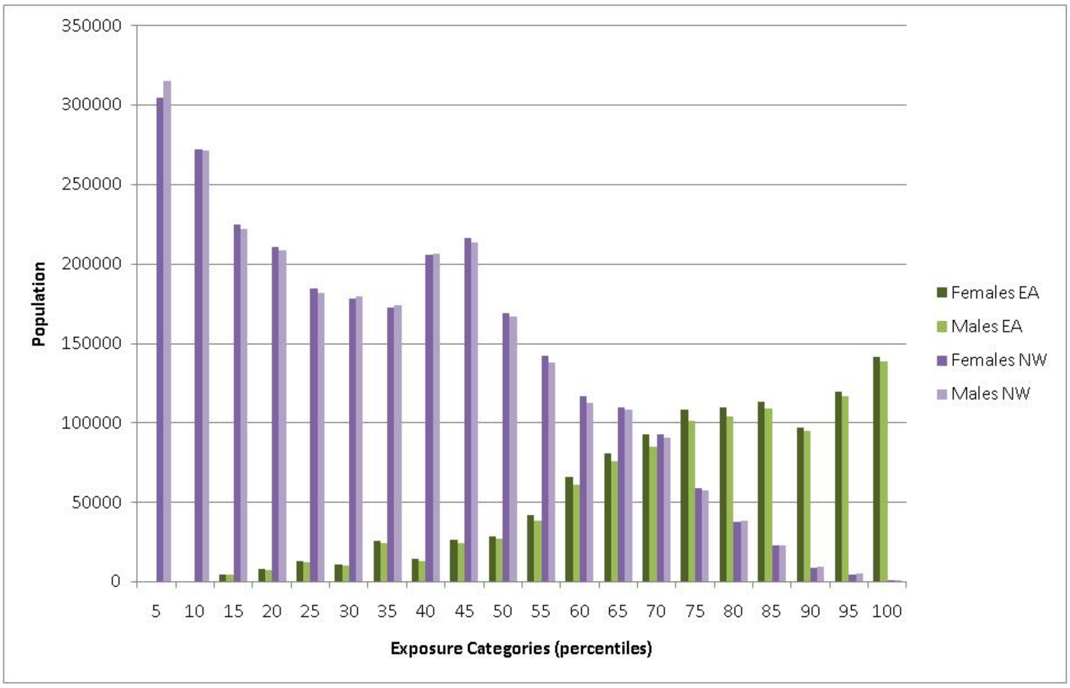


Figure 22. Exposure distribution (population in 2031): Percentiles of total pesticides from 250x250m grid

The more sensible result is probably Run 2 (Table 5) in which no risk was assumed for lowest categories rather than using the non-significant RRs in the calculation of impact. This does not affect the East Anglia result, but has a large impact on the northwest England results. While the scenarios themselves (B2020 and H2020) show greater excess cases compared to Run 1, the difference due to the land use change is reduced in the northwest. The burden in the northwest England due to land use change is an estimated 5 and 9 cases of breast and prostate cancer, respectively. For East Anglia, the attributable burden is 2 breast cancer and 3 prostate cancer cases per year. Excess risk was in areas with total pesticide concentrations exceeding 3.6 and 0.04 ng/m^3 for breast and prostate cancer, respectively.

This analysis with the hypothetical RR clearly shows that the use of non-specific RRs from the literature must be with care, especially when the RRs derive from studies with fundamentally different design or populations. As mentioned in section 3.3.1, many of the epidemiological studies referenced here related to exposure to specific active substances, perhaps now banned in the EU, most often in occupational settings. Furthermore, the majority of studies examined ever-never exposure (or binary exposed-unexposed) exposures rather than categories of exposure. None involved exposure modelling as has been done here. Supported by the sensitivity analysis, the results of this analysis are disregarded.

The RIF risk analysis was performed using the 250x250m exposure grids, however the derived RRs were applied at ward level for which population weighted exposures were computed. This was not considered problematic because the distribution of cases in the RIF risk analysis (12, 71 and 17% cases in the low, medium and high categories) was found to generally reflect the combined population within each category for the population weighted ward exposures.

The results of the toxicological risk analysis (section 4.1.1) for the six carcinogenic herbicides found an attributable burden of approximately 1 case of cancer per year in each study area, though a slightly higher excess in East Anglia reflecting the more general higher pesticide usage in that area. It is expected that this is an underestimate of the true risks due to land use change because we only look at a small fraction of the pesticides used in these study areas. If a full database of slope factors were available the advantage of the toxicological approach would be in focusing on the ASs known to have cacogenic risk.

That pesticides were aggregated in the geographical risk analysis complicates interpretation of the results. The number of ASs comprised: 57 herbicides, 20 insecticides, and 45 fungicides having different properties and toxicology. A better approach may be to couple the toxicological and geographical risk analysis approaches. For example by incorporating a toxicological index to give greater weight to the ASs know to have greater toxicity or carcinogenicity (Brown 2007), then derive appropriate RRs from groups of ASs using a RIF risk analysis.

As in the transport case study, we looked at population weighted PM exposures over larger areas (i.e. counties) rather than at ward level. The results indicated a very slight increase (0.5 per year for PM_{10}) in mortality due to the land use change across both study areas. Given that ERFs from traffic-related air pollution studies were used, where exposures would be expected to be higher, the attributable burden due to agricultural related PM is likely an over estimate. Modelled NH_3 and endotoxin exposures were also low, thus it is expected potential health risks or benefits for those would have been slight. This could be confirmed with a well designed RIF risk analysis.

One final important element of this assessment is the evaluation of the models used in estimating pollutant concentrations. Without monitored data to calibrate or validate the models, a quantitative assessment is not possible. The kernels used in the Focal Sum model, however, are based on existing, well tested models that simulate the dispersion processes (i.e. ADMS). In the Greek case study, a comparison between the Focal Sum and box model was also undertaken further showing that the two methods to be comparable.

Greek Case study

In the Greek case study, the effect of climate change on the agriculture practices is considered: based on the ATEAM output, the two climatic scenarios considered, the Business as Usual and the Mitigation, are used to determine the changes in arable land (at a lesser extent on pasture land) and furthermore on crops. First, baseline data are enhanced with the crop typology from the national statistics database (ESYE, 2001), and then future trends on crops are estimated (crop database). In addition, it was investigated the effect of agricultural policies to health impact, listed next: a) integration of CAP provisions to crops database, considering future climatic conditions and historic trends and b) allocation of arable land to energy crops, based on the ATEAM model output, according to the energy needs from bio-energy and bio-fuels in the domestic energy production mix.

The main pollutants considered as a result of agricultural practices are *pesticides* applied to crops, emitted *particulate matter*, *endotoxins* from animals and *pollen grains*. Both the quantity and quality of data on pesticides, from the ESYE (data at country level), was unsatisfactory for this study; therefore, a pesticide databases was created for the study regions. Through an extensive survey for collection of pesticide data, in the regions of interest, with the assistance of experts, sales data per active substance were combined with the corresponding application dosages, in order to calculate the intensity of use. A novel stochastic spatial allocation model was used to determine probabilistic estimates of pesticide usage rates per grid cell, thereby determining confidence intervals.

Emission from all pollutants based on suitable factors per AS and for the PM and endotoxins were used to determine their concentration per grid cell using atmospheric dispersion models (CALPUFF) together with an advanced numerical method (focal-sum) and a simplified box-volume model. Since a comparison between the two has shown no significant differences with regard to concentration maxima, for simplicity only the box volume model is employed throughout the assessment.

The exposure assessment, based only on the air pathway, was different for each pollutant considered: For the pesticides, a toxicological approach was employed based on AS with known toxicity and available dose-response functions (slope factor); an estimate of risk per grid cell was determined only for the farmers. For the particulate matter, the health impact on the general population was based on the available ERFs that directly relate to exposure.

Results show that the effect of cultivating energy crops on health impact is very small, since the total pesticides quantity used in comparison to that for edible crop is very small. In addition, the impact from pesticides applied to edible crops is also small; indeed, the risk estimates (for each scenario considered) are below the 10^{-6} value, commonly taken as an indicator for significant risk to human health. Furthermore, comparisons between scenarios (BAU – Mitigation) show also very small differences; based on results involving 20 carcinogenic active substances, the difference in the number of cases attributed to cancer is estimated to be 2E-5 and 1E-5, for the years 2020 and 2050, respectively. These small differences are in line with the estimated small concentration in air (maximum at 2.2 ng/m^3) and the concomitant very low risk (close to 3E-8).

For the particulates (PM10), the differences between the BAU and the mitigation scenarios with respect to various health effects are also very small. For example, change in the number of cases for the cardiovascular illness are 4.6E-2 (year 2020) and 8E-2 (year 2050). Similarly, for the cardiovascular illnesses, the difference in cases is 1.8E-2 (year 2020) and 3E-2 (year 2050).

Health impact assessment from pollen grains and endotoxins are not calculated due to the lack of suitable exposure response functions.

The estimated small health impact from all stressors, under the assumption employed herein, may be partly due to the pathway of exposure considered, i.e. the inhalation route. A qualitative assessment of the key factors influencing the health impact assessment can explain why the estimated impact indicator values are small. For example, the relatively small changes in area of the cultivated crops, and the concomitant small variations in the AS usage rates have an almost negligible effect on health impact. Furthermore, it is confirmed that very significant influences are due to the duration of exposure, the person’s body weight and the number of people exposed. Sensitivity analysis of these parameters has shown that change in the number of people exposed, greatly effect health impact. Lastly, it should be noted that the scale of the analysis (i.e. the 4x4km grid) does not appear to influence the health impact.

6. Conclusions

England Case study

Spatial methods were used to model and explore the health impacts of agricultural land use change in two areas of England. Only a slight increase in mortality due to particulates was detected (0.5 per year for PM_{10}) due to the land use change across East Anglia and the northwest England combined. Particulate ERFs from traffic-related studies were used for this county-level analysis. Several approaches were explored for modelling impacts of pesticides including a toxicological approach focusing on individual active substances known to be carcinogenic, and an epidemiological approach using the Rapid Inquire Facility (RIF) to derive RRs based on real population and cancer data held at SAHSU, Imperial College. No risk above the national average was detected for non-Hodgkin’s lymphoma, leukemia, brain, or kidney cancer in adults. Risk was detected, however, for breast and prostate cancer. Calculated at ward-level the attributable burden due to land use change gave an estimated 5 and 9 cases of breast and prostate cancer, respectively in the northwest, and 2 breast cancer and 3 prostate cancer cases per year in East

Anglia. Although exposures were generally lower in the northwest, the marginally larger increase in attributable cases occurred as a result of a greater proportion of the population shifting between exposure categories. The epidemiological risk analysis using RIF shows promise and in future work could be used to derive more appropriate RRs for exposures and health outcomes of interest, e.g. respiratory endpoints.

Greek Case study

In both the agricultural case studies, it was demonstrated, how a full chain health impact assessment can be integrated from source to impact, including various stressors. For the Greek case study, CAP provisions were considered in the scenarios, leading to changes in crop types cultivated. Under the conditions of the present study, results show that the health impact due to pesticide application and PM dispersion is small, with even smaller change between scenarios. The cultivation of energy crops and its cumulative health impact from both stressors (pesticide application and PM dispersion), is also small certainly related to the small emission rates. Unfortunately, the health impact from both pollen and endotoxins were not dealt with due to the lack of information on suitable ERFs; however, their effect on human health should be also considered small.

From all the stressors involved in this study, pesticides are considered to be the most significant, with regard to potential impact. Therefore, future impact assessment studies should consider several factors which are not fully addressed in the present study; e.g. inclusion of AS physical properties to emission and dispersion, population behavioural patterns to pesticide exposure, use of advanced pharmacokinetic models to determine individual's intake fraction and suitable exposure response functions.

Concluding remarks

The integrated health impact assessment due to agricultural land use changes has provided very useful insights at both the methodological and the practical level; it is noted, however, that under the assumptions made in the case studies, the calculated health impact due to agricultural activities appears to be small, in general. Moreover, a qualitative assessment of the results in conjunction with the main factors involved, indicates some interesting trends. In particular, foreseen changes in crop cultivation patterns (concerning both edible and energy crops), as a result of policies (for adaptation to, or mitigation of, climate changes), appear to have a small impact on human health; a similar effect is indicated for foreseen changes in animal husbandry. Additionally, these case studies clearly suggest topics that need to be addressed in future studies, notably patterns and duration of human exposure to agriculture-related pollutants and suitable dose response functions of all pollutants involved.

7. Glossary

Term	Definition	Ref
active ingredient	In any pesticide product, the component that kills, or otherwise controls, target pests. Pesticides are regulated primarily on the basis of active ingredients.	1
aerosol	A suspension in a gaseous medium of solid particles, liquid particles or solid and liquid particles having a negligible falling velocity.	3
agricultural pollution	Farming wastes, including runoff and leaching of pesticides and fertilizers; erosion and dust from plowing; improper disposal of animal manure and carcasses; crop residues, and debris.	1
air pollutant	Any substance in air that could, in high enough concentration, harm man, other animals, vegetation, or material. Pollutants may include almost any natural or artificial composition of airborne matter capable of being airborne. They may be in the form of solid particles, liquid droplets, gases, or in combination thereof. Generally, they fall into two main groups: (1) those emitted directly from identifiable sources and (2) those produced in the air by interaction between two or more primary pollutants, or by reaction with normal atmospheric constituents, with or without photoactivation.	1
allergen	A substance that causes an allergic reaction in individuals sensitive to it.	1

animal studies	In the context of health impacts, animal studies are generally those in which health outcomes have been associated or quantified with exposures using "animal models", as opposed to "human models" in epidemiological studies.	
attributable burden	Number of people in a certain health state as a result of exposure to the (environmental) factor that is being analyzed, not corrected for co-morbidity.	
bioaerosol	Micro-organisms suspended in the air.	3
carcinogen	Any substance that can cause or aggravate cancer.	1
climate change	A change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer. Climate change may be due to natural internal processes or external forcings, or to persistent anthropogenic changes in the composition of the atmosphere or in land use	2
concentratio n	The relative amount of a substance mixed with another substance. An example is five ppm of carbon monoxide in air or 1 mg/l of iron in water.	1
contaminant	Any physical, chemical, biological, or radiological substance or matter that has an adverse effect on air, water, or soil.	1
dose-response function	The quantitative relationship between the amount of exposure to a substance and the extent of toxic injury or disease produced.	1
emission	Pollution discharged into the atmosphere from smokestacks, other vents, and surface areas of commercial or industrial facilities; from residential chimneys; and from motor vehicle, locomotive, or aircraft exhausts.	1
emission factor	The relationship between the amount of pollution produced and the amount of raw material processed. For example, an emission factor for a blast furnace making iron would be the number of pounds of particulates per ton of raw materials.	1
endotoxin	Toxin present in the cell walls of bacteria that is released after the bacteria has died. May cause chills, fever, leukopenia, and shock depending on the bacterial species and the health of the infected person	4
exposure	Exposure to a chemical is the contact of that chemical with the outer boundary of the human body including the skin and openings of the body such as the mouth, nostrils, and punctures and lesions in the skin.	3
exposure pathway	The path from sources of pollutants via, soil, water, or food to man and other species or settings.	1
exposure-response	A factor (coefficient) representing the relationship between the amount of a chemical at the absorptive surfaces of an organism and a specific adverse effect, or the incidence of an adverse effect.	3
impact	A measure of the effect of an activity, object or exposure upon a receptor.	3
local administrati ve unit	The finest resolution at which most EU countries record statistical information. LAU1 are equivalent to districts, while LAU2 are communes, wards, or municipalities	5
pesticide	Substances or mixture there of intended for preventing, destroying, repelling, or mitigating any pest. Also, any substance or mixture intended for use as a plant regulator, defoliant, or desiccant.	1
pollen	The fertilizing element of flowering plants; background air pollutant.	1
pollutant	Generally, any substance introduced into the environment that adversely affects the usefulness of a resource or the health of humans, animals, or ecosystems.	1
reference dose	The RfD is a numerical estimate of a daily oral exposure to the human population, including sensitive subgroups such as children, that is not likely to cause harmful effects during a lifetime. RfDs are generally used for health effects that are thought to have a threshold or low dose limit for producing effects.	1
risk	The likelihood that a hazard will actually cause harm.	3

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Annexes
Annex 1. Issue Framing

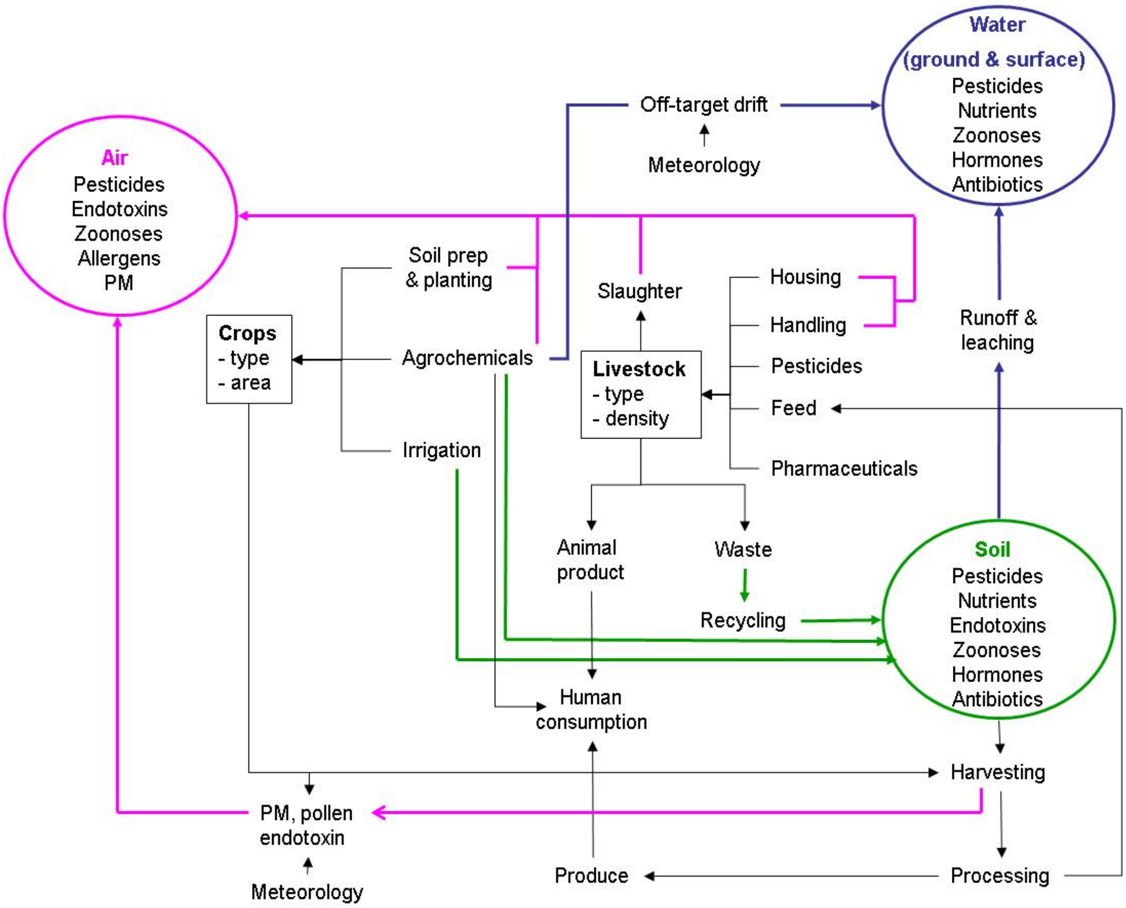

Figure 1. Agricultural system showing releases to environmental media

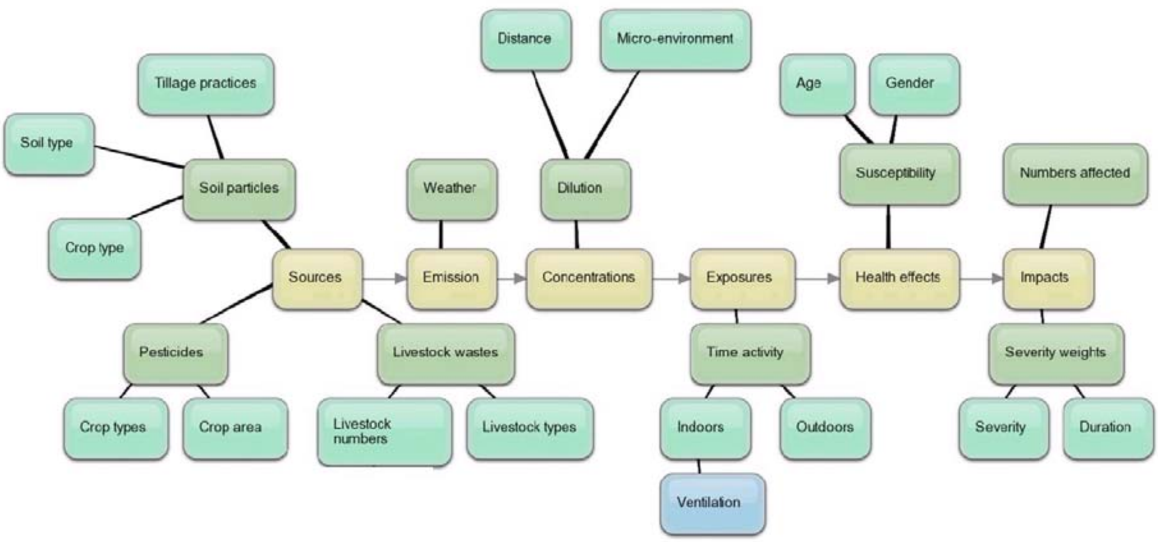

Figure 2. Mindmap exploring scope of issues related to agriculture

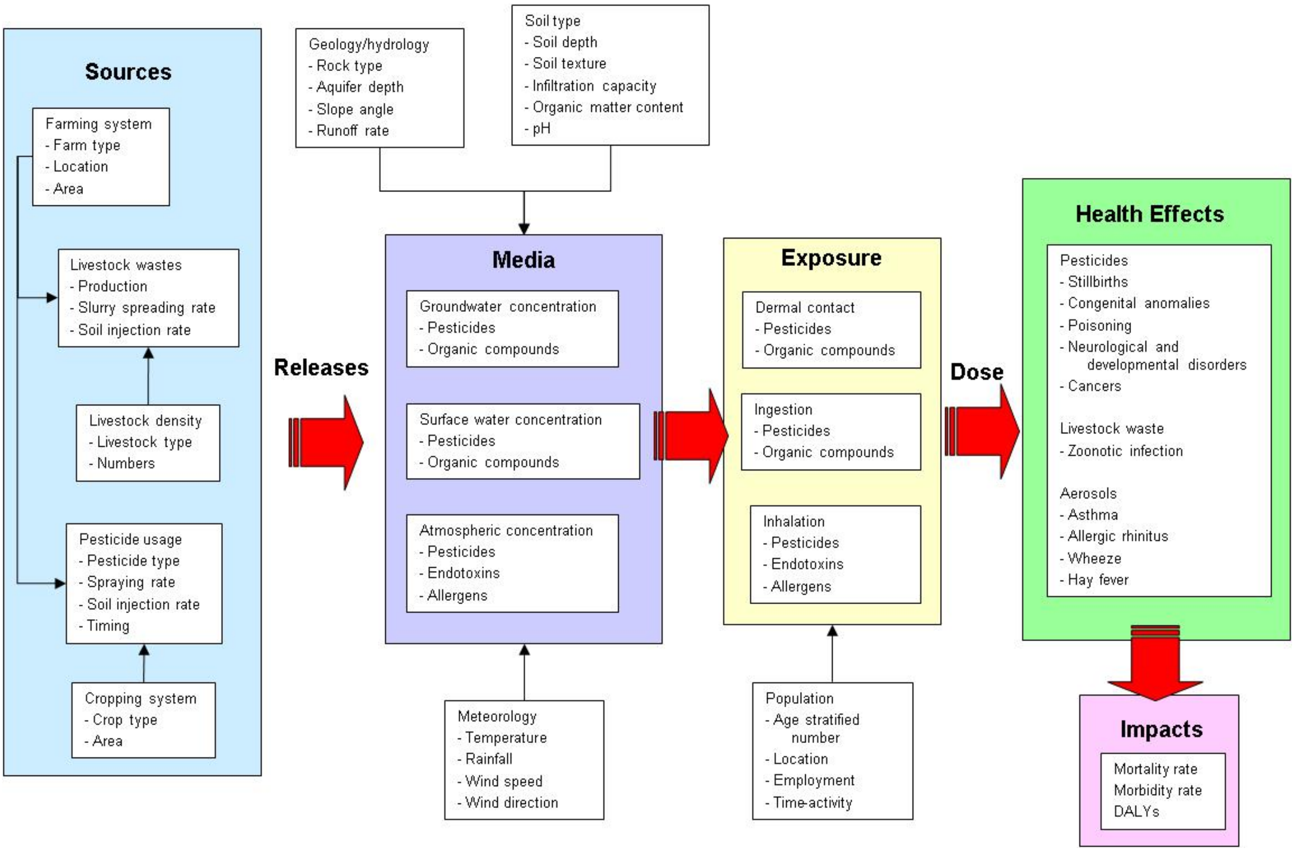

Figure 3. Systems diagram for agriculture – source to health effects

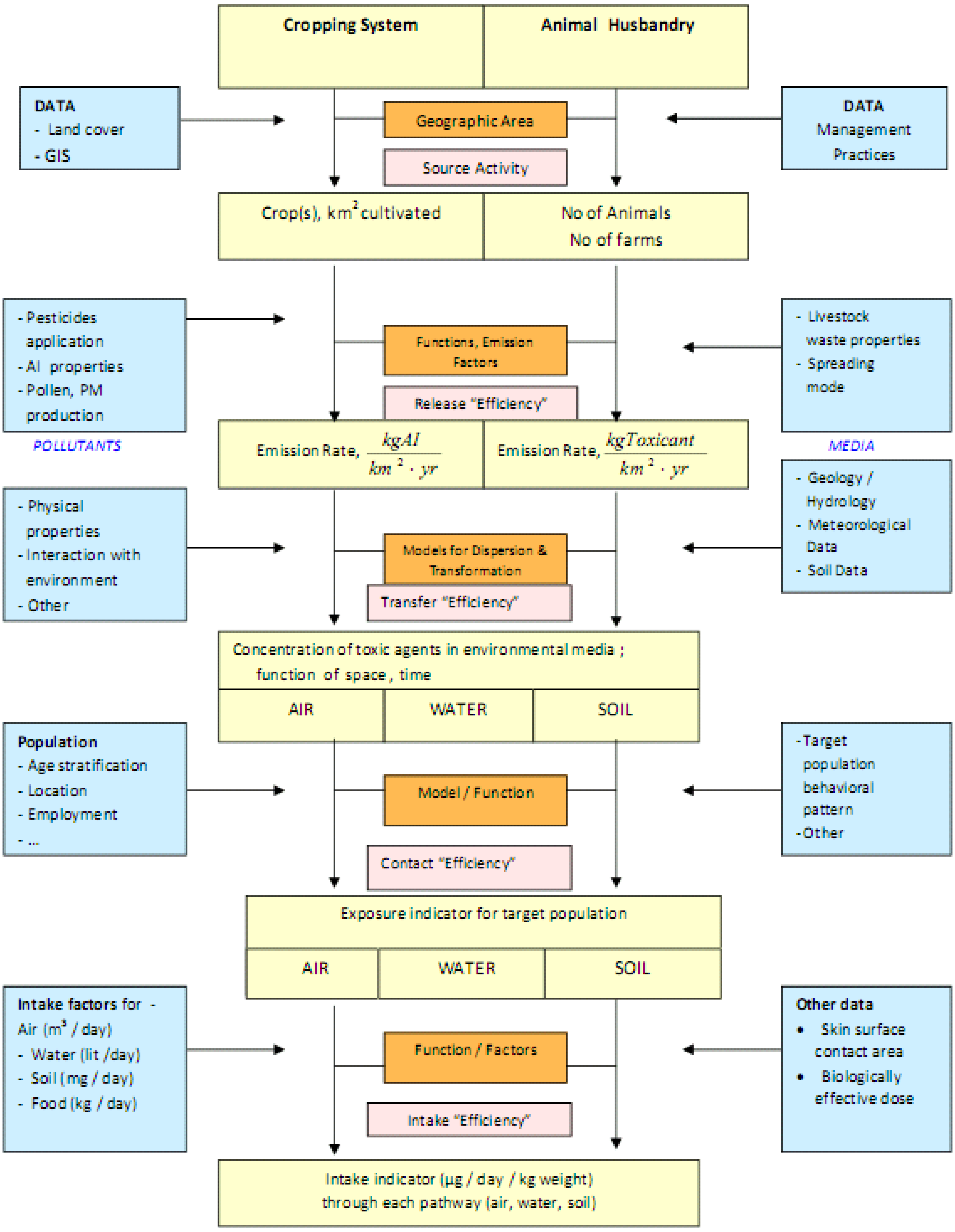

Figure 4. Systems diagram for agriculture – source to intake

Table 1. Potential stakeholders

Type/role	**Examples**	**Interest/role**
Farmers and their agents	Land owners, farm workers, unions, farmers' associations	Victims of exposure; risk management and reduction; potential victims/beneficiaries of risk response (e.g. loss of income)
Agricultural suppliers and services	Seed suppliers, pesticide manufacturers, fertiliser manufacturers, transport companies	Risk management and reduction; potential victims/beneficiaries of risk response
Food distributors and processors	Food wholesalers and retailers, transport companies	Potential victims/beneficiaries of risk response
National/regional health protection agencies	Public health institutions, food standards agencies, occupational health and safety agencies, local/regional health boards and environmental health departments	Risk management and regulation; risk communication
National/regional environmental protection agencies	Ministries of environment, environmental regulatory agencies, local authorities	Risk management and regulation
European and international agencies	European Commission (Directorates for Agriculture, Environment, Health); WHO, FAO	Risk management and regulation; risk communication
NGOs	Pesticide action groups, organic farming groups, animal welfare groups	Risk communication; representatives of victims of exposure; lobbyists for action
Others	1) Rural residents; 2) National and local media ; 3) Scientists (epidemiologists, toxicologists, environmental scientists)	1) Victims of exposure; 2) risk communication; 3) risk analysis, risk communication, potential beneficiaries of risk response

Annex 2. Emission Factors

Emission factors for PM10, PM2.5, (provided by IER Stuttgart, S.Wagner)

Table 1. Emission factors for PM for the year 2000 (IIASA)[1].

Table 1.a. From crops

	Greece				GB	
	PM10	PM10	PM10	PM2.5[2]	PM10	PM2.5
	land preparation	harvest	total		total	
Crop types	kg/ha/a	kg/ha/a	kg/ha/a	kg/ha/a	kg/ha/a	kg/ha/a
Barley	4.15	1.95	6.10	1.35	6.945	1.136
Cotton irrigated	4.43	3.78	8.21	1.82	.	.
Cherry trees	0.08	0.09	0.17	0.04	.	.
Fallow land	1.35	0.00	1.35	0.30	.	.
Fodder crops	4.48	0.00	4.48	1.00	3.192	0.240
Fruits	.	.	.	.	0.000	0.000
Maize irrigated	5.25	1.88	7.13	1.58	.	.
Maize non-irrigated	.	.	.	.	2.820	0.220
Oat	4.15	2.60	6.75	1.50	9.145	1.624
Oilseed	.	.	.	.	6.945	1.136
Olive groves	0.08	0.09	0.17	0.04	.	.
Other cereals	4.15	1.23	5.38	1.19	6.945	1.136
Pastures	0.00	0.00	0.00	0.00	0.000	0.000
Potatoes	25.56	1.91	27.46	6.10	2.870	0.231
Pomefruits	0.08	0.09	0.17	0.04	.	.
Pulses	.	.	.	.	6.945	1.136
Rice	22.42	1.88	24.30	5.39	.	.
Rough grazing					0.000	0.000
Rye	4.15	1.23	5.38	1.19	.	.
Soya	8.63	1.88	10.51	2.33	.	.
Stonefruits	0.08	0.09	0.17	0.04	.	.
Sugarbeets	25.56	1.88	27.44	6.09	2.820	0.220
Vegetables	.	.	.	.	2.820	0.220

	Greece				GB	
	PM10	PM10	PM10	PM2.5[2]	PM10	PM2.5
	land preparation	harvest	total		total	
Crop types	kg/ha/a	kg/ha/a	kg/ha/a	kg/ha/a	kg/ha/a	kg/ha/a
Vineyards	1.68	0.19	1.87	0.42	.	.
Wheat	4.15	2.25	6.40	1.42	9.480	1.698

[1]IIASA: GAINS model, http://www.iiasa.ac.at/web-apps/apd/gains/EU/index.login?logout=1

[2]There are no PM2.5 emission factors differentiating between land operations and harvesting.

Table 1.b. From animals (Hinz, 2007)[1]

	Greece		GB	
	PM10	PM2.5	PM10	PM2.5
Animal types	kg/head	kg/head	kg/head	kg/head
Beef	0.236	0.053	0.216	0.048
Cows	0.217	0.048	0.216	0.048
Horses	0	0	0	0
Laying hens	0.047	0.011	0.047	0.011
Other poultry	0.047	0.011	0.047	0.011
Pigs	0.438	0.078	0.423	0.075
Sheep, goats	0	0	0	0

[1]Hinz, Torsten; van der Hoek, Klaas: Particle Emissions from Plant Production. Presentation at the TFEIP meeting. Dublin, October 2007.

Table 2. Emission factors for NH_3 from animals for year 2000 (IIASA)[1].

	Greece	GB
	NH_3	NH_3
Animal types	kg/head	kg/head
Beef	12.06	8.833
Cows	18.10	30.320
Horses	8.05	12.750
Laying hens	0.36	0.459
Other poultry	0.30	0.168
Sheep, goats	0.88	0.499
Pigs	5.10	5.957

[1]IIASA: GAINS model, http://www.iiasa.ac.at/web-apps/apd/gains/EU/index.login?logout=1

Table 3. NH_3 emission factors from fertiliser use for year 2000 (IIASA)[1].

	Greece	GB
	kg NH_3/kg N	**kg NH_3/kg N**
Mineral fertiliser use	0.05	0.032
NH_3 from biological N fixation (legumes)	0.01	0.01

[1]IIASA: GAINS model, http://www.iiasa.ac.at/web-apps/apd/gains/EU/index.login?logout=1

To estimate NH_3 emissions from mineral fertiliser use, the N application rate must be available.

Table 4. Average mineral N application rates (from fertilizers) for various crops (FertiStat, IFA)[1].

	Greece	**GB**
Crops	**kg/ha**	**kg/ha**
Barley	75	118
Cotton	75	.
Fodder	43.4	103.7
Fruits	57	50
Maize	190	150
Oat		118
Oilseed		185
Olive groves	200	.
Other cereals	85	100
Pastures[2]	50	95
Potatoes	200	155
Pulses[2]		250
Rice	100	.
Rough grazing[2]		20
Soya	200	.
Sugarbeets	140	100
Vegetables		125
Vineyards	60	.
Wheat	70	183

[1]FAO Fertilizer Use Statistics.
http://www.fao.org/ag/agl/fertistat/fst_fubc_en.asp

[2]Biological N fixation.

Emission Factors for endotoxins

Table 5. Estimates of endotoxin emission factors for inhalable and respirable dust (Seedorf et al., 2004)[1].

	Housing period per year[2]	Inhalable endotoxin emissions		Respirable endotoxin emissions	
Animal types	**d/a**	**µg/a*LU[3]**	**µg/a*animal**	**µg/a*LU[3]**	**µg/a*animal**
Dairy cows	365	7683	7683	201	201
Beef	365	18238	12767	657	460
Calves	351	34437	10331	1856	557
Sows	365	36932	11080	19771	5931
Weaners	320	36838	1474	8891	356
Fattening pigs	347	24198	3872	3899	624
Laying hens	365	49266	197	2278	9
Broilers	256	546638	2187	122834	491

[1]Seedorf, J., An emission inventory of livestock-related bioaerosols for Lower Saxony, Germany. Atmospheric Environment 38 (2004) 6565–6581.

[2]country-specific production periods can be considered

[3]LU: Livestock Unit

Emission factors for pollen

Example for maize

Maize (Zea mays) is a cereal grain and belongs to the Poaceae family. The number of plants per square kilometer ranges from 65 $*10^5$ to $70*10^5$ (oral comm. Jan 2008). Maize pollen grains are spheroidal to avoidal and quite large in size, 93-107 µm in diameter (www.polleninfo.org). According to literature, an average-sized plant can produce 25 million pollen grains per year [average estimated from data in (Paterniani et al. 1974), (Emberlin et al. 1999)]. Using those data as input to the above equation and making the assumption that 50% of maize pollen production is shed, an EF of **$8.1*10^{13}$** pollen grains per km^2 is calculated. For maize, the period of pollen shedding is considered one month; in July, for S. Europe (oral comm. Jan 2010).

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Annex 3. Exposure Response Functions for endotoxins

Emissions from animal husbandry include a variety of biological, microbial and inorganic particulates. Exposure to bioaerosols (endotoxins, bacteria, fungi, parasites, pollen etc) can have adverse health effects. However, according to several studies, exposure to endotoxins may have also protective effect to humans and especially to children (Braun-Fahrlander et al., 2002; Downs et al., 2001; von Ehrenstein et al., 2000; Rennie et al., 2008). A strong inverse relationship has been found between endotoxins and sensitization to common allergens, atopic diseases in adult farmers and school-age children (Portengen et al., 2005; Braun-Fahrlander et al., 2002).

Table 1. Endotoxins exposure response functions for asthma, wheeze, hay fever, and atopic sensitization (Braun-Fahrlander et al., 2002).

HEALTH OUTCOME	TOTAL SAMPLE (N=812)				CHILDREN FROM NONFARMING HOUSEHOLDS (N=493)			
	ENDOTOXIN LEVEL		ENDOTOXIN LOAD		ENDOTOXIN LEVEL		ENDOTOXIN LOAD	
				Adjusted odds ratio (95% CI)*				
Hay fever	0.58	(0.39-0.85)	0.53	(0.35-0.81)	0.79	(0.52-1.19)	0.56	(0.33-0.95)
Sneezing and itchy eyes during previous yr	0.61	(0.43-0.86)	0.5	(0.34-0.72)	0.7	(0.47-1.05)	0.46	(0.28-0.76)
Atopic sensitization	0.78	(0.60-1.01)	0.76	(0.58-0.98)	0.8	(0.59-1.08)	0.73	(0.51-1.04)
Atopic asthma	0.73	(0.44-1.19)	0.48	(0.28-0.81)	0.68	(0.39-1.19)	0.52	(0.25-1.07)
Nonatopic asthma	1.25	(0.62-2.51)	1.13	(0.57-2.26)	1.29	(0.62-2.68)	1	(0.46-2.21)
Atopic wheeze	0.89	(0.57-1.39)	0.62	(0.39-0.99)	0.79	(0.46-1.33)	0.64	(0.33-1.25)
Nonatopic wheeze	0.97	(0.58-1.61)	1.14	(0.68-1.90)	1.36	(0.86-2.14)	1.82	(1.04-3.18)

Table 2. Endotoxins exposure response functions of endotoxins for hay fever and asthma (von Ehrenstein et al., 2000).

Health outcome	Farming				Part-time farming activity				Full-time farming activity			
	(N=1181)				(N=731)				(N=450)			
	Crude OR		Adjusted* OR		Crude OR		Adjusted* OR		Crude OR		Adjusted* OR	
		(95% CI)		(95% CI)		(95% CI)		(95% CI)		(95% CI)		(95% CI)
Doctor's diagnosis of hay fever	0.35	(0.23-0.55)	0.52	(0.28-0.99)	0.41	(0.24-0.69)	0.63	(0.31-1.29)	0.26	(0.12-0.59)	0.31	(0.10-1.03)
Runny nose and itchy eyes in the past 12 months	0.53	(0.37-0.75)	0.89	(0.54-1.47)	0.58	(0.38-0.89)	0.98	(0.56-1.74)	0.45	(0.24-0.82)	0.7	(0.31-1.58)
Doctor's diagnosis of asthma	0.51	(0.37-0.71)	0.65	(0.39-1.09)	0.56	(0.37-0.83)	0.8	(0.45-1.40)	0.45	(0.26-0.78)	0.38	(0.15-0.97)
Wheeze in the past 12 months	0.67	(0.52-0.87)	0.55	(0.36-0.86)	0.65	(0.47-0.91)	0.49	(0.27-0.86)	0.71	(0.47-1.06)	0.66	(0.36-1.23)
Doctor's diagnosis of eczema	0.87	(0.73-1.04)	1.09	(0.82-1.44)	0.9	(0.72-1.12)	1.09	(0.78-1.52)	0.82	(0.62-1.09)	1.09	(0.72-1.65)
Itchy rash in the past 12 months	0.83	(0.64-1.07)	1.04	(0.7-1.54)	0.78	(0.56-1.09)	0.97	(0.61-1.56)	0.9	(0.61-1.33)	1.13	(0.64-2.00)

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Annex 4. England Case Study

4.1 Scenario Development

A 5x5km land use database was created for scenarios including: 2000 JAR baseline, 2020 business as usual (BAU), and two 2020 land use change scenarios.

Construction of the scenarios is illustrated in Figure 1. The top part of the figure shows how the baseline was calculated, and the middle illustrates how the future scenarios were derived from the baseline. In addition, county pesticide usage (kg) from the FERA Pesticide Usage Survey was subsequently disaggregated to incorporate crop-specific amount of active ingredient (AI) for each 5x5km into the database. The procedure for pesticide disaggregation is shown with a flow diagram in Figure 2, while a mapped example in given in Figure 3.

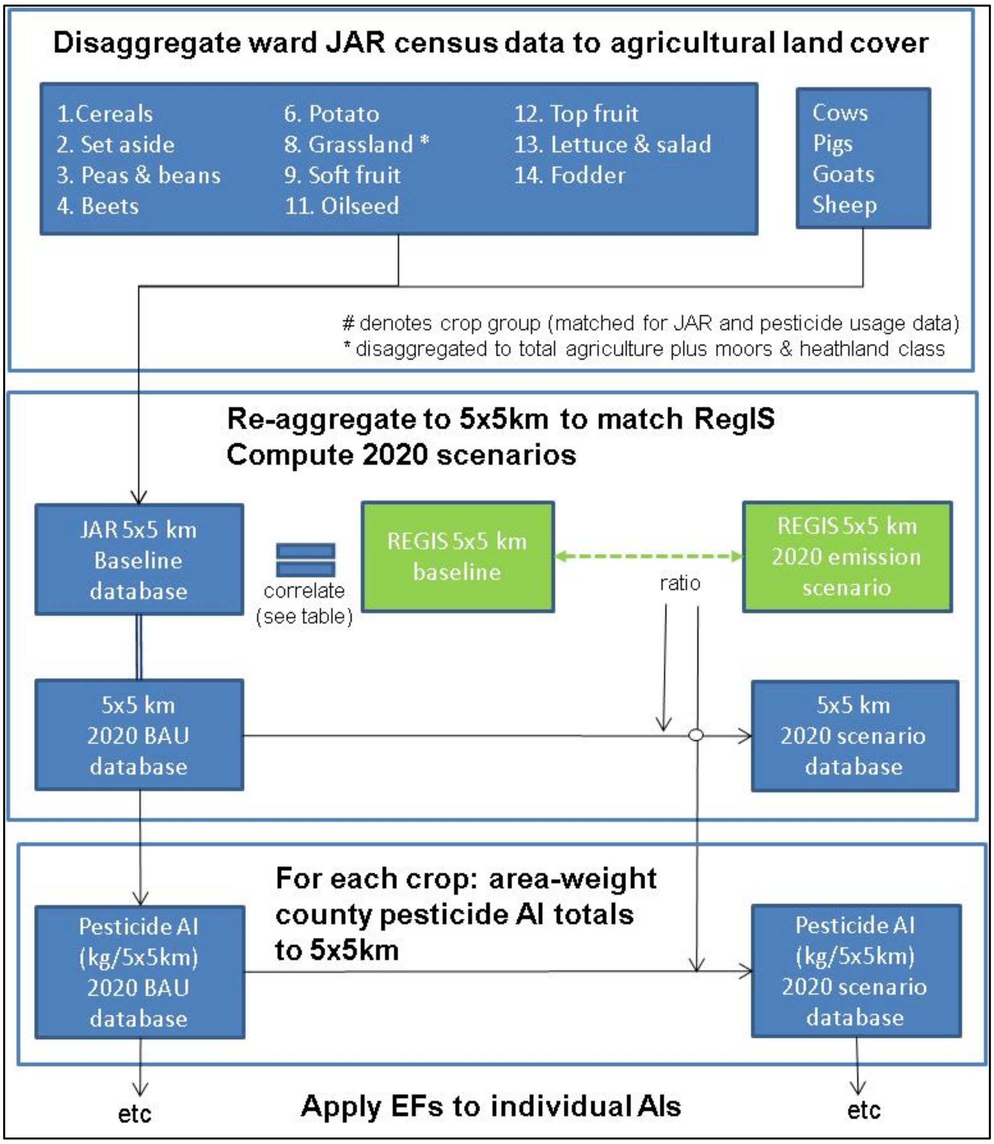


Figure 1. Modelling agricultural land use and pesticides for baseline and scenarios

Baseline (JAR 2000)

The 2000 JAR Baseline derived from actual data for the year ca. 2000 on land cover, agricultural land use surveys and pesticides statistics. Crops and livestock from June Agricultural Returns (JAR 2000) were disaggregated to 5x5km using CORINE land cover 2000. To identify the most suitable land cover classes by which to perform disaggregation (and ensure no loss of JAR data to "no-data" areas), ward-level correlations between JAR and agricultural land cover were computed with various aggregations of rural agricultural land cover classes. Crop correlations were 0.36–0.91 and 0.02-0.96 while livestock correlations ranged from 0.38-0.61 and 0.41-0.93 for East Anglia and the northwest, respectively. Based on these results, all crops and livestock were disaggregated on basis of 'total agriculture', except in the Northwest where moors and healthland was also included for disaggregating JAR grassland and sheep.

Future scenarios (2020)

Future agricultural land use projections derived from RegIS, with predictions for rural land use and cropping under low and high emission scenarios for the year 2020 used here.

RegIS also contains a baseline representative of the years 1961-1990, not to be confused with the JAR baseline (i.e. real data). This RegIS baseline was needed only to inform construction a spatial database of future land use. For each crop (y), future land use under different emission scenarios (LUC 2020) were derived from the JAR baseline using the ratio between the 'RegIS baseline' and 'RegIS 2020 emission scenario' at each 5x5km grid cell:

$$LUC_{2020}y = JAR_{2000}y * (RegIS_{2020}\ \text{scenario} / RegIS\ \text{baseline})$$

It should be noted that the crop categories in RegIS did not directly correspond to those in the JAR. Linear regression was thus first used to establish the best relationship between each JAR crop (independent variable) and the available RegIS baseline crops (Table 1).

After establishing the 2020 LUC scenario maps for crops (y), estimated livestock (z) numbers for the future scenarios were computed as the product of change in area of the single most important crop (Table 1 correlations) and actual livestock count in the JAR baseline:

$$LUC_{2020}z = JAR_{2000}z * (LUC_{2020}y / JAR_{2000}y)$$

For both crops and livestock, the 2020 BAU is a linear projection of the 2000 JAR baseline with no change in slope.

Table 1. RegIS variables used in deriving crop-specific ratios to compute LUC Scenarios

JAR crops	East Anglia		Northwest	
	REGIS crops	**r**	**REGIS crops**	**r**
1. Cereals	Winter wheat, summer and winter barley	0.58	Summer barley, summer and winter wheat	0.55
2.Set aside	Summer and winter wheat, winter oilseed	0.55	Winter wheat, maize, summer barley	0.62
3.Peas & beans	Winter wheat, potato, winter oilseed	0.57	Maize, beet	0.68
4.Beets	Beet, summer and winter barley, grass	0.55	Beet, maize	0.59
6.Potato	Potato, beet, winter barley	0.30	Potato, maize, beet	0.63
8.Grassland	Grass	0.19	Grass, potato	0.47
9.Soft fruit	Grass, maize	0.33	Winter barley, maize	0.30
11.Oilseed	Winter oilseed, winter wheat	0.51	Winter oilseed, winter wheat, maize	0.57
12.Top fruit	Winter wheat, winter oilseed	0.19	Potato, grass	0.43
13.Lettuce & salad	Winter barley, beet, maize	0.32	Maize, beet	0.52
14.Fodder	Grass, summer barley	0.27	Winter wheat, winter barley, grass, beet	0.80
Cows	Crop 14	0.76	Crop 14	
Sheep	Crop 8	0.53	Crop 8	
Goats	Crop 1	0.29	Crop 1	
Pigs	Crop 14	0.43	Crop 14	

Spatial Disaggregation

Estimates of rates of pesticide usage in the two study areas in England (East Anglia and the northwest) were required at the small-area scale (5 x 5 km grid) to reflect local variations in crop types and pesticide applications.

The only available data were based on surveys of sample farms, aggregated to county level. More detailed data were, however, available on both crop area (from the annual farm census - the June Agricultural Returns) and land cover (from the CORINE, satellite derived land cover map of Europe). As a basis for estimating potential exposures, therefore, these data were used to help disaggregate the county-level pesticide usage data to a 5 x 5 km grid using the approach illustrated in Figure 2. Figure 3 shows how the approach was applied to data for East Anglia. The final pesticide usage maps for East Anglia are shown in the main report.

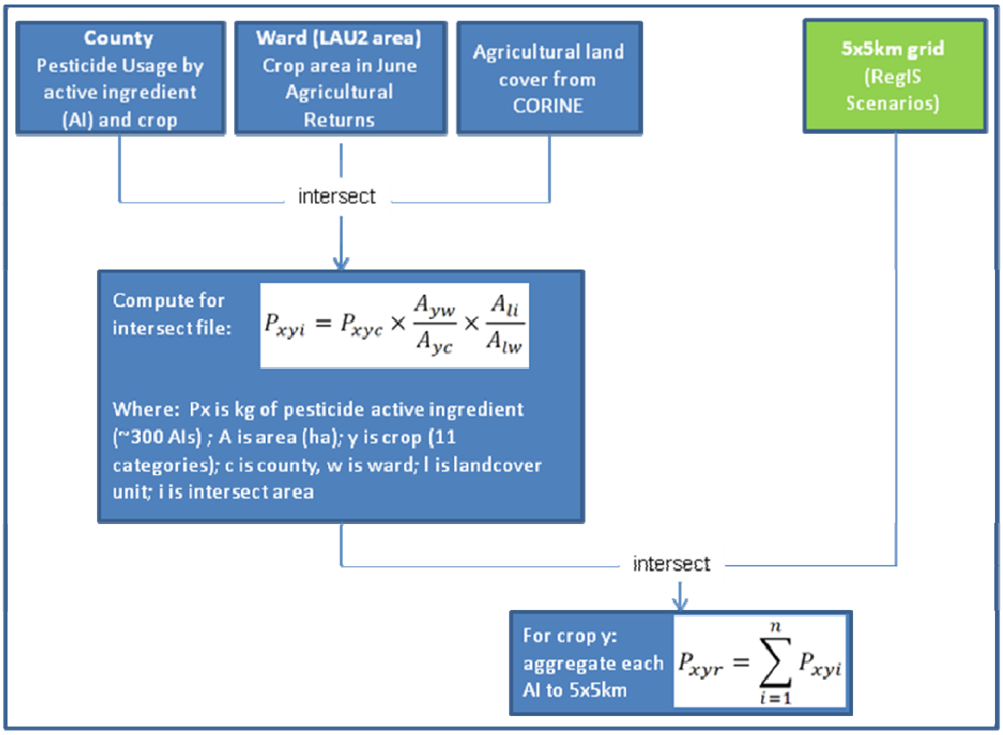


Figure 2. Disaggregation of county pesticide data to 5x5 km

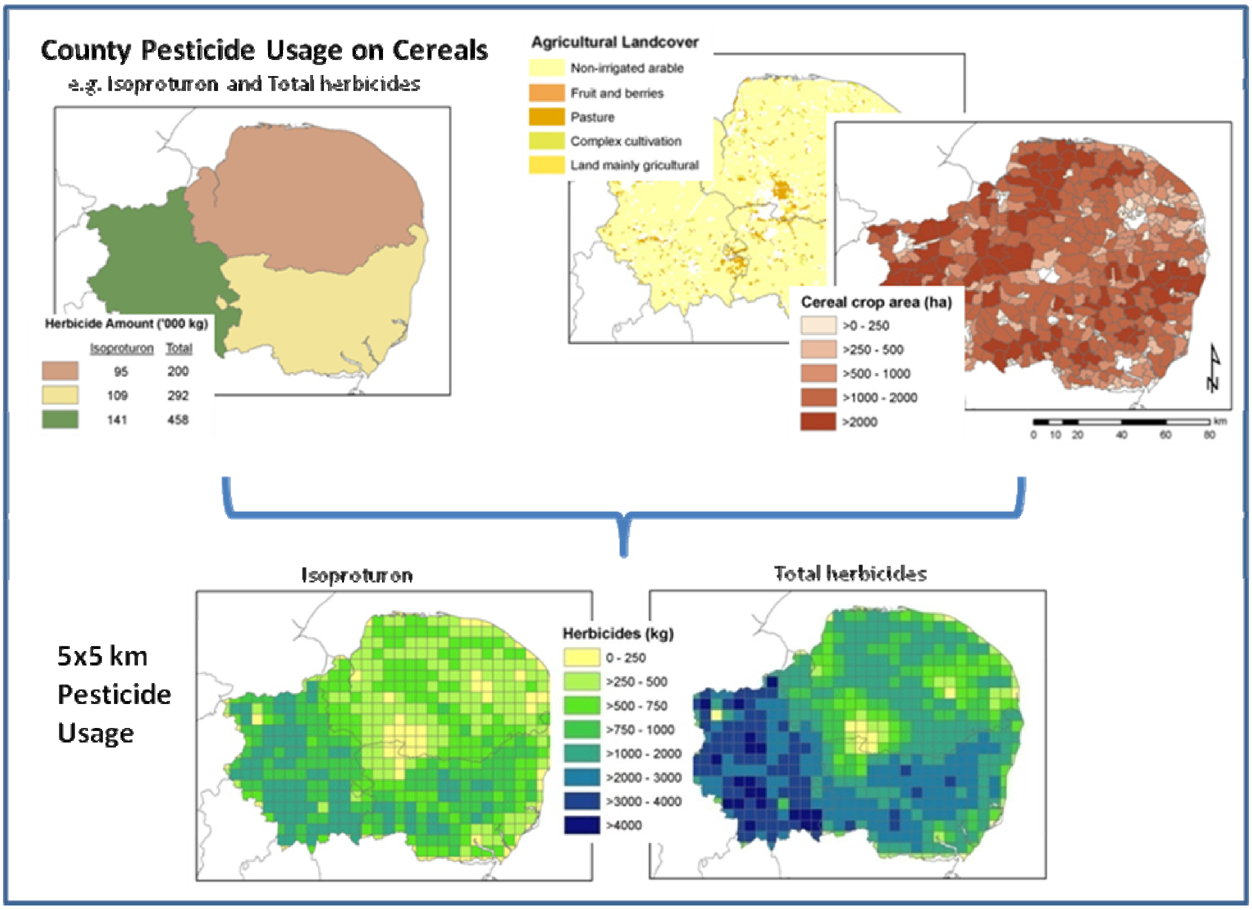
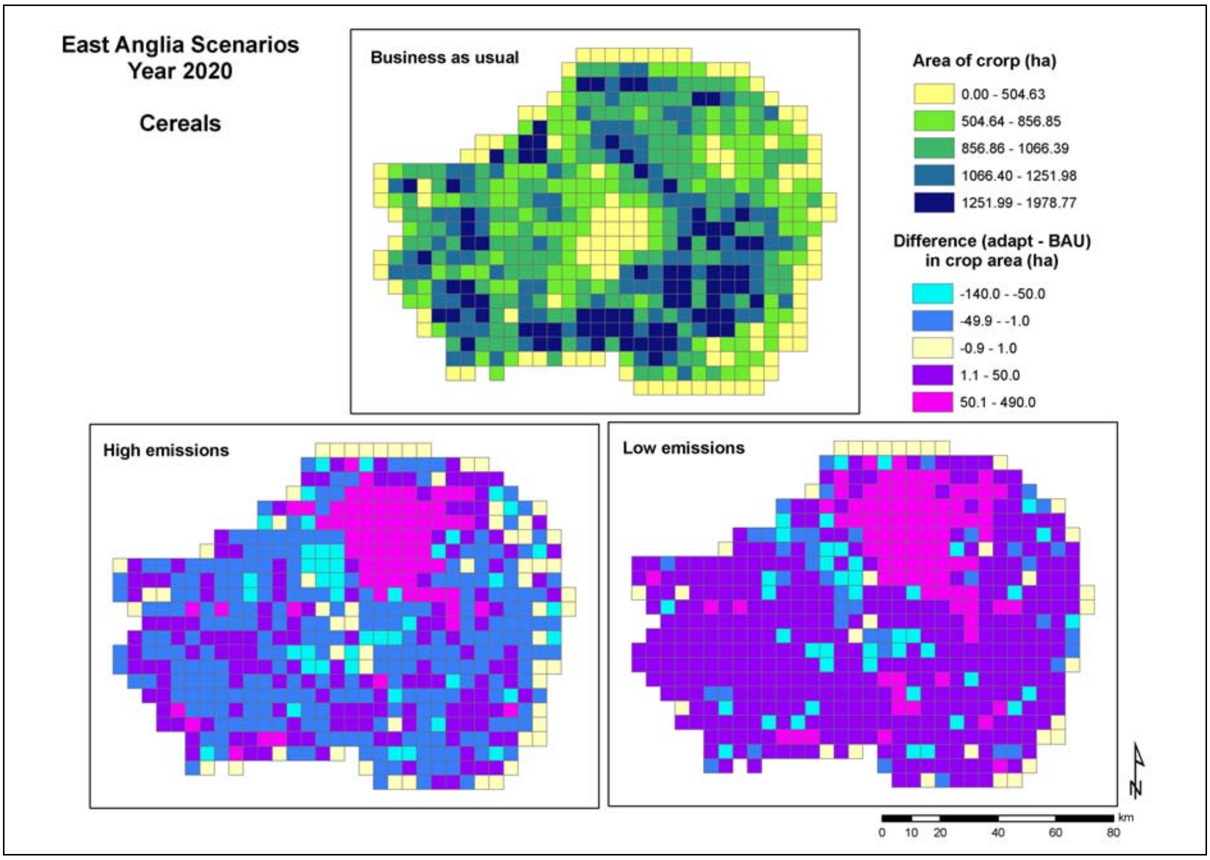
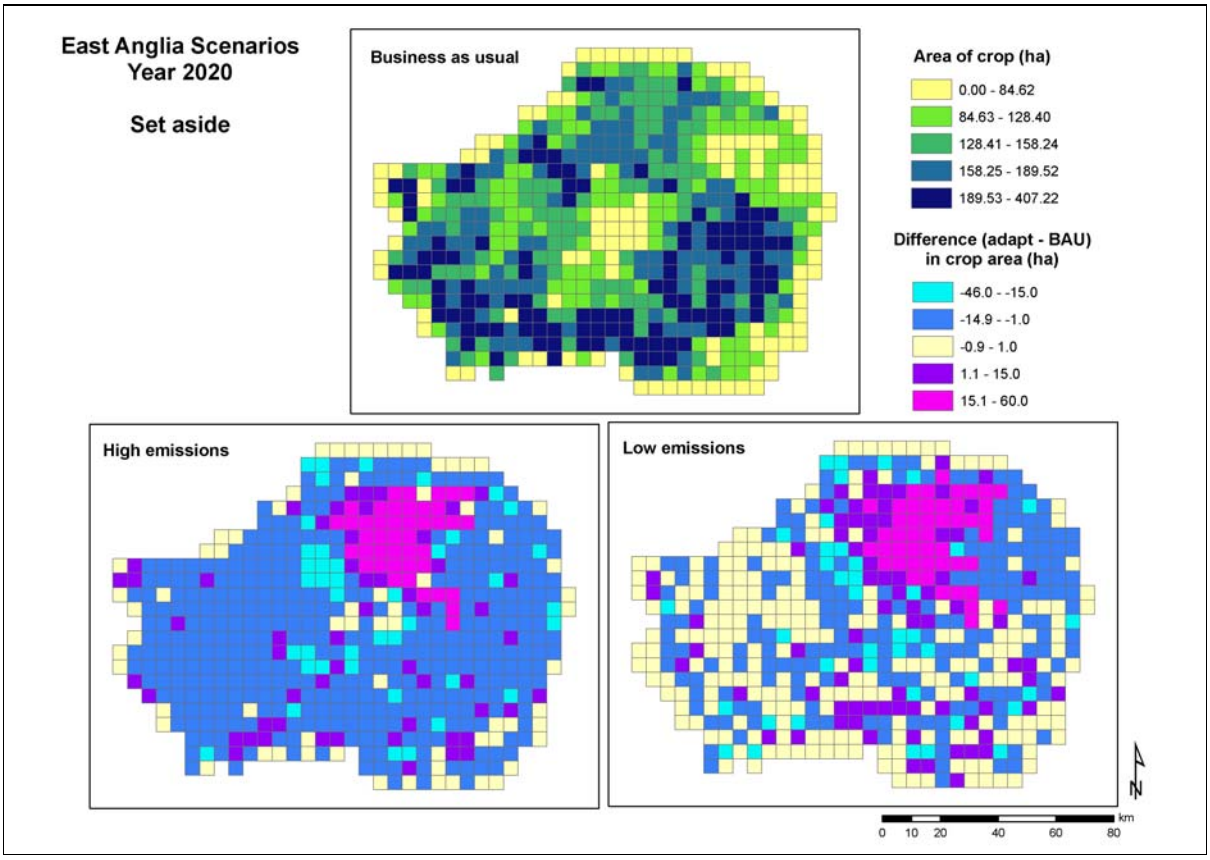


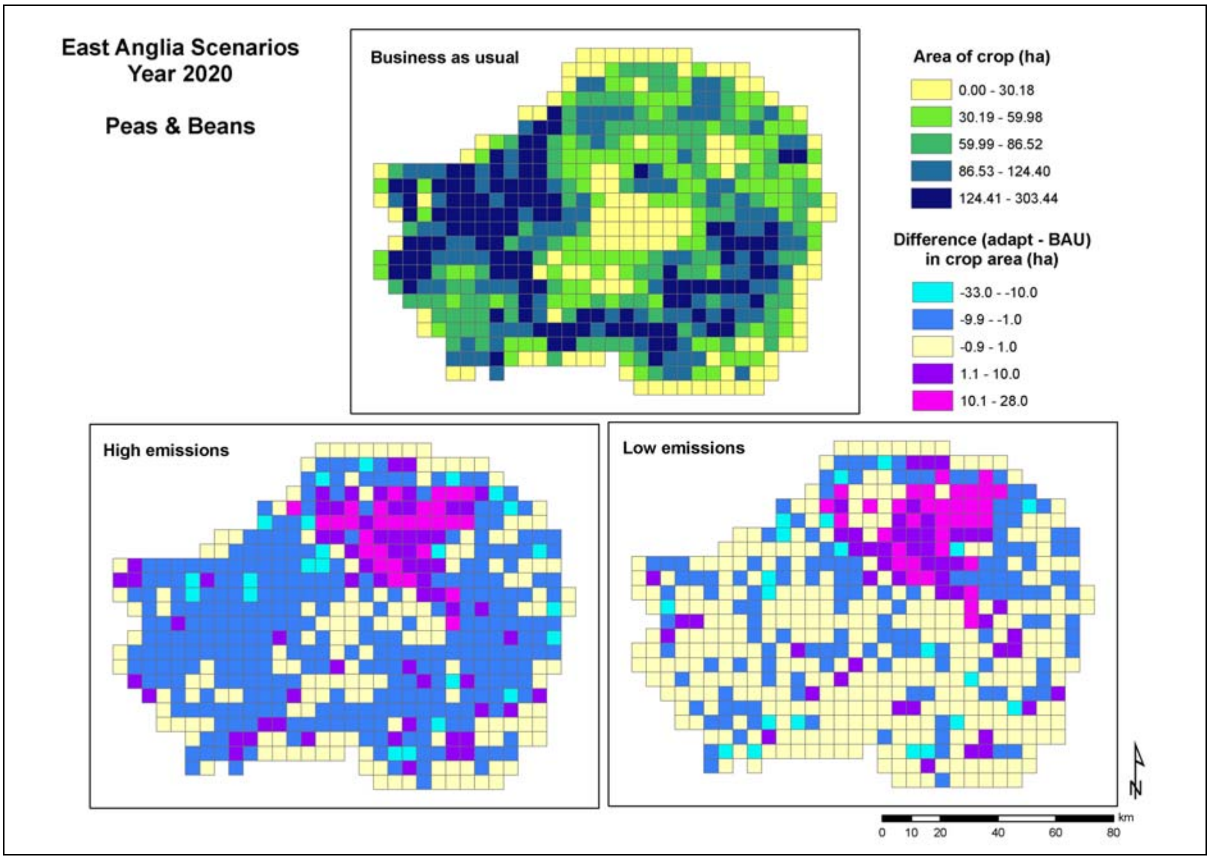
Figure 3. Example of pesticide disaggregation for Isoproturon and Total herbicides

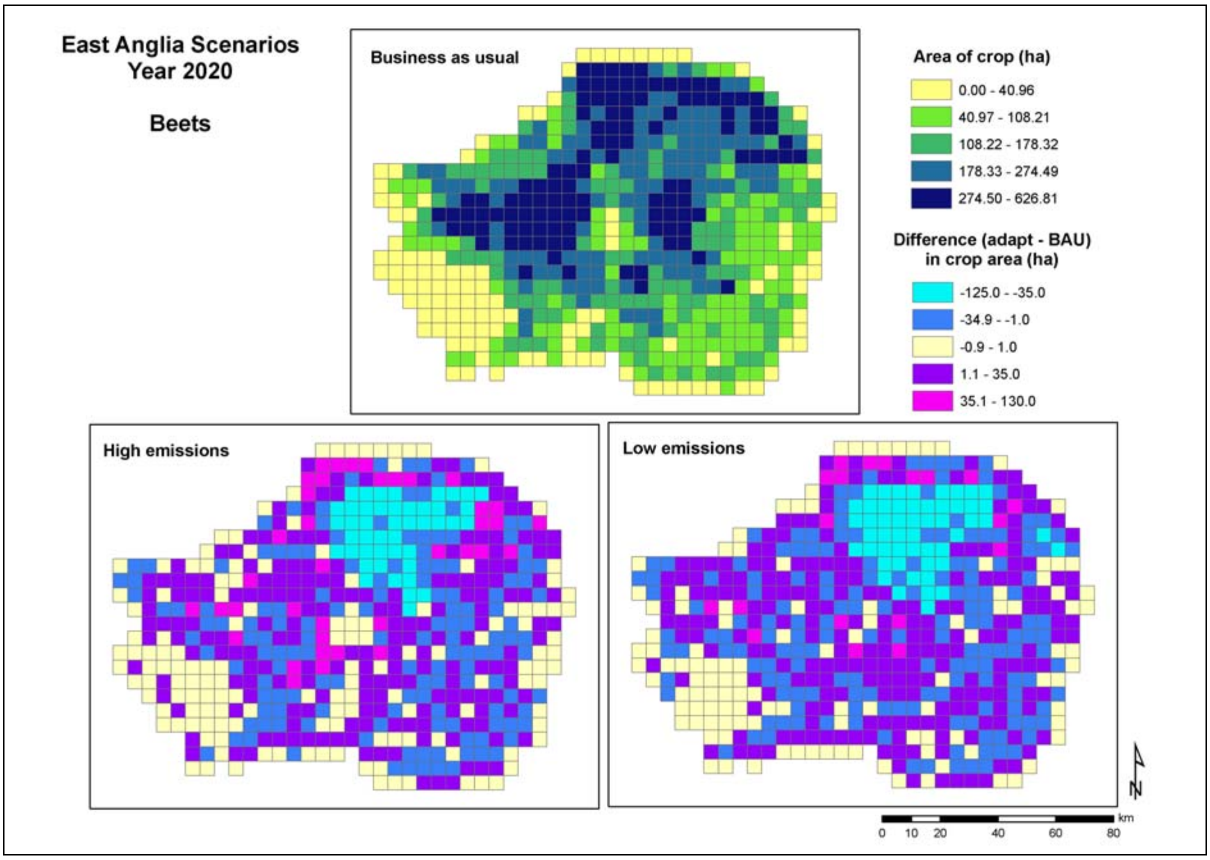
4.2 Regis Data

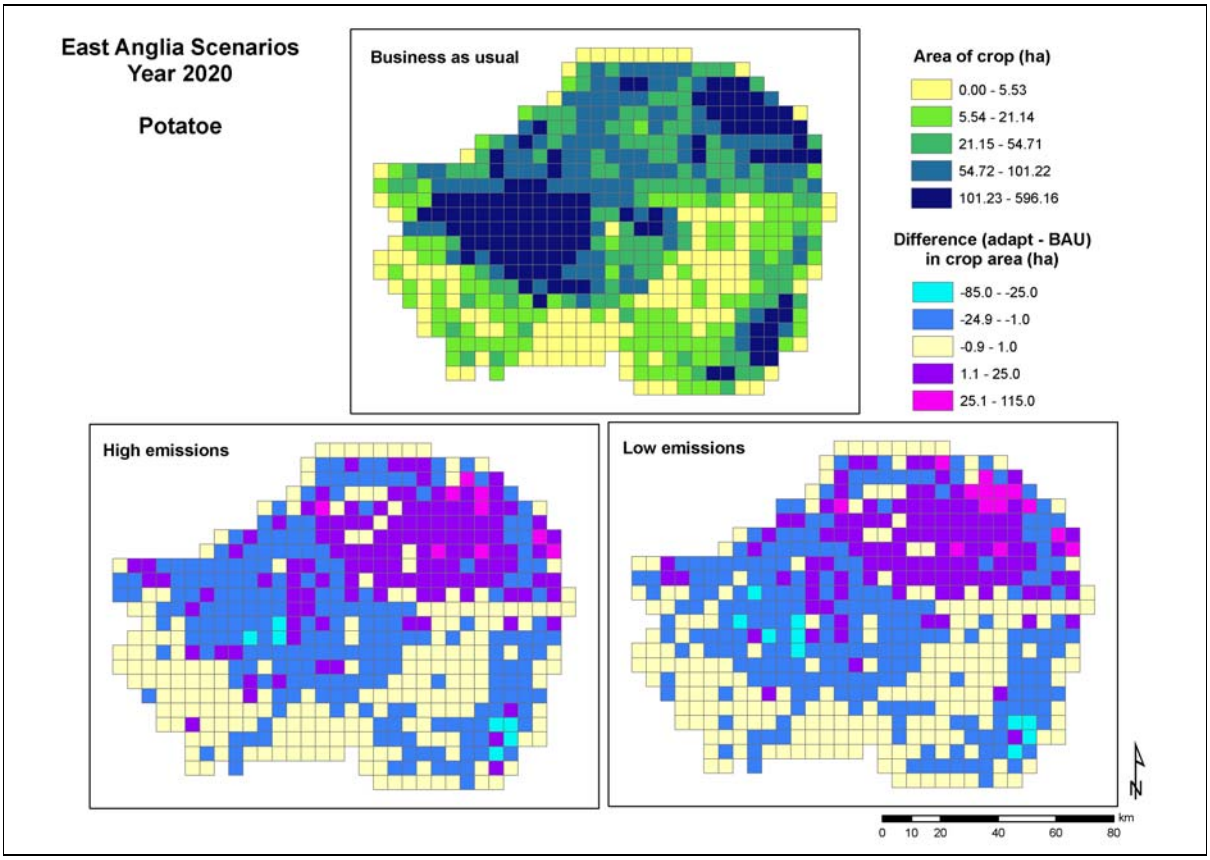
This appendix shows the crops for the three scenarios: BAU, and under low and high emission scenarios for the year 2020 from Regis, for East Anglia. These are the results of scenario development (Appendix x.1).

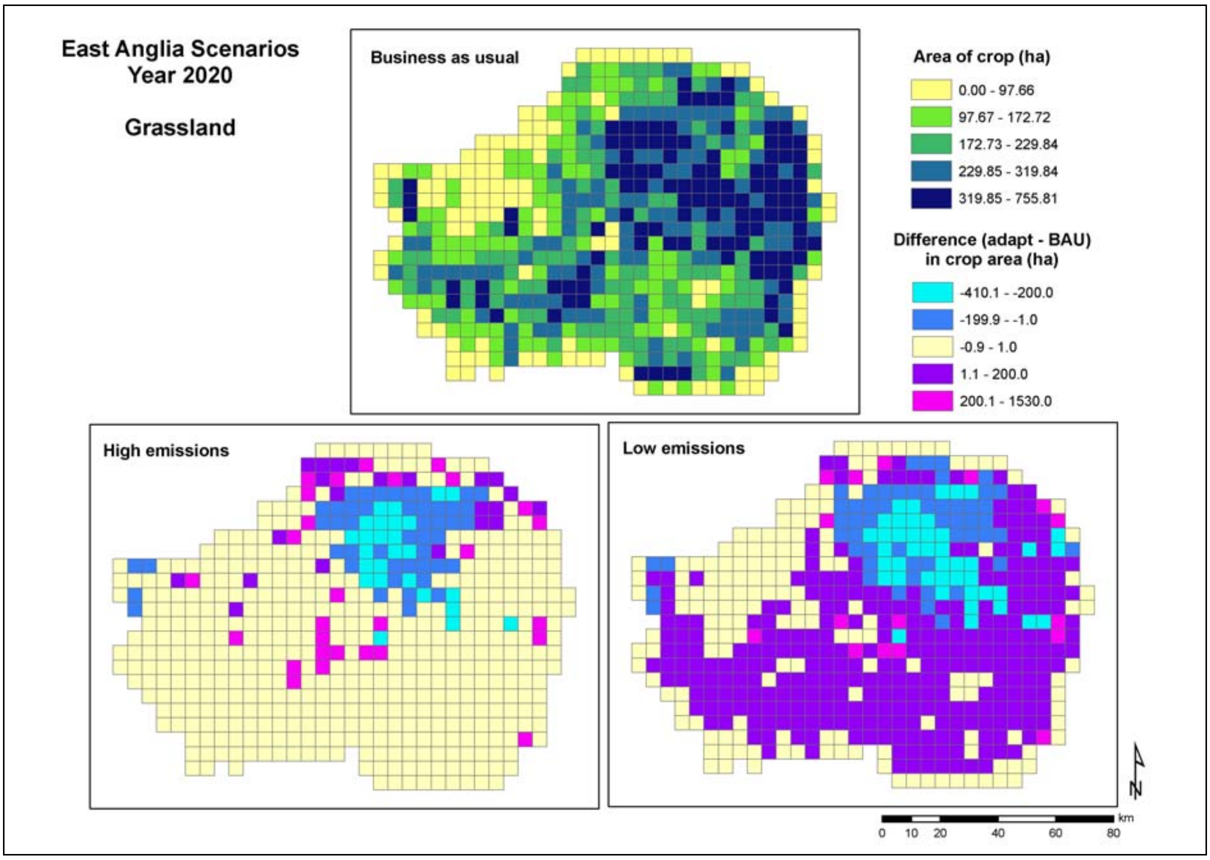

East Anglia Scenarios
Year 2020
Cereals
Business as usual
Area of crorp (ha)
0.00 - 504.63
504.64 - 856.85
856.86 - 1066.39
1066.40 - 1251.98
1251.99 - 1978.77
Difference (adapt - BAU)
in crop area (ha)
-140.0 - -50.0
-49.9 - -1.0
-0.9 - 1.0
1.1 - 50.0
50.1 - 490.0
High emissions
Low emissions
N
km
0 10 20 40 60 80

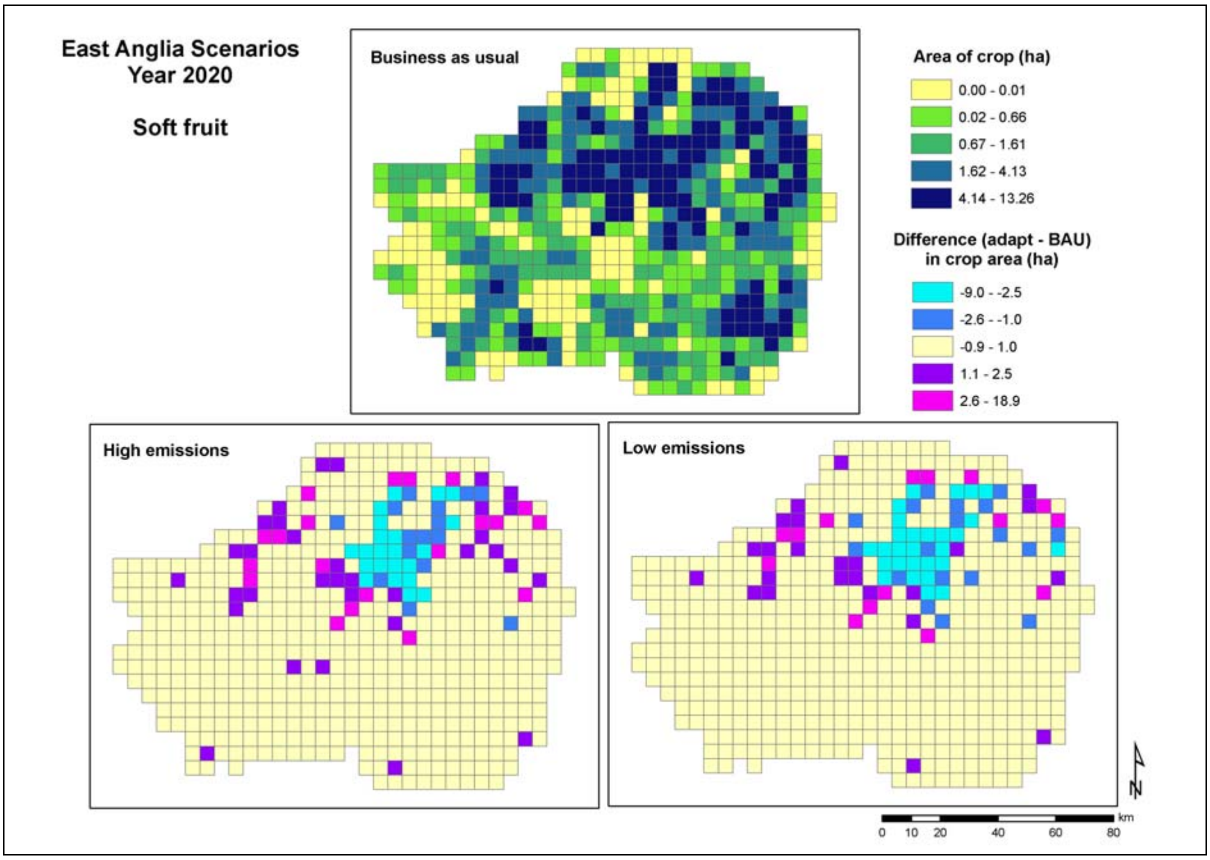

East Anglia Scenarios
Year 2020
Set aside
Business as usual
Area of crop (ha)
0.00 - 84.62
84.63 - 128.40
128.41 - 158.24
158.25 - 189.52
189.53 - 407.22
Difference (adapt - BAU)
in crop area (ha)
-46.0 - -15.0
-14.9 - -1.0
-0.9 - 1.0
1.1 - 15.0
15.1 - 60.0
High emissions
Low emissions
N
km
0 10 20 40 60 80

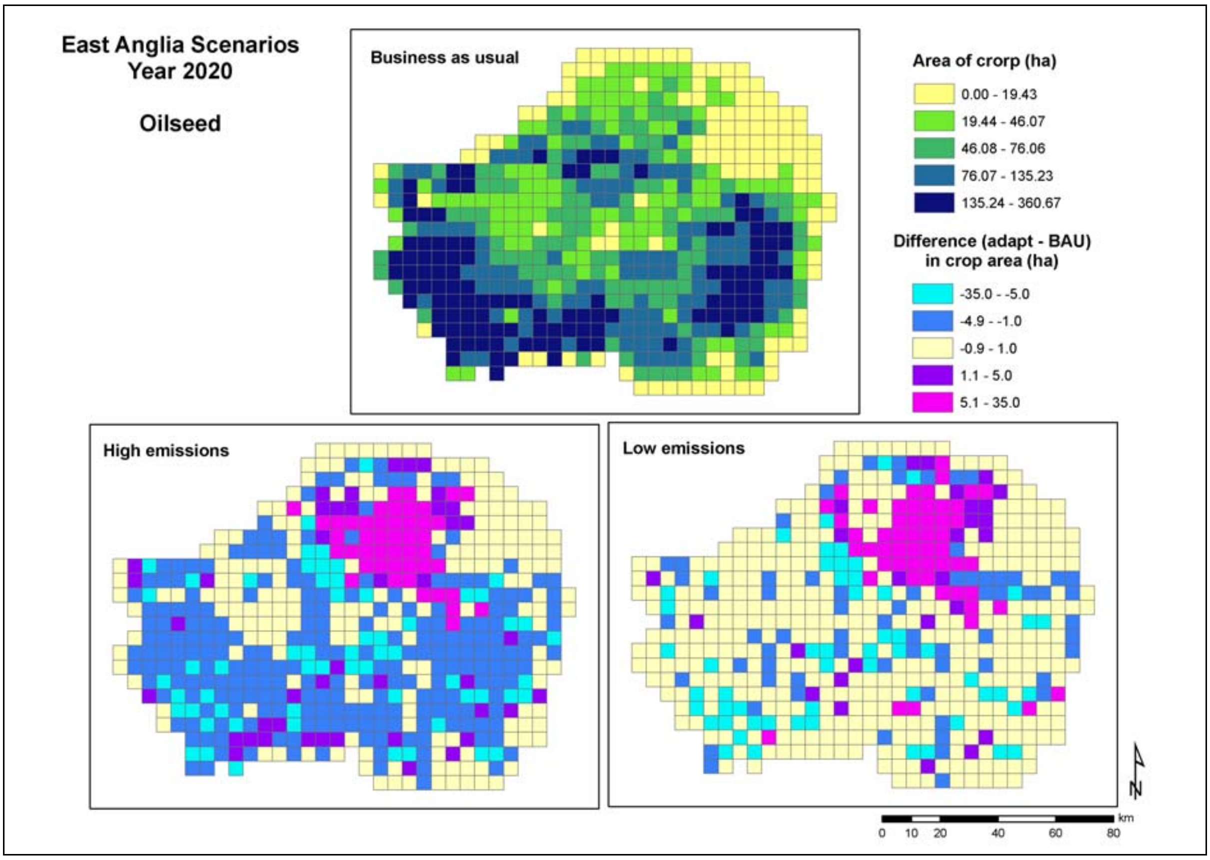

East Anglia Scenarios
Year 2020
Peas & Beans
Business as usual
Area of crop (ha)
0.00 - 30.18
30.19 - 59.98
59.99 - 86.52
86.53 - 124.40
124.41 - 303.44
Difference (adapt - BAU) in crop area (ha)
-33.0 - -10.0
-9.9 - -1.0
-0.9 - 1.0
1.1 - 10.0
10.1 - 28.0
High emissions
Low emissions
N
km
0 10 20 40 60 80

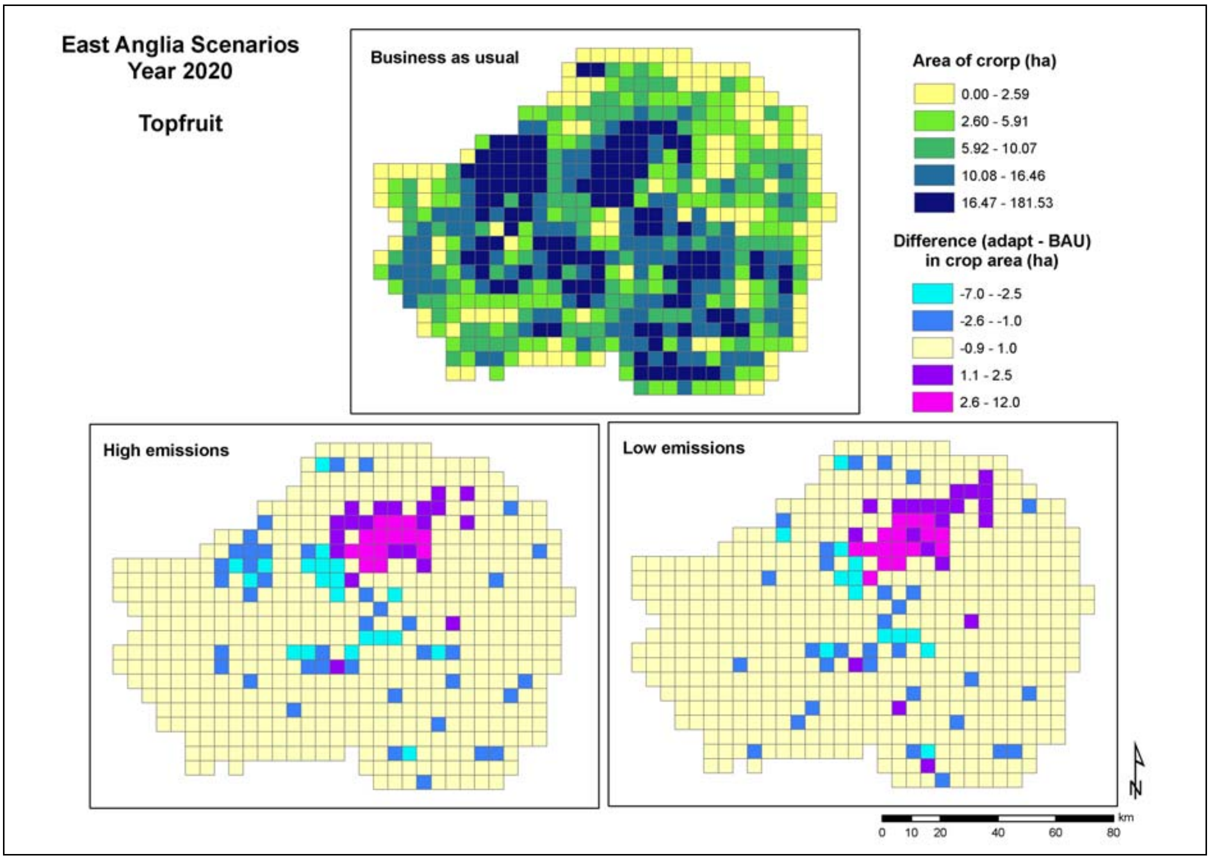

East Anglia Scenarios
Year 2020
Beets
Business as usual
Area of crop (ha)
0.00 - 40.96
40.97 - 108.21
108.22 - 178.32
178.33 - 274.49
274.50 - 626.81
Difference (adapt - BAU) in crop area (ha)
-125.0 - -35.0
-34.9 - -1.0
-0.9 - 1.0
1.1 - 35.0
35.1 - 130.0
High emissions
Low emissions
N
km
0 10 20 40 60 80

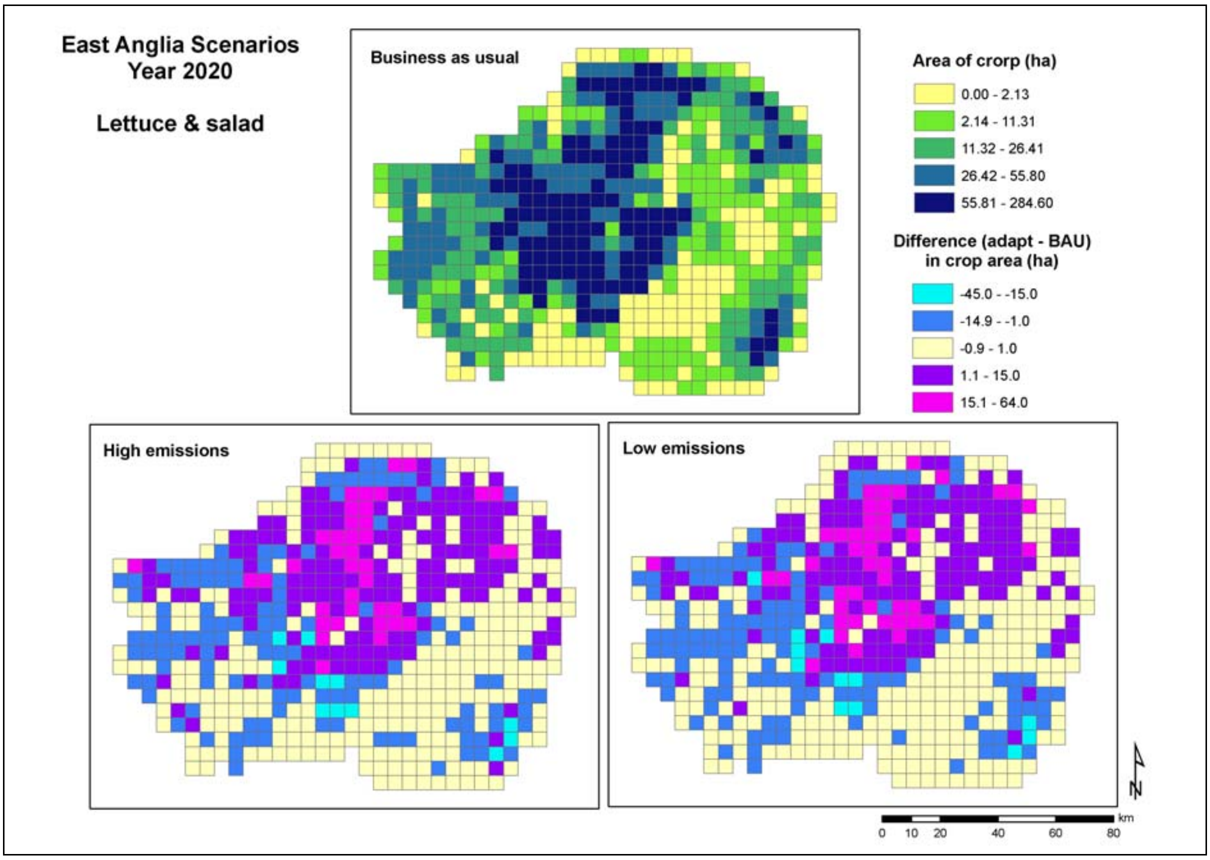

East Anglia Scenarios
Year 2020
Potatoe
Business as usual
Area of crop (ha)
0.00 - 5.53
5.54 - 21.14
21.15 - 54.71
54.72 - 101.22
101.23 - 596.16
Difference (adapt - BAU) in crop area (ha)
-85.0 - -25.0
-24.9 - -1.0
-0.9 - 1.0
1.1 - 25.0
25.1 - 115.0
High emissions
Low emissions
km
0 10 20 40 60 80

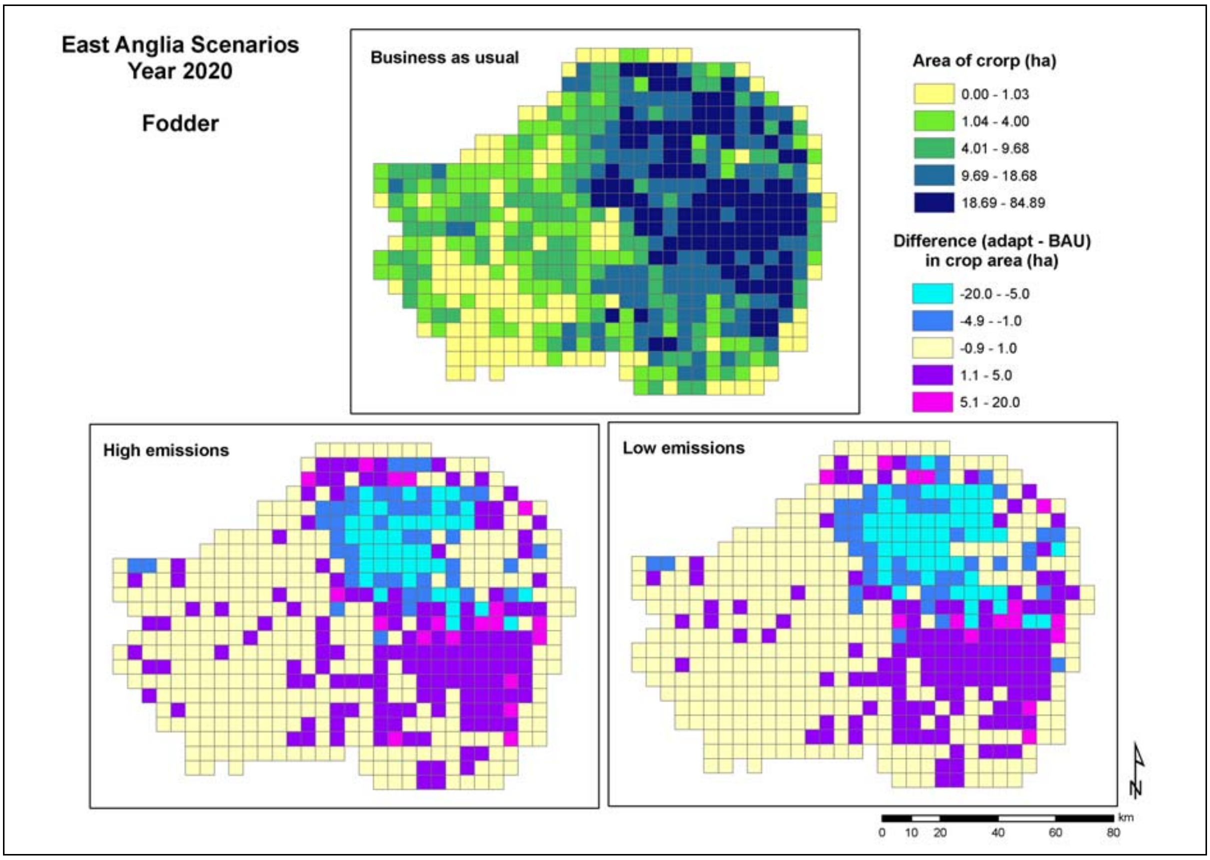

East Anglia Scenarios
Year 2020
Grassland
Business as usual
Area of crop (ha)
0.00 - 97.66
97.67 - 172.72
172.73 - 229.84
229.85 - 319.84
319.85 - 755.81
Difference (adapt - BAU) in crop area (ha)
-410.1 - -200.0
-199.9 - -1.0
-0.9 - 1.0
1.1 - 200.0
200.1 - 1530.0
High emissions
Low emissions
km
0 10 20 40 60 80


East Anglia Scenarios
Year 2020
Soft fruit
Business as usual
Area of crop (ha)
0.00 - 0.01
0.02 - 0.66
0.67 - 1.61
1.62 - 4.13
4.14 - 13.26
Difference (adapt - BAU) in crop area (ha)
-9.0 - -2.5
-2.6 - -1.0
-0.9 - 1.0
1.1 - 2.5
2.6 - 18.9
High emissions
Low emissions
N
km
0 10 20 40 60 80


East Anglia Scenarios
Year 2020
Oilseed
Business as usual
Area of crorp (ha)
0.00 - 19.43
19.44 - 46.07
46.08 - 76.06
76.07 - 135.23
135.24 - 360.67
Difference (adapt - BAU) in crop area (ha)
-35.0 - -5.0
-4.9 - -1.0
-0.9 - 1.0
1.1 - 5.0
5.1 - 35.0
High emissions
Low emissions
N
km
0 10 20 40 60 80


East Anglia Scenarios
Year 2020
Topfruit
Business as usual
Area of crorp (ha)
0.00 - 2.59
2.60 - 5.91
5.92 - 10.07
10.08 - 16.46
16.47 - 181.53
Difference (adapt - BAU) in crop area (ha)
-7.0 - -2.5
-2.6 - -1.0
-0.9 - 1.0
1.1 - 2.5
2.6 - 12.0
High emissions
Low emissions
N
km
0 10 20 40 60 80


East Anglia Scenarios
Year 2020
Lettuce & salad
Business as usual
Area of crorp (ha)
0.00 - 2.13
2.14 - 11.31
11.32 - 26.41
26.42 - 55.80
55.81 - 284.60
Difference (adapt - BAU) in crop area (ha)
-45.0 - -15.0
-14.9 - -1.0
-0.9 - 1.0
1.1 - 15.0
15.1 - 64.0
High emissions
Low emissions
N
km
0 10 20 40 60 80



4.3 Population weighted Exposures

Population weighted exposures were computed on the basis of the concentration grids. For England, postcode headcount data were used to estimate exposures at wards and county level (depending on health impact analysis), on the basis of the 250x250m grids (Table 1). The ward exposures for the different scenarios are presented in Table 2, and county in Table 3.

Population weighted ward exposures were used where categorical ERFs were available (i.e. in assessing the attributable burden of pesticides) (Table 2). Several individual active substances were also examined using a toxicological approach (Table 4). Where non-threshold linear relation ERFs were available (i.e. particulates), attributable burden was computed at the county level using the population weighted county exposures (Table 5).

Table 1. Population weighted 250x250m exposure (ng/m^3): Business as usual (B2020)

Percentile	Total pesticides	Insecticides	Herbicides	Fungicides
5	0.0475	0.0002	0.0233	0.0006
10	0.1308	0.0012	0.0595	0.0018
15	0.1615	0.0054	0.0716	0.0027
20	0.1873	0.0139	0.0847	0.0042

25	0.2154	0.0261	0.0987	0.0060
30	0.2475	0.0349	0.1240	0.0093
35	0.4575	0.0422	0.3125	0.0178
40	0.6250	0.0500	0.5144	0.0798
45	0.9550	0.0585	0.6228	0.3973
50	2.0066	0.0701	0.9318	0.9986
55	2.9950	0.0832	1.1999	1.5382
60	3.5752	0.0924	1.4597	1.8856
65	4.0766	0.1033	1.6813	2.1435
70	4.5402	0.1156	1.8585	2.3794
75	5.0668	0.1379	2.1070	2.6419
80	5.7212	0.1890	2.5449	3.0060
85	6.6718	0.2385	3.0810	3.5968
90	9.9107	0.8752	4.1339	4.7171
95	17.1422	1.1855	5.4470	11.1549
100	83.8219	2.3910	8.7289	72.7067

Table 2. Population weighted Ward exposure (µg/m^3)

		East Anglia (n = 527 wards)				**North west (n = 1005 wards)**			
	Scenario	**Min**	**Max**	**P95**	**Mean**	**Min**	**Max**	**P95**	**Mean**
Fungicides	BAU	4.10E-05	2.86E-02	1.17E-02	2.71E-03	0	6.18E-03	1.52E-03	2.83E-04
	H2020	3.41E-05	4.98E-02	9.15E-03	2.71E-03	0	9.72E-03	2.06E-03	3.52E-04
	L2020	3.42E-05	4.96E-02	9.08E-03	2.70E-03	0	9.56E-03	1.99E-03	3.33E-04
Herbicides	BAU	3.08E-05	5.69E-03	3.87E-03	1.65E-03	0	1.92E-03	8.80E-04	2.42E-04
	H2020	4.22E-05	1.24E-02	4.54E-03	1.84E-03	0	5.73E-03	1.63E-03	5.19E-04
	L2020	4.26E-05	1.25E-02	4.64E-03	1.83E-03	0	5.65E-03	1.57E-03	5.08E-04
Insecticides	BAU	6.81E-07	1.37E-03	8.56E-04	2.09E-04	0	3.37E-04	9.85E-05	2.26E-05
	H2020	5.86E-07	2.56E-03	1.04E-03	2.39E-04	0	1.24E-03	1.75E-04	3.90E-05
	L2020	5.93E-07	2.60E-03	1.06E-03	2.40E-04	0	1.21E-03	1.75E-04	3.84E-05
Total Pesticides	BAU	7.99E-05	3.51E-02	1.56E-02	4.58E-03	0	8.14E-03	2.40E-03	5.48E-04
	H2020	7.90E-05	6.06E-02	1.47E-02	4.78E-03	0	1.67E-02	3.51E-03	9.10E-04
	L2020	7.95E-05	6.05E-02	1.43E-02	4.77E-03	0	1.64E-02	3.31E-03	8.80E-04
NH3	BAU	9.45E-03	2.94E+00	1.16E+00	4.21E-01	0	4.69E+00	2.84E+00	8.46E-01

	Scenario	East Anglia (n = 527 wards)				North west (n = 1005 wards)			
		Min	Max	P95	Mean	Min	Max	P95	Mean
	H2020	9.88E-03	3.19E+00	1.22E+00	4.35E-01	0	4.73E+00	2.74E+00	8.27E-01
	L2020	9.69E-03	3.21E+00	1.23E+00	4.24E-01	0	4.75E+00	2.75E+00	8.22E-01
PM10	BAU	4.15E-03	5.85E-01	3.36E-01	1.56E-01	0	3.13E-01	1.10E-01	2.95E-02
	H2020	4.07E-03	5.95E-01	3.41E-01	1.59E-01	0	3.50E-01	1.14E-01	3.06E-02
	L2020	4.22E-03	6.00E-01	3.45E-01	1.60E-01	0	3.52E-01	1.16E-01	3.06E-02
PM2.5	BAU	6.53E-04	1.01E-01	5.79E-02	2.63E-02	0	4.97E-02	1.88E-02	5.15E-03
	H2020	6.60E-04	1.03E-01	5.89E-02	2.67E-02	0	5.40E-02	1.95E-02	5.30E-03
	L2020	6.56E-04	1.04E-01	5.92E-02	2.70E-02	0	5.46E-02	1.95E-02	5.29E-03
Inhalable endotoxin	BAU	1.82E-09	1.88E-06	6.58E-07	1.98E-07	0	1.73E-06	9.33E-07	2.84E-07
	H2020	1.92E-09	2.06E-06	7.18E-07	2.06E-07	0	1.55E-06	9.09E-07	2.76E-07
	L2020	1.94E-09	2.07E-06	7.14E-07	1.99E-07	0	1.54E-06	9.09E-07	2.75E-07
Respirable endotoxin	BAU	2.75E-10	4.06E-07	1.30E-07	3.70E-08	0	2.19E-07	5.48E-08	1.73E-08
	H2020	2.87E-10	4.44E-07	1.43E-07	3.86E-08	0	1.96E-07	5.67E-08	1.67E-08
	L2020	2.90E-10	4.47E-07	1.34E-07	3.74E-08	0	1.92E-07	5.45E-08	1.66E-08

Table 3. Population weighted County exposure (μg/m^3)

	Scenario	East Anglia (n = 3 counties)			North west (n = 5 counties)		
		Min	Max	Mean	Min	Max	Mean
Fungicides	BAU	1.13E-03	4.77E-03	2.39E-03	3.60E-06	7.66E-04	2.55E-04
	H2020	1.06E-03	4.67E-03	2.36E-03	3.45E-06	7.44E-04	3.35E-04
	L2020	1.08E-03	4.59E-03	2.34E-03	3.45E-06	6.67E-04	3.17E-04
Herbicides	BAU	8.48E-04	2.22E-03	1.43E-03	4.88E-05	4.32E-04	2.00E-04
	H2020	9.63E-04	2.71E-03	1.66E-03	7.39E-05	8.22E-04	4.34E-04
	L2020	9.30E-04	2.72E-03	1.66E-03	7.31E-05	7.88E-04	4.25E-04
Insecticides	BAU	2.55E-05	4.86E-04	2.00E-04	1.83E-06	5.51E-05	2.07E-05
	H2020	2.66E-05	5.87E-04	2.34E-04	4.17E-06	9.28E-05	3.66E-05
	L2020	2.71E-05	5.88E-04	2.35E-04	3.93E-06	9.17E-05	3.59E-05
Total Pesticides	BAU	2.14E-03	7.47E-03	4.01E-03	1.08E-04	1.22E-03	4.75E-04
	H2020	2.32E-03	7.97E-03	4.25E-03	1.70E-04	1.59E-03	8.05E-04
	L2020	2.31E-03	7.89E-03	4.23E-03	1.68E-04	1.48E-03	7.78E-04
NH3	BAU	1.64E-01	3.92E-01	3.16E-01	1.33E-01	1.37E+00	6.83E-01
	H2020	1.75E-01	4.36E-01	3.28E-01	1.30E-01	1.30E+00	6.69E-01
	L2020	1.74E-01	4.29E-01	3.20E-01	1.29E-01	1.30E+00	6.65E-01

PM10	BAU	1.21E-01	1.28E-01	1.24E-01	1.00E-02	4.35E-02	2.65E-02
	H2020	1.24E-01	1.29E-01	1.26E-01	1.09E-02	4.13E-02	2.74E-02
	L2020	1.25E-01	1.30E-01	1.27E-01	1.08E-02	4.15E-02	2.73E-02
PM2.5	BAU	1.99E-02	2.18E-02	2.09E-02	1.77E-03	7.45E-03	4.62E-03
	H2020	2.04E-02	2.20E-02	2.12E-02	1.91E-03	7.12E-03	4.74E-03
	L2020	2.07E-02	2.22E-02	2.14E-02	1.90E-03	7.17E-03	4.73E-03
Inhalable endotoxin	BAU	4.34E-08	2.04E-07	1.44E-07	4.82E-08	4.53E-07	2.29E-07
	H2020	4.94E-08	2.32E-07	1.51E-07	4.62E-08	4.31E-07	2.24E-07
	L2020	4.87E-08	2.27E-07	1.46E-07	4.55E-08	4.30E-07	2.22E-07
Respirable endotoxin	BAU	6.17E-09	4.12E-08	2.67E-08	4.77E-09	2.08E-08	1.34E-08
	H2020	7.01E-09	4.71E-08	2.81E-08	4.47E-09	1.91E-08	1.30E-08
	L2020	6.92E-09	4.60E-08	2.72E-08	4.39E-09	1.91E-08	1.29E-08

Table 4. Population weighted ward exposures: Six herbicide ASs common with Greek case study

Active Ingredient	**Scenario**	**East Anglia (n = 527)**				**North west (n = 1105)**			
		Min	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**
Clodinafop-propargyl	B2020	9.58E-08	2.49E-05	6.14E-06	5.05E-06	0	1.59E-06	3.73E-08	1.48E-07
	H2020	8.22E-08	5.82E-05	7.15E-06	6.92E-06	0	3.88E-06	7.65E-08	3.06E-07
	L2020	8.32E-08	5.91E-05	7.24E-06	6.97E-06	0	3.95E-06	7.51E-08	3.01E-07
Diclofop-methyl	B2020	9.22E-08	1.46E-05	4.32E-06	3.03E-06	0	0	0	0
	H2020	6.31E-08	3.42E-05	4.98E-06	4.10E-06	0	0	0	0
	L2020	6.40E-08	3.47E-05	5.06E-06	4.14E-06	0	0	0	0
MCPA	B2020	6.79E-07	1.28E-04	2.72E-05	2.08E-05	0	1.87E-04	2.26E-05	3.12E-05
	H2020	4.89E-07	2.43E-04	3.12E-05	2.90E-05	0	4.30E-04	5.80E-05	7.52E-05
	L2020	4.96E-07	2.40E-04	2.78E-05	2.34E-05	0	4.30E-04	5.75E-05	7.51E-05
Pendimethalin	B2020	8.69E-06	2.58E-03	6.92E-04	5.53E-04	0	6.73E-04	1.97E-05	6.82E-05
	H2020	8.56E-06	6.00E-03	7.71E-04	7.24E-04	0	2.58E-03	3.63E-05	1.69E-04
	L2020	8.68E-06	6.09E-03	7.80E-04	7.30E-04	0	2.52E-03	3.56E-05	1.67E-04
Tralkoxydim	B2020	1.09E-07	3.19E-05	7.23E-06	6.39E-06	0	0	0	0
	H2020	7.35E-08	4.18E-05	8.11E-06	7.27E-06	0	0	0	0
	L2020	7.45E-08	4.10E-05	8.26E-06	7.41E-06	0	0	0	0
Trifluralin	B2020	8.17E-06	1.75E-03	5.05E-04	3.76E-04	0	1.65E-04	9.48E-06	1.93E-05
	H2020	8.90E-06	4.07E-03	5.72E-04	4.93E-04	0	3.92E-04	1.23E-05	2.99E-05
	L2020	9.03E-06	4.13E-03	5.80E-04	4.96E-04	0	3.83E-04	1.21E-05	2.94E-05

Table 5. Population weighted particulate concentrations (μg/m^3) and population by county

	PM10			**PM2.5**			**Population 2031**	
COUNTY	**B2020**	**L2020**	**H2020**	**B2020**	**L2020**	**H2020**	**Men**	**Women**
East Anglia								
Cambridgeshire	0.1245	0.1255	0.1248	0.0212	0.0214	0.0212	491800	495700
Norfolk	0.1209	0.1256	0.1242	0.0199	0.0207	0.0204	521400	536700
Suffolk	0.1278	0.1304	0.1291	0.0218	0.0222	0.0220	444500	462100
Northwest								
Cheshire	0.0435	0.0415	0.0413	0.0075	0.0072	0.0071	564000	563900
Cumbria	0.0256	0.0277	0.0277	0.0047	0.0051	0.0051	280000	280000
Greater Manchester	0.0100	0.0108	0.0109	0.0018	0.0019	0.0019	1631248	1570860
Lancashire	0.0246	0.0270	0.0272	0.0043	0.0046	0.0046	857887	847425
Merseyside	0.0287	0.0297	0.0300	0.0048	0.0049	0.0050	539965	560414

4.4 Population Projections

The population datasets for the England study areas was computed on the basis of census data at ward level (i.e. LAU2) for the year 2001. This included age/sex stratified population counts. Where needed, postcode weighting was used to compute populations for different geographies (i.e. the 5km REGIS grid).

To the 2001 ward data, change rates derived from the Office of National Statistics (ONS 2010) official sub-national projections were applied to compute a spatial dataset of future populations. Change rates were the ratio between 2031:2001 populations (Table 1). The sub-national projections of interest here were available for local authorities and counties. In East Anglia this comprised 4 areas, and in the Northwest it comprised 10 (Figures 1 and 2 below).

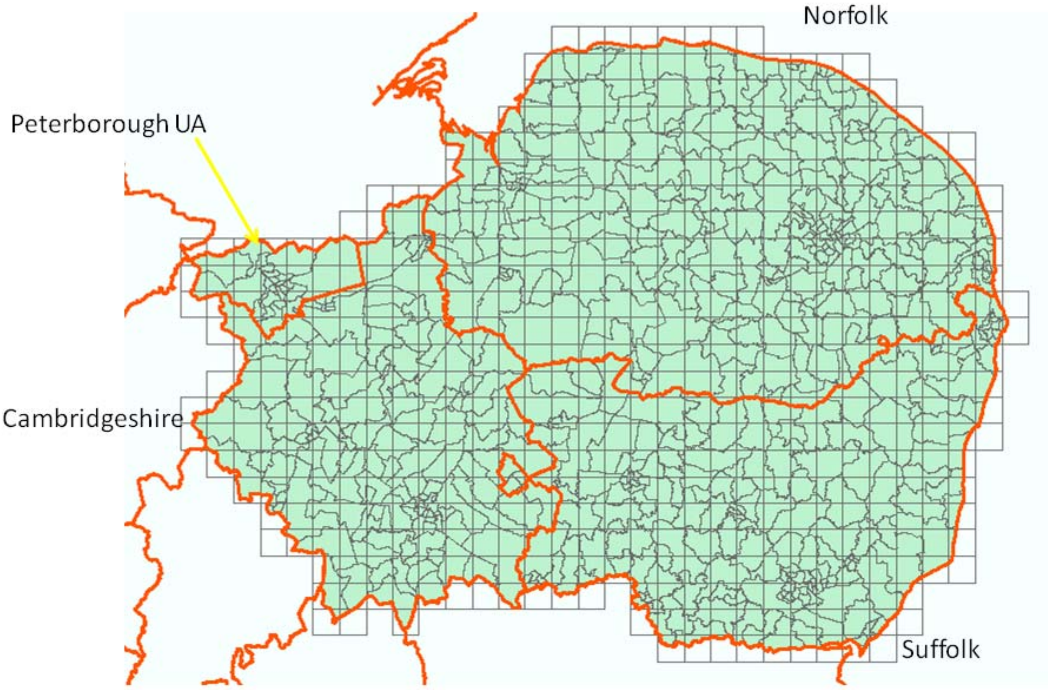


Figure 1. East Anglia Study area: showing wards, local authority and county boundaries (red) and 5km grid

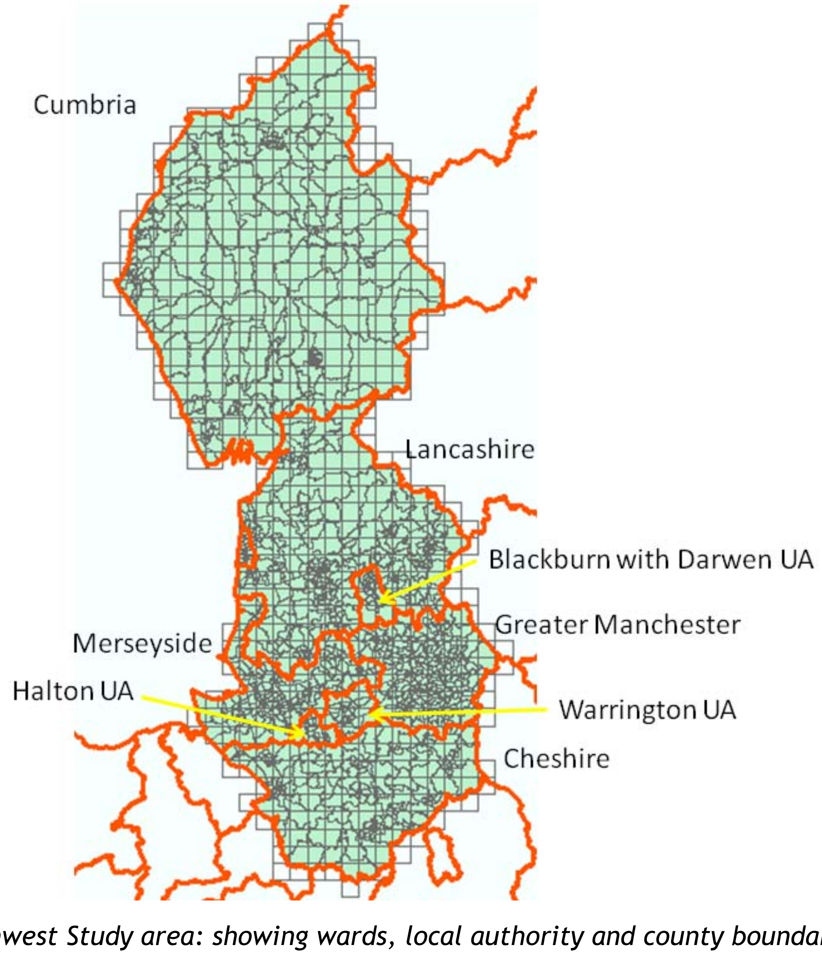


Figure 2. Northwest Study area: showing wards, local authority and county boundaries (red) and 5km grid

Table 1. Population change rates (year 2031:2001)

	Cambridgeshire	Norfolk	Suffolk	Peterborough	Greater Manchester	Merseyside	Cheshire	Cumbria	Lancashire	Halton	Warrington	Blackburn with Darwen	Blackpool
Males													
0-4	1.287	1.212	1.231	1.279	1.320	0.769	1.011	0.956	1.067	1.084	1.006	1.148	1.099
5-9	1.251	1.142	1.182	1.135	1.210	0.707	0.963	0.897	1.016	0.984	0.970	1.086	1.058
10-14	1.253	1.139	1.159	1.116	1.158	0.675	0.984	0.934	0.996	0.920	0.977	1.089	1.019
15-19	1.349	1.217	1.244	1.231	1.259	0.723	1.111	1.039	1.094	0.976	1.074	1.194	1.243
20-24	1.419	1.400	1.308	1.292	1.503	0.983	1.294	1.197	1.370	1.167	1.183	1.397	1.508
25-29	1.350	1.244	1.180	1.180	1.477	0.885	1.053	0.991	1.201	1.004	0.983	1.144	1.182
30-34	1.200	1.067	1.055	1.109	1.291	0.717	0.943	0.856	1.017	0.906	0.861	1.013	0.913
35-39	1.248	1.116	1.100	1.239	1.307	0.726	0.977	0.906	1.054	0.941	0.880	1.092	1.007
40-44	1.436	1.265	1.242	1.396	1.551	0.824	1.169	1.022	1.227	1.091	1.095	1.242	1.229
45-49	1.407	1.260	1.286	1.317	1.528	0.853	1.163	1.098	1.223	1.039	1.144	1.196	1.270
50-54	1.117	0.964	1.017	1.065	1.133	0.607	0.877	0.830	0.905	0.758	0.898	0.933	0.957
55-59	1.298	1.151	1.219	1.357	1.346	0.738	1.062	1.089	1.124	1.100	1.121	1.234	1.093
60-64	1.680	1.543	1.627	1.592	1.575	0.947	1.397	1.456	1.492	1.384	1.406	1.485	1.312
65-69	1.852	1.684	1.787	1.598	1.682	1.026	1.607	1.682	1.687	1.600	1.691	1.494	1.484
70-74	1.766	1.653	1.778	1.520	1.607	1.097	1.559	1.768	1.671	1.498	1.691	1.476	1.338
75-79	1.898	1.709	1.813	1.538	1.573	1.208	1.684	1.844	1.714	1.848	1.744	1.520	1.326
80-84	2.925	2.604	2.675	2.335	2.451	1.870	2.637	2.869	2.713	2.734	2.644	2.086	1.951
85p	4.348	4.134	4.186	3.886	3.968	2.944	4.777	4.207	4.055	4.918	5.041	3.321	3.040
Females													
0-4	1.324	1.214	1.247	1.242	1.311	0.775	1.000	0.972	1.083	1.039	0.963	1.164	1.134
5-9	1.305	1.159	1.203	1.136	1.212	0.695	0.978	0.914	1.003	0.994	0.972	1.134	1.059
10-14	1.305	1.150	1.165	1.082	1.134	0.665	0.978	0.932	0.982	0.902	0.951	1.122	1.105
15-19	1.362	1.210	1.283	1.135	1.203	0.716	1.045	1.000	1.055	0.931	0.999	1.195	1.247
20-24	1.347	1.363	1.291	1.165	1.356	0.885	1.156	1.072	1.224	1.052	1.153	1.220	1.335
25-29	1.224	1.160	1.136	1.098	1.259	0.740	0.945	0.859	1.032	0.905	0.938	1.025	1.000
30-34	1.122	1.042	1.030	1.002	1.078	0.603	0.815	0.749	0.877	0.805	0.754	0.925	0.778

	Cambridgeshire	Norfolk	Suffolk	Peterborough	Greater Manchester	Merseyside	Cheshire	Cumbria	Lancashire	Halton	Warrington	Blackburn with Darwen	Blackpool
35-39	1.204	1.079	1.081	1.096	1.129	0.616	0.869	0.835	0.927	0.826	0.786	0.971	0.849
40-44	1.403	1.249	1.293	1.236	1.330	0.720	1.069	0.981	1.093	0.989	1.050	1.161	1.111
45-49	1.410	1.232	1.318	1.220	1.380	0.775	1.098	1.025	1.132	0.969	1.085	1.152	1.143
50-54	1.136	0.969	1.051	1.073	1.065	0.605	0.818	0.845	0.874	0.789	0.849	0.983	0.902
55-59	1.355	1.208	1.305	1.292	1.254	0.782	1.051	1.133	1.134	1.146	1.067	1.233	1.018
60-64	1.763	1.577	1.750	1.609	1.534	0.979	1.405	1.490	1.493	1.532	1.448	1.451	1.261
65-69	1.886	1.686	1.882	1.521	1.636	1.094	1.588	1.648	1.606	1.613	1.809	1.458	1.344
70-74	1.707	1.512	1.665	1.454	1.427	1.031	1.407	1.480	1.472	1.570	1.521	1.287	1.099
75-79	1.660	1.460	1.542	1.418	1.258	0.976	1.388	1.429	1.357	1.583	1.437	1.169	0.950
80-84	2.197	1.940	2.019	1.827	1.637	1.214	1.947	1.793	1.800	1.827	1.905	1.439	1.130
85p	2.698	2.347	2.357	2.160	1.903	1.464	2.429	2.301	1.959	1.963	2.432	1.491	1.425

4.5 Attributable burden calculations for PM

For the England case study, attributable burden for PM10 and PM2.5 was calculated in Analytica using the model shown in figures 1 and 2. Calculations were done at county level, using age-standardised mortality rates for men and women. Population weighted exposures were thus calculated for counties on the basis of the 250m modelled concentration grids (i.e. shown in Annex 2.3, Table 5).

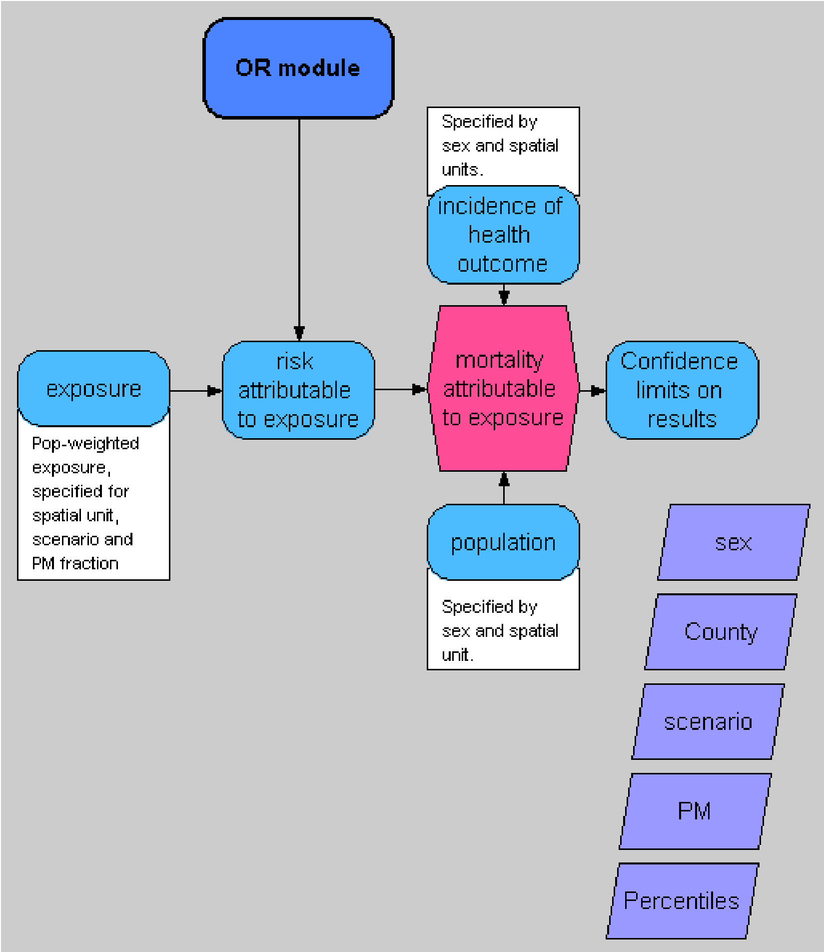


Figure 1. Full Analytica model for computing attributable burden for particulates

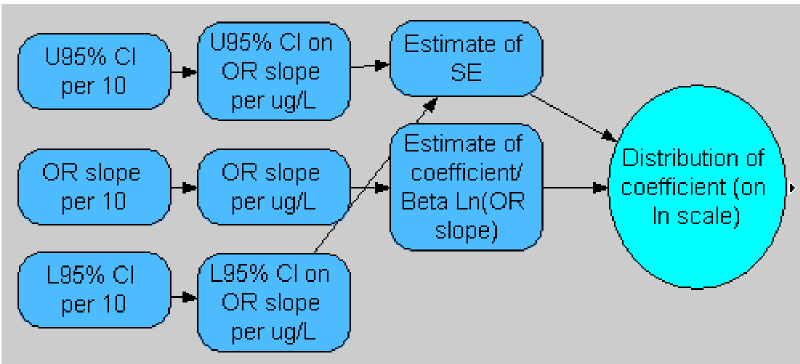


Figure 2. OR (odds ratio) model for the full Analytica model shown in Figure 7.1

4.6 Exposure Response Functions and Health Data

For the England case study, the existing ERFs for traffic-related PM10 and PM2.5 from the IEHIAS toolkit were used (Table 1). Age-standardised mortality rates by county were obtained from the Office for National Statistics (Table 2). The hypothetical RRs for pesticides are presented in Table 3. Also in Table 3 is the background cancer incidence rates derived from the Office for National Statistics.

Table 1. Exposure response functions for air pollution concentrations in outdoor air (traffic related): England case study

Source	**Health outcome**	**Relative risk**	**Lower confidence limit (P5)**	**Upper confidence limit (P95)**	**Unit**
PM10	Mortality	1.058	1.027	1.089	10 µg/m3
PM2.5	Mortality	1.060	1.030	1.090	10 µg/m3
PM10	Respiratory hospital admissions	1.009	1.007	1.010	10 µg/m3
PM10	Cardiovascular hospital admissions	1.006	1.005	1.008	10 µg/m3

See document Concentrations - response functions for traffic-related air pollution, IRAS

http://www.integrated-assessment.eu/resource_centre/exposure_response_functions_dataset

Table 2. Age-standaridised mortality rates: by area of usual residence by sex, 2008 registrations for England and Wales

Area of usual residence	Persons	Males	Females
Peterborough UA	615.8	727.7	525.1
Cambridgeshire	509.3	600.3	434.8
Norfolk	527.7	622.9	447.7
Suffolk	514.4	602.4	439.1
Cheshire	560.3	647.9	485.4
Cumbria	592.2	692.5	513.7
Greater Manchester	680.4	803.0	573.5
Lancashire	631.5	742.6	535.2
Merseyside	688.8	813.4	588.6

Age standardized death rates per 100,000 population

Office for National Statistics © Crown copyright 2010

Table 3. Hypothetical pesticide ERFs for cancers (loosely based on literature)

Outcome / ICD10 Code	Studies reported in the literature[1]						Weighted Hypothetical OR for assumed tertiles	Baseline Rate England (per 100,000)[2]	Severity Weight[3]
	Ref	Rank (7= best)	Study Design	Exposure	Population	Reported OR			
Cancer									
Breast / C50	Duell 2000	5,6	Case-control (North Carolina)	Insecticides, herbicides, fungicides, questionnaire	Females >25years	OR 1.8 (CI 1.1-2.8) in field during/shortly after application	T: 1.62, 1.8, 1.98	Female 116.9	0.9
Pancreas / C25	Ji 2001	5,4	Case-control (USA)	Insecticides, herbicides, fungicides, questionnaire, occupational	Adults >25years	Fungicides OR 1.5 (CI 0.3-7.6) Herbicides OR 1.6 (CI 0.7-3.4)	F: 1.35, 1.5, 1.65 H: 1.44, 1.6, 1.76	Male 10.0 Female 7.5	0.2
Non-Hodgkin's lymphoma / C82-85	Morrison 1994	4,5	Retrospective cohort (Saskatchewan)	Herbicides, acres sprayed	Males >25years	Herbicides RR 2.11 (CI 1.1-3.9)	I: 1.29, 1.43, 1.57 F: 2.78, 3.11, 3.42 H: 1.73, 1.93, 2.12	Male 15.3	0.6
	Hardell 2002	4,5	Case-control (Sweden)	All pesticides, questionnaire		Herbicides OR 1.75 (CI 1.26-2.42) Insecticides OR 1.43 (CI 1.08-1.87) Fungicides OR 3.11 (CI 1.56-6.27)			
Leukaemia / C91-95	Richardson 1992	4,4	Case-control (France)	Occupational exposure, questionnaire	Adults >30years	Herbicides OR 3.5 (CI 1.1-10.8) Insecticides OR 2.1 (CI 0.8-5.4)	H: 3.15, 3.5, 3.85 I: 1.89, 2.1, 2.31	Male 11.8 Female 7.2	0.9

Outcome / ICD10 Code	**Studies reported in the literature[1]**						**Weighted Hypothetical OR for assumed tertiles**	**Baseline Rate England (per 100,000)[2]**	**Severity Weight[3]**
	Ref	**Rank (7= best)**	**Study Design**	**Exposure**	**Population**	**Reported OR**			
	Ma 2002	6,7	Case-control (California)	Home exposure, questionnaire, all pesticides	Children <15years	Household pesticides OR 2.8 (CI 1.0-3.6)	T: 2.01, 2.23, 2.45		
	Meinert 2000	5,5	Case-control (Germany)	Home exposure, interview with parents		Pesticides on farms OR 1.5 (CI 1.0-2.2)			
Brain / C71	Kristensen 1996	6,6	Large retrospective cohort (Norway)	Mixed pesticide exposure, pesticide purchases	Children <10years	RR 1.71 (CI 1.11-2.63)	T: 1.67, 1.85, 2.03	Male 7.8 Female 5.1	Other 0.9
	Efird 2003	5,6	Case-control (international)	Farm-related pesticide exposure, questionnaire		OR 2.0 (CI 1.2-3.2)			
Prostate / C61	Alavanja 2003	7,7	Large prospective cohort (USA)	45 common pesticides, questionnaire	Males >25years	SIR 1.14 (CI 1.05-1.24)	T: 1.03, 1.14, 1.25	Male 91.4	0.13
Kidney / C64	Buzio 2002	4,4	Case-control	Mixed pesticide exposure, interview, occupational	Adults >25years	OR 2.0 (CI 0.8-4.7) for prolonged exposure	T: 1.70, 1.89, 2.08	Male 10.4 Female 5.3	Other 0.9
	Hu 2002	5,5	Case-control (Canada)	Mixed pesticide exposure, questionnaire, occupational		OR 1.8 (CI 1.4-2.3) all pesticides			

Bassil, K.L., Vakil, C., Sanborn, M., Cole, D.C., Kaur, J.S. and Kerr, K.J. 2007 Cancer health effects of pesticides: systematic review. Canadian Family Physician 53, 1704–1711.

Sanborn, M., Kerr, K.J., Sanin, L.H., Cole, D.C., Bassil, K.L. and Vakil, C. 2007 Non-cancer health effects of pesticides: systematic review and implications for family doctors. Canadian Family Physician 53(10), 1712-1720.

ONS. 2005 Cancer incidence and mortality in the United Kingdom 2001-03. National Cancer Intelligence Centre, Office for National Statistics.
http://www.who.int/healthinfo/global_burden_disease/GBD2004_DisabilityWeights.pdf

Annex 5. Greece case study

5.1 The impacts of the CAP

According to the ATEAM scenarios, there is a significant reduction in future arable land in the regions of study (Thessaly and Central Macedonia). The area of arable land is anticipated to fall from 9547 km^2 (baseline) to 7096 km^2 (under the BAU scenario) and 8025 km^2 (under the mitigation scenario) in 2020; by 2050, the area would further decline tyo 5610 km^2 and 7448 km$_2$, respectively.

The most significant decrease in arable land occurs for the BAU scenario in 2050, where the available arable land is reduced by about one half. In the Greek case study, cotton cultivation currently accounts for the majority of arable land: as Figure 1 (below) shows, the area of cotton was relatively stable from 1960 to 1980, but the subsidies available after Greece had joined the EU encouraged a tripling of the area under cotton, to ca. 2800 km^2 by the year 2000. Under the present CAP policies, whereby subsidies will be eliminated, a significant reduction in cotton cultivation is anticipated. In recognition of this, and expected water scarcity, the BAU therefore foresees that the cultivated area will fall back to its historic levels (Figure 1). It is also expected that other crops will be expanded to fill the land released, especially cereal and maize - the latter also considered an energy crop: cereals are projected to expand by 45% and maize by 30%.

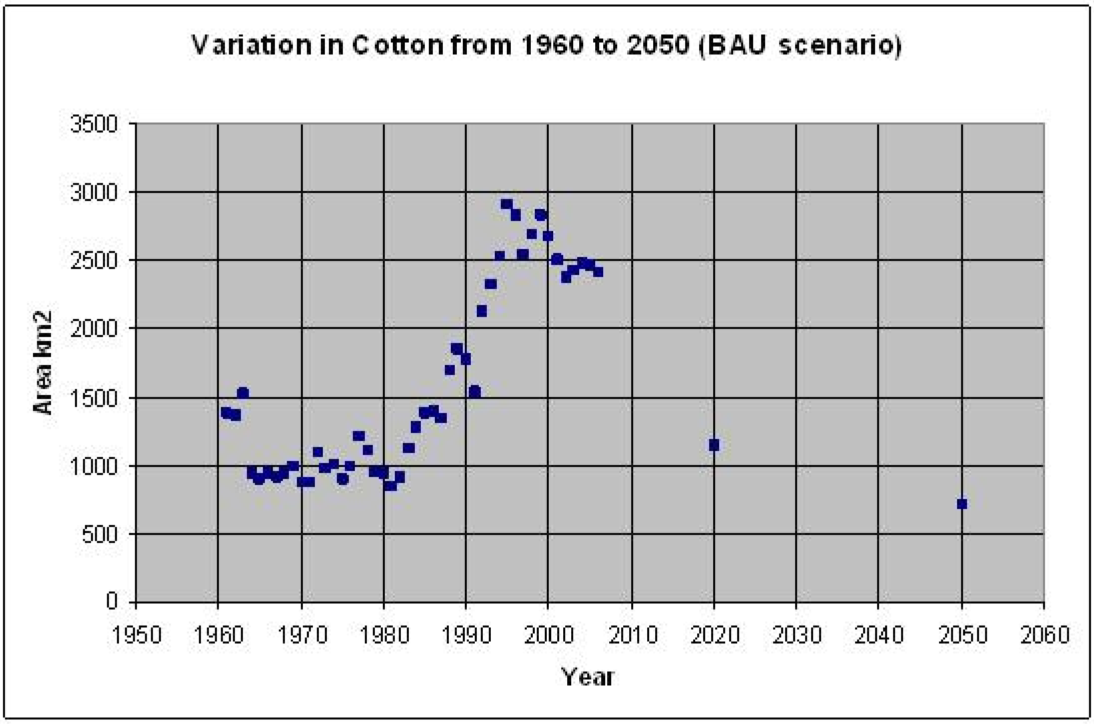


Figure 1. Variation of area cultivated with cotton between 1960 and 2006 and projections to year 2020 and 2050 for the Business As Usual (BAU) scenario in Thessaly and Central Macedonia.

Under the mitigation scenarios, the reduction in cotton cultivation is not expected to be so marked, largely because water shortages will be less severe due to the smaller rise in global temperatures. As Figure 2 shows, cultivation of cotton is thus assumed to decline to about 1500 km^2 by 2050 - i.e. greater that the historic average of 1950 to 1980, but significantly smaller than the maximum seen around the year 2000.

As for the BAU, the areas of cereals and maize are anticipated to increase (by 35% and 25% respectively).

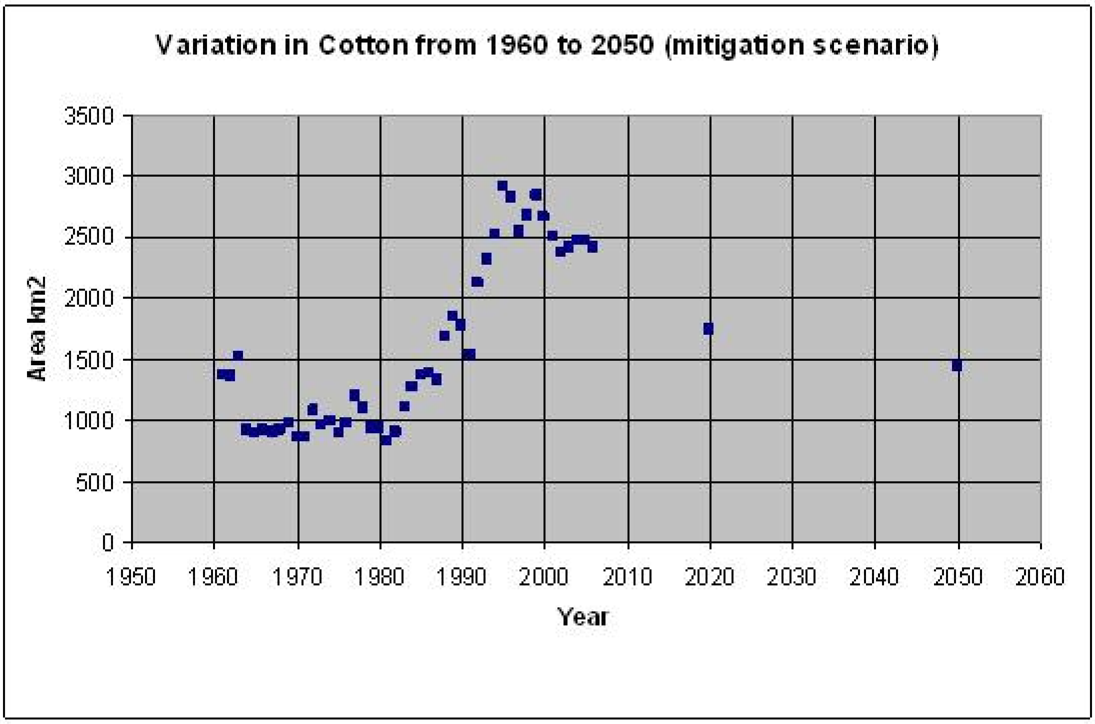


Figure 2. Variation of area cultivated with cotton between 1960 and 2006 and projections to year 2020 and 2050 for the Mitigation (MIT) scenario in Thessaly and Central Macedonia.

5.2 Crop allocation

A major task in developing the scenario for this assessment was to re-allocate crops in the Greek case study for the future scenarios, in 2020 and 2050. This is accomplished by a crop allocation algorithm, which distributes the areas of each crop on a 4x4km grid, applying the available area per grid as a constraint. The crop allocation algorithm employs two inputs: the ATEAM model estimates of arable land at 16x16km for the baseline year 2004, and the arable land data (ESYE) at a 4x4 km grid.

Firstly, for the baseline year 2004, arable land data (ESYE) are aggregated from LAU-2 to a 16x16km grid and compared to the estimated arable land (ATEAM) for the entire region of study. Variations between the two are used to normalise all scenario maps (ATEAM) for the years 2020 and 2050.

Secondly, all crop data available at LAU-2 level for the baseline scenario are re-allocated to the 4x4 km grid and fed into the crop algorithm.

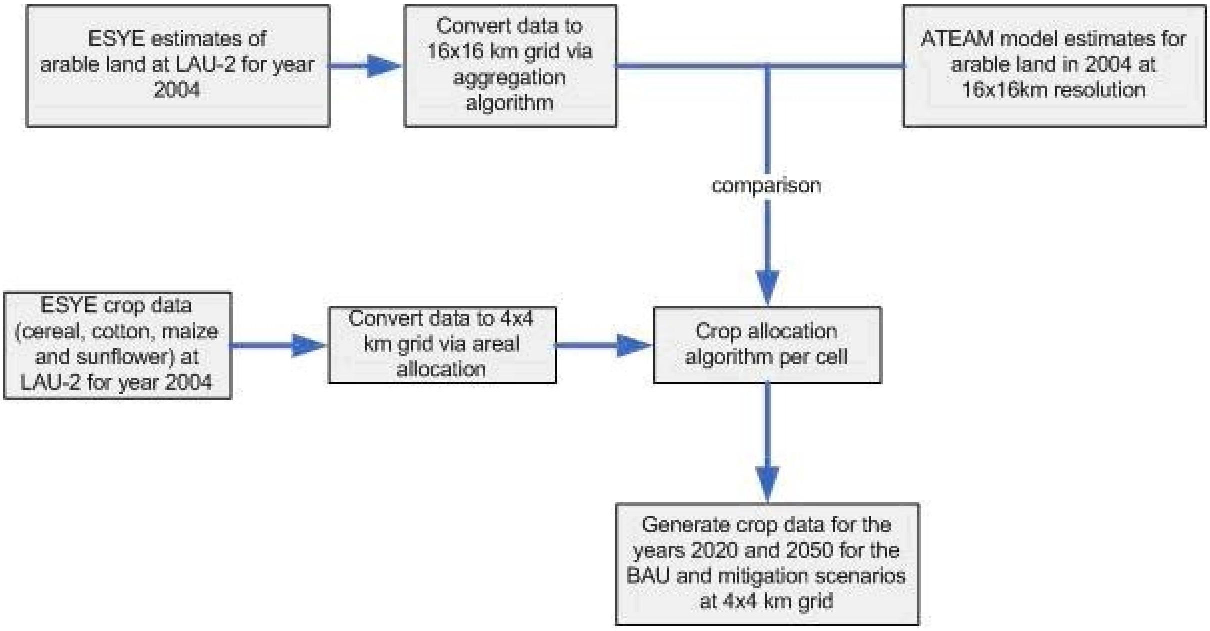


Figure 3. Flow chart of the method used to re-allocate crop data to the finer resolution

5.3 Energy crop scenarios

A. Mitigation scenario

The land requirements to cultivate energy crops is based on a recent EEA study (2009), where suitable land is from the arable land and at a lesser extent from the set-aside land. Any estimation on the land requirements is based on the following points:

1. The substantial increase of bio-energy production is apparently due to crop cultivation. The data for 2020 and 2030, and extrapolated to year 2050, constitute the part of the mitigation scenario referring to energy crops.
2. It is foreseen that forestry makes a small contribution to energy production in the context of the mitigation scenario; this prediction is in accordance with other stakeholders' opinions (e.g. Europa Bio 2007).
3. In estimating equivalent energy production under the scenarios, account has to be taken of:
   - agricultural residues related to the crops, in addition to the main product (seeds or grain); and
   - an appropriate yield for both main crop (seed and grain) and the remainder of biomass (from the plant, where applicable) - i.e. the total biomass produced per unit area cultivated.
4. The estimates of equivalent energy (MToe or eJ per year) derived for these scenarios differ from those indicated in Table 6.1 (attached below) in that :
   - more detailed yield values are employed; and
   - both main crop/product (grain, seed) and plant biomass is considered in the yield estimates.

B. Business-as-usual (BAU) scenario

The rate of increase of biomass production in EU-27 before year 2003 was approximately 1.25 Mtoe/yr, as shown in Figure 1, below. In 2003, a reform to the CAP established subsidies for energy crops cultivated in EU-27 up to a total area of 2.0 Mha. The above rate of increase is attributed largely to the general trend of increasing yield of the various crops and possibly to increased utilisation of agricultural residues. Only part of that increase is considered to be due to explicit land reallocation to energy crops. For the purpose of selecting a BAU scenario, an average yield of of 10t TS/ha is assumed for energy crop. This is based on the observation that approximately 50% of the increase in biomass production seen in recent years (~1.25 Mtoe/year) is due to land allocation to such crops. The typical trend on biomass production is presented in figure 4.

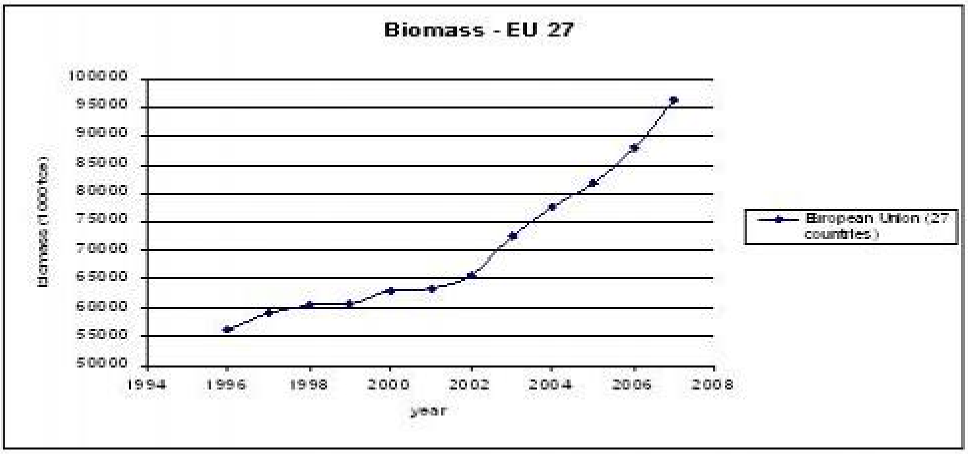


Figure 4. Total biomass production in EU-27 years, 1996 to 2007 (Eurostat 2008)

C. Total land requirements for the energy crops

To estimate land requirements for energy crops in the two Greek case study areas (Thessaly and Central Macedonia), the national data are scaled down proportional to the area of total arable land. Table 1, below, shows the resulting projections for the different scenarios and years.

Table 1. Area of land (km^2) devoted to energy requirements in the Greek case study areas under the BAU and mitigation scenarios.

Scenario	Total (all energy crops)	Sunflower	Sorghum	Cardoon
Baseline	-	-	-	-
BAU 2020	581	194	194	194
Mitigation 2020	1104	368	368	368
BAU 2050	329	110	110	110
Mitigation 2050	413	138	138	138

5.4 Stochastic disaggregation of pesticide quantity - Greek Case Study

Stochastic allocation provides a means of making probabilistic estimates of source activities at each study location, on the basis of prior, geographically aggregated information. It consists of two parts:

1. a procedure to generate quantity histograms on the basis of the prior information (e.g. the geographic distribution of the activity)
2. an optimisation algorithm in which quantities are re-allocated to new positions on the quantity histograms according to an objective function.

The methodology is illustrated here in relation to modelling of active ingredients (AIs) in agricultural pesticides, as part of a case study of agricultural land use in Greece. In this example, the original information on land use and pesticide application rates was available at NUTS-3 level (e.g. prefecture). The aim is to model AI usage at a finer grid resolution.

Required input data

1. Crop cultivation data (in km^2) in the target grid resolution.
2. A list of ASs used on each crop together with:
    - o the maximum applied dosage (in kg/km^2) and number of application;
    - o chemical class;
    - o type of action (e.g. herbicide, insecticide, plant growth regulator);
    - o toxicity characterization;
3. AS usage data at aggregated (e.g. region, prefecture, LAU-1) level collected via local survey or from national statistics;
4. Optionally, other data (soil data, patterns of pesticide usage, meteorological conditions) could be integrated in the algorithm.

Data initialization

a) Select a group of ASs with the same type of action.

b) Divide ASs into sets of 2 or more, according to the toxicity characterisation or the chemical class.

c) Based on the area each AS covers for each crop (calculated as the ratio between quantity of pesticide used and the maximum reported dosage) estimate the percentage contribution to the total reported crop. If the estimated area covered and the reported cultivated crop area (at prefecture level) are different, changes to the maximum dosages are allowed in order to ensure that the AS cover the entire crop (applicable only for herbicides). The AS contributions to crop area, are termed allocation factors.

d) Generate a random sequence of grid cells (e.g. maize in km^2) based on a uniform distribution.

Generation of AS usage data per cell per crop

Starting from a single random grid cell ordering (according to a uniform distribution), for a particular crop, a random weighting (according to a normal distribution) to each set of ASs is multiplied by the AS allocation factors. The allocation factors are multiplied by the AS dosages per cultivated crop area (per grid), in order to estimate the AS quantities, based on the area weighting method. Figure 5 illustrates this procedure. The area weighting method is repeated for all cells for a single random sequence, until the AS quantity from a particular set is depleted (mass balance). Once AS mass is depleted, the allocation factors are normalised according to the remaining ASs. Calculations are repeated until all AS quantities are depleted for a single cell sequence. The same procedure is repeated for a large number of random cell orderings. After the end of the simulations, histograms for each AS (quantity) per cell are generated and suitable distribution functions are fitted, according to known statistical criteria. In this way, AS quantities for all crop cells are presented as a histogram, converted to probability density plots, (as seen in Figure 5) Once probability density plots have been calculated, estimates of mean AS quantity and standard deviation can be performed, with no guarantee that the AS mass balance is attained.

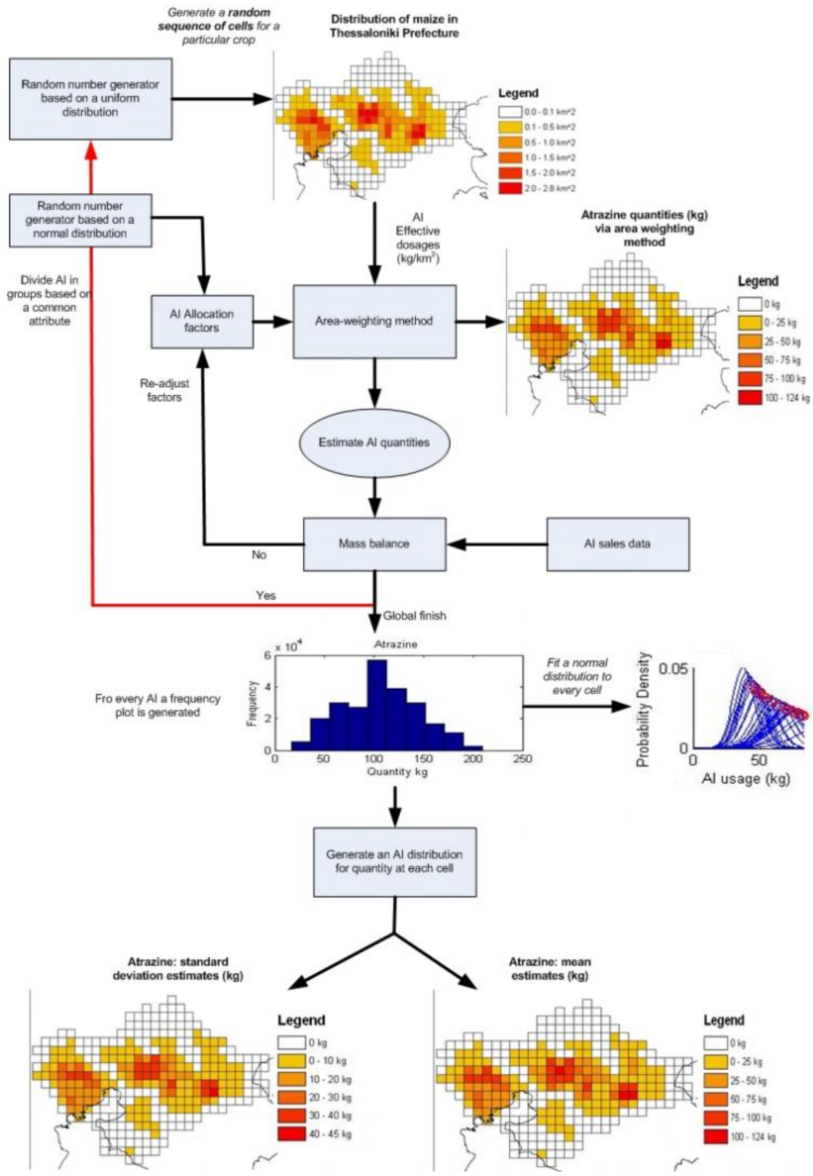


Figure 5. Flow chart: Procedure to generate usage data according to some prior knowledge

Spatial allocation of pesticides according to an optimization function

In this section, it is illustrated how AS quantities could be spatially distributed according to an objective function. Starting with some initial spatial estimates of AS usage (based on the area weighting method), an objective function is formulated, with scope to minimise (or maximise) according to criteria such as:

a) spatial patterns in the geographic activity of pesticides

b) assumed effects of meteorological conditions on pesticide usage

c) level of each AS probability density estimate relative to the maximum probability density of each cell; the weighted sum of all these ratios in a cell is termed the *uncertainty index*, and the sum of indices in all cells is termed the *global uncertainty index*.

In this example, we illustrate the third approach. Here the objective is to maximise the weighted sum of the AS ratios (initial probability density estimate of the maximum probability density for each AS) present in a cell. Therefore, it is possible to re-allocate all AS quantities from a low probability density to maximum (if applicable) - i.e. quantities with the highest frequency used - ensuring no violation in the total crop cell area (Figure 6).

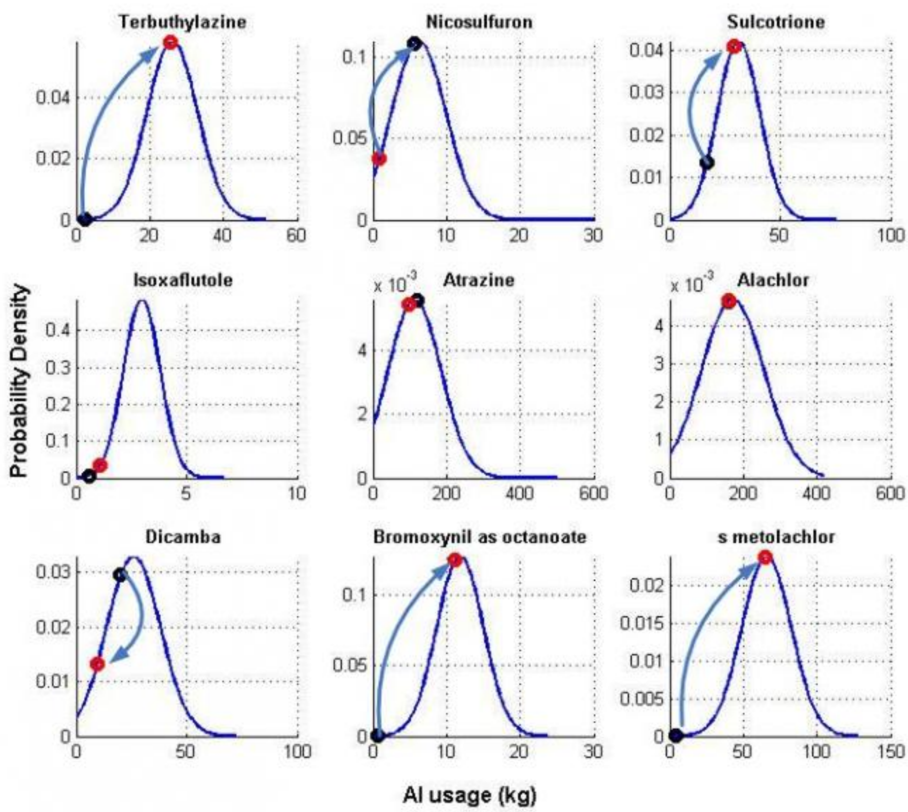


Figure 6. Re-allocation of pesticides from an initial location (black dots- initial estimates) to new location (red dots - optimal estimates)

The procedure followed to re-allocate quantities is presented in Figure 7. Starting from the fitted AS distribution functions for each cell, a large number of random cell realisations are generated (according to a uniform distribution). For each realisation, for each cell, a nonlinear algorithm (trust region reflective algorithm) is implemented. The constraints imposed on the algorithm are on AS quantity and crop area per cell. During the optimisation, if an AS is depleted the objective function changes to exclude that particular AS, and a solution is given for the remaining ASs. Once an optimal solution is found, the next cell in the sequence is processed, until all cells in a prefecture are covered.

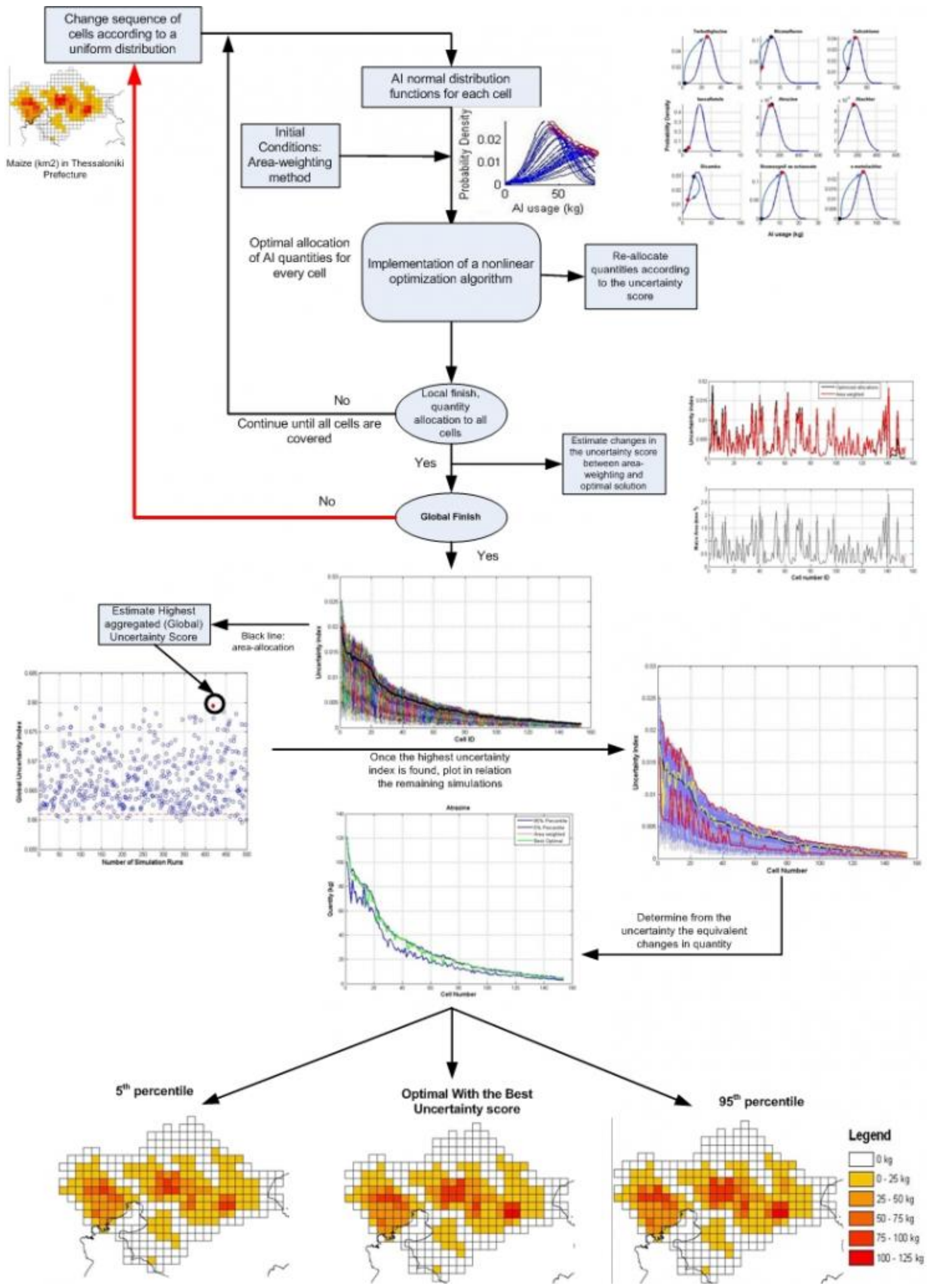


Figure 7. Flow chart: Representation of the steps followed to re-allocate quantities according to an objective function

This procedure is repeated for a number of cell realisations, and estimates of the objective function (i.e. uncertainty index) are then sorted in a descending order (in this case, according to the maize crop area, each cell number having a unique ID). In Figure 7, estimates of the objective function are aggregated (to give the global uncertainty index), in order to determine the highest score: ASs closer to the maximum probability density are considered to provide the optimal solution. Figure 8 illustrates variations in the uncertainty index for all cells, where a comparison is made between the optimal solution (yellow line) and results from the area weighting method (initial conditions, black line), together with both confidence intervals (red lines).

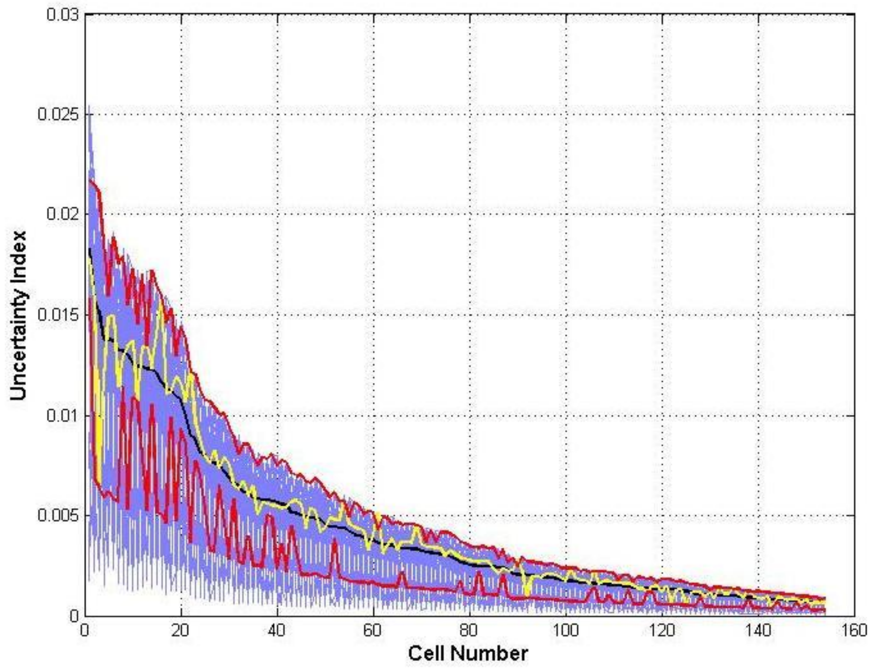


Figure 8. Spatial variation in the estimated objective (uncertainty index), sorted in descending order (maize area). Red line shows the 5 and 95 percentile, the black line shows the initial conditions (area weighting method and yellow line an optimal allocation with the best aggregated (uncertainty index) score.

Once the best solution for the selected objective function has been identified, the corresponding AS quantities are determined, as presented in Figure 9, together with the corresponding confidence intervals. The spatial distribution of an AS is presented before (figure 10) and after the optimization (figure 11).

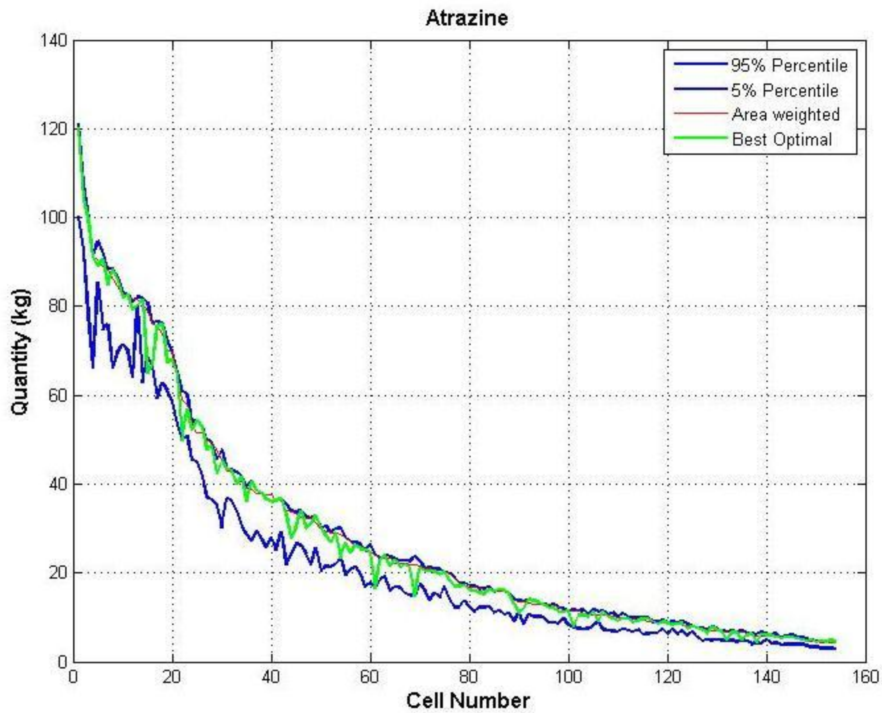


Figure 9. Spatial variation in quantity for Atrazine, sorted by the crop area (shown by the cell number ID) together with the 5 and 95 uncertainty estimates.

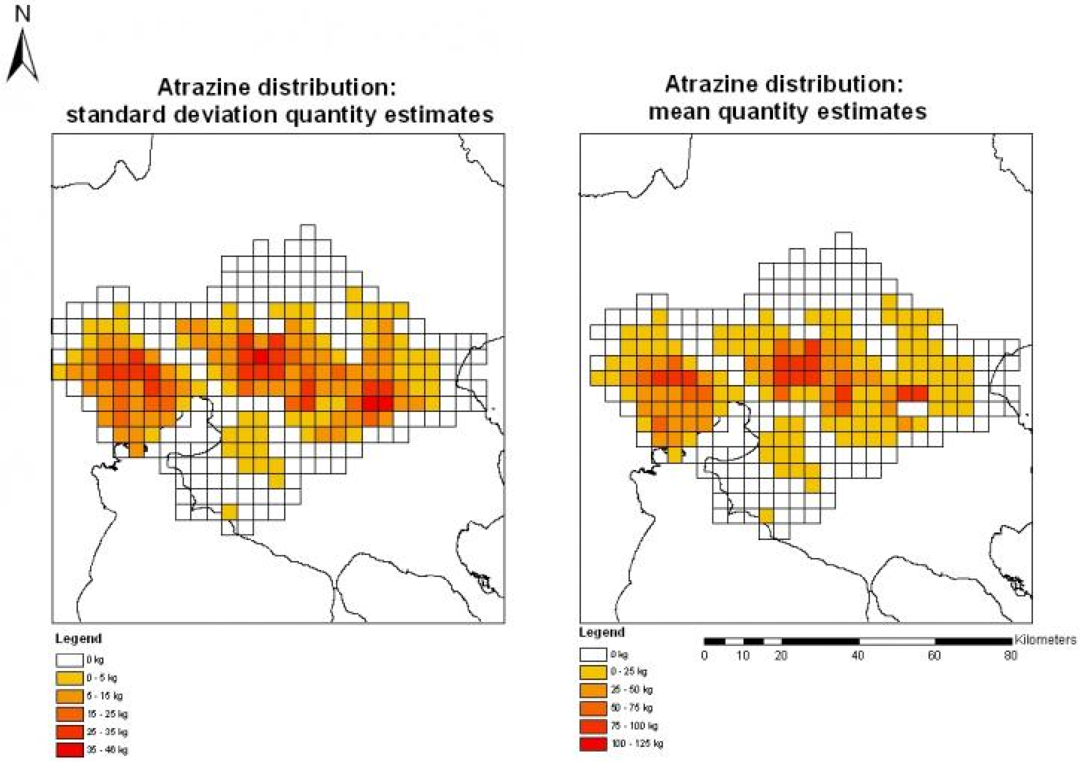


Figure 10. Stochastic variation in quantity for Atrazine, prior to optimization.

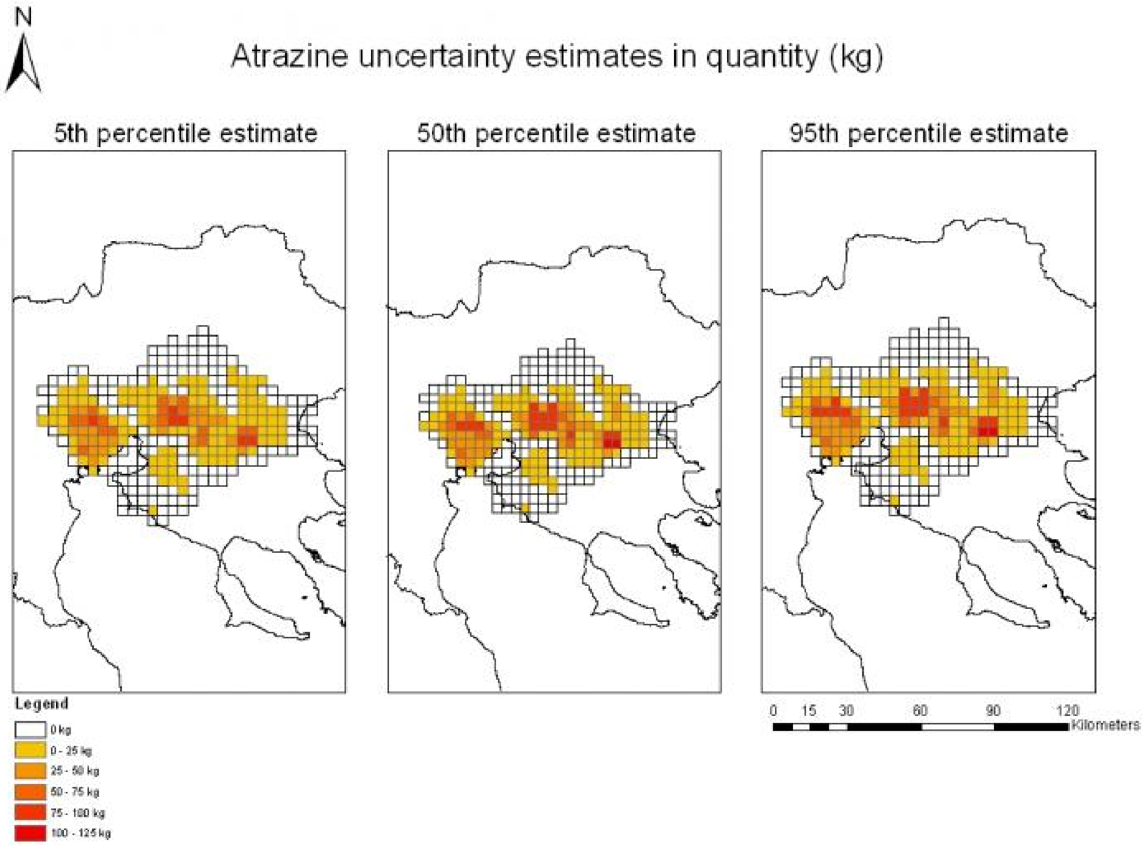


Figure 11. Confidence intervals to the quantity for the Atrazine after optimization.

5.5 Meteorological and Dispersion Models used

CALMET model (CALPUFF, 2010)

Surface meteorological data were employed from six surface meteorological stations; i.e the stations Thessaloniki, Serres, Trikala Imathias for C. Macedonia and Trikala Thessalias, Larisa, N. Agxialos for Thessaly, operating by the Hellenic National Meteorological Service (HNMS, 2010). It should be mentioned that in all simulations average meteorological data (March-September) were utilised for temperature and relative humidity. Considering wind direction and wind speed, prevailing values were selected.

Unfortunately, there was only one upper air radiosonde meteorological station within the modeling domain; i.e. in the Thessaloniki airport (HNMS, 2010). Thessaloniki station is located in an area characterized by the presence of strong sea-land breeze circulation strongly affecting the micro-meteorological variables. Proxy upper air data were generated for the N. Agxialos meteorological station. Using 12-hour meteorological data (from the above surface station and from the Thessaloniki upper air station as a reference), data were generated for the wind speed and its direction, the temperature and the relative humidity. In particular, it was assumed that the above meteorological parameters follow the same vertical profiles as reported in the Thessaloniki upper air station.

CALPUFF model (CALPUFF, 2010)

CALPUFF simulations were performed using average meteorological data (see CALMET model). Pesticides were treated as a typical gas in CALPUFF model. Dry deposition losses of pesticides were included using default parameters for alpha star, reactivity and mesophyll resistance. The diffusivity of pesticides was estimated using the following formula (Hashimoto, 1989):

$$D = \frac{0.0043 T^{3/2} \sqrt{(1/M_1 + 1/M_2}}{P_0 (V_1^{1/3} + V_2^{1/3})^2} \qquad (1)$$

where:

P_0 = atmospheric pressure, atm (1 atm)

V_1, V_2 = the molar volumes of a pesticide at the boiling point and air (cc/mol), respectively

M_1, M_2 = the molar masses of the pesticide and air, respectively

The V_1, V_2 values where calculated by using the Le Bas method (table of atomic volumes) (Reid et al. 1997).

After the estimation of the diffusivity for all the pesticides using the equation 1, an average value of 0.04 cm/sec was selected for the simulations. All other model parameters were set to default values.

5.6 Exposure Response Functions and Health Data

Exposure response functions for pesticides

Toxicity characterization and slope factors from carcinogenic pesticides used in C. Macedonia and Thessaly are presented in the following table.

Table 2. Exposure response functions for carcinogenic pesticides used in C. Macedonia and Thessaly.

Active substances	Action[1]	Chemical class[2]	Carcinogenicity (US EPA)[4]	Slope factor (in $(mg/kg/day)^{-1}$)[5]
Alachlor	H	Chloroacetanilide	Likely (high doses), Not likely (low doses)	8.000E-02
Clodinafop_propargyl	H	Aryloxyphenoxy propionic acid	Suggestive	1.290E-01
Cypermethrin	I	Pyrethroid	C, Possible	1.047E-02
Diclofop_methyl	H	Chlorophenoxy acid or ester, Aryloxyphenoxy propionic acid	Likely	7.360E-02
Dicofol	A	Organochlorine	C, Possible	1.047E-02
Dimethipin	PGR	Unclassified	C, Possible	1.047E-02
Fluometuron	H	Urea	C, Possible	1.800E-02
Isoxaflutole	H	Isoxazole[3]	Likely	1.020E-02
MCPA	H	Chlorophenoxy acid or ester	C, Possible	1.047E-02
Pendimethalin	H	2,6-Dinitroaniline	C, Possible	1.047E-02
Propargite	A	Sulfite ester[3]	B2, Probable	1.920E-01
s_metolachlor	H	Chloroacetanilide	C, Possible	1.047E-02
Thiacloprid	I	Neonicotinoid	Likely	4.060E-02

Active substances	Action[1]	Chemical class[2]	Carcinogenicity (US EPA)[4]	Slope factor (in $(mg/kg/day)^{-1}$)[5]
Thiodicarb	I	N-Methyl Carbamate	B2, Probable	1.880E-02
Tralkoxydim	H	Cyclohexenone derivative	Suggestive	1.680E-02
Trifluralin	H	2,6-Dinitroaniline	C, Possible	2.930E-03

[1]H: Herbicides, I: Insecticides, A: Acaricides, PGR: Plant Growth Regulator.

[2] PAN Pesticides Database. Chemicals; 2008. available in http://www.pesticideinfo.%20org/Search_Chemicals.jsp.

[3] FOOTPRINT. Creating tools for pesticide risk assessment and management in Europe; 2008. available in http://www.eu-footprint.org/ppdb.html.

[4] US Environmental Protection Agency (US EPA. ; 2008. available in http://www.epa. gov/pesticides/.

[5] Rowland, J. 2006 Chemicals Evaluated for Carcinogenic Potential, Office of Pesticide Programs, US EPA.

Exposure response functions for Particulate Matter

PM exposure response functions for respiratory and cardiovascular hospital admissions have been obtained from a literature review (Le Tertre et al., 2002; Medina et al., 2005; Dominici et al., 2005). Although PM10 relative risks are available for all ages, PM2.5 relative risks are only available for elderly (>65 years old). Moreover, a distinction between different health effects related to PM2.5 has been made (e.g. COPD and respiratory tract infection hospital admissions). The following exposure response functions have been selected as the most appropriate for the Greek case study.

Table 3. PM exposure response functions for respiratory and cardiovascular hospital admissions.

Pollutants	Population	Health Indicator	ICD9	Relative Risk (95% CI)	95% C.I.	Unit
PM10	All ages	Cardiovascular hospital admissions	390-429	1.011[1]	1.004-1.019	10 μg/m^3
PM10	All ages	Respiratory hospital admissions	460-519	1.003[2]	0.9985-1.0075	10 μg/m^3
PM2.5	Elderly (> 65 years of age)	Peripheral vascular diseases hospital admissions	440-448	1.0086[3]	0.9994-1.0179	10 μg/m^3
PM2.5	Elderly (> 65 years of age)	Ischemic heart diseases hospital admissions	410-414, 429	1.0044[3]	1.0002-1.0086	10 μg/m^3
PM2.5	Elderly (> 65 years of age)	Dysrhythmias hospital admissions	426-427	1.0057[3]	0.9999-1.0115	10 μg/m^3
PM2.5	Elderly (> 65 years of age)	COPD hospital admissions	490-492	1.0091[3]	1.0018-1.0164	10 μg/m^3
PM2.5	Elderly (> 65 years of age)	Respiratory tract infection hospital admissions	464-466, 480-487	1.0092[3]	1.0041-1.0143	10 μg/m^3

[1]Le Tertre A., Medina S., Samoli E., et al. 2002 Short term effects of particulate air pollution on cardiovascular diseases in eight European cities, *J Epidemiol Community Health*. 56, pp 773-779.

[2]Medina S., Boldo E., Saklad M., Niciu E.M., Krzyzanowsky M., Frank F., Cambra K., Mucke H.G., Zorrilla B., Atkinson R., Le Tertre A., Forsberg B., and the contributing members of the Apheis group. 2005 APHEIS Health Impact Assessment of Air Pollution and Communications Strategy. Third year report, 2002–2003. Saint-Maurice: Institut de Veille Sanitaire. pp 232

[3]Dominici F., McDermott A., Daniels M., Zeger S.L. and Samet J.M. 2005 Revised analyses of the National Morbidity, Mortality, and Air Pollution Study: mortality among residents of 90 cities, *J Toxicol Environ Health*. 68, pp 1071–1092.

5.7 Health data for particulate matter

The *incidence rates* used in this application have been calculated for cardiovascular and respiratory health effects. The Age standardized incidence rates are calculated by estimating the age-specific rates and then these rates are applied to reference population (the standard world population) (WHO methodology).

Age standardized incidence per 100000 world population = $(\frac{d_i}{y_i}) * w_i$ (1)

where di: the number of cases for age group i

yi: persons at risk for age group i

wi: the standard world population for age group i

Incidence rates of specific health effect= $\sum_{i=1}^{n}(\frac{d_i}{y_i}) * w_i$ (2)

In this study the *number of cases* for each age group has been estimated from the recorded number of patients exiting the hospitals in a year, obtained from the Greek National Statistical Service (ESYE, 2010). As the exact number of people that are hospitalized more than once is not known, assumptions have been made based on the age group and the health effect. For instance, it is assumed that older people (>55 years old) are hospitalized four times in a year for cardiovascular problems, while people belonging in the age group of 25-54 are hospitalized twice; thus the number of people exiting the hospital is divided by 2 and 4 depending on age group.

Annual incidence rates for both respiratory and cardiovascular health effects for the whole population for year 2000 have been calculated by using the aforementioned equations. The values computed for respiratory and cardiovascular health effects are 0.0038 (380 patients per 100000) and 0.0027 (270 patients per 100000), respectively (Table 4).

Table 4. Age-standardized incidence rates for whole Greece.

	Incidence rates[1]						
Age group	**Cardiovascular disease**	**Respiratory disease**	**Ischemic heart disease**	**Heart rythm**	**Peripheral vascular disease**	**Respiratory tract infections**	**COPD[2]**
0-4	0	124	0	0	0	17	62
5-14	0	80	0	0	0	7	24
15-24	3	27	1	1	1	5	9
25-34	7	32	2	2	1	3	8
35-44	24	22	12	5	2	3	5
45-54	75	31	45	10	4	8	6
55-64	57	20	33	8	6	13	6
65-74	63	25	31	11	7	19	6
75+	40	20	14	8	4	14	4
Total	**270**	**381**	**138**	**45**	**25**	**88**	**130**

[1]Age standardized incidence rates per 100,000 population

[2]COPD: Chronic obstructive pulmonary disease

5.8 Re-allocation of Population to the 4x4km grid

A very important task in the health impact analysis is to disaggregate population data from low to high resolution grid, recognizing the spatial distribution of the population settlements. In the Greek case study, data are available at LAU-2 level (as provided by the national statistics agency), per sex and age group for the year 2001. In addition, a land use map from CORINE is available, presenting most of the population settlements. The proposed methodology according to Figure 12, includes the following steps:

1. Locate all population settlements (polygons) within each LAU-2 warden.
2. Transfer all data from LAU-2 warden to the population polygons, presented in a map
3. Intersect the population polygon map, with the 4x4 km grid
4. Using an area weighting algorithm, transfer data from polygons to grid

Once population data are transferred to the 4x4 km grid, the population for the years 2020 and 2050 are estimated at country level, using the ESYE factors seen in tables 5 and 6. These factors are used uniformly, to the entire region of the study.

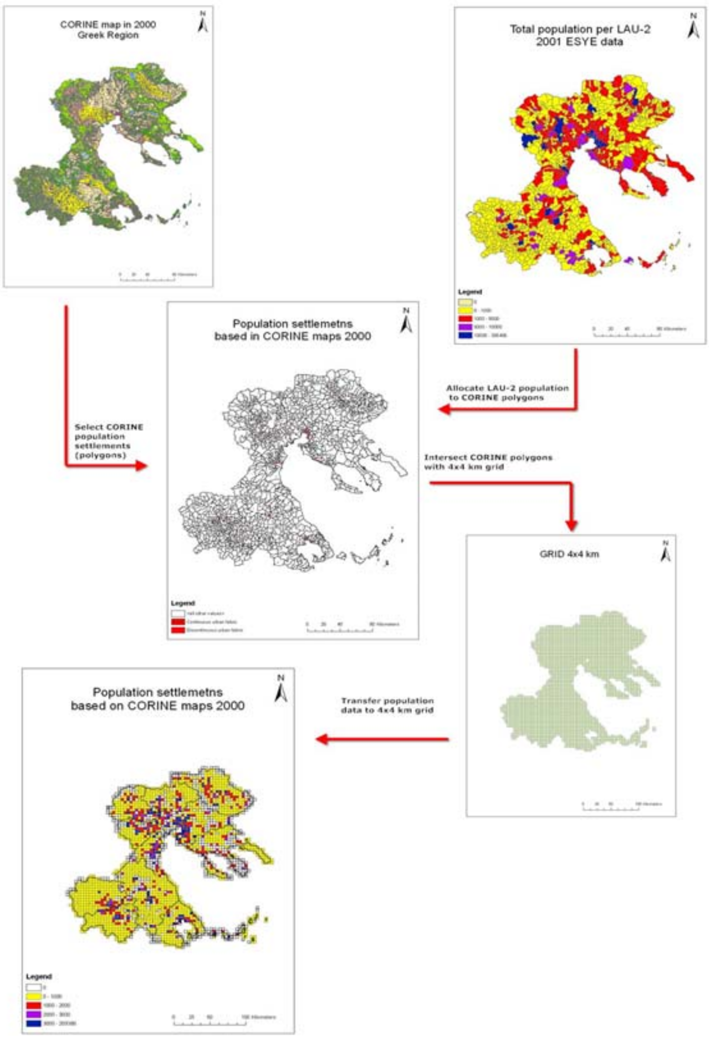


Figure 12. Methodology used to allocate population data to the 4x4 km grid

Table 5. Country based population factors for both male and female for the year 2020

Population group	Total	Male	Female
Total	1.04	1.05	1.03
0 to 14 yr	1.04	1.04	1.03
15 to 24 yr	0.87	0.86	0.87
25 to 39 yr	0.83	0.85	0.82
40 to 54 yr	1.16	1.19	1.13
55 to 64 yr	1.21	1.22	1.20
65 to 79 yr	1.02	1.04	1.00
Above 80 yr	2.19	2.09	2.27

Table 6. Country based population factors for both male and female for the year 2050

Population group	Total	Male	Female
Total	1.03	1.05	1.01
0 to 14 yr	0.94	0.94	0.93
15 to 24 yr	0.80	0.79	0.80
25 to 39 yr	0.70	0.71	0.69
40 to 54 yr	0.87	0.91	0.83
55 to 64 yr	1.12	1.19	1.05
65 to 79 yr	1.47	1.61	1.35
Above 80 yr	4.54	4.55	4.55

Estimation of Farmer Population

Farmer population is allocated to the 4x4km grid, via areal weighting where farmer numbers per prefecture (ESYE, table 7) are crossed with the total population data at 4x4km grid. Furthermore, it is assumed that farmers live in areas with population density smaller than 100 people/km^2. For the estimation of the number of farmers in scenarios, the ratio of farmers to the total population is assumed to remain constant. Table 7 presents the number of farmers per prefecture and scenario.

Table 7. Number of farmers per prefecture and scenario.

	Total Number of Farmers		
Prefecture	**Baseline (ESYE)**	**2020**	**2050**
Karditsa	16214	16781	16246
Larissa	27173	27091	27418
Magnisia	9950	9453	10547
Trikala	13390	12587	12694
Imathia	13844	14398	13978
Thessaloniki	19164	18781	19350
Kilkis	6657	6923	6722
Pella	21461	20173	20817
Peieria	13357	12956	13487
Serres	22413	21920	22630
Xalkidiki	8122	7984	8201

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