WITCH documentation

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Chapter 1

Introduction

TThis documentation is the essential guide for the users of the WITCH integrated assessment model. A model overview is available in a dedicated website http://www.witchmodel.org. In particular, the website http://doc.witchmodel.org contains an updated and ongoing documentation of the current WITCH model, on which this paper is based upon.

This documentation is organized into different chapters. The second chapter provides a general presentation of the model. The third chapter describes in detail how the economy in general is modelled in WITCH. Chapter four presents the bottom-up modelling of the energy sector. The extraction and market solution for the fossil fuel resources is outlined in chapter 5 while the land-use part and the soft link to the GLOBIOM model is described in chapter six. How emissions of greenhouse gases are modelled and the link to the global carbon cycle, radiative forcing, and global mean temperature is detailed in chapter 7. Since WITCH can be run in a Cost Benefit Analysis mode including impacts and adaptation, their specification is described in chapter eight. The different climate and other policy options that can be run in the WITCH model are outlines in chapter 9. Finally, the implementation of the Shared Socioeconomic Pathways (SSP) and some results are presented in chapter 10.

Chapter 2

The WITCH model

2.1 General Framework

WITCH (World Induced Technical Change Hybrid) is an integrated assessment model designed to assess climate change mitigation and adaptation policies. It is developed and maintained at the Fondazione Eni Enrico Mattei and the Centro Euro-Mediterraneo sui Cambiamenti Climatici. For descriptions of previous model version, please refer to (Bosetti, Massetti, and Tavoni 2007) and (Bosetti et al. 2009)

WITCH consists of a dynamic global model that integrates in a unified framework the most important elements of climate change. The economy is modelled through an inter-temporal optimal growth model which captures the long term economic growth dynamics. A compact representation of the energy sector is fully integrated (hard linked) with the rest of the economy so that energy investments and resources are chosen optimally, together with the other macroeconomic variables. Land use mitigation options are available through a soft link with a land use and forestry model (GLOBIOM). A climate model (MAGICC) is used to compute the future climate. Climate change impacts the economic output through a damage function, depending also on the rate of investments in adaptation. This allows accounting for **the complete dynamic of climate change mitigation and adaptation**.

2.1.1 Methodology and features

WITCH represents the world in a set of representative native regions (or coalitions of regions); for each it generates optimal mitigation and adaptation strategies for the long term (from 2005 to 2100) as a response to either climate damage or some external constrain on emissions, concentrations or temperature. These strategies consist of investment profiles resulting from a maximization process in which the welfare of each region (or coalition of regions) is chosen strategically and simultaneously accordingly to other regions. This makes it possible to capture regional free-riding behaviours and strategic interaction induced by the presence of global externalities. The non-cooperative, simultaneous, open membership game with full information, is implemented through an iterative algorithm which yields the open-loop Nash equilibrium. In this game-theoretic set-up, regional strategic actions interrelate through GHG emissions, dependence on exhaustible natural resources, trade of oil and carbon permits, and technological R&D spillovers.

The endogenous representation of R&D diffusion and innovation processes constitute a distinguishing feature of WITCH, allowing to describe how R&D investments in energy efficiency and carbon free technologies integrate the currently available mitigation options. The model features multiple externalities, both on the climate and the innovation side. The technology externalities are modelled via international spillovers of knowledge and experience across countries and time. In each country, the productivity of low carbon mitigation technologies and of energy depend on the region stock of energy R&D and by the global cumulative installed capacity, two proxies for knowledge and experience respectively. The R&D stock depends on domestic investments, domestic knowledge stock, and foreign knowledge stock through international spillovers. The spillover term depends on the interaction between the countries' absorptive capacity, and the distance of each region from the technology frontier. This formulation of technical change affects both decarbonization as well as energy savings.

2.1.2 Policy Applications

A distinctive feature of WITCH is the ability to assess the optimal response to climate policies with all degrees of cooperation (from non-cooperative to fully cooperative), by appropriately defining the coalition structure. In the cooperative solution all externalities are internalized and therefore it can be interpreted as a first-best solution. The Nash equilibrium instead can be seen as a second-best solution.

The model can also perform both cost effective analysis, as well as cost benefit analysis, depending on whether exogenous constraints are placed on the climate (e.g. emissions caps or carbon taxes) and whether the climate feedback on the economy is activated. By definition the non-cooperative setting cannot handle global constraints; global constraints can be implemented via a recursive procedure in which regional policies (e.g. cap and trade or carbon taxes) are adjusted till the global cap is met.

The model is calibrated on a set of predefined policies. They are used as benchmark or as a starting point for further policy assessments. Below is an illustrative set of these predefined policies:

- Business as usual (BAU);
- Damage Induced Mitigation (BAU with Climate Damage Feedback);
- Concentration target of 450 ppm;
- Radiative forcing target at 2.8 W/m^2 in 2100;
- Global temperature increase limits at 2 degree Celsius.

2.2 Model scope

2.2.1 Energy Sector

The energy sector is fully integrated with the rest of the economy. It is distinguished in an electric sector, a transportation sector, and an aggregated non-electric (industry, services and residential) sectors.

The primary and secondary forms of energy are:

Primary Energy	Secondary Energy
Coal	Electricity
Oil	
Gas	
Uranium	
Bioenergy	

The following power plant technologies are included:

Power plant
Coal with and without CCS
Oil without CCS
Gas with and without CCS
Wind onshore and offshore
Solar PV and CSP
Nuclear LWR and advanced
Bioenergy with and without CCS
Hydro power

Technologies that are subject to endogenous technological change are: advanced biomass and advanced nuclear. Overall energy efficiency is also subject to endogenous technical change. Moreover, learning-by-doing is taken into account for wind and solar energy.

2.2.2 Land Use Sector

The land use sector is represented in the WITCH model through a soft-linkage with the GLOBIOM land use and forestry model. GLOBIOM is emulated via a response function obtained from a large number of scenarios generated varying the price of biomass (both residues and plantations) and the price of carbon emission from land-use and agriculture. GLOBIOM also provides to WITCH the quantity of available biomass, the CO_2 emissions from deforestation and afforestation, the CH_4 and N_2O emissions from agriculture.

2.2.3 Greenhouse gases and air pollutants

The model computes many emissions species, either endogenously, or based on exogenous assumptions. Mitigation of these emissions is possible through transformation in the energy system, energy efficiency improvements, substitution of fossil fuels, the use of Carbon Capture and Storage (CCS), and land use change. Moreover, for certain emissions, direct abatement is modelled through Marginal Abatement Cost (MAC) curves, or end of pipe measures via emission factors.

Emissions	Source	Mitigation
CO_2	Endogenous	see text
CH_4	Partially endogenous	Substitution/MAC
N_2O	Partially endogenous	Substitution/MAC
F-gases	Exogenous	MAC
SO2	Partially endogenous	Emissions factors
VOC	Partially endogenous	Emissions factors
NOx	Partially endogenous	Emissions factors
BC	Partially endogenous	Emissions factors
OC	Partially endogenous	Emissions factors
CO	Partially endogenous	Emissions factors
NH_3	Exogenous	RCP database

2.2.4 Regions

The original version of the model has 13 regions consistent on the basis of geography, income and the structure of energy demand.

The following table describes the regional compositions.

Region Name	Countries
cajaz	Canada, Japan, New Zeland
china	China and Taiwan
easia	South East Asia, including Indonesia
india	India
kosau	South Korea, South Africa, Australia
laca	Latin America, Mexico and Caribbean
mena	Middle East and North Africa
neweuro	EU new countries
oldeuro	EU old countries (EU-15) + EFTA
sasia	South Asia (excluding India)
ssa	Sub Saharan Africa
te	Non-EU Eastern European countries, including Russia
usa	United States of America

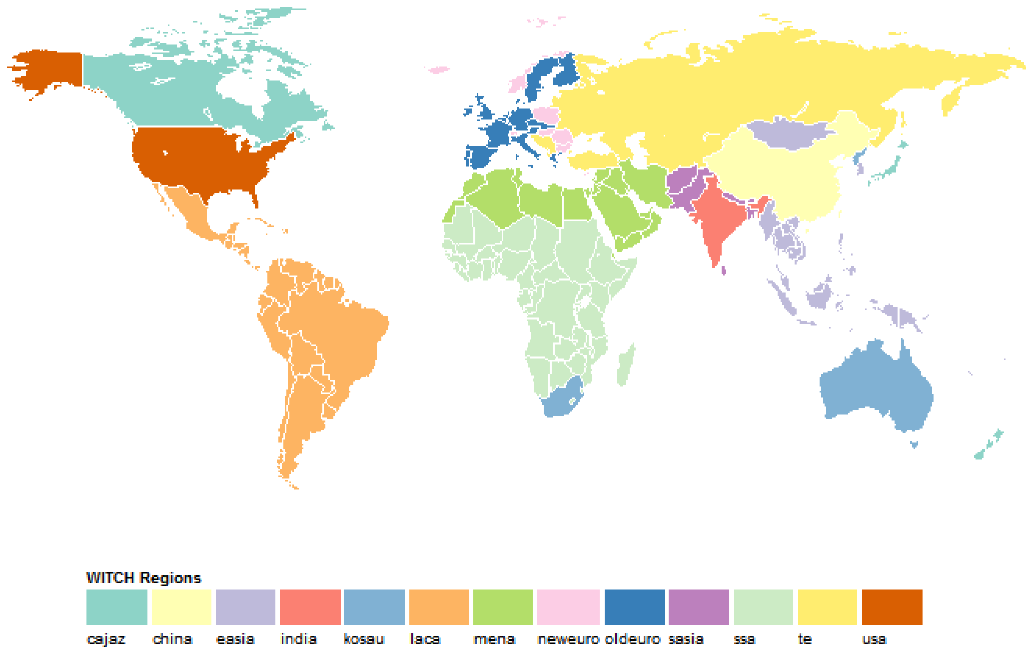

Figure 2.1: WITCH original regions

2.2.5 Coalitions

The regions of WITCH a priori solver their respective optimization program by default. However, any set of regions cooperating can be modelled as a coalition, which then in turn maximizes the sum of welfare of their members. Two important special cases of coalitions are already defined:

- no-cooperation : each region is mapped to a coalition containing only this region. This is the default setting.
- full-cooperation: the Grand Coalition containing all world regions.

Coalitions and regions interact with each other because of the presence of economic (technology, exhaustible natural resources) and environmental global externalities.

For each coalition, a forward-looking representative agent maximizes her own inter-temporal social welfare function, strategically and simultaneously to other regions.

The inter-temporal equilibrium is calculated as an open-loop Nash equilibrium. Through the optimization process, regions choose the optimal dynamic path of a set of control variables, namely investments in various technologies. The oil market price, global temperature increase, and emission permits market price–if a cap and trade system is being modelled–are the outcome of the regional strategies and are iteratively solved until the equilibrium is achieved.

2.2.6 Time horizon

The base year of WITCH is 2005 and all economic values are expressed in USD of 2005. The time horizon is 150 years, modelled in 30 periods of 5-year time steps and we denote by $\Delta_t = 5$ the duration of one time step in years. Longer time horizon can also be run until 2300 to avoid any end-of-horizon effect, but 2150 is generally sufficient. Results are usually reported for the period 2005-2100. The periods 2005, 2010 and 2015 are calibrated to the energy and economic historical statistics where available.

Chapter 3

The Economy

3.1 Welfare function

In WITCH, a social planner maximises the sum of regional discounted utility W of each coalition, clt. The regional utility function at any point in time and each region is based on a power or constant relative risk aversion (CRRA) utility function derived from consumption per capita. For different coalitions, the non-cooperative solution, and the globally optimal mode, the objective function can take different forms based on the implied set of coalitions clt.

3.1.1 Utility function

The WITCH model can be run in a non-cooperative mode, where each region n acts as one player maximising its welfare. In this case, the set of players or coalitions clt consists each of a single region. For each region n and time period t, intertemporal utility is computed as discounted sum of utility (taking into account the region's population $l(t,n)$) based on a utility function with a degree of relative risk aversion of η:

$$W(n) = \sum_t l(t,n) \frac{\left(\frac{C(t,n)}{l(t,n)}\right)^{1-\eta} - 1}{1-\eta} \beta^t.$$

C is total consumption, l is population, and the pure time preference discount factor β is given by the standard geometric discounting rule:

$$\beta = (1+\rho)^{\Delta_t}$$

where $\Delta_t = 5$ is the duration of one time step in years and rho the discount rate.

3.1.2 Welfare of coalitions

In the cooperative mode, different coalitions can be formed including the Grand Coalition containing all regions. With cooperation, there are hence one or several coalitions clt, who maximise total welfare in their member region(s). The coalition clt maximises a sum of the welfare of the member regions. There are several welfare concepts admissible to aggregate welfare across coalition members.

The default option is a (disentangled) Utilitarian solution, taking into account inequality across regions through a degree of inequality aversion. This welfare concept is related to Epstein-Zin preferences (Epstein and Zin 1989) and welfare of a coalition clt is given by the equation:

$$W(clt) = \sum_{t=1}^{T} \left[\frac{1}{1-\eta} \left(\left(\sum_{n \in clt} l(t,n) (\frac{C(t,n)}{l(t,n)} \right)^{1-\gamma} \right)^{\frac{1-\eta}{1-\gamma}} - 1 \right] \beta^t$$

Note that by default, we consider no inequality aversion($gamma = 0$), since this equalises marginal welfare across regions, leads to a unique social cost of carbon, and is quantitatively similar to the common use of

Table 3.1: Welfare parameters

Symbol	Definition	GAMS	Default value
η	Inverse of IES	eta	1.50
ρ	Pure rate of time preference	srtp(t)	0.01
γ	Degree or inequality aversion	gamma	0.00

Negishi weights (Negishi 1960). As an alternative, time varying Negishi weights (Nordhaus and Yang 1996) can be used in which case the welfare function has the form of

$$W^{Negishi}(clt) = \sum_t \sum_{n \in clt} w_{t,n} l(t,n) \frac{\left(\frac{C(t,n)}{l(t,n)}\right)^{1-\eta} - 1}{1-\eta} \beta^t$$

where $w_{t,n}$ are the time- and region-specific Negishi weights which are computed as

$$w_{t,n} = \frac{\frac{1}{c(t,n)^{\eta}}}{\sum_{n' \in clt} \frac{1}{c(t,n')^{-\eta}}}.$$

For the current version of WITCH, the parameters are based on an overview of recent contributions in the literature on discounting, with an intermediate parametrizations of a one per-cent utility discount rate and a degree of constant risk aversion of 1.5. The full parametrization is reproduced in Table 3.1.

```
##       Symbol                   Definition    GAMS Default value
## 1:   $\\eta$               Inverse of IES     eta          1.50
## 2:   $\\rho$  Pure rate of time preference srtp(t)          0.01
## 3: $\\gamma$ Degree or inequality aversion   gamma          0.00
```

3.2 The general economy

3.2.1 Consumption

The single argument of the utility function is per-capita consumption of the representative agent in each region. Total consumption C is thereby defined by the budget constraint, whereby from net output Y, see next section for a definition, the following investments, and operation and maintenance costs (computed as coefficients of the installed capacity) are subtracted:

- final good investments, I_{FG},
- investments in energy technology j, I_j and
- research and development investments in energy technology j, (R&D), $I_{RD,j}$,
- extraction sector investments, $I_{OUT,f}$
- infrastructure for the electric grid investments, I_{GRID}
- operation and maintenance costs in energy technology j, $oem(j)$ and
- extraction costs of fuel f, $oem\_ex(f)$.
- Investments in adaptation ($I(PRADA,t,n)$, $I(SCAP,t,n)$, $I(RADA,t,n)$)

$$
\begin{aligned}
C(t,n) = & Y(t,n) \\
& - I_{FG}(t,n) \\
& - \sum_{j} \left(I_{RD,j}(t,n) + I_j(t,n) + (oem_j(t,n) * K_j(t,n)) \right) \\
& - \sum_{f} \left(I_{OUT,f}(t,n) + (oem\_ex_f * Q_{OUT,f}(t,n)) \right) \\
& - I_{GRID}(t,n) \\
& - I(PRADA,t,n) - I(SCAP,t,n) - I(RADA,t,n)
\end{aligned}
$$

where

- Energy technologies are denoted j
- Fossil fuels are denoted f

3.2.2 Output

The production side of the economy is very aggregated. Each region produces one single commodity that can be used for consumption or investments. The final good Y is produced via a nested CES function that combines capital(K), labour (L) and energy services (ES). Capital and lobar are aggregated using a Cobb-Douglas production function. This output aggregate is then combined with energy services with a CES production function. The climate impacts $\Omega(t,n)$ affect gross output, so that a certain share of output is lost due to climate change impacts. Moreover, the costs of fossil fuels, C_f, are subtracted from gross output. Also, costs related to mitigation of GHG emissions $C_{ghg}(t,n)$ are subtracted here: they include costs of direct emission mitigation including Carbon Capture and Storage (CCS), the costs of avoided deforestation and degradation (REDD+), the carbon tax revenues, and, in the case of a permit trading scheme, the net imports of permits. Net output is thus obtained as

$$
\begin{aligned}
Y(t,n) = & \frac{tfp0(n) \left(\alpha(n) \left(tfpy(t,n) K_{FG}(t,n)^{\beta(n)} l(t,n)^{(1-\beta(n))} \right)^{\rho} + (1-\alpha(n)) ES^{\rho}(t,n) \right)^{\frac{1}{\rho}}}{\Omega(t,n)} \\
& - \sum_{f} C_f(t,n) \\
& - \sum_{ghg} C_{ghg}(t,n),
\end{aligned}
$$

where the CES parameters are $\alpha(n)$ and ρ. The parameter ρ is computed such that $\rho = \frac{\int -1}{\int}$, where $\int$ is the elasticity of substitution. The parameter $\beta(n)$ represents the Cobb-Douglas coefficient of the capital-labour aggregate.

Total factor productivity $tfpy(t,n)$ is dynamically calibrated and evolves exogenously with time. Labour l is assumed to be equal to to population, thus assuming no unemployment. Finally, the parameter $tfp0(n)$ is calibrated to match GDP in the base year.

3.2.3 Capital

The capital stock in the final good sector accumulates following the standard capital accumulation rule with exponential depreciation:

$$
K_{FG}(t+1,n) = K_{FG}(t,n) \times (1-\delta_{FG})^{\Delta_{\mathrm{t}}} + \Delta_{\mathrm{t}} \times I_{FG}(t,n)
$$

3.2.4 Energy Services

Energy services ES are provided by a combination of physical energy input and a stock of energy efficiency knowledge. This allows for endogenous improvements in energy efficiency. Energy efficiency can be increased through investments in energy R&D, which build up the stock of knowledge. The stock of knowledge can then substitute physical energy in the production of energy services. More details on the stock of knowledge are available in Research and Development.

Energy services ES are an aggregate of the amount of energy consumed, EN, and a stock of knowledge, $RDEN$, combined within a CES function:

$$ES(t,n) = \phi_{ES}(n)\left(\alpha_{ES}(n)RDEN(t,n)^{\rho_{ES}} + (1-\alpha_{ES}(n))tfpn(t,n)EN(t,n)^{\rho_{ES}}\right)^{\frac{1}{\rho_{ES}}}$$

The CES parameters $\phi_{ES}(n)$, $\alpha_{ES}(n)$, and ρ_{ES} are statically calibrated for each region based on prices and quantities in the base year 2005. The factor productivity of energy $tfpn(t,n)$ calibrated is presented in the Dynamic calibration section. The elasticities including ρ_{ES} are chosen to fit empirical substitution between different energy uses and fuels, notably referring to (Koetse, Groot, and Florax 2008) and (Stern 2012a). The elasticity between electric and non-electric energy of 0.66 has been chosen to match the estimates of (Koetse, Groot, and Florax 2008).

3.2.5 Energy

Energy used in the economy is a combination of electricity and non-electric energy. Electric energy can be generated using a set of different technology options. Non-electric energy comprises the use of different fuels, namely coal, gas, oil, biomass, and a backstop technology for industry, residential households, and transportation. The aggregation uses a CES function with parameters $\alpha_{EN}(n)$ and ρ_{EN}.

$$EN(t,n) = \left(\alpha_{EN}(n)EL(t,n)^{\rho_{EN}} + (1-\alpha_{EN}(n))NEL(t,n)^{\rho_{EN}}\right)^{\frac{1}{\rho_{EN}}}$$

Each factor is further decomposed into several sub-components. The components are aggregated using CES, linear and Leontief production functions, which is described in detail in the Energy module.

3.3 Calibration of future Productivity and Energy Demand

Statically, the nested production function of the economy is calibrated using the price and quantity data of the base year. The dynamic calibration module is used to calibrate crucial input parameters that change over the time horizon. The idea is to replicate certain stylized facts about the dynamics of crucial variables to calibrate parameters that have not (yet) been endogenized in the model. For the moment, this includes three main series of parameters: population, total factor productivity $tfpy(n,t)$, and the productivity of energy (the inverse of energy intensity) $tfpn(n,t)$.

3.3.1 Population

Population forecasts are taken from the common scenarios that have been developed at IIASA (International Institute for Applied Systems Analysis) and the OECD based on individual country forecasts. In the standard version of the model, We use the OECD projection developed for the SSP2 “middle of the road” scenario aggregated over WITCH regions.

3.3.2 Total Factor Productivity

Similarly, **GDP** baseline projections have been developed at the OECD and are common across different models. These GDP baseline forecasts are done for individual countries using Purchasing Power Parities (PPP). We convert the data into USD through market exchange rates using the conversion factor of 2005. Given that current calibration of all prices and quantities is in MERs and projecting PPP/MER convergence rates is notoriously difficult, for now we keep the exchange rates kept constant and aggregate the MER converted series over WITCH regions, denoted by $Y_{kali}(n,t)$.

The GDP projected by the model is then used to calibrate the time series of total factor productivity $tfpy(t,n)$ for the model. The data series from the OECD are given until the year 2100. In order to obtain the data until the time horizon of WITCH, the GDP is extrapolated continuing with the growth rate in 2100 but decreasing it linearly to zero growth at the end of the time horizon. All baseline data can be accessed at the SSP database. The total number of countries available from the database is 184 and thus covering over 95 of the world population.

3.3.3 Energy Intensity

In order to calibrate energy demand across regions and over time, an estimated energy demand elasticity $\varepsilon_{Y,E}(n,t)$ is used to compute total primary energy supply (PES) across regions and over the time horizon. The calibration of factor productivity of energy services (tfpn) is run based on the SSP2 default scenario. The following income elasticity rule is used for the different regions: Industrialized countries (OECD members) are characterized by an elasticity of 0.40 in 2005 whereas non-OECD members have an elasticity of 0.55 based on the higher share of energy expenditures. To take into account economic progress and convergence, the elasticity is assumed to fall exponentially to finally reach a value of 0.2 in the year 2150. These assumptions are based on the stylized facts that energy intensity tends to converge across regions, and that energy demand income elasticities are higher in developed countries, see e.g., Stern (2012b), Webster, Paltsev, and Reilly (2008) and Mahadevan and Asafu-Adjaye (2007).

This table shows the income elasticities of energy used for the calibration:

Region	$\varepsilon_{Y,E}(n,2005)$	$\varepsilon_{Y,E}(n,2005)$
OECD	0.40	0.20
non-OECD	0.55	0.20

The following graph illustrates global energy intensity in MJ/$ since 1820 and the 2005 values of the WITCH regions, plotted in which year global EI did or will reach their respective values:

The income elasticity of energy for each year and region is then computed assuming a constant growth rate over the time horizon (30 periods). Therefore, we can obtain the set of elasticities as:

$$\varepsilon_{Y,E}(n,t) = \varepsilon_{Y,E}(n,2005) \times e^{t/30} \times log(\varepsilon_{Y,E}(n,2150))/\varepsilon_{Y,E}(n,2005))$$

Based on these elasticities, the projected energy demand can be computed based on the GDP projection. Since the GDP the model is calibrated in the above way to the projection by the OECD ($Y_{kali}(n,t)$), the predicted demand for total primary energy in each region and at each time $TPES_{kali}(n,t)$ is computed iteratively as

$$TPES_{kali}(n,t) = TPES_{kali}(n,t-1) \times (1 + \varepsilon_{Y,E}(n,t)) \left(\frac{Y_{kali}(n,t)}{Y_{kali}(n,t-1)} - 1 \right)$$

.

During the process of the dynamic calibration, the model is run and iteratively both factor productivity parameters are updated until the projected GDP and total primary energy demand converge sufficiently close to the calibration values.

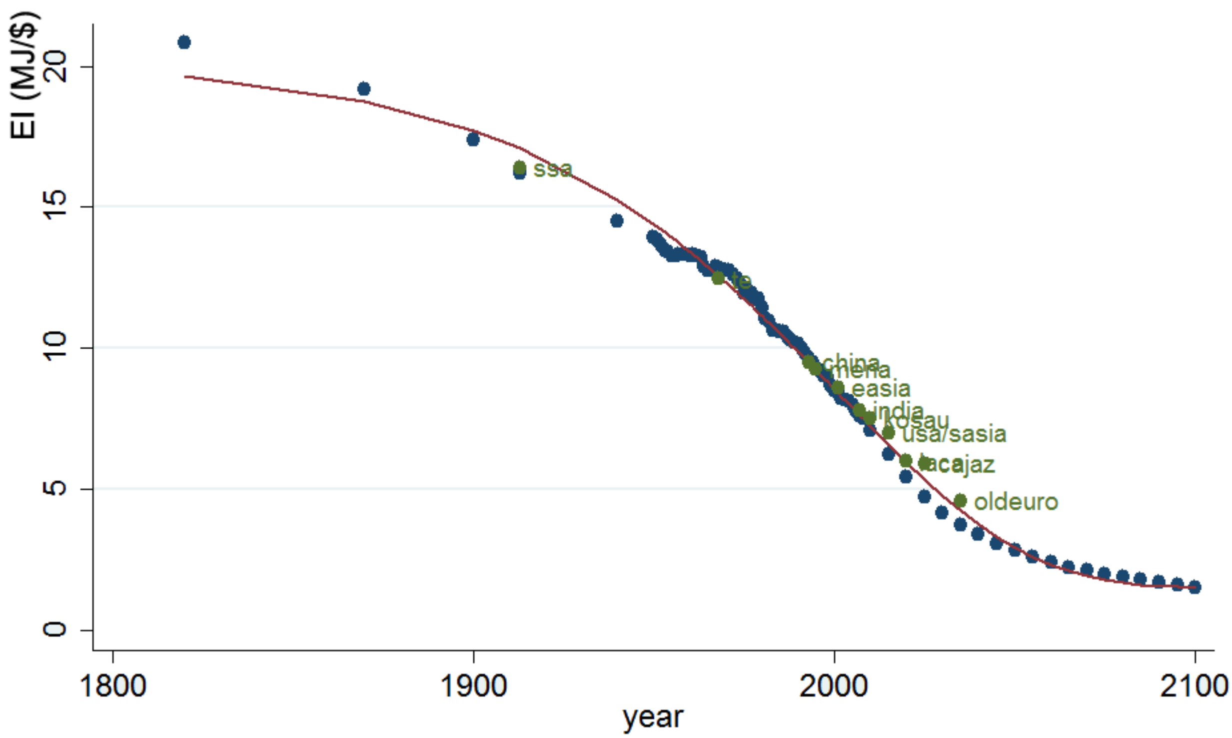

Figure 3.1: Energy intensity

Chapter 4

The Energy sector

4.1 Energy supply

WITCH includes a comprehensive range of technology options to describe the final use of energy and the generation of electricity. The energy sector is described by a production function that aggregates different factors at various levels and with associated elasticities of substitution ρ. The main distinction is among electric generation and non-electric consumption of energy.

The key technological-economic features represented are: yearly utilisation factors, fuel efficiencies, investment, and operation and maintenance costs, capital depreciation.

The following graph shows the fundamental CES nest structure of the economy and energy system. The number below a node represents the elasticity of substitution at a given nested CES.

4.1.1 Electric energy technology sectors

Electricity is generated by a series of traditional fossil fuel-based technologies and carbon-free options. Fossil fuel-based technologies include natural gas combined cycle (NGCC), fuel oil and pulverised coal (PC) power plants. Coal-based electricity can also be generated using integrated gasification combined cycle (IGCC) production with carbon capture and storage (CCS). Low carbon technologies include hydroelectric and nuclear power, renewable sources such as wind turbines and photovoltaic panels and CSP (wind and solar), and two carbon-free backstop technologies, which represent a basket of technological options far from commercialization.

The cost of electricity generation is endogenous and combines capital costs, O&M expenditure, and the costs for fuels. For nuclear power, waste management costs are also modelled, but no exogenous constraint is assumed.

The following table provides a full list of the CES nodes including all energy options:

Abbreviation	Name	Abbreviation	Name
KL	Capital-labor aggregate	ELNUKE&BACK	Electricity generated with nuclear and backstop
K	Capital invested in the production of the final good	ELBACK	Electricity generated with backstop
L	Labor	ELNUKE	Electricity generated with nuclear
ES	Energy services	ELW&S	Wind turbines and photovoltaic panels
RDEN	Energy R&D capital	NEL	Nonelectric energy
EN	Energy	TradBiom	Traditional Biomass
EL	Electric energy	COALnel	Coal for nonelectric energy
ELYHYDRO	Electricity generated with hydroelectric	OGB	Oil, backstop, gas, and biofuel
EL2	Electricity generation	GASnel	Gas for nonelectric energy

Abbreviation	Name	Abbreviation	Name
ELFF	Fossil fuel electricity	OIL&BACK	Oil and backstop for nonelectric energy
ELCOALBIO	Electricity generated with Coal and Biomass	BACKnel	Backstop for nonelectric energy
EPC	Electricity generated with pulverized coal	OILnel	Oil for nonelectric energy
ELIGCC	Electricity generated with integrated gasification combined cycle coal plus carbon capture and storage	Biofuels	Traditional and advanced biofuels
ELOIL	Electricity generated with oil	Trad Bio	Traditional biofuels
ELGAS	Electricity generated with gas	ELWIND	Electricity generated with Wind Energy
ELGASTR	Electricity generated with Gas turbines	ELPV	Electricity generated with Photovoltaics
ELGASCCS	Electricity generated with Gas with CCS	ELCSP	Electricity generated with Concentrated Solar Power
WINDON	Electricity generated with Onshore Wind	WINDOFF	Electricity generated with Offshore Wind
ELPC	Electricity generated with Pulverised Coal	ELCIGCC	Electricity generated with Coal IGCC plus CCS
ELPB	Electricity generated with biomass	ELBIGCC	Electricity generated with Biomass with CCS

4.1.2 Capital accumulation for electric energy technology sectors

The capital of some electricity production technologies accumulates as follows:

$$K_j(t+1,n) = K_j(t,n)\left(1-\delta_j(t+1,n)\right)^{\Delta_t} + \Delta_t \times \frac{I_j(t,n)}{SC_j(t,n)}, \forall j \in \mathcal{J}_{inv},$$

where $\mathcal{J}_{inv}$ is the set of electric energy technology sectors in which one can invest. For less mature technologies, endogenous technical change is modelled: On the one hand, the investment cost SC for solar and wind energy is decreasing with the world cumulative installed capacity by means of Learning-by-Doing. On the other hand, the investment costs SC for backstop technologies are computed using a Two Factor Learning Curve: costs reductions are driven by both, growth in cumulated installed capacity and accumulation of R&D knowledge.

The aforementioned methodology is shown in the Research and Development section.

Given that we use a standard exponential depreciation rule, we calibrate the depreciation rate $\delta_j(t,n)$ based on a finite lifetime of the power plant with a linear depreciation rate of 1% per year until the end of the life time and full depreciation thereafter. Based on realistic plant specific life times, the exponential depreciation rate is computed equalizing the integral of both depreciation schedules, in order to obtain the equivalent potential output from the capacity.

4.1.3 Production in electric sector

The structure of WITCH in the figure above is represented by the following CES production functions. As above, the value shares α, efficiency parameters ϕ, and substitution parameter ρ are obtained from the Static Calibration of the model. The tree for the power sector is defined by the three following equations combining electricity from fossil fuels $ELFF$, nuclear and the electrical backstop $EL_nucback$, and intermittent renewable EL_intren with hydro power EL_hydro to electricity $EL(t,n)$:

$$EL(t,n) = EL2(t,n) + \alpha_{el_{hydro}}(n)EL_{hydro}(t,n)$$

$$EL2(t,n) = \phi_{el2}(n)\left(\alpha_{el2}(n)ELFF(t,n)^{\rho_{el2}(n)} + \beta_{el2}(n)EL_{nucback}(t,n)^{\rho_{el2}(n)} + \gamma_{el2}(n)EL_{intren}(t,n)^{\rho_{el2}(n)}\right)^{\frac{1}{\rho_{el2}}(n)}$$

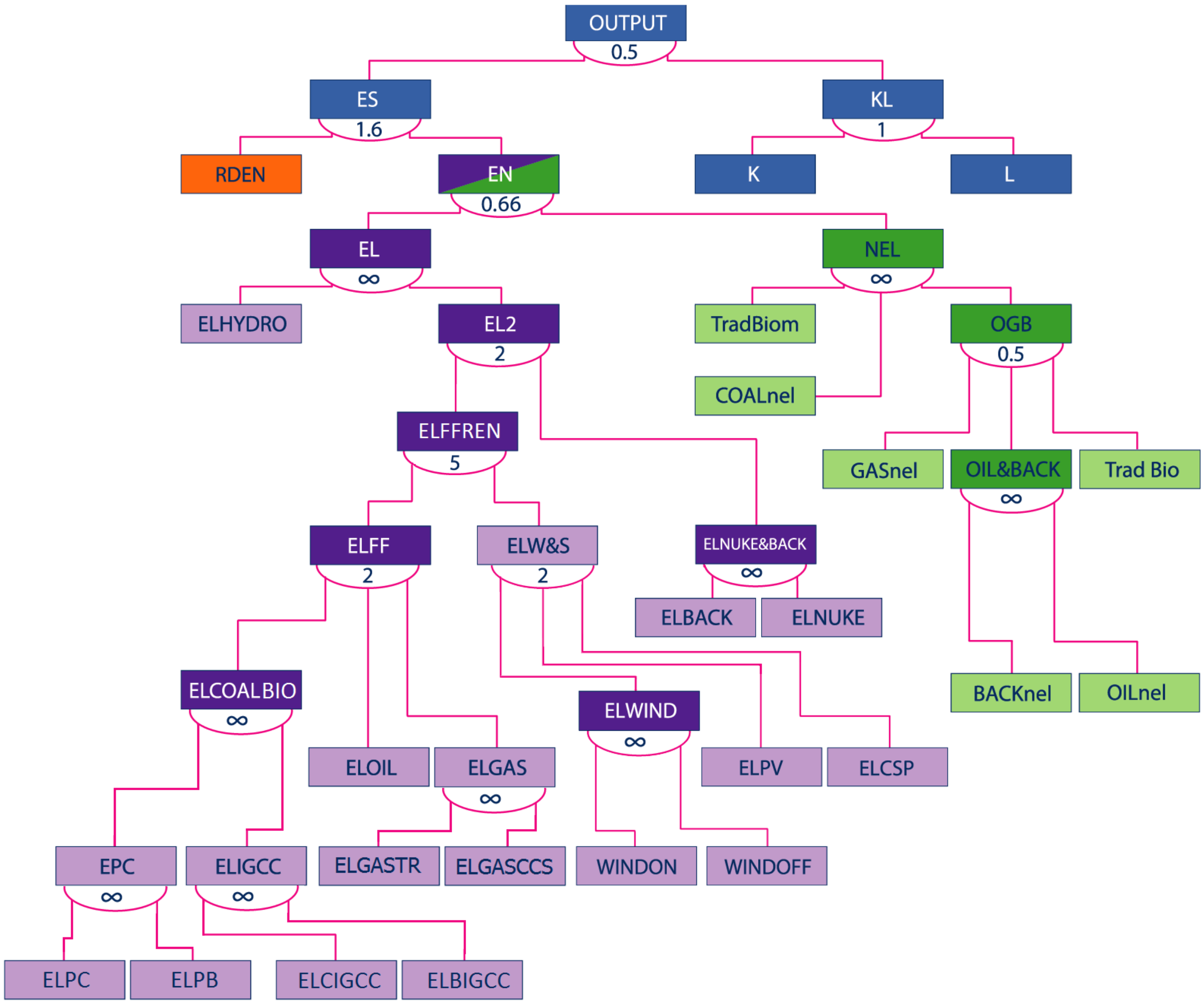

Figure 4.1: CES Production Function of WITCH

$$ELFF(t,n) = \phi_{elff}(n)\left(\alpha_{elff}(n)EL_{coalwbio}(t,n)^{\rho_{elff}(n)} + \beta_{elff}(n)EL_{oil}(t,n)^{\rho_{elff}(n)} + \gamma_{elff}(n)EL_{gas}(t,n)^{\rho_{elff}(n)}\right)^{\frac{1}{\rho_{elff}}(n)}$$

4.1.4 Additional constraints in the electric sector

In the electric sector, the production capacity is bounded by the capital stock times the capacity factor μ (**mu**):

$$EL_j(t,n) \leq \mu_j(t,n) \times KEL_j(t,n)$$

For sectors that have are fuel fed, the production capacity, Q_j, is equal to the energy consumed times the overall efficiency rate of the sector ξ:

$$Q_j(t,n) = \sum_f \xi_{j,f}(t,n) \times Q_{j,f}(t,n)$$

For the backstop technology in the electric sector (*advanced nuclear*), while Research and Development brings down the future costs (see above), the penetration is limited to 5% of total energy demand in the respective sector per period: EL_{elback}, is bounded by the coefficient **lim_elback** = 5%.

$$EL_{elback}(t+1,n) - EL_{elback}(t,n) \leq lim\_elback \times (EL(t,n) - EL_{elback}(t,n))$$

4.1.5 Non-electric energy sectors

Energy consumption in the non-electric sector is based on traditional fuels (traditional biomass, oil, gas and coal) and bio-fuels. This sector comprises transportation, industrial, and residential and commercial energy use.

The road transport sector is separated out from the CES structure and is described in detail in the section Road Transport (mod_road_transport). The stationary sector comprising industrial, commercial, and residential use of fuels is defined through a CES nest. It combines non-electric energy use from coal $NEL_{c}oal$, traditional biomass in developing countries ($NEL_{t}rbiomass$), and an aggregate of Oil&Gas (and traditional biofuels) use ($NEL_{l}og$). This CES nest is thus defined by the following two equations, where the CES parameters are as before calibrated in the Static Calibration:

$$NEL(t,n) = \alpha_{nel_{coal}} NEL_{coal}(t,n) + NEL_{log}(t,n) + \alpha_{nel_{trbiomass}} NEL_{trbiomass}(t,n)$$

The ($NEL_{l}og$) aggregate combines Oil, Gas, and traditional biofuel which are rather easy substitutable in a separate CES nest:

$$NEL_{log}(t,n) = \phi_{nelog}(n) \Big(\alpha_{nelog}(n) NEL_{oilback}(t,n)^{\rho_{nelog}(n)} + \beta_{nelog}(n) NEL_{gas}(t,n)^{\rho_{nelog}(n)} + \gamma_{nelog}(n) NEL_{trbiofuel}(t,n)^{\rho}$$

4.1.6 Primary Energy Supply of Fuels

The total primary energy supply of the different fuels is the sum of the consumption from all the sectors:

$$Q_f(t,n) = \sum_j Q_{j,f}(t,n)$$

The consumption of fuel f, Q_f, equals the total level of extraction by balancing domestic extraction and fuel imports X_f:

$$\sum_n Q_f(t,n) = \sum_n X_f(t,n)$$

If the country is a net exporter, X_f is negative. The net cost of the different fuels is equal to the cost of extracted fuels consumed fuels minus the cost of the (net-)imported fuels at the world market price $p_f(t)$

$$C_f(t,n) = MC_f(t,n) \times Q_f(t,n) - p_f(t) \times X_f(t,n)$$

The price of fossil fuels and exhaustible resources (f, oil, gas, coal and uranium) is determined by the marginal cost of extraction, MC_f, which in turn depends on current and cumulative extraction. A regional mark-up is added to mimic different regional costs including transportation costs.

4.2 Research and Development

One of the main features of the WITCH model is the characterisation of endogenous technical change. Albeit difficult to model, technological innovation is key to the decoupling of economic activity from environmental degradation, and the ability to induce it using appropriate policy instruments is essential for a successful climate agreement, as highlighted also in the Bali Action Plan.

Both innovation and diffusion processes are modelled. We distinguish dedicated R&D investments for enhancing energy efficiency from investments aimed at facilitating the competitiveness of innovative low carbon technologies (backstops) in both the electric and non-electric sectors. The returns to R&D investment depend on the stock of previously accumulated knowledge. Higher knowledge stock facilitates generation of new, energy saving innovations. In addition, international spillovers of knowledge are accounted for to mimic the flow of ideas and knowledge across countries.

4.2.1 Knowledge stock in backstop technologies and energy efficiency

Stocks of knowledge are defined for two backstop technologies, and overall energy efficiency improvements. At each point in time, new ideas are produced using a Cobb-Douglas combination between domestic investments in innovation, I_{rd}, the existing stock of knowledge, RD_{rd} and the knowledge of other countries, $SPILL$. That is, for three sectors $rd_{el\_back,nel\_back,RDEN}$ we have a knowledge stock, which accumulates with the perpetual rule and with the contribution of international knowledge spillovers, $SPILL$, in the respective sector RD

$$RD_{rd}(n,t+1) = RD_{rd}(n,t)(1-\delta_{rd})^{\Delta_t} + \Delta_t I_{rd}^b \times SPILL_{rd}(t,n)^d$$

The contribution of foreign knowledge to the production of new domestic ideas depends on the interaction between two terms: the first describes the absorptive capacity whereas the second captures the distance from the technology frontier, which is represented by the stock of knowledge in OECD countries (USA, OLDEURO, NEWEURO, CAJANZ and KOSAU).

$$SPILL_{rd}(t,n) = \frac{RD_{rd}(n,t)}{\sum_{n\in \mathrm{OECD}} RD_{rd}(n,t)} \times \left(\sum_{n\in \mathrm{OECD}} RD_{rd}(n,t) - RD_{rd}(n,t) \right)$$

The knowledge stock dedicated for energy efficiency is combined with energy supply and autonomous energy efficiency improvement to form energy services. Energy services are then used as an input in production of final good.

In backstop technologies, the knowledge stock is used to lower installation costs, SC, which are determined by a two-factor learning curve.

4.2.2 Two-Factor Learning Curve

In two-factor learning curves (see e.g. (Klaassen et al. 2005) and (Söderholm and Sundqvist 2007)), investment costs decrease as a result of the accumulation of knowledge (learning-by-researching) or experience (learning-by-doing). The accumulation of knowledge is produced by investments in research and development, as discussed above, while the stock of experience is proxied with global cumulated installed capacity, $wcum$ (full global technology spillover is assumed). The two-factor learning curve takes the following form:

$$\frac{SC_j(t,n)}{SC_j(0,n)} = \left(\frac{RD_j(t,n)}{RD_j(0,n)}\right)^{-lbr\_factor} \left(\frac{wcum_j(t,n)}{wcum_j(0,n)}\right)^{-lbd\_factor}$$

where lbr_factor and lbd_factor measure the strength of the learning effect. They relate to the corresponding learning rates, lbr_rate and lbd_rate, which measure the rate at which unit costs decrease for each doubling of the knowledge or capacity stock, through the following relationship:

$$lbd\_rate = 1 - 2^{-lbd\_factor}$$

The equation is written for learning-by-doing, but the same applies to learning-by-researching, obviously.

4.2.3 One-Factor Learning Curve

The cost evolution of wind (onshore and offshore) and solar (PV and CSP) technologies follows a technical change framework as well, but in this case only learning-by-doing is taken into account. Thus, investment costs decrease according to the progressive technology deployment (global cumulative capacity), while no dedicated R&D investments are considered.

$$\frac{SC_j(t,n)}{SC_j(0,n)} = \left(\frac{wcum_j(t,n)}{wcum_j(0,n)}\right)^{-lbd\_factor}$$

On the contrary, the cost evolution of vehicle batteries follows a one-factor learning curve based on learning-by-researching. The relevant cost equation can easily be derived.

4.3 Solar power

In WITCH, both solar PV (Photovoltaic) and CSP (Concentrated Solar Power) are modelled as individual technologies.

The supply curves are provided by the German Aerospace Centre (DLR) and the Potsdam Institute for Climate Impact Research (PIK), see (Pietzcker et al. 2014). They provide the maximum amount of capacity which can be installed in each region as a function of:

1. capacity factor / full load hours (solar_class in the model) - Twenty-six classes: from 350 to 2450 h/yr for PV, from 700 to 6600 h/yr for CSP (which is modelled in a SM2 configuration, i.e. with a 6h-thermal storage)
2. distance from load centres (solar_distance in the model) - Two classes: near (1-50 km), far (50-100 km)

The following table summarizes the parameters at the global level:

Parameter	PV	CSP
Global capacity	3 GW (2005)	0.4 GW (2005)
	38 GW (2010)	1 GW (2010)
	170 GW (2015)	5 GW (2015)
Base year investment cost	4650 USD/kW	6123 USD/kW
Lifetime	25 years	25 years
O&M cost	43 USD/kW	120 USD/kW
Learning rate	17%	10%
Floor cost	400 USD/kW	1500 USD/kW

The capacity is fixed up to the year 2015 in order to allow the model capturing the tremendous growth which has been taking place in recent years and which otherwise would not be replicated.

Investment costs are the same in all regions and decline over time through a learning-by-doing process. The learning process thus depends on the cumulative capacity installed worldwide and the learning rate.

The relevant variables in this section are investments, energy generation and capacity in PV and CSP. The equations which combine these variables perfectly replicate the scheme described in the "Energy sector" module. However, the variables are now specified per capacity factor class and distance from load centres.

4.3.1 Competition area

Solar PV and CSP partially compete for the same land. Indeed, CSP requires types of ground characterized by a lower slope, so the curves provide information on the "PV-only" area and the "Competition" area, where both PV and CSP can be installed. The module thus reports the total installable PV capacity (PV-only + Competition) and the total installable CSP capacity (Competition), and moreover it adds a constraint on land occupation in the Competition area:

$$\sum_{solar\_class} (K_{EN\_PV}(solar\_distance, solar\_class, t, n) * 1e6/dens('elpv', n) + K_{EN\_CSP}(solar\_distance, solar\_class, t, n) * 1e$$

4.4 Wind power

The module distinguishes between onshore and offshore wind generation.

The supply curves for wind are provided by the National Renewable Energy Laboratory (NREL), see the reference paper by Euret et al. (2016, forthcoming) and (Arent et al. 2012). The curves provide the maximum amount of capacity which can be installed in each region as a function of four factors:

1. capacity factor / full load hours (onshore and offshore) (wind_class in the model) - Nine classes: 9%, 20%, 24%, 28%, 32%, 36%, 40%, 44%, 48%
2. distance from load centres (onshore only) (wind_distance in the model) - Three classes: near (0-50 miles), transitional (50-100 miles), far (100-5000 m)
3. distance from shore (offshore only) (wind_distance in the model) - Three classes: near (5-20 nautical miles), transitional (20-50 nautical miles), far (50-100 nautical miles)
4. sea depth (offshore only) (wind_depth in the model) - Three classes: shallow (0-30 m), transitional (30-60 m), deep (60-1000 m)

The following table summarizes the main parameters for wind power:

Parameter	Onshore wind	Offshore wind
Global capacity	63 GW (2005) 194 GW (2010) 420 GW (2015)	0 GW (2005) 3 GW (2010) 11 GW (2015)
Base year investment cost	1467 USD/kW	2641 USD/kW (shallow) 2861 USD/kW (transitional) 3081 USD/kW (deep)
Lifetime	30 years	30 years
O&M cost	{25,30} $/kW	2 × onshore
Learning rate	10%	13%
Cross learning	80%	80%
Floor cost	500 USD/kW	900 USD/kW

The capacity is fixed up to the year 2015 in order to allow the model capturing the strong growth which has been taking place in recent years.

Investment costs are the same in all regions and decline over time through a learning-by-doing process (learning-by-researching is not modelled). The decline rate depends on the cumulative capacity installed worldwide and on the learning rate. The cross learning parameter indicates the share of the installed capacity of wind onshore (offshore) which is accounted for to calculate the cost reduction of wind offshore (onshore). As in the case of Solar, the standard equations of the energy module also apply for wind, only that now the variables are specifically defined per capacity factor classes, distance from load centres, and in the case of off-shore, the distance from the shore and depth.

4.5 System integration

The system integration module of WITCH is dedicated to modelling the integration of variable renewable energies (VRE) - specifically wind and solar PV - into the electrical grid. A detailed description of this modeling is available in (Carrara and Marangoni 2016).

Apart from the implicit constraint represented by the CES structure, the limitation to VRE penetration into the electrical grid is modelled through two explicit constraints, based on (Sullivan, Krey, and Riahi 2013).

1. A constraint on the flexibility of the power generation fleet

2. A constraint on the installed capacity of the power generation fleet

4.5.1 Flexibility constraint

The flexibility constraint requires that the annual average energy production be sufficiently flexible to be borne by the grid and to be able to follow the load. All energy technologies are assigned a value from -1 to

1 accounting for their grade of flexibility. Negative values are assigned to inflexible, variable technologies (i.e. VREs). Zero is assigned to those technologies which are not inflexible, but, due to technical constraints, cannot assure flexibility to follow the load (e.g. nuclear and concentrated solar power, CSP, which we assume coupled with a thermal storage which guarantees some dispatchability). Higher and higher positive coefficients are instead assigned to the progressively more flexible technologies, up to 1 which characterises storage, that by definition provides full flexibility. Gas is assigned 0.5 because in WITCH we only model Combined Cycles: Combustion Turbines would be characterised by full flexibility (1). A negative value (-0.1) is also assigned to the overall demand, in order to account for the fact that the grid itself requires some flexibility to meet changes and uncertainty in the load.

Power technology	Flexibility coefficient
Load	-0.1
Wind	-0.08
PV	-0.05
CSP	0
Nuclear	0
Coal	0.15
Oil	0.3
Biomass	0.3
Gas	0.5
Hydro	0.5
Storage	1

The constraint is then formulated so that the sum of the energy generated by the different technologies weighted on the corresponding flexibility coefficients, which can be called flexible generation, result higher or equal than zero.

$$\sum_{jel} Q_{EN}(jel,t,n) \times f(jel) + Q_{EN}('el',t,n) \times f(LOAD) \geq 0$$

Storage is not supposed to actually generate useful electricity, being essentially adopted for flexibility purposes (indeed, it could be thought as a flexibility measure not only on the generation side, but also for the demand side management). Within this constraint, the equivalent electricity contribution from storage is obtained by multiplying its capacity by a fixed value of 2000 h/yr.

4.5.2 Capacity constraint

The capacity constraint guarantees that sufficient capacity is built to meet the instantaneous peak electricity demand. In particular, the so called *firm capacity* must be at least 1.5-2 times (depending on the region) as the yearly average load, the latter being simply calculated as the yearly energy demand divided by the yearly hours (8760). The firm capacity represents the capacity that is considered guaranteed. For non-variable technologies it is simply the nameplate capacity. For variable technologies, the firm capacity is calculated multiplying the installed capacity by two parameters: the capacity factor and the capacity value. The capacity factor is the ratio between the actual energy output over a time period and the maximum theoretical output which would be achievable by running the plant at the nameplate capacity over the same time period. It substantially indicates the average capacity in normalised terms. The capacity value is a factor decreasing with increasing penetration in the electricity mix (starting from 0.9 with no penetration) which indicates that for variable technologies not only is the average capacity not always guaranteed (thus the 0.9 even with no penetration), but this fact becomes more and more critical with increasing levels of VRE penetration. Storage capacity is multiplied by a capacity value as well, fixed to 0.85, which takes into account the reduction of its contribution at high shares of VRE penetration.

$$\sum_{jel(non-VRE)} K_{EN}(jel_{non-VRE},t,n) + \sum_{jel(VRE)} K_{EN}(jel_{VRE},t,n) \cdot cf(jel,t,n) \cdot cv(SHARE_{EL}) + K_{EN}('elstorage',t,n) \cdot cv_{storag}$$

where:

$$SHARE_{EL}(jel,t,n) = Q_{EN}(jel,t,n)/Q_{EN}('el',t,n)$$

4.5.3 Electrical grid

In order to take into account the investment in the electrical grid needed, we use a stylized model based only on grid capital:

$$K_{EN\_GRID}(t+1,n) = K_{EN\_GRID}(t,n)\,(1-\delta\_grid(t+1,n))^{\Delta_t} + \Delta_t \cdot \frac{I_{EN\_GRID}(t,n)}{grid\_cost}$$

The grid capital stock is adjusted to power capacity, taking into account a linear relationship between grid capacity and the capacity of traditional power generation technologies (indicated as standard in the formula). Moreover, it includes an additional grid stock requirement for i) connecting wind and solar plants located far from load centres or shore, and ii) building a wider interconnection for the integration of VREs (curtailment reduction, dispatchability increase, etc.), which increases exponentially with VRE penetration.

$$\begin{aligned} K_{EN\_GRID}(t,n) = & \sum_{jel(standard)} K_{EN}(jel_{standard},t,n) \\ & + \sum_{jel}\sum_{distance} K_{EN}(jel,t,n) \cdot \frac{transm\_cost(jel,distance)}{grid\_cost} \\ & + \sum_{jel(VRE)} K_{EN}(jel_{VRE},t,n) \cdot (1 + SHARE_{EL}(jel_{VRE},t,n)^k) \end{aligned}$$

where the coefficient k is calibrated to be equal to 1.55.

4.6 Advanced bio-fuels (non-electric backstop technology)

Advanced biofuel represents a new generation of fuel coming from the conversion of woody biomass into biofuels. This conversion is subject to a learning by researching curve and represent a backstop technology. Advanced biofuels is a substitute to oil in the non-electrical sector.

The new production capacity of *non-electric backstop* technologies are bounded by the potential in advanced biofuels, following a logistic curve over time:

$$NEL_{nelback}(t+1,n) - NEL_{nelback}(t,n) \le \left(1 - \frac{NEL_{nelback}(t+1,n)}{advbiofuel\_pot(n)}\right) \times NEL_{nelback}(t+1,n)$$

4.7 Carbon capture and storage (CCS)

This module introduces the Carbon Capture and Storage (**CCS**) in the model. For CCS, supply costs of injections and sequestration reflect sites availability at the regional level, as well as energy penalties, capture and leakage rates. CCS can be used with Gas, Coal, and biomass power plants in the model and competes with traditional fuel power plants for a sufficiently high carbon price signal.

The quantity of carbon captured, Q_{CCS}, is computed from all CCS technologies according to a specific capture rate:

$$Q_{CCS} = \sum_{f,j} Q_{f,j}(t,n) \times ccs\_capture\_rate_f$$

The total amount of storage needed $M_{CCS}(t,n)$ is then computed cumulatively as

$$M_{CCS}(t,n) = \sum_{t'<t} \Delta_{t'} \times Q_{CCS}(t',n).$$

The unit costs for CCS transportation and storage $C_{CCS}(n,t)$ are then a convex function of the cumulative sequestrated emissions, where the parameters are chosen to calibrate costs and capacity of storage to the available estimates, notably (IPCC 2005), who estimate a total storage capacity of between 1678 and 11100 GtCO2.

$$C_{CCS}(n,t) = a_{CCS}(n)e^{\alpha_{CCS}(n) \times M_{CCS}(t,n)^{\beta_{CCS}(n)}}$$

and the total cost for the CCS is then computed as

$$C_e(n,t) = C_{CCS}(n,t) \times Q_e(n,t), \forall e \in \{CCS\}$$

4.8 Traditional Biomass

Traditional Biomass involves wood fuels, agricultural by-products and dung which are burned for cooking and heating purposes. This source of energy is therefore easily available and covers a crucial role in accommodating energy demand of over two billion people living in developing countries. (IEA 1998) indicates that the share of biomass in the global energy consumption has remained roughly the same over the last 30 years ranging from 14 to 15% of the global final energy consumption, while accounting for more than 90% of household energy consumption in some developing countries. Only recently this trend has shown a decreasing pattern thanks to the adoption of new environmental policies. According to the (IEA 2006), in 2004, almost 10% of world primary energy demand came from traditional biomass.

As pointed out by (IEA 2006) about 1.3 million people - mostly women and children - have died prematurely due to causes directly linked to the exposure to indoor air pollution from biomass. Therefore forecasting the future pattern of traditional biomass consumption is crucial to the understanding of the consequences linked to the use of traditional biomass.

The inclusion of traditional biomass module in WITCH model is performed by modelling the correlation between economic growth and use of traditional biomass as source of energy and projecting the share of traditional biomass of total energy demand across regions.

In WITCH, the quantity of primary energy supply of traditional biomass at time t and for each witch region n is defined as follow:

$$Q_{trbiomass,t,n} = TPES_{t,n} \cdot \frac{\phi_n \cdot (1-r)}{1 + \phi_n \cdot (1-r)}$$

where phi, the share of traditional biomass on total primary energy supply, is given by:

$$\phi_n = \left(\frac{Q_{trbiomass_{t_0}}}{TPES_{t_0}} \right) \cdot \left(\frac{1}{r} \right)$$

where $Q_{trbiomass_{t_0}}$ and $TPES_{t_0}$ are the supply quantity of traditional biomass and the total primary energy supply at time t_0, respectively.

What is r? Scientific literature has dealt with the relationship between economic growth and consumption of biomass energy. (Kammen, Bailis, and Herzog 2001) and (Berndes, Hoogwijk, and Broek 2003) find an inverse relationship between gross domestic product and the use of traditional biomass. Hence, we relationship between economic growth and demand for traditional biomass as follows:

$$r = min\left(1, \quad \alpha + \beta \cdot \ln\left(GDP_{PPP}\right)\right)$$

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4.9 Road transport

Road transport is explicitly modelled in WITCH, in two modules representing the passenger (in particular Light Duty Vehicles, LDVs) and the freight sectors. The rest of the transport sector is indirectly modelled in the aggregated non-electric sector in the CES structure.

The LDV types (**jveh**) represented in the model are:

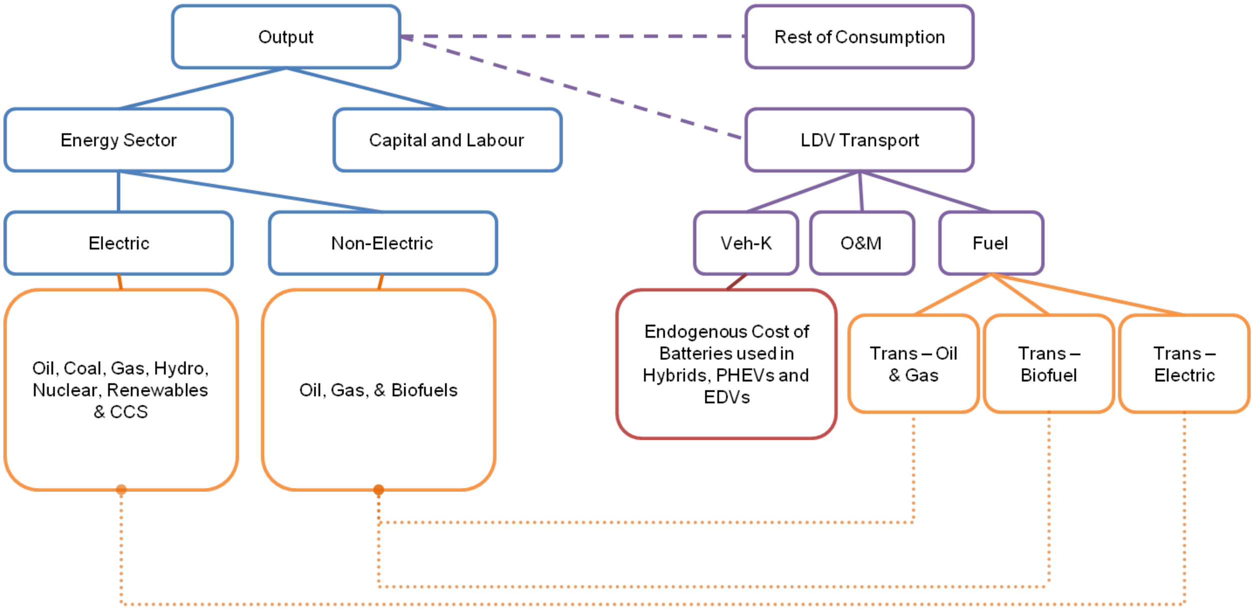

Figure 4.2: Transport Sector Structure

- traditional combustion cars, **trad_cars**;
- hybrid cars, **hybrid**;
- plug-in hybrid cars, **plg_hybrid**;
- electric drive cars, **edv**.

The same vehicle classification is applied to trucks, **jfrt**:

- traditional combustion trucks, **trad_stfr**;
- hybrid trucks, **hbd_stfr**;
- plug-in hybrid trucks, **plg_hbd_stfr**;
- electric drive trucks, **edv_stfr**.

The figure below shows how the structure of the road transport sector fits within WITCH. The composition of vehicle types (denoted in the figure as Veh-K) is determined by a Leontief function of a range of different costs. These comprise the vehicle cost, including battery cost ($/kWh), O&M costs, fuel costs and any associated carbon costs based on the fuel mix within the sector. Fuels are sourced from the Energy sector.

4.9.1 Number of Vehicles

The number of vehicles (both LDV and freight) is set equal to a projection depending on GDP and population growth. This projection is not part of the optimization process (i.e. given GDP and population, demand is given).

Concerning LDVs, the calculation of the number of vehicles per thousand capita $ldv\_pthc(t,n)$ is based on the IEA/SMP model (Fulton and Eads 2004) which is in turn based on the work of (Dargay and Gately 1999). The following equation has been implemented with parameters set to those in the table below. In particular, the Autonomous Increase (AI) and the Ownership Growth Elasticity (OGE) values depend on the GDP per capita and on the relevant ownership level.

$$ldv\_pthc(t,n) = ldv\_pthc(t-1,n) \times \left(1 + (\frac{gdp\_pc(t,n)}{gdp\_pc(t-1,n)} - 1) \times OGE\right) + AI$$

gdp_pc levels	Maximum ownership level	Ownership Elasticity	Autonomous Increase (AI)
$\leq$ \$5000	no maximum	0.30	3
$>$ \$5000	300 vehicles per thousand capita	1.30	3
$>$ \$5000	500 vehicles per thousand capita	0.60	3
$>$ \$5000	600 vehicles per thousand capita	0.25	4
$>$ \$5000	n/a	0.10	4

The total number of vehicles is obtained by multiplying this value by the population.

$$ldv\_total(t,n) = ldv\_pthc(t,n) \times population(t,n)$$

Concerning trucks, the total number of vehicles, $strf\_total$, grows over time according to the GDP per capita growth (again, following the IEA/SMP modelling assumption, Fulton and Eads (2004)).

$$strf\_total(t,n) = strf\_total(t-1,n) \times \frac{gdp\_pc(t,n)}{gdp\_pc(t-1,n)}$$

The composition of the vehicle fleet, for both LDVs and freight, is then determined by the optimization model, where a linear competition among the vehicle types takes place (mitigated by the presence of additional restrictions and constraints, see below).

$$ldv\_total(t,n) = \sum_{jveh} K_{EN}(jveh,t,n)$$

$$strf\_total(t,n) = \sum_{jfrt} K_{EN}(jfrt,t,n)$$

4.9.2 Kilometre Demand and Fuel Consumption

Energy consumption associated to the different vehicle types is given by the product of the number of vehicles, the kilometre demand per vehicle (km_d) and the specific fuel consumption (fuel_cons):

$$Q_{EN}(jveh,t,n) = km\_d\_ldv(t,n) \times fuel\_cons(jveh,t,n) \times K_{EN}(jveh,t,n)$$

The equation is written for LDVs (**jveh**), but the same applies to freight (**jfrt**).

Fuel consumption is the energy consumed by each vehicle for covering one kilometre. It exponentially decreases over time in order to simulate advancements in vehicle efficiency, approximately halving by the end of the century.

$$fuel\_cons(jveh,t,n) = fuel\_cons\_2005(jveh,n) \times t^{fueleff\_rate(t,n)}$$

Concerning LDVs, the kilometre demand is calculated starting from the travel intensity, derived from IEA/SMP and considered constant over time in the different regions, according to the following scheme:

$$km\_d\_ldv\_tot(t,n) = travel\_intensity\_ldv(t,n) \times GDP(t,n)$$

$$km\_d\_ldv(t,n) = \frac{km\_d\_ldv\_tot(t,n)}{ldv\_total(t,n)}$$

Service demand is given by the kilometre demand multiplied by the load factor, i.e. the number of average occupants per vehicle.

$$s\_d\_ldv(t,n) = load\_factor\_ldv(t,n) \times km\_d\_ldv(t,n)$$

For trucks, the kilometre demand is given and fixed over time. Service demand is again given by the multiplication between the kilometre demand and the load factor, which for trucks is given by the average tonnes of freight carried:

$$s\_d\_stfr(t,n) = load\_factor\_stfr(t,n) \times km\_d\_stfr(t,n)$$

4.9.3 Cost of Vehicles

While the cost of traditional combustion vehicles is held constant at 2005 levels, the cost of battery integrated vehicles decreases with investments in R&D for batteries. The learning rate is fixed to 12.5%.

An example of how the cost of batteries impacts the cost of vehicles is shown in the following equation for electric LDVs:

$$veh\_cost(\text{edv}, t, n) = inv\_cost\_trad\_cars \times 0.75 + size\_battery(\text{edv}) \times SC(\text{battery}, t, n)$$

Twenty five percent of the base traditional combustion vehicle cost (inv_cost_trad_cars) is removed so as to allow for the lack of a combustion engine.

The battery size of vehicles is reported in the table below along with the initial cost of vehicles.

Vehicle type	Battery size (kWh)	Initial vehicle cost (thousand $)
trad_cars	na	25
hybrid	1.5	27
plg_hybrid	13.3	44
edv	75	74
trad_stfr	na	154
hbd_stfr	8.75	165
plg_hbd_stfr	78.75	253
edv_stfr	262.5	445

4.9.4 Technology Restrictions and Constraints

Being based on cost considerations not moderated by lower-than-infinite elasticities, one of the main problems with linear competition among technologies is that irregular behaviours might take place, and in particular a sudden switch from one technology to another. Linear models thus normally introduce a set of restrictions or constraints which weaken this effect.

One example is given by the growth curves applied within the model as an endogenous constraint upon the introduction of interim technology options. A logistic functional form is the default, which is defined as follows:

$$K_{EN}(jinv, t+1, n) - K_{EN}(jinv, t, n) < 1.124 \times \left(1 - \frac{K_{EN}(jinv, t, n)}{ldv\_total(t, n)}\right) \times K_{EN}(jinv, t, n)$$

The value of 1.124 has been set using a logistic function fitted to projections of the number of hybrid vehicles for the period between 2010 and 2035 sourced from World Energy Outlook 2010. The equation is applied to both LDVs and trucks.

In addition to an S-shaped diffusion path due to the above function, additional constraints related to the diffusion of technology include:

- a limit on the amount of biofuel that can be used in each vehicle (a maximum of 50/50 biofuel/oil mixture is set up to 2020, then linearly increasing up to 100% allowed biofuel share in 2100),

- a restriction which constrains investments in a specific vehicle type to at least 30% of what they were in the previous period. Note that this restriction is intended to prevent investments disappearing in a interim technology at too fast a pace.

More details regarding the LDV modelling can be found in (Bosetti and Longden 2013), while the freight sector modelling is described in Carrara and Longden (forthcoming, 2016).

Chapter 5

Fossil Fuel Resources

5.1 Oil extraction

This section describes the modelling of conventional and unconventional crude oil investment and extraction in the WITCH model (Massetti and Sferra 2010). Producing one unit of crude oil requires at least one unit of extractive capital. Extraction capital is accumulated through (irreversible) investments that depreciate exponentially. The rate of capital utilisation may be equal to or less than 100%. Emissions associated with oil extraction are also calculated.

Unit costs of extractive capacity are increasing in both cumulative extraction and changes in capacity. Increasing long-run costs reflect the effects of resource depletion: lower cost resources are exploited first. This component of the cost curve is modelled as a series of cost steps between different 'grades' of oil. Transitions between steps are smoothed through the inclusion of a cubic term. Inclusion of additional terms that make adjustments of capacity costly, ensures that the model simulates the simultaneous extraction of resources in different regions with different costs.

The WITCH model database provides for eight grades of oil resources in each region. (A more aggregated set of four grades has also been defined and can be used instead, when desired.) Higher grades have higher base unit costs of extractive capacity and higher CO_2 emissions coefficients. The higher costs are intended to reflect both increasingly difficult geologies and increasingly difficulty of discovery.

5.1.1 Oil production

Production of crude oil cannot exceed the extraction capacity available for any given category in any given region. However, capacity may be underused if the rate of production is falling rapidly.

$$OIL_{prod}(t,n,g) \leq OIL_{cap}(t,n,g)$$

Cumulative oil production (**CUM_OIL**) in each category and in each region is bounded by the total oil resources in place (**resmax_oil**).

5.1.2 Extraction capacity

The oil extraction capacity is built cumulatively over time. It is subjected to depreciation rate, and it can be increased by means of dedicated investment in the oil extraction sector.

$$OIL_{cap}(t+1,n,g) = OIL_{cap}(t,n,g) \times (1-\delta_{oilg})^{\Delta_t} + \Delta_t \times \Delta CAP(t,n,g)$$

The depreciation rate parameter δ_{oilg} is set by default to the value of 0.1.

In the base year (2005) both oil capacity and oil production are assumed to be equal to the observed extraction data (source: Enerdata).

Investments for oil extraction capacity are equal to the expenditure for financing the expansion of oil capacity (ΔCAP):

$$I_{OILCAP}(t,n,g) = \Delta CAP(t,n,g) \times OIL_{capcost}(t,n,g)$$

The amount of investment needed to increase the oil capacity is then governed by the investment cost function.

The cost of oil extraction capacity function has short-term increasing marginal extraction cost. The cost of additional oil capacity is governed by three elements:

1. a specific investment cost that represents a cost floor (specific to each category) ($\lambda(g)$).
2. a short term cost component that becomes large if investments exceed a certain threshold to mimic adjustment costs and reduce incentive to over-invest in oil extraction capacity
3. a long term cost component that is inversely related to remaining oil resources for each category, to reflect resource depletion effects and smooth the transition from a lower (cheaper) to a higher (more expensive) category of oil

$$OIL_{capcost}(t,n,g) = \lambda(g)+\phi(g)\Delta CAP(t,n,g)^{1/\psi}+\phi(g)\left(\left[\frac{\Delta CAP(t,n,g)}{\zeta(n,g)}\right]^{\psi}-1\right)+\mu(g)\left(\frac{\sum_{s=1}^{t-1} OIL_{prod}(t,n,g)}{\theta OIL_{res}(t,n,g))}\right)^{\chi}$$

For the current version of WITCH, the following parameters are used by default:

Symbol	Default value
δ_{oilg}	0.1
θ	1
χ	3

5.1.3 Emissions from Oil extraction

Emissions from the oil extraction sector are obtained using a stoichiometric coefficient for oil combustion. We assume that the ratio of extraction to combustion emissions increases by category and that there are no extraction emissions for the first category. The idea behind this assumption is that non conventional oil requires higher consumption of energy for extraction, and thus higher emissions. Total emissions are then computed by summing the quantities emitted over all categories.

5.2 Coal and Gas: extraction and trade

The Coal and Gas module introduces extraction for these fuels. Trade (net import of these two fossil fuels) emerges as the ex-post difference between consumption and fossil fuel extraction.

5.2.1 Fossil fuel availability curves

Extraction of coal and gas is modelled by means of fossil fuel availability curves, which define the relationship between cumulative extraction and the cost of producing fossil fuels. In fact, under the hypothesis of perfect competition in the markets, marginal costs equal fuel price, and therefore it is possible to determine the optimal amount of cumulative extraction at the regional level $cum\_prodpp(f,t,n)$, associated to the international price $p_f(t)$.

Annual production of fossils is given by the difference between cumulative extraction in (t+1) and cumulative extraction in time (t), divided by the time step (Δ_t) which is 5 years, in the standard version of the model.

Besides, in order to avoid negative production of fossils, we impose that cumulative production cannot decrease over time:

$$cum\_prodpp(f,t+1,n) = \max\left(cum\_prodpp(f,t,n) + 1e-5 \times tstep, cum\_prodpp(f,t+1,n)\right)$$

The availability curves have been calibrated using polynomial functions, which consider either short term forecasts (based on World Energy Outlook 2012 projections) and long term assumptions (using curves provided by the ROSE project).

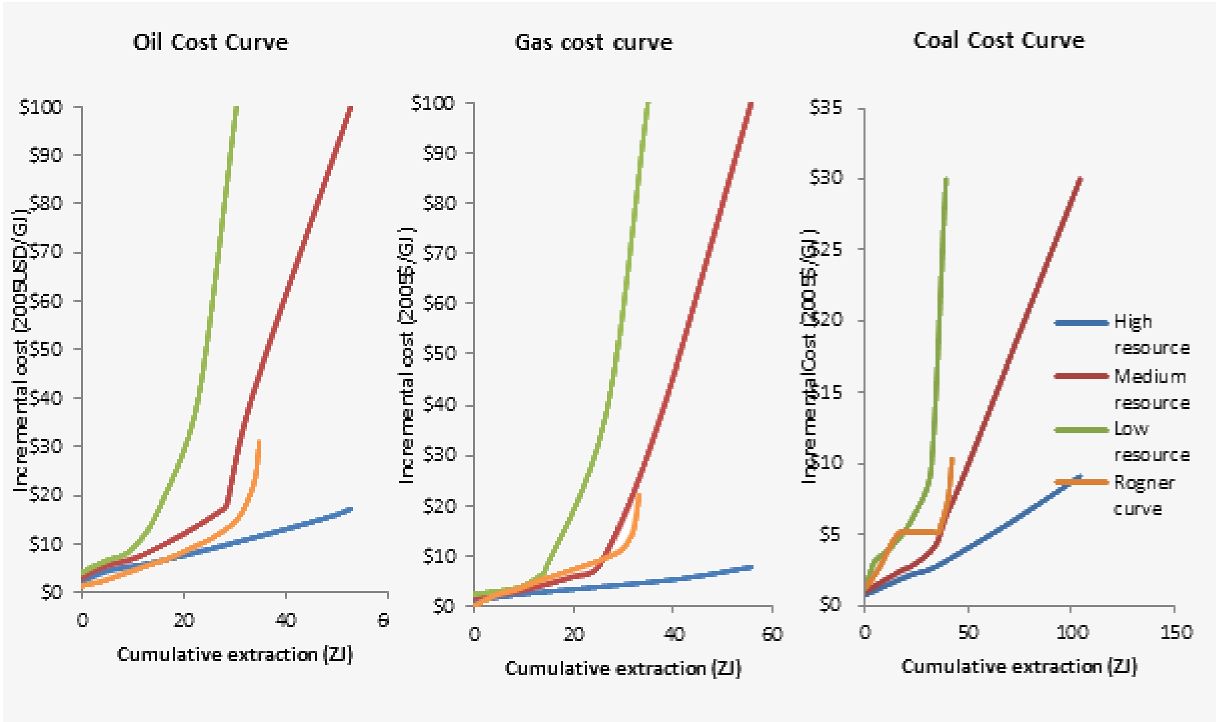

Figure 5.1: ROSE supply curves

Given that trade emerges as the difference between consumption and extraction of fossils, the availability curves have been calibrated to assure the balance between world consumption and demand. Thus the market clearing conditions are embedded in the parametrization of the availability curves.

$$cum\_prodpp(f,t,n) = \max(0, (fp_{f,n}(p_f(t))))$$

The parameters of the availability curves implemented as n-th order polynomials $fp_{f,n}(p_f(t)))$ vary according to the type of fuel f and region n. The following figure shows the global supply curves for which each a High, Medium, and Low case have been specified. By default, the Medium variant is used in the WITCH model.

By definition, we assume that cumulative extraction is equal to zero in 2005. In order to replicate observed data in the base year, we impose regional cumulative extraction in 2010 to be equal to the amount of actual production in 2005 multiplied by the time step (embedded in the parametrisation of the availability curves).

Since polynomial functions can replicate realistic cumulative production patterns only for a confined range of values, after 2100 we assume constant regional extraction shares.

$$prodpp(f,t,n) = \sum_n Q_f(t,n) \times \left(\frac{prodpp(f,'20',n)}{\sum_n prodpp(f,'20',n)} \right) \forall t > 20$$

While GHG emissions from Oil extraction are considered, see the previous section, emissions associated with the extraction of coal and gas are not considered.

Chapter 6

Land-use

In this section we describe how land use it modelled in WITCH. Given the importance of land use emissions, of the link between agriculture, biomass energy and forest management, modelling land-use is of key importance in integrated assessment models. Rather than being modelled in its full detail, land-use in WITCH is represented by the mean response functions produced by the Global Biosphere Management Model (GLOBIOM) land-use model (Havlik et al. 2014). GLOBIOM is a partial equilibrium model that covers agriculture and forestry, including bioenergy. It is used for analysing land-use scenarios over many years. In GLOBIOM, the world is divided into 30 economic regions, in which consumer behaviour is modelled through isoelastic demand functions. Commodity uses "Simulation Units", which are aggregates of 5 to 30 arcmin pixels belonging to the same altitude, slope, and soil class in the same country. For crops, grass, and forest products, Leontief production functions covering alternative production systems are calibrated from biophysical models including EPIC (Izaurralde et al. 2006). Economic optimization is based on a spatial equilibrium approach and regional price-quantity equilibria are computed. The model is calibrated to year 2000 activity levels and then recursively solved in 10-year time steps from 2000 to 2050 (Herrero et al. 2014).

6.1 Land-use modeling

The following categories are included in GLOBIOM and its sectoral representation:

6.1.1 Livestock

GLOBIOM incorporates a detailed representation of the global livestock sector (Havlik et al. 2014). Distinctions are made among dairy and other bovines, dairy and other sheep and goats, laying hens and broilers, and pigs. Livestock production activities are defined by production systems: for ruminants, grass-based (arid, humid, and temperate/highlands), mixed crop-livestock (arid, humid, and temperate/highlands), and other; for monogastrics, smallholders and industrial. For each species, production system and region, a set of input-output parameters is calculated. Feeds consist of grass, crop residues, grain concentrates, and other feedstuffs. Outputs include four meat types (beef, sheep and goat meat, poultry and pork), milk, and eggs, and environmental factors (manure production, N excretion, and GHG emissions). Switches among production systems allow for feed substitution and for intensification or extensification of livestock production.

6.1.2 Land use

GLOBIOM defines six land types: cropland (arable and perennial), grassland, short-rotation tree plantations, managed forest, unmanaged forest and other natural vegetation. Depending on the profitability of activities by land type, land can move from one type to another subject to boundary conditions. Comprehensive greenhouse gas quantities are calculated for each land type by activity.

6.1.3 Crop yields

For the three SSPs, projected yields for 2010-2100 are implemented in the GLOBIOM model through collaboration with the ISI-MIP framework. In GLOBIOM, spatial expansion of crops goes into less productive land. Moreover, cities take away the best land and push agriculture towards more marginal land. Spatial results from the biophysical crop simulation model EPIC are modified by an exogenous technological factor, which is calibrated to GDP growth. This calibration allows yield increases as a function of the change from good cropland to marginal cropland.

6.1.4 Nitrogen fertilizers

The use of nitrogen fertilizers is derived from crop input-output tables that are quantified in the narratives. Recent studies show that no major change in mineral N use efficiency can be evidenced at the global scale and for the main annual crops (J.-F. Soussana, personal communication). For N fertilizer, SSP factors affect the ratio of N fertilizer-supply increase to crop grain DM yield increase in relative units. The following values were set by SSP: SSP1: 0.75; SSP2: 1.00; and SSP3: 1.25. These modifiers are applied initially in the same way for all regions.

6.1.5 Pasture productivity

GLOBIOM defines pasture productivity from the EPIC model and from the CENTURY model. Initial values of pasture productivity are calibrated from survey data. Feed ratios are standardized by system and by region.

6.1.6 Food wastes and agricultural losses

The three SSPs are based on FAO (2011), which includes four categories of farm product losses. Post-harvest losses are functions of GDP growth under the assumption that waste-saving technologies are cheaper and more widely available in high-income nations.

6.2 Link with the WITCH model

The major interaction with the core of the WITCH model comes from the woody biomass supply curve which is one of the out coming from the GLOBIUM model. The supply curves, representing a mapping from production of woody biomass levels to production cost, are provided for each time period and for each shared socio-economic scenario. Moreover, the supply curves are also dependent of the price of land-use related CO2 emissions.

$$COST_{wbio} = f_t(Q_{wbio}, P_{CO2})$$

Chapter 7

Emissions and the climate

7.1 Greenhouse gas emissions

7.1.1 CO_2 emissions

Total CO_2 emissions are the sum of CO_2 emissions from fossil-fuel combustion in the power sector, for transportation, in heavy industries, and from land-use change minus emissions from avoided deforestation

$$Q_{CO2}(t,n) = Q_{CO2ind}(t,n) + Q_{CO2lu}(t,n) - Q_{redd}(t,n)$$

Emissions from land-use change (and REDD) are provided by the land-use module.

CO_2 emissions from fossil-fuel combustion in the power sector, for transportation, in heavy industries are computed given the fuel consumed in these sectors multiplied the stoichiometric coefficient **emi_sf**. Emissions deriving from fossil fuel extraction, EX_f are also added and emissions stored underground, Q_{CCS}, (when the option is active) are subtracted.

$$Q_{CO2ind}(t,n) = \sum_f (emi_s t(f) \times Q_f(t,n)) + \sum_f (t,n) - Q_{CCS}(t,n)$$

7.1.2 Other greenhouse gas emissions

The other Kyoto greenhouse gases are CH4, N2O, short-lived and long-lived F-gases. The baseline emissions for these gasses are following the EPA projections. This baseline paths are corrected to account for endogenous and costly effort in abatement:

$$Q_{oghg}(t,n) = emi\_baseline(oghg,t,n) \times (1 - ABAT(oghg,t,n) \times emi\_abat\_max(oghg,t,n))$$

emi_abat_max is the maximum possible abatement expressed as a share of baseline emissions (*emi_baseline*).

7.1.3 Emission costs

Costs of emissions in case of a climate policy are given by the carbon tax or permit prices, see the section on Climate Policy.

The non-CO_2 GHG emission costs are based on marginal abatement curves.

$$\begin{aligned} C_e(n,t) =& ref_e(n,t) \times \overline{abat}_e(n,t) \times \left(a_e \times ABAT_e(n,t) + \frac{b_e}{c_e} \times \exp\left(c_e \times ABAT_e(n,t) - 1\right) \right), \\ & \forall e \in \{CH_4, N_2O, slf, llf\} \end{aligned}$$

where a_e, b_e and c_e are the coefficient of the marginal abatement curves.

7.2 Climate module

WITCH included an internal climate module, which translates the regional emissions into global temperature through atmospheric concentrations. It has been building upon the DICE climate equations (Nordhaus and Sztorc 2013). Alternatively, and to make the climate outcome comparable with other models, it allows a soft link with the MAGICC6 climate model (Meinshausen, Raper, and Wigley 2011) for reporting a number of climate outcomes based on this widely used model. IN the following, we describe the internal WITCH climate module.

The greenhouse gases **ghg** that are accounted for in the model are: carbon dioxide **CO2**, methane **CH4**, oxide nitrous **N2O**, short-lived greenhouse gases **slf**, long-lived greenhouse gases **llf**. The regional emissions $Q_E(\text{ghg}, t, n)$ are summed up into global emission $WE(\text{ghg}, t)$ and converted into Gton equivalent carbon.

$$WE(\text{ghg}, t) = \sum_n \frac{Q_E(\text{ghg}, t, n)}{\text{wemi2qemi(ghg)}}$$

Non-CO_2 greenhouse gases are converted in CO_2 equivalent using the global warming potentials over a time horizon of 100 years (AR4 IPCC report, 2007) and in carbon equivalent by multiplying by 12/44.

$$\text{wemi2qemi(oghg)} = \text{gwp(oghg)} \times 12/44$$

GHG	emi_gwp
CO_2	1
CH_4	25
N_2O	298
slf	1430
llf	22800

7.2.1 Carbon-cycle

The carbon-cycle model is a 3-layer model calibrated to MAGICC (Meinshausen, Raper, and Wigley 2011). The carbon dioxide emissions go into the atmosphere box **a** and alter the atmospheric carbon concentration, then the carbon is exchanged through the ocean-biosphere-atmosphere carbon fluxes. The ocean carbon sink is divided in two layers: the upper layer **u** (shallow oceans) and the lower layer **l** (deep oceans). In this representation, the upper layer also includes the biosphere, and $M_{\text{box}}(t)$ denotes the CO2 concentrations expressed in GtC.

The carbon cycle is described in the model as

$$\begin{aligned}
M_a(t+1) &= \mathbf{A}_{a,a} \times M_a(t) + \mathbf{A}_{u,a} \times M_u(t) + \Delta_\text{t} \times WE(\text{CO}_2, t) \\
M_u(t+1) &= \mathbf{A}_{a,u} \times M_a(t) + \mathbf{A}_{u,u} \times M_u(t) + \mathbf{A}_{l,u} \times M_l(t) \\
M_l(t+1) &= \mathbf{A}_{u,l} \times M_u(t) + \mathbf{A}_{u,l} \times M_l(t)
\end{aligned}$$

$\Delta_\text{t} = 5$ and is the number of years in one time step, and the transition matrix is

$$\mathbf{A} = \begin{pmatrix} 0.88 & 0.04704 & \\ 0.12 & 0.94796 & 0.00075 \\ & 0.005 & 0.99925 \end{pmatrix}$$

Initial CO2 stocks in 2005 are reported below.

Stock in 2005	emi_gwp
$M_a(2005)$	808.9

Stock in 2005	emi_gwp
$M_l(2005)$	10000
$M_u(2005)$	1000

7.2.2 Accumulation of non-CO2 ghg in the atmosphere

the non-CO2 greenhouse gases are accumulated in the atmosphere as follows:

$$\begin{aligned} M(\text{oghg}, \text{atm}, t+1) =& d_1(\text{oghg})^{\Delta_t} \times M(\text{oghg}, \text{atm}, t) + \\ & d_2(\text{oghg}, t) \times \frac{1}{2}\left(E(\text{oghg}, t) + E(\text{oghg}, t+1)\right) + \\ & (1 - d_1(\text{oghg})^{\Delta_t}) \times \overline{\text{stock}}(\text{oghg}) \end{aligned}$$

where $d_1(\text{oghg})$ is the yearly retention factor, and $d_2(\text{oghg}, t)$ is the one-period retention factor, which is however kept constant.

stock(oghg) is the stock of each greenhouse gas at equilibrium, which is not subject to decay, and expressed in GtC. It is calculated as a fraction of $stock_0$, the stock of non-CO2 greenhouse gases in 2005.

ghg	cmdec1	cmdec2	emi_eqstock	emi_stock0
CH_4	0.917	4.2361	1.9352	4.838
N_2O	0.9917	4.9177	1.3411	1.524
slf	0.931	4.3560		0.000347
llf	0.9997	4.9969		0.000848

7.2.3 Radiative Forcing

The radiative forcing of all greenhouse gases $F(t)$ are summed up in the following equation:

$$F(t) = \sum_{\text{ghg}} RF(\text{ghg}, t) + RF_{\text{aerosols}}(t)$$

The exogenous radiative forcing from aerosols are based on the average response obtained from many runs and the MAGICC outputs.

The CO2 radiative forcing is calculated according to the IPCC Third Assessement Report expressions, i.e. proportional to the natural logarithm of the ratio of the current concentration to pre-industrial levels. M_{pre} are the pre-industrial CO_2 concentration level in GtC.

$$RF(\text{CO}_2, t) = \alpha \times (\ln(M(\text{CO}_2, \text{atm}, t)) - \ln(M_{\text{pre}}))$$

parameter	value
α	5.35
M_{pre}	592.14

The radiative forcing of the greenhouse gases CH4 and N2O is given below. In reality, these radiative forcing are interdependent and have a complex formulation. An approximation is obtained using the term *inter* in the equations.

$$RF(\text{oghg}, t) = \text{inter} \times \text{fac} \times \left(\sqrt{\text{stm} \times M(\text{oghg}, t)} - \sqrt{\text{stm} \times M_{\text{pre}}(\text{oghg})} \right),$$
$$\text{oghg} \in \{\text{CH}_4, \text{N}_2\text{O}\}$$

Parameter	CH_4	N_2O
inter	0.85	0.92
fac	0.036	0.12
stm	351	206.7
M_{pre}	1.95	1.29

The radiative forcing of slf and llf are proportional to the concentration levels.

$$RF(\text{oghg}, t) = \text{fac}(\text{oghg}) \times M(\text{oghg}, t), \text{oghg} \in \{\text{slf}, \text{llf}\}$$

parameter	slf	llf
fac	2.571	13.026

7.2.4 Global temperature increase from pre-industrial levels

The global temperature increase from pre-industrial level $T(t)$ is obtained from the energy balance 2-layer model.

$$T(t+1) = T(t) + \sigma_1 \times (F(t) - \lambda \times T(t) - \sigma_2 \times (T(t) - T^o(t))).$$

σ_1 is a lag parameter. σ_2 is a atmosphere-ocean exchange coefficient. The climate feedback parameter $\lambda = \frac{4.1}{s}$, where s is the climate sensitivity.

The ocean temperature $T^o(t)$ is given as

$$T^o(t+1) = T^o(t) + \sigma_{ho} (T(t) - T^o(t)),$$

where σ_{ho} is a coefficient of the heat capacity of the ocean.

Parameter	Value
σ_1	0.208
σ_2	0.31
σ_{ho}	0.05
λ	1.36667
s	3.0

7.3 Air pollutant emissions

The air quality module relates the pollution economic activities to emission levels of the most important air pollutants. It allows the assessment of air pollution emissions in baseline scenarios or under a climate or pollution regulation scenario. The implementation originates from the LIMITS project and its emission factors have been calculated from the GAINS model in the context of the EMF30 exercise. In the WITCH model we use information on both fuel use and the type of electricity generation technologies employed to compute the emissions E of pollutant p at time period t according to

$$E_p = \sum_j A_j ef_{j,p}(t)$$

where $ef_{j,p}(t)$ is the emission factor related to activity, A of sector j. We consider the air pollutants **p**: carbon monoxide **CO**, methane **CH4**, black carbon **BC**, organic carbon **OC**, sulphur dioxide **SO2**, nitrogen oxides **NOx**, ammonia **NH3** and volatile organic compounds **VOC**.

The emission factors $ef_{j,p}(t)$ are calculated using the ratio of emissions(E) over activities(A) provided by GAINS, these are at a first stage aggregated over the WITCH sectors (see sector mapping on the Appendix),

$$ef_{j,p}(t) = \frac{E_{j,p,\mathrm{GAINS}}}{A_{j,\mathrm{GAINS}}},$$

where j are the WITCH sectors and p is the pollutant.

The emission factors are then aggregated into the WITCH regions, using the mean weighted by country's level of CO_2 emissions.

In WITCH we do not model all the activities that generate air pollution, therefore the non-energy-related pollution is accounted for exogenously. For this non-modelled sector the emissions are taken directly from available databases and mapped into the (SNAP sectors), which are generally sector categories for reporting air pollutant levels. The emissions of the exo-sectors (sectors that are related to energy but are not accounted in the model directly, see the table in appendix), from the EMF30 database. The non-energy sectors, such as solvents, waste (landfills, waste water, non-energy incineration), agriculture waste burning on fields, agriculture, Grassland burning and Forest burning and the ammonia emissions follow the RCP8.5 emissions from the RCP database.

7.3.1 Air pollution Policies

Air pollution emissions depend on two important factors, activity levels of the pollutant sector, and the emission factor of that given activity.Therefore the implementation of policies can be done via structural measures, such as changes on the model endogenous activities, or via air pollution controls. the latter is undertaken by controlling the emission factor $ef_{j,p}(t)$ for activity category j and for pollutant p.

Accordingly, the $ef_{j,p}(t)$ are defined per air pollution scenario/baseline/policy, which corresponds to different levels of control, also called End-of-Pipe (EOP), measures. The air pollution scenarios are CLE (current legislation), SLE (stringent legislation) and MFR (maximum feasible reduction). The CLE scenario corresponds to the implementation until 2030 of all the legislation already (in 2013) foreseen and/or enforced for that period; The SLE scenario foresees the implementation of 75% of the MFR scenario which corresponds to the maximal technological frontier of EOP. For the exogenous sectors the implementation of policies has to be carried out via emission pathways.

Chapter 8

Impacts and Adaptation

8.1 Economic impacts from climate change

As outlined in the Economy chapter, a set of regional reduced-form damage functions (Ω) links the global average temperature increase above pre-industrial levels to changes in regional gross domestic product. Damage functions consist of two components accounting for both negative and positive impacts. Adaptation, $Q(ADA, t, n)$, reduces the extent to which temperature increase reduces output:

$$\Omega(t,n) = 1 + \frac{\left(\omega^-_{1,n} T(t,n) + \omega^-_{2,n} T(t,n)^{\omega^-_{3,n}} + \omega^-_{4,n}\right)}{1 + Q(ADA,t,n)^{\epsilon(n)}} + \left(\omega^+_{1,n} T(t,n) + \omega^+_{2,n} T(t,n)^{\omega^+_{3,n}} + \omega^+_{4,n}\right)$$

Economic damages as a percentage of GDP can be computed from $\Omega(t, n)$ as follows:

$$Damages(\%\ of\ GDP) = 1 - \frac{1}{\Omega(t,n)}$$

8.1.1 Calibration

The damage functions implemented in the WITCH model are based on sectoral climate impact estimates from the ClimateCost project (Watkiss 2011), described in detail in (Bosello and De Cian 2014), and they are integrated with estimates for the impact categories health and catastrophic events from (Nordhaus 2008). For the category settlements and ecosystems, new estimates are computed using a Willingness-To-Pay approach (see below).

Of the sectors examined by the ClimateCost project, only those overlapping with Nordhaus and Boyer (2000) have been included, namely coastal impacts, energy demand (which is included in the other vulnerable markets category), agriculture, and health for Europe (reduced work capacity due to thermal discomfort). The direct impacts on specific sectors have been evaluated by sectoral models (Brown et al 2011, Vafeidis et al 2008; Mima et al 2011, Criqui 2001, Criqui et al 2009; Iglesias et al 2011; and Kovats and Lloyd 2011, respectively). All estimates, with the exception of health, which are only available for Europe, have been assessed for the thirteen WITCH regions (Chapter 2). Macroeconomic impacts on regional GDP have been calculated for each impact category separately using the computable general equilibrium (CGE) model ICES (Eboli et al 2010, Bosello et al 2012). Therefore, the damage estimates for these three categories include autonomous, or market-driven adaptation. Indirect impact estimates resulting from CGE models are generally smaller than the direct impact estimates from sectoral studies, especially when production factors, such as land or crop yields, are affected. Input substitution makes it possible to buffer the direct impacts. Input substitution interacts with terms of trade effect, differentiating the resulting indirect impacts from direct impacts from bottom-up models quite significantly.

Impacts have been estimated for a temperature increase above pre-industrial levels of 1.9 degree Celsius and they have been extended to other temperature increases, including the calibration point 2.5 degree Celsius, using sector specific assumptions. For the categories coastal impacts and agriculture we use a power relationship as in Nordhaus and Boyer (2000). We assume that for warming above 3 degree Celsius all regions begin to lose, following the evidence that crop productivities decline in all regions for such a threshold. Energy and health impacts have been extended using a linear trend. Catastrophic impacts are interpolated using a linear function up to the temperature increase of 3 degree Celsius above pre-industrial levels, and using a quadratic equation above that threshold. Below we briefly summarize how impacts have been estimated in each impact category. More details can be found in (Bosello and De Cian 2014).

Agriculture. Changes in the average productivity of crops are from the ClimateCrop model (Iglesias et al. 2011). Crop response depends on temperature. CO2 fertilisation and extreme events, and water management practices are also taken into account. Spatially integrating all these elements, the ClimateCrop model estimates climate change impacts and the effect of the implementation of different adaptation strategies.

Coastal. Estimates of coastal land loss due to sea-level rise (Brown et al 2011) are from the Dynamic Integrated Vulnerability Assessment (DIVA) model (Vafeidis et al 2008). DIVA is an engineering model designed to study the vulnerability of coastal areas to the rise in sea-level. The model is based on a world database of natural system and socio-economic factors for world coastal areas. Changes in natural as well as socio-economic conditions of possible future scenarios are implemented through a set of impact-adaptation algorithms. Impacts are then assessed both in physical (i.e. sq. km of land lost) and economic (i.e. value of land lost and adaptation costs) terms.

Health. This category refers to damages due to malaria, dengue, tropical diseases and pollution. Impact estimates are from Nordhaus (2007). For Europe, impacts also include damages on labour productivity estimated by Kovats and Lloyd (2011). They assess the change in working conditions due to heat stress produced by the increase in temperature, and they estimate the expected decrease in labour productivity for four European macro-regions (Western, Eastern, Northern and Southern).

Settlements and ecosystems. WITCH estimates rely on a Willingness-To-Pay (WTP) approach, as in Nordhaus and Boyer (2000). Those estimates have been replaced with updated calculations of the WTP following the approach used in the MERGE model (Manne and Richels, 2005). In MERGE, the WTP to avoid the non-market damages of a 2.5 degree Celsius temperature increase above pre-industrial levels is 2% of GDP when per capita income reaches 40,000 USD 1990. The 2% figure was the US EPA expenditure on environmental protection in 1995. A s-shaped relationship between per capita income and WTP is then used to infer the WTP for other regions. WITCH follows a similar approach, but using an updated proxy for the WTP, considering the EU expenditure on environmental protection. The most recent Eurostat data (Environmental Protection Expenditure in Europe by public sector and specialized producers 1995-2002) referring to public sector expenditure reports a total value in 2001 of 54 billion EUR, 0.6% of EU25 GDP, or of 120 EUR per capita. This value covers activities such as protection of soil and groundwater, biodiversity and landscape, noise protection, radiation, along with more general research and development, administration and multifunctional activities. We then use the expression reported in Warren et al. (2006), which links average per capita environmental expenditure and per capita income to extrapolate a relationship between WTP and per-capita income. The s-shaped relationship between per-capita income and WTP has been used to compute the WTP in the different model regions. The resulting estimates fall between Nordhaus and Boyer (2000) and MERGE estimates as described in Warren et al. (2006). The WTP reference value used for rich countries crucially determines the final results . Using the EU values as the benchmark for calculations yields lower damages than in the MERGE model, but higher than Nordhaus and Boyer (2000). A WTP approach tends to produce higher evaluations for non-market ecosystem losses in high-income countries, although ecosystem/biodiversity richness is highly concentrated in developing countries.

Other vulnerable markets. This category refers to the effect of climate change on energy. WITCH uses the change in residential energy demand due to increasing temperatures derived from the POLES model (Mima et al. 2011, Criqui 2001, Criqui et al. 2009). POLES is a bottom-up partial-equilibrium model of the world energy system extended to include information on water resource availability and adaptation measures. It determines future energy demand and supply according to energy price trends, technological innovation, climate impacts and alternative mitigation policy schemes. The model considers both heating and cooling degree-days in order to determine the evolution of demand for different energy sources (coal, oil, natural gas, electricity) over the time-horizon considered.

Catastrophic. This category refers to the willingness to pay to avoid catastrophic events, and it is based on Nordhaus (2007).

Figure 8.1 below decomposes regional climate impacts at the calibration point (2.5 degree Celsius global average temperature increase above pre-industrial levels) by impact category.

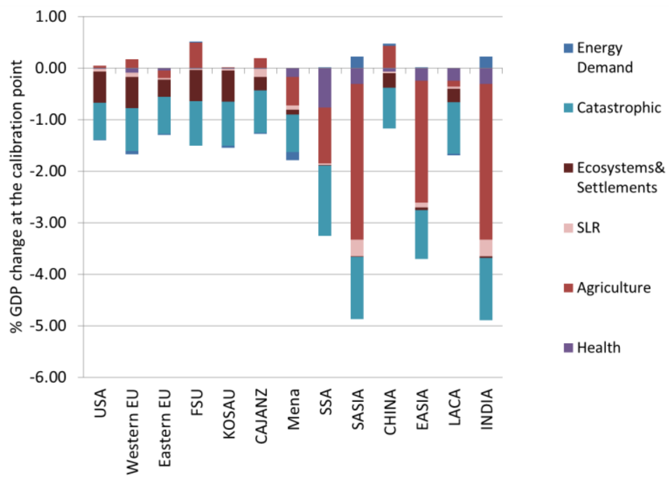

Figure 8.1: **Climate change impacts at calibration point when global average temperature increases 2.5 degree Celsius above pre-industrial levels.**

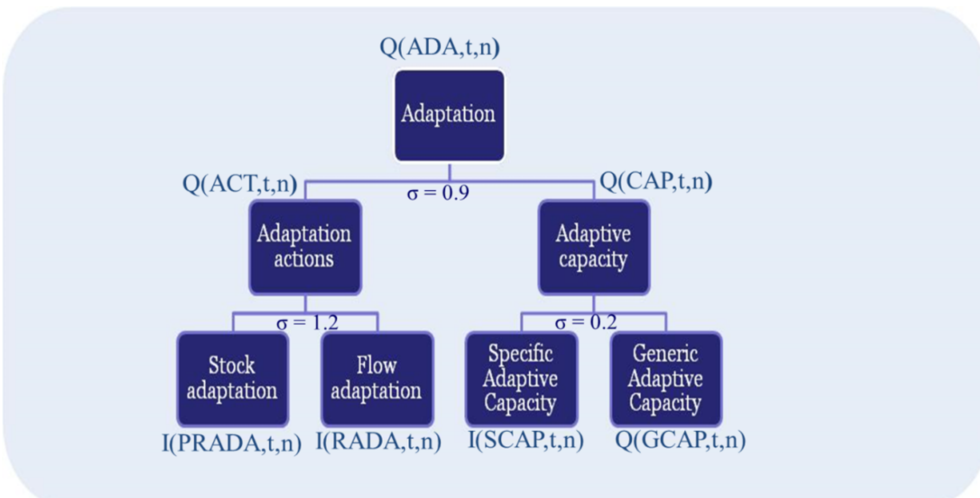

Figure 8.2: **Adaptation strategies**

8.2 Adaptation

At the core of the adaptation module introduced in the WITCH model there are three control variables that broadly represent various possible adaptive responses, namely building specific adaptive capacity, proactive adaptation, and reactive adaptation, see Figure 8.2.

Adaptation at the top nest of the adaptation tree, denoted by the variable $Q(ADA,t,n)$, reduces the extent to which temperature increase affects output:

$$\Omega(t,n) = 1 + \frac{\left(\omega_{1,n}^{-}T(t,n) + \omega_{2,n}^{-}T(t,n)^{\omega_{3,n}^{-}} + \omega_{4,n}^{-}\right)}{1 + Q(ADA,t,n)^{\epsilon(n)}} + \left(\omega_{1,n}^{+}T(t,n) + \omega_{2,n}^{+}T(t,n)^{\omega_{3,n}^{+}} + \omega_{4,n}^{+}\right)$$

Adaptation combines activities (ACT) and capacity (CAP) to produce adaptation services:

$$Q(ADA,t,n) = (\omega_{act(n)}Q(ACT,t,n)^{\rho_{ada}} + (1-\omega_{act(n)})Q(CAP,t,n)^{\rho_{ada}})^{\frac{1}{\rho_{ada}}}$$

Adaptation activities can take the form of reactive adaptation (RADA) and proactive adaptation (PRADA):

Table 8.1: Adaptation symbolic terms

Symbol	Definition	GAMS	Unit
$I_{PRADA}(t,n)$	Investment in proactive adaptation	I('PRADA',t,n)	T$
$I_{SCAP}(t,n)$	Investment in specific ad. capacity	I('SCAP',t,n)	T$
$I_{RADA}(t,n)$	Investment in active adaptation	I('RADA',t,n)	T$
$I_{RADA}(t,n)$	Investment in active adaptation	I('RADA',t,n)	T$

$$Q(ACT,t,n) = \omega_{eff(n)}(\omega_{rada(n)}I(RADA,t,n)^{\rho_{act}} + (1-\omega_{rada(n)})K(PRADA,t,n)^{\rho_{act}})^{\frac{1}{\rho_{act}}}$$

Proactive adaptation describes measures requiring a stock of defensive capital to be operational before damage materializes, such as the construction of dikes. Reactive adaptation are actions implemented right after climatic impacts effectively occur for the purpose of dealing with any residual damages that anticipatory adaptation or mitigation has been unable to obviate. Examples of these strategies include change in the use of air conditioning or hospitalization and use of health services

Adaptation capacity depends on generic capacity (GCAP) and specific capacity (SCAP):

$$Q(CAP,t,n) = \omega_{eff(n)}(\omega_{gcap(n)}Q(GCAP,t,n)^{\rho_{cap}} + (1-\omega_{gcap(n)})K(SCAP,t,n)^{\rho_{cap}})^{\frac{1}{\rho_{cap}}}$$

Generic capacity is exogenous and grows at the growth rate of total factor productivity, $tfp_y(t,n)$. The initial level is given by the 2005 average stock of knowledge (R&D) and human capital (EDU):

$$Q(GCAP,t,n) = \frac{k0(R\&D,n) + k0(EDU,n)}{2} tfp_y(t,n)$$

The human capital and R&D stock are exogenous and have been computed using the expenditure in total R&D (or education) from the World Development Indicators (2008). The R&D stock is not linked to the energy R&D investments, which instead are endogenous.

Specific adaptive capacity accounts for the investments dedicated to facilitate adaptation activities, such as improvement of meteorological services, early warning systems, the development of climate modelling and impact assessments. Specific capacity and proactive adaptation are stocks that accumulate following the standard perpetual rule:

$$K(SCAP,t,n+1) = K(SCAP,t,n+1)(1-\delta_{SCAP})^{\Delta_t} + \Delta_t I(SCAP,t,n)$$

$$K(PRADA,t,n+1) = K(PRADA,t,n+1)(1-\delta_{PRADA})^{\Delta_t} + \Delta_t I(PRADA,t,n)$$

The depreciation rate for proactive adaptation (δ_{PRADA}) is 10% and the depreciation rate for specific adaptive capacity is 3%. All forms of adaptation expenditure reduce the resources available for other uses and are subtracted from the budget constraint, see the chapter Economy.

Table 8.1 defines the main variables of the adaptation module.

8.2.1 Calibration of adaptation costs

The WITCH model uses relevant literature supplemented with ad hoc assumptions to estimate the optimal levels of adaptation and its effectiveness. For each impact category, regional data on costs and benefits of adaptation possibilities are collected and used to calibrate the parameters of the adaptation functions used in the model. The calibration process of adaptation costs is described in detail in (Agrawala et al. 2011) and has been updated in (Bosello and De Cian 2014). Costs of adaptation actions and their effectiveness in the sectors considered in the reduced-form damage function have been collected and grouped into three categories of proactive, reactive, and specific capacity.

For the following impact categories only **proactive adaptation** measures are considered:

Agriculture. WITCH assumes that the most significant cost component of climate change adaptation in agriculture is related to irrigation and water conservation practices, and therefore models adaptation in agriculture as a proactive strategy. The main data source is (UNFCCC 2007), which reports estimates of the future total cost on water infrastructure in a climate change scenario (B1 SRES scenario), assuming that 25% of those investments will be climate change driven. As in (Agrawala et al. 2010) and (Agrawala et al. 2011), we assume that the agricultural sector absorbs 70% of the water infrastructure costs reported by the UNFCCC study, and that 15% (see Agrawala et al. 2010 for a discussion) of these will be necessary in the future for adapting to climate change. Assumptions about adaptation effectiveness follow (Agrawala et al. 2010, Agrawala et al. (2011)).

Coastal. WITCH model uses estimates from the DIVA model as described in (Agrawala et al. 2010) and (Agrawala et al. 2011).

Settlements and ecosystems. For the ecosystem category, WITCH uses the (UNFCCC 2007) study to revise adaptation costs. We use the observed expenditure on conservation of protected areas (PAs) as a proxy of investments needed to protect natural ecosystems. The global value reported is $7 billion. UNFCCC (2007) estimates an annual increase in expenditure to increase protected areas by 10% up to $12-22 billion in 2030. That range refers to the estimated cost of improving protection, expanding the network of protected areas, and compensating local communities that currently depend on resources from fragile ecosystems. We scaled up the estimated range $12-22 billion to 2050 linearly using the ratio of temperature increase in 2060 relative to the temperature increase in 2030 in the WITCH model (to $21-38 billion), and compute a lower and higher bound for adaptation costs. In this study we use the lowest estimate. The global estimated adaptation costs are allocated to the different regions proportionally to the damage in the ecosystems category.

To estimate adaptation costs in the settlements category we apply the methodology described in (UNFCCC 2007) to the model investments in physical capital in 2060. According to that study, the average annual share of infrastructure vulnerable to the impacts of climate change is 2.7% of average annual investments in infrastructure globally. The World Bank (2006 2011) estimates the additional costs of adapting vulnerable infrastructure to climate change between 5% and 20% of investments. We consider the rate of 5%. The expenditure needed to eliminate the infrastructure gap identified in (Parry, N. Arnell, and Nicholls. 2009) is assumed to be zero for developed countries, and it is included in the specific capacity category. We use aggregate figures for low and middle income countries provided by (Parry, N. Arnell, and Nicholls. 2009) in Table 6.1 to compute the average annual regional investments needed to address the infrastructure adaptation deficit. Assumptions about adaptation effectiveness follow (Agrawala et al. 2010, Agrawala et al. (2011)).

For the following impact categories only **reactive adaptation** measures are considered:

Other vulnerable markets (energy). Follow (Agrawala et al. 2010) and (Agrawala et al. 2011), we use adaptation costs related to changes in heating and cooling expenditure from De Cian et al. (2013), an econometric study that estimates the elasticity of electricity, natural gas, coal and oil products to temperature changes by using panel data. With respect to effectiveness, it is assumed that in developed countries the protection level is quite high, 80%, while it is 40% in developing countries, as in (Agrawala et al. 2010) and (Agrawala et al. 2011).

Health. WITCH assumes that adaptation in the health sector is reactive, and cost estimates are from (Tol RSJ 2001), as in (Agrawala et al. 2010) and (Agrawala et al. 2011). Tol and Dowlatabadi (2001) assess the treatment cost associated with climate-driven malaria, dengue, schistosomiasis, diarrhoeal, cardiovascular and respiratory diseases, for different scenarios of temperature increases on a global scale. The effectiveness of adaptation is based on a survey of the literature, which shows that protection levels range between 20% in Africa and 40% in other non-OECD countries. In developed regions protection levels are much higher, ranging from 60% to 90%. The WITCH model relies on the assumptions described in (Agrawala et al. 2010, Agrawala et al. (2011)).

Catastrophic. As the events considered in this category are large-impact events and catastrophes, the potential to reduce their impacts through adaptation is assumed to be small. Therefore, both protection costs and protection levels are assumed to be small. The costs to address catastrophic events through early warning systems are based on (Agrawala et al. 2010) and (Agrawala et al. 2011), and are considered part of specific capacity. Protection levels are also assumed to be very low, 10% in developed countries and 0.10% in developed countries).

Specific capacity includes:

- Expenditure needed to eliminate the infrastructure gap identified in (Parry, N. Arnell, and Nicholls. 2009). It is assumed to be zero in developed countries.

		usa	oldeuro	neweuro	kosau	cajaz	te	mena	ssa	sasia	china	easia	laca	india
Agriculture														
Agriculture (irrigation) (%)	PL	0.48	0.43	0.43	0.27	0.38	0.38	0.33	0.23	0.33	0.33	0.33	0.38	0.33
Proactive	PC	0.01	0.02	0.30	0.14	0.01	0.10	0.26	0.25	0.29	0.02	0.02	0.02	0.16
	Net damages	-0.04	-0.15	0.27	-0.01	-0.17	-0.57	1.00	1.97	5.35	-0.49	4.26	0.20	5.35
Coastal														
Coastal Protection (%)	PL	0.75	0.54	0.63	0.62	0.37	0.37	0.55	0.30	0.47	0.76	0.25	0.46	0.47
Proactive	PC	0.01	0.02	0.01	0.02	0.02	0.02	0.01	0.02	0.03	0.00	0.03	0.04	0.01
	Net damages	0.08	0.12	0.05	0.06	0.24	0.04	0.12	0.04	0.49	0.04	0.15	0.07	0.49
Settlements & Ecosystems														
Infrastructure (%)	PL	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
Proactive	PC	0.03	0.03	0.02	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02
Ecosystems (%)	PL	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
Proactive	PC	0.02	0.02	0.02	0.03	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Net damages	0.61	0.61	0.54	0.61	0.50	0.61	0.25	0.02	0.03	0.52	0.23	0.54	0.03
Other vulnerable markets														
Cooling Expenditure (%)	PL	0.80	0.80	0.80	0.80	0.80	0.80	0.40	0.40	0.40	0.40	0.40	0.40	0.40
Reactive	PC	0.01	-0.03	-0.02	0.15	-0.06	0.01	0.20	0.20	0.25	0.13	0.25	0.01	0.25
	Net damages	0.01	0.08	0.03	0.06	0.03	-0.02	0.20	0.00	-0.29	-0.05	-0.02	0.05	-0.29
Health														
Disease Treatment Costs (%)	PL	0.90	0.90	0.60	0.81	0.69	0.70	0.60	0.20	0.35	0.40	0.36	0.80	0.80
Reactive	PC	0.00	0.00	0.00	0.02	0.02	0.00	0.02	0.00	0.00	0.00	0.03	0.03	0.09
	Net damages	0.02	0.12	0.06	0.02	0.02	0.02	0.23	1.01	0.40	0.09	0.32	0.32	0.40
Capacity														
Expenditure in adaptation R&D (%)	PL	0.48	0.43	0.43	0.27	0.38	0.38	0.33	0.23	0.33	0.33	0.33	0.38	0.33
	PC	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Address infrastructure deficit	PL	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
	PC	0.00	0.00	0.00	0.00	0.00	0.00	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Empower women (% of GDP)	PL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.00	0.01	0.01	0.02
Early Warning Systems (%)	PL	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.00	0.00	0.10	0.01	0.00	0.00
	PC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Catastrophic events	Net damages	0.95	1.10	0.95	1.12	1.08	1.13	0.97	1.80	1.58	1.05	1.24	1.31	1.58

Figure 8.3: **Adaptation costs (PC), protection levels (PL, share of gross damage reduced) and net damages (as % of GDP)**

- Expenditure needed to empower women through education (Brian et al. 2010)
- Early warning systems (Adams, Houston, and McCarl 2000)
- R&D expenditure in the agriculture sector (UNFCCC 2007)

Table 8.3 summarize adaptation costs (PC), protection levels (PL), and net damages at the calibration point when temperature increases by 2.5 degree Celsius above pre-industrial levels.

Chapter 9

Climate Policy

9.1 Policy Options

Climate policies can be implemented in different ways in WITCH: Based on the non-cooperative solution, a market for permits can be introduced with permit trading across regions. Optionally, banking and borrowing can be allowed for.

Alternatively, a carbon tax schedule can be implemented, which is recycled as regional lump-sum transfers as evident from the global budget constraint in the chapter on the Economy. The tax can be chosen as too target a given climate variable of MAGICC based on the model variables.

Subsidies of Investments in Research and Development, or portfolio standards or minimum renewable shares are additional policy options that can be implemented in the model.

Finally, in a coalition setting with one or more coalitions, the Cost-Benefit mode will implement an endogenous policy based on climate damage feedbacks and other externalities that are (partly) internalized by the coalitions.

9.1.1 Carbon market clearing

In the case of a global carbon permit market, the sum of regional net import of carbon permits (Q_{nip}) has to be equal to zero.

$$\sum_n Q_{nip}(n,t) = 0$$

The CO_2 emission costs are then equal to the carbon permit price times the amount of net import of carbon permits.

$$C_{CO2}(n,t) = p_{nip}(n,t) \times Q_{nip}(n,t)$$

9.1.2 Bank and borrowing

When banking and borrowing of permits is allowed, the (stock of) permit savings M_{SAV} are computed as the sum of existing savings plus net emission savings Q_{SAV}:

$$M_{SAV}(t+1,n) = M_{SAV}(t,n) + \Delta_t \times Q_{SAV}(t,n)$$

To avoid speculation of regions by buying more permits than needed, emission savings can be bounded by net import of carbon permits:

$$Q_{SAV}(t,n) \leq bigM \times \left(|Q_{nip}(t,n)| - Q_{nip}(t,n)\right),$$

where $bigM$ is a very high level of maximum trade of emissions.

Chapter 10

Implementation of the SSPs

10.1 Implementation of the Shared Socioeconomic Pathways (SSPs)

This page presents the assumptions taken for the implementation of the Shared Socio-economic Pathways (SSP) in the WITCH model. The SSPs represent 5 different scenarios that have been qualitatively described through story lines and henceforth quantified, see (O'Neill et al. 2015). These scenarios are implemented matching the story lines and quantification throughout the WITCH model to generate the different scenarios. Building on these scenarios, a baseline and four different policy targets have been formulated relying on the RCPs (Representative Concentration Pathways) which consist in four targets on total radiative forcing in 2100 of 2.6, 3.7, 4.5, and 6.0 W/m2. The third dimension of the SSPs consists in a first-best global policy implementation starting immediately versus a second best delayed action policy, which can also differ across regions and is specified differently for each SSP. These different policy architecture are referred to as Shared Policy Assumptions (SPAs).

The five SSPs are illustrated via the mapping in the challenges to mitigation/adaptation space:

10.1.1 Gross Domestic Product (GDP) and Population

Population forecasts for the different SSPs are based on the common scenarios that have been developed at IIASA (International Institute for Applied Systems Analysis), see (KC and Lutz 2015).

Similarly, **GDP** baseline projections have been developed and we use the projections made by the OECD (Dellink et al. 2015). These GDP baseline forecasts are implemented using Purchasing Power Parities (PPP) and based on individual countries. We convert the data into USD using market exchange rates using the

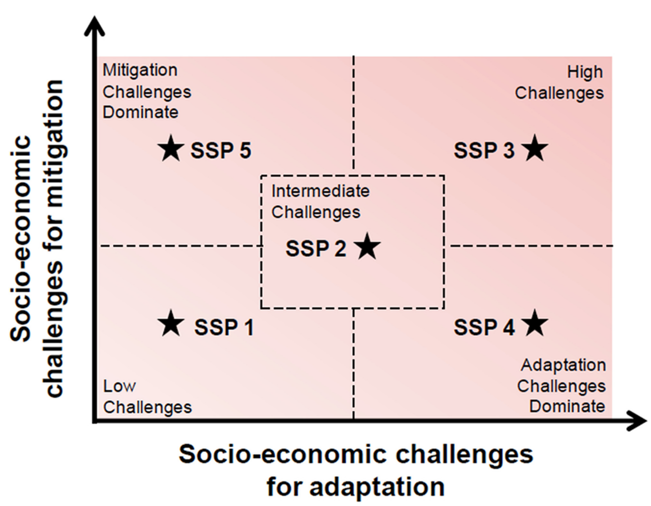

Figure 10.1: SSP challenges

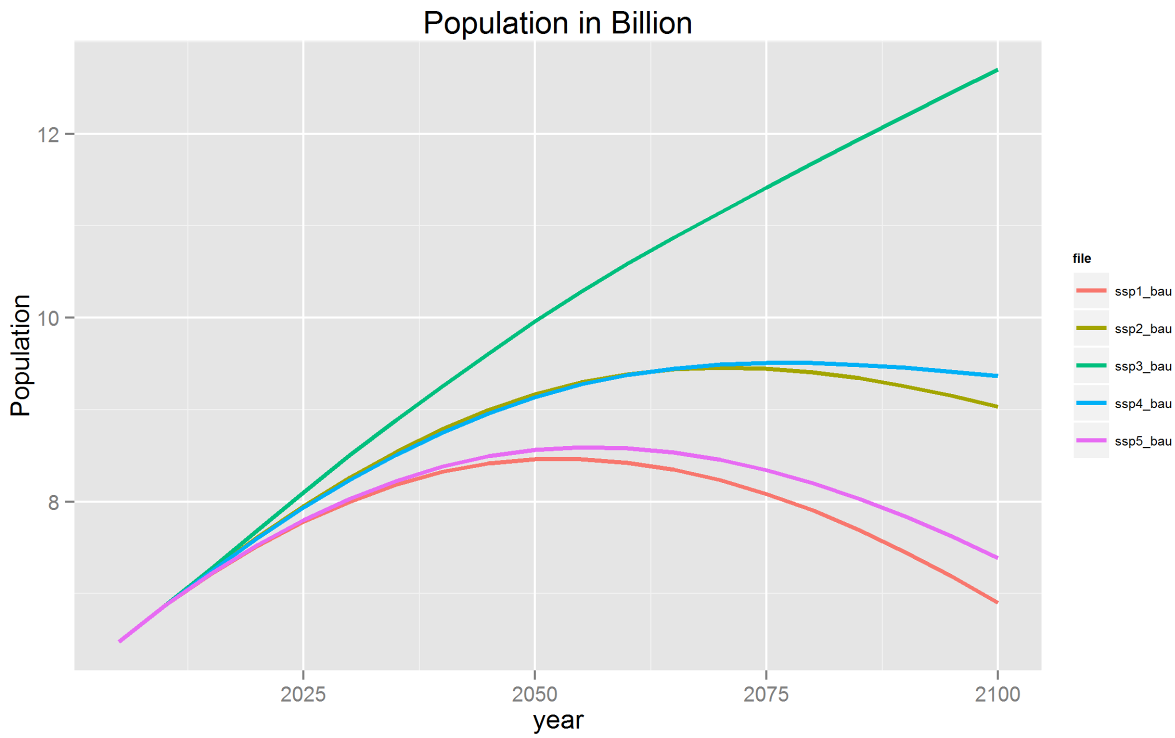

Figure 10.2: Population

conversion factor of 2005 (also given by the OECD and assumed constant over time) and aggregate the series into WITCH regions. The GDP projected is then used to calibrate the time series of total factor productivity (''tfpy") for the model.

All data series are given until the year 2100. Extrapolations until the time horizon of the models are based on linearly decreasing growth rates starting from 2100 towards zero at the end of the time horizon. All of the baseline data can be accessed at the SSP database. After adding some missing values for 2005 and 2010 and the PPP exchange rate, the total number of countries available from the database is 184.

10.1.2 Energy Intensity

The dynamic calibration of factor productivity of energy services (''tfpn") is run based on the SSP2. The following income elasticity rule is used for the different regions: industrialized countries (OECD members) are characterized by an elasticity of 0.40 in 2005 whereas non-OECD members have an elasticity of 0.55 based on the higher share of energy expenditures. To take into account economic progress and convergence, the elasticity is assumed to fall exponentially to finally reach a value of 0.2 in the year 2150.

Based on the obtained time series of regional energy productivity changes for SSP2, the same series is used for SSP4, and SSP5. Only for the "sustainable world" SSP1, the series is adjusted increasing the improvement in the factor productivity of energy by 1 percentage point per year to reflect the higher efficiency improvement in this scenario. Similarly, for the SSP3, the improvement is reduced by 1 percentage point per year to take into account slower energy efficiency improvement in this scenario. These values result in reasonable primary energy demand projections for the respective story lines and baseline GDP and population projections.

10.1.3 Land-use

Land-use representation is carried out through a soft linkage with the land-use model GLOBIOM, so the representation of the SSP follows the GLOBIOM implementation. GLOBIOM represents 3 pathways focusing

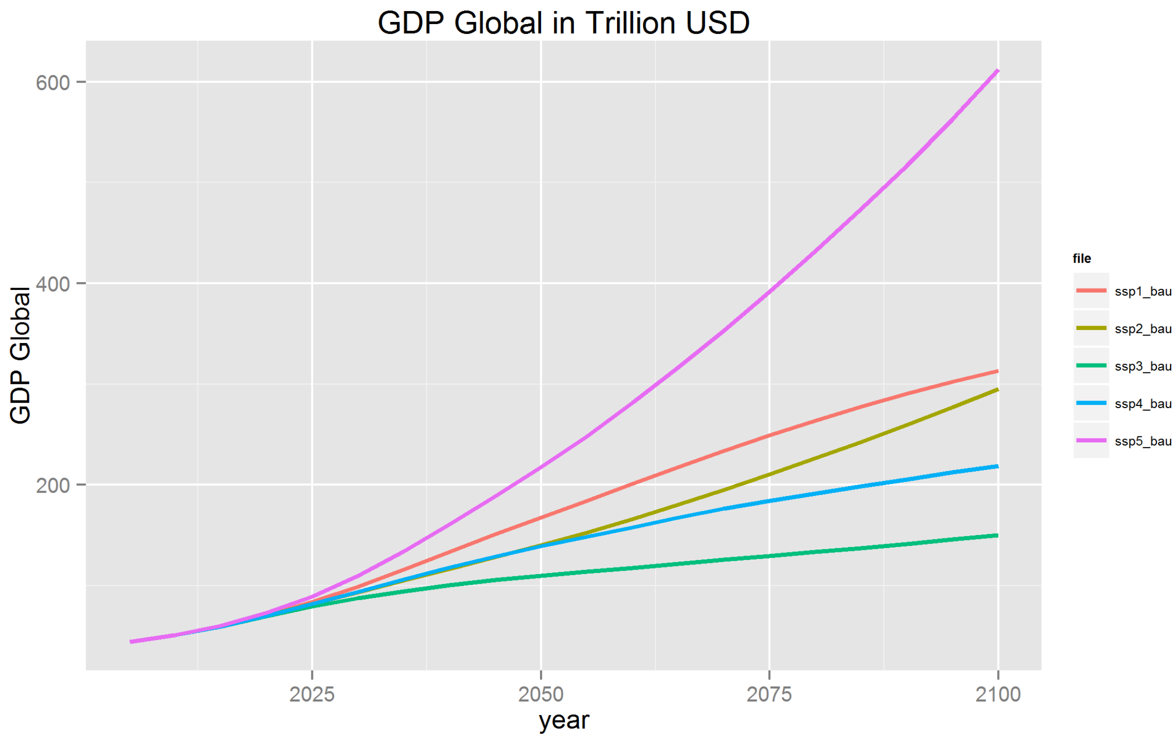

Figure 10.3: Population

on three narratives that cover a wide range of plausible future developments and that, at the same time, prevent inflation in the number of scenarios under different assumptions on future climate (Representative Concentration Pathways – RCPs) and different Global Circulation Models (GCMs). The three variants consist in: a sustainable intensification scenario with high economic growth, high GDP growth, changing diets and a high degree of technological change (SSP1); a continuation of current trends (SSP2); and a degradation scenario with little technological change, poor economic growth and high population growth (SSP3). The implementation of the SSPs thus follows the implementation in GLOBIOM.

GDP is the main driver for calorie intake per capita and for the fraction of animal products in the total diet. Projections for the three SSPs in terms of food habits were incorporated into the SSPs (Havlik and others, 2012) in the following way. - In SSP1, a convergence (driven by elasticities) towards nutritional targets is considered, using both the IIASA definition and the WHO definition. Income elasticity for calories and animal products rises in developing countries and falls in the United States; - The same rising and falling pattern of elasticities would occur in SSP2 but at a slower pace. GDP convergence tends to make regions converge on diet patterns. This also matches the FAO 2030 projections ; - In SSP3, no convergence to nutritional targets was found, current trends are reinforced by GDP changes with less consumption in developing regions, but higher or stable consumptions in developed regions (same elasticities as in SSP2).

10.1.4 Technology

The following matrix is applied to power technologies in the different SSP scenarios. “Low” indicates low penetration or high costs; “Medium” indicates the baseline assumptions; “High” indicates high penetration or low costs.

Technology	SSP1	SSP2	SSP3	SSP4	SSP5
CCS	Low	Medium	Medium	Medium (OECD) - High (non-OECD)	High
Nuclear	Low	Medium	High (OECD) - Medium (non-OECD)	Medium (OECD) - High (non-OECD)	Medium
Renewables	High	Medium	Low	High	Medium

In the "High" cases, investment costs of CCS and nuclear plants decrease over time by 1%/yr; lower costs of CO2 and waste storage are applied to CCS and nuclear, respectively; concerning renewables, learning rates are increased by 50% and floor costs are reduced by 50%, additionally flexibility coefficients are reduced by 50% and a more relaxed version of the capacity constraint (i.e. without the capacity factor) is applied.

In the "Low" case, the opposite applies (except for learning rates which are decreased by 33%).

10.1.5 Personal transport

The following matrix is applied to the different SSP scenarios in the transport sector.

Quantity	SSP1	SSP2	SSP3	SSP4	SSP5
Vehicle number	Low	Medium	High	High	Medium
Travel intensity	Low	Medium	High	High	Medium
Fuel efficiency improvement rate	High	Medium	Low	High (OECD) - Low (non-OECD)	Low
Battery learning progress factor	High	Medium	Low	High	Low

- Vehicle number: OGE is multiplied by 0.8 in the Low cases, by 1.2 in the High cases;
- Travel intensity: it decreases by 1%/5yr from 2015 in the Low cases, the opposite in the High cases;
- Fuel efficiency improvement rate: it is -0.25 by default; it is multiplied by 3/2 in the High cases, by 4/5 on the Low cases;
- Battery learning rate: it is 0.144 by default; it is multiplied by 5/4 in the High cases, by 2/3 in the Low cases.

10.1.6 Air pollutant emissions

SSP are implemented under the form of a set of air quality emission factors following the SSP narratives for air pollution.

SSP	Reg Group	2030	~2050	~2100	Narrative Summary
High-Middle Income Countries (currently)					
1/5	H-M (all)	0.75 * CLE_{30}	SLE_{30}	MTFR	Increasingly strict, well-enforced policies, substantial technology RDD&D
2	H-M-Strong	CLE_{30}	SLE_{30}	Lowest SLE_{30} or lower	Current near-term policies, gradual strengthening of goals, gradual technology RDD&D.
2	H-M-Rest	CLE_{30}	Min CLE_{30}	WEU SLE_{30}	Similar to the above trajectory, with lower emissions goals.
3/4	H-M (all)	CLE_{20}	CLE_{30}	~SLE_{30}	Near-term policy achievements delayed by about a decade (CLE_{30} closer to 2040 than 2050), less ambitious long-term goals. Some "globalized" sectors may reach SLE control levels.
Low Income Countries (currently)					
1/5	L	CLE_{30}	WEU CLE_{30}	~SLE_{30}	Improved policy implementation over near-term, followed by relatively rapid technology and policy transfer and "catch-up" with high-income regions. Some "globalized" sectors may reach SLE control levels.
2	L	CLE_{20}	Min CLE_{30}	WEU CLE_{30}	Near-term policies not fully implemented. Gradual improvement over century. Some "globalized" technologies approach H-M control levels.
3/4	L	CLE_{10}	CLE_{30}	WEU CLE_{20}	Failed near-term policy implementation and slower approach to future control.

Figure 10.4: SSP income categories and pathways

For the SSP implementation the countries are classified according to the their income, (income categories in fig.1.) and their emission factor path is computed. The countries are then regrouped by the WITCH regions, performing a weighted mean according to their GDP.

The [SSP income categories and pathways] Figure shows the implementation of the emission factor pathways witch depends on SSP and on income group. There are 3 emission factor pathways, SSP 1 and 5 and SSP3 and 4 share the same narratives in terms of air pollution although their energy, technology and economic baseline assumptions will necessarily lead to different emission profiles.

10.1.7 Fossil Fuel Resources

The fossil fuel supply curves are taken from the ROSE project, which developed High/Medium/Low supply curves for oil, coal, and gas reserves, see the depicted global curve in the chapter on Fossil fuel resources.

SSP	Oil	Gas	Coal
SSP1	Low	Low	Low
SSP2	Medium	Medium	Medium
SSP3	High	High	High
SSP4	Low	Medium	Medium
SSP5	Low	High	High

10.1.8 Adaptation

The table below describes the implementation of adaptation across SSPs in the WITCH model. We assume that slow development, low investments in human capital and technology, increased inequality, and bad institutions in SSP3 reduce the effectiveness of adaptation actions, whereas the more optimistic institutional and growth set-up of SSP5 increases adaptation effectiveness. We assume that a dollar invested in proactive or reactive adaptation in SSP5 and SSP1 is 25% more effective at reducing damage than in SSP2 (the marginal productivity of these actions is assumed to be 25% higher). Symmetrically, a dollar invested in adaptation in SSP3 and SSP4 is 25% less effective at reducing damage than in SSP2. Moreover, the WITCH model links the growth of generic adaptive capacity to GDP growth, which varies across SSPs.

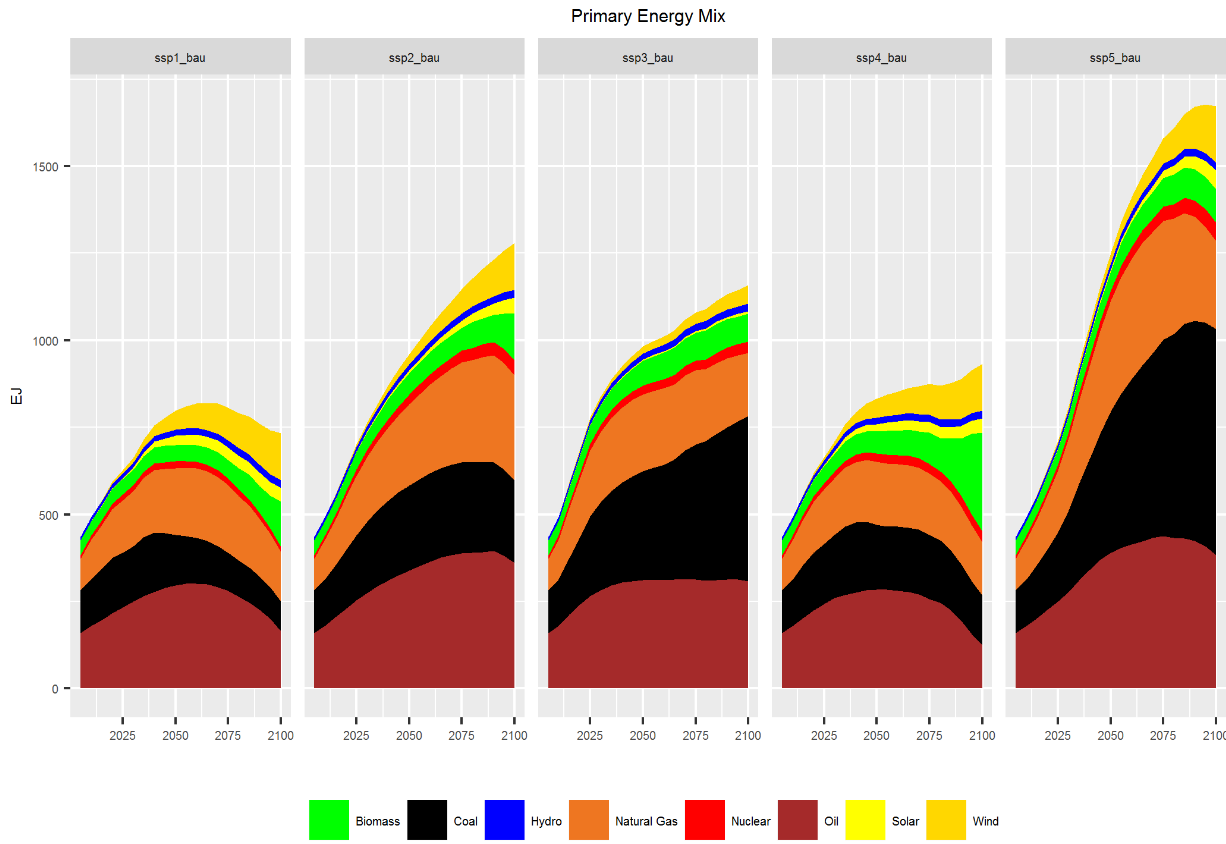

Figure 10.5: Primary Energy Supply

are in between those two extremes. Moreover, with respect to the Energy Mix, different fossil fuel reserves assumptions lead to a higher permanence of fossil fuel dependence in SSP3 and 5 whereas notably in SSP1 renewables are becoming increasingly competitive.

10.2.2 Emissions

Together with the climate policies according to the different RCPs (including an intermediate RCP34 forcing target of $3.4W/m^2$), **CO2 Emissions** differ across SSPs following the assumptions about fossil fuel consumption and land-use emissions, and different challenges to mitigation. Notably, the potential to net-negative emissions mainly through bioenergy with CCS is visible notably in SSP2 and SSP1.

10.2.3 Policy costs

This emission pathways translate into different resulting policy costs of the different targets in terms of radiative forcing. The policy costs are lower in the sustainable scenario SSP1 and the scenario with low baseline growth SSP4. IN SSP5 on the other hand with radix expansion of energy demand including fossil fuel resource use, policy costs are substantially higher than in the other SSPs (Note that the most stringent RCP26 policy turned out to be infeasible within the SSP scenario in WITCH).

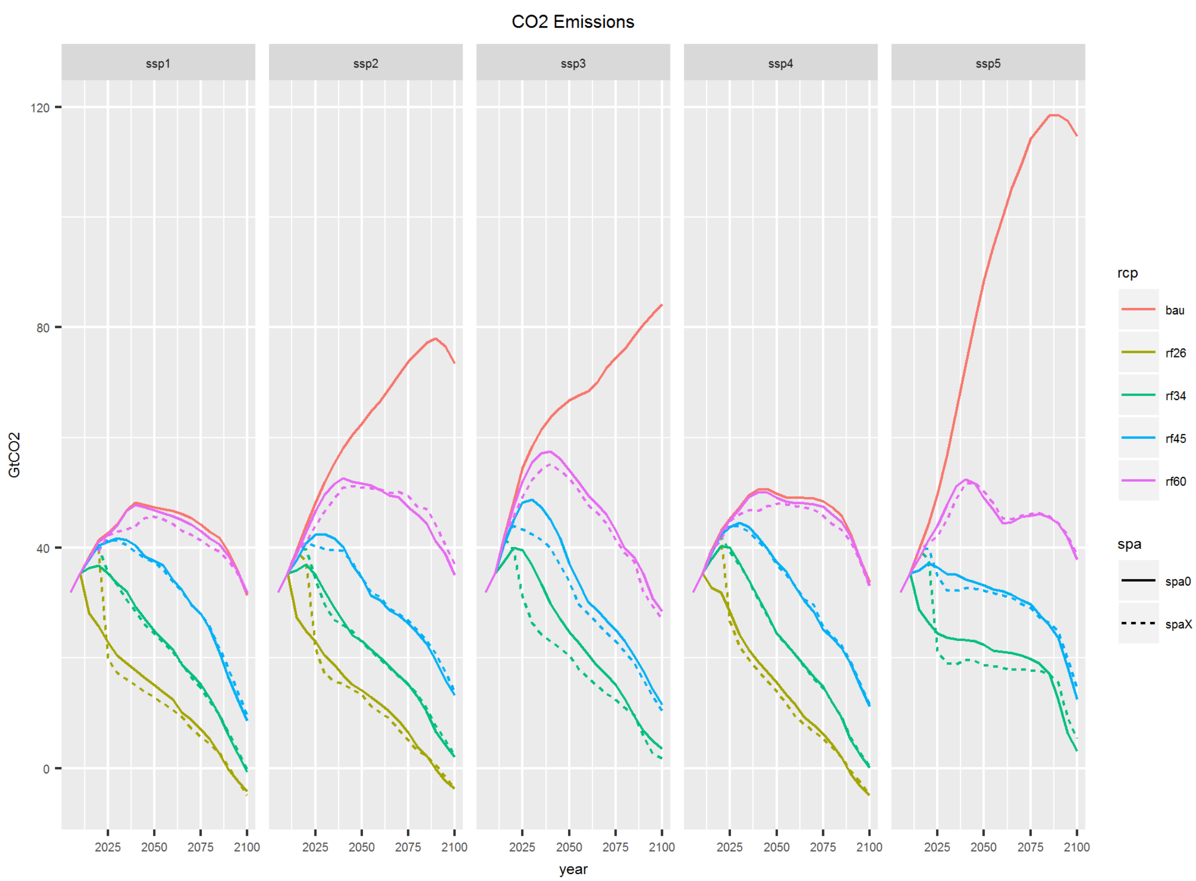

Figure 10.6: CO2 Emissions

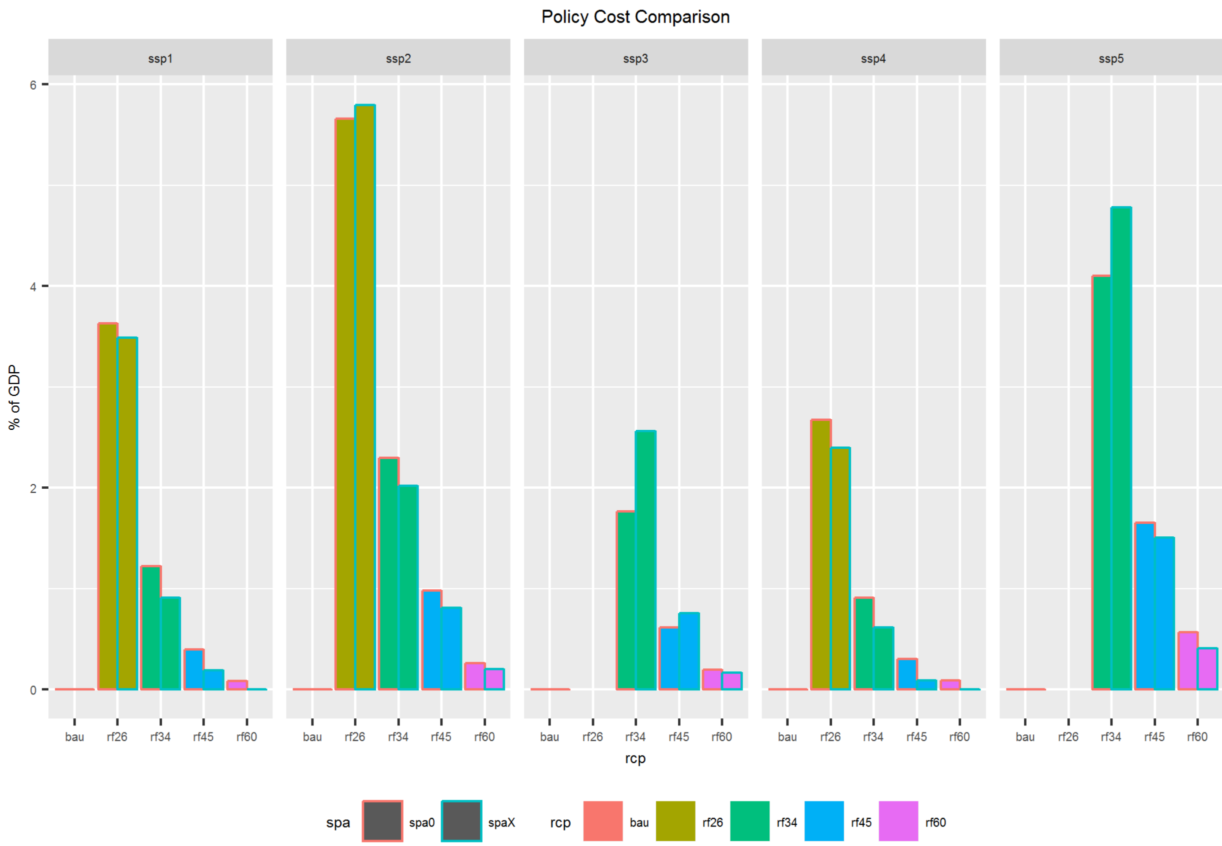

Figure 10.7: Policy Costs

Chapter 11

Appendix

11.1 Flowchart

The flowchart of the WITCH model shows the different steps in the model generation and algorithm.

11.2 List of parameters, variables, GAMS names, and parameter values

Table 11.1: Symbolic terms and GAMS names

Symbol	Definition	GAMS
$W(clt)$	Aggregated welfare	UTILITY
$w_{t,n}$	Negishi weights	w_negishi(t,n)
$C(t,n)$	Consumption	Q('CC',t,n)
$l(t,n)$	Population	l(t,n)
β	Utility discount factor	stpf(t)

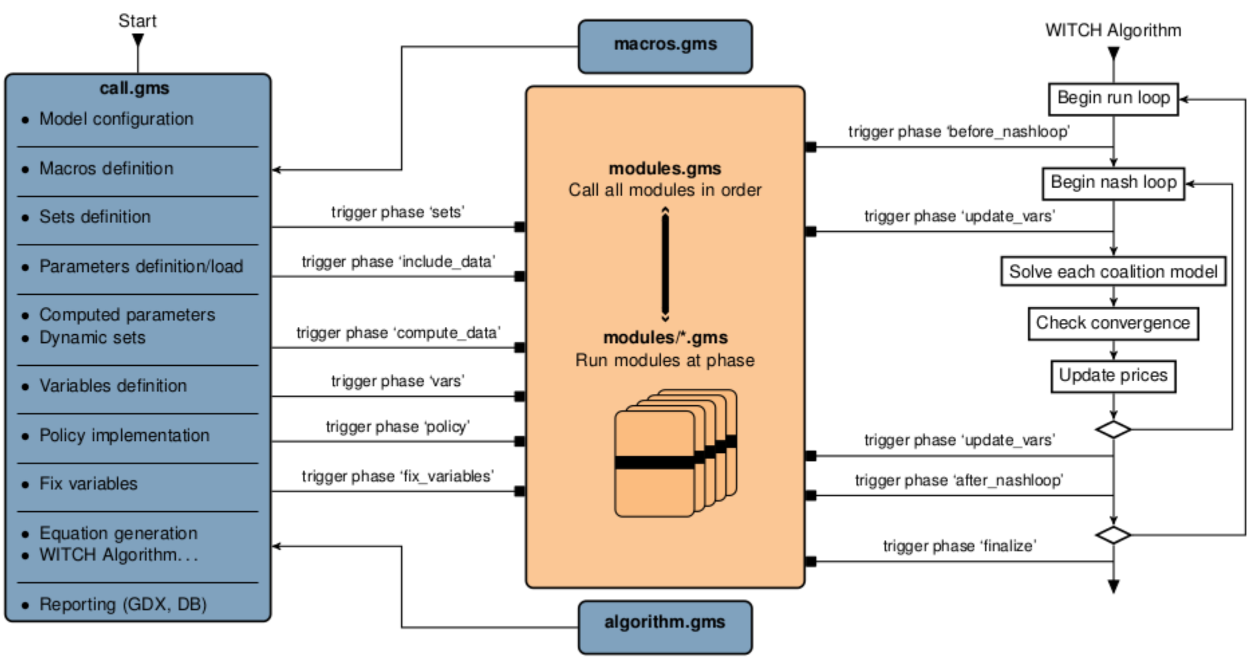

Figure 11.1: WITCH flowchart

η	Inverse of IES	eta
ρ	Pure rate of time preference	srtp(t)
γ	Degree or inequality aversion	gamma
$C(t,n)$	Consumption	Q('CC',t,n)
$I_{FG}(t,n)$	Investment in final good	I('FG',t,n)
$I_j(t,n)$	Investment in energy technologies	I_EN(jinv,t,n)
$I_{GRID}(t,n)$	Investment in electric grid	I_EN_GRID(t,n)
$I_{OUT,f}(t,n)$	Investment in extraction	I_OUT(f,t,n)
$I_{RD,j}(t,n)$	Investment in R&D	I_RD(rd,t,n)
$I_{PRADA}(t,n)$	Investment in proactive adaptation	I('PRADA',t,n)
$I_{SCAP}(t,n)$	Investment in specific ad. capacity	I('SCAP',t,n)
$I_{RADA}(t,n)$	Investment in active adaptation	I('RADA',t,n)
$Y(t,n)$	Net Output	Q('Y',t,n)
$oem_j(t,n)$	O&M costs in energy technologies	oem(j,t,n)
oem_ex_f	O&M coefficient in extraction	oem_ex(f)
$K_j(t,n)$	Capital in energy tech.	K_EN(j,t,n)
$Q_{OUT,f}(t,n)$	Total extraction of fuel f	Q_OUT(f,t,n)
$tfp0(n)$	Initial level of TFP	tfp0(n)
$C_e(t,n)$	GHG emissions costs	COST_EMI(j,t,n)
$C_f(t,n)$	Net cost of Primary Energy Supplies	COST_PES(f,t,n)
$C_j(t,n)$	Energy technology penalty costs	COST_EN(j,t,n)
$ES(t,n)$	Energy services	Q('FEN',t,n)
$K_{FG}(t,n)$	Capital in final good	K('FG',t,n)
$Q_E(ghg,t,n)$	Emissions	Q_EMI(ghg,t,n)
$tfp_y(t,n)$	Total factor productivity	tfpy(t,n)
$l(t,n)$	Population	l(t,n)
δ_{FG}	Yearly depreciation rate of capital	delta('fg',t,n)
Δ_{t}	Time step duration	tstep
$EN(t,n)$	Energy aggregate	Q('en',t,n)
$HE(t,n)$	R&D Capital in energy efficiency	K_RD('en',t,n)
$tfpn(t,n)$	Factor productivity of energy	tfpn(t,n)
$EL(t,n)$	Energy aggregate from the electric sector	Q('el',t,n)
$NEL(t,n)$	Energy aggregate from the non-electric sector	Q('nel',t,n)
$I_j(t,n)$	Investment in energy tech.	I_EN(jinv,t,n)
$K_j(t,n)$	Capital in energy tech.	K_EN(j,t,n)
$SC_j(t,n)$	Average investment cost	MCOST_INV(j,t,n)
$\delta_j(t,n)$	depreciation rate	delta(j,t,n)
$EL(t,n)$	Electric sector aggregate	Q('el',t,n)
$EL2(t,n)$	Electric sector aggregate (w/o hydro)	Q('el2',t,n)
$EL_{coalwbio}(t,n)$	Coal & wood biomass power plant aggregate	Q('coalwbio',t,n)
$EL_{gas}(t,n)$	Gas power plant sector	Q('gas',t,n)
$EL_{hydro}(t,n)$	Hydroelectric sector	Q('ces_elhydro',t,n)
$EL_{intren}(t,n)$	Intermittent renewable aggregate	Q('ces_elintren',t,n)
$EL_{nucback}(t,n)$	Nuclear and backstop aggregate	Q('ces_elnuclearback'
$EL_{oil}(t,n)$	Oil power plant sector	Q('oil',t,n)
$ELFF(t,n)$	Fossil-fuel power plants aggregate	Q('elff',t,n)
$NEL(t,n)$	Non-electric sector aggregate	Q('nel',t,n)
$NEL_{coal}(t,n)$	Energy in Coal sector	Q_EN('nelcoal',t,n)
$NEL_{log}(t,n)$	Other non-electric sector aggregate	Q('nelog',t,n)
$NEL_{trbiomass}(t,n)$	Energy in traditional biomass sector	Q_EN('neltrbiomass',

$NEL_{oilback}(t,n)$	Energy in oil and backstop non-electric	Q_EN(’neloilback’,t,n
$NEL_{gas}(t,n)$	Energy in gas sector	Q_EN(’nelgas’,t,n)
$NEL_{trbiofuel}(t,n)$	Energy in Traditional biofuel	Q_EN(’neltrbiofuel’,t,
$Q_f(t,n)$	Total amount of fuel consumed	Q_PES(f,t,n)
$Q_{j,f}(t,n)$	Total amount of fuel consumed per sector	Q_IN(f,jfed,t,n)
$Q_f(t,n)$	Total amount of fuel consumed	Q_PES(f,t,n)
$X_f(t,n)$	Total amount of fuel extracted	Q_OUT(f,t,n)
$C_f(t,n)$	Primary Energy Supplies cost	COST_PES(f,t,n)
$MC_f(t,n)$	Average cost of Primary Energy Supplies	MCOST_PES(f,t,n)
$Q_f(t,n)$	Total amount of fuel consumed	Q_PES(f,t,n)
$X_f(t,n)$	Total amount of fuel extracted	Q_OUT(f,t,n)
$p_f(t,n)$	World market fuel prices	FPRICE(f,t)
$EL_j(t,n)$	Electric production capacity	Q_EN(jel,t,n)
$KEL_j(t,n)$	Capital in electric production	K_EN(jel,t,n)
$\mu_j(t,n)$	Capacity factor of maximum production	mu(jel,t,n)
$EL_{elback}(t,n)$	Electric backstop capacity	Q_EN(’elback’,t,n)
$KEL_j(t,n)$	Total electric capacity	Q_EN(’el’,t,n)
$Q_j(t,n)$	Production capacity	Q_EN(jfed,t,n)
$Q_{j,f}(t,n)$	Amount of fuel consumed per sector	Q_IN(f,jfed,t,n)
$\xi_{j,f}(t,n)$	Sector efficiency ratio	csi(f,jfed,t,n)
$Q_j(t,n)$	Production capacity	Q_EN(j,t,n)
$I_{PRADA}(t,n)$	Investment in proactive adaptation	I(’PRADA’,t,n)
$I_{SCAP}(t,n)$	Investment in specific ad. capacity	I(’SCAP’,t,n)
$I_{RADA}(t,n)$	Investment in active adaptation	I(’RADA’,t,n)
$I_{RADA}(t,n)$	Investment in active adaptation	I(’RADA’,t,n)
$NEL_{nelback}(t,n)$	Non-electric backstop capacity	Q_PES(’backnel’,t,n)
$Q_{CCS}(t,n)$	CCS emissions	Q_EMI(’ccs’,t,n)
$M_{CCS}(t)$	CCS cumulated emissions	CUM_EMI(’ccs’,t,n)
$C_{CCS}(n,t)$	CCS costs	MCOST_EMI(’ccs’,t,
$Q_E(\text{ghg},t,n)$	Regional emissions	Q_EMI(ghg,t,n)
$WE(\text{ghg},t)$	World emission	W_EMI(ghg,t,n)
$M(\text{ghg},t)$	Concentrations	WCUM_EMI(ghg,t,n
$TRF(t)$	Total radiative forcing	TRF(t,n)
$RF(\text{ghg},t)$	Gas radiative forcing	RF(t,n)
$T(t)$	Global temperature increase	TEMP(’atm’,t,n)
$T^o(t)$	Ocean temperature increase	TEMP(’low’,t,n)
$Q_{CO2}(t,n)$	CO2 emissions	Q_EMI(’co2’,t,n)
$Q_{CO2ind}(t,n)$	CO2 emissions from fossil-fuel	Q_EMI(’co2ind’,t,n)
$Q_{CO2lu}(t,n)$	CO2 emissions from land-use change	Q_EMI(’co2lu’,t,n)
$Q_{redd}(t,n)$	Avoided emissions from REDD	Q_EMI(’redd’,t,n)
$Q_{CCS}(t,n)$	CCS emissions	Q_EMI(’ccs’,t,n)
$EX_f(t,n)$	CO2 emissions from extraction	Q_EMI_OUT(’co2’,t,
$Q_{oghg}(t,n)$	other ghg emissions	Q_EMI(oghg,t,n)
$ABAT(oghg,t,n)$	level of abatment	ABAT(oghg,t,n)
$Q_{nip}(t,n)$	net import of carbon permits	Q_EMI(’nip’,t,n)
$C_{CO2}(t,n)$	CO2 costs	COST_EMI(’co2’,t,n)
$Q_{nip}(t,n)$	net import of carbon permits	Q_EMI(’nip’,t,n)
$p_{nip}(t,n)$	carbon permits price	CPRICE(’nip’,t,n)
$C_{e}(n,t)$	Non-CO2 emission costs	COST_EMI(oghg,t,n)
$ref_e(n,t)$	Baseline emissions	emi_baseline(oghg,t,n

$\overline{abat}_e(n,t)$	Maximum abatement	emi_abat_max(oghg,
$ABAT_e(n,t)$	Non-CO2 emission abatment	ABAT(t,n)
$C_{e}(n,t)$	Emission sink costs	COST_EMI(e,t,n)
$Q_{e}(t,n)$	Emission sink	Q_EMI(e,t,n)
$M_{SAV}(t,n)$	Accumulated emission savings	CUM_EMI('sav',t,n)
$Q_{SAV}(t,n)$	Emission savings	Q_EMI('sav',t,n)
$\Omega(t,n)$	Damage coefficient	OMEGA(t,n)
$\omega_{i,n}^-$	coefficients with negative impact	comega_neg(n,i)
$\omega_{i,n}^+$	coefficients with positive impact	comega_pos(n,i)
$T(t,n)$	atmospheric temperature increase from pre-industrial levels	TEMP('atm',t,n)
$Q(ADA,t,n)$	Adaptation factor	Q('ADA',t,n)
$HE(n,t)$	R&D Capital in energy efficiency	K_RD('en',t,n)
$RD_{j}(n,t)$	R&D Capital in backstop technologies	K_RD(rd,t,n)
$SPILL(n,t)$	Spillover knowledge	SPILL(rd,t,n)
$wcum_{j}(t)$	Cumulated Installed Capacity	wcum(jrd,t)
δ_{RD}	Depreciation rate for R&D knowledge	delta_RD('en')
a	Internal spillover	crda('en',t,n)
b	Elasticity w.r.t. R&D Investment	crdb('en')
c	Elasticity w.r.t. own past knowledge	crdc('en',t,n)
d	Elasticity w.r.t. spillover knowledge	crdd('en')
$lbrrate$	Learning by Searching Coefficient	lbr_rate('jrd')
$lbdrate$	Learning by Doing Coefficient	lbd_rate('jrd')
$kpat0$	knowledge stock in 2005	kpat0
$pat0$	annual flow of patents in 2005	pat0
$enintg0$	5 years decline in energy intensity (2005-2010)	enintg0
$peng0$	5 years growth in energy price (2005-2010)	peng0
$gdpg0$	5 years growth in gdp (2005-2010)	gdpg0
$OIL_{cap}(t,n,g)$	Oil extraction capacity (by category)	OILCAP(t,n,oilg)
$\Delta CAP(t,n,g)$	Additional oil capacity (by category)	ADDOILCAP(t,n,oilg
$I_{OILCAP}(t,n,g)$	Oil investment (by category)	I_OIL(t,n,oilg)
$OIL_{capcost}(t,n,g)$	Oil Investment cost (by category)	COST_OIL(t,n,oilg)
$OIL_{prod}(t,n,g)$	Oil production (by category)	OILPROD(t,n,oilg)
	Cumulative production (by category)	CUM_OIL(t,n,oilg)
	Total Oil investment (all categories)	I_OUT(t,n)
	Total oil production (all categories)	Q_OUT(oil,t,n)
	Emissions from oil extraction (all categories)	Q_EMI_OUT(t,n)
$\lambda(g)$	Fixed floor cost component (by categories)	data_oilcost(n,oilg)
$\zeta(n,g)$	Annual Expansion threshold	esp_cap(n,oilg)
$\mu(g)$	Fixed floor cost difference (among categories)	cum_param_oil(n,oilg
$OIL_{res}(t,n,g)$	Oil resources	resmax_oil(n,oilg)
	Stoichiometric coefficient for oil extraction	emi_st_oil(n,oilg)
$K_{EN}(jel,t,n)$	Electric capacity	K_EN(jel,t,n)
$Q_{EN}(jel,t,n)$	Electric energy generation	Q_EN(jel,t,n)
$K_{EN}(jel_{solar},t,n)$	Electric capacity	K_EN(jel_solar,t,n)
$dens(jel_{solar},n)$	Installation density	inst_density(n,jel_sol
$area(solar_{distance},n)$	Competition area	inst_area(n,solar_dist
$SHARE_{EL}(jel,t,n)$	Share in the electricity mix	SHARE_EL(jel,t,n)
$c(n)$	Peak load fraction	firm_coeff(n)
$cf(jel,t,n)$	Capacity factor	cap_factor(jel,t,n)
$cv(SHARE_{EL})$	Capacity value	cap_value(jel,t,n)

$f(jel)$	Flexibility coefficient	flex_coeff(jel)
$K_{EN\_GRID}(t,n)$	Capital of the electrical grid	K_EN_GRID(t,n)
$I_{EN\_GRID}(t,n)$	Investments in the electrical grid	I_EN_GRID(t,n)
$delta\_grid(t,n)$	Grid depreciation rate	grid_delta(t,n)
$grid\_cost$	Grid specific investment cost	grid_cost
$transm\_cost(jel,distance)$	Distance-dependant transmission cost	transm_cost(jel,distan
$tfpy(t,n)$	Total factor productivity	tfpy(t,n)
$tfpn(t,n)$	Factor Productivity of energy	tfpn(t,n)
$Y_{kali}(n,t)$	Calibration GDP	ykali(t,n)
$TPES_{kali}(n,t)$	Calibration Energy demand	tpes_kali(t,n)
$\varepsilon_{Y,E}(n,t)$	Investment in extraction	income_ela(t,n)
r	Relationship between traditional biomass consumption and GDP	trbio_ctr
ϕ_{n}	Share of traditional biomass on TPES	trbio_ctr('phi',n)
$Q_{trbiomass,t,n}$	Quantity of primary energy of traditional biomass	Q_PES('trbiomass',t,
$ldv\_total(t,n)$	Total number of ldvs	ldv_total(t,n)
$ldv\_pthc (t,n)$	Number of ldvs per thousand capita	ldv_pthc(t,n)
$stfr\_total(t,n)$	Total number of trucks	ldv_total(t,n)
$K_{EN}(jveh,t,n)$	Number of ldvs per type	K_EN(jveh,t,n)
$Q_{EN}(jveh,t,n)$	Energy used by ldvs	Q_EN(jveh,t,n)
$fuel\_cons(jveh,t,n)$	Fuel consumption per ldv	fuel_cons(jveh,t,n)
$fueleff\_rate(t,n)$	Fuel efficiency improvement rate	fueleff_rate(t,n)
$travel\_intensity\_ldv(t,n)$	Travel Intensity LDV	travel_intensity_ldv(
$km\_d\_ldv(t,n)$	Kilometre demand per LDV	km_d_ldv(t,n)
$km\_d\_ldv\_tot(t,n)$	Total kilometre demand LDV	km_d_ldv_tot(t,n)
$km\_d\_stfr(t,n)$	Kilometre demand per truck	km_d_stfr(t,n)
$km\_d\_stfr\_tot(t,n)$	Total kilometre demand freight	km_d_stfr_tot(t,n)
$load\_factor\_ldv(t,n)$	Load factor LDV	load_factor_ldv(t,n)
$load\_factor\_stfr(t,n)$	Load factor freight	load_factor_stfr(t,n)
$s\_d\_ldv(t,n)$	Service demand per LDV	s_d_ldv(t,n)
$s\_d\_ldv\_tot(t,n)$	Total service demand LDV	s_d_ldv_tot(t,n)
$s\_d\_stfr(t,n)$	Service demand per truck	s_d_stfr(t,n)
$s\_d\_stfr\_tot(t,n)$	Total service demand freight	s_d_stfr_tot(t,n)
$veh\_cost(jveh,t,n)$	Vehicle cost	MCOST_INV(jveh,t,
$inv\_cost\_trad\_cars$	Capital cost of traditional cars	inv_cost_veh('trad_c
$size\_battery(jveh)$	Battery size	size_battery(jveh)

Chapter 12

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