Econometric forecasting of final energy demand using in-sample and out-of-sample model selection criteria

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Abstract

In order to come up with robust short- to medium term forecasts of final energy demand, we test a whole space of econometric panel data models using both in-sample and out-of-sample selection criteria in an approach similar to those used by Auffhammer and Steinhauser (2012) and Auffhammer and Carson (2008) and compare the results. We use this approach to translate new scenarios for GDP per capita, population and urbanisation development in the 21st century into appropriate short- to medium-term energy demand scenarios, differentiated by economic sector and final energy type.

Keywords: energy demand, econometrics, panel data, forecasting, developing countries

1 Introduction

The main cause for anthropogenic climate change is human energy use: More than three quarters of man made Greenhouse Gases (GHGs) stem from burning of fossil fuels (Edenhofer et al. 2014). Therefore, if we want to make any statements about future means to mitigate climate change, we need to think about future energy use. Energy use, in turn, is strongly related to affluence levels, both in quantity and in composition.

In order to say anything about mitigation efforts that might stem from a global or regional climate agreement, it is vital to know something about future energy demand, because it will be this demand that will mainly cause further GHG-emission if there are no changes in behaviour on the demand

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or energy supply side. Findings e.g. by Steckel et al. (2013) show that especially in the early phases of economic development, the need for final energy types that can only at high cost be substituted against other energy types is comparatively higher than for countries at a later stage of economic development: The buildup of infrastructure, which is a precondition for later growth of other sectors, comes along with high demand for cement and steel, both of which require solid fuels which can only at high cost be substituted against other types of final energy. These necessities have yet to be included into Integrated Assessment Models (IAM) of Climate Change like REMIND (Luderer et al. 2013). One possible way for this inclusion is to calibrate these models to fulfill exogenous final energy demand scenarios like the one developed by this paper, leaving the fulfillment of the demand to the energy supply system implemented in the IAM.

The release of GHGs is an external effect of energy demand. What is demanded are not GHGs, but energy services like heat, cold, mechanical power, light, information processing or entertainment. These energy services are provided with the help of final energy and specific capital or (durable) consumption goods. From an econometric point of view it is difficult to start an analysis of energy service demand directly since there hardly is data on energy service demand. Data availability is much better for final energy, which is the reason the present study will use this data.

We have created a country panel dataset on historical GDP, sector shares, population and urbanisation and energy demand for the five final energy types solid fuels, liquid fuels, gases, heat and electricity by economic sector from different sources. We use this dataset to estimate more than hundred econometric models for each economic sector and select the *best* according to several model selection criteria. The approach is similar to the one used by Auffhammer and Steinhauser (2012) and Auffhammer and Carson (2008), but focuses less on the size of the model space and rather on creating a more detailed dataset. We took special care in making the approach easily to reproduce and extend.

The results of the econometric analysis are used to translate projections of GDP per capita and population development in the 21st century into appropriate scenarios of final energy demand, separated by type of final energy.

The principal question in this paper is not new: What is the relationship between income per capita and energy demand? There is a vast amount of literature concerning this question. Many of these papers, e.g. Stern and Enflo (2013), Chontanawat, Hunt, and Pierse (2008), and Huang, Hwang, and Yang (2008) try to solve the question whether income drives energy demand or the other way round. This question is of lesser interest in our context, especially since it seems like the direction of causality between energy demand and income is not stable (Fouquet 2013; Fouquet 2010). Liu (2004) estimates residential and industrial price and income elasticities of demand for different types of energy types for 23 developed countries. He uses a dynamic panel data approach and a simple partial adjustment model between unobservable *desired* demand and actual demand, which is less flexible due to technological (capital stock) and psychological reasons.

The contribution of this paper is that it puts forward an approach to translate exogenous pathways of GDP, economic structure, population and urbansation into according final energy pathways. The method described in this paper requires little assumptions – basically those that are hidden in the exogenous pathways and the used econometric models. The latter are clear. It is flexible with respect to changes in input of historical data and future pathways of GDP, economic structure and other regressors. The straightforward econometric methods can be substitued with more advanced ones.

We proceed by giving an overview of the mechanisms of energy demand (section (2)). Section (3) describes the data used and how it is aggregated into regions. In section 4 we describe the space of econometric models used (4.1) and the used measures to select a *best* one (4.2). Resulst are discussed in section (**??**) on the global (5.1) and the regional level (5.2). Section (6) concludes.

2 Overview

It is important to understand the relation between final energy and energy services. Figure 1 depicts the way from primary energy carriers via final energy to energy services. Primary energy carriers are grouped via their state of matter (solid, liquid, gas, electricity). The focus here is on the process of energy service provision from different final energy types. It is clear that the different final energy types show different flexibility in providing energy services. [1]

Different types of energy services can be provided using different types of final energy, which again can be provided using different types of primary energy.

[1]We leave out some conversions that are feasible, but not in use anymore or only in niches, like using kindlings for lighting like it was done in the middle ages. We also do not depict the level of *secondary energy*, which is, basically the output of primary energy conversion before it is delivered to the final customer. To put it another way, final energy is secondary energy net losses occuring in storage and transport.

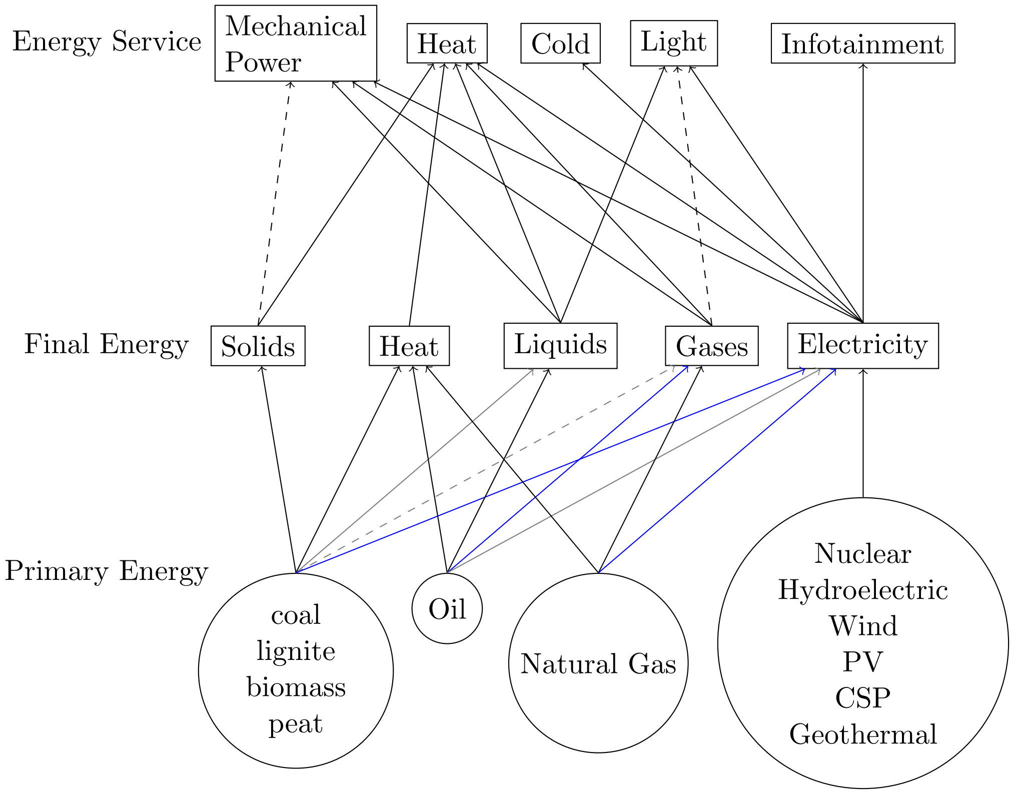

Figure 1: Schematic overview of the conversion from primary energy to final energy to energy services. Blue lines between primary and final energy indicate technologies mainly in use today. Dashed lines indicate technologies that are possible, but hardly in use anymore.

3 Data

3.1 Historical data

Final energy demand data

The main source for historical data on final energy consumption is the *Global Energy & CO2* data base from ENERDATA[2]. This database contains sector specific final energy demand data for different economic sectors, covering up to 181 countries and starting in 1970. The length of the time series for specific countries varies and some show gaps of a few years. We have closed these gaps using linear interpolation.

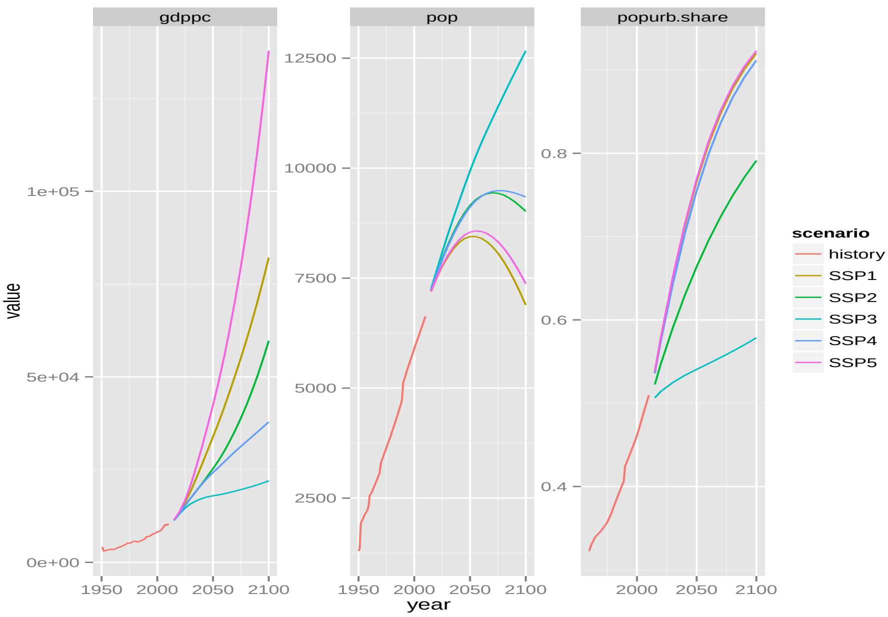

Figure 2: Overview of historical and scenario data on the global scale for GDP per capita, population and urbanisation. Sources: WDI, Penn World Tables, SSP database, own calculations

Many other papers on energy-economic issues use the energy data provided by the *International Energy Agency* (IEA) (IEA 2014). However, this data does deliver less detail: It only covers 126 distinct countries. Other countries are aggregated regions like *Other Africa*. It remains unclear how detailed the data underlying these aggregated regions are.

We aggregate different energy demand figures into five categories of final energy demand: solid fuels, liquid fuels, gases, heat and electricity. Table (1) gives an overview. This aggregation is motivated by different possibilities of

[2] `http://www.enerdata.net/enerdatauk/knowledge/subscriptions/database/energy-market-data-and-co2-emissions-data.php`

substitution. Within each category, substitution between the different fuels is possible without major difficulties.

Electricity is special in that it can be used for all economic tasks where energy is required. However, supply and demand have in general to be balanced carefully since storage is expensive. Usually electricity has the highest price of all final energy types.

ENERDATA contains demand data separately for the five sectors residential, transport, agriculture, industries and services.

Macroeconomic data

We use historical GDP per capita and population data from the most up-to-date version of the Penn World Tables *(PWT)* (Feenstra, Inklaar, and Timmer 2013). This database covers 163 countries from 1950 onwards. Since its geographical coverage is lowest of all datasets, its the limiting factor with respect to the spatial coverage of the dataset.

Information regarding the economic structure is taken from the World Developmetn Indicators. The database provides information on the shares of value added by the three classical economic sectors agriculture, industry and services on a country level from 1960 onwards for most countries.

WDI is also the source for historical data on urban population and country area.

3.2 Scenario data

The shared socioeconomic pathways

Scenarios on the future development of GDP per capita, population and urbanisation are taken from the *Shared socioeconomic pathways* (SSP) database [3]. The SSPs were developed in a joint effort by several teams of the Integrated Assessment Modelling Community and are described in O'Neill et al. (2013), Chateau et al. (2014), Dellink (2014), KC and Lutz (2014), and Leimbach et al. (2014). They provide data on GDP per capita, population and urbanization up to the year 2100 on a country level[4].

The assumptions underlying the different SSP scenarios are described in detail in O'Neill et al. (2014) and the scenarios used here are described in Chateau et al. (2014). SSP1 is a scenario that can best be described with the keyword "Sustainability". GDP per capita rises quite fast on a global scale and income equality between countries goes down. At the same time environmental impact is comparably low because adverse socioeconomic effects

[3] `https://secure.iiasa.ac.at/web-apps/ene/SspDb/dsd?Action=htmlpage&page=welcome`

[4] The SSP scenarios provide data up to 2100. However, this study does not intend to provide energy demand forecasts for such a long time frame.

of conventional growth are, at least partly, internalized. SSP2 is characterized as a "business as usual" scenario which basically extrapolates the trends that showed up over the past decades and is generally described as the most likely sceanrio without behavioural changes or policy intervention. SSP3 is characterized by a low level of international cooperation, leading to comparatively low income growth while population keeps on growing for the whole scenario time-frame. In SSP4, growth is distributed very inequally between countries (and in countries as well), leading to a situation which is slightly better than SSP3, but still worse than all other scenarios. Finally, SSP5 shows many of the characteristics of SSP1, but the focus is on conventional development. This leads to GDP growth even higher but is assumed to have much more adverse impacts on the environment.

Since SSP2 is the reference scenario, in the following, we usually present the results for SSP2, if not otherwise mentioned.

Economic structure

The SSP database described in section 3.2 do not contain scenario data on economic structure. To use, it seems evident that it is important to take the structural composition of an economy into account when thinking about the economy's energy demand:

- Industrial production usually involves large amounts of energy for processing raw materials, refining and shaping material goods. Certain processes – like the production of iron and steel – need special fuels like coke both for its energy content and as an chemical agent. These are difficult to substitute by other types of final energy.

- The service sector, on the other hand, has a much higher flexibility with respect to its energy consumption and requires less of it since human labour does play the dominant role in the creation of value added. However, the service sector requires that industrial goods like steel and cement for buildings and roads are abundant (Steckel et al. 2013; Radebach, Schult, and Steckel 2014).

Therefore we need to come up with a way to associate the SSP pathways of future GDP into pathways of structural composition. However, since this translation is not the focus of this paper, we cannot spend to much effort on it. We therefore decide to fix the shares in value added at 2010 levels. Without diving deeper into the matter, any assumption regarding future structural change is arbitrary, so no generality is lost by assuming fixed sector shares.

Figure 3 shows the result of this fixation for the United States (USA), China (CHN) and sub-saharan Africa (AFR) as well as the global results – a graph containing the results for all regions can be found in the appendix.

One can see that the assumption of fixed sector shares results in quite strong differences in scenario data for the regions. This is not surprising since we simply set in stone todays differences.

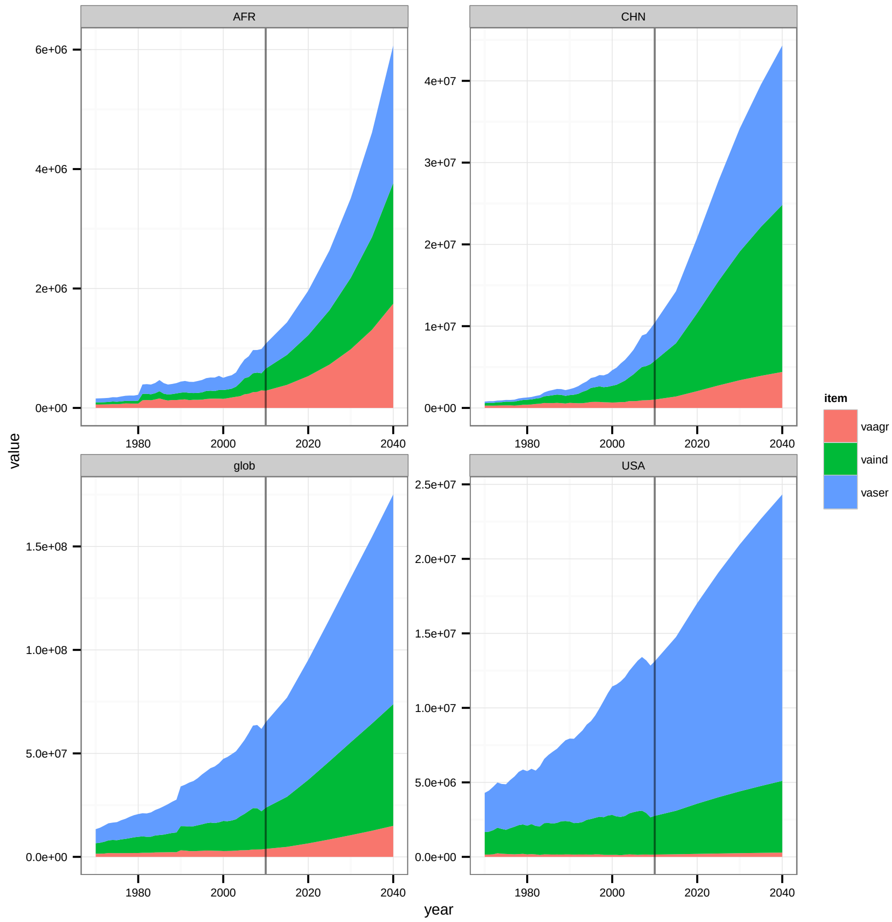

Figure 3: Historical and scenario data (SSP2) of structual composition for selected regions.
Source: WDI, SSP-Database, own calculations

3.3 Aggregation

The goal of this paper is to create forecasts of sectoral final energy demand patterns on a global scale. Normally this would mean that one estimates econometric models using only a sample of countries for which data availability is very good. The results are then transferred to the global setting under the assumption that a relationship found in the sample is also valid for countries not in the sample.

Final energy category	Final energy types	Provided energy services
Solid fuels	Coal (all types), biomass	Heating, process heat, cooking, re
Liquid fuels	Oil, Liquid biofuels	transportation, heating, cooking, l
Gases	Natural gas, manufactured gas, biogas	heating, cooking, lighting
Heat	Heat	heating, process heat
Electricity	Electricity	all energy services

Table 1: Overview of aggregation into final energy demand categories

Our approach is different. We want to directly create an econometric forecast using a historical dataset with at least close to global coverage. Like this, we do not need to make any assumptions regarding the validity of results out of sample (in the spatial dimension).

The method depicted in section (4) has higher demand to data quality than usual panel data models. In order to estimate and check an individual model, we need 21 years of data for each country or region: 10 years of data out-of-sample and at least 11 years of in-sample data.

We assume that, in general, given the high quality and coverage of todays macroeconomic and energy specific data, the lack of data for a specific variable means that there is no such demand. An example: There is no district heating in Africa and nowadays there are no steam locomotives or ships in most industrialized regions (apart from those kept and run for reasons of nostalgia) and therefore no demand for solid fuels in transport. In China, on the other hand, in some regions there are still a number of steam locomotives in everyday active duty [5].

We aggregate country specific data into regions. A graphical overview is shown in figure 9, table 3 in the appendix contains the associated regions for all countries.

4 Methodology

4.1 Model space

For each final energy type and economic sector, we estimate several dozen econometric models that can all be classified as *fixed effects* estimators. The fixed effects estimators allow for region specific intercepts that are constant over time. They are allowed to be correlated with the exogenous variables (sectoral value added / GDP per capita, population density and urbansation) and are assumed to capture all unit specific, time constant heterogeneity like, e.g. climatic or geographic influences, resource endowments and cultural differences.

[5] `http://www.economist.com/news/china/21590921-steam-trains-struggle-remote-north-west-rarer-pandas`

The basic model is depicted by equation (1).

$$D_{esit} = \sum_{k=1}^{K} \beta_k \text{va}_{sit}^k + \sum_{j=1}^{J} \gamma_j \text{popdens}_{it}^j + \sum_{h=1}^{H} \lambda_h \text{urban}_{it}^h + c_i + t + u_{ui} \quad (1)$$

Explanation:

- D_{esit} is per capita demand for final energy type e in country i's sector s at time t.
- va is sectoral added value per capita for agriculture, industry and services, respectively. For transport and residential final energy demand, va represents GDP per capita.
- $k = 1, ..., K$, $j = 1, ..., J$ and $h = 1, ..., H$ are the orders of the polynomials of *va*, *popdens* and *urban*, respectively.
- β, γ and λ are the coefficients sof the polynomials of *va*, *popdens* and *urban* to be estimated, respectively.
- c_i a country specific, time-constant intercept.
- t is the year of the observation, representing a linear time trend.
- u_{it} is an error term.

We vary the lenght of the polynomials between one and five for sectoral value added / GDP per capita and between one and three for population density and urbanisation and estimate all combinations of the different polynomials. We always include the country fixed effect. We estimate all combinations with and without time trend. With these variations, we arrive at 160 models for each sectoral final energy demand type. For all combinations of sectors and energy types, we arrive at a model space comprising 3840 equations.

4.2 Model selection

We need to select models that qualify as *best* models from the model space depicted in section 4.1 for each combination of final energy type and economic sector/activity. Since already for the comparatively small model space used in this study this is too large a task to do manually, we need model selection criteria (MSC). These are algorithms that provide us with a numerical value which can be used to decide on the best model according to the criterion at hand.

MSC can be classified according to their data requirements. If we can use the same data used for estimation to calculate the value of the MSC, then we call this MSC an *in-sample* MSC.

Examples of widely uses in-sample MSC are the R-squared (2) and its adjusted counterpart (3).

$$1 - \frac{\sum_i \sum_t \frac{u_{it}^2}{n}}{\sum_i \sum_t (y_{it} - \bar{y_i})} \tag{2}$$

$$1 - \frac{n-1}{n-k}(1 - R^2) \tag{3}$$

R-squared lies between 0 and 1 and depicts how much of the sample variance can be attributed to the regressors. Its main disadvantage is that it can never get smaller when additional regressors are included. This may lead researchers relying on R-squared to include more and more explanatory variables in their model in order to drive up R-squared. The adjusted R-squared introduces a penalty for the lower degrees of freedom that result from introducing additional regressors. Adjusted R-squared rises only if the additional explanatory power of including an additional variable is greater than the loss in explanatory power due to the loss in degree of freedoms (Greene 2012).

The same holds true for the *Akaike Information Criterion* (AIC) (4) and and the *Schwarz* or *Bayesian Information Criterion* (BIC) (5). Both criteria penalize for adding further variables stronger than the adjusted R-squared, with the BIC penalizing strongest. The theory behind the AIC and BIC is well beyond the scope of this text, they are included here because they are from an theoretical point of view much more accepted in-sample MSCs than the (adjusted) R-squared.

$$ln(\sum_i \sum_t \frac{u_{it}^2}{n}) + \frac{2k}{n} \tag{4}$$

$$ln(\sum_i \sum_t \frac{u_{it}^2}{n}) + \frac{k}{n} ln(n) \tag{5}$$

The second class of MSCs uses different data for model estimation and selection and are therefore called *out-of-sample* MSC. An econometric model is estimated using one dataset and then its results are checked using different data on the same variables.

Given one specific dataset and given the will to conduct model selection out-of-sample, we have to decide on how to split up the data into subsamples used for model estimation and model selecton. We have to decide whether we want to split up our data in the spatial or in the temporal dimension. A split in the spatial dimension would in our case of country-level data mean we only use data on certain countries for estimation. Then we use the data on the remaining countries for model selection. A split in the temporal dimension usually means that we use data up to a certain point in time for estimation and data after that time for model selection.

We follow the approach by Auffhammer and Steinhauser (2012) and use a temporal split, since like that we are able to capture unit specific heterogeneities for all units in our dataset. Implicitely, this decision means that we assume that unit specific heterogeneities do play a more important role than heterogeneities in time [6]

Another question arising from the necessity of splitting up a specific dataset into two separate subsamples is the criterion by which to perform the split: Which regions enter the estimation data set and which ones are used for the model selection in the case of a spatial split and which years are used for estimation and which years for model selection in case of a temporal split? Since any hard cut-off is somewhat arbitrary, methods were developed to overcome at least some of this arbitrariness.

The *Mean Squared Forecast Error* (MSFE) (6) does this by averaging a forecast error over multiple forecasts for multiple years. T is the final year in our historical dataset (2010), L is the number of forecast to be computed, τ is the number of years we drop initially from our complete dataset: If $\tau = 10$, in the first iteration we use all data up to the year 2000 to estimate our econometric models, then make predictions $d_{ei,t+\tau}$ for the year 2010 and compute the squared deviation from the real, observed value in 2010. This deviation is summed up for all regions to attain the squared forecast error. In the next step we use all data up to the year 1999 to estimate the model, predict a value for 2009 and again compute the squared forecast error. This process is repeated L times and then we average the squared forecast error over the iterations. This process is done for each model from the model space considered model with the lowest MSFE is chosen to be the one to have the highest predictive ability.

$$\frac{1}{L}\sum_{t=T-\tau}^{T-L-\tau}\sum_{i}(d_{ei,t+\tau} - \hat{d}_{ei,t+\tau}) \tag{6}$$

The process depicted in the paragraph above implicitly assigns equal weights to the forecast errors of the individual countries/regions. However, it can be argued, that for a global forecast it is more important to get the global values right than to get the regional values right. For this reason, we also compute the *Aggregated Mean Squared Forecast error* (AMSFE) (7) where we use the respective regions population as weight. Like this, errors in populous regions like China are weighted more heavily, leading to a selection of a model that provide more accurate forecasts of final energy demand on a global level.

[6]Some time specific heterogeneity (aka technological progress) is assumed to be captured by the inclusion of a linear time trend.

$$\frac{1}{L}\sum_{t=T-\tau}^{T-L-\tau}\sum_{i}(pop_{it} \times d_{ei,t+\tau} - pop_{it} \times \hat{d}_{ei,t+\tau}) \quad (7)$$

A big advantage of both the MSFE and the AMSFE is that by testing the predictive power of econometric models against out-of-sample data, we have to think a lot less about correct specification of the tested model. A model is suitable for the task – prediction – if it delivers predictions that show small deviations from actual values. Using in-sample-model selection, we have to be much more careful about specification issues because incorrect specification could lead to invalidity of the model selection criteria.

However, there is also one big disadvantage in using out-of-sample model selection criteria like the *(A)MSFE*: We need a higher quality of dataset, either in spatial or in the temporal dimension. In our case of a temporal split we need at least $\tau + L + 1$ years of data for each region, for $tau = 10$ and $L = 10$ this means our dataset has to go back at least 21 years into the past because we need at least two years of data to estimate the FE estimator depicted in section (4.1).

5 Results

5.1 Global results

Electricity

Figure 4 shows the results separately for electricity for residential and transport uses as well as for the industry and service sector. We leave out the results for the agricultural sector since they are not very relevant in absolute numbers and would only clutter the representation. They can, however, be found in the appendix (figure 11).

In figure 4, the black lines depict historical data. The grey area is the range of forecasts from all models in the respective model space, both for historical and scenario data. The different coloured lines show the forecasts from models selected by different model selection criteria (see section 4.2). The blue and orange lines are the forecasts from the models selected by AIC and BIC, respectively. In the case of electricity, both selection criteria always choose the same model that gives forecasts in the middle of the range of all forecasts. The same holds true for MSFE and AMSFE in the case of industry (figure 4b), where both criteria select the same model depeicting a lower increase in industrial electricity demand than the in-sample model selection criteria.

This is different for the other sectors, where MSFE and AMSFE select different models. For the residential (figure 4a) and transport sector (figure 4d), MSFE selects a model giving higher forecasts than in-sample selection criteria while AMSFE gives lower forecasts. In the service sector (figure 4c), all model selection criteria give very similar results and both out-of-sample selection criteria provide slightly higher forecasts than their in-sample counterparts.

Taken alltogether, all models forecast a steep increase in electricity demand across the sectors. But, looking at figure 4, one has to take into account the difference in scales. The highest absolute demand is likely to come from the industrial sector, increasing from around 20 EJ to somewhere between 70 and 90 EJ in 2040, conditional on the model selection criterion. For both residential and service sector energy demand is forecasted to rise from less than 20 EJ to between 50 and a bit less than 75 EJ in 2040. The transport sector shows a large increase but on low absolute levels.

Liquid fuels

Figure 5 shows the results for liquid fuels (again, the results for the agricultural sector are shown in the appendix in figure 12. Here, the differences between the models selected by the different criteria are more distinct than for electricity. Except for the case of the transport sector, AIC and BIC select the same models. The models selected by in-sample model selection criteria perform poor even in predicting the historical data – this is especially pronounced in the cases of industry and services. It is peculiar, in general, that all models predict a lower liquid fuel demand than actually observed at least for the first decade of historical data – in the case of industry even a few years into the 1980s. The model selected by MSFE for residential liquid fuel demand is rather on the extreme edge of the forecasting range, even more so than the model selected by AIC/BIC. The AMSFE selection seems very plausible and continues the stagnant historical development in spite of a rising and wealthier world population (see figure 2). For industry, both MSFE and AMSFE select a model that continues historical trends. In case of services, MSFE and AIC/BIC select similar models that rather show a slight break in long-run historical liquid fuel demand against the backdrop of a large increase in value added provided by the service sector (see figure 3). AMSFE results for the service sector depict a liquid fuel demand slightly going down over the next decades. Finally, the range of forecasts in the transport sector is smallest and all models forecast a steep rise in liquid fuel demand from the transport sector with the AMSFE giving results in the middle of the range.

Solid fuels

Figure 6 shows the range of results for solid fuels (coal, biomass). The results are somewhat similar to those of the liquid fuel demand: The models selected by in-sample criteria show a relatively bad fit for the historical data as well as not very convincing forecasts for the residential sector. The model selected both by MSFE and AMSFE show a clearly declining trend in residential solid fuel demand – and are in contrast to the increased use of solid fuels in households over the first decade of the current century. The (A)MSFE selected model probably takes into account past trends in switching to cleaner fuels like kerosene, LPG, fuel oil and natural gas for cooking and heating albeit their higher costs. It might be that these tendencies have been weakened recently due to reasons like nostalgia (fireplaces at home) and economic necessity due to the financial crisis in the years since 2008.

5.2 Regional results

In this section we compare the composition of final energy demand across regions. Since it became clear from section 5.1 that the AMSFE delivers the most convincing forecast, we here focus exclusively on the results delivered by this model selection criterion.

We have 25 regions. It is not possible nor worthwhile to go into detail for every region. We therefore focus on regions of special interest – see table 2 for details:

- The United States (USA) are the *largest economy today*. Both their population and their per capita income have been rising in the past and are projected to further rise over the next decades continuing past trends.

- China (CHN) was and is the *most populus* country in the world and has shown to be an extremely dynamic economy over the past decades. Its population is projected to stagnate while Chinese per capita income is projected to increase more than fourfold.

- Sub-saharan Africa (AFR) represents only a small fraction of world GDP today, but is projected to have nearly 1,5 billion inhabitants in 2040 in SSP2 compared to less than 800 million today. So even with a comparatively low income in per capita terms, sub-saharan *Africa will make up a significant share of the worlds economy* and therefore of its energy demand.

- India (IND) has a population equal to China today. In contrast to China, both Indias population and its per capita income is projected to increase.

The discussion in section (5.1) has shown that the models selected by MSFE and AMSFE generally provide different results. The MSFE implicitely assigns equal weights to all regions in the computation of the forecast error: China with its more than one billion inhabitants then has the

	Population [millions]			GDP per capita [I$05]		
country	1980	2010	2040	1980	2010	2040
USA	230	310	383	25021	42287	63461
AFR	346	778	1491	1315	1523	4680
CHN	971	1326	1349	1388	7859	32849
IND	700	1225	1646	1075	3432	11575

Table 2: Overview of historical and scenario (SSP2) data for USA, China (CHN), India (IND) and sub-saharan Africa (AFR)

same weight as the United States. The AMSFE corrects for that by multiplying the forecast error with the regions population, therefore assigning more weight to region with greater population. Figures (7) and 8) compare the results of AMSFE and MSFE, respectively.

The most pronounced differences can be seen between the results for China and India: MSFE chooses a model that projects a lower energy demand for China and a higher one for India compared to AMSFE. The AMSFE assigns a higher value to the forecasting error for India, since over the model selection time-frame 2001-2010, it had a lower population than China.

There are hardly any differences in the total final energy demand for the USA. However, electricity does play a more important role when model selection is done by MSFE.

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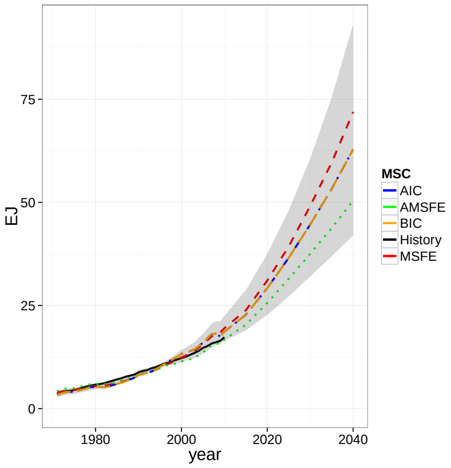
6 Conclusion

We have shown that our approach is fit to model the future development of final energy demand. Our results indicate that for SSP2, final energy demand could rise fourfold until 2040.

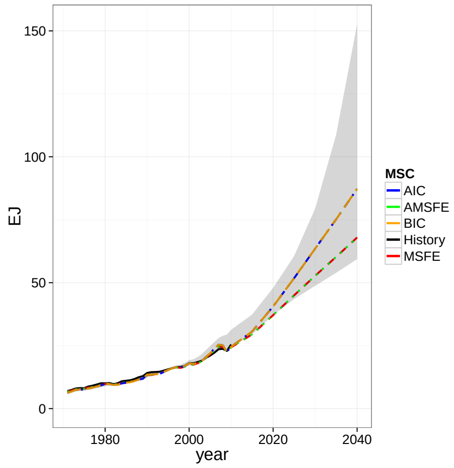
Especially for develping regions, results show a strong increase in the demand for fossil fuels. This demand could only be fulfilled by coal. Since coal has the highest carbon intensity of all final energy types, this poses a significant threat to the world climate. Policy measures will be necessary to change these demand patterns towards being more sustainable.

Region	Contained countries
AFR	AGO, ATF, BDI, BEN, BFA, BWA, CAF, CIV, CMR, COD, COG, COM, CPV, DJI, ERI, ETH, GAB, GHA, GIN, GMB, GNB, GNQ, IOT, KEN, LBR, LSO, MDG, MLI, MOZ, MRT, MUS, MWI, MYT, NER, NGA, REU, RWA, SDN, SEN, SHN, SLE, SOM, STP, SWZ, SYC, TCD, TGO, TZA, UGA, ZMB, ZWE
ARG	ARG
AUS	AUS
BRA	BRA
CAN	CAN
CHN	CHN, HKG, MAC
DEU	DEU
EUR	AUT, BEL, BGR, CYP, CZE, DNK, ESP, EST, FIN, GIB, GRC, GRL, HUN, IRL, LTU, LUX, LVA, MLT, NLD, POL, PRT, ROU, SVK, SVN, SWE
FRA	FRA
GBR	GBR
IDN	IDN
ITA	ITA
JPN	JPN
KOR	KOR
LAM	ABW, AIA, ATG, BHS, BLZ, BMU, BOL, BRB, BVT, CHL, COL, CRI, CUB, CYM, DMA, DOM, ECU, FLK, GLP, GRD, GTM, GUF, GUY, HND, HTI, JAM, LCA, MSR, MTQ, NIC, PAN, PER, PRI, PRY, SGS, SLV, SUR, TCA, TTO, URY, VCT, VEN, VGB, VIR
MEA	ARE, ARM, AZE, BHR, DZA, EGY, ESH, GEO, IRN, IRQ, ISR, JOR, KAZ, KGZ, KWT, LBN, LBY, MAR, OMN, PAK, QAT, SAU, SYR, TJK, TKM, TUN, UZB, YEM
MEX	MEX
OAS	AFG, ASM, BGD, BRN, BTN, COK, FJI, FSM, GUM, KHM, KIR, LAO, LKA, MDV, MHL, MMR, MNG, MNP, MYS, NCL, NIU, NPL, NRU, PCN, PHL, PLW, PNG, PRK, PYF, SGP, SLB, THA, TLS, TON, TUV, TWN, VNM, VUT, WLF, WSM
ROW	ALB, BIH, BLR, CCK, CHE, CXR, FRO, HMD, HRV, ISL, MDA, MKD, NFK, NOR, NZL, TKL, UKR
RUS	RUS
TUR	TUR
USA	SPM, UMI, USA
ZAF	ZAF

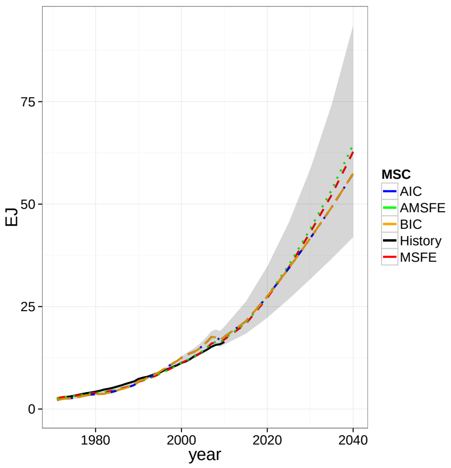
Table 3: Regional mapping



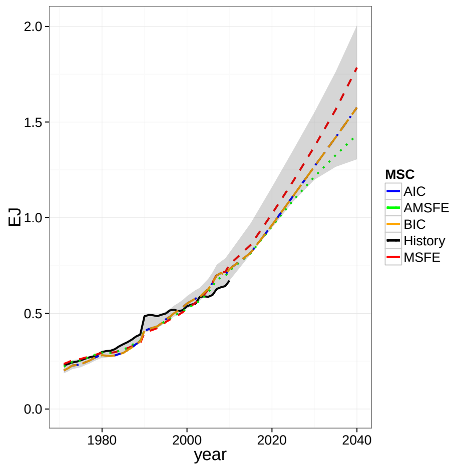
(a) Residential



(b) Industry

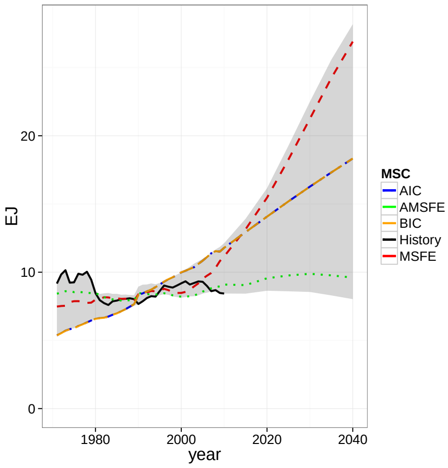


(c) Services

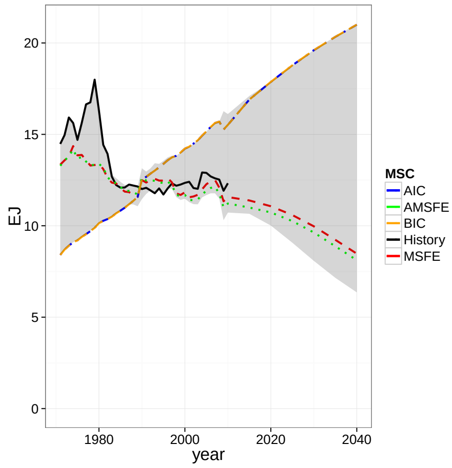


(d) Transport

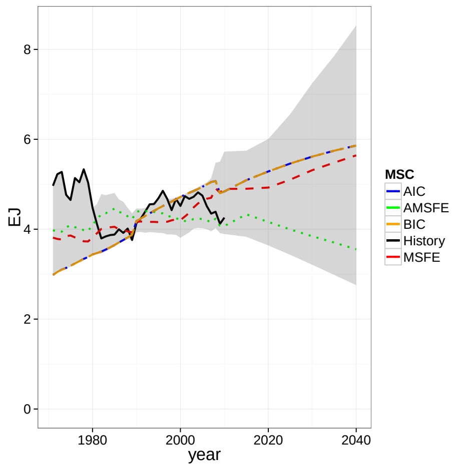
Figure 4: Results for global electricity demand
black: historical data
coloured lines: model selected by respective selection criterion (red: MSFE, green: AMSFE, blue: AIC, orange: BIC), see text



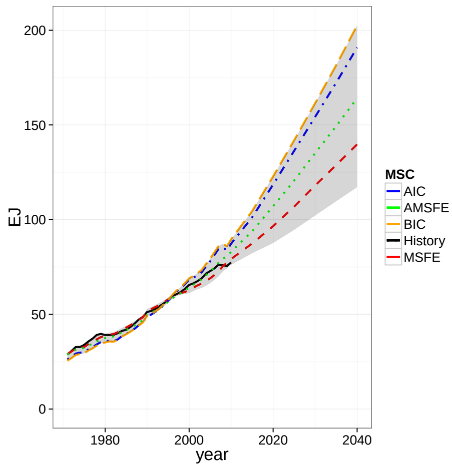
(a) Residential



(b) Industry

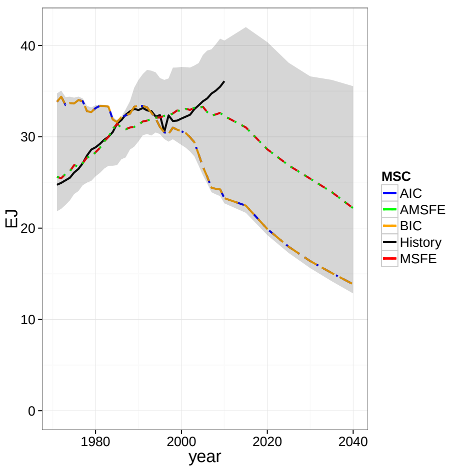


(c) Services

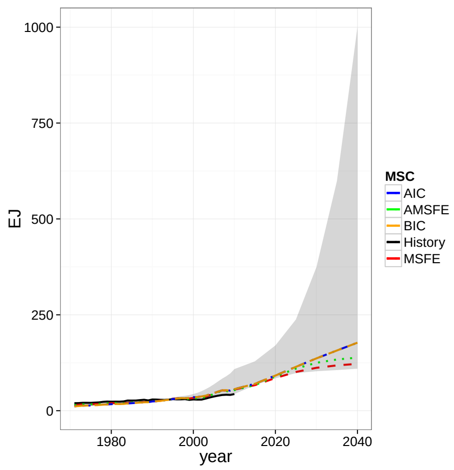


(d) Transport

Figure 5: Results for global liquid fuel demand
black: historical data
coloured lines: model selected by respective selection criterion (red: MSFE, green: AMSFE, blue: AIC, orange: BIC), see text



(a) Residential



(b) Industry

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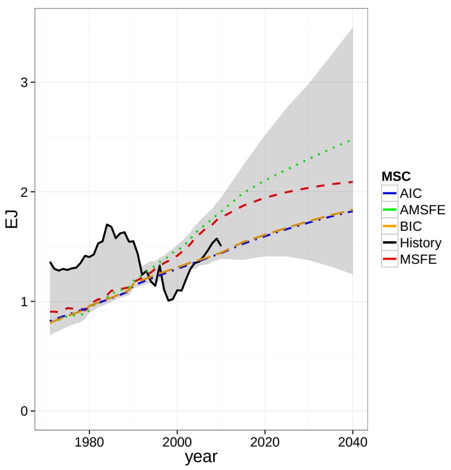
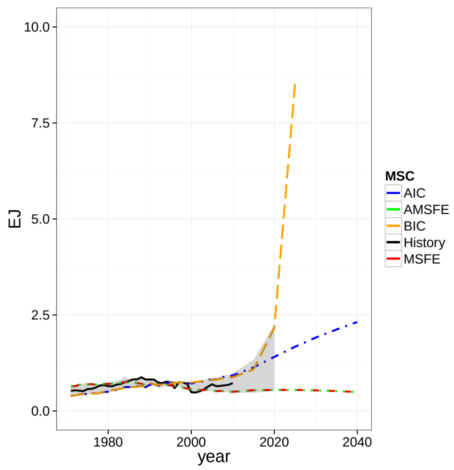


(c) Services



(d) Agriculture

Figure 6: Results for global solid fuel demand
black: historical data
coloured lines: model selected by respective selection criterion (red: MSFE, green: AMSFE, blue: AIC, orange: BIC), see text

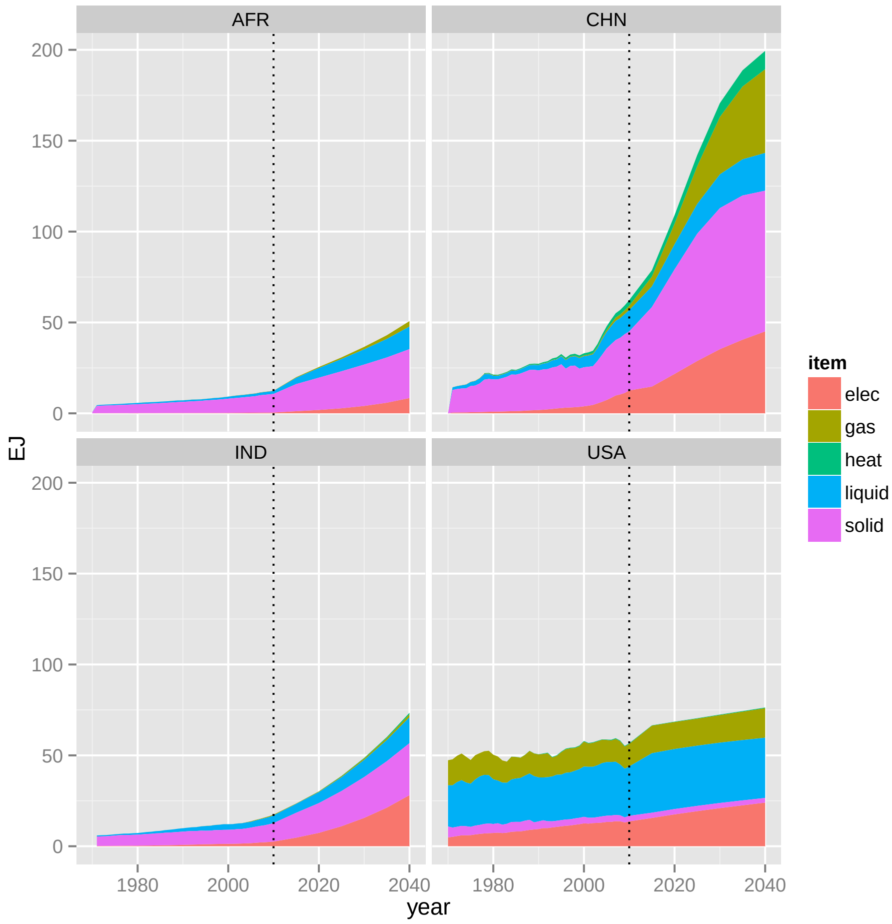


Figure 7: Final energy demand by region. Model selection criteria is AMSFE, future scenario is SSP2

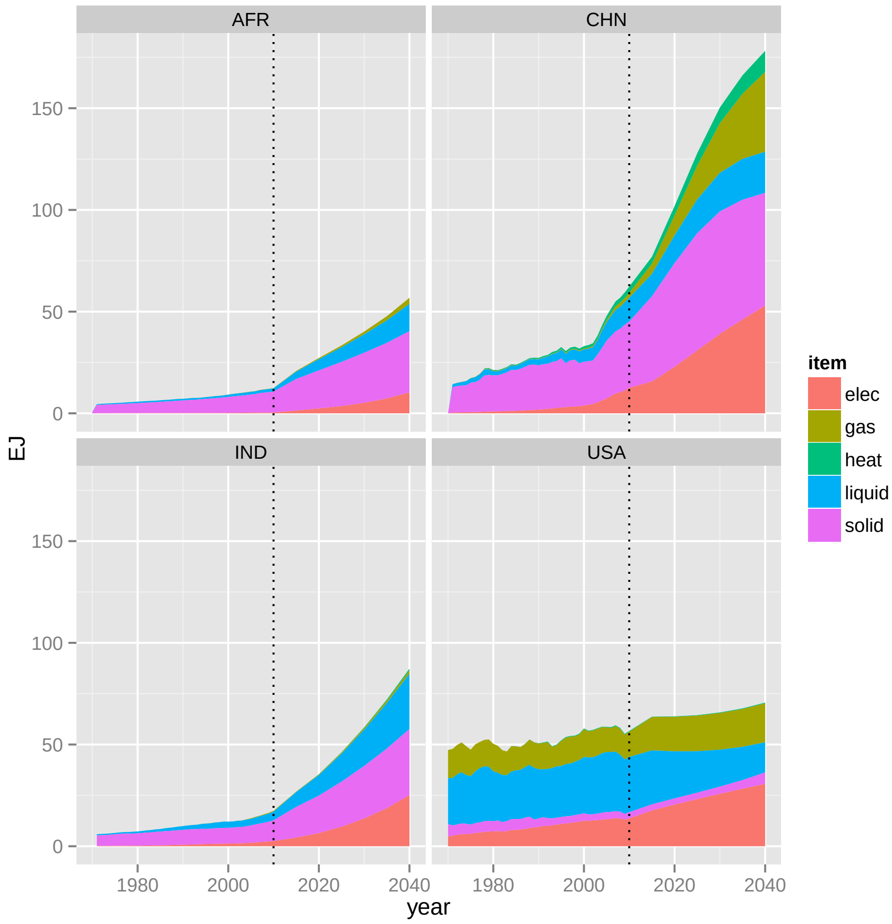


Figure 8: Final energy demand by region. Model selection criteria is MSFE, future scenario is SSP2

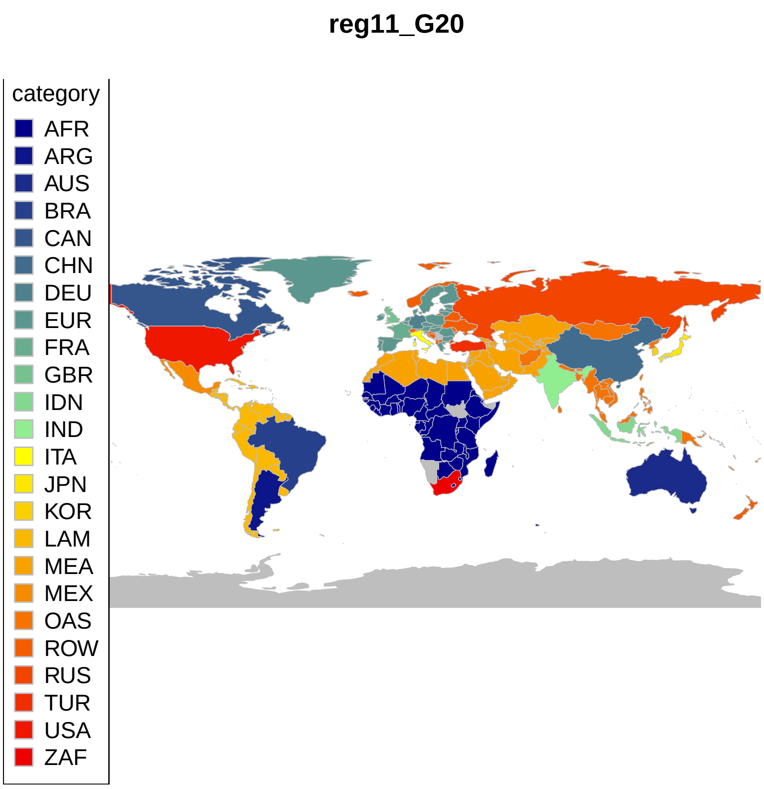


Figure 9: Regional mapping

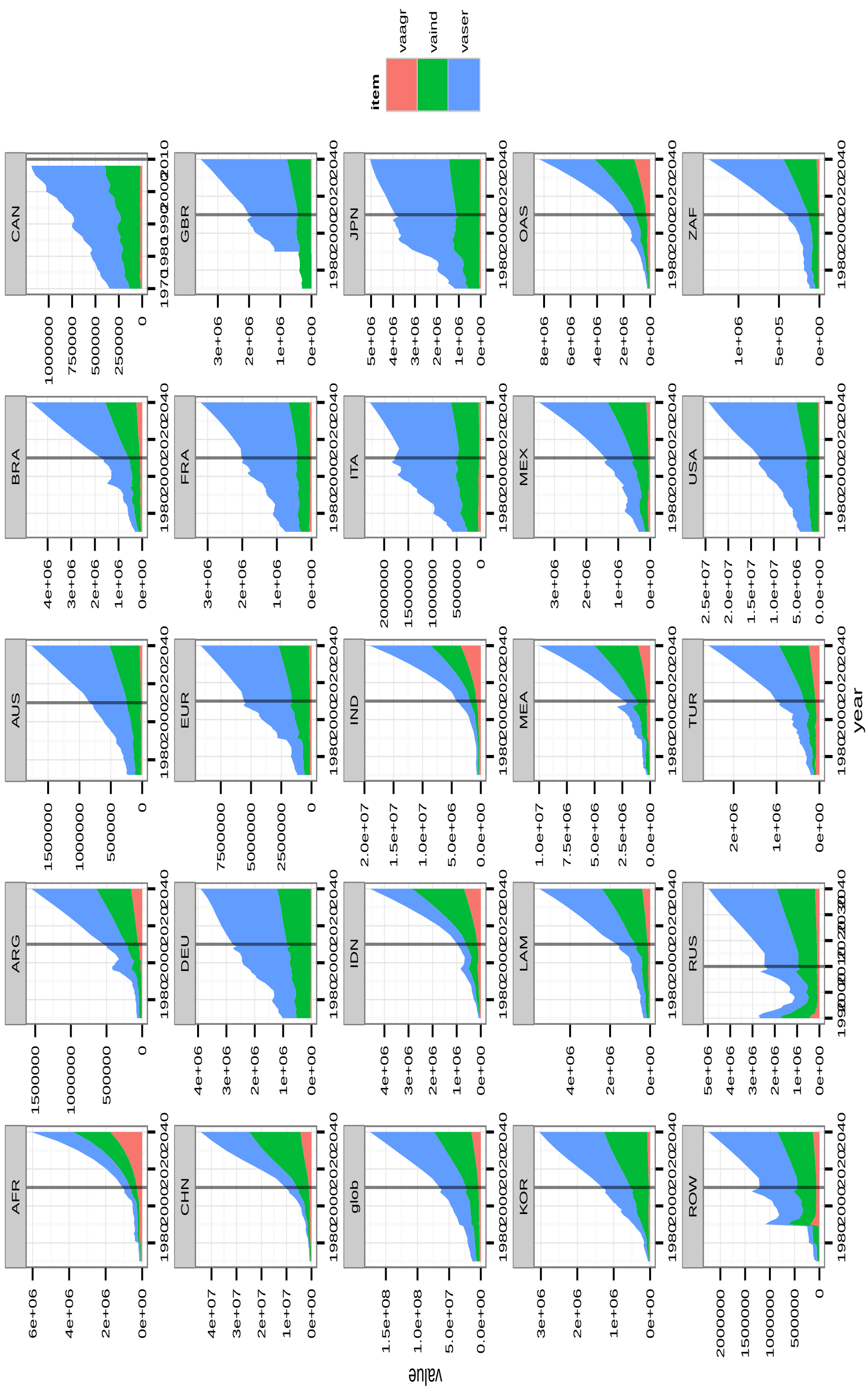


Figure 10: Historical and scenario data (SSP2) of structural composition. Source: WDI, SSP-Database, own calculations

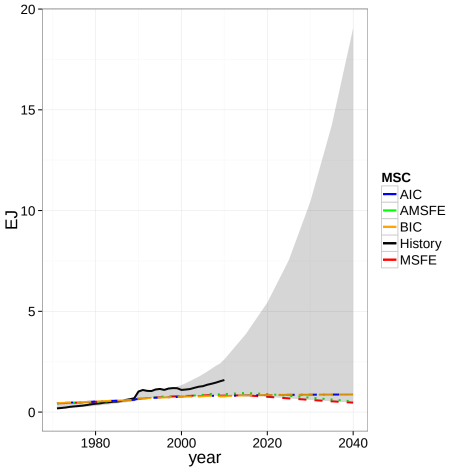


Figure 11: Results for global electricity demand in agriculture

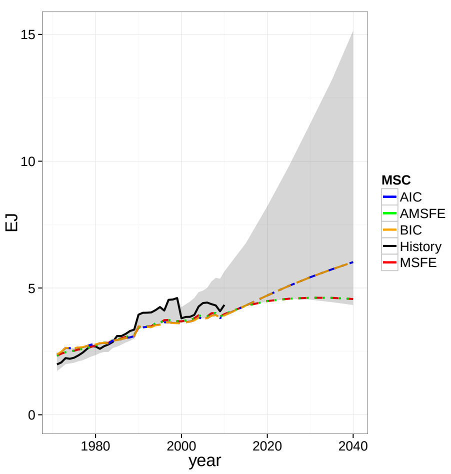


Figure 12: Results for global liquid fuel demand in agriculture

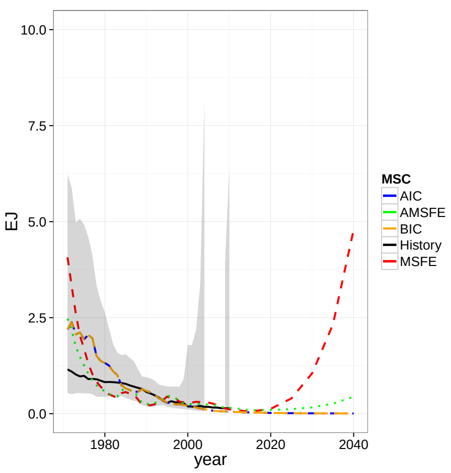


Figure 13: Results for global solid fuel demand in transport

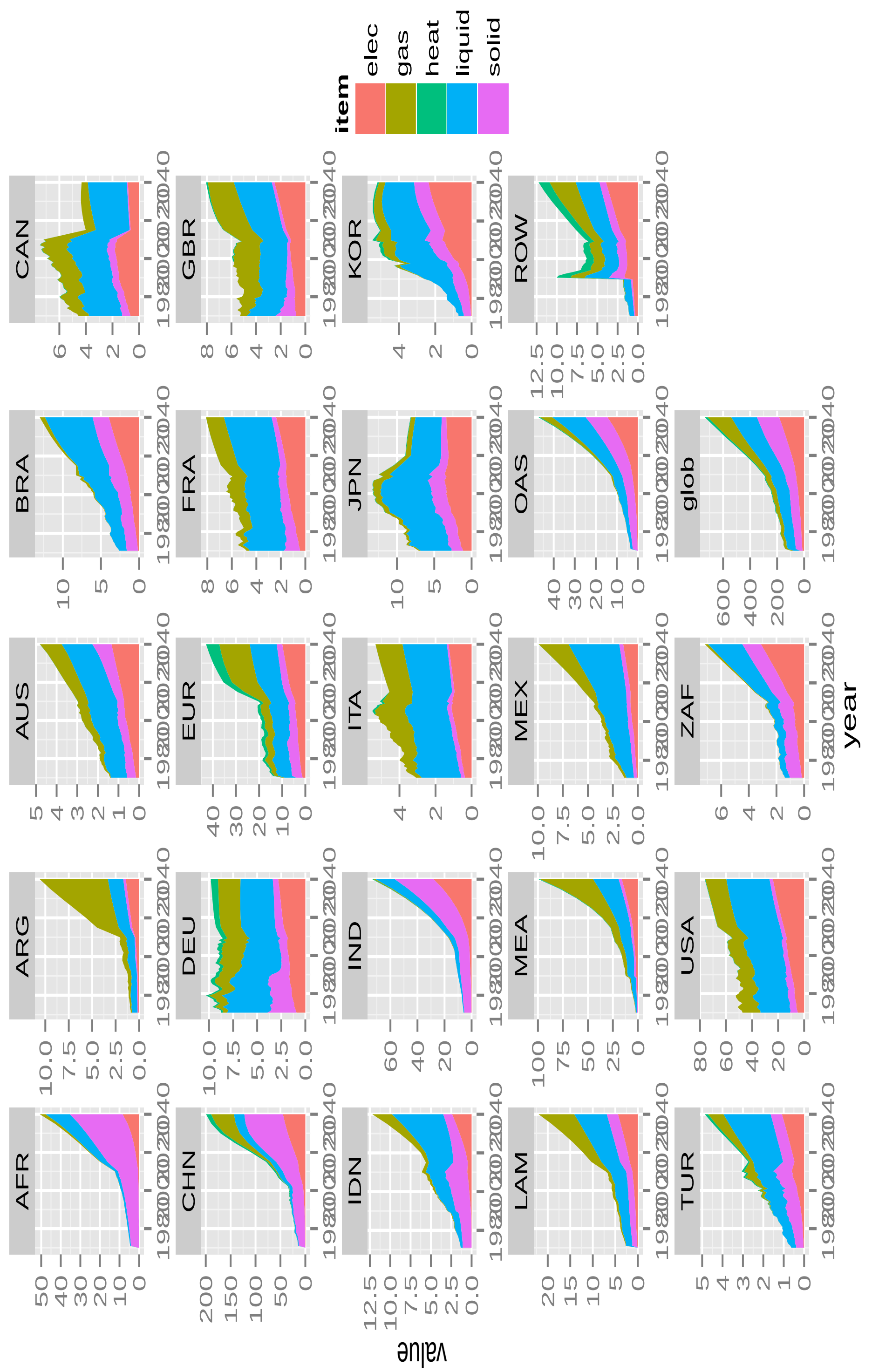


Figure 14: Final energy demand by region. Model selection criteria is AMSFE, future scenario is SSP2