GAINS-Asia
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Final Report on
Policy Analysis with the
GAINS-Asia model

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Abstract

This report describes initial policy analyses with the Greenhouse gas – Air pollution Interactions and Synergies (GAINS) model. It summarizes the exogenous projections on energy and agricultural activities up to 2030 and discusses the resulting implications on air quality and greenhouse gas emissions. An illustrative scenario explores the health benefits from a substitution of solid fuels in households by LPG and explores the side-effects on greenhouse gas emissions. The paper summarizes the optimization methodology that has been developed for the GAINS-Asia model and presents a range of alternative strategies to improve air quality and reduce greenhouse gas emissions. It shows that with a targeted approach, emission control costs can be reduced by up to 80 percent compared to an across-the-board application of technologies. Furthermore, the paper presents systematic analyses of the costs (i.e., cost curves) for reducing health impacts from fine particulate matter as well as for reducing greenhouse gas emissions.

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1 Introduction

Economic reforms after the year 2000 have led to an unprecedented economic growth in many Asian countries. While in the decade from 1990 to 2000 economic output of India and China (measured in GDP) grew by five to six percent annually, after the year 2000 annual growth rates boosted to 10 percent and more, outstripping that of all other major countries. This rapid expansion of economic activities, and in particular the concomitant growth in the consumption of fossil fuels, has dramatically increased the pressure on air, land, water and ecological resources. Poor air quality is now a major public concern in virtually all larger cities throughout Asia (Molina and Molina, 2004). The intercontinental transport of pollutants causes increasing background pollution levels at the hemispheric scale (Akimoto, 2003). The rapid raise in Asian greenhouse gas emissions has been recognized as the key factor for the accelerated increase in global CO_2 concentrations (Raupach *et al.*, 2007).

All projections for these countries envisage a continuation of the current growth dynamics, reflecting the rapid economic development, industrialization, urbanization and improved quality of life. For 2030, national development plans as well as international analyses expect economic output to grow between a factor of 7 to 11 compared to the year 2000 (Office of the Principal Scientific Adviser to the Government of India, 2006; Government of China, 2006). Although it is likely that the envisaged growth in economic output will decouple from the growth in energy consumption, current projections envisage a tripling of total energy consumption in these countries (IEA, 2007).

Unless effective countermeasures are taken, these trends will further intensify the pressure on the atmosphere at the local, regional and global scales. For instance, assuming continuation of current energy policies and no further tightening of existing emission control legislation, concentrations of fine particles that are harmful for human health are poised to triple in India and China in the coming decades. The sheer size of these growing economies will have implications on the global environment too. It is estimated for the reference case that by 2030 India and China together would account for 45 percent of the global growth in greenhouse gas emissions. Thereby, in 2030 additional emissions from India and China would equal the current emissions of the United States and the EU-27 combined. Obviously, such a development would put unprecedented burden on the local and global environment.

However, a wide range of technical and non-technical measures is available to reduce the release of harmful emissions to the atmosphere. For air pollutants, advanced emission controls are now widely applied in industrialized countries. Responding to public concern about poor air quality in Asian cities, certain measures for controlling vehicle emissions are now also being introduced in many Asian countries (Cofala *et al.*, 2007). Comparatively little is done to control air pollutant emissions from stationary sources (other than SO_2 from Chinese power stations). Also for controlling greenhouse gas emissions a variety of mitigation options is available (IPCC, 2007). However, control of greenhouse gas emissions is currently not seen as a priority for domestic policy in many developing countries in Asia, essentially because of concerns that mitigation costs would hinder economic development.

Given the stark increase in economic activities that is envisaged for the coming decades in Asia, it will be a formidable task for Asian policy makers to secure continued economic development while providing acceptable levels of air quality to their citizens and assuring sustainable conditions to vegetation and ecosystems in their countries. At the same time, the envisaged growth in Asian greenhouse gas emissions will seriously challenge efforts of the world community to control global climate change.

For a number of historic reasons, response strategies to air pollution and climate change are often addressed by different policy institutions. However, there is growing recognition that a comprehensive and combined analysis of air pollution and climate change could reveal important synergies of emission control measures (Swart *et al.*, 2004), which could be of high policy relevance. Insight into the multiple benefits of control measures could make emission controls economically more viable, both in industrialized and developing countries. However, while scientific understanding on many individual aspects of air pollution and climate change has considerably increased in the last years, little attention has been paid to a holistic analysis of the interactions between both problems.

The Greenhouse gas – Air pollution Interactions and Synergies (GAINS) model has been developed as a tool to identify emission control strategies that achieve given targets on air quality and greenhouse gas emissions at least costs. GAINS considers measures for the full range of precursor emissions that cause negative effects on human health via the exposure of fine particles and ground-level ozone, damage to vegetation via excess deposition of acidifying and eutrophying compounds, as well as the six greenhouse gases considered in the Kyoto protocol. In addition, it also considers how specific mitigation measures simultaneously influence different pollutants. Thereby, GAINS allows for a comprehensive and combined analysis of air pollution and climate change mitigation strategies, which reveals important synergies and trade-offs between these policy areas.

Under the EU Sixth Framework Programme on Research (FP6), an international team of research institutions has implemented the GAINS model for India and China. The research team, headed by the International Institute for Applied Systems Analysis (IIASA, Laxenburg, Austria), included The Energy and Resource Institute (TERI, Delhi, India), the Chinese Energy Research Institute (ERI, Beijing, China), the Institute for Environment and Sustainability of the Joint Research Centre of the European Commission (IES-JRC, Ispra, Italy) and the University of Bern (Switzerland). The GAINS model with all databases is now freely accessible for interactive use at the Internet (www.iiasa.ac.at/gains).

This report provides a brief introduction to the methodology of the GAINS-Asia model and discusses the methodological changes that have been introduced to appropriately reflect Asian-specific conditions. Section 3 summarizes the key input on economic projections that have been provided by the Asian project partners and explores the implications on future air quality and greenhouse gas emissions under baseline assumptions. Section 4 introduces the optimization approach of the GAINS model and presents some initial analyzes to demonstrate the potential for increased cost-effectiveness. Section 5 provides systematic assessments of the costs for reducing health impacts from air pollution as well as greenhouse gas emissions. Conclusions are drawn in Section 6. The material presented in this report will serve as input for further policy analyses that will be developed in cooperation with the project partners in India and China with close involvement of key stakeholders in these countries.

2 The GAINS-Asia model

2.1 *The integrated assessment concept*

The Greenhouse and Air pollution Interactions and Synergies (GAINS) model explores cost-effective strategies to reduce emissions of greenhouse gases and conventional air pollutants. The GAINS model produces emission scenarios for all major air pollutants for any exogenously supplied projection of future economic activities, abatement potentials, and costs as well as interactions in abatement between various pollutants (Klaassen *et al.*, 2004). Essentially, the GAINS model follows pollutants from their driving forces (i.e., economic activities such as energy consumption, agricultural production, industrial activities, etc.), it considers region- and source-specific emission characteristics, it analyzes the potentials for reducing emissions through a variety of technical and non-technical measures and estimates the associated costs, it simulates the fate and dispersion of emissions in the atmosphere and it computes impact indicators for human health, ecosystems, and greenhouse gas emissions.

The GAINS model considers emissions of sulphur dioxide (SO_2), nitrogen oxides (NO_x), fine particulate matter (PM2.5 and PM10), ammonia (NH_3) and volatile organic compounds (VOC) as well of the greenhouse gases carbon dioxide (CO_2), methane (CH_4), nitrous oxides (N_2O) and the three F-gases that are included in the Kyoto protocol. It quantifies health impacts from fine particles and ground-level ozone, excess deposition of acidifying (sulphur and nitrogen) compounds and excess nitrogen input to ecosystems, and total greenhouse gas emissions using the global warming potentials specified in the Kyoto protocol (Figure 2.1). GAINS constitutes an extension of the RAINS (Regional Air Pollution Information and Simulation) model (Schöpp *et al.*, 1999) to greenhouse gases with special emphasis on the interactions between air pollutants and greenhouse gas emissions.

	PM	SO_2	NO_x	VOC	NH_3	CO_2	CH_4	N_2O	CFCs HFCs SF_6
Health impacts: PM	√	√	√	√	√				
O$_3$			√	√			√		
Vegetation damage: O$_3$			√	√			√		
Acidification		√	√		√				
Eutrophication			√		√				
Radiative forcing: - direct						√	√	√	√
- via aerosols	√	√	√	√	√				
- via OH			√	√			√		

Figure 2.1: The GAINS multi-pollutant/multi-effect framework

The Asian implementation of GAINS holds economic statistics, energy and agricultural projections and emission inventories for 32 administrative regions in China (provinces) and 23 States in India. Based on a set of source-receptor relationships derived from a sample of calculations with the TM5 atmospheric chemistry and transport model (Krol *et al.*, 2005), GAINS-Asia computes air quality indicators for rural areas with a 1 degree*1 degree spatial resolution (Dentener, 2008). For estimating health impacts, GAINS calculates urban concentrations of PM2.5 for the major cities in India and China.

GAINS uses exogenously supplied projections of energy consumption and industrial as well as agricultural activities up to 2030 as economic driver for its emission projections. For India and China, the baseline projections reflect current governmental expectations and policy targets (Office of the Principal Scientific Adviser to the Government of India, 2006, Government of China, 2006). Based on these activity projections, GAINS considers more than 160 options for mitigating CO_2 emissions, 28 options for methane, 18 options for N_2O and 22 options for F-gases (Klaassen *et al.*, 2005, Höglund-Isaksson and Mechler, 2005, Winiwarter, 2005, Tohka, 2005). For air pollutants (SO_2, NO_x, PM, NH_3, VOC), GAINS includes in total more than 1500 specific emission control measures (Cofala and Syri, 1998, Cofala and Syri, 1998, Klimont *et al.*, 2000, Klimont *et al.*, 2002). The model quantifies for each of the emission source regions the emission reduction potentials for each of these options and the associated costs. The GAINS database contains cost parameters that are derived from the international literature and country expert information. It is in the nature of the subject, however, that much of this cost information originates from practical experience in Western countries, while there is are very few observations of emission control costs in developing countries. It is known, however, that in Asian countries local prices for certain domestically produced technologies are lower than on the world market, inter alia due to lower labour costs. Therefore, the economic analysis in GAINS-Asia adjusts costs for emission control equipment by factor that takes into account the share of labour costs and local purchasing power in comparison to the market exchange rates.

The GAINS-Asia model can be used for a number of different purposes. As a database it provides activity data and control strategies for future scenarios in India and China, as an emission model it estimates emissions and costs of currently planned or potential air quality policies, and as a reduced-form atmospheric dispersion model it can be used to calculate the reductions in environmental impacts as a consequence of changed air pollution policies. In addition, the optimization module of the GAINS model can be used to find sets of cost-effective control measures that meet given environmental objectives at a future point in time. These environmental objectives ('targets') can be defined either in terms of emissions or in terms of impacts, such as loss of life expectancy due to exposure to fine particles (PM2.5). A detailed description of the optimization module of GAINS is provided in Wagner *et al.*, 2007.

2.2 The cost concept for developing countries

The GAINS database contains cost parameters that are based on literature reviews and country expert information, mostly from European countries. While appropriate for the use in other developed countries, these cost data cannot be used directly in developing countries, in particular China and India. Local prices are typically lower because these countries often can produce comparable technologies at lower costs domestically and do not need to buy them at world market prices. In particular, since average wages are lower in these countries than in Europe, the manufacturing is cheaper.

The above requires an adjustment of the energy system and emission control costs for developing countries. In the following sections we describe a methodology for how this can be done, starting from the cost parameters that are available for developed countries and local costs available in market exchange rates.

2.2.1　Adjustment of cost parameters for developing countries

2.2.1.1 Investments

We assume that, in general, investments in developing countries are lower than or equal to the costs of investing in developed countries. This difference is reflected by a technology-specific ratio of investment cost in a developing country relative to international investment cost r_t. On top of this, there can be country-specific reasons for cost differences, like different local experience, different local production and construction capacities, different price structure/price distortions, etc. All those differences are captured by a country-specific coefficient c_i. The coefficient c_i is applicable only to a subset of control technologies, determined by appl_c_t.

With these assumptions the investment costs for each country and technology can be calculated according to the following formula:

for $r_t \neq 1$ and appl_$c_t = 1$:

for $r_t * c_i < 1$

$$INV_{ti} = INV\_INT_t * r_t * c_i$$

for $r_t * c_i \geq 1$

$$INV_{ti} = INV\_INT_t$$

for $r_t \neq 1$ and appl_$c_t = 0$:

$$INV_{ti} = INV\_INT_t * r_t$$

for $r_t = 1$:

$$INV_{ti} = INV\_INT_t$$

Where:

r_t	ratio of investment cost in a developing country relative to international investment cost for technology t
INV_{ti}	investment cost for technology t in country i
INV_INT_t	international investment cost for technology t
c_i	correction factor for country i (includes all reasons for differences in investment costs level in a given country)
$appl\_c_t$	"applicability" of correction factor c to technology t (1 – applicable, 0 – not applicable).

Variable costs already include country-specific prices of local inputs and thus do not need any adjustments.

2.2.1.2 Costs of technologies where only cost per activity is specified

Adjustment for technologies where only cost per activity is specified (without distinguishing investment-related costs and operation and maintenance costs) is based on similar principles. This time ratios and correction factors will be applied to total unit costs. Formulas are as follows:

For $r_t \neq 1$ and $appl\_c_t = 1$:

  for $r_t * c_i < 1$

$$UC_{ti} = UC\_INT_t * r_t * c_i$$

  for $r_t * c_i \geq 1$

$$UC_{ti} = UC\_INT_t$$

  for $rt \neq 1$ and $appl\_c_t = 0$:

$$UC_{ti} = UC\_INT_t * r_t$$

  for $r_t = 1$:

$$UC_{ti} = UC\_INT_t$$

where:

r_t	ratio of cost in a developing country relative to international cost for technology t
UC_{ti}	unit cost for technology t in country i
UC_INT_t	international unit cost for technology t.

2.2.1.3 Input data

In GAINS-Asia, we use an arithmetic average of (already manipulated) ratios. For air pollutants ratios r_t are pollutant-specific. Ratios for technologies with costs per activity only depend on the type of technology. Assumptions on r_t and $appl\_c_t$ are summarized in Table 2.1.

Coefficients c_i (Table 2.2) have been calculated for China and India so that the resulting ratios are possibly close to the original ratios for energy technologies from the national assessment.

Table 2.1: Technology-specific correction factors

Technology	r_t	appl_c_t
Energy technologies:		
Coal conventional	0.7	1
Coal IGCC	0.7	1
Fuelwood plants	0.7	1
Natural gas plants	0.75	1
Geothermal	1.0	1
Heavy fuel oil plants	0.7	1
Hydro	0.5	1
Medium distillates plants	0.7	1
Nuclear	0.8	1
Small Hydro Power	0.4	1
Solar Photovoltaics	1.0	1
Wind	0.8	1
Waste fuels, non-renewable	1.0	1
Waste fuels, renewable	1.0	1
SO_2 emission controls		
All except low S fuels	0.7	1
Low S fuels	1.0	0
NO_x controls		
Stationary sources	1	0
Mobile sources	1	0
PM controls:		
Industry, power plant, process (add-on)	0.7	1
Industry, power plant, process (good practices)	0.5	0
Domestic	0.5	0
Methane controls		
Technologies with investments	0.7	1
Technologies with unit abatement cost only	0.5	0
Ammonia (all technologies)		
All technologies	0.5	0
N_2O and F-gases controls		
All technologies	0.5	0

Table 2.2: Country-specific correction factors ci

Country	ci
China	0.93
India	1.07

2.2.2 Representation in the GAINS-Asia database

The above methods lead to useful scaling factors. However, in the above form, in addition to a technology-specific ratio and a country-specific correction factor c_i , one needs also an additional parameter *applic*$_c$, which is again technology-specific. The above setup is not suitable to be implemented in the database and raises serious issue about data maintenance.

The idea of the alternative methodology is a kind of bootstrap method: We start with the best guess of the parameter values, and then improve the estimate by further averaging. In an intermediate step we generate parameter values that depend on both region and technology.

The starting point is the formulation of the adjusted investment costs in country c as a linear combination of the international investment costs $INV_{int,t}$ and a 'purely local' investment cost R_c * $INV_{int,t}$ where R_c is a country-specific correction factor:

$$(1) \qquad INV_{c,t} = (SH_t + (1-SH_t) * R_c) * INV_{int,t}$$

Originally we had considered $R_c = 1/PPP$, but then found that, even though the PPP value for India is higher then for China, investment costs are lower. Thus a different value for R_c has to be used to be consistent with the empirical data. The key requirement in this approach is that R_c only depends on the country, and the share SH_t only depends on the technology. The trick is to take an intermediate step in which R_c becomes also technology-dependent and SH_t also becomes country-dependent, and then to get rid of these additional dependencies by averaging out.

If appl_$c_t <> 0$ and $r_t * c_i < 1$, from the above follows:

$$(2) \qquad SH_t + (1-SH_t) * R_c = r_t * c_i$$

and Equation (2) can be reformulated as:

$$(3) \qquad R_c = (r_t * c_i - SH_t)/(1-SH_t)$$

Or, alternatively:

$$(4) \qquad SH_t = (r_t * c_i - R_c)/(1- R_c)$$

We use (4) and with the initial condition $R_c = 1/PPP$ to calculate the share for each technology. In this first step, we do this for China and India separately, so that $SH_t = SH_{t,c}$, i.e., the share at this stage is country-specific. We then take the average of the share across both countries so that the average share becomes[1]

$$(5) \qquad SH_t^{av} = ½ * (SH_{tChina} + SH_{tIndia})$$

We then calculate a technology- and country-dependent scaling factor $R_{c,t}$, by plugging in SH_t^{av} into (3), i.e.,

$$(6) \qquad R_{c,t} = (r_t * c_i - SH_t^{av})/(1- SH_t^{av})$$

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[1] Here we consider the case of India and China, but it is straightforward to generalize and to embrace more countries.

We then calculate the average of $R_{c,t}$ across all technologies to get a region-specific $R_c^{av} = \text{mean}_t$ ($R_{c,t}$). Thus, we have found a technology dependent share SH_t^{av}, and country-dependent correction factor R_c^{av}. With this we replace the left-hand side of (2) as

(7) $SH_t^{av} + (1 - SH_t^{av}) * R_c^{av}$

and compare with the empirical values on the right hand side of (2): in an x-y-plot for some 180 technologies for India the resulting regression coefficient $R^2 = 0.9982$. The R_c^{av} value for India is 0.46, and for China 0.37.

2.3 The GAINS-Asia optimization module

2.3.1 Rationale and setup

The GAINS-Asia model can be used for a number of different purposes. As a database it provides activity data and control strategies for future scenarios in India and China, as an emission model it estimates emissions and costs of currently planned or potential air quality policies, and as a reduced-form atmospheric dispersion model it can be used to calculate the reductions in environmental impacts as a consequence of changed air pollution policies.

In addition, the optimization module of the GAINS model is a tool which can be used to find sets of cost-effective control measures that meet given environmental objectives at a future point in time. These environmental objectives ('targets') can be defined either in terms of emissions or in terms of impacts, such as loss of life expectancy due to exposure to fine particles ($PM_{2.5}$). Thus a typical model setup would address the questions: What would be the most cost-effective set of control measures that would reduce the exposure by x% relative to the level in the baseline scenario? What would these control measures cost beyond the costs of currently implemented or planned policies? In which regions or sectors can the most cost-effective measures be implemented, and what are the costs that each region/sector will carry in the most-cost-effective case?

Figure 2.2 shows a conceptual representation of the logical flow and the optimization module of GAINS.
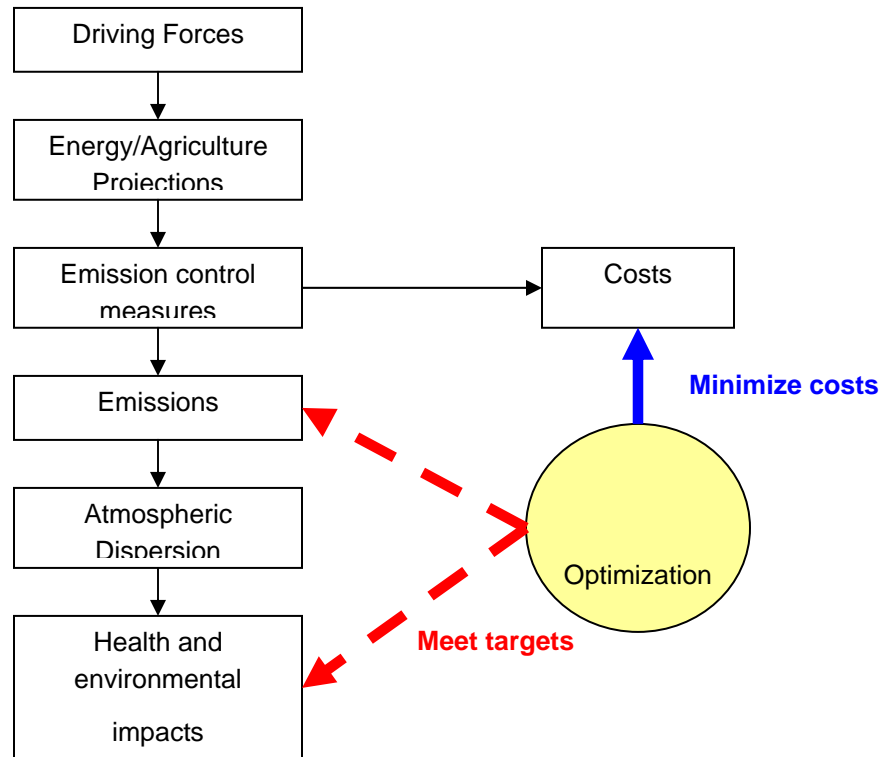
Figure 2.2 Conceptual representation of the GAINS optimization module

Starting from a given baseline scenario the result of the optimization then consists in the following:

- A comprehensive list of control measures and the extend to which they would be implemented in each (sub-)region.

- A set of emission levels (or ceilings) that would result from the implementation of these technologies.

- The (minimal) costs that would result from employing the optimal mix of control technologies.

- Naturally, with the list of control measures and their implementation rates costs and emissions can be calculated at each level of aggregation as needed (such as for each sector-activity combination, SNAP1 macro sector, region or national total, etc.)

A detailed description of the optimization module of GAINS is provided in Wagner *et al.*, 2007. The methodology described in there also applies in the context of GAINS-Asia. The most significant difference is that in GAINS-Asia the loss of life expectancy due to exposure to fine particles is modelled as a function of the emissions of primary particles, sulphur dioxide and nitrogen oxides, but not of the emissions of ammonia. Also, other environmental indicators, such as the acidification and eutrophication of ecosystems and the exposure of humans and crops to ozone (as described in Wagner *et al.*, 2007) is not used in GAINS-Asia at this stage.

GAINS-Asia offers the possibility to model two basic kinds of technical measures to reduce emissions:

1. **Add-on measures** (also known as 'end-of-pipe' technologies), which can be applied without changing the underlying activity rates. Examples of such technologies include the use of catalytic converters or sulphur scrubbers. Most of the measures represented in GAINS are of this type, and they are applied in all sectors in GAINS. For example, in the agriculture sector various manure management practices can be applied to reduce the emissions of CH_4, N_2O or NH_3, leaving the underlying activity data (the number of animals) unchanged.

2. **Activity substitutions** relative to the baseline. Measures of this type are available at this stage only in the energy sector, where they represent fuel substitutions, efficiency improvements and changes in power plant type. For example, in GAINS is it possible to replace fossil fuel power plants to a certain extent (and at a certain cost) with renewables, such as hydropower, wind and solar power. Activity substitutions change the structure of the fuel uses in the energy sector, and consistency is ensured by a number of balance equations that ensure that amount of useful energy is kept at the baseline level.

Naturally activity substitutions have an influence on CO_2 emissions, but they also influence the emissions of air pollutants, such as SO_2, NO_x and PM. At times it is useful to consider the activity data in the baseline as fixed, so that emission reductions can only be achieved by add-on measures. In the GAINS model this is possible by disabling the activity substitution options, and in this case we say that we use the model in the '***RAINS mode***' of GAINS, since in the earlier RAINS model only add-on measures were available in the first place. In contrast, in the '***GAINS mode'*** of GAINS both add-on measures as well as activity substitution options are available. Naturally, in the RAINS mode of GAINS the emissions of CO_2 are kept constant at the baseline level (in GAINS carbon capture and storage is modelled like an activity substitution and not as an add-on measure).

The optimization module of GAINS-Asia can also be used to explore the potentials for co-benefits and trade-offs between air pollution and greenhouse gas mitigation policies, or, more generally, the potentials for economic and physical interactions in the control of multiple pollutants. As we will illustrate below, a reduction of CO_2 emissions in general also entails a significant reduction in the emissions of SO_2, NO_x and PM2.5. However, an increased use of biomass can also lead to higher emissions of PM2.5 – depending on the combustion technology.

2.3.2   Mitigation options in the power sector

A full description of all the greenhouse gas emission and cost calculations as well as the mitigation options in GAINS are described the documentation of GAINS Version 1.0 (see Klaassen *et al.*, 2005; Höglund-Isaksson and Mechler, 2005; Winiwarter, 2005 and Tohka, 2005). Since then some of the methodologies have been updated to improve the consistency with international databases and enhance the comparability. Also, the structure of the power sector has been revised to reflect the complexity of mitigation options without sacrificing the commitment to simplicity and universality.

In this section we briefly review some of the most important features of the structure of the power sector.

In the power plant sector in GAINS now also Integrated Gasification Combined Cycle (IGCC) plants are modelled explicitly, because they not only have higher conversion efficiencies than conventional coal fired plants, but also different emission characteristics. In GAINS IGCC plants can be fuelled with solid and liquid fuels. GAINS also now explicitly models combined heat and power (CHP) plants, and we distinguish those plants that can provide heat to the industry sector from those that provide district heat. For conventional plants we also model district heating plants that provide heat only. Each of the plant types in principle can also be fitted with a carbon capture device.

Activity substitutions include substitution of conventional plants with IGCC plants, non-CHP plants with CHP plants (including replacing industrial boilers with CHP), and fuel substitutions. Finally, carbon capture (CCS) is modelled in GAINS as an activity substitution (substituting non-CCS with CCS plants), as this representation is consistent with the general modelling framework.

2.3.3 Potentials and constraints

We now briefly describe the role of potentials and constraints play in the design of cost-efficient emission control scenarios. Given a target on an environmental impact indicator, the optimization searches for a set of technologies whose application leads to emission reductions, which in turn reduce the indicator to the target level. This is achieved in such a way that the sum of the costs over all technologies applied is the lowest possible.

Which set of technologies is eventually chosen by the optimization routine, and to what extent, depends both on their marginal cost for achieving the target level and their availability. The availability of add-on technologies is modelled in GAINS as the maximum application rate (between 0% and 100%) which applies to the best available technologies for each sector-activity combination. The availability of substitution options is governed by the maximum potential for alternative technologies. For example, the supply potential for renewable energies, such as hydro-electric power and wind, determines the potential for substituting fossil fuels with renewables. The potentials for renewables, as well as for energy saving options are determined by comparing the baseline scenarios with the alternative scenarios. The penetration of new technologies, such as Integrated Gasification Combined Cycle (IGCC) and Carbon Capture and Storage (CCS) largely determines their potentials in the decades to come. For example, the potential for capturing CO_2 is expected to not exceed 230 Mt CO_2/yr (Singh *et al.*, 2006).

The marginal cost of add-on measures is determined both by their unit cost and removal efficiency, as well as by the unit cost and removal efficiency of the technology (if any) already in place. Analogously, the marginal cost for a substitution option depends on how much the alternative installation would cost, but also on what the technology costs that would be replaced.

For this report we took a conservative approach to possible changes in control strategies in the transportation sector. While efficiency improvements are possible in accordance with Klaassen *et al.*, 2005, the same efficiency improvements over time are assumed for all of scenarios. This is also consistent with how GAINS is being used for assessments in Europe. One of the reasons not to make

the control strategy subject to optimization is emission standards for vehicles are valid across borders. In other words, in the EU an emission standard (in GAINS language a Euro-standard package) applies to all countries or to none – there is no unilateral implementation of such a standard. It can be argued analogously that in India and China emission standards for vehicles will be applied at the national level, so that the control strategies at the sub-national level must not be independent. A detailed analysis of the potentials for further improvements of control standards is warranted at a later stage.

The GAINS model relies to some extent on substitution potentials that can be derived from alternative scenarios. A comparison, however, of the baseline scenario and the alternative scenario yields a maximal reduction in CO_2 in 2020 of only 10.5% in China and 28% in India. For China, we have identified further potentials for reducing CO_2 through combined-heat and power, so that we calculate a total CO_2 reduction potential of 17%. We consider this still a conservative estimate.

2.3.4 The cost-optimal baseline case

An important notion in the context of optimization in the GAINS model is the concept of a cost-optimal baseline (COB) scenario. In the optimization we start with a baseline scenario and the model responds to a given target. What happens, however, if we do not specify a target value on the environmental impact indicator or the emission levels? Naively one would expect that in the absence of such target values the model would reproduce the baseline, but in general this is not exactly the case because it employs available measures with negative costs.

It is important to appreciate an additional aspect of the optimization philosophy in GAINS. Obviously, for each sector-activity combination in the baseline there are associated emissions of various pollutants. These emissions depend on the control technologies present in the baseline. In the optimization we now let the model choose freely among the available technologies as long as the application limits for the technologies are not exceeded. Also, we require that, whatever mix of technologies is chosen in any optimized scenarios, the emissions for each sector-activity combination are never higher than in the baseline. This ensures that even in the absence of an emission target the model does not revert to the case in which no emission controls whatsoever are present: the baseline thus provides a minimum control standard for each sector-activity combination. If available, however, in the optimization the model selects a mix of technologies that is less costly than those present in the baseline. Indeed, in some cases such a mix of more cost-effective technologies can be found. In rare cases, this mix of technologies not only is cheaper than that in the baseline, but it also reduces emissions relative to the baseline.

 We call this mix of technologies, which is potentially less costly than the baseline and does not exceed the emission levels of the baseline scenario (emissions may actually be lower) the ***cost-optimal baseline*** (COB) scenario. The COB helps to understand better the cost-effectiveness of the baseline, and serves as a reference point in all subsequent optimization scenario as it represents the solution of optimization problem without any target values. In this report we consistently report costs as costs on top of the COB scenario. In this way we can separate distortion effects due to a non-cost-effective baseline from the implications of target values on environmental impact indicators or emission levels.

We may further distinguish the COB scenario in the RAINS mode (COBR) and in the GAINS mode (COBG). In the COBR scenario the model can select cost-effective set of add-on control technologies, whereas in the COBG the model can also select cost-effective activity substitution options.

There are a number of reasons why the COB scenario is not identical to the baseline scenario, i.e., when the mix of measures in the baseline is not cost-effective in the GAINS model. For example, the baseline may represent a policy in which certain technologies are prescribed independently of their cost-effectiveness. Second, GAINS uses by default a discount rate of 4 percent per year., i.e., it takes the social planner's perspective, and with this certain technologies may be cost-effective, while at higher discount rates (as used by actors in specific sectors) they may not.

2.4 Modelling atmospheric dispersion

In this section we briefly outline the methodology we use to model health impacts from fine particles. In GAINS-Asia we apply a similar methodology for modeling air quality as in Europe (see for example, Amann *et al.*, 2006) in that we model health effects of fine particles, accounting for regional transport of primary particles and precursor substances of secondary particles, as well as for additional contributions below the grid scale that correct for higher exposure in urban areas. We then use a statistical approach to convert concentrations of particles to loss in life expectancy (Mechler *et al.*, 2002). There are, however, a number of differences: (1) since there are no data readily available on critical loads in ecosystems, we neither model acidification nor eutrophication in this study. (2) Moreover, since this study does not cover the emissions of NH_3 in the policy analysis, we consider them constant, so that though in the formation of secondary inorganic particles NH_3 plays an important role, we take into account that role implicitly without representing its contribution explicitly.

2.4.1 Modelling fine particulate matter in Asia at the regional scale

The health impact assessment in GAINS relies on epidemiological studies that associate premature mortality with annual mean concentrations of PM2.5 monitored at urban background stations. A series of model experiments with the TM5 model (Krol *et al.*, 2005) has been used to derive source-receptor relationships for GAINS-Asia (Dentener, 2008) that describe the contributions of emissions from the individual source regions to air quality throughout the model domain. These source-receptor relationships developed for GAINS describe, for a limited range around a reference emission level, the response in annual mean PM2.5 levels to changes in the precursor emissions SO_2 and NO_x, and primary PM2.5. The formulation reflects the interplay between SO_2 and NO_x emissions in the formation of secondary sulfate and nitrate aerosols in winter. The linear response in annual mean PM2.5 produced by the TM5 model towards changes in annual emissions of fine primary particulate matter (PM2.5) and of SO_2, NO_x, and NH_3 is represented as:

$$PM_j = \sum_i pm_i \cdot PP_{ij}^A + \sum_i s_i \cdot S_{ij}^A + \sum_i a_i \cdot A_{ij}^A + \sum_i n_i \cdot N_{ij}^A + k_{0,j} \qquad (7)$$

with

PM_j	Annual mean concentration of PM2.5 at receptor point j
s_i, n_i, a_i, pm_i	Emissions of SO_2, NO_x, NH_3 and primary PM2.5 in country i
$A^X_{ij}, N^X_{ij}, S^X_{ij},$ PP^X_{ij}	Matrices with coefficients for reduced (A) and oxidized (N) nitrogen, sulfur (S) and primary PM2.5 (PP), for season X, where $X=W$ (winter), S (summer) and A (annual)
$c_0, c_1, c_2, c_3,$ $k_{0,j}, k_{1,j}, k_{2,j}$	Model parameters.

As mentioned above, for this study we consider the emissions of NH_3 constant and absorb the 'A' term into the constant. The transfer coefficients have been derived from model runs performed with the TM5 model over permutations of emission reduction targets around the 2000 emission levels. The GAINS optimization module then uses the local derivatives at the target levels, and this reduced form model results in an accurate representation of the underlying TM5 model despite the simpler mathematical formulation.

The above formulation only describes the formation of PM from anthropogenic primary PM emissions and secondary inorganic aerosols. It excludes PM from natural sources and primary and secondary organic aerosols due to insufficient confidence in the current modelling ability. Thus, it does not reproduce the full mass of PM2.5 that is observed in ambient air. Consequently, results of this approach need to be compared against observations of the individual species that are modelled. The health impact assessment in GAINS is consequently only conducted for *changes* in the specified anthropogenic precursor emissions, and excludes the (largely) unknown role of secondary organic aerosols and natural sources.

2.4.2   Modelling fine particulate matter in Asia at the urban scale

In GAINS-Asia the regional-scale assessment is performed with a spatial resolution of 1 degree longitude * 1 degree latitude. Health impacts are, however, most pertinent to urban areas where a major share of the European population lives. Any assessment with a 50-100 km resolution will systematically miss out higher pollution levels in cities and agglomerations. Based on the results of the City-delta model intercomparison, which brought together the 17 major European urban and regional scale atmospheric dispersion models (Thunis *et al.*, 2006), a generalized methodology was developed to describe the increments in PM2.5 concentrations in urban background air that originate – on top of the long-range transport component – from local emission sources.

These relationships associate urban increments in PM levels, i.e., incremental (PM2.5) concentrations in a city originating from emissions of the same city with the spatial variations in emission densities of low-level sources in that city and city-specific meteorological and topographic factors. In a second step, urban background PM2.5 concentrations within cities are then computed by correcting the PM concentration value computed by a 1 degree*1 degree regional dispersion model with a "city-delta", i.e., the local increase in concentration in the city due to emissions in the city itself. In the regional-scale calculations this contribution is smeared out over the whole grid element. In the City-delta approach the mass within the km grid element is redistributed in such a way that the concentration in the city is increased by the "citydelta" increment, whereas the concentration in the country-side

consequently is decreased. In this way mass is being conserved. More details on the City-delta methodology can be found in Amann *et al.*, 2006.

2.4.3   Modelling ground-level ozone

The GAINS-Asia model, in its current form, also enables a preliminary assessment of regional-scale ground-level ozone in India and China. As for PM, computations of regional ozone fields are based on source-receptor relationships that have been derived from the sample of model experiments conducted with the TM5 model (Dentener, 2008). However, the current assessment in GAINS-Asia must be considered as provisional for a number of reasons:

- Most importantly, GAINS-Asia does not include an emission inventory and projection feature for VOC emissions in Asia. This shortcoming is essentially caused by the poor understanding of (anthropogenic and natural) VOC emissions in India and China. While a first assessment of current anthropogenic VOC emissions has been recently published for China (Wei *et al.*, 2008), for India no assessment is yet available. Even less is known about biogenic emissions of VOC in these countries.

- There is still uncertainty about the ability of contemporary hemispheric-scale atmospheric chemistry and transport models to reliably reproduce ozone concentrations over the Indian subcontinent (Stevenson *et al.*, 2006). Poor model performance might be caused by the absences of inventories of anthropogenic and biogenic VOC emissions. A validation of model results is hampered by the lack of quality-controlled ozone monitoring data for rural sites on the Indian subcontinent.

- There is currently no methodology available to reliably estimate population exposure to ground-level ozone with the current hemispheric-scale atmospheric models because models do not have sufficiently fine spatial resolutions to address ozone concentrations within cities where the majority of people live.

For this reason, GAINS-Asia takes a simplistic approach by relating changes in ozone concentrations purely to changes in NO_x emissions, based on the responses computed with the TM5 model. Thereby, it is implicitly assumed that the NO_x to VOC ratio will not change with changing NO_x emissions, i.e., that changes in NO_x emissions are paralleled by equivalent changes in (anthropogenic and biogenic) VOC emissions – or alternatively, that ozone formation would be everywhere NO_x limited.

To assess health risks from ground-level ozone, GAINS-Asia employs the co-called SOMO35 ozone indicator as recommended by the Working Group of the World Health Organization for health impact assessment (WHO, 2007). SOMO35 (the sum of maximum daily 8-h means over 35 ppb) is a measure of the accumulated ozone concentration in excess 35 ppb (70 µg m^{-3}) and is seen as one of the most relevant ozone-related health indicators. This SOMO35 is defined as:

$$SOMO35_{uncorrected} = \sum_i \max\{0, C_i - 35\,ppm\}$$

where C_i is the maximum daily 8-hour mean concentration and the summation is from day $i=1$ to 365 per year. SOMO35 has a dimension of ppb.day if 35 ppb is used and $(\mu g\ m^{-3})$.day if 70 $\mu g\ m^{-3}$ is used in the equation.

In principle, following the methodology recommended by WHO, 2007 the cases of premature mortality could be estimated with the SOMO35 metric, provided that reliable base mortality statistics are available. However, acknowledging the serious uncertainties about the performance of the available ozone model for Asian cities, the GAINS assessment refrains from producing such estimates.

2.5 Modelling health impacts of air pollution

2.5.1 Health impacts from outdoor pollution

GAINS-Asia quantifies health impacts that are attributable to the human exposure to fine particulate matter (PM2.5), which is formed as a secondary product of emissions of primary particles, SO_2, NO_x and NH_3. As health impact indicator the assessment quantifies the loss in statistical life expectancy (Mechler *et al.*, 2002) based on evidence from international epidemiological long-term studies that followed the survival of cohorts over several decades under different PM exposure (e.g., Pope *et al.*, 2002). A key uncertainty of such an approach, however, relates to the transferability of results obtained for conditions in Western countries to Asia. Among others, a critical question pertains to the fact that current and projected future ambient concentrations of PM2.5 in Asia are well above the levels for which the original studies were conducted. While the analysis in Pope *et al.*, 2002 holds observational evidence for concentrations up to 30 $\mu g/m^3$, contemporary levels in Asian cities typically reach 50 $\mu g/m^3$ and more, and they are expected to increase further in the future. Unfortunately, epidemiological cohort studies for Asia that cover such concentration ranges are unavailable. However, an analysis of Asian short-term studies, which assess changes in short-term mortality due to daily variations in PM concentrations (HEI, 2004), confirm the validity of the responses in health outcomes found for western countries also for higher PM concentrations in Asian countries.

To reflect the inherent uncertainty about the validity of concentration-response functions derived from studies in the west, GAINS-Asia performs two alternative assessments. A pessimistic variant assuming the validity of a linear concentration-response function throughout the entire range of PM25 concentrations. An alternative more optimistic variant assumes that a microgram of PM2.5 at concentrations above 50 $\mu g/m^3$ would cause only half of the impacts from a microgram below that level.

2.5.2 Health impacts from indoor pollution

As a new element, GAINS-Asia quantifies health impacts from indoor pollution due to the use of solid fuels in household. Numerous studies have shown strong correlations between disease, such as chronic bronchitis, tuberculosis, cataracts and acute respiratory infection (ARI), and exposure to indoor air pollution (IAP) from burning biomass fuels on unventilated, inefficient stoves (Ezzati *et al.*, 2002). Most of the premature deaths affect women and children.

GAINS-Asia applies the methodology for estimating the global burden of disease that has been developed by the World Health Organization (Smith *et al.*, 2004). This methodology associates gender-specific health effects, such as acute lower respiratory infections (ALRI) for children, chronic obstructive pulmonary diseases (COPD) and lung-cancer of selected cohorts with the indoor use of solid fuels.

The environmental burden of disease quantifies the amount of disease caused by environmental risks. Disease burden can be expressed in deaths, incidence or in Disability-Adjusted Life Years (DALY). The latter measure combines the burden due to death and disability in a single index. Using such an index permits the comparison of the burden due to various environmental risk factors with other risk factors or diseases. GAINS-Asia holds data on current and future use of solid fuels in the domestic sector for each source region, which can be readily used to estimate the number of households using solid fuels and the number of affected people in the different age cohorts. In a second step, the risk factors identified in Smith *et al.*, 2004 can then be applied to the exposed population, and the attributable burden is due to solid fuel use is estimated as a product of attributable fraction for solid fuel use and current disease level. The attributable fraction, AF_{sfu}, can be estimated as

$$AF_{sfu} = \left[\frac{p_e\,(r_r - 1)}{p_e\,(r_r - 1) + 1} \right]$$

where p_e represents the population exposed to the solid fuels and r_r the relative risk due to solid fuel use. Similarly, attributable burden due to the solid fuel, AB_{sfu}, use can be estimated as

$$AB_{sfu} = AF_{sfu}\,CDL = \left[\frac{p_e\,(r_r - 1)}{p_e\,(r_r - 1) + 1} \right] CDL$$

where CDL represents the current disease level.

The relative risk ratios that have been used for the various health outcomes that are considered in the GAINS-Asia calculations are listed in Table 2.3. Details on how health impacts from indoor pollution are calculated in GAINS are provided in Purohit and Amann, 2008. Data on current disease levels for India and China are taken from WHO, 2007.

Table 2.3: Relative risks for strong and moderate health outcomes

Evidence	Health outcome	Group (sex, age in years)	Relative risk	Confidence Interval (CI)
Strong	ALRI	Children<5	2.3	1.9-2.7
	COPD	Women≥30	3.2	2.3-4.8
	Lung cancer (from exposure to coal smoke)	Women≥30	1.9	1.1-3.5
Moderate	COPD	Men≥30	1.8	1.0-3.2
	Lung cancer (from exposure to coal smoke)	Men≥30	1.5	1.0-2.5

Source: Desai *et al.*, 2004

With data on fuel consumption, baseline health data and the relative risk factors listed in Table 2.3, the burden of disease attributable to indoor pollution can be calculated and expressed in terms of

"Disability Adjusted Life Years" (DALYs). Computed DALYs for the year 2000 are presented in Table 2.4 for the central estimate and the confidence intervals resulting from the quantified uncertainties in the relative risk factors.

Table 2.4: Attributable burdens from solid fuel use for China and India in 2000

| Disease, sex, age group | Attributable burden (DALYs lost, in thousands) | | | | | |
| | China | | | India | | |
	Low	Medium	High	Low	Medium	High
ALRI, Children < 5 year	1558	1991	2338	8167	10026	11403
COPD, Women > 30 years	1235	1666	2125	1170	1482	1770
COPD, Men > 30 years	0	1361	2552	0	1104	1845
Lung cancer, Women > 30 years	28	196	376	1	5	11
Lung cancer, Men > 30 years	0	249	563	0	10	28

3 Baseline and alternative scenarios

In this section we briefly summarize salient features of the baseline and alternative scenarios for India and China that were produced by GAINS-Asia project partners (TERI, 2008; Kejun and Yixiang, 2008). We begin with data on India.

3.1 India

3.1.1 Baseline emissions

India is a rapidly developing country with a population of 1.096 billion people in the year 2005. The population of India is projected to grow by 27 percent over the next 25 years (by 2030) to nearly 1.5 billion[2]. The economic outlook for India is projected to increase even more rapidly than the population. Projections used for GAINS-Asia model assume the gross domestic product (GDP) to increase seven fold between 2005 and 2030. The same baseline scenario projects carbon dioxide (CO_2) emissions to grow by more than four fold over that time period. Particulate matter emissions (measured as PM10) for the same time period are only expected to grow 31 percent above 2005 levels under the existing regulatory framework (i.e., without additional controls). Figure 3.1 provides this comparison normalized to the year 2005.
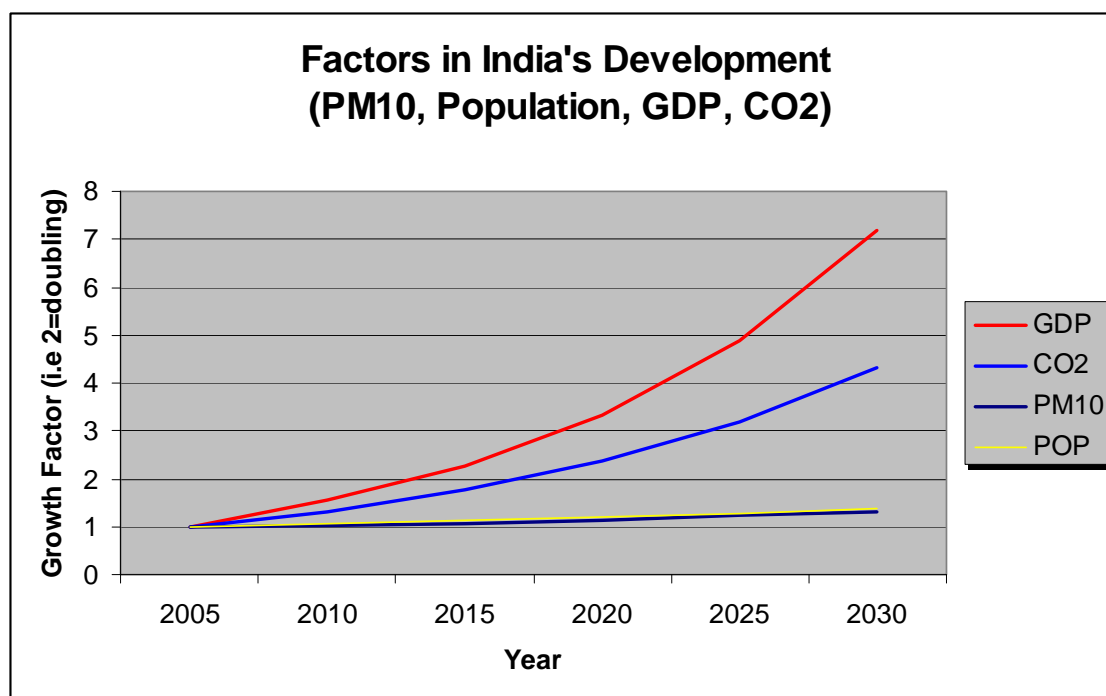
Figure 3.1 GAINS-Asia baseline scenario for India

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[2] Population values taken directly from the GAINS-Asia model for the India Baseline Scenario. Data sources are highlighted in the forthcoming report on the GAINS-Asia model under development by The Energy Research Institute, New Delhi, India.

Factors in India's Development (PM10, Population, GDP, CO2)
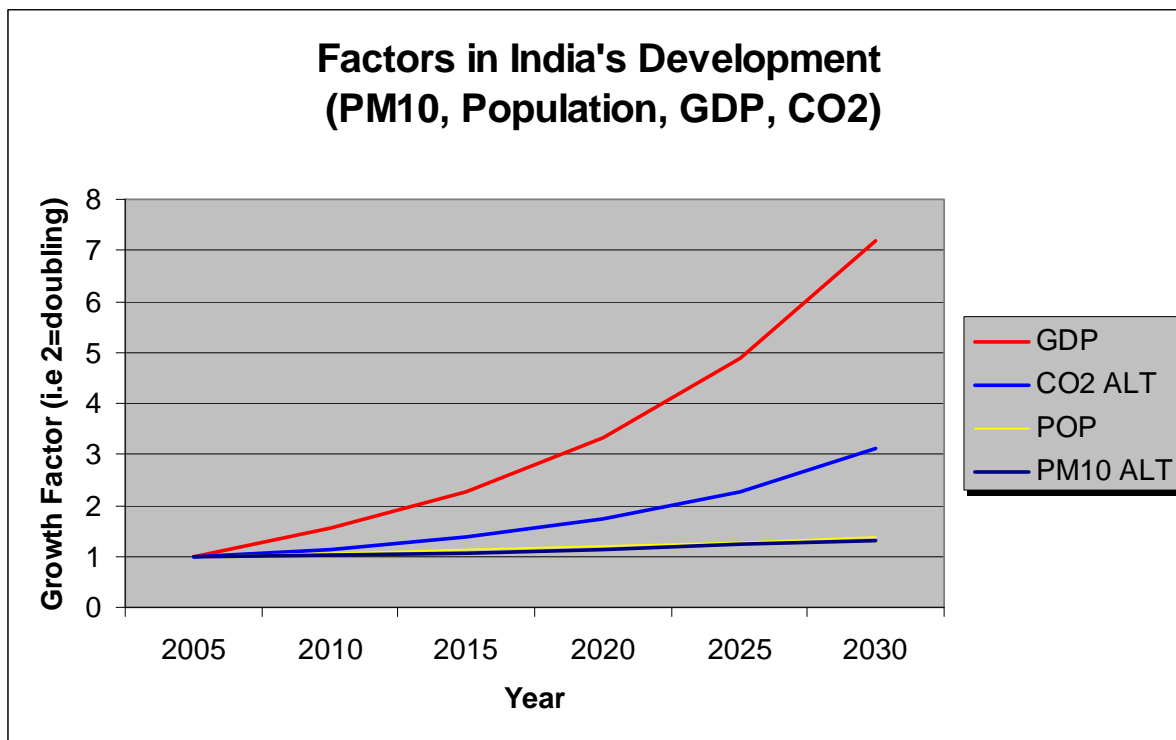
Figure 3.2 GAINS-Asia alternative scenario for India

The GAINS-Asia model also contains an alternative scenario projection as displayed in Figure 3.2. The two figures rely on the same macroeconomic and population projections. The alternative scenario exemplifies the CO_2 emissions impacts associated with adopting energy efficiency and a cleaner energy mix. In the year 2030, the absolute difference between the baseline and alternative scenario is 1.6 billion tons of CO_2 emissions. To put these emissions reductions into context, India's CO_2 emissions were 1.1 billion tons CO_2 in calendar year 2005 (IEA, 2007). Thereby, in 2030 the alternate scenario results in 38 percent lower CO_2 emissions than the baseline projection. The figure below provides a comparison of the trajectory of the two CO_2 emission scenarios.

Then two scenarios have been taken from the *National Energy Map for India: Technology Vision 2030* (Office of the Principal Scientific Adviser to the Government of India, 2006). The GAINS-Asia baseline scenario aligns with the business-as-usual scenario in this report and "… considers the Government of India's targets and existing policies and plans. In addition, the adoption of efficient and new technological options continues as per the likely progression, without any major interventions". The GAINS-Asia alternative scenario closely aligns with the Hybrid Scenario developed in the same document. The Hybrid Scenario assumes business-as-usual with high nuclear energy penetration, aggressive investments in renewable energy, and increased energy efficiency for transmission, distribution and the demand-side.
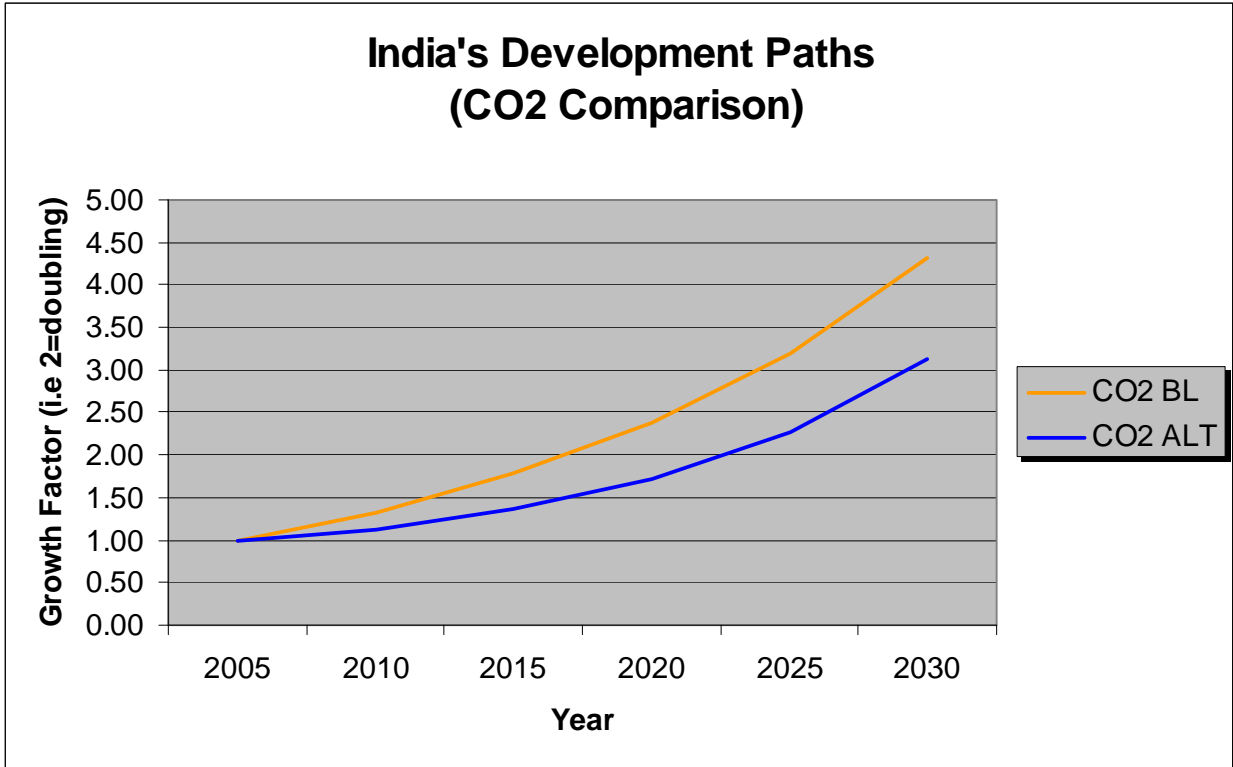
Figure 3.3: GAINS-Asia baseline and alternative scenario CO_2 emission projections for India

The projections provided in Figure 3.3 can be further disaggregated by state, providing a resolution for analyzing the impact of national policies on the individual sub-regions. This is a unique feature of the GAINS-Asia model providing the ability to create activity scenarios both from top-down and bottom-up perspectives. Figure 3.4 and Figure 3.5 exemplify these modeling capabilities for the Indian state of Andhra Pradesh.
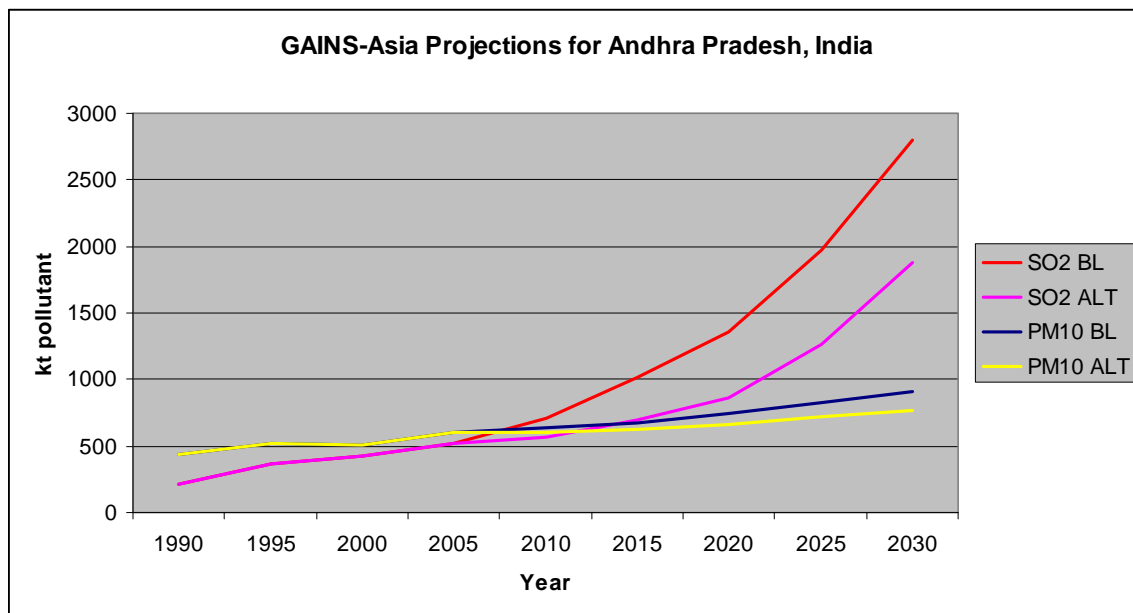
GAINS-Asia Projections for Andhra Pradesh, India

Figure 3.4: Baseline and alternative scenarios for sulfur dioxide (SO_2) and particulate Matter (PM10) in Andhra Pradesh, India - developed with the GAINS-Asia model

CO2 Emissions for Andhra Pradesh, India
(Baseline and Alternative Scenarios)
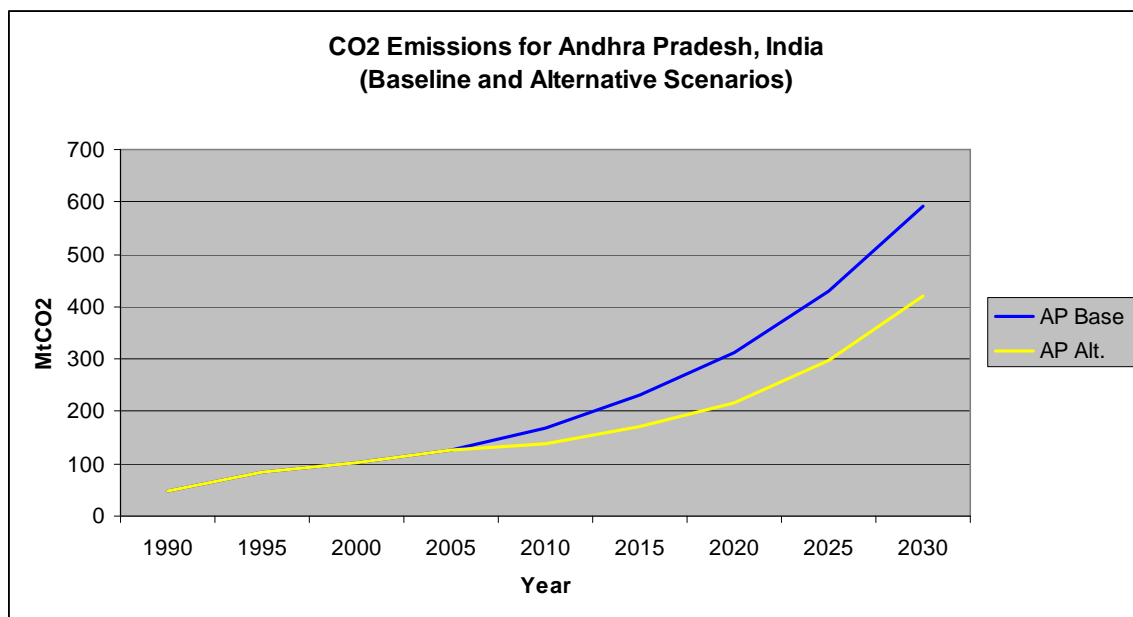
Figure 3.5: Baseline and alternative scenarios for carbon dioxide (CO_2) in Andhra Pradesh, India - developed with the GAINS-Asia model

The graphs depicted in Figure 3.4 and Figure 3.5 provide insight into the options for the Indian state of Andhra Pradesh. All pollutants, including greenhouse gases, are reduced in the alternative scenario. Sulphur dioxide and carbon dioxide are reduced by a much larger percentage than PM10.

In the year 2030 the alternative scenario presents a CO_2 emission reduction of 29 percent, a SO_2 reduction of 33 percent, and a PM10 reduction of 16 percent. In order to have a full understanding of the causes behind the emission reductions displayed in Figure 3.4 and Figure 3.5 it is necessary to have a clear understanding of the assumptions behind the alternative scenarios. The biggest factor affecting the differences in emissions is the future penetration of civilian nuclear power generation. Currently, India has very few nuclear power plants that produce two percent of the country's electricity generation. India is in the process of building several nuclear power plants and the country is brokering bilateral fuel agreements with the United States (United States White House, 2006). Further factors that lead to lower emissions in the alternative scenario are the increased use of renewable biomass fuels, the increased use of natural gas, and a much lower hard coal consumption (Figure 3.6). Most notably, total energy consumption is distinctively different in the alternative scenario due to aggressive implementation of energy efficiency measures (Figure 3.6), mainly by more efficient energy transmission and distribution on the supply side and improved energy management on the demand side. In summary, a six percent increase in the nuclear energy share and a 17 percent reduction in overall energy consumption can lead to a 27 percent reduction in national carbon dioxide emissions in the year 2030.
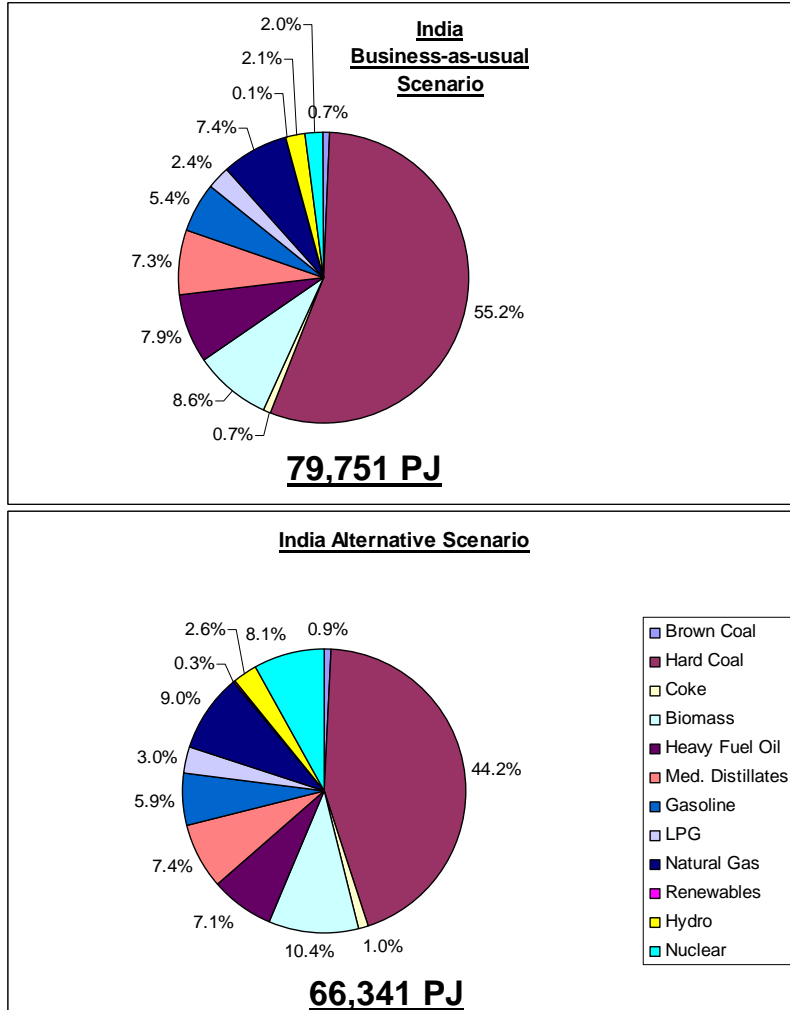
Figure 3.6: Year 2030 energy mix comparisons for two GAINS-Asia scenarios – Business-as-usual and India's Alternative Scenario

3.1.2 Air quality

For each of the emission patterns generated for an emission control scenario, the GAINS-Asia model computes the resulting fields of selected air quality indicators. Figure 3.7 compares ambient PM2.5 concentrations computed with GAINS for the year 2000 (left panel) and for the case with less stringent implementation of emission control legislation in 2020 (right panel). The graph presents for each grid cell population-weighted concentrations, i.e., the population-weighted average of urban and rural concentrations. The projected change in health-relevant ozone concentrations (in terms of SOMO35) is shown in Figure 3.8.
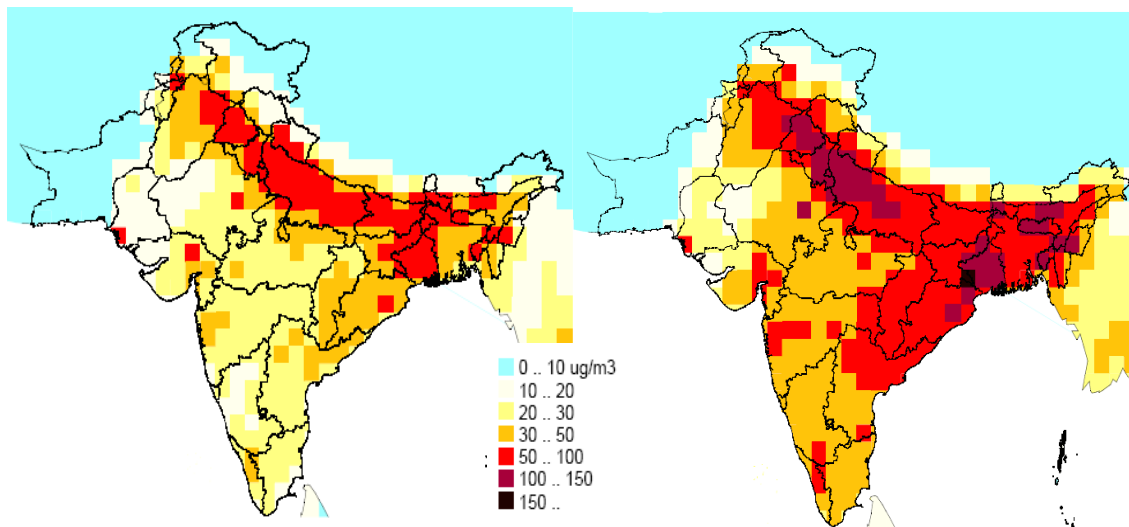
Figure 3.7: Ambient concentrations of PM2.5 in India for 2000 (left panel) and the baseline projection for 2020 (right panel)
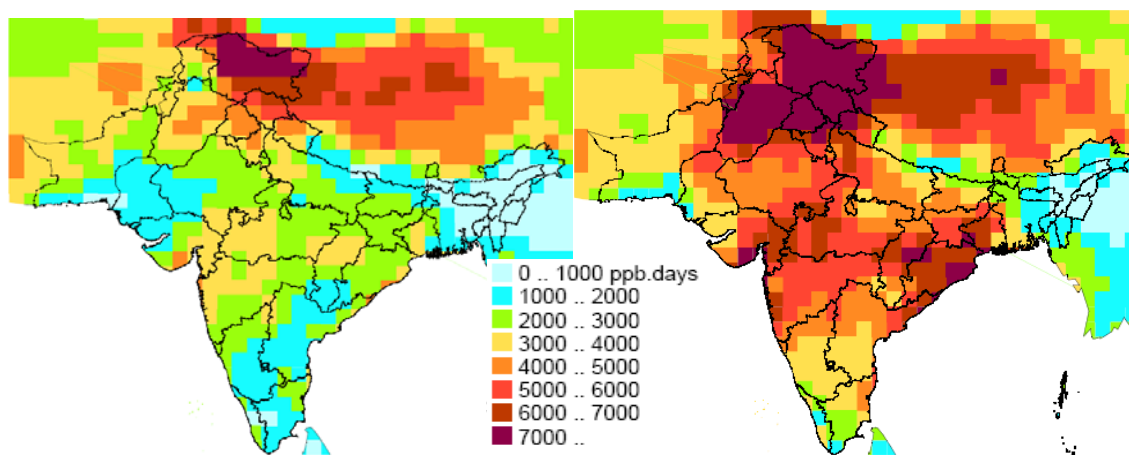
Figure 3.8: Health-relevant ozone concentrations (in terms of SOMO35) for 2000 (left panel) and the baseline projection for 2020 (right panel)

3.1.3   Health impacts

GAINS-Asia estimates health impacts from indoor and outdoor air pollution. For outdoor pollution, GAINS quantifies premature mortality that can be associated with the exposure to PM2.5. Figure 3.9 presents the spatial patterns of life shortening due to outdoor PM2.5 concentrations for the year 2000 (left panel) and for the less stringent implementation case in 2020 (right panel), assuming validity of a linear concentration-response function.
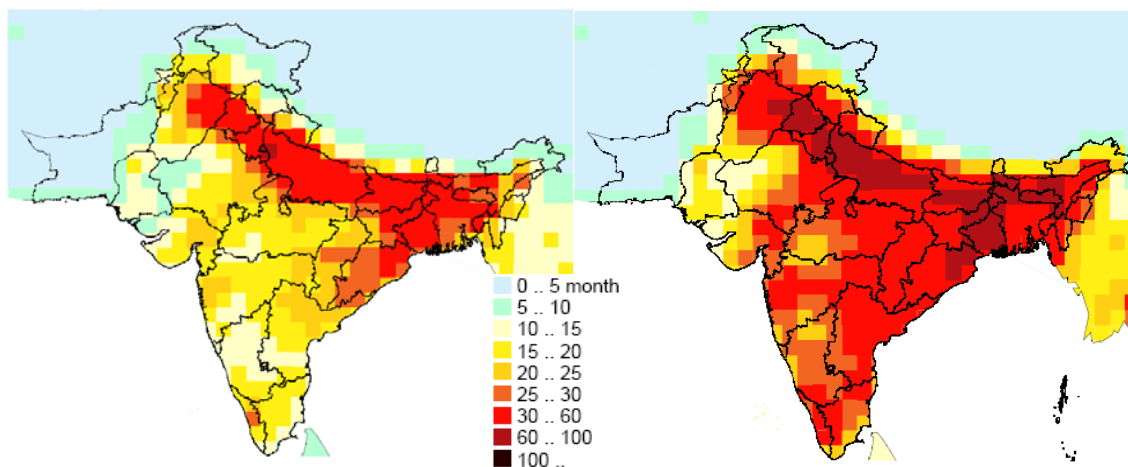
Figure 3.9: Loss in statistical life expectancy attributable to the outdoor exposure of PM2.5 for 2000 (left panel) and the baseline projection for 2020 (right panel) assuming a linear concentration-response function
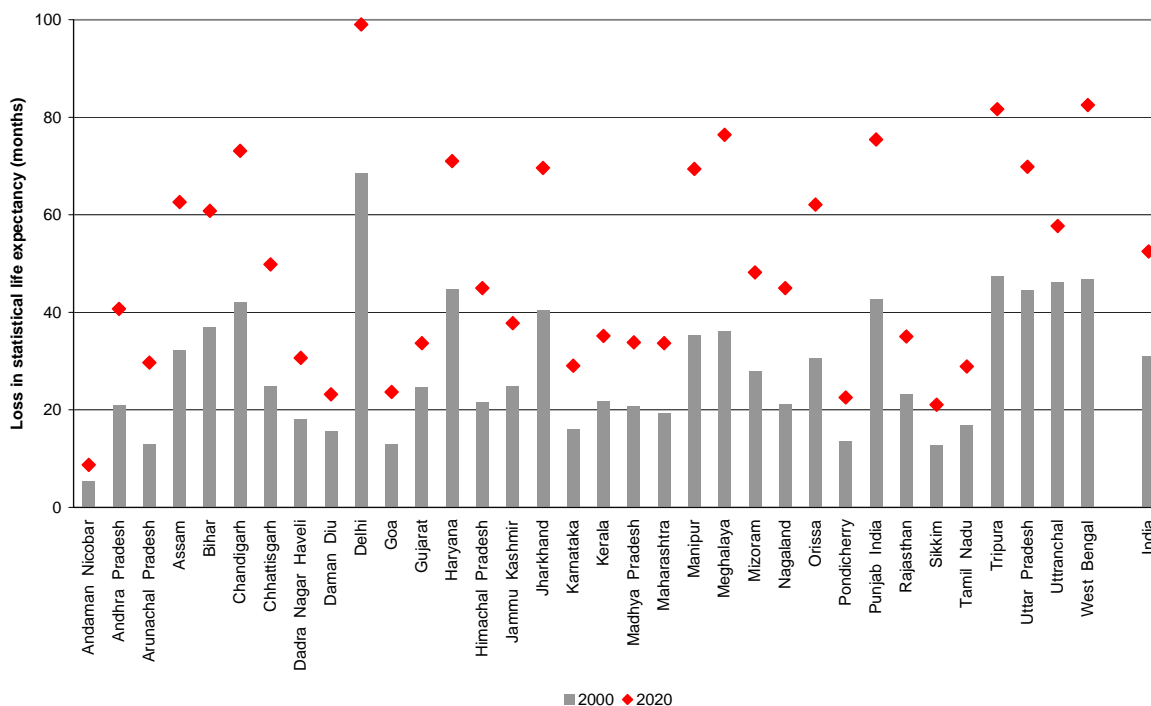
Figure 3.10: Loss in statistical life expectancy attributable to the outdoor exposure of PM2.5 for 2000 and the baseline projection for 2020 with current air pollution legislation assuming a linear concentration-response function

Table 3.1 presents the burden of disease attributable to the use of solid fuels in Indian households. In the baseline scenario, DALYs will increase by 20% in 2030 compared to level calculated for the year 2000.

Table 3.1: Disability adjusted life years attributable burdens from solid fuel use in China for the baseline scenario with less stringent implementation of emission control legislation

Disease, sex, age group	DALYs lost (in 000)			
	2000	**2010**	**2020**	**2030**
ALRI, Children < 5	10026	12739	12517	12272
COPD, Women > 30	1482	1881	1848	1812
COPD, Men>30	1104	1404	1380	1353
Lung cancer, Women > 30	5	4	4	4
Lung cancer, Men>30	9	9	9	9
Total indoor pollution	**14625**	**18046**	**17777**	**17479**
For comparison: DALYs from outdoor pollution	20918	34867	58368	108833

Figure 2.1 compares disability adjusted life years (DALYs) from indoor and outdoor pollution in India for the baseline projection up to 2030. Under the assumption of the validity of a linear concentration-response curve, health impacts from outdoor pollution would dominate total air pollution health impacts, essentially for two reasons: (i) Outdoor pollution affects the total population, while only a fraction of the population is exposed to indoor pollution. (ii) For outdoor pollution, largest health impacts have been identified from cardio-vascular and cardio-pulmonary mortality, while these endpoints have not yet been analyzed for indoor pollution (impacts of indoor pollution are quantified for acute lower respiratory infections (ALRI), chronic obstructive pulmonary disease (COPD) and lung cancer). The graph shows for India a slightly declining trend in health impacts from indoor pollution due to the phase-out of solid fuel use in households. Health effects of outdoor pollution are expected in sharply increase in the future and thereby dominate total health impacts of air pollution.
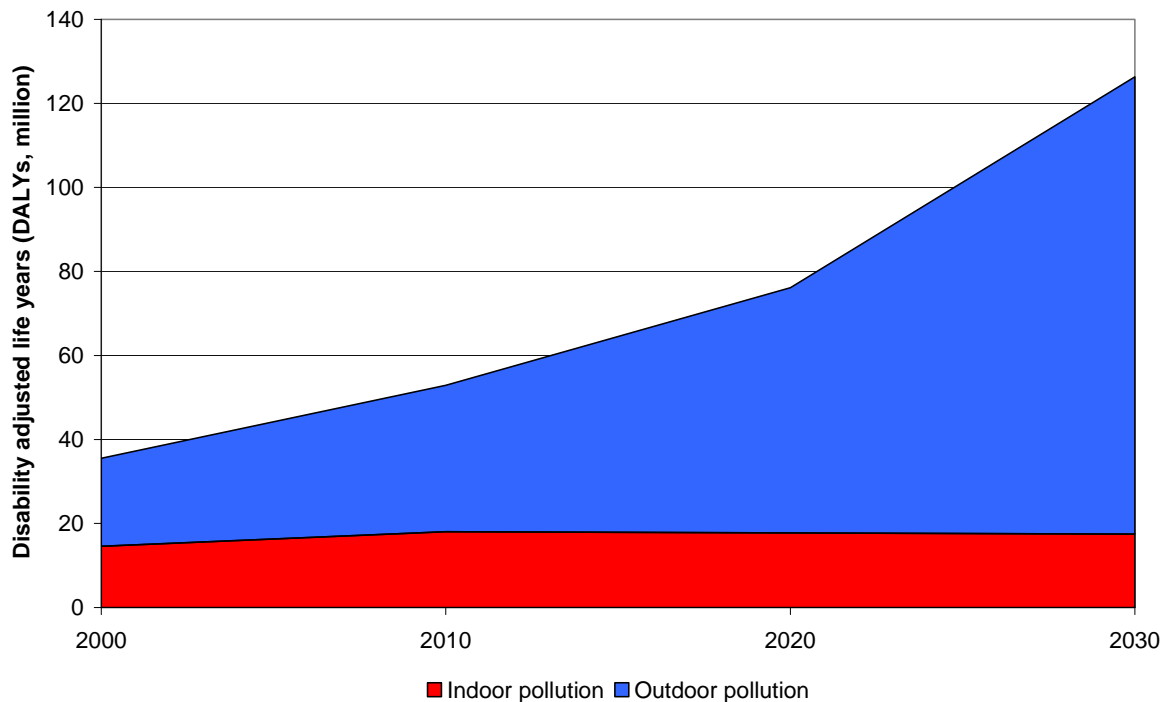
Figure 3.11: Disability adjusted life years from indoor and outdoor pollution in India for the baseline projection with less stringent implementation of current emission control legislation, assuming the linear concentration-response function for outdoor pollution

3.1.4   Alternative emission control scenarios

In addition to the Business-as-usual and the alternative scenarios which were extracted from the Indian Energy Map 2030, the GAINS-Asia team prepared two emission control scenarios that are based on the two activity projections. These scenarios should be seen as hypothetical scenarios that can be used to initiate policy discussions. The first scenario – a 'what-if' scenario - probes into the question of 'what if India adopted European Union air pollution emission control technologies in 2020'? This scenario applies the current German legislation on air pollution control to India in the year 2020. The second hypothetical scenario assumes a total replacement of solid fuels in households with liquefied petroleum gas (LPG) between 2020 and 2030. These two scenarios are displayed in Figure 3.12 and Figure 3.13 below.

Andhra Pradesh Emissions Year 2020
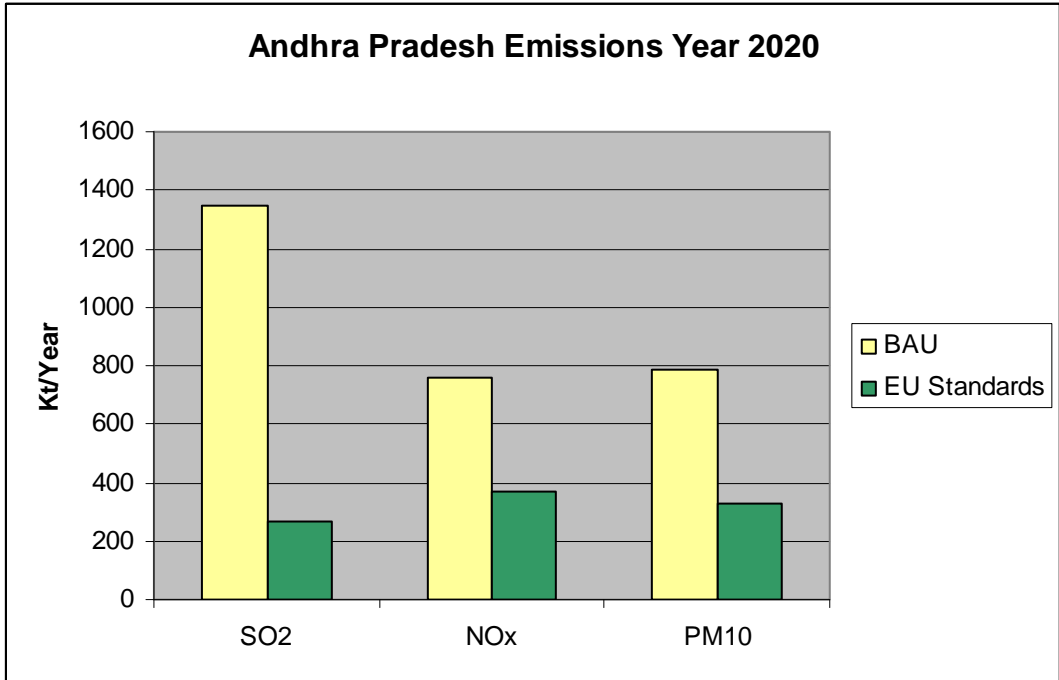
Figure 3.12 Air pollution emissions from the business-as-usual and the "Application of European Air Pollution Emissions Standards" scenarios in Andhra Pradesh, India – Year 2020

Figure 3.12 compares air pollution emissions in 2020 in Andhra Pradesh for the business as usual scenario and the scenario where Andhra Pradesh would adopt Germany's air pollution control measures. Leaving aside for a moment economic considerations of the assumption taken for the advanced technology scenario, the analysis assesses the technical potential for emission reductions that is offered by technologies that are currently readily available on the world market.

Figure 3.13 conducts the same analysis for the LPG scenario, which assumes a replacement of domestic household biofuels with government subsidized liquefied petroleum gas (LPG). The figure analyzes, in addition to the emissions of air pollutants, the concurrent implications on methane (CH_4), which is an important greenhouse gas. The figure clearly indicates that, as a result of the replacement of solid fuels in the domestic sector by natural gas, not only emissions of conventional air pollutants (SO_2, NO_x, PM) decline, but that there are also simultaneous reductions on the emissions of methane.
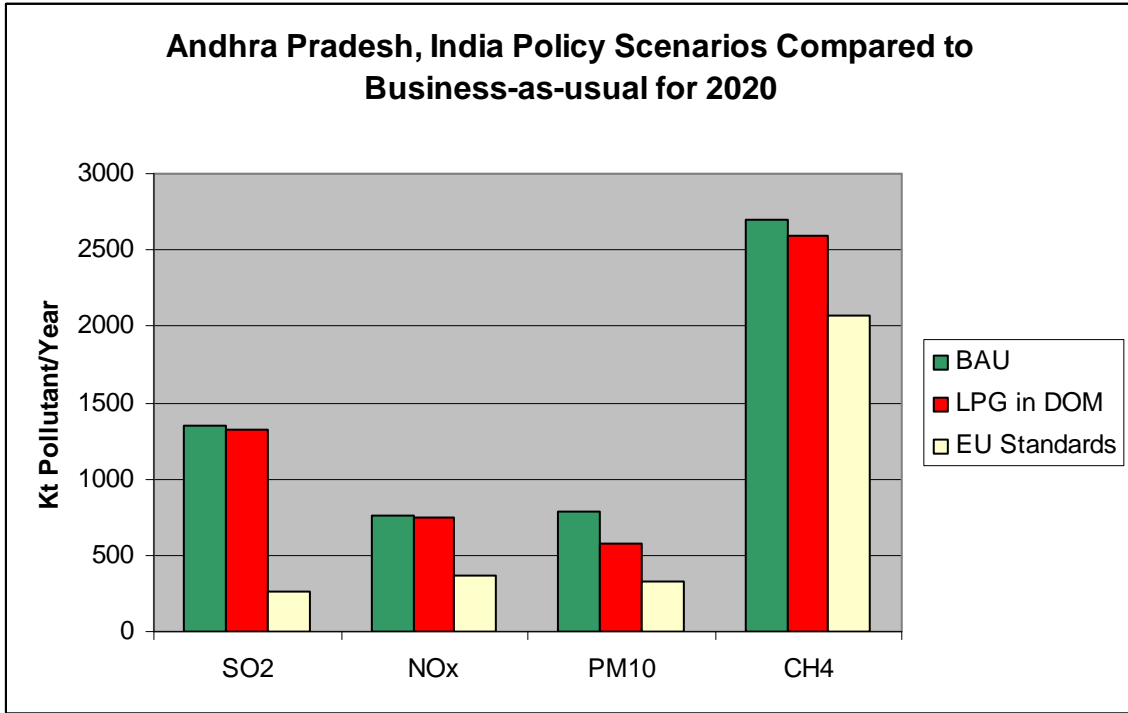
Figure 3.13: Comparison of three policy scenarios for Andhra Pradesh, India – Business-as-usual, Replacement of all solid fuels with LPG in the domestic sector, and the EU standards applied in Figure 3.12.

Below, Figure 3.14 takes the case study presented in Figure 3.13 and expands the region from the single Indian state of Andhra Pradesh to the entire country of India. The country-wide results of LPG replacement are similar to the results generated for Andhra Pradesh. There is a slight air pollution benefit and a slight greenhouse gas reduction from a national biomass replacement policy in the year 2020. Nitrous oxide (N_2O) has been included in the India-wide results, there is a not a noticeable change in N_2O emissions between the two scenarios. The CH_4 reductions are due to improved combustion efficiency of LPG and the decrease in biomass combustion. Biomass combustion is a much larger source of CH_4 emission than LPG combustion. The emission factor used in GAINS for uncontrolled biomass combustion is 0.350 kt CH_4/PJ while the emission factor for uncontrolled domestic LPG combustion is 0.001 kt CH_4/PJ.
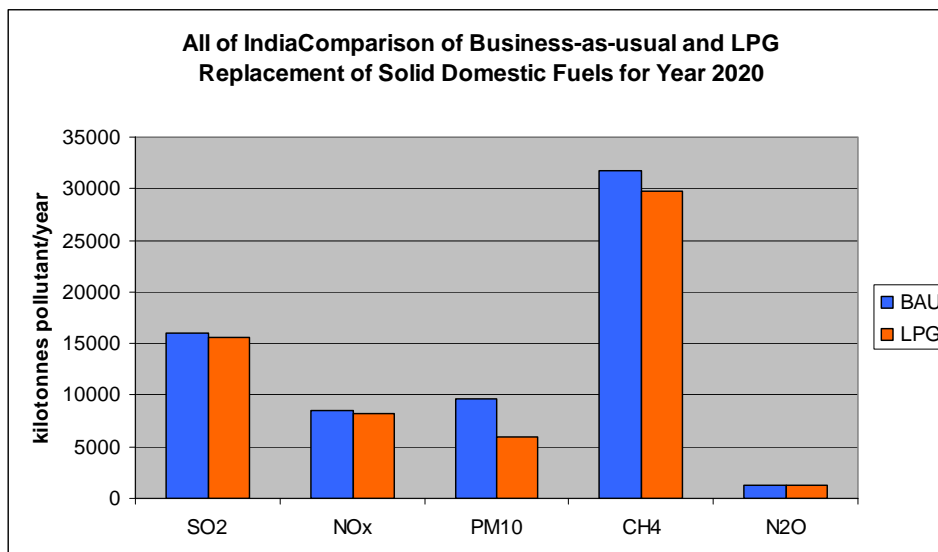
Figure 3.14: Business-as-usual versus LPG replacement of solid fuels in the domestic sector for all of India

The final emissions component of the LPG vs. BAU comparison is carbon dioxide (CO_2). As to be expected, the increased consumption of LPG increases CO_2 emissions compared to the use of carbon-neutral biomass, however due to the substantially higher combustion efficiency of LPG compared to the combustion of biomass in domestic cook stoves, the resulting increase in CO_2 emissions is rather moderate.

Once again it is important to highlight that the GAINS-Asia model does not attempt to address the carbon benefits associated with leaving biomass in the forest or agricultural fields rather than collecting that biomass for combustion in domestic fires and stoves. Without considering these forestry and land-use changes, the CO_2 increase from a national LPG policy initiative in India amounts to 100 Mt CO_2 or an approximate 3 percent increase in national carbon dioxide emissions in the year 2020. This difference is displayed graphically in Figure 3.14 and seems nominal when compared with the overall greenhouse gas inventory of India. It might be a worthwhile academic exercise to weigh the GHG benefits and costs independent of the air pollution and sustainability benefits. Figure 3.15 weighs the different GHG benefits and increases under the common denominator of CO_2 equivalents using the GWP of the Kyoto protocol (CH_4 = 21 and N_2O = 310). The reduction in methane emissions attributable to the reduction in biomass burning combined with the slight reduction in nitrous oxide emissions is not sufficient to offset the carbon dioxide emission surplus attributable to increased LNG combustion. The surplus balance is approximately 52,000 kilotons.

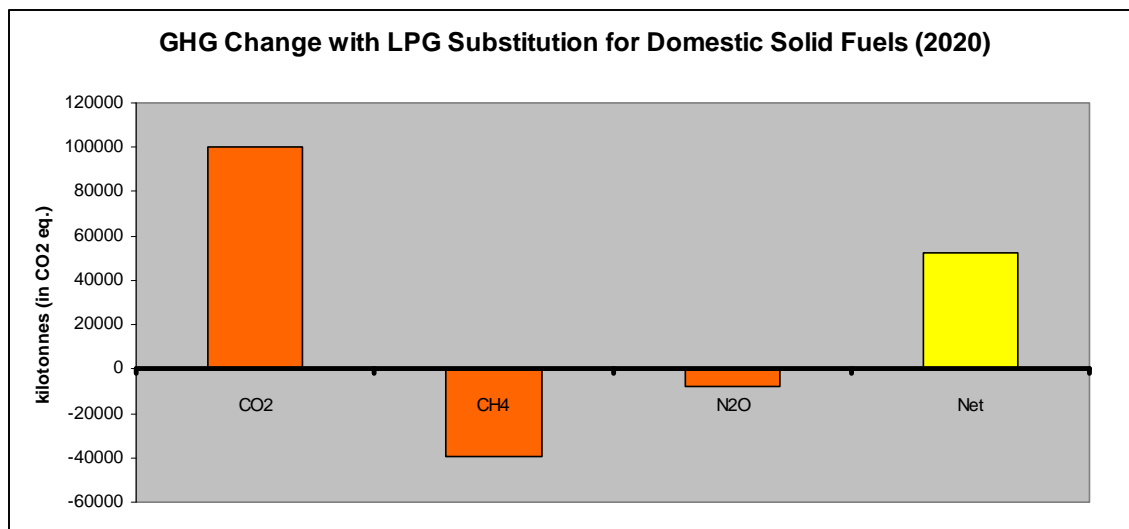**GHG Change with LPG Substitution for Domestic Solid Fuels (2020)**

Figure 3.15: Net greenhouse gas changes when comparing Business-as-usual with LPG substitution for solid fuels in the domestic sector (expressed in units of CO_2 equivalents)

The surplus of GHG emissions are only one component of the LPG for biomass substitution policy analysis, there are other less quantitative factors that should also enter into the equation. In order to perform a complete analysis, policy makers should weigh the reduction in human life years under the business-as-usual scenario compared to the added health improvements of switching from biomass to LPG. As shown later in this report, inclusion of the health benefits of LPG would likely tip the decision in favor of biomass replacement with LPG for cooking and heating. Taking this thinking one step further, the quality of life improvements associated with the LPG switch should also enter into the equation. Under the LPG scenario, women and children would save time under the LPG scenario because the time that is currently invested in gathering fuel wood and biomass could be spent doing other productive tasks. These other productive tasks often add more to the economic bottom line of the household and thereby increase household income. This section provides a real life yet simplified development pathway for the country of India including the different options analysis for making policy decisions. The GAINS-Asia model is instrumental and central to these [and other] policy discussions. GAINS-Asia will not provide a clear cut answer but rather provide decision making support and knowledge. In the end, policy decisions are made by humans and not by complicated computer models.

3.2 China

In this section we describe the energy consumption scenarios for China and their implications for air pollutants emissions and greenhouse gas emissions.

3.2.1 Energy consumption

3.2.1.1 Baseline scenario

The Chinese Energy Research Institute (ERI) has developed a baseline scenario for GAINS based on calculations with its IPAC-AIM/Local model. In the baseline scenario, the primary energy demand is projected at 123 EJ in 2020 and 158 EJ in 2030 (including traditional biomass). The results indicate that with a 59% share in total energy demand in 2030 coal will be a major energy input in China (92 EJ in 2030) followed by oil (29 EJ), nuclear (12 EJ), biomass (9EJ), natural gas (6 EJ) and so on. For the year 2030, a rapid increase in Chinese natural gas demand is observed that will increase 5 times as compared to the base year 2000. With respect to final energy use, electricity and natural gas increase rapidly whereas coal and oil demand increase slowly. Coal use in the residential sector will generally decrease (from 17% in 2000 to 14% in 2030) and be replaced by gas and electricity; coal will be mainly used in large equipment such as boilers. Demand for oil products used for transport will increase quickly, with the rapid growth of vehicles in China. Oil use in transport will increase from 4 EJ in 2000 to 29 EJ in 2030 (Source: Kejun and Yixiang, 2008).

3.2.1.2 Alternative scenario

ERI developed a policy scenario that assumes adoption of energy and environmental policy measures in China. However, some assumptions in that policy pathway were not consistent with the ERI Baseline. Thus, that scenario could not be directly used for developing a 'storyline' within the GAINS China Project. Instead, ERI and IIASA prepared an Alternative Pathway that is consistent with the ERI Baseline and takes into account – to a maximum extent – potential for CO_2 reduction options from the policy scenario.

Table 3.2 presents the general macro-economic indicators and energy consumption in China whereas Figure 1 presents the total energy consumption (in PJ/year) over time. In 2030, the population will increase by 13.2% as compared to the base year 2000. For the same period, the electricity generation will increase by 6 times whereas the electricity intensity of GDP will decrease 47% as compared to the base year 2000. The energy intensity of GDP will also decrease by 71% for the same period. It may be noted that in the alternative scenario, energy demand in 2030 decreases by 2.4 EJ as compared to the baseline scenario.

Table 3.2: Macro-economic indicators and energy consumption in China

Indicators	Unit	Year			
		2000	2010	2020	2030
Population	Million	1262	1351	1442	1458
GDP	10^9 Euro 2000	945	2637	5716	10263
GDP/Capita	Euro 2000	1952	3964	7038	2847
Electricity generation	1000 TWh	1360	3373	4741	7942
Energy intensity of GDP	MJ/Euro 2000	52	38	21	15
Electricity intensity of GDP	kWh/Euro 2000	1.44	1.28	0.83	0.77

Source: The population data for the years 2000 and 2005 is taken from *China Statistical Yearbook* whereas from 2010 to 2030 the data is taken from *National Population Development Strategy*. The GDP growth rate for the year 2000 is the actual value whereas for 2005-10 the data has been taken from 11th five-year plan and for rest of the years the GDP growth values are forecast results.

The power sector in China is highly dominated by coal (Kroeze *et al.*, 2004) and is expected to remain dependent on coal (IEA, 2007). Figure 3.18 and Figure 3.19 present the sectoral energy consumption by fuel use in China and changes over time. In the base year 2000 the share of coal in the power sector was 94%. In 2030, share of coal in power sector will decrease up to 69% whereas share of natural gas and nuclear will increase.
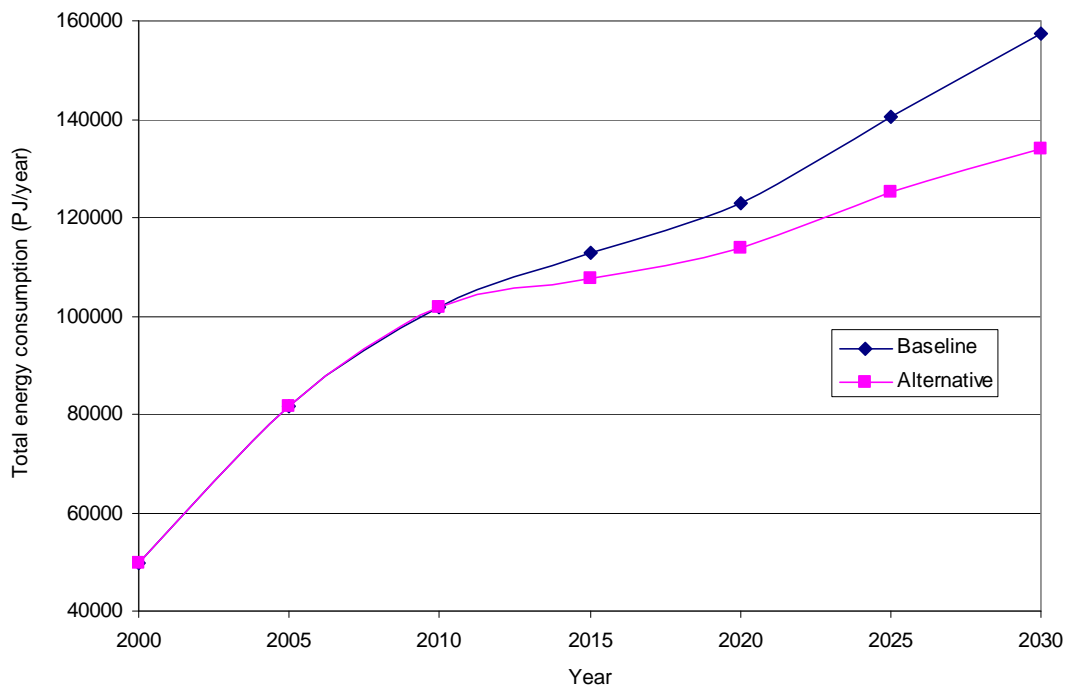
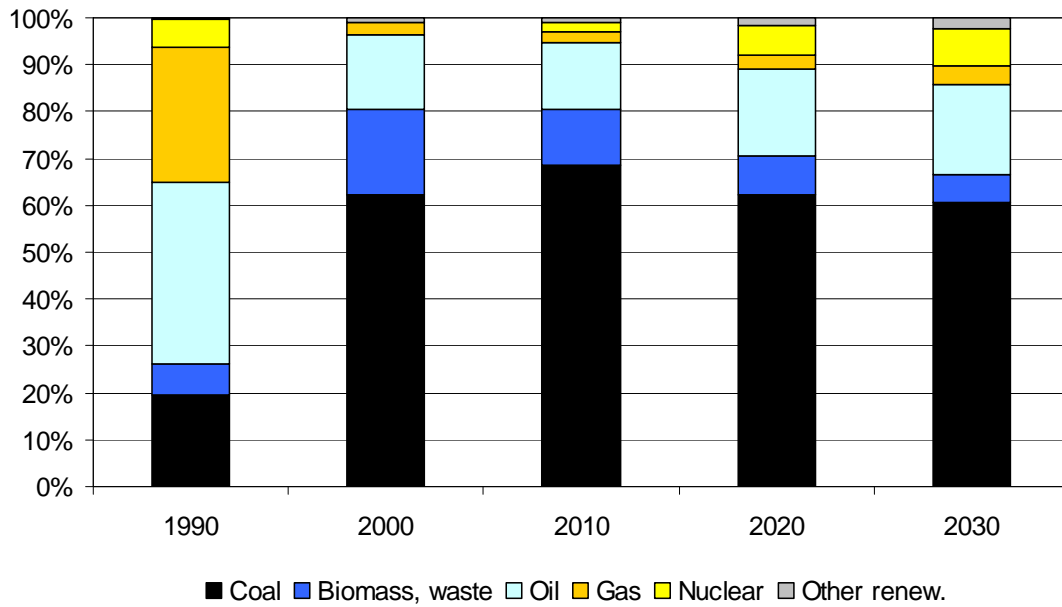**Figure 3.16 Total energy consumption (PJ/yr) over time in China**

Figure 3.17 Structure of energy consumption in China for the baseline scenario

In the domestic sector, use of solid fuels (coal, fuel wood, agricultural residuals, etc.) is prevalent in china. The share of solid fuels was more than 84% during 2000. Up to 2030, the share of solid fuels in the domestic sector will remain 49% only whereas the share of natural gas and electricity will increase (Figure 3.18).
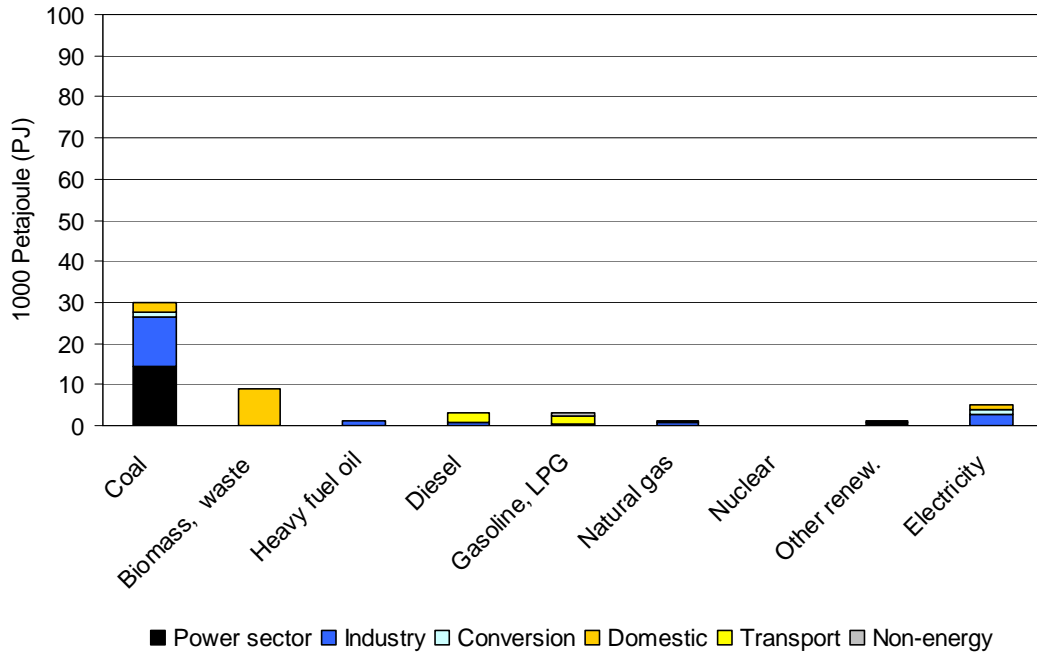

Figure 3.18 Sectoral energy consumption by fuel use in China in the base year 2000
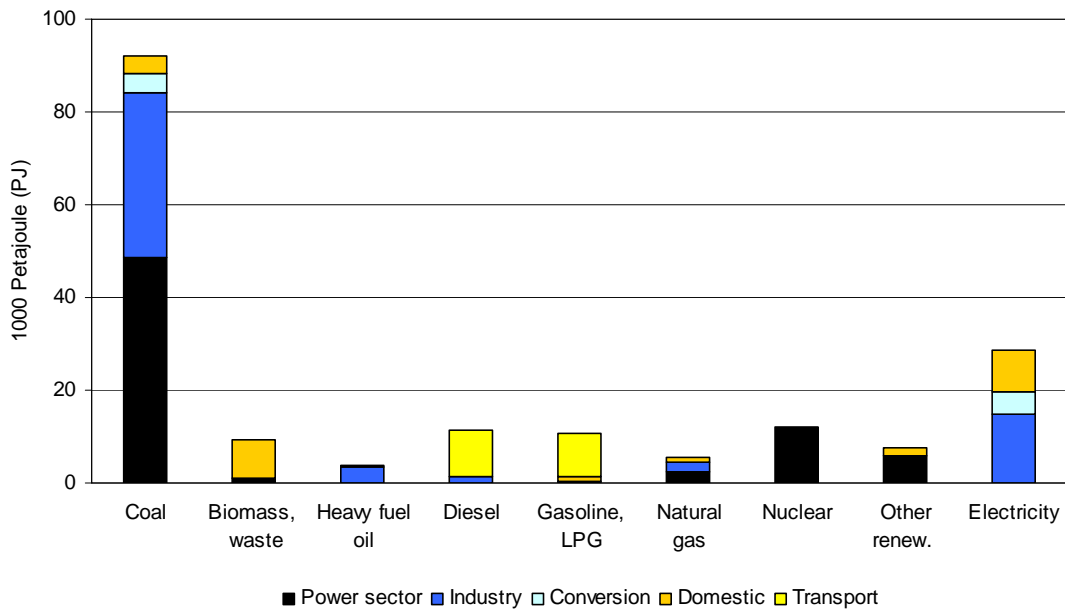
Figure 3.19 Sectoral energy consumption by fuel use in China in the year 2030

3.2.2 Emission of air pollutants and greenhouse gases

On the basis of the activity data provided by ERI, the associated Air Pollution and GHG emissions in China are estimated in the baseline and alternative scenarios. It is observed that China has several legislations for the control of air pollution and GHG emissions however, the implementation of such policies is strict. For, e. g., use of flue gas desulfurization (FGD) in the power sector is mandatory in China however it is not being strictly followed. Therefore, in each scenario, we have analyzed three cases of control strategies namely (i) less stringent implementation of the emission control policies (LS), (ii) strong stringent implementation of the emission control policies (ST), and (iii) best available technologies (BAT). The control strategies of the first two cases are provided by Tsinghua University, whereas for the latter case we have used the technologies being used in Europe.

GHG emissions in the baseline and alternative scenarios aggregated by CORINAIR SNAP1 sector are presented in Figure 3.21 and Figure 3.20. CO_2 emissions were more than 3000 million tons in China during 2000. The results indicate that for the year 2030, CO_2 emissions will increase three times as compared to the 2000 levels in the baseline scenario.
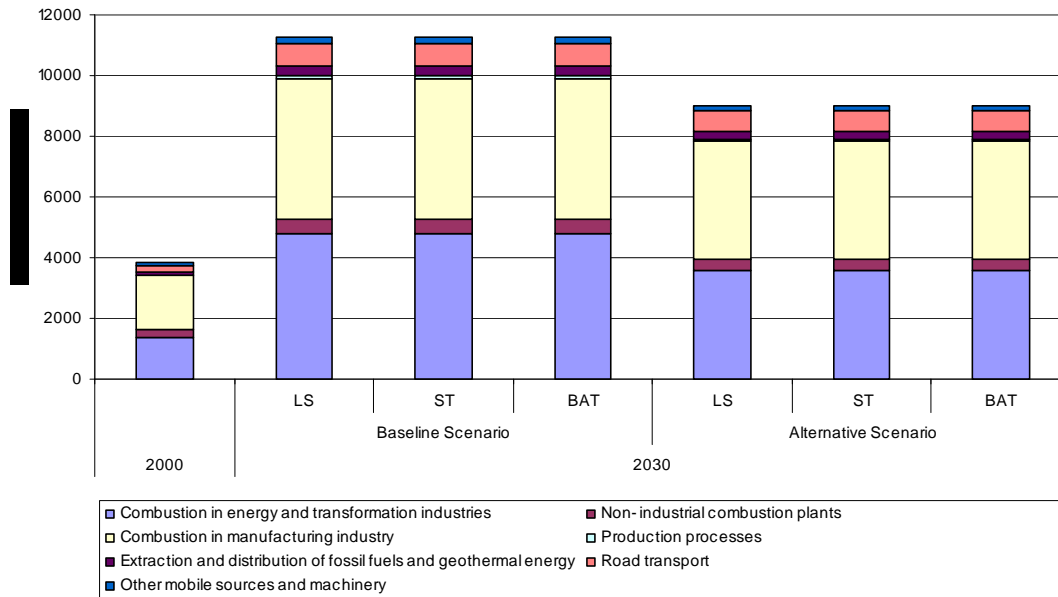

Figure 3.20: CO₂ emissions aggregated by CORINAIR SNAP1 sector in the baseline and alternative scenario (LS … less strict application of current legislation, ST … strict application of current legislation, BAT … application of best available technology)

For the base year 2000 CH$_4$ emissions were around 48 million tons. Until 2030, CH$_4$ emissions increase by 14% as compared to the 2000 level in the optimistic scenario if the best available emission control policies would be strongly implemented.
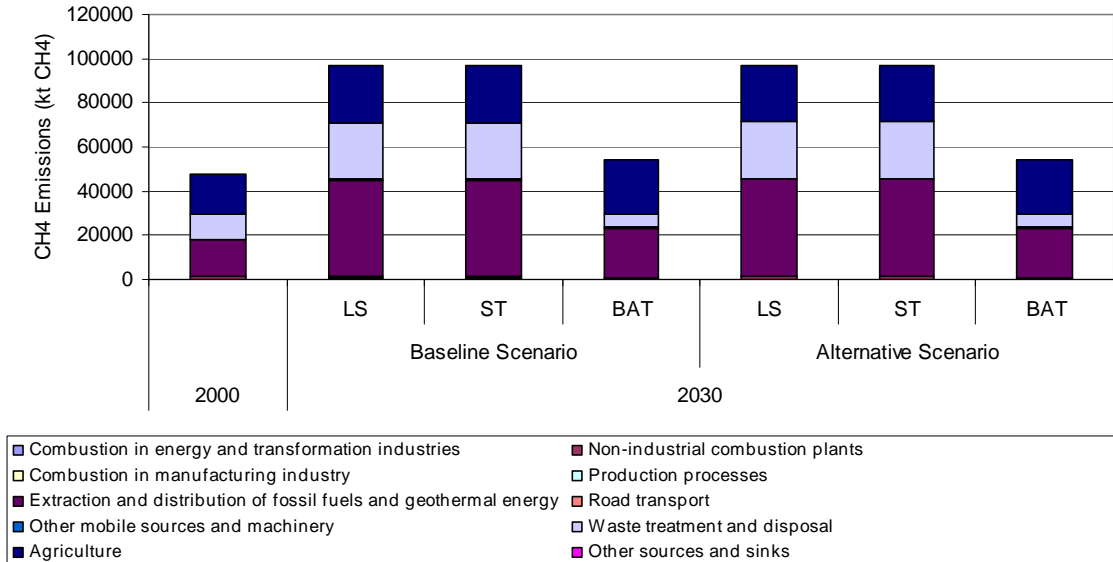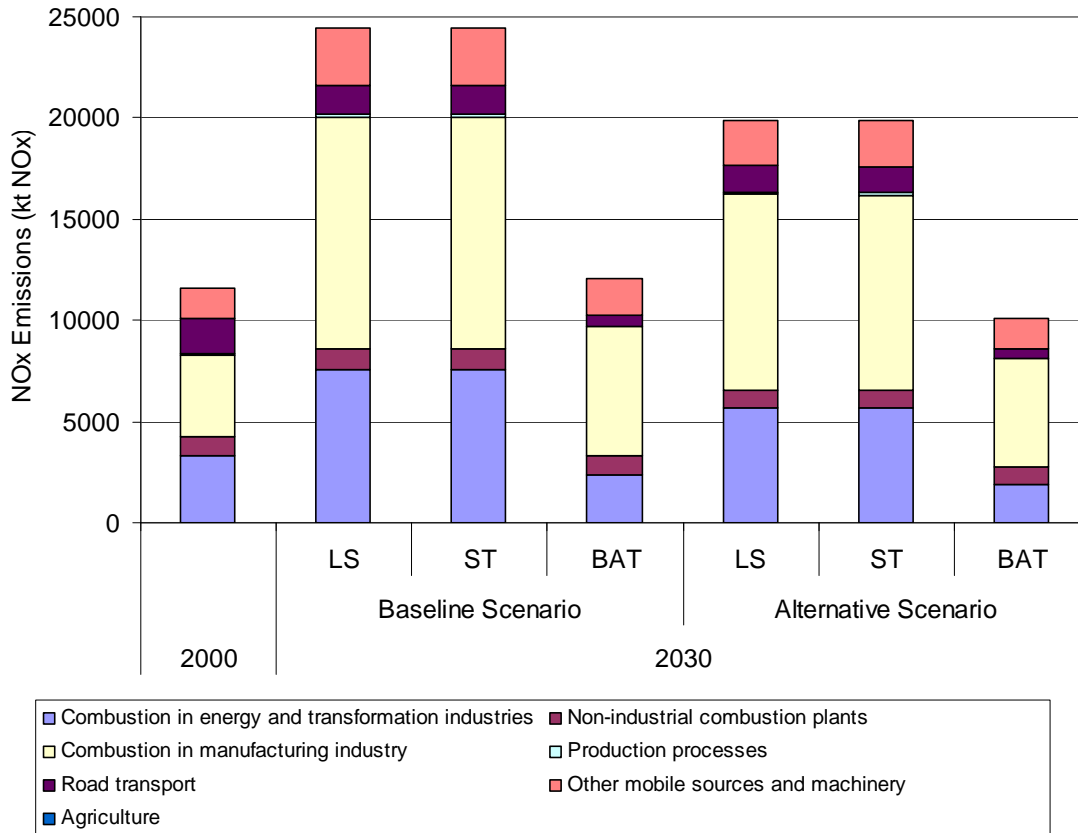

Figure 3.21: CH$_4$ emissions aggregated by CORINAIR SNAP1 sector in the baseline and alternative scenario (LS … less strict application of current legislation, ST … strict application of current legislation, BAT … application of best available technology)

Figure 3.22 presents NO_x emissions in the baseline and alternative scenarios aggregated by CORINAIR SNAP1 sector. It may be noted that NO_x emissions will increase by 2.1 times in 2030 as compared to the 2000 level in the baseline scenario whereas it will increase by 1.7 times in 2030 as compared to the 2000 level in the so called alternative scenario whereas the use of best available technologies can reduce NO_x emissions by 10% in 2030 (as compared to the 2000 level).

Figure 3.22 NO_x emissions aggregated by CORINAIR SNAP1 sector in the baseline and alternative scenario (LS … less strict application of current legislation, ST … strict application of current legislation, BAT … application of best available technology)

SO$_2$ emissions in the baseline and alternative scenarios aggregated by CORINAIR SNAP1 sector are shown in Figure 3.23. By 2030 SO$_2$ emissions decrease by 10% as compared to the 2000 level in the baseline scenario if the emission control policies would be strongly implemented. SO$_2$ emissions can be reduced by 40% (as compared to the 2000 level) in 2030 when the best available technologies will be used in the alternative scenario.
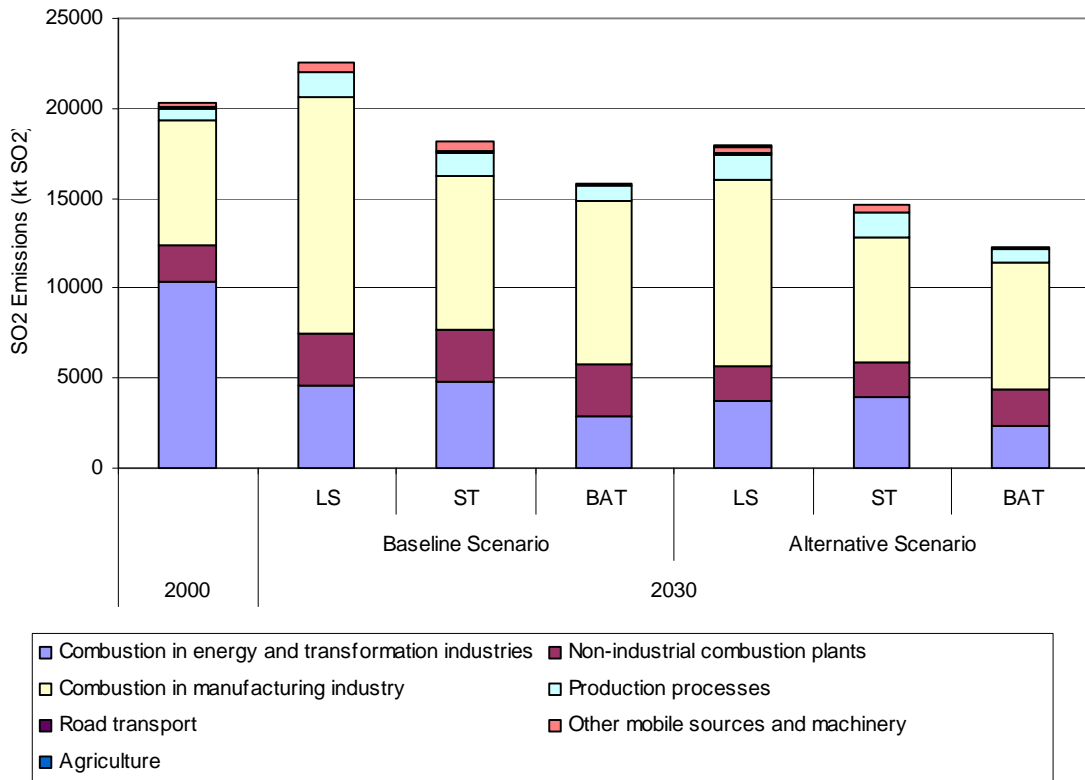

Figure 3.23 SO$_2$ emissions aggregated by CORINAIR SNAP1 sector in the baseline and alternative scenario (LS … less strict application of current legislation, ST … strict application of current legislation, BAT … application of best available technology).

Figure 3.24 through Figure 3.26 present PM emissions in the baseline and alternative scenarios aggregated by CORINAIR SNAP1 sector. For the year 2030, PM2.5 emissions will decrease by 42% as compared to the 2000 level in the baseline scenario if the emission control policies would be strongly implemented (Figure 3.24). PM2.5 emissions can be reduced by 65% (as compared to the 2000 level) in 2030 when the best available technologies will be used in the alternative scenario.
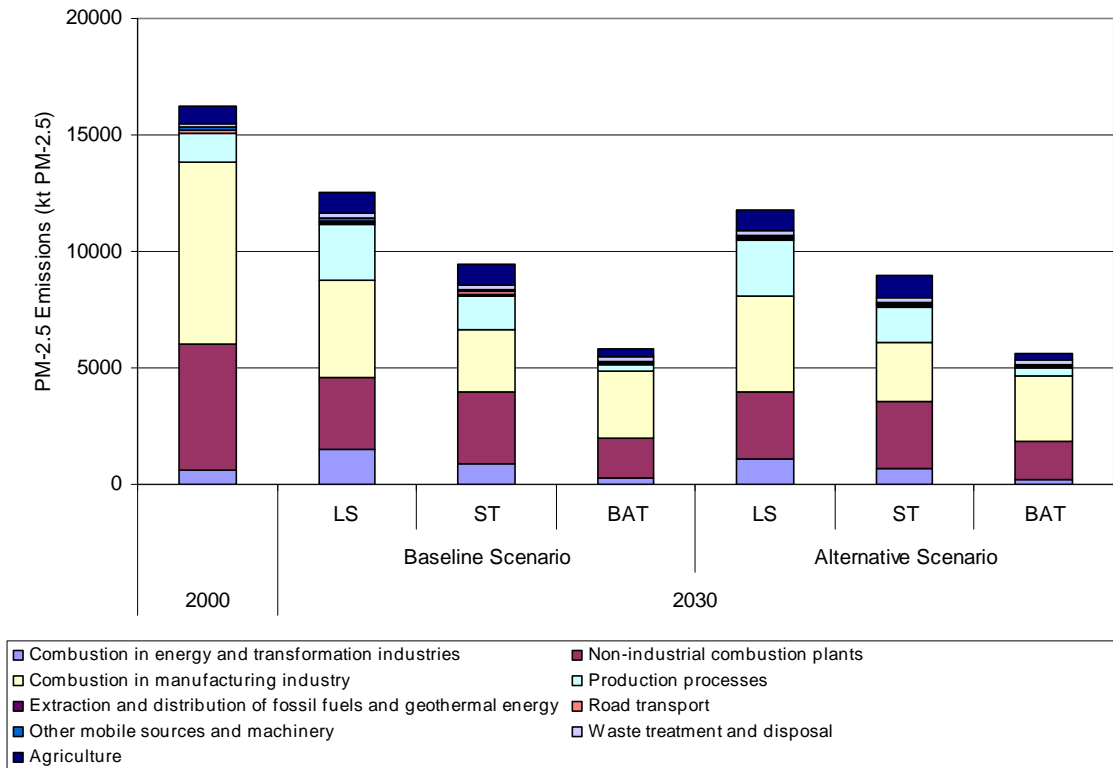

Figure 3.24 PM2.5 emissions aggregated by CORINAIR SNAP1 sector in the baseline and alternative scenario. (LS … less strict application of current legislation, ST … strict application of current legislation, BAT … application of best available technology)

PM10 emissions in the baseline and alternative scenarios aggregated by CORINAIR SNAP1 sector are shown in Figure 3.25. In 2000, the PM10 emissions were more than 22 million tons in China. The results indicate that for the year 2030 PM10 emissions will decrease by 36% as compared to the 2000 level in the baseline scenario if the emission control policies would be strongly implemented. PM-10 emissions can be reduced by 63% (as compared to the 2000 level) in 2030 when the best available technologies will be used in the alternative scenario.
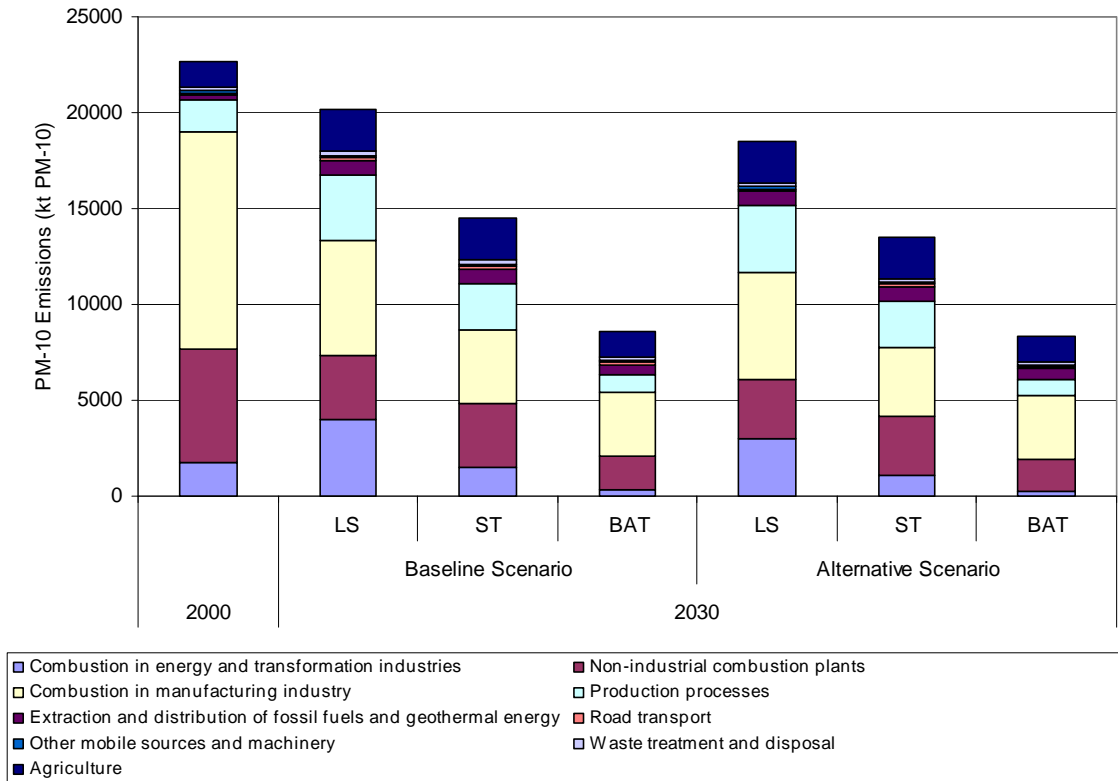

Figure 3.25 PM10 emissions aggregated by CORINAIR SNAP1 sector in the baseline and the alternative scenario (LS … less strict application of current legislation, ST … strict application of current legislation, BAT … application of best available technology).

Figure 3.26 presents TSP emissions in the baseline and alternative scenarios aggregated by CORINAIR SNAP1 sector. TSP emissions are estimated at more than 34 million tons in China for 2000. The results indicate that for the year 2030 TSP emissions will decrease by 34% compared to the 2000 level in the baseline scenario, and by 39% in the alternative scenario if emission control policies would be strongly implemented. PM-10 emissions can be reduced by 62% (as compared to the 2000 level) in 2030 when the best available technologies will be used in the alternative scenario.
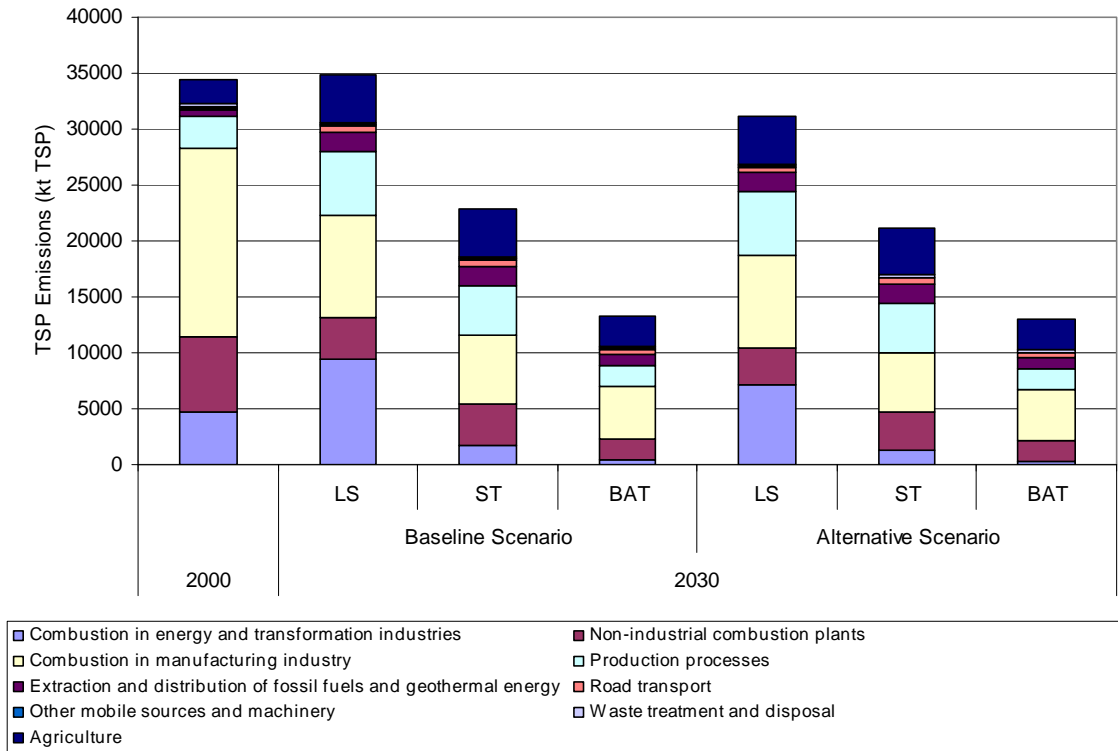

Figure 3.26 TSP emissions aggregated by CORINAIR SNAP1 sector in the baseline and alternative scenario (LS … less strict application of current legislation, ST … strict application of current legislation, BAT … application of best available technology)

3.2.3 Air quality

For each of the emission patterns generated for an emission control scenario, the GAINS-Asia model computes the resulting fields of selected air quality indicators. Figure 3.27 compares ambient PM2.5 concentrations computed with GAINS for the year 2000 (left panel) and for the case with less stringent implementation of emission control legislation in 2020 (right panel). The graph presents for each grid cell population-weighted concentrations, i.e., the population-weighted average of urban and rural concentrations. The projected change in health-relevant ozone concentrations (in terms of SOMO35) is shown in Figure 3.28.
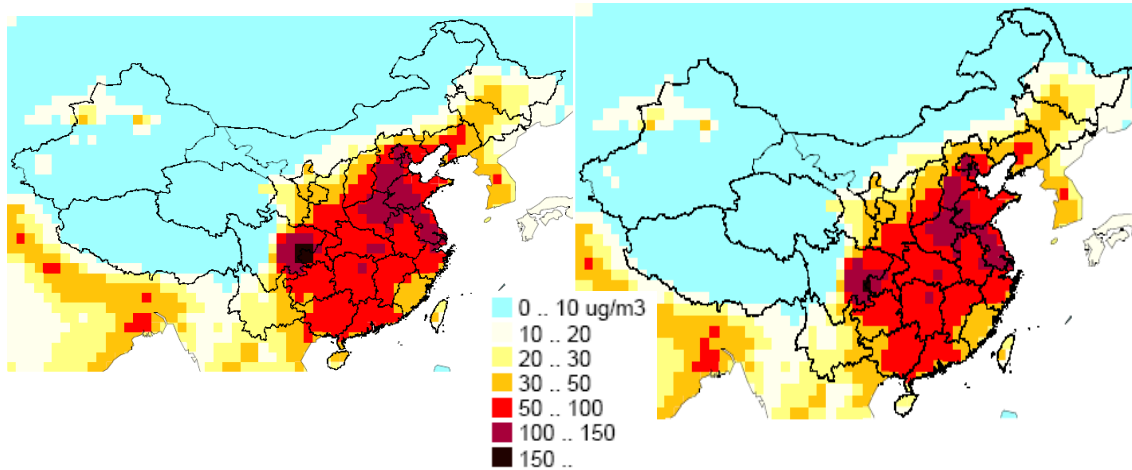

Figure 3.27: Computed ambient concentrations of PM2.5 in 2000 (left panel) and 2020 (less stringent implementation of legislation, right panel)
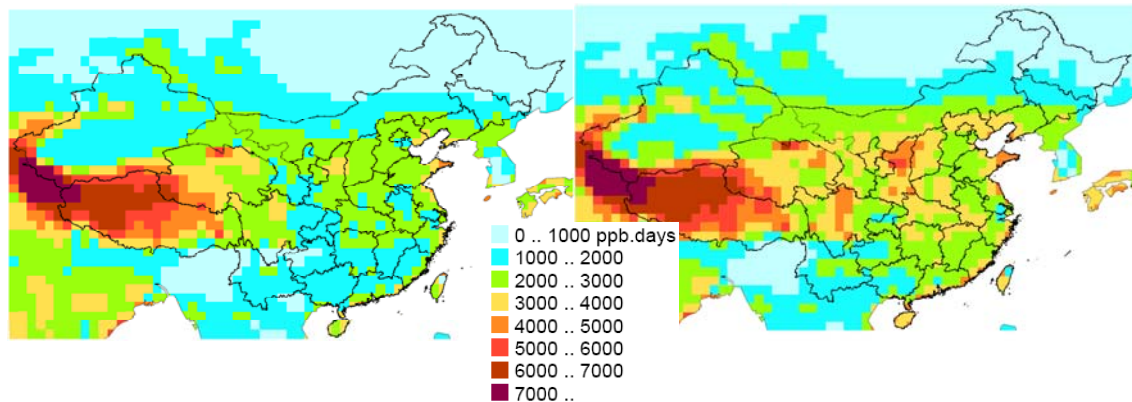

Figure 3.28: Health-relevant ozone concentrations (in terms of SOMO35) in 2000 (left panel) and 2020 (less stringent implementation of legislation, right panel)

3.2.4   Health impacts

GAINS-Asia estimates health impacts from indoor and outdoor air pollution. For outdoor pollution, GAINS quantifies premature mortality that can be associated with the exposure to PM2.5. Figure 3.29 presents the spatial patterns of life shortening due to outdoor PM2.5 concentrations for the year 2000 (left panel) and for the less stringent implementation case in 2020 (right panel), assuming validity of a linear concentration-response function.
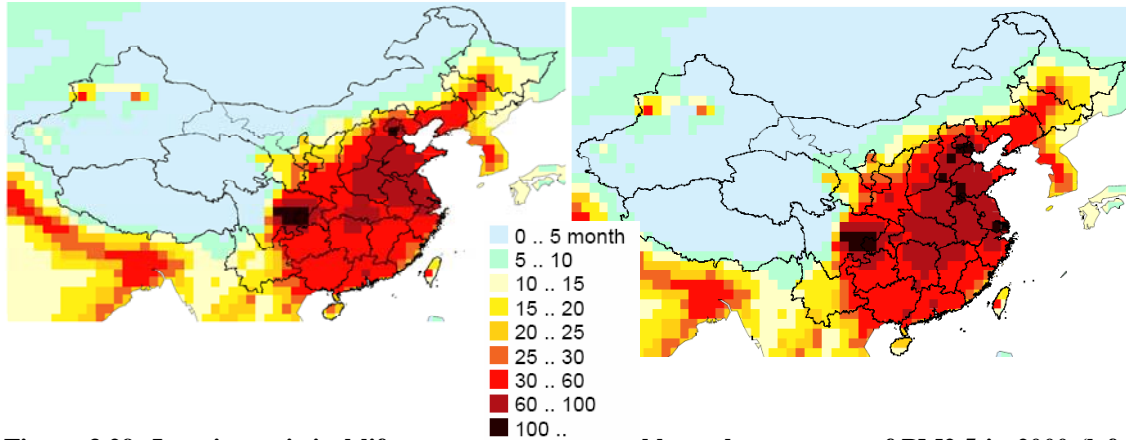

Figure 3.29: Loss in statistical life expectancy attributable to the exposure of PM2.5 in 2000 (left panel) and 2020 assuming a linear concentrations-response function (less stringent implementation of legislation, right panel)
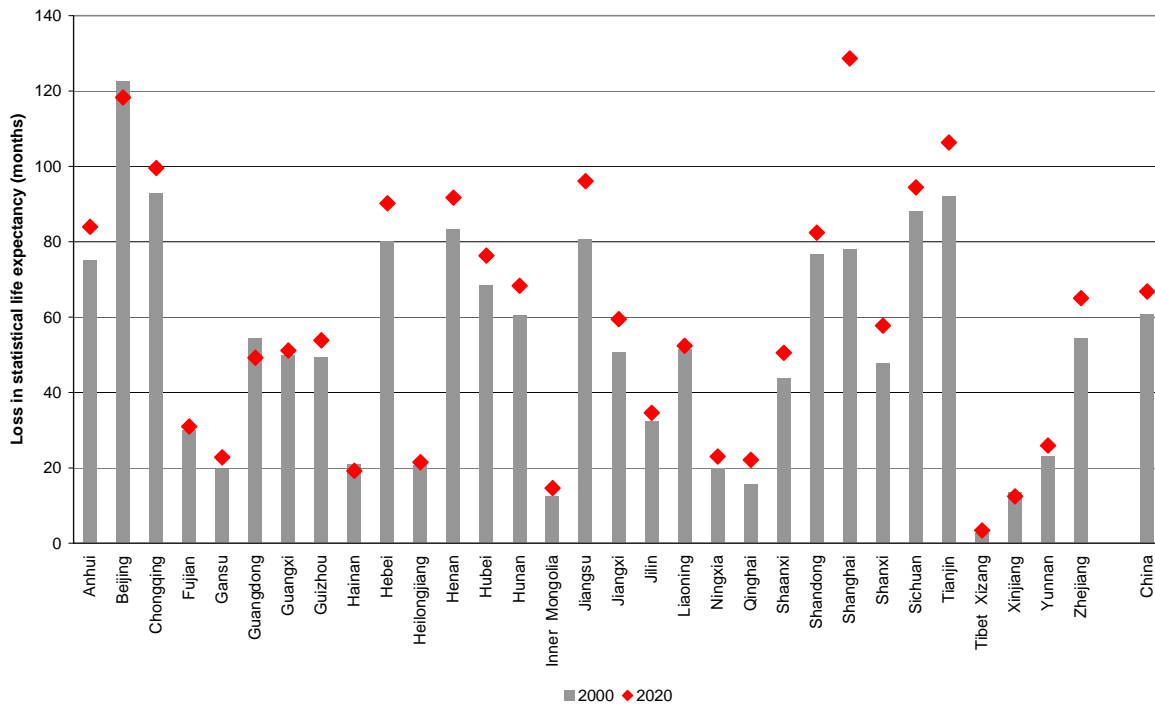

Figure 3.30: Loss in statistical life expectancy attributable to the outdoor exposure of PM2.5 for 2000 and the baseline projection for 2020 with the less stringent implementation of current legislation assuming a linear concentration-response function

Table 3.3 presents the disability adjusted life years attributable to the use of solid fuels attributable to indoor pollution from solid fuel use in Chinese households for the baseline scenario with less stringent implementation of emission control legislation. Overall, the burden of disease from indoor pollution would increase until 2010 and than decline due to the phase-out of solid fuels in the domestic sector that is enshrined in the baseline energy projection.

Table 3.3: Disability adjusted life years (DALYs) lost attributable to indoor pollution from solid fuel use in Chinese households for the baseline scenario with less stringent implementation of emission control legislation

Disease, sex, age group	DALYs lost (in 000)			
	2000	2010	2020	2030
ALRI, Children < 5	1991	2445	1764	1143
COPD, Women > 30	1666	2045	1475	957
COPD, Men>30	1361	1671	1206	781
Lung cancer, Women > 30	196	224	264	315
Lung cancer, Men>30	249	284	335	400
Total indoor pollution	**5463**	**6668**	**5044**	**3596**
For comparison: DALYs from outdoor pollution	65307	100943	96895	91177

Figure 2.1 compares disability adjusted life years (DALYs) from indoor and outdoor pollution in China, for the baseline projection with less stringent implementation of current emission control legislation. Under the assumption of the validity of a linear concentration-response curve, health impacts from outdoor pollution would dominate total air pollution health impacts, essentially for two reasons: (i) Outdoor pollution affects the total population, while only a fraction of the population is exposed to indoor pollution. (ii) For outdoor pollution, largest health impacts have been identified from cardio-vascular and cardio-pulmonary mortality, while these endpoints have not yet been analyzed for indoor pollution (impacts of indoor pollution are quantified for acute lower respiratory infections (ALRI), chronic obstructive pulmonary disease (COPD) and lung cancer). The graph shows for China a declining trend in health impacts from indoor pollution due to the phase-out of solid fuel use in households, while health effects for outdoor pollution are expected in increase up to 2010 and decline afterwards.
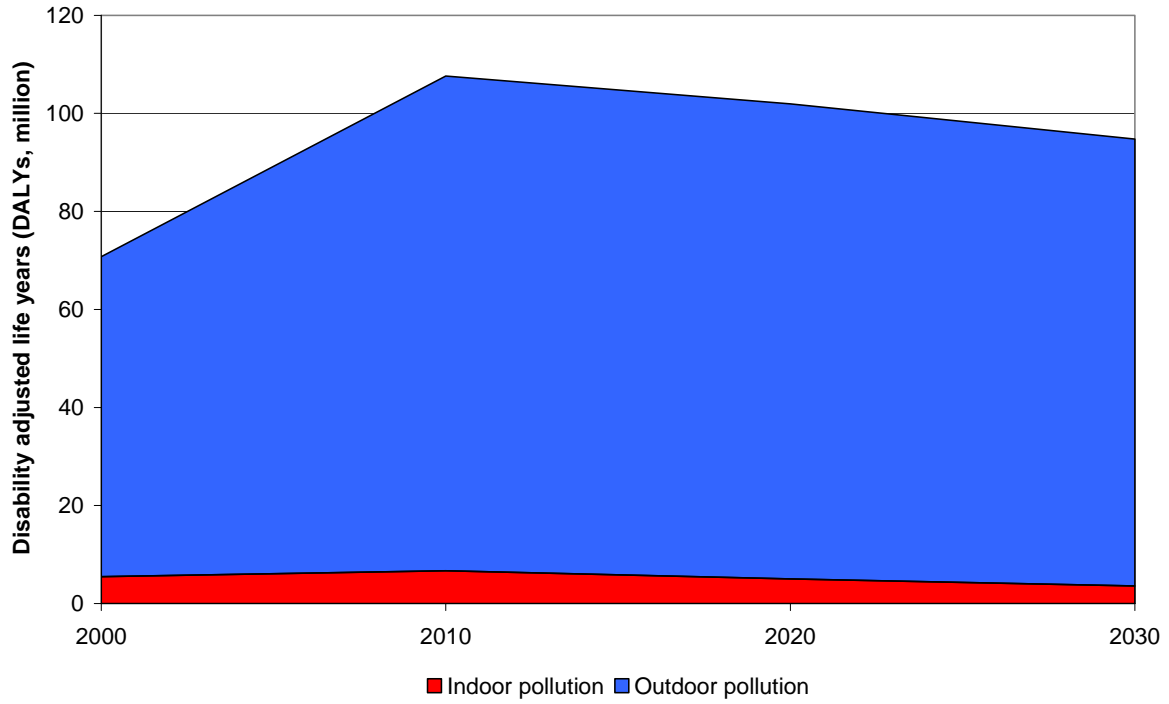
Figure 3.31: Disability adjusted life years from indoor and outdoor pollution in China for the baseline projection with less stringent implementation of current emission control legislation, assuming the linear concentration-response function for outdoor pollution

4 Optimized emission control scenarios

4.1 Introduction

The GAINS-Asia baseline scenarios were defined and generated by the GAINS-Asia partner organizations in India and China, in collaboration with IIASA (TERI, 2008) and Kejun, 2008). In an earlier section of this report we have discussed the structure of a set of alternative scenarios that were designed to reflect the effect of less carbon-intensive energy systems, as well as – in the case of India – the impact of increased use of LPG in the domestic sector, and – in the case of China – the differences between a partial and full implementation of current policies. These alternative scenarios were designed independently of cost-effectiveness considerations, i.e., they are used to illustrate the impact of changes in the activity data and control policies without having to worry about how much these changes would cost.

In contrast, in the following sections we present policy scenarios that were generated with the GAINS optimization module, i.e., typically they meet given environmental constraints, but among all scenarios that meet these criteria they are achieved at lowest costs.

The least-cost approach allows us to identify a set of control measures that meet the objectives and come at the lowest possible cost. Such information can be used as input to a policy process, but it would not be appropriate to simply use the model output to prescribe the *exact* control strategies for the future. The model output, however, can be used to estimate costs and emissions that would be required, and to estimate which sub-regions and macro sectors would contribute to achieving the targets.

The starting points of our analysis are the two baseline scenarios provided by the GAINS-Asia partners in India and China. In particular, for India we use a scenario labeled 'India_Baseline_Scenario' in the GAINS-Asia Web version, and a scenario labeled 'ERI_BL_CLE_LS_Dec07' for China (the latter label indicates that this the baseline current legislation scenario with a less strict interpretation of the current legislation).

In the next section we briefly introduce the concept of maximum feasible emission reductions, which are used to set the stage by defining the ranges for potential emission reductions. We then turn to more realistic emission control scenarios that go beyond the currently planned policies. The results illustrate that environmental objectives can be achieved in different ways: for example by prescribing a set of technologies, by setting emissions ceilings for individual pollutants, by applying uniform targets across different regions. We illustrate, however, that the effects-based cost-effectiveness approach has advantages over all of them and that it is important to take into account technological and economic interactions between air pollution control and climate change mitigation.

4.2 The scope for emission reductions

The GAINS model makes use of another useful optimization concept: the maximum feasible reduction. Given a baseline scenario a natural question to ask is: by how much could the emissions be reduced? What is the potential for improvement on air quality? This is less a pragmatic question than a hypothetical one, because the application of the best technologies in each and every sector is potentially extremely expensive and thus such a scenario is not realistic. However, the maximum feasible reduction scenario allows us to gauge the scope for possible targets and identify possibly infeasible environmental ambitions. It also serves as a check on how the model reacts to extreme targets and of the constraints on the application of the best technologies.

The maximum feasible reduction can be formulated as an optimization problem. The objective in such a maximum feasible reduction scenario is to bring down emissions as much as possible – no matter what the costs are.[3] However, for a given baseline the maximum technically feasible scenario may not be unique for two reasons:

1. The GAINS model also contains multi-pollutant measures, i.e., measures that affect more than one pollutant, and in most cases the pollutants affected are actually *reduced* by the technology. However, this also means that a technology may be the best available technology for, say, pollutant A (in which case it would be implemented if the task was to bring A emissions down as much as possible), but not for pollutant B. Thus, depending on whether the emissions of A or B would be minimized, the measure would be taken or not. Thus there may not be a single solution that would minimize A and B simultaneously. In GAINS-Asia this non-uniqueness can be observed when one tries to minimize CO_2 emissions: then more biomass is used, which however, may increase PM emissions. If, however, A and B are both air pollutants SO_2, NO_x, PM this problem does not arise the maximum feasible reduction is unique.

2. The other reason is that we can operate the GAINS model in the RAINS mode or the in GAINS modes (see above). In the GAINS mode, typically emissions can be further reduced than in the RAINS mode. It is thus useful to distinguish the "maximum technically feasible reduction" (MTFR) scenario obtained in the GAINS mode from the "maximum feasible reduction in RAINS" (MRR) scenario.

Figure 4.1 and Figure 4.2 illustrate this last point graphically. They show the potential for reductions of air pollutants relative to the respective baseline scenarios for India and China in 2020. The light bars show the range between the baseline level and the MRR level, the dark bar show the additional potential due to the inclusion of substitution options, and the end of the dark bars represent the MTFR levels.

It can be seen from Figure 4.1 that add-on technologies can bring emissions of SO_2 so far down (e.g., through flue gas desulphurization) that the further reduction potential by saving energy, switching to CHP etc. is comparatively small. Figure 4.2 shows the corresponding ranges for China.

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[3] We have, however, added a scaled penalty term so that if two technologies were to give the emission reductions, the cheaper of the two would be chosen in the maximum feasible reduction scenario.
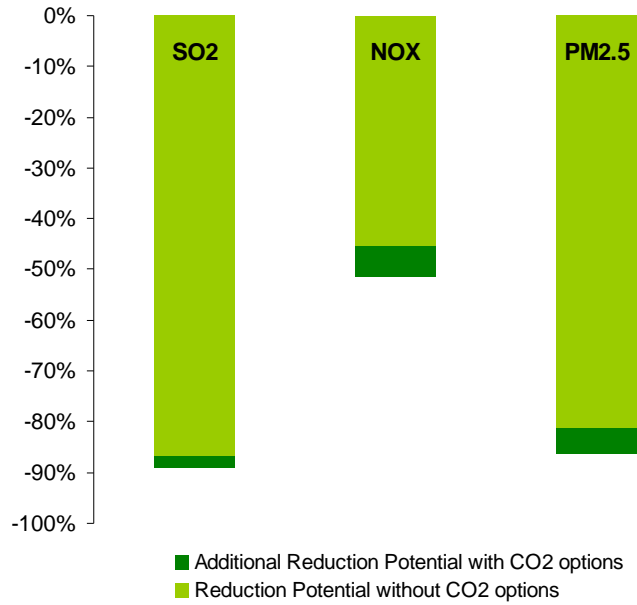
Figure 4.1 Potential for reducing the emissions of air pollutants. The light range shows the potential between the baseline level and the MRR level, the dark range shows the additional potential resulting from activity substitution options such as fuel switches and efficiency improvements (India, 2020).
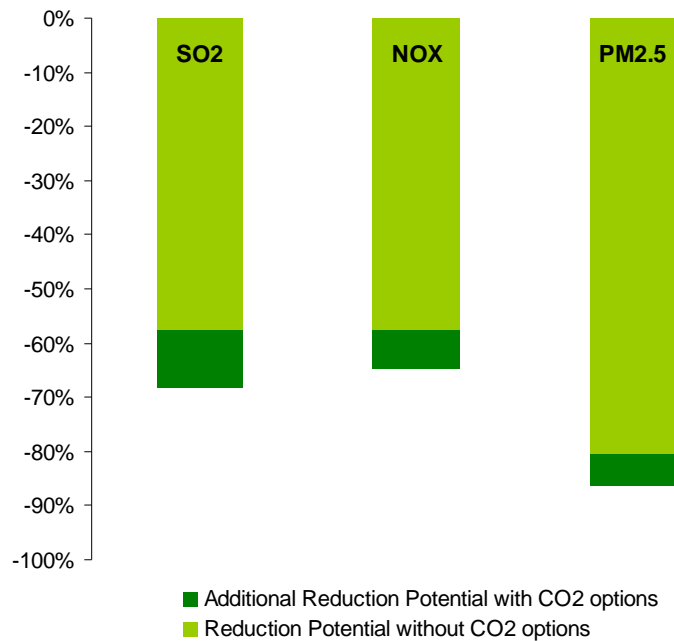

Figure 4.2 Potential for reducing the emissions of air pollutants. The light range shows the potential between the baseline level and the MRR level, the dark range shows the additional potential resulting from activity substitution options such as fuel switches and efficiency improvements (China, 2020).

More generally the MTFR or MRR scenarios are defined always with respect to a certain objective, e.g., in the above case the emissions of individual pollutants. However, this objective can also be an environmental impact indicator, such as YOLLs (statistical Years of Life Lost) due to exposure to fine particles. In this case the objective is to minimize the cumulative YOLL indicator (summed over, e.g., the whole country). The values of the indicator in the baseline and the MTFR (or MRR) scenario define then the range of what reductions are possible in the model. Figure 4.3 and Figure 4.4 illustrate this with the additional dimension that here we show the ranges for each region in India and province in China and the indicator is normalized per person. As can be seen there are naturally regions that face higher risks than others, but also that the potential for improvement is not uniform but also depends on the region (i.e., the energy system and the available control technologies).

The MRR scenario can also be used in various target setting procedures for air quality improvements. It turns out that certain gap closure approaches to target setting, which are applied for instance in GAINS for the European context, can address equity issues to a certain extent, as they take into account the limitations of and regional differences in the possibilities for emission reductions.
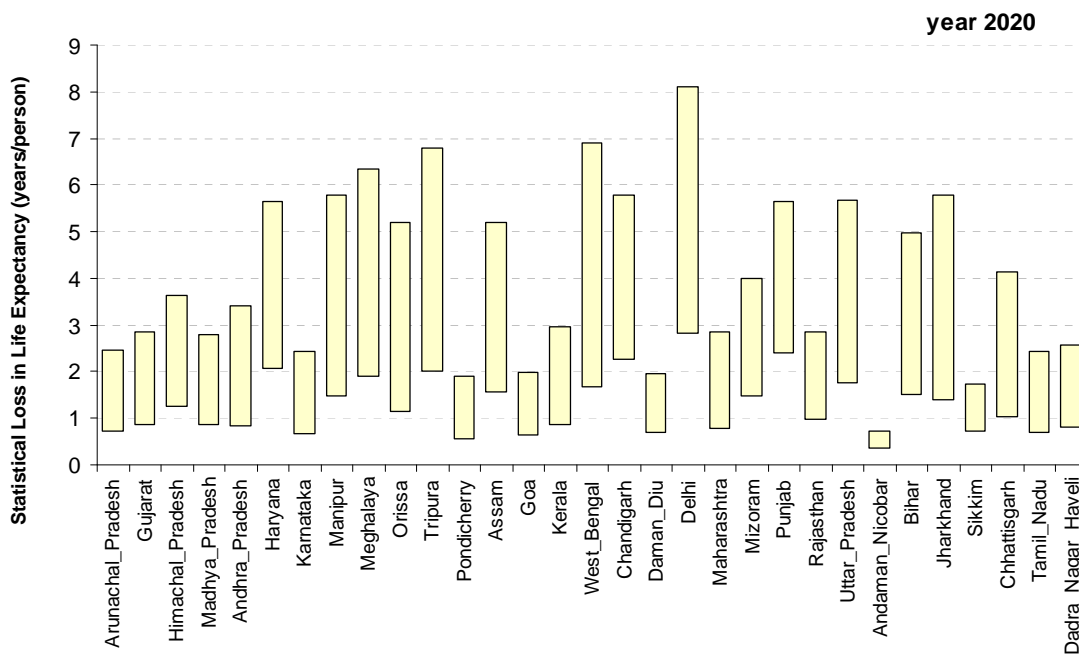

Figure 4.5 Ranges for loss in statistical life expectancy due to exposure to PM2.5 concentrations in India in the year 2020. The upper level shows the situation in the CLE scenario, the lower level represents the MTFR scenario.
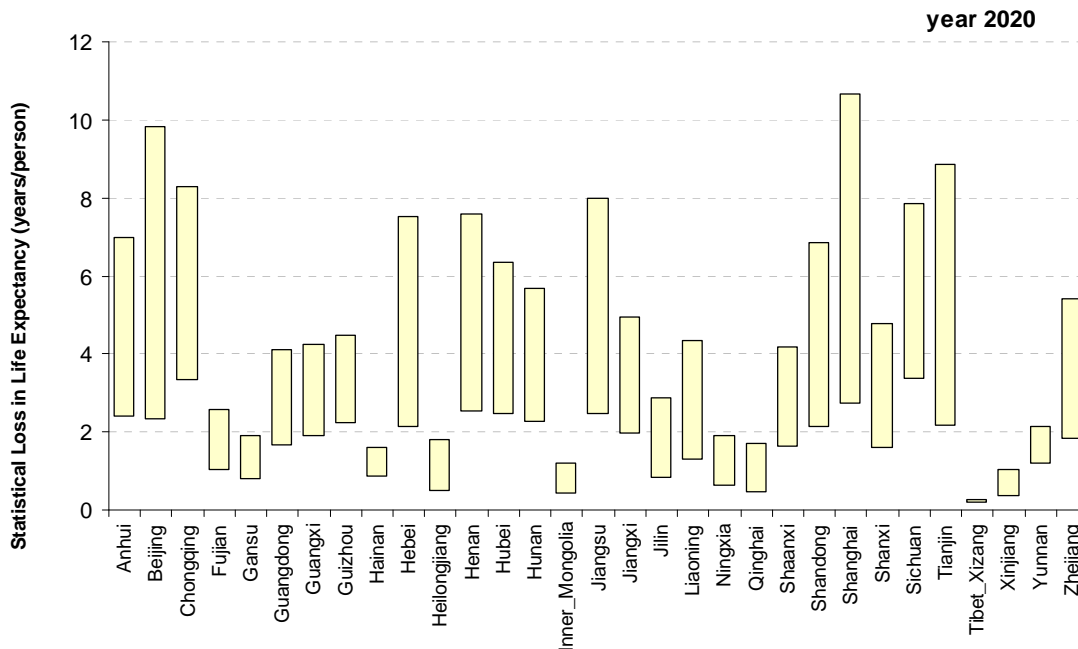
year 2020

Figure 4.6 Ranges for loss in statistical life expectancy due to exposure to PM2.5 concentrations in China in the year 2020. The upper level shows the situation in the CLE scenario, the lower level represents the MTFR scenario.

4.3 More cost-effective approaches than a uniform application of western technology

In this section we illustrate the effects-based cost-effectiveness approach by comparing it with a 'best-technology' approach. The analysis proceeds in three steps. First we generate a new scenario by taking the activity data of the baseline scenario, but instead of applying to these the technologies as projected in the baseline scenario, we apply those technologies that are applied in the baseline scenario of a Western European country (Germany). We call this scenario the BAT scenario. [4] The emission control standards in this scenario are fairly strict, as in Germany very efficient control technologies are used quite extensively. In a second step we calculate the emissions that would result from such a control strategy in India and China and use these emissions to calculate the average statistical loss in life expectancy for India and China, respectively. These values we use then as target values in an optimization and obtain a scenario that has the same health benefits as the in the BAT scenario but can be achieved at lower costs. Also the geographic distribution of emission reduction changes because it is more efficient to reduce emissions in densely populated areas and the optimized scenario allows a spatial reallocation of emission reductions. Finally we observe that the emissions at

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[4] A strict 'best available technology' (BAT) approach would look very similar to the MRR scenario, but is not a realistic policy scenario. However, what we are trying to achieve here is to generate a scenario that uses a realistic mix of technologies – as applied in an industrialized country.

the national level are higher than in the BAT scenario, while meeting the same YOLL target. Here we restrict ourselves to an analysis for the year 2020 but for other years the analysis could be carried out as well.

Applying the German control strategy to the activity data of the baseline scenario in India results in emissions of 3,635 kt of SO_2, 4,701 kt of NO_x and 4,704 kt of PM2.5 in the year 2020. This in turn causes a loss of statistical life due to the exposure to PM2.5 of 1.396 billion years (YOLL). This value is then used as the target value for the optimization, first in the RAINS mode, then in GAINS mode GAINS. Figure 4.7 summarizes the differences in emissions for these three scenarios. It can be seen that in the optimization runs SO_2 and NO_x emissions are higher than in the BAT scenario, whereas PM emissions are lower. In fact, in the scenario generated in GAINS mode, however, NO_x emissions are slightly lower than in the scenario generated in RAINS mode.
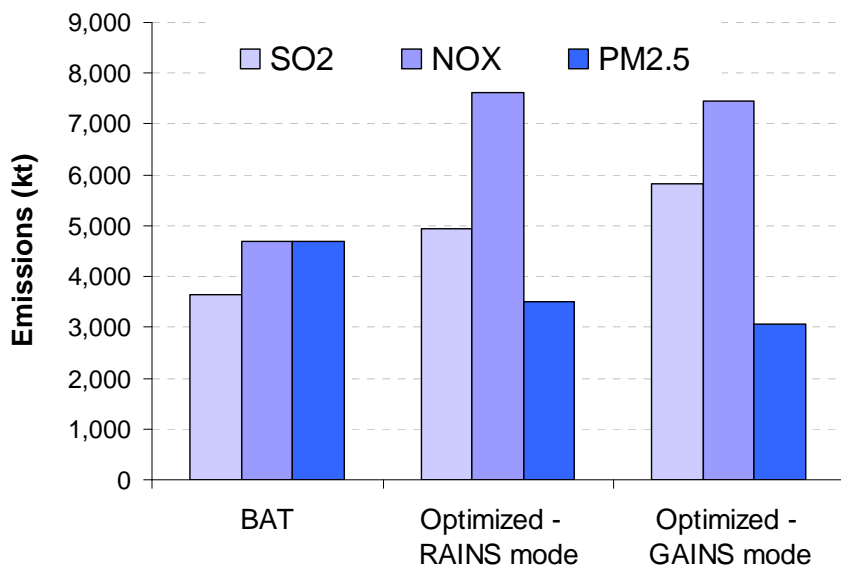

Figure 4.7 Comparison of air pollutant emissions for India. All three scenarios achieve the same YOLL target.

We now compare the costs in these three scenarios that all achieve the same environmental target. The overall control cost for the air pollutants in the BAT scenario is 32.1 billion Euros above the baseline scenario, whereas the RAINS-mode optimized scenario costs only 6.8 billion Euros on top of the baseline figure. Comparing the GAINS-mode optimized scenario in terms of costs requires some more explanation. In terms of pure add-on control costs this scenario only costs 2.5 billion Euros. However, one has to take into account that in the GAINS mode the energy system is flexible. In fact, what happens is that CO_2 emissions are reduced by 6.1 percent relative to the baseline (and relative to the BAT and RAINS mode optimized scenario for that matter). That is, 4.6 percent CO_2 are reduced in the COBG scenario, see above, but there is another 1.5 percent reduction of CO_2 as a direct response to the health target. The CO_2 reduction by 4.6 percent comes at a negative cost of 1.6 billion Euros, the addition 1.5 percent reduction costs 170 million Euros just in energy system costs, so that −

even ignoring the cost savings in the COBG scenario – the total cost for achieving the BAT YOLL target in the GAINS mode is only 2.65 billion Euros. The costs for the three scenarios are summarized in Figure 4.8.
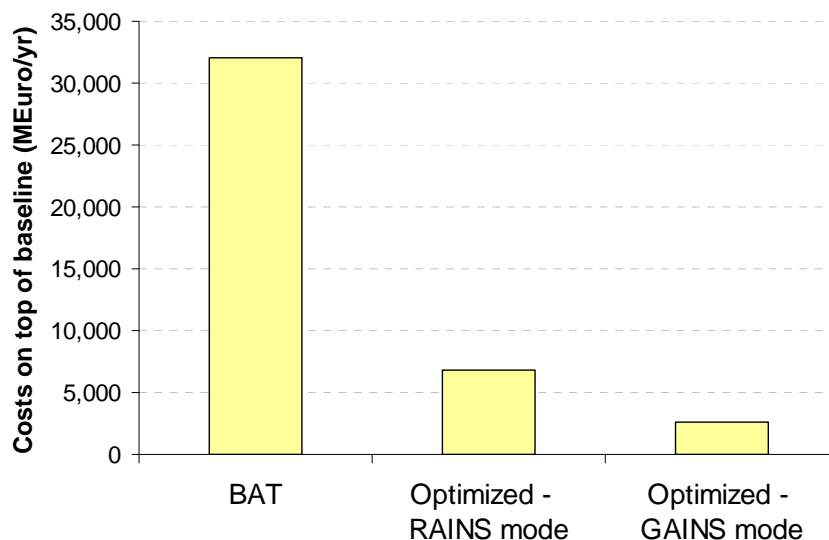

Figure 4.8 Add-on technology costs on top of the baseline scenario for achieving the same level of statistical loss in life expectancy, India, 2020.

There is an important lesson to be learned: a cost-effective response to an air quality target can be to take measures that also reduce greenhouse gas emission substantially.

4.4 Reducing health impacts of PM at least costs

The previous section may have raised the question how ambitious the health target (in terms of Years of Life Lost (YOLLs) is in relation to the MTFR and MRR cases. In this section we are answering this question both in terms of health effects and cost by constructing the cost curves for reductions in YOLLs. These cost curves generalize the concept of a single pollutant cost curve in that these curve show the costs for reducing a single impact, while underlying is a change in the emissions of three air pollutants (SO_2, NO_X, PM) and, implicitly, also of CO_2.

Figure 4.9 shows the two YOLL cost curves for India in 2020, obtained in the RAINS and GAINS modes, respectively. Naturally, the potential for reductions in YOLLs is higher in the GAINS mode (this is consistent with what was observed in Section **Error! Reference source not found.**): the MRR level is 948 million years, the corresponding MTFR level is 851 million years. Also, for any given level of YOLL, in the GAINS mode the costs are approximately 30 percent lower than in the RAINS mode. The results for China are analogous (cf. Figure 4.10).
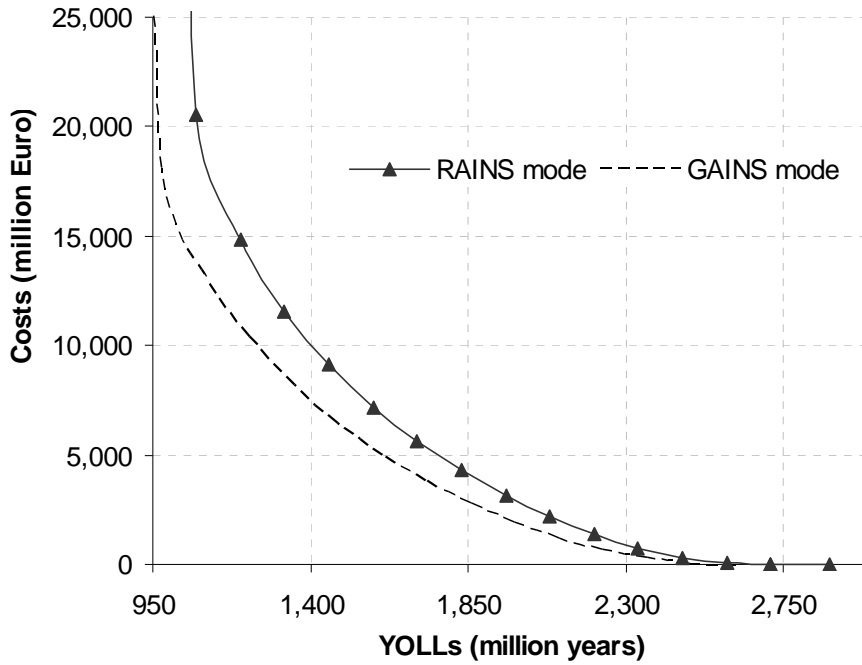
Figure 4.9 Comparison of the YOLL cost curve calculated in RAINS (bold line) and in GAINS mode (dashed) for India in 2020.
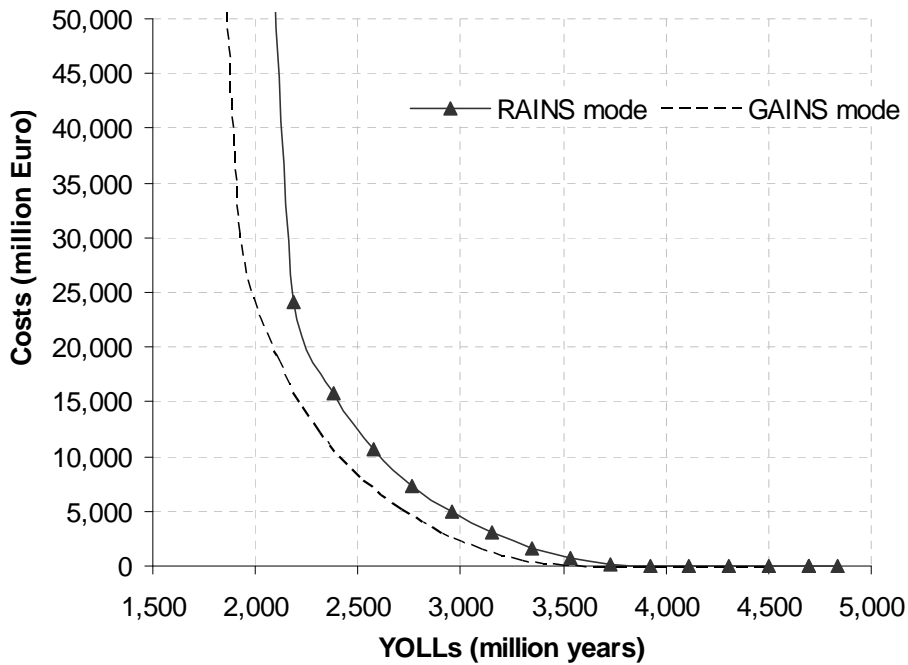

Figure 4.10 Comparison of the YOLL cost curve calculated in RAINS (bold line) and in GAINS mode (dashed) for India in 2020.

4.5 Co-benefits of reducing health impacts on CO_2 emissions

We have shown above (and will further see below) that CO_2 mitigation options can help to reach air quality indicator targets such as YOLL targets. Is the converse also true, i.e., will cost effective responses to YOLL targets also include reductions in CO_2? As we have seen that is indeed the case. In order, however, to answer this question more systematically, in this section we show how CO_2 is reduced as a function of the YOLL target between the baseline and MTFR level.

Figure 4.11 CO_2 emission reduction as a function of the YOLL target value, India, 2020. The dotted line indicates the changes from the baseline value to the COBG level. The MTFR reduction in YOLLs implies a CO_2 reduction of 17.5 percent (off the graph).

Figure 4.11 shows the implied CO_2 reductions as a function of the YOLL target in India in 2020. The overall effect is small, considering the changes already implied just by the COBG scenario: a reduction from 2.5 billion YOLLs down to 1.0 billion YOLLs (-60%) reduces CO_2 by only about 2.5 percent. In China (cf. Figure 4.12) there is hardly any effect of a YOLL target on CO_2 emissions, the emissions stay constant over YOLL targets between 4.5 and 2 billion YOLLs.
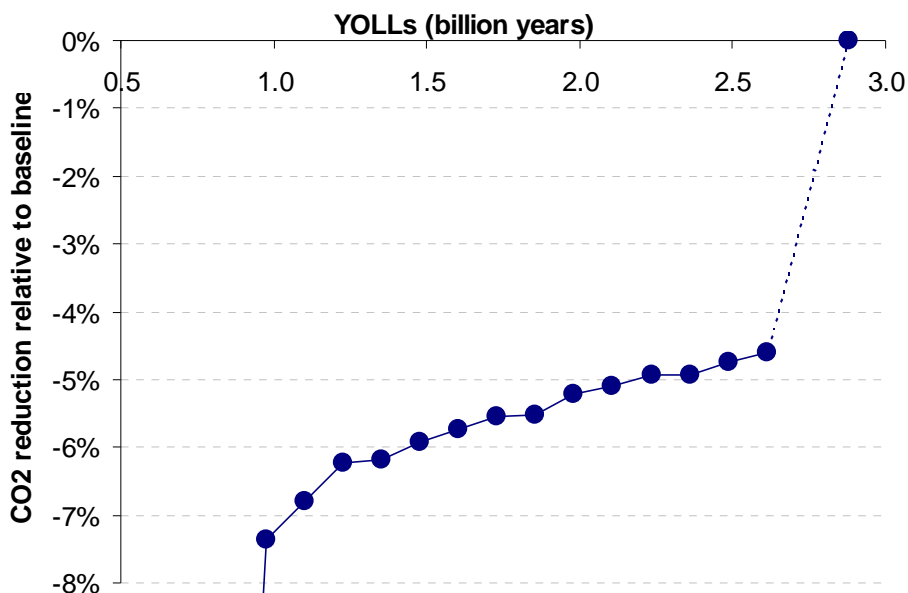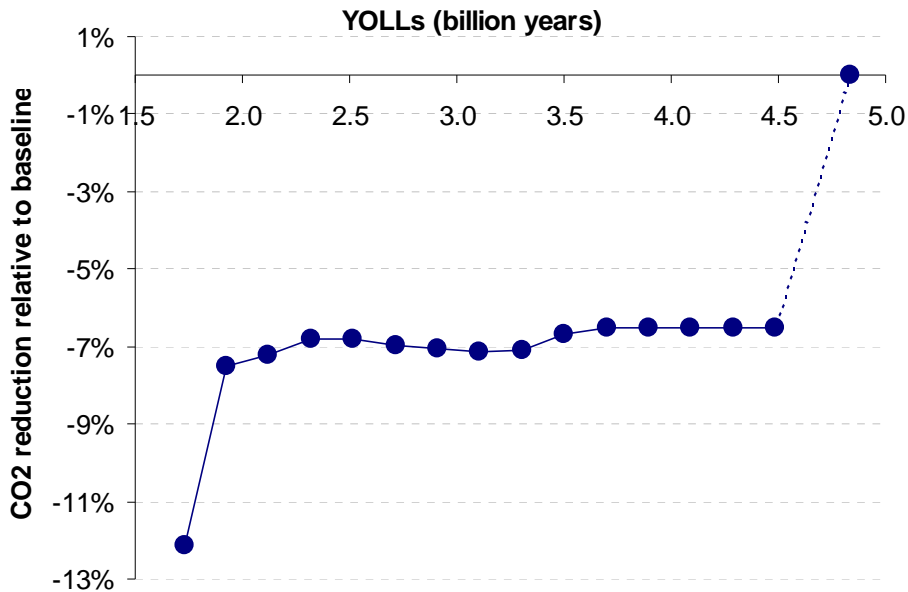
Figure 4.12 CO$_2$ emission reduction as a function of the YOLL target value, China, 2020. The dotted line indicates the changes from the baseline value to the COBG level.

4.6 Co-benefits of CO$_2$ reductions

We have repeatedly alluded to the fact that CO$_2$ emission reductions also (typically) imply reductions in the emission of SO$_2$, NO$_X$, and PM2.5. In this section we quantify this relationship systemically.

Figure 4.13 shows for India the implications that CO$_2$ emission reductions have on the emission levels of air pollutants. In the COBG scenario there is a reduction in CO$_2$ by 4.6 percent (see above). What is quite striking is that, while there is a relatively steep reduction in SO$_2$ and NO$_x$ as a consequence of a reduction in CO$_2$ emissions from -5% to -25%, PM emissions stay almost constant over that same interval. This can be explained by the fact CO$_2$ emissions are partly reduced by replacing fossil fuels with biomass, and – if there are no further constraints on air quality beyond what is in the baseline – PM2.5 emission may actually increase in certain sectors.
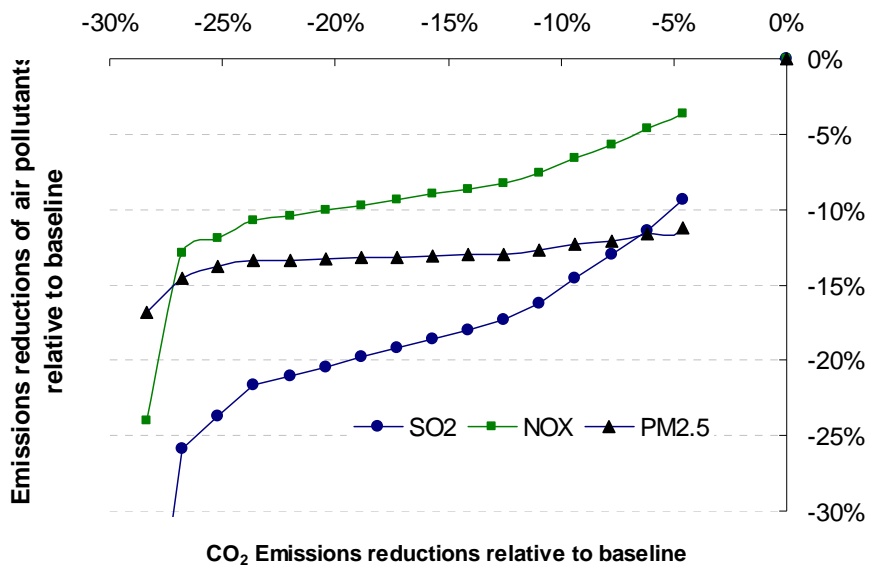
Figure 4.13 Co-benefits from CO_2 emission reductions for emissions of air pollutants, India, 2020.

Naturally, these emission reductions of air pollutants result in reductions in lower values of the impact indicator (YOLLs). Figure 4.14 shows the corresponding relationship between CO_2 emission reductions and reductions in impact indicator. A reduction from -5% to -25% in CO_2 emissions leads to a reduction in YOLLs by some 10 percent.
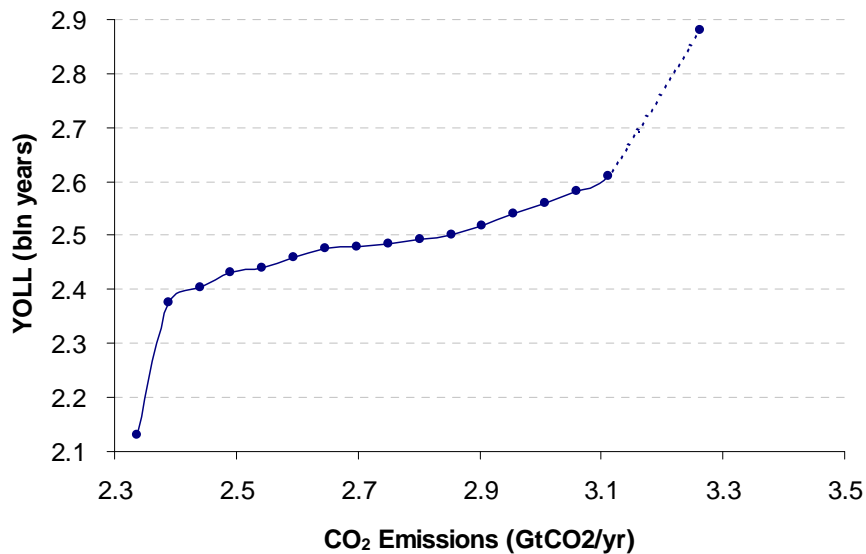
Figure 4.14: Health co-benefits of CO_2 emission reductions for exposure to PM2.5, India, 2020.

4.7 Potential health improvements: 2020 vs 2030

In this section we compare the potentials (and costs) for health improvements in the year 2020 and 2030. As emissions are growing in the baseline scenarios between 2020 and 2030, one expects that the health impact indicators as well as the potentials for improvements also increase.

Figure 4.15 shows the two cost curves for the YOLL impact indicator in India for the years 2020 and 2030. The curve for 2020 has already been discussed above, let us here focus on the curve in 2030. As expected the impact indicator in the baseline has a much higher value in 2030 than in 2020, in fact it lies close to 5 billion YOLLs compared to 2.8 billion YOLLs in 2020. Second, expenses on air pollution control equipment are higher in 2030 than in 2020. In the figure we actually show the costs above the 2020 COBG level, so that the 2030 curve starts some 7 billion Euros above the level of the COBG in the year 2020, due to an increase in activity level in 2030. We have cut off the graph at 40 billion, but the lines continue beyond that.

While indicator starts at a higher level, also the potential for reduction is larger (from 5 billion down to 1.3 billion years vs from 2.8 billion to 0.9 billion years).
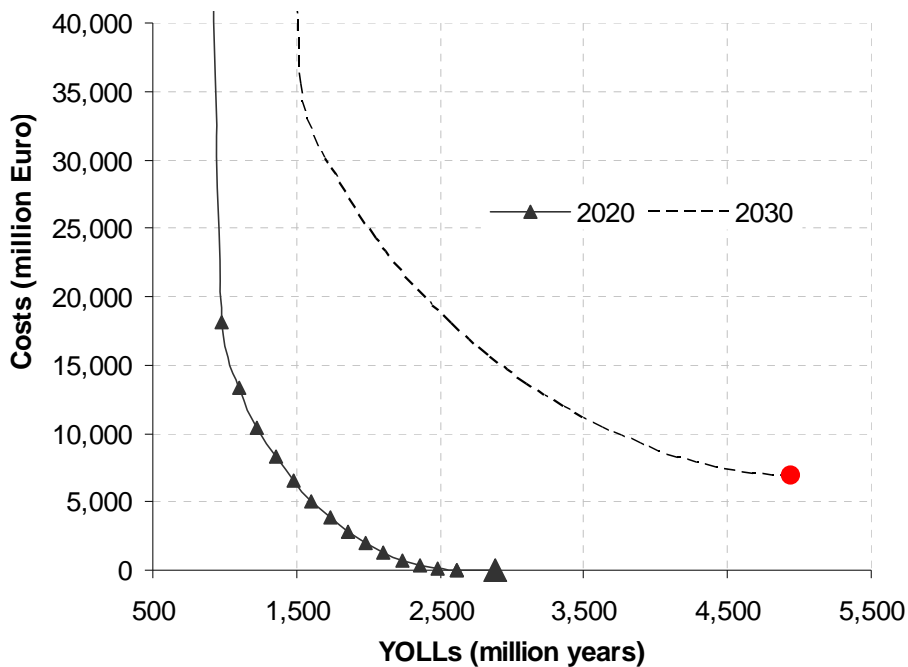
Figure 4.15 YOLL cost curve for India, for the year 2020 and 2030. For explanation see text.
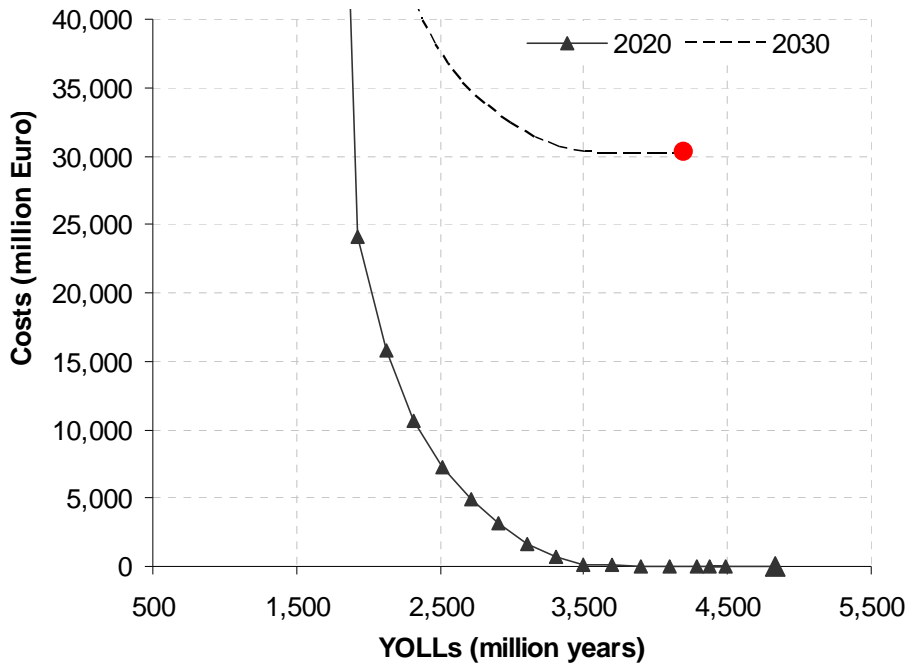
Figure 4.16 YOLL cost curve for China, for the year 2020 and 2030. For explanation see text.

Figure 4.16 shows the corresponding graph for China, and we have chosen to display the results on the same scale. The first thing to notice is that qualitatively we observe something very different than in India: by 2030 the YOLL indicator has actually decreased due to further penetration of control technologies, and despite the growth in the underlying activities. Also, additional control equipment costs some 30 billion Euros extra, so the 2030 curve starts much higher than in the case of India. Finally, even though the two curves begin at very different YOLL values in the baseline, both curves end (in their respective MTFR scenarios) at almost the same YOLL value (approximately 1.7 billion YOLLs), though at different costs (90 billion Euros in 2020, 137 billion Euros in 2030, both values relative to the 2020 COBG value). We have cut off the graph at 40 billion, but the lines continue beyond that.

5 Single pollutant cost curves

5.1 Introduction

The GAINS model utilizes a large-scale database containing a large amount of technology- and region-specific information, including cost parameters, efficiencies and potentials. When designing cost-effective control strategies to meet given environmental target values, all of these data are used in the optimization framework.

Cost curves provide a tool for looking at a large set of complex data of this kind at a high level of aggregation. They allow us to understand not only discrete solutions but also neighbourhoods of solutions or solution spaces. Cost curves represent mixes of technologies and they can make us understand the distribution of reduction efforts across regions, sectors and pollutants.

Thus single pollutant cost curves are useful tools for monitoring large sets of complex input data in a compact fashion. We have to bear in mind, however, that they have their limitations. In particular, multi-pollutant measures cannot be consistently represented in single pollutant cost curves. This also implies, as mentioned above in Section **Error! Reference source not found.**, that MFR scenarios may look different depending on which pollutant emissions were minimized.

The GAINS model offers two ways of constructing cost curves: 1) by applying sophisticated sorting algorithms that order technologies by marginal abatement costs, taking into account their respective potentials; 2) by applying optimization methods, i.e., by iteratively setting more ambitious emission reduction targets and ex post observing the cost for meeting the target.

For this study we have generated single pollutant cost curves for India and China using optimization methods. This approach also allows us to operate the model in the full GAINS mode and to compare the GAINS mode results with the RAINS mode results.

At the end of the chapter we also provide examples of cost curves for individual provinces/states to illustrate that these methods can be applied also at the sub-national level.

5.2 India

Figure 5.1 shows the cost curve for SO_2 in India in 2020, both in the RAINS and in the GAINS mode. As can be seen, switching to the GAINS mode does not significantly increase the overall potential for SO_2 reductions (cf. Section **Error! Reference source not found.**). This is due to the fact that the best add-on technologies for SO_2 removal in many sectors are very efficient and that further reductions from fuel substitutions or energy savings do not reduce emissions much further.
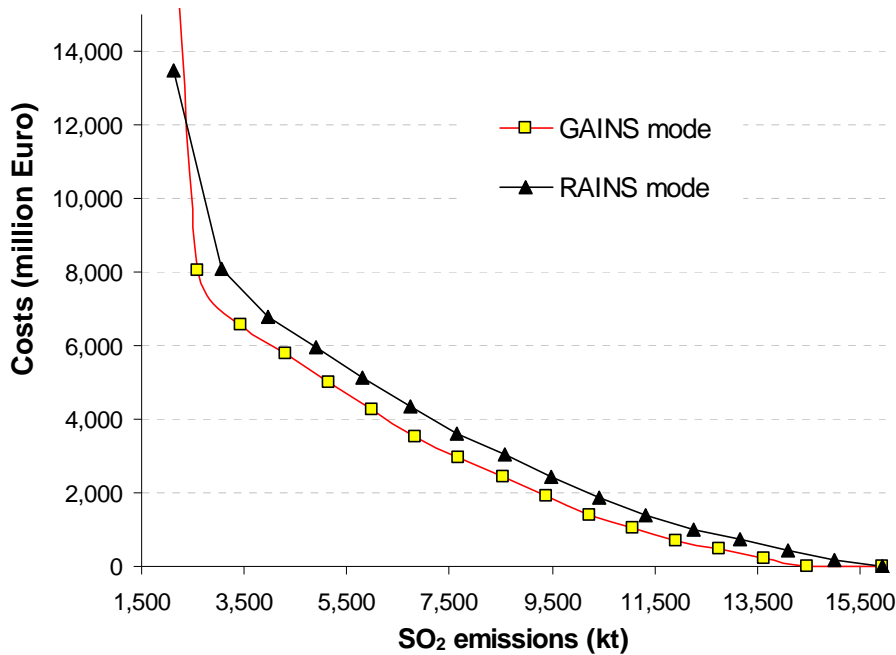
Figure 5.1 SO$_2$ cost curve for India in 2020, in RAINS and in GAINS mode.

Qualitatively, the corresponding curves for NO$_x$ and PM look similar (cf. Figure 5.2 and Figure 5.3). Note that in all three cases we have truncated the vertical axis.
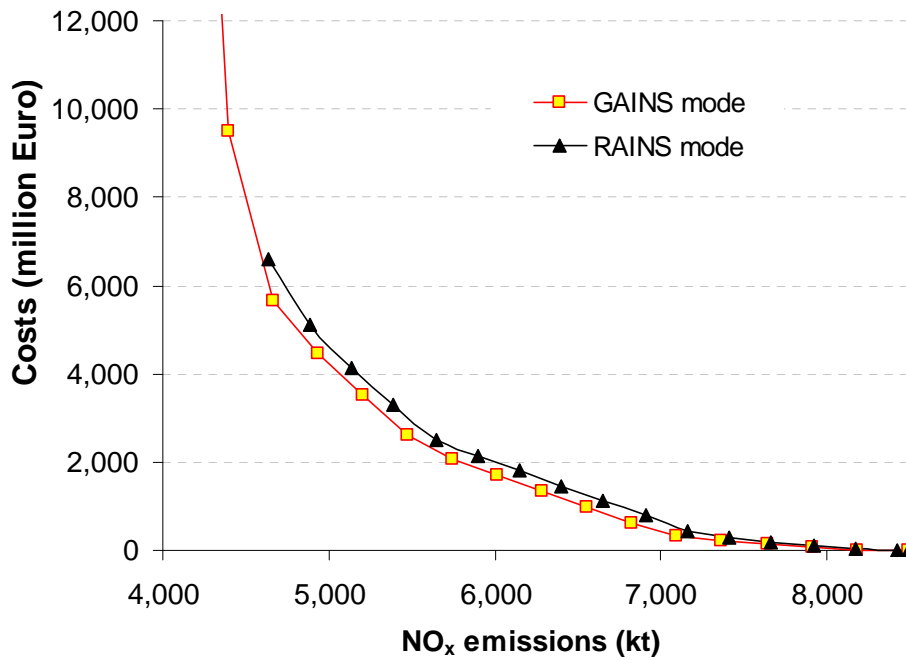
Figure 5.2 NO$_x$ cost curve for India in 2020, in RAINS and in GAINS mode.
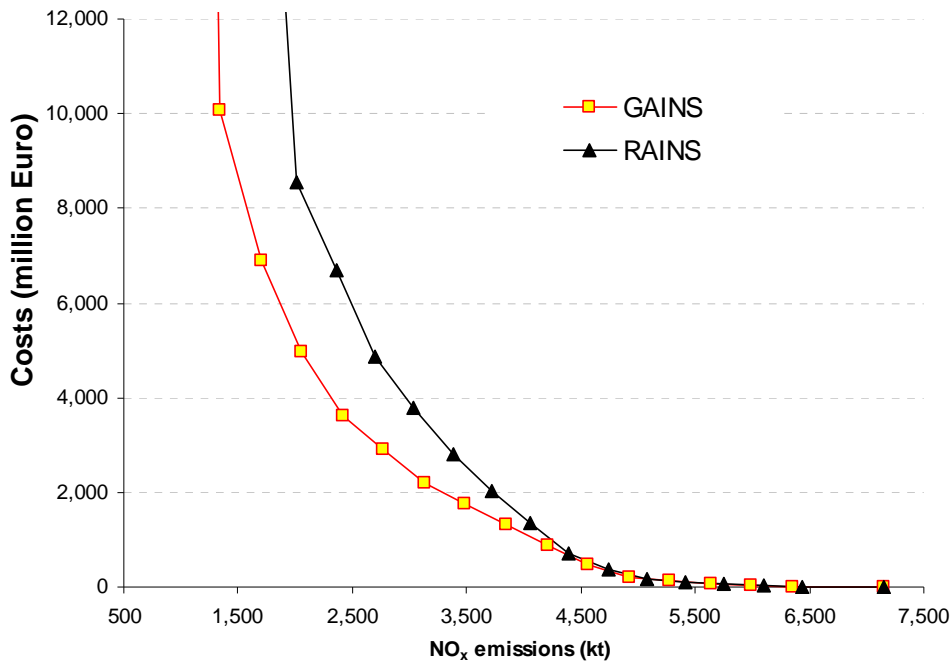
Figure 5.3 PM2.5 cost curve for India in 2020, in RAINS and in GAINS mode.

The cost curves for the greenhouse gases in India were obtained in the GAINS mode of GAINS (Figure 5.10 to Figure 5.12).
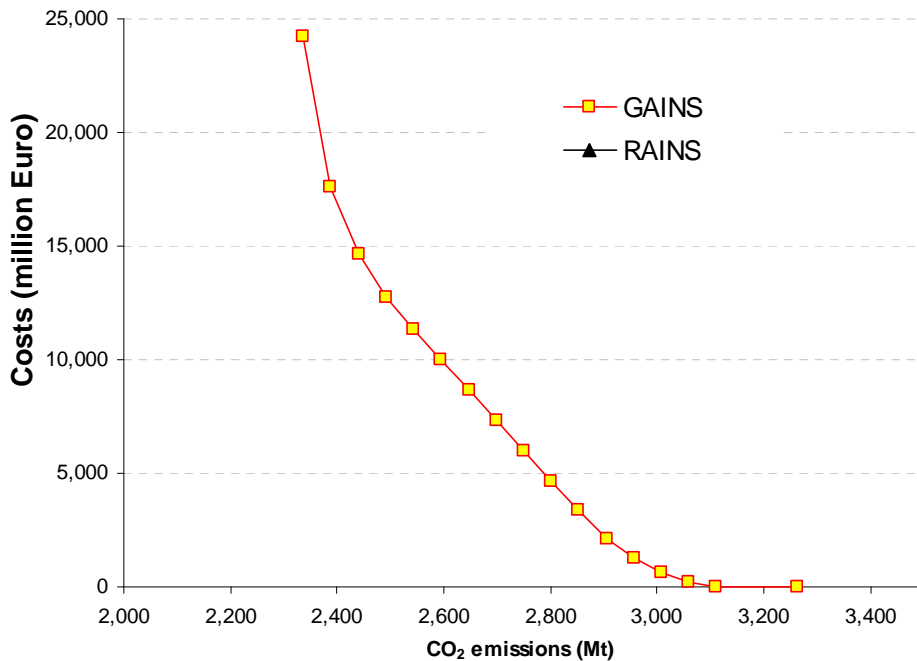
Figure 5.4 CO_2 cost curve for India in 2020.
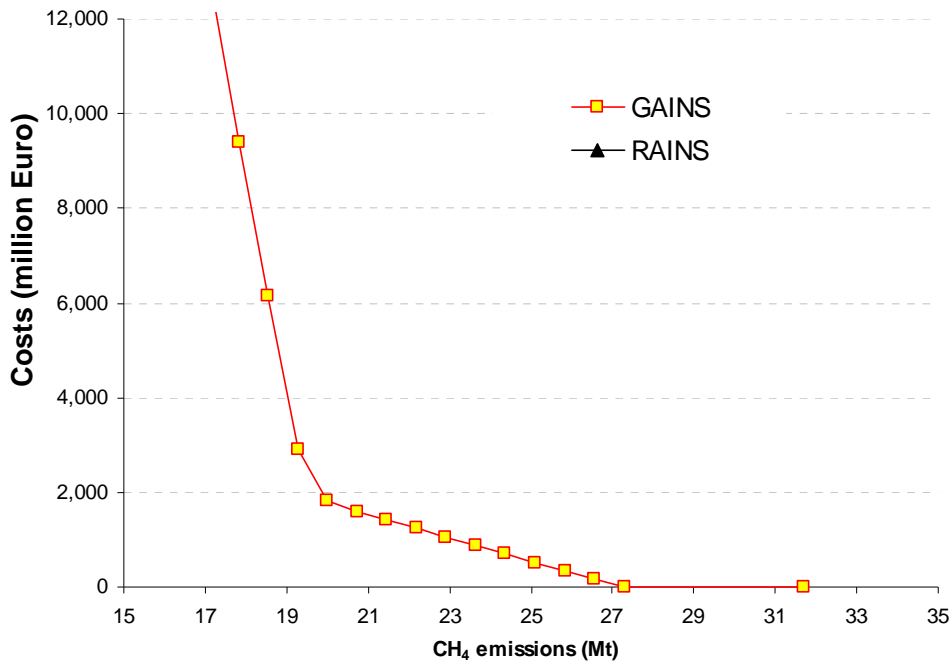
Figure 5.5 CH$_4$ cost curve for India in 2020.
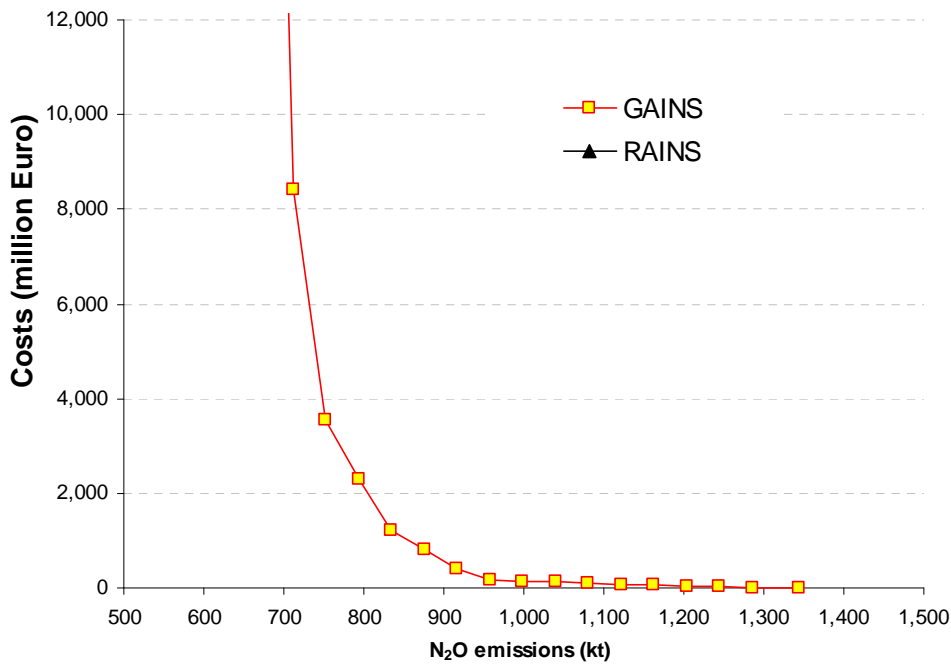
Figure 5.6 N$_2$O cost curve for India in 2020.

5.3 China

In this section we present the corresponding single pollutant cost curves for China in 2020.
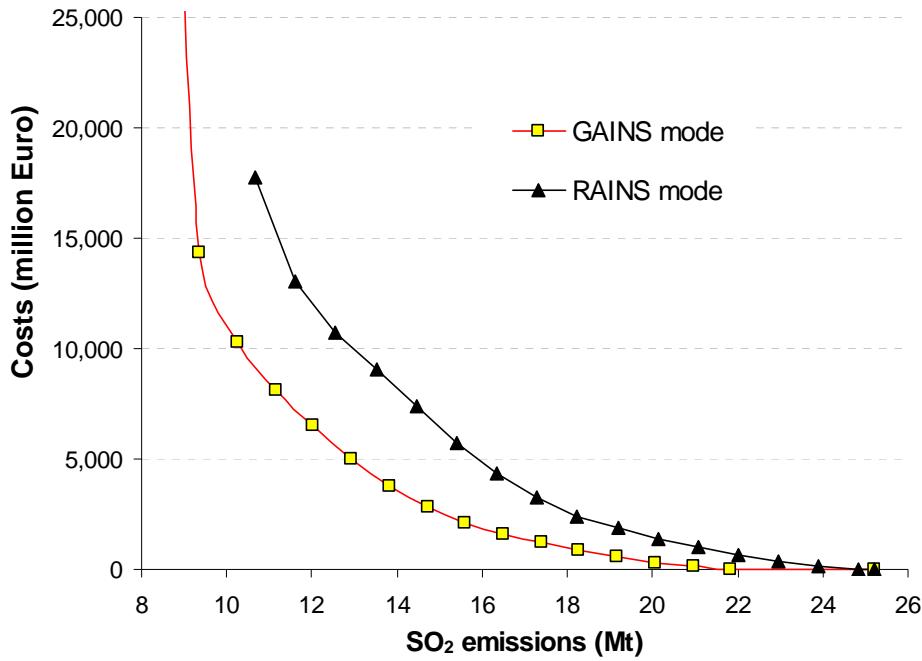
Figure 5.7: SO$_2$ cost curve for China in 2020, in RAINS and in GAINS mode.
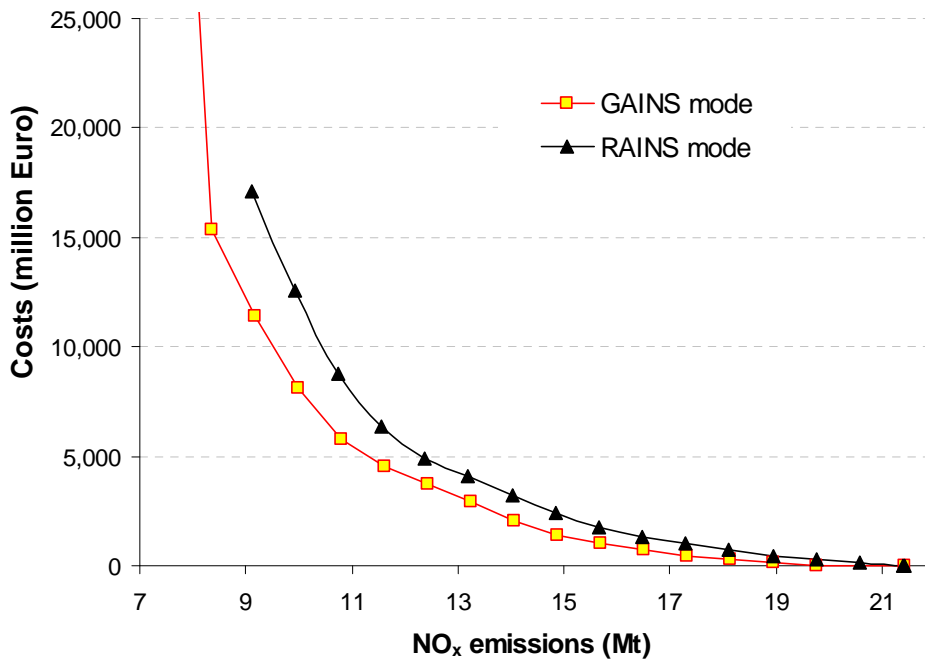
Figure 5.8 NO$_x$ cost curve for China in 2020, in RAINS and in GAINS mode.
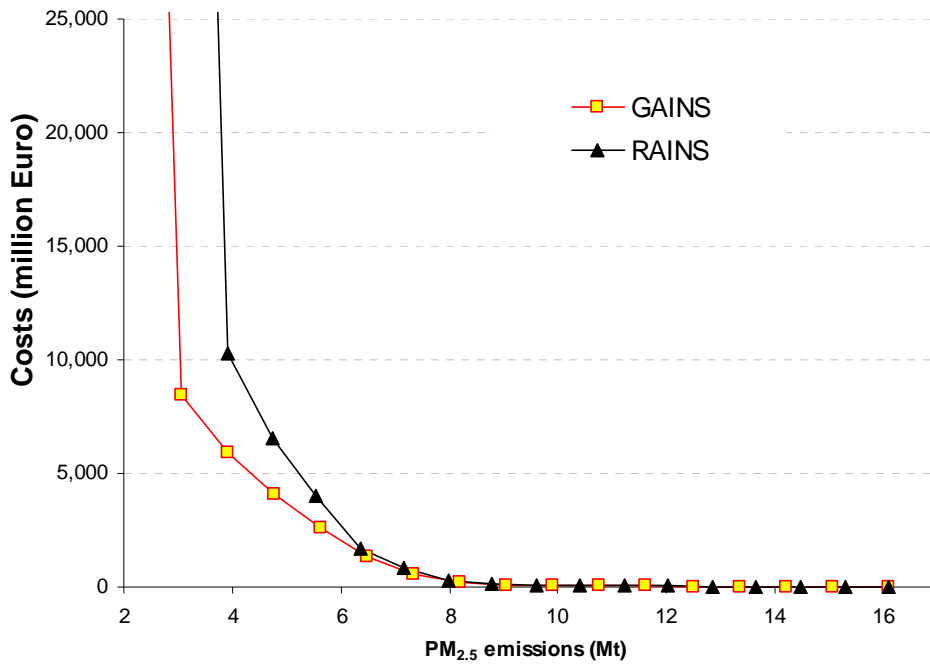
Figure 5.9 PM2.5 cost curve for China in 2020, in RAINS and in GAINS mode.
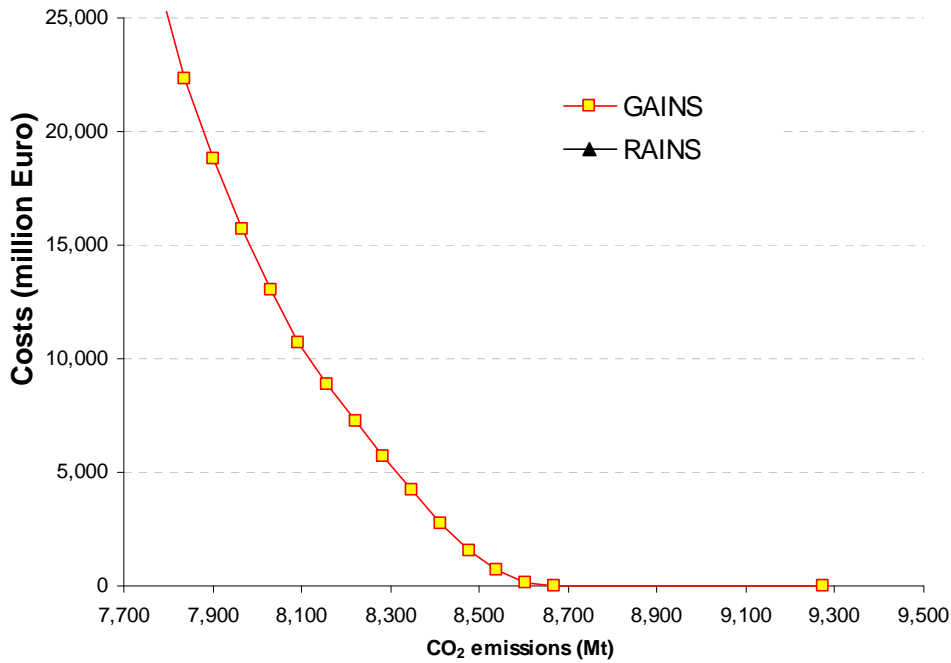
Figure 5.10 CO_2 cost curve for China in 2020.
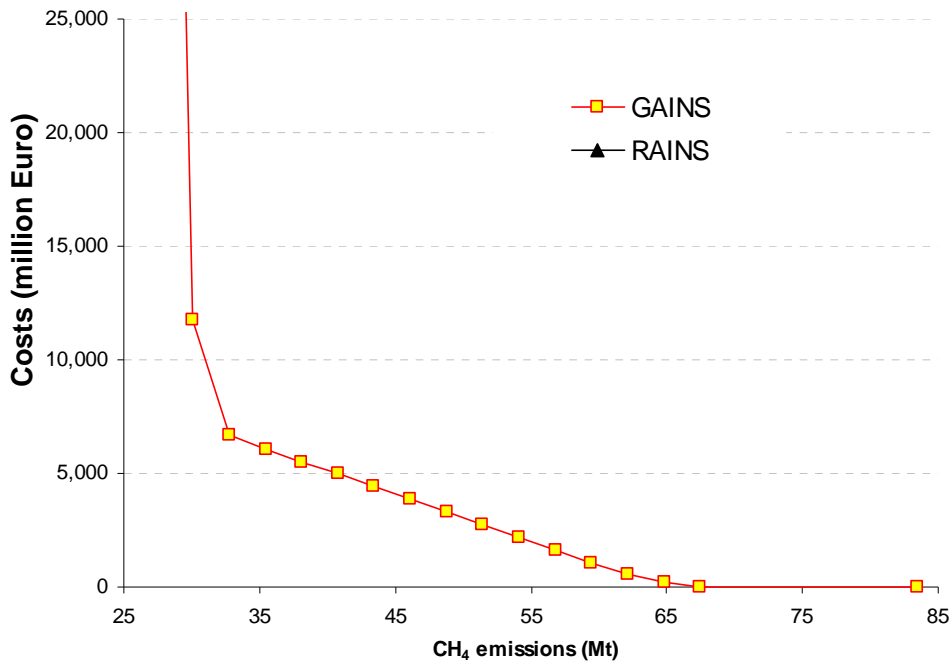
Figure 5.11 CH$_4$ cost curve for China in 2020.
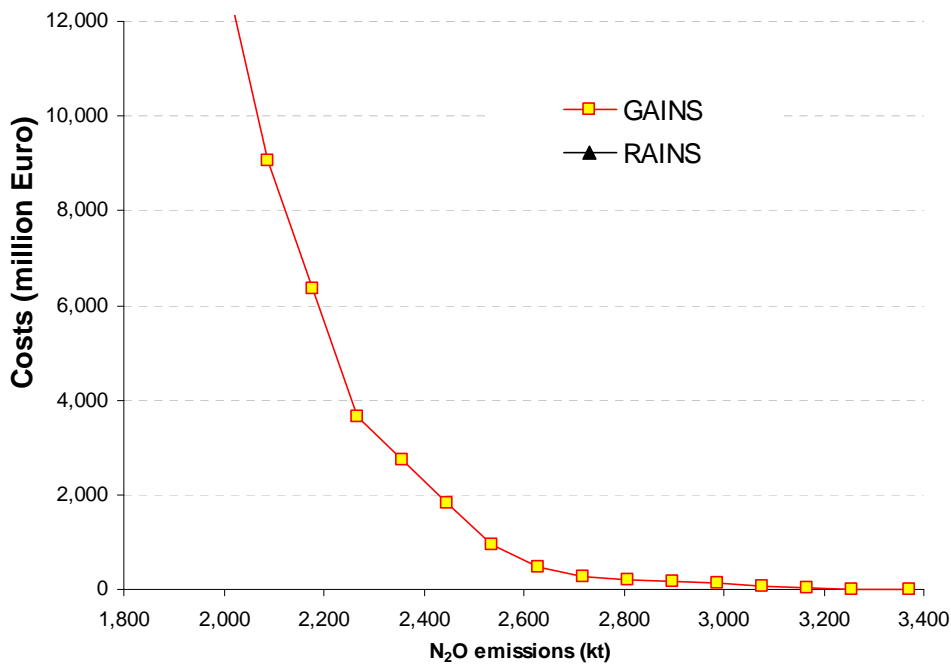
Figure 5.12 N$_2$O cost curve for China in 2020.

5.4 Cost curves of sub-national regions: some examples

In this final section we present some examples of single pollutant cost curves for sub-national regions. Figure 5.13 shows the SO_2 cost curves for Andhra Padresh, a state in India. The shape of the curve is very similar to the national curve, i.e., the state is quite representative for the whole country in this respect. However, the shape is distinctively different to that of the cost curve for Nadil Tamu, in which a larger fraction of SO_2 emissions originates from the power sector, which can be controlled at lower costs (Figure 5.14). Graphs like these can be generated for any state in India/province in China for any of the GAINS-Asia pollutants, both for 2020 and 2030.
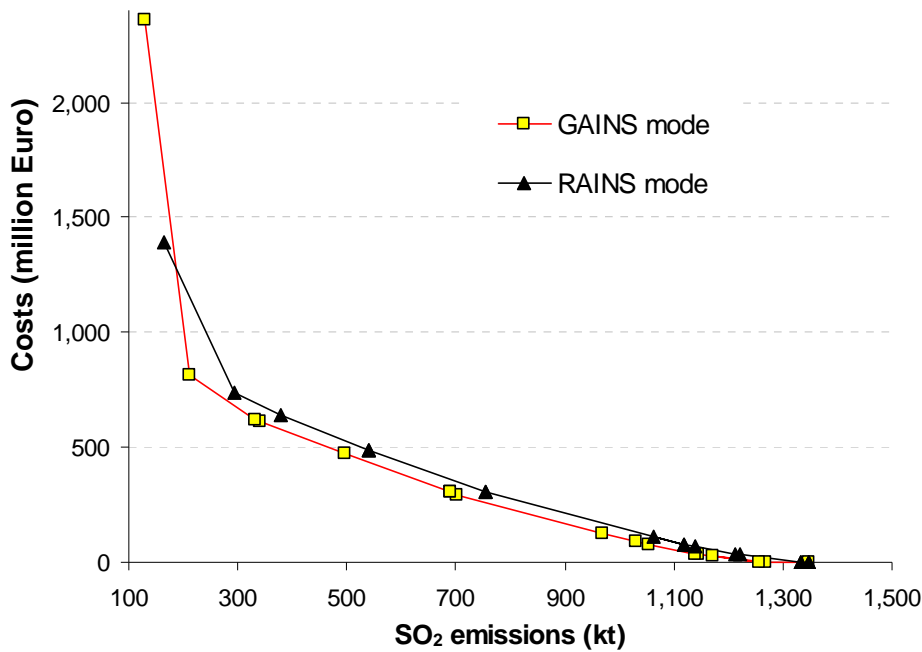
Figure 5.13 SO_2 cost curve for Andhra Padresh (India) in 2020, in RAINS and in GAINS mode.
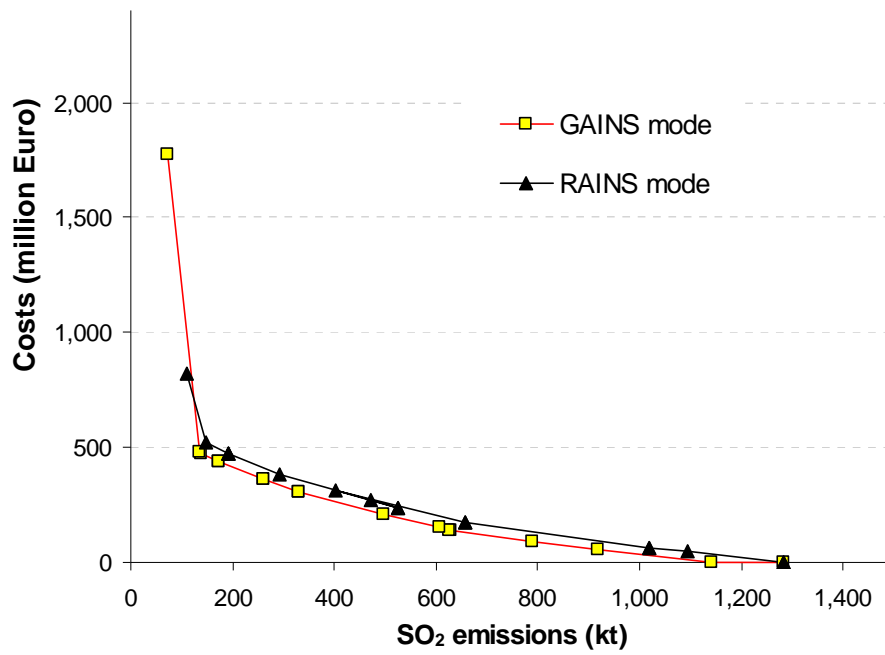
Figure 5.14 SO$_2$ cost curve for Tamil Nadu (India) in 2020, in RAINS and in GAINS mode.

6 Conclusions

The GAINS-Asia model has been implemented for India and China to assess synergies and trade-offs between air pollution control and greenhouse gas mitigation. The specific situations for India and China have been reflected in the GAINS-Asia model through:

- Collections of alternative energy and agricultural projections up to 2030 for each State in India and each province in China. These projections have been provided by the Indian and Chinese partners in this project and reflect current governmental perspectives on the business-as-usual economic development path and current energy policy. In addition, alternative scenarios have been collected that illustrate the implications of more sustainable development pathways in quantitative terms.

- Estimates of current levels of air pollutants (SO_2, NO_x, PM2.5, NH_3) and greenhouse gases (CO_2, CH_4, N_2O) from anthropogenic activities, by State/Province in India and China, including the relevant local emission factors.

- Quantifications of atmospheric dispersion characteristics for aerosols and ground-level ozone for India and China, specifying for each source region (province/state) the impact of the most important precursor emission of aerosols (i.e., primary PM2.5, SO_2 and NO_x) on ambient PM2.5 levels and of NO_x on ground-level ozone with a 1*1 degree spatial resolution.

- Local costs for the application of air pollution control and greenhouse gas mitigation measures in India and China, how these costs differ from international world market prices and how these relationships might change in the future with progressing economic development.

- Illustrative quantifications of health impacts of fine particles on the life expectancy of Asian population, assuming validity of the concentration-response relationships that have been identified for North America, and taking into account the population structures of China and India.

With these ingredients, the GAINS-Asia projects demonstrates that, unless more stringent measures to control air pollution are adopted in China and India, the envisaged economic development will lead to severely aggravated air pollution problems in the coming decades. Health impacts would reach levels that have not been experienced before anywhere in the world, following the increase in air pollutants that accompanies the projected growth in energy consumption. As a consequence, air quality problems that are experienced at present are likely to significantly intensify despite the envisaged decoupling of economic growth and the level of energy consumption. Greenhouse gas emissions would in general follow the increase in energy consumption, and thereby grow up to a factor of 10 in the coming decades.

However, there are numerous technological options available that can reduce emissions of air pollutants. Analysis shows that, for instance, if technological solutions that are today common in Western countries were fully applied in the future in India and China, the growth of air pollutant emissions could be significantly limited, and to some extent ambient air quality could be even improved compared to the current situation. However, country-wide full application of such measures

would require significant economic resources. Compared to the envisaged level of economic development, the costs for such uniform and indiscriminate pollution control strategies would consume much higher shares of the gross economic output in these countries than what is spent currently in more industrialized countries.

It is obvious that a uniform application of most advanced emission control technologies might not be the most cost-effective approach for improving air quality. The cost-effectiveness of measures can by substantially enhanced if those measures are prioritized that have larger impacts on sensitive receptors (e.g., emissions that affect human health of a large number of people within urban areas, compared to emissions from remote and sparsely populated areas, or emissions that deposit on sensitive ecosystems, or emissions from sources that are cheaper to control than others). The optimization feature of GAINS-Asia is a powerful tool to identify those packages of emission control measures that achieve exogenously specified air quality targets at least cost. As a result of such optimization analysis, the GAINS-Asia analysis shows that the air pollution control costs for reducing health impacts from PM2.5 can be reduced by up to 80 percent if one follows an optimized cost-effectiveness approach instead of a uniform across-the-board strategy.

The GAINS-Asia analysis also demonstrates that many structural measures that reduce greenhouse gas emissions lead at the same time to lower air pollutant emissions. Typically, strategies that result in 1 percent lower CO_2 emissions cut SO_2 emissions by 1.5 percent and NO_x and PM emissions by 0.5 to 1 percent- at no additional costs. As a consequence, such strategies have important co-benefits on air quality and human health that is impaired by air quality. The GAINS model quantifies such co-benefits for China and India and helps finding strategies that maximize these synergies.

If such measures are deliberately included in an air pollution control strategy, they offer an additional potential for cost-effective emission controls. For the targets analyzed for India and China, emission control costs could be reduced by even up to 90 percent compared to a uniform across-the-board approach. In addition, such a strategy would also reduce CO_2 emissions by six percent compared to the baseline projection.

Annex 1: Emission ranges

In this section we present some disaggregated for the current legislation scenarios (baseline), the cost-optimal baseline of the GAINS model (COBG), and the MTFR and MRR scenarios. As we have discussed above the MTFR and MRR scenarios are not unique but depend on the objective that is minimized. In this section we have again chosen to define the MTFR and MRR scenario by minimizing the YOLL indicator in the GAINS mode and RAINS mode, respectively.

6.1 India

6.1.1 Emissions by SNAP1 sector

India SNAP1 Sector	SO_2				NO_x				$PM_{2.5}$			
	CLE	COBG	MRR	MTFR	CLE	COBG	MRR	MTFR	CLE	COBG	MRR	MTFR
1	7,693	6,531	468	322	2,611	2,439	524	209	359	331	84	10
2	319	295	296	254	489	438	400	309	3,607	2,882	663	396
3	7,315	7,013	1,153	976	2,031	1,945	474	405	2,108	2,057	104	96
4	474	474	95	95	134	134	27	27	153	153	46	46
5	0	0	0	0	0	0	0	0	4	4	3	3
6	0	0	0	0	0	0	0	0	0	0	0	0
7	91	91	91	91	1,223	1,223	1,223	1,223	51	51	51	51
8	40	40	24	40	1,981	1,981	1,981	1,981	205	205	205	205
9	3	3	2	2	3	3	2	2	172	172	161	161
10	17	17	0	0	16	16	0	0	494	494	22	22
Total	15,951	14,464	2,128	1,779	8,487	8,179	4,633	4,156	7,154	6,349	1,339	991

Table 6-1 Emissions of SO_2, NO_x and PM2.5 by SNAP sector in India, 2020.

6.1.2 Emissions by region

Emissions (kt/yr)	SO$_2$				NO$_x$				PM$_{2.5}$			
GAINS region	CLE	MRR	MTFR	% MTFR vs CLE	CLE	MRR	MTFR	% MTFR vs CLE	CLE	MRR	MTFR	% MTFR vs CLE
India-Andhra_Padresh	1,346	165	133	-90%	759	370	101	-87%	531	104	59	-89%
India-Assam	163	50	46	-72%	118	78	48	-60%	159	37	21	-87%
India-Bihar	306	42	36	-88%	218	146	31	-86%	273	57	34	-88%
India-Chhattisgarh	900	132	114	-87%	465	188	73	-84%	349	51	34	-90%
India-Delhi	128	22	19	-85%	131	90	21	-84%	27	11	5	-80%
India-Goa	61	11	8	-87%	27	23	3	-88%	6	3	1	-78%
India-Gujarat	1,806	287	258	-86%	625	294	99	-84%	411	67	35	-92%
India-Haryana	358	72	63	-82%	293	225	33	-89%	142	31	12	-91%
India-Himachal_Pradesh	138	24	23	-84%	78	49	13	-83%	68	13	8	-89%
India-Jammu-and-Kashmir	13	6	5	-59%	40	37	8	-80%	76	17	9	-88%
India-Jharkhand	392	85	77	-80%	210	97	39	-81%	241	41	32	-87%
India-Karnataka	650	83	67	-90%	336	198	53	-84%	379	72	40	-89%
India-Kerala	266	57	49	-82%	180	155	35	-80%	207	49	26	-87%
India-Madhya_Pradesh	977	117	97	-90%	567	287	74	-87%	436	89	51	-88%
India-MDN_HDD	2,150	240	188	-91%	819	407	125	-85%	595	101	60	-90%
India-North_East	313	61	53	-83%	226	98	141	-38%	247	34	23	-91%
India-Orissa	1,101	135	112	-90%	479	187	73	-85%	475	80	50	-90%
India-Punjab	423	58	47	-89%	304	214	32	-90%	186	35	13	-93%
India-Rajasthan	487	82	62	-87%	494	340	66	-87%	573	109	58	-90%
India-Tamil_Nadu	1,283	111	70	-95%	616	394	69	-89%	270	68	33	-88%
India-Uttar_Pradesh	1,453	166	143	-90%	866	441	109	-87%	808	167	91	-89%
India-Uttaranchal	39	8	6	-85%	43	30	7	-83%	144	9	5	-97%
India-West_Bengal	1,196	114	91	-92%	597	286	75	-87%	551	94	54	-90%
India-Total	**15,951**	**2,128**	**1,768**	**-89%**	**8,487**	**4,633**	**1,327**	**-84%**	**7,154**	**1,339**	**755**	**-89%**

Table 6-2 Emissions by regions in India, 2020.

6.2 China

6.2.1 Emissions by SNAP1 sector

India	SO$_2$				NO$_x$				PM2.5			
SNAP1 Sector	CLE	COBG	MRR	MTFR	CLE	COBG	MRR	MTFR	CLE	COBG	MRR	MTFR
1	5,231	5,188	1,446	1,198	5,240	5,391	1,214	660	1,144	1,171	180	88
2	2,581	2,218	1,767	779	1,015	949	1,003	431	4,529	4,376	1,451	668
3	15,422	12,464	6,214	5,262	11,245	9,492	3,075	2,654	6,288	5,371	405	394
4	1,471	1,471	772	772	120	120	24	24	2,821	2,821	419	419
5	0	0	0	0	0	0	0	0	57	57	48	48
6	0	0	0	0	0	0	0	0	0	0	0	0
7	50	50	50	50	1,193	1,193	1,193	1,193	76	76	76	76
8	427	427	427	427	2,589	2,589	2,589	2,589	133	133	133	133

9	0	0	0	0	0	0	0	0	183	183	173	173
10	21	21	0	0	20	20	0	0	861	861	234	234
Total	25,203	21,840	10,676	8,487	21,422	19,755	9,099	7,551	16,091	15,048	3,118	2,232

Table 6-3 Emissions of SO$_2$, NO$_x$ and PM2.5 in China by SNAP sector, 2020.

6.2.2 Emissions by region

Emissions (kt/yr)	SO₂				NOₓ				PM₂.₅			
GAINS region	CLE	MRR	MTFR	*% MTFR vs CLE*	CLE	MRR	MTFR	*% MTFR vs CLE*	CLE	MRR	MTFR	*% MTFR vs CLE*
China-Anhui	920	383	277	*-70%*	933	353	282	*-70%*	614	136	75	*-88%*
China-Beijing	340	165	125	*-63%*	303	126	107	*-65%*	207	34	29	*-86%*
China-Chongqing	1,221	568	522	*-57%*	453	170	154	*-66%*	363	75	54	*-85%*
China-Fujian	301	119	92	*-69%*	359	166	146	*-59%*	257	53	46	*-82%*
China-Gansu	269	123	94	*-65%*	324	146	120	*-63%*	234	45	30	*-87%*
China-Guangdong	980	326	257	*-74%*	1,076	483	414	*-62%*	800	171	130	*-84%*
China-Guangxi	670	327	254	*-62%*	399	182	144	*-64%*	552	162	111	*-80%*
China-Guizhou	763	353	283	*-63%*	397	156	130	*-67%*	395	135	111	*-72%*
China-Hainan	28	15	11	*-59%*	61	38	35	*-42%*	58	18	14	*-76%*
China-Hebei	1,786	836	651	*-64%*	1,503	661	550	*-63%*	1,319	216	167	*-87%*
China-Heilongjiang	450	171	116	*-74%*	760	313	229	*-70%*	446	92	38	*-92%*
China-Henan	1,082	439	339	*-69%*	1,023	383	297	*-71%*	987	175	115	*-88%*
China-Hong_Kong_Macau	30	27	26	*-14%*	186	150	148	*-21%*	16	12	12	*-29%*
China-Hubei	1,195	525	430	*-64%*	880	338	288	*-67%*	633	126	93	*-85%*
China-Hunan	543	269	216	*-60%*	459	221	194	*-58%*	550	130	111	*-80%*
China-Inner_Mongolia	489	177	117	*-76%*	552	198	140	*-75%*	359	72	39	*-89%*
China-Jiangsu	1,454	525	393	*-73%*	1,531	553	422	*-72%*	1,312	207	124	*-91%*
China-Jiangxi	397	182	151	*-62%*	379	156	136	*-64%*	393	79	65	*-83%*
China-Jilin	1,558	638	488	*-69%*	1,285	514	423	*-67%*	686	129	93	*-86%*
China-Liaoning	941	384	290	*-69%*	842	272	198	*-77%*	415	77	46	*-89%*
China-Ningxia	162	63	49	*-70%*	166	53	33	*-80%*	102	16	7	*-93%*
China-Qinghai	77	36	30	*-61%*	123	38	32	*-74%*	67	10	6	*-91%*
China-Shaanxi	668	270	208	*-69%*	423	165	131	*-69%*	356	67	49	*-86%*
China-Shandong	1,313	520	455	*-65%*	1,161	650	598	*-48%*	505	87	79	*-84%*
China-Shanghai	1,754	666	504	*-71%*	1,702	705	568	*-67%*	1,308	211	139	*-89%*
China-Shanxi	1,525	708	581	*-62%*	969	359	288	*-70%*	591	87	67	*-89%*
China-Sichuan	1,866	903	756	*-60%*	715	318	246	*-66%*	962	221	120	*-88%*
China-Tianjin	513	245	208	*-59%*	731	532	518	*-29%*	149	33	29	*-81%*
China-Tibet-Xizang	48	5	3	*-93%*	62	15	5	*-93%*	22	4	2	*-92%*
China-Xinjiang	361	121	86	*-76%*	287	124	100	*-65%*	192	41	27	*-86%*
China-Yunnan	389	196	165	*-57%*	402	161	129	*-68%*	383	92	77	*-80%*
China-Zhejiang	1,110	392	290	*-74%*	974	402	343	*-65%*	855	105	91	*-89%*
China-Total	25,203	10,676	8,468	*-66%*	21,422	9,099	7,548	*-65%*	16,091	3,118	2,194	*-86%*

Table 6-4 Emissions by regions in China, 2020.

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