Towards a global high resolution water demand dataset

Effect of data quality and downscaling techniques - the case for Europe

by

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Abstract

The development of water resource models requires reliable projections of gross and net water demand, and the ambition to bring these models to hyper-resolution makes this requirement even more important. The problem arises that high-resolution water demand data are universally missing resulting in absence of relevant studies that assess global water demand at high spatial resolution. As water scarcity threatens sustainable, economical and technological development, as well as worsen conditions for the urban poor there is a need to explore the underlying drivers, which are water availability and demand. This study focuses on two sectors that contribute to total water demand, households and industries. Drivers of domestic water demand are population growth, per capita demand, socio-economic development, demographics, lifestyle, technological development and urbanisation level. The main aim of this research is to set up a flexible framework to define high-resolution water demand for households and industries in Europe, using existing downscaling concepts and datasets with the final objective to develop and improve high-resolution global water demand estimates that may benefit from forthcoming data sources. A conceptual top-down approach on global water demand at 5 arc minute is used as a foundation, developed by Wada, which is changed to a high-resolution method by classifying possible improvements. These improvements are based on the methods of existing water demand approaches, with special focus on the pan-European empirical study of Bernhard to assess water use at high resolution. Possible improvements are conceptual changes, increase in resolution of used variables and changing the downscaling technique. A consistency problem is found as it was not possible to recreate the same outcome as Wada, although it did still perform well when measured against an observational dataset from EUROSTAT, with a higher performance when compared to higher resolution observations. Spatial distribution of domestic water demand follows along the contours of population density and through the years simulates the demographic changes of Europe: urbanisation and development of eastern Europe increase water demand, while the water use intensity and urbanisation stagnate in developed regions. For industrial water demand the same patterns are found, but total water demand is higher. Due to a higher increase in economic development in eastern Europe through time than technological development, industrial water demand relocates through the years with higher intensities in eastern Europe. Adapting the method with conceptual change on waste water connection shows this is the most dominant factor which, when incorporated correctly improves the performance of the method, but when the concept is misunderstood adds additional error causing the performance of net water demand to have no explained variation. Increasing the resolution of variables adds to the spatial distribution of domestic and industrial water demand in a country, which before was only done by the downscaling technique. GDP (main driver for industrial water demand) and population (main driver for domestic water demand) are increased and add to the spatial distribution within-country water demand. The downscaling techniques improve the performance of the method and are essential components in reaching a high-resolution dataset. Finally, a high-resolution water demand method for households and industries was constructed with a spatial resolution of 30 arcsec. This method performed significantly well for simulating both gross and net water demand in Europe for households, which was spatial distributed along population density. The performance of the industrial side of this method was much lower, which is probably caused by the wrong incorporation of the recycling ratio, adding much noise. An industrial land cover fraction downscaling method was used as well as a population map for industrial water demand, and both had nearly the same performance. Future research should test the created high-resolution water demand method for multiple years against an observational dataset. NUTS-2 level data are at this moment not retrievable anymore from EUROSTAT, and it could be recommended to use the simulated dataset from Bernhard.

Key words: high-resolution water demand, modelling, industrial water demand, domestic water demand, water stress, sectoral water demand, hydrology

Acknowledgements

I would like to compare the research that I have conducted in the last seven months with doing a multiple-week hike in the Himalayan region. The climb was at times very steep and being on an adventure for such a long time made that the goal was not always clear and visible. High peaks seemed impossible to pass at certain moments while leaving me breathless, and the valleys deep made me scared of crashing down. But the views at the top and the things I learned on the way were amazing and well worth the climb. On this trail it was easy to get lost and as hiking is not one-man sport in these areas I could not have done this without external help.

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List of acronyms and abbreviations

AGE15	*Proportion of Population younger than 15*
BIC	*Bayesian Information Criterion*
cnt	*country level*
CRU	*Climatologic Research Unit*
DDA	*Dry Days per Year*
DWD	*Domestic water demand*
DWUI	*Domestic water use intensity*
EDev	*Economic development*
EF	*Efficiency Factor*
EL	*Electricity production*
EN	*Energy consumption*
E-PRTR	*European Pollutant Release and Transfer Register*
FAO	*Food and Agriculture Organization*
GDP	*Gross Domestic Product*
GHM	*Global Hydrological Model*
GVA	*Gross Value Added*
HC	*Household consumption*
HK	*High-income, cold climate cluster*
HW	*High-income, warm climate cluster*
IEA	*International Energy Agency*
IWD	*Industrial water demand*
KTOE	*Kilotonnes of oil equivalent*
LC	*Low-income, cold climate cluster*
LUISA	*Land Use-based Integrated Sustainability Assessment*
LW	*Low-income, warm climate cluster*
OECD	*Organisation for Economic Co-operation and Development*
NUTS	*Nomenclature of Territorial Units for Statistics*
NUTS-0	*NUTS at country level*
NUTS-1	*NUTS at first subdivision: regions or states*
NUTS-2	*NUTS at second subdivision: regions, states or provinces*
NUTS-3	*NUTS at third subdivision: provinces or counties*
pc	*Per capita*
PCR-GLOBWB	*PCRaster Global Water Balance*
SDG	*Sustainable Development Goals*
SSP	*Shared Socio-economic Pathways*
T	*Temperature*
t0	*benchmark year 2000*
t	*time (year)*
TDev	*Technological development*
UNEP	*United Nations Environment Programme*
WEF	*World Economic Forum*
WP	*Water Productivity*
WU	*Water Use*
WWDR-II	*World Water Development Report II*

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1
Introduction

The development of water resource models on a regional (e.g. Wflow) or global scale (e.g. PCR-GLOBWB), requires reliable estimations of gross and net water demand into the past by reconstructions for validation purposes, and into the future to create awareness and to develop mitigation and adaptation strategies. The objective to bring these models to hyper-resolution, being globally applicable but still locally relevant supports this requirement all the more. The problem that high-resolution water demand are universally missing, results in an absence of relevant studies that consider global water demand methods at high spatial resolution.

This chapter will therefore explore the effects of (future) water scarcity and its drivers: water demand and availability, emphasizing on all aspects of water demand before elaborating on global hydrological models and hyper-resolution modeling. Increasing the resolution of existing methods raises the question whether the understanding of the system or the quality of the data is limiting. Using the mentioned problem, a framework is defined in which this underlying question can be answered.

1.1. Water scarcity

Water scarcity affects humans in more places, more frequent and over longer periods as pressures on the available water resources are rising. This existing imbalance between water availability and demand is an impending global issue and will become a key societal problem, threatening sustainable, economical and technological development, as well as worsen conditions for the urban poor [Bijl et al., 2016].

The World Economic Forum (WEF) considers water scarcity as the largest global risk in terms of impact [World Economic Forum, 2015]. Four billion people, which corresponds to two-thirds of the global population, experience severe water scarcity during at least part of the year [Mekonnen and Hoekstra, 2016]. This is therefore implying a serious future threat, making it important to regulate the growing competition for water between the involved stakeholders and to forecast and project future water scarcity problems.

The United Nations created a set of Sustainable Development Goals (SDGs) to guide global development in achieving sustainability [Gain et al., 2016; Greve et al., 2018; Rasul, 2016]. Sustainable development goal 6 tries to ensure availability and sustainable management of water globally, which directly relates to solving water scarcity.

The nature of water scarcity can be subdivided in two components, physical and economical freshwater scarcity (see Figure 1.1) [Kummu et al., 2010, 2016; Rijsberman, 2006]:

1. *Physical freshwater scarcity*, occurs because the global human population and water resources are not evenly distributed across the globe. It consists of two aspects that are linked through water use per capita:

    (a) *Water shortage* (also population-driven scarcity) refers to a low availability per person, e.g. water might become a limited resource due to pollution and even with low demands, a large population can cause water shortage.

    (b) *Water stress* (also demand-driven scarcity) refers to the ratio between freshwater withdrawals and renewable freshwater resources, taking into account the environmental water requirements, and is influenced by demographic and socio-economic changes, technological innovations, urbanisation and climate change. It is defined in this way by Alcamo et al. [2007]; Döll et al. [2003]; Wada et al. [2011a]. Water stress occurs because the availability of water is temporally and spatially variable.

2. *Economical freshwater scarcity* occurs when there are sufficient freshwater resources to meet human demands but through a lack of investment in water infrastructure those resources are unavailable for people. A positive feedback loop might arise where low development status leads to economic water scarcity which in turn will suppress economic development.

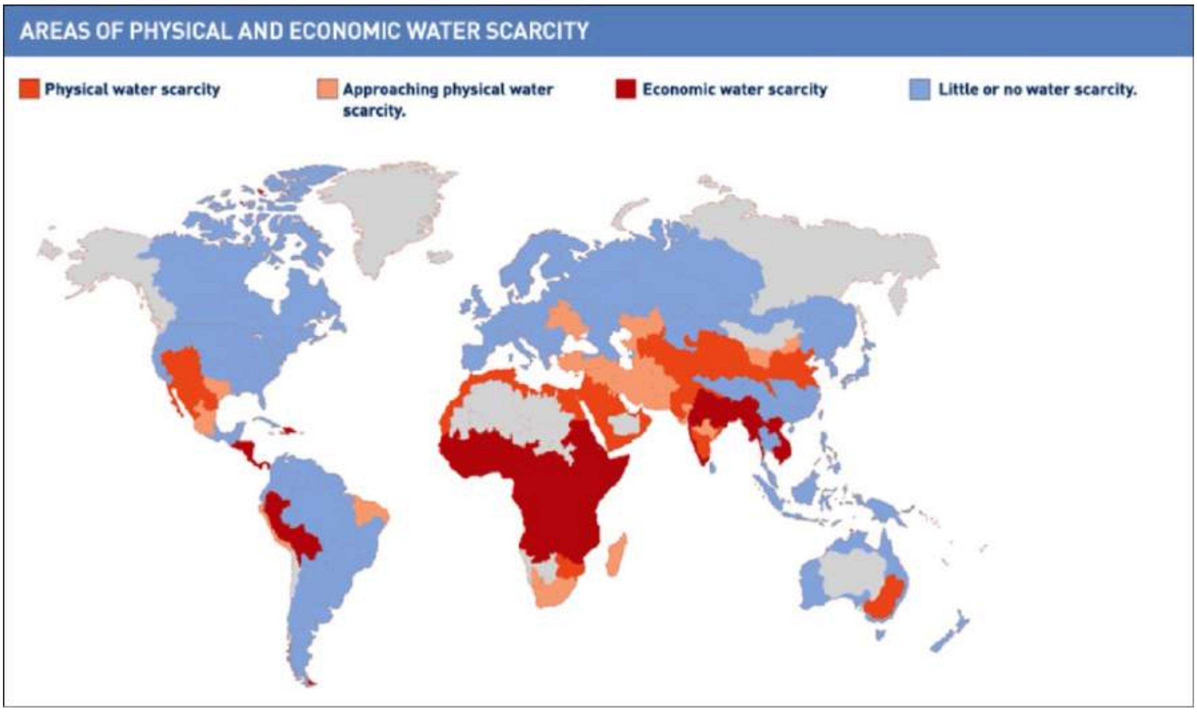

Figure 1.1: Economical and physical global freshwater scarcity in 2007 [Shah et al., 2007].

1.2. Gross versus net water demand

Water withdrawal and demand are important aspects in defining water scarcity. Water demand indicates the potential amount, i.e. the water that would be used by a sector if no limitations to availability would arise. Water withdrawal refers to the actual amount of water withdrawn from available resources to satisfy gross water demand. Gross water demand, is that portion of water withdrawals that is potentially required [Wada et al., 2011a]. Net water demand are the water withdrawals minus the return flow and is sometimes defined as potential consumptive water use. Actual consumptive water use may be lower because a portion of water withdrawn is lost from its source because of evaporation, transpiration, incorporation into crops and products, or consumption by people and livestock [Mouratiadou et al., 2016; Wada et al., 2011a]. Net water demand is lower than gross water demand since water withdrawn globally is partially returned back to river network [Wada et al., 2011b].

Water demand can be subdivided in sectors comprising the agricultural (i.e., irrigation and livestock), industrial and domestic sector. Agriculture is globally the most dominant sector comprising 70% of total annual water use [FAO, 2010; Vörösmarty et al., 2005b; Wada et al., 2013]. However, on a national scale this is not necessarily the case as developed countries have a higher rate of industrial and domestic water demand which concentrates in areas with a high population density, i.e. they are driven by external factors. As a result, industrial and domestic water demand may have a strong local effect on the hydrology and this problem becomes more significant with an increase in resolution.

Agriculture has been considered extensively in water resource modelling in global hydrological models (GHMs), and is more predictable within the limits of what is plausible. GHMs take into account water demand to analyse the effect of withdrawals on (local) hydrology. Additionally, evapotranspiration is a key component in estimating future agricultural water demand, however predicting exact changes to the hydrological cycle is difficult. Calculating variables in agricultural water demand consist mostly of climate variables and with the anticipated climate change, high uncertainties arise for projecting future irrigation water demand due to changing temperature and precipitation variability [Wada et al., 2011a, 2013]. The difference between these sectors allows this research to set the agricultural sector aside as a well covered variable [Bijl et al., 2016] with large uncertainties when it comes to projections. Meaning, this research will focus on domestic and industrial water demand only.

1.2.1. Present and future drivers of change

It is important to emphasize on the direct and indirect drivers of change for water demand. Population growth and per capita water demand are two direct key drivers of water demand [Rasul, 2016], influencing the spatial variability of domestic water demand. The world's population is projected to reach between 9.6 and 10 billion people by 2050. Population growth influences water demand also indirectly through agriculture, energy and industry, as food and energy demand and demand for industrial materials are needed which add to total water demand [Alexandratos et al., 2012; United Nations, 2013, 2017]. Other drivers are lifestyle, economic and technological development and the urbanisation level [Bijl et al., 2016; Meinzen-Dick and Ringler, 2008].

Climate change is considered to be a major driver in water demand [Hanasaki et al., 2013; Mouratiadou et al., 2016; Wang et al., 2016]. Climate change will cause increases in temperature globally and intensification of extremes of the global hydrological cycle, such as precipitation patterns [Hoegh-Guldberg et al., 2018]. As a consequence water demand will increase due to a rise in temperature, and net water demand will rise because potentially more water is lost due to higher evapotranspiration rates [Wang et al., 2016]. Changes should be monitored and assessed since water demand influences socio-economic development [Wang et al., 2016], sustainability, food security [Biemans, 2012], ecosystems [UNEP, 2012] and people's well being [Pereira et al., 2009]. This is done in external water demand assessments and is quantified for households [Bernhard et al., 2017; Flörke et al., 2013; Wada et al., 2011a, 2016] and industry [Arbués et al., 2010; Bernhard et al., 2018; Flörke et al., 2013; Vassolo and Döll, 2005; Wada et al., 2011b, 2016].

1.2.2. Domestic water demand

Next to population and per capita use of water, domestic water demand is a complex function of societal behaviour, socio-economic and technological development, climatic factors as well as public water management and strategies [Arbués et al., 2010; Vörösmarty et al., 2000a]. Even if domestic water demand makes up only a modest share of the global total water withdrawal (22% in Europe, 15% in the Americas and 9% in Asia), population growth and a higher living standard contribute to higher water demand. On the other side, technological innovations contribute to efficient water use [Flörke et al., 2013; Parker and Wilby, 2013], resulting in opposite trends. Water efficiency is reached by implementing water efficient appliances, such as shower heads, washing machines, dish washers and toilet flushing systems.

Annual temporal variability in domestic water demand is exhibited by seasonal fluctuations linked to temperature. Long-term temporal variability is driven by the concept of technological innovations, i.e. structural change, linked to the observation that water use intensity first rises when incomes increase, due to a water intensive lifestyle. After a maximum level of water use intensity is reached, water use intensity per capita either stabilizes or declines. According to FAO [2010], water use intensity of Hungary rises from 1970-1992, to 689 $m3/cap/year$ before declining and reaching 463 $m^3/cap/year$ in 2017; the USA have decreasing intensities since data is available, from 2211 $m^3/cap/year$ (1980) to 1369 $m^3/cap/year$ (2015); China has almost stable water use intensities in the same years from 424 $m^3/cap/year$ (1980) to 415 $m^3/cap/year$ (2015). Globally, spatial variability in domestic water demand is high-lighted in dominant water-use regions: eastern USA, Europe, India and China. At national level, urban areas may be identified by their high water demand driven by population density and water use intensity [Flörke et al., 2013].

Wada et al. [2011a] assessed global domestic water demand and he understood the complexity of the drivers behind domestic water demand, making it dependent on socio-economic factors, urban population, climatic variables, water use intensity and total population. Bernhard et al. [2017] assessed regional domestic water use in Europe and recognized three complex drivers behind it: income combined with water price, dry days per year as climatic variable and population below fifteen as demographic variable. Flörke et al. [2013] calculates domestic water use through drivers on water use intensity, population, GDP and technological changes. Arbués et al. [2010] estimates household water demand using drivers on water price, population ages, household size and a climate variable.

1.2.3. Industrial water demand

According to Flörke et al. [2013], total industrial water use has not an outspoken standard driver as domestic water demand has, but in order to reconstruct past industrial water demand a driver that is available for the whole period is needed (e.g. gross value added). Technological development make industrial processes more water efficient, decreasing total water demand.

Temporal variability in industrial water demand shows a global increase since the 1950's, where industrial water demand increases with economic development. China's growing population and economy resulted in doubling of total water withdrawals, of which changes in industrial water use were large due to a transition from an agricultural-based economy to an industrialized country (industrial water use increased from 7% to 26% between 1987 and 2002). Industrial water use decreased in most developed countries and the total increase in the last decades is thus a consequence of increasing industrial water use in emerging countries, newly industrialized with growing economies such as China and India [Flörke et al., 2013].

Water use in industry from public water supply accounts for 2%-50% of the total water use in European countries, making industries one of the most intensive water users. Cooling water for electricity production is categorised within production of electricity and accounts for more than 90% of total industrial water in Bulgaria (94.6%), Cyprus (99.4%), Poland (90.6%) and Serbia (97.1%). Decreasing water demand for industries will go faster for the production than for the cooling process, as the ability to take up heat by water will remain invariable.

The main aims of industrial water use for the near future focus on increasing water efficiency and decreasing the pollution of waste water. Additionally, the economic value of water within industry is higher than for households and agriculture and is without proper studies not usable for economic assessments. This makes it important to include industry in a study on water demand and including the component on cooling water [Förster, 2014].

Vassolo and Döll [2005] assessment of global industrial water use is dependent on both cooling water and manufacturing water use and withdrawals. Dependencies of cooling systems, electricity production, production volume of eight manufacturing sectors and their water intensity were included. Bernhard et al. [2018] assessment of European regional water use for industry quantified water use by using gross value added and water productivity, differentiating between different volumes used and the economic value of water used. Additionally, he subdivided industry in seven manufacturing sectors, mining, construction and services, which partially overlaps with Vassolo and Döll [2005]. Wada et al. [2011a] assessed global industrial water demand quantified by dependencies on one driver: the recycling ratio to differentiate between gross industrial water demand from a specific data source and net demand, he takes into account cooling water. Flörke et al. [2013] calculates industrial water use by dividing into thermo-electric and manufacturing water use. Key drivers are amount of electricity produced, gross value added, GDP and technological changes.

1.2.4. Historical water demand

Globally, 19% of the withdrawn water was used in 2000 for the industrial sector and 11% by the domestic sector. On a continental scale these water profiles look different. In Asia, where agriculture has a key position in society, 82% of withdrawn water is for agriculture, against 5% and 13% for industries and the domestic sector respectively. On the contrary, Europe withdraws most water for industrial activities (57%), against 21% for agriculture and 22% for households [FAO, 2010; Flörke et al., 2013]. Continental estimates on absolute water withdrawals varies extremely, were Europe abstracted 82 m^3 of water per capita in 2010, Asia withdrew 642 m^3 of water per capita [Flörke et al., 2013].

During the last centuries, global water withdrawals have experienced an exponential growth and have been linked to population growth and economical development (see Figure 1.2). Between 1800 and 1980, global water withdrawals increased fifteenfold to sustain a growing food demand and increased living standards for the world population that grew by a factor of four [Wada et al., 2014]. Since 1900 water withdrawals increased with a factor of six, coming to a 17% increase per decade between 1960 and 2000 [Vörösmarty et al., 2005a; Wada et al., 2011b]. Regions that developed the earliest, North America and Europe, saw only a small increase in water withdrawals after the 1980's, while Africa, Asia, South America and Oceania consistently increased in water withdrawn in the period 1960 to 2000 [Wada et al., 2011b].

Total global water withdrawals in 2000 were around 4000 km^3 for agricultural, domestic and industrial purposes [FAO, 2010; Vörösmarty and Sahagian, 2000b; Wada et al., 2011b]. Total water withdrawals are estimated to consist of 600-1100 km^3 groundwater abstractions [Döll, 2009], corresponding to a fifth and a third of the total fresh water withdrawals. Wada et al. [2014] found surface water withdrawal to increase between 1979-2010 from 1350 km^3 to 2100 km^3, while groundwater withdrawal almost doubled in the same period from 650 km^3 to 1200 km^3. Recently, in the period of 1990-2010, groundwater withdrawals increased relatively faster than surface water withdrawals.

Although some of the values mentioned and trends analysed come from observations, other data and trends are modelled. Data gaps in observed data from FAO AQUASTAT are filled using GIS, water balance models and regression analysis [FAO, 2010]. Döll [2009], computed the groundwater abstractions using the WaterGAP model [Döll et al., 2003]. Data by Flörke et al. [2013] in the last paragraph are retrieved from FAO AQUASTAT's databases.

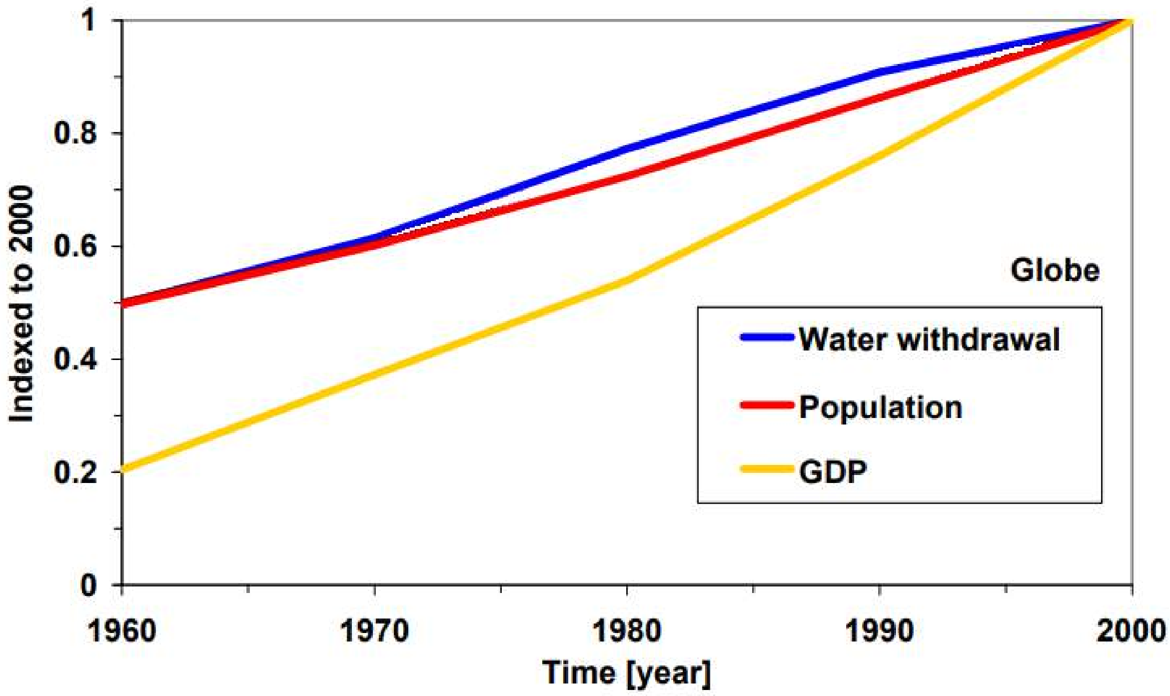

Figure 1.2: Global water withdrawals, population and GDP from 1960-2000, indexed to 2000 making it able to characterize against water withdrawal. Adapted from Wada et al. [2011b].

1.2.5. Future water demand

Future water demand, as projected in Figure 1.3, has high uncertainty for the coming thirty years, which is also mentioned in Greve et al. [2018]. Due to discontinuity, incomplete and non-existent data on past domestic and industrial water use, comprehensive global historical time series are still inadequate. Reconstructing past water use is vital in projecting future water use and in understanding how anthropogenic water demand affects the hydrological water cycle [Flörke et al., 2013; Showstack, 2011]. Wang et al. [2016] predicts that the global freshwater demand will increase with 55% by 2050, mostly in developing countries with emerging economies that are already under water stress.

The continental hydrological water cycle is directly affected by e.g. irrigation, industry and human demands. Ten percent of the global water supply was withdrawn from the continental runoff, while water resources are not unlimited. For example, most arid countries withdrew relative more groundwater than the global average: Libya used 770% of their sustainable water supplies in the 1990's. Our modern society is dependent on and limited by the terrestrial water cycle [Vörösmarty and Sahagian, 2000b]. Simultaneously, climate change affects the terrestrial water fluxes by aggravating the change in individual components, impacting water demand and availability [Haddeland et al., 2014]. Understanding how humans affect the global water cycle will contribute to lower uncertainties in projecting the future water cycle, its components and how water demand is a variable in this function. Examples of alterations and their consequences to the hydrological cycle by human hands are listed below [Vörösmarty and Sahagian, 2000b].

Aquifer mining	Translocation of water from aquifer to atmosphere. Causes a depletion of continental storage and a(n temporary) increase in atmospheric water vapor.
Surface water diversion and volume changes of inland lakes	Results in an increase in evaporation and a loss of continental water.
Desertification	Dries marginal soils, resulting in a net loss of soil water storage, an increase in storm runoff and a decrease in evaporation.
Wetland drainage	Decrease of water storage in the system, resulting in lower evapotranspiration and higher variable hydrographs.
Soil erosion in agriculture	Change to the surface topography and alteration to the groundwater table, changing the net water storage in the area.
Deforestation	Releases the vascular water storage, reducing soil water, resulting in release of water from the continental storage system. Consequently, there will be lower evapotranspiration, increased runoff and elevated groundwater tables.
Dam building	Traps freshwater runoff on continents, resulting in more evaporation from reservoirs and altering the overall water balance.

To assess future behaviour of water demand, socio-economic development and climate change scenarios should be considered, using Shared Socio-economic Pathways (SSPs) [Greve et al., 2018] as is done in e.g. Hanasaki et al. [2013]; Mouratiadou et al. [2016]. Five SSps have been created for use in global climate change studies to represent challenges for adaptation and mitigation. They depict different future global situations with e.g. SSP1 representing a sustainable world where it is easy to adapt and mitigate to climate change. Future water demand is expected to decrease globally except for African countries. SSP2 represents the continuation of socio-economic trends of the last decades, in this pathway it is expected that global water demand will increase [Hanasaki et al., 2013].

The mentioned industrial and domestic water demand method by Wada et al. [2011a], is a conceptual top-down approach, assessing water demand at a global scale. The top-down approach allows for increasing to hyper-resolution, and the influencing variables are all readily derivable from existing data sources. As it includes drivers such as economic and technological development which can be estimated using SSPs, reconstructions of past water demand are possible and projections for the future might be possible. His method is already used as input in the water resource model of PCR-GLOBWB van Beek and Bierkens [2009]. For this study, Wada's method will therefore be used as a starting point to achieve a high-resolution water demand method and dataset.

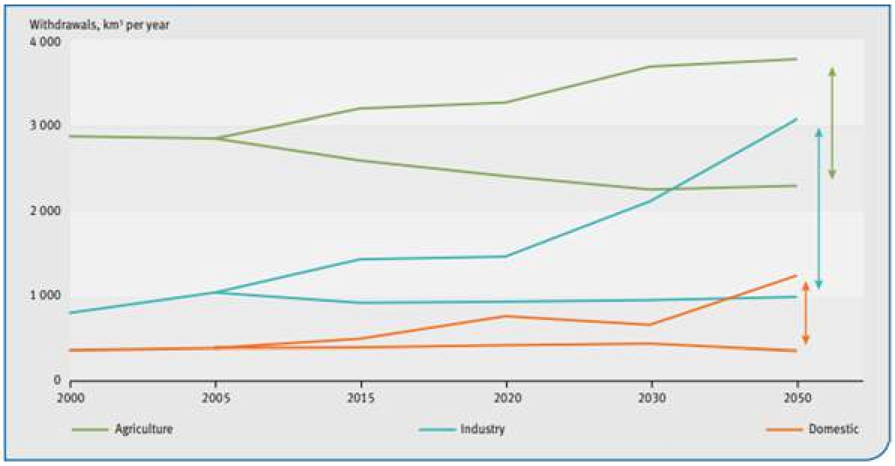

Figure 1.3: Current and projected water withdrawals by agriculture, industry and households from 2000 to 2050. Adapted from Environment Programme United Nations [2012].

1.3. Global hydrological models

The growing importance of embedding water demand correctly and on a high-resolution scale in global hydrological models (GHMs) becomes clear from the effect human induced changes have had and will have in the future on the global water cycle. Furthermore, GHMs require reliable estimations of water demand into the future to develop mitigation and adaptation strategies and to map (looming) water scarcity. Until around 2011, water demand and availability were treated independently, with no direct feedback to the terrestrial water cycle [Sutanudjaja et al., 2018].

The amount of GHMs has exponentially increased in the last two decades [Bierkens et al., 2015; Kauffeldt et al., 2016; Sood and Smakhtin, 2015; Sutanudjaja et al., 2018], e.g. the model WaterGAP by Döll et al. [2003], H08 by Hanasaki et al. [2008] and PCR-GLOBWB (PCRaster Global Water Balance) by van Beek and Bierkens [2009] and on a regional level there is Wflow by Schellekens [2017]. GHMs are important in understanding the global terrestrial water cycle by simulating the hydrological response to different external forces, e.g. climate variability and extreme weather events. PCR-GLOBWB is a grid-based GHM and shows that GHMs could be used to compare freshwater availability with sectoral water demand to assess global water stress [Sutanudjaja et al., 2018]. This is done at higher resolution than used in general circulation models (GCMs), making them useful for countless different applications and assessments, including Sutanudjaja et al. [2018]:

- Current and future flood hazards and risks;
- Current and future water scarcity under population growth and climate change;
- Projection/estimation of future flood and drought events;
- Global groundwater depletion;
- Global sea level change;
- The influence of teleconnections on climate oscillations and water availability;
- The global impact of land use change on water resources;
- Trends in surface water temperature and the potential of cooling water.

The increase in existing and used GHMs:

1. answers to the growing need to forecast and predict potential risks (water scarcity) and to understand the dynamics in a changing water cycle [Sood and Smakhtin, 2015]

2. and their applications, show what kind of valuable and leading tools they have become in global climate change assessments and environmental studies [Sutanudjaja et al., 2018; Wada et al., 2013].

In the last years, the spatial and temporal resolution has increased for demand and supply in GHMs, e.g. see Sutanudjaja et al. [2018] for PCR-GLOBWB. The resolution of the model was increased from 30 arcminutes to 5 arcminutes, and simulations showed clear improvements of the model, because the spatial heterogeneity of water use was better captured. On top of that, because of the high temporal resolution in PCR-GLOBWB water scarcity can be assessed because the temporal variability of water availability can be captured. The large-scale water demand assessment within PCR-GLOBWB is process driven and conducted in a conceptual research using global data at national level [Wada et al., 2011a, 2016].

Wood et al. [2011] and Bierkens et al. [2015] argue that spatially hyper-resolution GHMs are needed to assess future water problems, which have a resolution of 0.5 arcminutes or higher. A research in 2000 by Vörösmarty et al. [2000a], studied water scarcity projections using different resolutions. Vörösmarty et al. showed that relative water demand data at a low resolution, neglecting local-scale processes, highly underestimates the amount of people living under conditions of water scarcity.

Increasing water demand in an existing method [Wada et al., 2011a, 2016] from low to high spatial resolution to be used as an input in GHMs improves representation and increases reliability of the effects of spatial heterogeneity and thus projections on (looming) water scarcity [Vörösmarty et al., 2000a; Wang et al., 2016; Wood et al., 2011]. Accurate projections can only be made when the drivers of water demand and their influence are considered and adopted in global water demand assessments. Moreover, when regional details are considered this will allow for new insights in water demand allocation [Bijl et al., 2016]. Incorporating water demand on a global level in a high-resolution model presents a knowledge gap for different reasons, as mentioned in Bierkens et al. [2015].

1. It is difficult to find reliable recent user data on water demand with global covering on a high-resolution.

   High-resolution datasets are available for regions such as the United States, Europe (through EUROSTAT) or Australia, but not for developing regions or political closed regions, e.g. Africa [Flörke et al., 2013], where it is already hard to find national covering data at a regular timescale.

2. Higher resolution will cause supply and demand to disconnect on model scale.

Concepts that have been designed for low resolution models to contain small-scale processes would not be usable when resolution is increased. Where at a low scale explicit dynamics could have been included as a simple cell processes, at high-resolution the total dynamics have to be included, while dominant physics assumptions disintegrate. In addition, the connections of water demand and availability break up with increase in resolution.

3. Increasing the resolution of water demand will result in challenges for computational demands.

   Process time will exponentially increase with an increase in resolution, e.g. a factor of 5 increase for the resolution will increase the process time and computational demands by a factor 25. On top of this, increasing spatial resolution will ask for inclusion of explicit small-scale process dynamics, which increases process power.

1.4. Problem definition

The development of water resource models - be they implemented on a regional (e.g. Wflow) or global scale (e.g. PCR-GLOBWB) - requires reliable projections of gross and net water demand into the past for validation purposes and into the future to create awareness on looming water scarcity and to explore mitigation and adaptation strategies in respect to climate change. The goal to bring these model efforts to hyper-resolution under the credo "globally applicable but locally relevant" [Bierkens et al., 2015; Wood et al., 2011] makes this requirement all the more pressing. Yet, the problem arises that high-resolution water demand data are universally missing resulting in an absence of relevant studies that assess global water demand at high spatial resolution.

Global studies estimating water demand are often conceptual and use data at national level [Döll et al., 2003; Shiklomanov, 1997; Wada et al., 2016]. They have a resolution of 10 or 50 kilometer grid cells which neglect the impact of local characteristics, making it hard to distinguish related patterns and trends. Furthermore, limited availability and accuracy of data sources contributed to a more basic portrayal of water demand in global scale water demand modelling assessments.

At the same time, studies on water demand with high spatial resolution containing variables at regional scale use more refined methods [Bernhard et al., 2017, 2018; Reynaud, 2015], but they cover only a specified study area and do not consider global water demand. These models can simulate more, yet the same method cannot be applied on a different area since data sources for other areas have often lower data densities.

1.5. Aim and research goals

This research will address the point of Bierkens et al. [2015]: the difficulty of finding reliable user data on water demand with global covering at high resolution in connection to the sectoral water demand of households (including municipalities) and industry (manufacturing only). As mentioned before, this choice is made by the fact that these sectors constitute a substantial part of the total water demand in areas with high population densities and therefore have a strong local effect on the hydrology through water withdrawals. In the future, the impact of these two sectors on a local to global hydrology scale may increase as a result of the growing water demand due to projected population growth, rising living standards and ongoing urbanization on the one hand and the changes in water availability due to climate change on the other.

The estimation of water demand for these sectors (hereafter called households and industry) is largely data-driven (by external factors) and therefore different from modelling irrigation water demand which is mostly constrained by environmental factors and thus is more receptive for direct incorporation into hydrological water resource models [Wada et al., 2014]. The same story holds for thermo-electric cooling [Van Vliet et al., 2016, e.g.] which often is lumped with the industrial water demand [Vassolo and Döll, 2005].

The spatial scope of this study will be the European Union as data are regularly published by EUROSTAT for all the member states that still all have different environmental, socio-economic and institutional factors. The highest resolution possible on EUROSTAT - the statistical office of the European Union - is on NUTS-3 level (Nomenclature of Units for Territorial Statistics). Point one of Bierkens et al. [2015] foresees a problem with high-resolution data at global scale, which will be bypassed here as high-resolution data for Europe is in fact often available.

This study is conducted to track down the possibilities and the restrictions of existing downscaling techniques in context of a high-resolution water demand method and to determine the effect of data quality for the purpose of global applications. The approach should be flexible so when forthcoming high-resolution data sources become available its effect can be determined and it can be implemented without changing the model. The existing top-down conceptual approach by Wada et al. [2011a], will be used as a foundation for this study. Components of a high-resolution pan-European water use method by Bernhard et al. [2017, 2018] will be used to achieve a high-resolution water demand method and dataset. The aim of this resolution can be captured as:

"To set up a flexible framework to define and test high-resolution water demand for households and industries in Europe, using existing downscaling concepts and datasets with the final objective to develop and improve high-resolution global water demand estimates that may benefit from forthcoming data sources."

To understand and achieve the aim, four research objectives are formed with a corresponding explanation, which will be reached with the help of literature, data collection, sensitivity analysis and validation:

1. Identifying the potential improvements on the existing water demand method by Wada and analysing other water resource approaches.

   It is important to investigate the existing method of Wada and the possible improvements to be able to identify which variables should be altered, added, updated or left out. The global low-resolution method of Wada will be discussed in chapter 2, along with the pan-European method of Bernhard to classify potential variables that could be improved. The usability of Wada's method depends on the outcome of the validation with observational data.

2. Analysing the quality of interpreting the recreated method and datasets of Wada to estimate European water demand for households and industry.

   It is necessary to develop a reference dataset on water demand using Wada's method against which the improved datasets and method can be compared. When created, the reference dataset should be measured against (1.) the outcome of the original research by Wada to find (in)consistencies; and (2.) observational data on water demand from an external source to measure the quality of the method and where it stands now.

3. Adapting the individual parameters and concepts that contribute to the improvements of the domestic and industrial water demand method and analysing their quality.

   One by one parameters and data are improved and concepts are changed in the existing reference dataset. This enables measuring the most dominant, robust and essential factors that improve the method to best resemble water demand observations and counteracting overparameterization by means of a sensitivity analysis. Robustness allows to apply the adapted method outside given temporal and spatial boundaries. The adapted sectoral water demand is also compared against the reference dataset to find how improvements are spatially distributed.

4. Measure to what extent the improved high-resolution method and dataset are applicable for construction of a European water demand dataset.

   All contributing parameters, data and concepts to resemble observational water demand data are added together in the flexible framework. The amount of information that is left when comparing the high-resolution flexible framework against low resolution or uncertain global datasets. The method itself should allow for changes in data input when higher resolution and/or global covering data becomes available by being flexible.

1.6. Organization of the thesis

After the introduction (Chapter 1), which includes a background in water scarcity, water demand and their applications in global hydrological models, this thesis will be built up in 5 additional parts.

The second chapter elaborates on existing water resource approaches with special attention to the water demand method developed by Wada and the regional water use method developed by Bernhard. This chapter is concluded by comparing these approaches and identifying similarities as well as improvements possible for the method of Wada.

In the method section, the third chapter, the methods are described which are used in this study to achieve the aim. First, the validation dataset and the difference in water resource terminology will be explained. The recreation of the method of Wada to serve as a reference dataset is explained next. The need for a sensitivity analyses and the drivers behind it are then given, before explaining which results are needed to be generated to achieve the goals of this research. In addition, an elaboration is given on the changed components, before ending this chapter with the method for the high-resolution water demand dataset.

In the results in chapter 4, existing water resource approaches are compared with each other and with observational data for both sectors. The outcome of the reference dataset is then given in absolute values and compared to the original outcome of Wada and to the validation set. Subsequently, the results of the sensitivity analysis, and there will be elaborated on the influence and dominance of all adapted variables, concepts and downscaling techniques. With the gained knowledge, the high-resolution water demand dataset is created, and its performance is also measured.

Chapter 5, the discussion, will be organised in a way that the four research objectives, which contribute to achieving the aim of this research will be discussed in order. The potential improvements of a conceptual top-down approach and the implementation by Wada are considered first before emphasizing on components which improve sectoral water demand methods using other approaches. The individual parameters and concepts that contribute to the needed improvements and their quality are analysed. Subsequently, the outcome of the high-resolution water demand method is discussed. Finally, the uncertainties of this research are explained and advice for future research is given.

Finally, in chapter six, a conclusion is drawn on the performance and the ability to construct a high-resolution water demand method.

2

Existing water demand approaches

This chapter compares the conceptual water demand methodology of Wada and the empirical method for assessing water use by Bernhard respectively. It will describe each method first and list the underlying data and assumptions. It will conclude with comparing the two methods. This provides the basis for the methodology of this study as defined in Chapter 3.

2.1. Global water demand assessed by Wada

Yoshihide Wada assessed global water stress using simple rules at a seasonal scale but at low resolution - 0.5°or 5 arcminutes - as he was driven by a global water problem [Wada et al., 2011a]. The most essential aim of his assessment was to include the long-term projection for water demand, for the past and the present. Expanding on existing annual assessments, Wada used a finer, monthly temporal scale to capture the seasonal phase shifts in water demand and availability peaks.

Wada defined water demand as the net water demand, i.e. the water withdrawal minus the return flow from fresh surface water or blue water. In the same way, blue water demand is defined as net blue water demand, i.e. the potential consumptive use from available resources. Global blue water demand comprises of the agricultural, consisting of irrigation and livestock, industrial and domestic sectors aggregated to the same spatial resolution. Net blue water demand is lower than gross blue water demand as part of the industrial and domestic water demand is recycled and returned, whereas part of gross irrigation water demand is met by green water availability. As blue water demand is used to study water stress an assumption is made as this leads to an optimistic assessment. By reasoning that (1.) The return flow of water is to some extent constant, and (2.) losses by evapotranspiration in irrigation add to a large amount of the total water demand, gross and net, net blue water demand is used to estimate consumptive water use [Döll and Siebert, 2002].

Examining the water stress consisted of two parts: assessing natural water availability and water demand, the latter being the focus in this chapter. Additional information on the concepts of his method were retrieved from [Wada et al., 2014; Wada and Bierkens, 2014]. Throughout the years, this method was used and improved in ways that it better resembled present and historical water demand [Wada et al., 2016]. Wada has adapted his original method by incorporating recent datasets, population changes and socio-economic and technological development to come to net and gross, industrial and domestic water demand. For a flowchart that visualizes the dependencies and data sources to retrieve domestic and industrial water demand, see Figure 2.1.

2.1.1. Industrial water demand

In Wada et al. [2011a, 2016], gross gridded industrial water demand data for 2000 were taken from the WWDR-II dataset at a resolution of 30 arcmin, and was assumed to be constant over the year [Shiklomanov, 1997; Vörösmarty et al., 2005b; World Resources Institute et al., 1998], see Appendix B, Figure B.3. This is a pre-established dataset, calculating gross water demand for industry from World Resources Institute et al. [1998]. This report mentions all industrial sectors are included in the calculation and states that cooling water is a huge part of their total withdrawals, which is thus assumed to be part of the demand but exact values are not given.

It should be kept in mind that most of the industrial water use is for cooling of nuclear and thermal power generation, which will generate a large return flow. In developed countries, industrial water is partially recycled or reused, adding to this return flow. Consequently, this means it is important to consider water recycle rates and since not all withdrawn water will be used, differences between gross and net water demand could arise.

There is a data gap in global recycling rates, thus a method was developed by Wada et al. [2011a], where recycling rates in Japan derived from Ministry of Land, Infrastructure, and Transport in Japan (MLIT) [2007] were interpolated between years on the basis of GDP and the level of economic development and extrapolated to other countries to cover globally, see Table 2.1. The historical development of Japan was used for this, considering deflation for indexed data of the year 2000. Once a country was developed the recycling ratio was kept at a level of 80%.

For the method of 2011, gross industrial water demand was retrieved from the WWDR-II dataset, whereas net industrial water demand was calculated combining the gross demand and the actual consumption [Wada et al., 2011a].

Development stage	**GDP/year**	**Average GDP**	**Recycling Ratio**	**Actual consumption**
Developing economies	< US$755	US$359	40%	60%
Emerging economies	US$756-US$9,265	US$2,843	65%	35%
Developed economies	>US$9,266	US$21,880	80%	20%

Table 2.1: Global recycling rates from the historical GDP development and recycling rates of Japan [Wada et al., 2011a].

$$\mathrm{EDev}_{\mathrm{cnt},t} = \mathrm{average}\left(\left(\frac{\mathrm{GDP}_{\mathrm{pc},t}}{\mathrm{GDP}_{\mathrm{pc},t0}}\right)^{0.5}, \left(\frac{\mathrm{EL}_{\mathrm{pc},t}}{\mathrm{EL}_{\mathrm{pc},t0}}\right)^{0.5}, \left(\frac{\mathrm{EN}_{\mathrm{pc},t}}{\mathrm{EN}_{\mathrm{pc},t0}}\right)^{0.5}, \left(\frac{\mathrm{HC}_{\mathrm{pc},t}}{\mathrm{HC}_{\mathrm{pc},t0}}\right)^{0.5}\right) \tag{2.1}$$

$$\mathrm{TDev}_{\mathrm{cnt}} = \left(\frac{\mathrm{EN}_{\mathrm{pc}},t}{\mathrm{EL}_{\mathrm{pc}},t}\right) \;/\; \left(\frac{\mathrm{EN}_{\mathrm{pc},t0}}{\mathrm{EL}_{\mathrm{pc},t0}}\right) \tag{2.2}$$

$$\mathrm{IWD}_{\mathrm{gr}_{\mathrm{t0}}} = (\mathrm{IWD}_{\mathrm{gr}_{\mathrm{t0}}})_{cnt} \times (POP_{5arcmin}/POP_{cnt}) \tag{2.3}$$

$$\mathrm{IWD}_{gr_t} = \mathrm{EDev}_{\mathrm{cnt},t} \times \mathrm{TDev}_{\mathrm{cnt},t} \times \mathrm{IWD}_{gr_{t0}} \tag{2.4}$$

$$\mathrm{IWD}_{net_t} = \mathrm{IWD}_{gr_t}(1 - R_{industry}) \tag{2.5}$$

Wada et al. [2011a] was improved to Wada et al. [2016] which linked socio-economic factors at country level to temporal development of industrial water demand. The calculation of industrial water demand relies on the gross industrial water demand dataset by the WWDR-II as input and considers the change in population and socio-economic and technological development, as well as taking into account the generalized recycling ratio. The assessment opted to use the year 2000 as the benchmark, indicated as $t0$.

Economic development (EDev, see equation 2.1) constitutes of four socio-economic drivers: Gross domestic product (GDP), electricity production (EL), energy consumption (EN) and household consumption (HC). GDP is the per capita (pc) sum of gross value added by all resident producers at purchaser's prices, EL is the sum per capita of the electrical energy production by all the generating sets concerned, EN is the sum of energy consumption per capita by the different end-use sectors and HC is the value of all goods and service per capita purchased by households. All four socio-economic variables can be calculated for year t between 1961 and 2014 and are divided by the benchmark year which is established at 2000 ($t0$), this allows for temporal development linked to economic development at national level.

Technological development (TDev, see equation 2.2), associated with industrial water demand and its future changes, is estimated by energy consumption per unit of electricity production. They were indexed against the base year 2000, which will make the units disappear and will give a relative meaning to the proxy for economic and technological development. This estimation accounts for improved water use or industrial restructuring. Again, the benchmark year is considered here as the relative development of electricity production and energy consumption against the reference year are compared, allowing for temporal development.

Dis-aggregating the dataset from WWDR-II, consisting of gross industrial water demand at 30 arcminute (50x50km) in 2000 is achieved by calculating the total industrial water demand for a country (cnt), the first part of equation 2.3, and subsequently redistributing the water demand by downscaling to the gridded 5 arcmin resolution population density map for 2000, based on night-time light intensity using the weight of population per cell (see Appendix B Figure B.5).

Gross global blue water demand for a chosen year *t* in a time series is subsequently calculated by multiplying the two development indicators at country level with the disaggregated gross industrial water demand at 5 arcminute (see equation 2.4). Multiplying technological development and economical development yields the water use intensity. The objective of Wada to create water demand at 5 arcmin allows for a much better representation of the spatial heterogeneity globally [Sutanudjaja et al., 2018].

Net water demand is defined as the water withdrawals minus the return flow, so to estimate yearly global industrial water demand, the recycling ratio has to be integrated (see equation 2.5. The gross industrial water demand is multiplied with the actual consumption as in Table 2.1.

In Table 2.2 an overview is given of the variables mentioned in the four equations as well as their definition, spatial and temporal resolution, the data source and for which years data was retrieved in order of appearance, followed by their subscripts. In Appendix A, Table A.2 extended information on webpages can be found.

Variable	**Definition**	**Resolution spatial/temporal**	**Source**	**Year**
EDev	Economical development	country/year	equation 2.1	1961-2014
GDP	Gross Domestic Product	capita/year	World Bank	1961-2014
EL	Electricity Production	capita/year	UNEP	1961-2014
EN	Energy consumption	capita/year	UNEP	1961-2014
HC	Household consumption	capita/year	UNEP	1961-2014
TDev	Technological development	country/year	equation 2.2	1961-2014
$\mathbf{IWD_{gr_{t0}}}$	Gross industrial water demand	30 arcmin/2000	WWDR-II	2000
$POP_{5arcmin}$	downscaling map population	5 arcmin/2000	IMAGE26	2000
POP_{cnt}	total population	country/2000	IMAGE26	2000
$\mathbf{IWD_{gr_t}}$	Gross industrial water demand	5 arcmin/year	equation 2.4	1961-2014
$R_{industry}$	Recycling rate	country/year	Table 2.1	1961-2014
$\mathbf{IWD_{net}}$	Net industrial water demand	5 arcmin/year	equation 2.5	1961-2014
cnt	per country	-	-	-
pc	per capita	-	-	-
t	year	-	-	1961-2014
t0	benchmark year	-	-	2000

Table 2.2: Variables for calculating industrial water demand [Wada et al., 2011a,b, 2016].

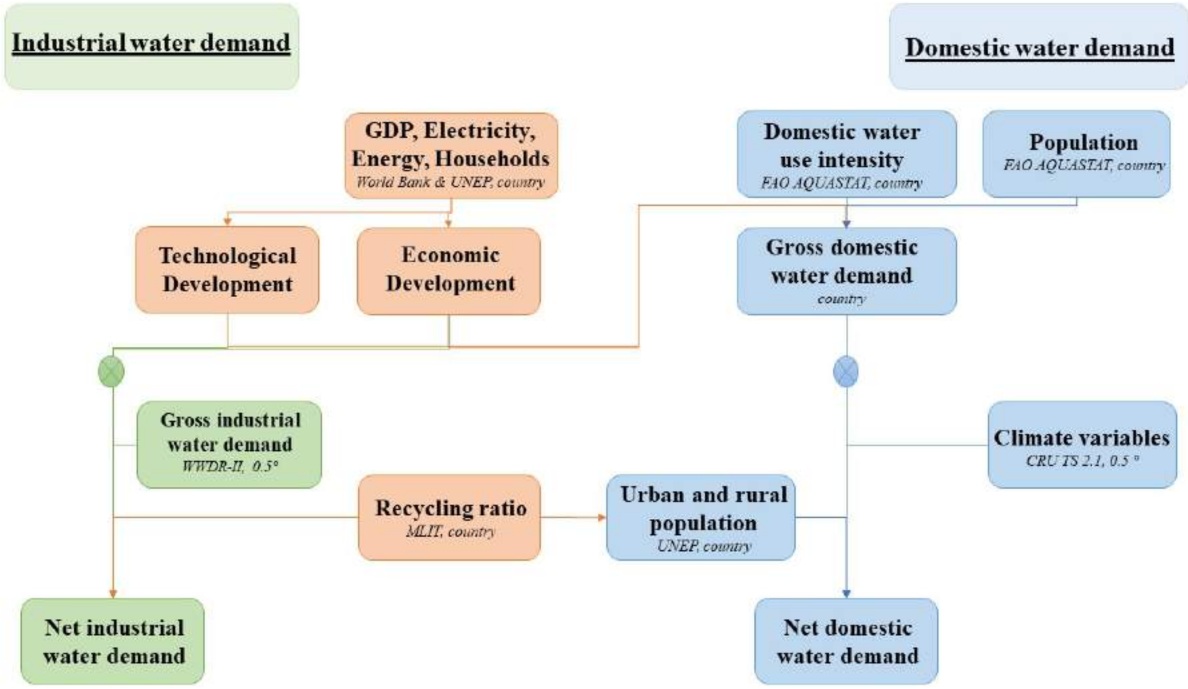

Figure 2.1: Flowchart of computation of the dependencies for industrial and domestic water demand [Wada et al., 2011a,b, 2016]. Orange blocks denote variables that are used both in industrial and domestic, net and gross water demand. Green blocks denote variables used in industrial water demand, and blue ones are for domestic water demand. The crossed circles show were downscaling is applied in the process.

2.1.2. Domestic water demand

The study of Wada et al. [2011a] and Wada et al. [2016] on blue domestic water demand are elaborated in the same way with the same equations, but use different data for gross domestic water demand. Both studies recognize domestic water demand to be a complex function of climate variables and socio-economic indicators which were linked to temporal development of domestic water demand.

In Wada et al. [2011a], the WWDR-II dataset [Shiklomanov, 1997; Vörösmarty et al., 2005b; World Resources Institute et al., 1998] was used to extract gross domestic water demand data at 30 arcmin for the year 2000. This was then used as input variable W_{Dom_a} in equation 2.8, to come to monthly net domestic water demand via equation 2.9.

In Wada et al. [2016] this method was partially changed by using equation 2.6 estimating gross yearly domestic water demand, instead of the WWDR-II dataset for 2000. Equation 2.6 multiplies the economic and technological development of a country, calculated with equation 2.1 and 2.2, with their population and the water use intensity in m^3 per capita of the reference year 2000.

Resulting gross domestic water demand was downscaled to 5 arcmin (W_{dom_a}) by distributing the gross demand through downscaling to the gridded 5 arcmin resolution population density map for 2000, based on night-time light intensity, using the weight of population per cell. This is the same technique as for redistributing gross industrial water demand, see equation 2.6 and Appendix B Figure B.5.

Seasonal fluctuations in gross water demand were evaluated for selected countries that represent a wide range of socioeconomic and environmental conditions (Japan, Spain, Australia, Iran and Nigeria). This was used to disaggregate from gross domestic water demand in 2000 to monthly gross domestic water demand using temperature (see equation 2.8). Additionally, a monthly time scale will capture the summer out-of-phase shifts between peak water demand and peak water availability, compared to annual assessments which might underestimate the intensity of water stress due to within-year variations [Wada et al., 2011a]. W_{Dom_a} is inserted in equation 2.8 and divided by 12 to find monthly gross domestic water demand as W_{Dom_m}.

Long-term climate variability from 1961-2014 were taken to obtain a good representation of the average historical climate. The temperature components consist of T, T_{avg}, T_{max} and T_{min} which respectively denote the monthly temperature, and the average, maximum and minimum temperature averaged over the years. For example, T for January would consist of the average of T for January between 1961 and 2014 for the specific grid cell. Values were derived from the Climatologic Research Unit TS 2.1 (CRU) database through

Mitchell and Jones [2005] (see Appendix B Figure B.4).

Note that the variable of R_{Dom} represents a dimensionless amplitude of the relative difference between gross water demand in summer and winter. A global value of 10% was used to fit the small variations in seasons for Japan and Spain and the almost constant values for Nigeria best. This means that the daily temperature shows little variation over the year, the domestic water use remains fairly constant. If daily temperature lays close to T_{max}, withdrawals are 5% higher, whereas they are 5% lower when daily temperature is close to T_{min}. The amplitude is 10% but it is dependent on how long T lingers near T_{max} or T_{min}, which is not that long in the tropics.

As mentioned before, net domestic water demand is defined as the water withdrawals minus the return flow, which is the last step of this method. Monthly net blue domestic water demand was calculated using equation 2.9, taking into account the fraction of urban population (F_{urban}) and the recycling ratio ($R_{industry}$). As in the industrial water sector, a significant part of the gross water demand (water withdrawals) is recycled and returned to the river network. This equation assumes that urban population is connected to the sewage network and recycles withdrawn water based on their GDP according to Table 2.1. Rural population consumes all water they withdraw. Monthly net water demand is qualified as the fraction of gross water demand that is used as actual consumption by the urban population and the full withdrawals of the rural population.

$$\mathrm{DWD}_{\mathrm{cnt,t}} = \mathrm{POP}_{\mathrm{cnt,t}} \times \mathrm{EDev}_{\mathrm{cnt,t}} \times \mathrm{TDev}_{\mathrm{cnt,t}} \times \mathrm{DWUI}_{\mathrm{cnt},t\,0} \tag{2.6}$$

$$\mathrm{W}_{\mathrm{dom_a}} = \mathrm{DWD}_{\mathrm{cnt,t}} \times (POP_{5arcmin}/POP_{cnt}) \tag{2.7}$$

$$W_{Dom_m} = \frac{W_{Dom_a}}{12}\left[\left(\frac{T - T_{avg}}{T_{max} - T_{min}} R_{Dom}\right) + 1.0\right] \tag{2.8}$$

$$D_{Dom_m} = W_{Dom_m}[1 - (F_{urban} R_{industry})] \tag{2.9}$$

In Table 2.3 an overview is given of the variables mentioned in equations 2.6 to 2.9 as well as their definition, resolution, source and year in order of appearance, followed by their subscripts.In Appendix A, Table A.1 extended information on webpages can be found.

Variable	Definition	Resolution (spatial/temporal)	Source	Year
DWD	Gross domestic water demand	country/year	equation 2.6	1961-2014
POP	National population	country/year	FAO AQUASTAT	1961-2014
EDev	Economical development	country/year	equation 2.1	1961-2014
TDev	Technological development	country/year	equation 2.2	1961-2014
DWUI	Domestic water use intensity	country/2000	FAO AQUASTAT & (2)	2000
$\mathbf{W_{Dom_a}}$	Gross domestic water demand	5 arcmin/year	equation 2.7	1961-2014
$POP_{5arcmin}$	downscaling map population	5 arcmin/2000	IMAGE26	2000
POP_{cnt}	total population	country/2000	IMAGE26	2000
$\mathbf{W_{Dom_m}}$	Gross domestic water demand	5 arcmin/month	equation 2.8	1961-2014
T	Monthly temperature	30 arcmin/year	CRU TS 2.1 (1)	1961-2014
T_{avg}	Average temperature	30 arcmin/year	CRU TS 2.1 (1)	1961-2014
T_{max}	Maximum temperature	30 arcmin/year	CRU TS 2.1 (1)	1961-2014
T_{min}	Minimum temperature	30 arcmin/year	CRU TS 2.1 (1)	1961-2014
R_{Dom}	Difference water demand between warmest and coldest months	country/year	-	1961-2014
$\mathbf{D_{Dom}}$	Net domestic water demand	5 arcmin/year	equation 2.9	1961-2014
F_{urban}	Fraction urban/total population	country/year	UNEP	1961-2014
$R_{industry}$	Recycling rate	country/year	Table 2.1	1961-2014
m	per month	-	-	-
a	per year	-	-	-
cnt	per country	-	-	-
t	year	-	-	1961-2014
t0	reference year	-	-	2000

Table 2.3: Variables for calculating domestic water demand with their source, resolution and which years they cover [Wada et al., 2011a,b, 2016]. (1) Mitchell and Jones [2005] (2) Gleick et al. [2009].

2.2. European water use assessed regionally by Bernhard

Jeroen Bernhard [Bernhard et al., 2017, 2018] assessed the European water system, water use and water productivity for households and industry at a regional level using high quality data to develop a statistical regression analysis. As a side effect, his method is only applicable in regions where this level of data is available. He has used the subdivision for regions of Europe from EUROSTAT, called NUTS-levels (Nomenclature of Units for Territorial Statistics), where NUTS-0 indicates country level and NUTS-3 indicates the highest level for subdivision at provinces or counties (40 regions in the Netherlands). Maps of those subdivisions for NUTS-2 and NUTS-3 can be seen in Appendix B Figure B.1 and B.2).

2.2.1. Domestic water demand

Bernhard's paper on domestic water use, assesses water stress on a regional pan-European scale [Bernhard et al., 2017]. He was driven by the need for more detailed knowledge on the European water system to make accurate and relevant impact assessments. Additionally, the increasing pressures on European water resources and the impact of socio-economic changes on water use in the future has led to a growing need of optimization of water allocation. A method and dataset were created containing information on NUTS-3 level for household water use, water prices, socio-economic and climate variables for 2000-2013.

Data sources
Data on water use and water prices are collected by Bernhard et al. [2017] for each country from national statistical offices and other national data sources at NUTS-3 level. Gross Domestic Product (GDP) was used as an economic indicator for household incomes, which is available at NUTS-3 level from EUROSTAT. A climate variable is added in the form of the number of dry days per year (DDA), which is considered to account for the fact that warmer and drier conditions increase water use. DDA is calculated from the EFAS-Meteo dataset [Ntegeka et al., 2013], starting with counting the days without precipitation for each year at 5 km resolution, subsequently the annual average DDA for NUTS-3 level was calculated. The proportion of the population that is younger than fifteen (AGE15) works as a demographic indicator for household compositions, and is obtained from EUROSTAT. An overview of data can be found in Table 2.4.

Variable	**Definition**	**Resolution (spatial/temporal)**	**Source**	**Year**
Water use	total of water extracted per capita from public network by households	NUTS-3/annual	National statistics offices	2000-2013
Water price	Average water price paid by an average household for the water supply	NUTS-3/annual	National statistics offices	2000-2013
GDP	Gross Domestic Product per capita	NUTS-3/annual	EUROSTAT	2000-2013
Dry days	Total days without precipitation	NUTS-3/annual	[Ntegeka et al., 2013]	2000-2013
Age 0-15	Fraction of population under 15	NUTS-3/annual	EUROSTAT	2000-2013
Total population	Total number of people	NUTS-3/annual	EUROSTAT	2000-2013

Table 2.4: Variables for calculating domestic water use with their source, resolution and which years they cover for Bernhards assesment [Bernhard et al., 2017].

Influence of drivers
Bernhard quantified the influence of the socio-economic and climate drivers for domestic water use [1] with an approach of a water use function, as in equation 2.10. It is a log-log equation which can directly show the elasticities of the coefficients. The three unknown variables are W, I and P, where W represents water use ($m^3/year$), I represents GDP (€/$capita$) and P the water price (€ $per\ m^3/year$). An assumption has been made that income elasticities and price have the same magnitude but an opposite sign, which means that $\alpha_I = -\alpha_P = \alpha_{IP}$. Rewriting IP = I/P, equation 2.10 can be changed to equation 2.11. IP is used as a single indicator since most countries in Europe experienced major changes in income and water pricing in the last decade, making it difficult to capture them individually.

$$\ln(W) = \alpha_I \ln(I) + \alpha_P \ln(P) + \alpha_{DDA} \ln(DDA) + \alpha_{AGE15} \ln(AGE15) \tag{2.10}$$

$$\ln(W) = \alpha_{IP} \ln(IP) + \alpha_{DDA} \ln(DDA) + \alpha_{AGE15} \ln(AGE15) \tag{2.11}$$

The database created consists of multiple observations from 2000-2013 per NUTS-3 region, referred to as a panel dataset. Bernhard discusses panel data techniques in water demand literature and following Reynaud [2015], the most appropriate model for the data retrieved was determined by fitting both fixed-effect and random-effect models and subsequently applying the Hausman test [Hausman, 1978]. It was found that fixed-effect modeling was better. Fixed-effect modelling, fixes the model parameters allowing to capture differences across NUTS-3 regions, immeasurable variables can be statistically controlled. The Hausman test

[1] Bernhard used the term water demand in his section on the influence of drivers, and as his paper was not finished yet, it might be a small mistake. For clarity, this assessment has chosen to change water demand with water use when this seemed like the right term to use.

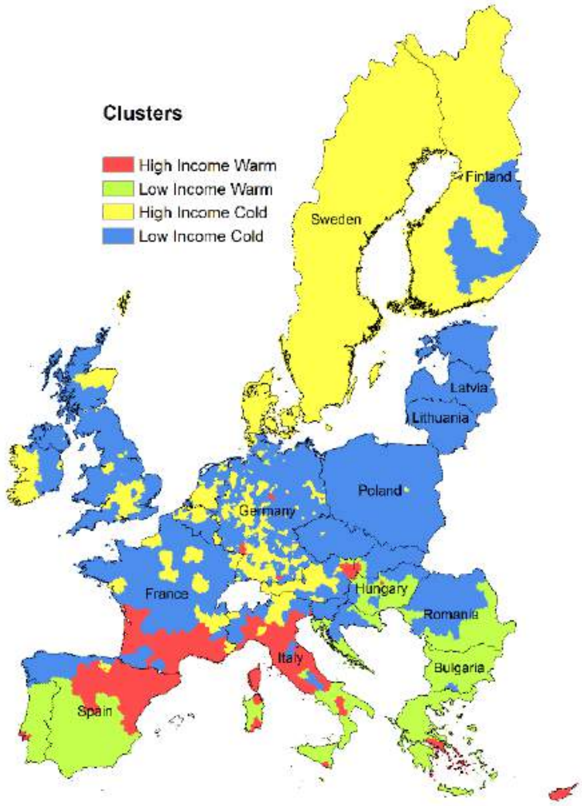

Figure 2.2: Four clusters of high & low income and warm & cold climates as subdivided by Bernhard, following Bernhard et al. [2017].

evaluates the consistency of an estimator when compared to a less efficient estimator already known to be consistent.

Fixed-effect was used to obtain statistically sound models in four grouped clusters which differ in climate and economic development: High and low income clusters were created using a threshold of 23.000€ GDP & warm and cold climate clusters subdivided the economy clusters again using 2 mm average daily evapotranspiration as a threshold. This creates a high-income warm (HW), high-income cold (HK), low-income warm (LW) & low income cold (LC) cluster, see Figure 2.2.

Statistically sound models for each European country could not be obtained as the relatively short time series for most countries in the constructed dataset were inadequate. That is why the NUTS-3 regions have been divided in four clusters. For each cluster, the best water use model was selected using all combinations of the predictor variables present in equation 2.11 to calculate the relative quality. The water use function was used for all four clusters (HW, HK, LW, LC). This was done by using the most recent observation of domestic water use on NUTS-3 level and from this starting point, simulate past and future water use. There were some data limitations making it impossible to keep enough data aside to do a validation. This means that there is no uncertainty quantified with regards to the reconstructed water use at NUTS-3 level.

There is a risk of overparameterization, which is discussed and the solution brought up was to do a variable selection method on the basis of the Bayesian Information Criterion (BIC) to select which parameters work best for each cluster [Schwarz et al., 1978]. This BIC score is generally used to compare relative quality of models, informing on the relative quality of fit, while correcting the score for model complexity. All clusters were tested with the set of predictor variables (IP, DDA and AGE15). The model with the lowest BIC score was chosen, as long as all included variables were significant at a 0.05 level, all possible combinations of predictor variables were tested.

Results

For all four clusters the water use model including all three predictor variables, thus IP, $AGE15$ and GDP had the best fit. This means that all three parameters are essential and add to predicting domestic water use. Higher water use is observed in warmer regions compared to colder regions and in both climatic regions high GDP also results in higher water use. National trends show that water use is relatively constant. Simulations by the study of Bernhard differ in general by <5 $m^3/year$ from EUROSTAT, indicating a high explained variance level between observed values from EUROSTAT and modelled values by Bernhard.

In Table 2.5 all elasticities can be seen as a relative change in the dependent variable of water use against a one percent change in the independent variable (IP, DDA and AGE15). If the income-price ratio (IP) would increase 100%, water use will increase with 25% in the HW cluster. The results Bernhard found on domestic

Cluster	IP	DDA	AGE15
HW	0.25 (0.03)***	0.08 (0.03)**	-0.53 (0.17)**
LW	0.11 (0.02)***	0.19 (0.03)***	0.29 (0.11)*
HK	0.19 (0.03)***	0.11 (0.03)***	-0.75 (0.26)**
LC	0.06 (0.02)***	0.06 (0.01)***	0.41 (0.05)***

Table 2.5: Outcome for elasticities by Bernhard et al. [2017], for all predictor variables in the water use function per cluster. The standard error is between round brackets and the alpha level of statistical significance is <0.001 = ***, <0.01 = **, <0.05 = *.

water use varied widely on a spatial scale. In 2013, the average water use per capita is over 50 $m^3/year$ in Europe, and warm southern regions have a higher use than colder northern regions. Lowest water uses of Europe can be found in eastern Europe. Where GDP is highest, water use is also higher. Through time, water use per capita decreases in the HW and LW cluster significantly, and decreases slight in the LC cluster, while increasing from 49 to 51 $m^3/year$ in the HK cluster (see Figure 2.3.

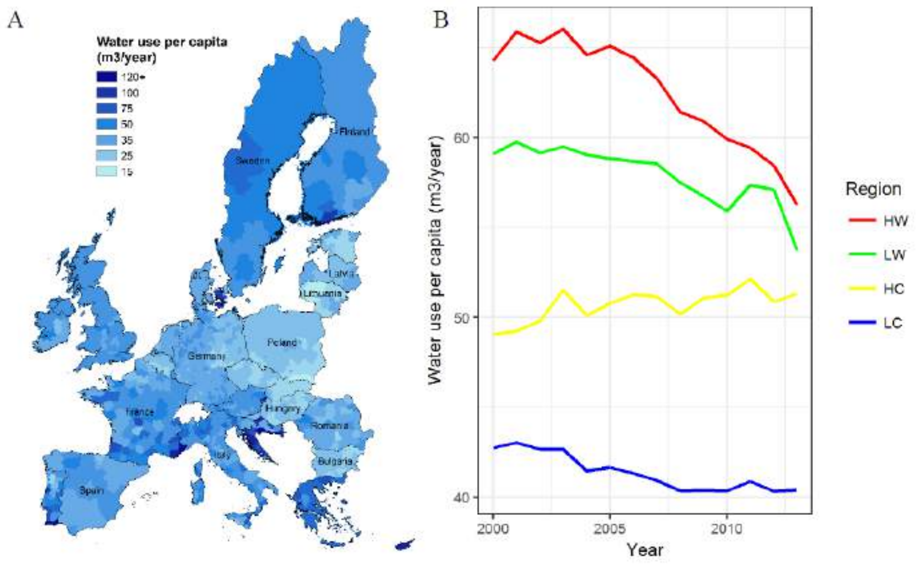

Figure 2.3: Map with water use per capita in $m^3/year$ (left) and the plot over time for all four clusters with average water use (right) [Bernhard et al., 2017].

The water use results were also compared to the outcomes of EUROSTAT and it was found that in general they do have the same magnitude, as the outcome of Bernhard's assessment.

2.2.2. Industrial water demand

Jeroen Bernhard's paper on industrial water use [Bernhard et al., 2018] approaches water use (WU) through projections of Gross value added (GVA) and water productivity (WP). For this assessment, Bernhard was driven by the same need for detailed knowledge as for household water use. Another motivation for his study was that most existing approaches gave a lumped representation of the total industrial water use without taking sectoral industrial water use into account. Industry is sub-divided in mining, manufacturing (food, textiles, paper, chemical, metals, transport equipment, other manufacturing), construction and services. Sub-dividing industry will take into account the different volumes and qualities of water needed by different industrial components and the economic value of water is variable along the sectors mentioned.

WP is defined as what is produced using a certain activity from a specified unit of water input (kg/m^3 or $€/m^3$ of water). WU can be calculated according to equation 2.12. GVA refers to the output value (€) with the costs of intermediate consumption subtracted.

The approach of the sectoral industrial water use study by Bernhard is to first collect historical data on GVA and WU to make a reconstruction of water productivity in the past. The reconstructions were analysed to quantifying trends on a sectoral, spatial and temporal scale. The obtained data was used to create water use maps for all 10 sub-sectors within industry for the year 2010. After this, WP projections for all 10 sub-sectors and all European countries were made based on the extrapolation of found temporal trends in the reconstructed historical WP, which were combined with GVA projections obtained from an economic model. Subsequently, with both of the variables projected, water use projections were made on a pan-European scale for all sub-sectors from 2010 to 2050. This research ends with developing a downscaling method which takes the locations of individual industries into account.

$$WP = \frac{GVA}{WU} \tag{2.12}$$

Reconstructing water productivity
First, a reconstruction of WP was made with historical data (2000-2015) on WU and GVA from EUROSTAT. An analysis was performed to quantify sectoral (within ten industrial sub-sectors), spatial and temporal trends. The collected data was used to create maps of WP for the year 2010. Industry is sectoral subdivided in mining, manufacturing, construction and services. Manufacturing consists of the following industries: food, textiles, paper, chemical, metal, transport equipment, and other manufacturing.

WP was indexed for 2010 to quantify differences between the ten sectors and countries. Temporal trends were examined by considering the average annual change in WP for every sector and for every country that had more than four years of data.

Projecting water use & availability
Industrial WU projections were made using equation 2.13, with subscript i implying the sub-sector and t the year that is projected between 2010 and 2050. Notice that this is equation 2.12 rewritten with a temporal dimension for every sub-sector.

$$WU_{i,t} = \frac{GVA_{i,t}}{WP_{i,t}} \qquad \text{for t = 2010, 2011 ... 2050} \tag{2.13}$$

For $GVA_{i,t}$ the projections used come from the GEM-E3 model, available for multiple industrial sub-sectors for five year intervals up to 2050. This model uses 2010 as reference year. For $WP_{i,t}$, values are based on reconstructed WP values of 2010 and are extrapolated using temporal trends. To project future $WP_{i,t}$ for all industrial sub-sectors i an efficiency factor (EF) is needed, see equation 2.14. Water productivity changes over time due to more efficient water use, this has thus to be embedded in water projections.

$$WP_{i,t} = WP2010_i(1+EF)^{t-2010} \tag{2.14}$$

EF is the annual fractional change in WP of all industries, calculated using the average annual change in WP of the industrial sector for all European countries with more than four years of data. It represents two aspects, the annual change in GVA per unit of produced goods on the one hand, and the change in water efficiency to produce said good in the other. Differences in EF between sectors are too small to use an individual EF values between sub-sectors, thus the average annual change in WP of the industry for all countries containing more than four years of data was applied as EF for all sub-sectors. EF is assumed to not change over the coming decade.

Downscaling water productivity
Finally, a sub-sector downscaling method, developed in Bernhard's assessment is compared to a traditional lumped downscaling method. The developed method by Bernhard takes in the locations of individual industrial facilities to subdivide national WU projections to a regional scale per sub-sector.

The sub-sector downscaling method that was developed in this assessment, relies on the *European Pollutant Release and Transfer Register* (E-PRTR). E-PRTR registers the emission of pollutants per industrial facility within the European Union. This database contains the location and the type of sector for 140.000 industrial facilities across Europe, in this way national WU can be downscaled to fraction of industry per NUTS-2 region.

The traditional downscaling method, consists of national WU values being downscaled proportionally to the industrial land use fraction without sub-sectors of the total land use maps from *Land Use-based Integrated Sustainability Assessment* (LUISA).

Using both methods showed that the E-PRTR downscaling technique was better at indicating which region had relatively low or high water use. Additionally it allows for a better spatial differentiation of the sub-sectors within industry.

Results

The most interesting results from Bernhard's assessment of industrial water use are on the sub-sectoral water use of Europe as can be seen in Figure 2.4. There are significant differences between countries and within sub-sectors. Countries were industry is strongly developed have higher water use (e.g. The Netherlands, Germany, Belgium, France and Italy). This water is mostly used by the manufacturing industry, with a focus on chemicals, but also the production of food and beverages, manufacturing metals and the service industry.

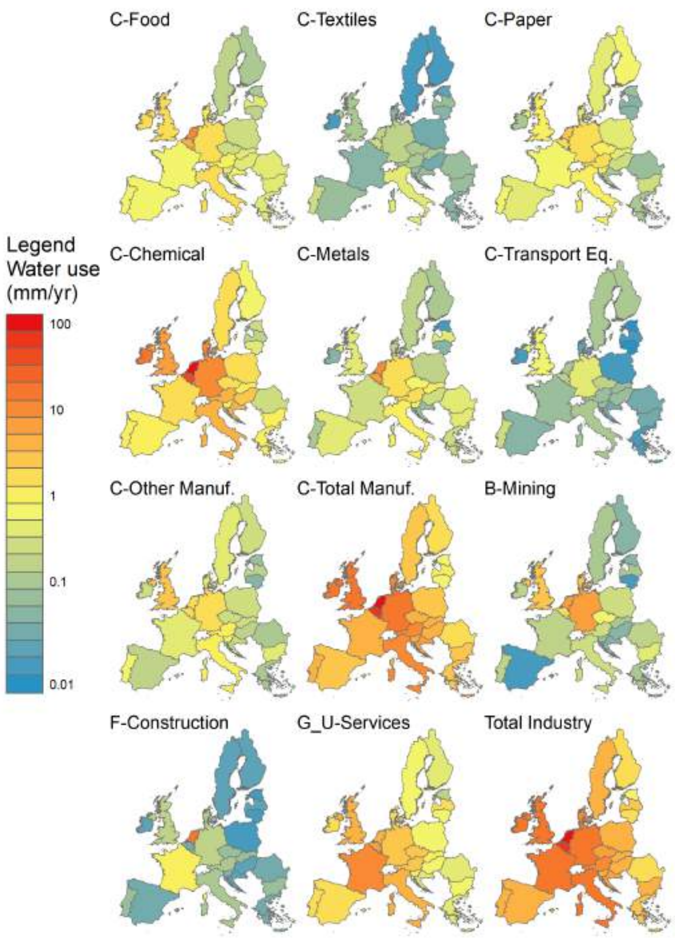

Figure 2.4: Map with water use per country in $mm/year$ between all sub-sectors of industry [Bernhard et al., 2018].

2.3. Comparing water demand approaches

The methods of Wada and Bernhard show that there are different approaches to assess water resources. Other methods include Bijl et al. [2016]; Flörke et al. [2013]; Vassolo and Döll [2005], and different approaches will be compared in the sectoral sub-sections below.

2.3.1. Wada versus Bernhard

Wada defined water demand as the net water demand, i.e. the water withdrawal minus the return flow from fresh surface water or blue water. In the same way, blue water demand is defined as net blue water demand, i.e. the potential consumptive use from available resources. Net blue water demand is lower than gross blue water demand as part of the industrial and domestic water demand is recycled and returned, whereas part of gross irrigation water demand is met by green water availability. Wada's method is a conceptual, top-down approach assessing global water demand at 5 arcmin.

Bernhard defined water use as the annual total of water extracted from the public network by households per capita without considering small commercial units, which is expected to be sandwiched between net and gross water demand as defined by Wada. Bernhard used a empirical approach, assessing regional water use in Europe using only a couple of essential parameters while leaving out the processes.

The difference between the two assessments in terminology is that demand is defined as the desired volume, whereas water use is defined as the demand that can be satisfied when taking supply constraints into account. Furthermore, Wada's assessment is fundamentally different from Bernhard's as Wada's goal was to project water demand in the past and present, using a method which consisted of general rules that could be applied everywhere. Bernhard's approach was focused on determining the relation between predictors per area (DDA, AGE15, IP) and water use as predictand. Bernhard tried to find a general image by finding correlations between components. Wada was looking for driving factors which he assumed did not change, while Bernhard assumed that the correlations will always change.

2.3.2. Domestic water demand

Wada assessed domestic water demand driven by a global water problem and was thus focusing on a high temporal scale instead of a high spatial scale. He used variables at national level and distributed water demand according to weighed population density. He takes into account socio-economic, demographic, climate, technological and drivers on recycling ratio (and thus indirectly water policies and culture) [Wada et al., 2011a, 2016].

Bernhard et al. [2017] incorporated socio-economic, water price, demographic and climate components when he assessed regional European domestic water use, driven by the lack of European assessments that incorporate economic components together with other drivers. He only assessed households, whereas Wada includes the service sector, small businesses and local institutions next to households.

Flörke et al. [2013] calculates domestic water use from 1950 to 2010 through drivers on water use intensity, population, GDP and technological changes at a global scale. She determines the relation between water use intensity and GDP, and appoints a static technological change depending on the development stage of a country. Spatial variability is accomplished by using historical population density maps and downscaling with their weight to 5 arcmin grid cells, making it a top-down approach. This method resembles Wada's method, but is based on more assumptions and relations between variables instead of data sources as recognizes that reconstructing past water demand is limited by datasets being discontinuous, incomplete or non-existent.

Bijl et al. [2016] defines water demand as the amount that would be used in the absence of supply constraints and estimates this for 1970-2100, as he is driven by better capturing water scarcity, the same motivation as Wada had. For households which included the same sectors as Wada, he derived a conceptual model with population size as the driver, and other dependencies included GDP, water use intensity, and efficiency. Three future scenarios along the story lines of three SSPs enabled for assessing different possible outcomes of domestic water demand in 2100.

In general, domestic water resource modelling differentiates between net and gross water demand, water use, consumption and withdrawal. Main drivers are in all mentioned studies population density and water use intensity per capita, while economic (especially GDP) and technological development, demographics, water price (and thus water management policies), climate and recycling variables also play a major role. Preference is given to a top-down approach as much data is globally available at national level and dis-aggregating to grid cell at 5 arcmin level or higher is possible by using population density maps.

2.3.3. Industrial water demand

Industrial water demand by Wada is based on relationships with variables of industrial activity, such as GDP, electricity production and energy consumption which are used as a proxy for economic development. To make the model temporal variable, a water use efficiency factor is introduced which increases water efficiency by means of technological development and four socio-economic variables at national are also linked for temporal variability. Limited data availability on industrial variables has caused that most global-scale water use studies for industry are basic representations, without taking sub-sectors into account [Wada et al., 2011b, 2016].

Bernhard et al. [2018] developed an empirical approach with sectoral detail as he noticed conceptual approaches of a lumped global representation do not present industrial water use accurately. Dividing industrial water demand in sectors which included their own cooling water use processes is important since all activities require different volumes and quality of water, causing differences in the value of water used for industry. Calculating water use through Bernhard's empirical method makes it suitable for economic studies and cost-benefit analyses. Finally, incorporating information of regional variation in industrial water demand is important to increase the spatial details. Bernhard uses gross value added (GVA) as a driver and focuses on water productivity to calculate water use between 2010 and 2050.

Vassolo and Döll [2005] recognizes a data gap as global-scale information on industrial water resources only exist as per country data from AQUASTAT, while no information on consumption is available. Additionally, existing data sets of industrial water use did not differentiate between cooling water and manufacturing, which both have different drivers, relevant when assessing future industrial water use. The goal of Vassolo and Döll [2005] is to estimate global-scale 30 arcmin industrial water withdrawal and consumptive use around 1995. Consumption is defined as amount withdrawn that evaporates during use. She takes electricity production and water intensity for global thermal power stations into account, depending on the cooling stations. Manufacturing water use is estimated by calculating country averages, further dis-aggregated by city night-time lights and sub-divided in paper and paper board, fabrics, crude steel, sugar, beer, cement and pig iron. The annual production volume of the eight manufacturing sectors and the sector-specific water intensity are included as drivers, and future manufacturing water use can be developed by recognizing production volumes, including technological changes and including a decrease in sectoral water demand. Bernhard et al. [2018] and Vassolo and Döll [2005] both differentiate between sub-sectors within industry, acknowledging sectors using different water volumes and appointing different values to water.

Flörke et al. [2013] differentiates between thermo-electric water withdrawals and consumption and manufacturing water use, as do Bernhard et al. [2018]; Bijl et al. [2016]; Vassolo and Döll [2005]. The thermo-electric cooling water use is estimated using electricity production per country as a driver. Gross value added is a driver for estimating manufacturing water use together with water withdrawal for manufacturing per country and their intensity, technological change and are dis-aggregated using the distribution of urban population.

Bijl et al. [2016] differentiated between electricity generation, where water is used for cooling thermo-electric power plants and all industrial activities with an own water supply when assessing industrial water demand. This differentiation is similar to Bernhard et al. [2018] who also differentiated in sub-sectors for industry. Water demand for the electricity sector is calculated by using the amount of excess heat, while often electricity production is used as a driver [Flörke et al., 2013; Vassolo and Döll, 2005]. Other dependencies for electricity water demand include fuel input, energy balance, population size, economic activity and water efficiency over time. For the industry sub-model, Bijl et al. [2016] uses industry value added (IVA) as a driving force, as it covers a wide range of industrial processes and is documented widely. Additionally, water use intensity, structural change and water efficiency are named as contributing to change water use.

Industrial water resource methods are assessed through water demand, consumption and withdrawals. Most studies Bernhard et al. [2018]; Bijl et al. [2016]; Flörke et al. [2013]; Vassolo and Döll [2005] differentiate between manufacturing and cooling water, capturing the large differences of the purpose of water within industry. Wada's is the only method that does not actively differentiate in cooling water, as it is already included in the WWDR-II dataset. Main drivers for the thermo-electric cooling assessments are electricity production and excess amount of heat, while for manufacturing use industry/gross value added are seen as main drivers. Temporal variability with past reconstructions and future projections is reached by including structural change, technological and economical development. Downscaling is mostly done for industrial water resource modelling by population density, night-time light or urban population maps Flörke et al. [2013]; Vassolo and Döll [2005]; Wada et al. [2011a], while Bijl et al. [2016] aggregates to 26 image regions and Bernhard et al. [2018] dis-aggregates on the basis of both pollutant measurements and land cover fraction.

3
Methods

This chapter will describe which methods are used in this study to achieve the aim. First, the validation dataset and the difference in terminology with this method will be explained. How to recreate the method of Wada to serve as a reference dataset is explained next. The need for a sensitivity analyses and the drivers behind it are then given, before explaining which results are needed to be generated to achieve the goals of this research. In addition, an elaboration is given on the changed components, before ending this chapter with the approach for the high-resolution water demand dataset.

3.1. Validation dataset

To test and evaluate existing approaches, they should be compared against a validation set consisting of observational data on water resources. The method of Wada is compared to global water withdrawal data from AQUASTAT at country level, which reports data on average every five years [FAO, 2010; Sutanudjaja et al., 2018; Wada et al., 2011a]. Bernhard's regional assessments use water use data from EUROSTAT as a validation set, which are reported at an annual interval and for different resolution levels, from country to NUTS-2 level.

As this study will focus on Europe and on high resolution modelling, the validation set will be based on observational data on water use for different sectors by EUROSTAT (hereafter referred to as validation set). The fact that data on water use are yearly available, and at different resolution levels allows to analyse how well Wada's conceptual approach estimates water demand as the resolution is increased.

3.1.1. Water demand versus water use

Studies on water resources focus on different aspects of the cycle: water use [Bernhard et al., 2017; Flörke et al., 2013; Vassolo and Döll, 2005] and water demand [Bijl et al., 2016; Wada et al., 2011a], but available reported data is limited to water use (EUROSTAT) and water withdrawals (AQUASTAT), forcing assumptions to be made on relations between different water resource aspects. Demand is defined as the desired volume, whereas water use is defined as the demand that can be satisfied when taking supply constraints into account, and water use is expected to be sandwiched between net water demand (total water consumption) and gross water demand (total water withdrawn without limitations). The created method in this research will be compared in a scatter plot against the validation set, but will also be put in a table to see if water use falls indeed between net and gross water demand.

First, the overestimation or underestimation between gross and net water demand on the one hand and water use derived from EUROSTAT on the other hand should be consistent for this research to be able to compare the two [EUROSTAT, 2020].

This analyses is focusing on two scales, temporal (fig. 3.1) and spatial (fig. 3.2). The ratio of water use from EUROSTAT divided by net water demand from Wada and the ratio of gross water demand from Wada divided by water use are calculated for all data points at NUTS-0 and NUTS-2 level for households and industry in 2010 and visualized in a box and whisker plot for a spatial scale. Gross demand is also compared as net demand contains more noise through the influence of the return flow. Additionally, those two ratios are also calculated at NUTS-0 level for 1990, 2000 and 2010 for both sectors to capture the temporal trend. Outliers altering the scale of the graph too much have been removed for clarity.

As can be seen in figure 3.1, the average ratio of domestic water use against net demand decreases a little through time as does the spread, but could be concluded as fairly constant. For domestic gross demand against water use, the spread and average ratio also seem to be consistent through time except for 2010 (note the different scales). Comparing industrial water use against net demand shows that spread and the average ratio increase over time, but are quite steady between 2000 and 2010, whereas comparing gross demand against water use shows that spread decreases and the average ratio is consistent between 2000 and 2010.

Figure 3.2 shows that for domestic water demand the average ratio of water use against water demand at country level is lower while more spread out between data points than at NUTS-2 level. Comparing the same water use with gross water demand shows in general a higher spread and a lower average ratio for NUTS-2 than country level, in general both ratios are consistent. For industry, there are more outliers when comparing water use against net demand, but the average ratio and spread decrease when the scale increases. Comparing industrial gross demand with water use yields high average ratios with a large spread, increasing at a higher resolution.

On a concluding remark, at a spatial level both domestic ratios are consistent and at temporal scale both ratios are also consistent up to 2010. For industry at a spatial level, there is less consistency and more spread, as what is included in the industrial demand and/or use may have changed over time. At temporal scale, the spread is less consistent but the average ratio is consistent between the three years. This means that water use from EUROSTAT can be used as observational data to compare the created method against as it should fall in general in between net water demand and gross water demand, with the sidenote that it is important to also compare the two with scatter plots.

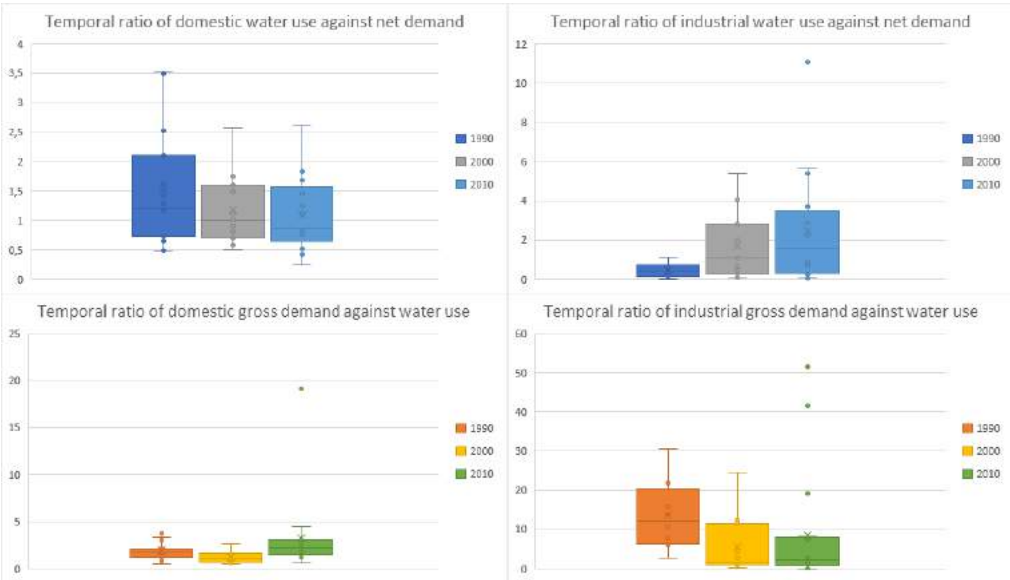

Figure 3.1: Temporal ratio in a box and whisker plot for households (left) and industries (right) between water use and net demand (top) and gross demand and water use (bottom).

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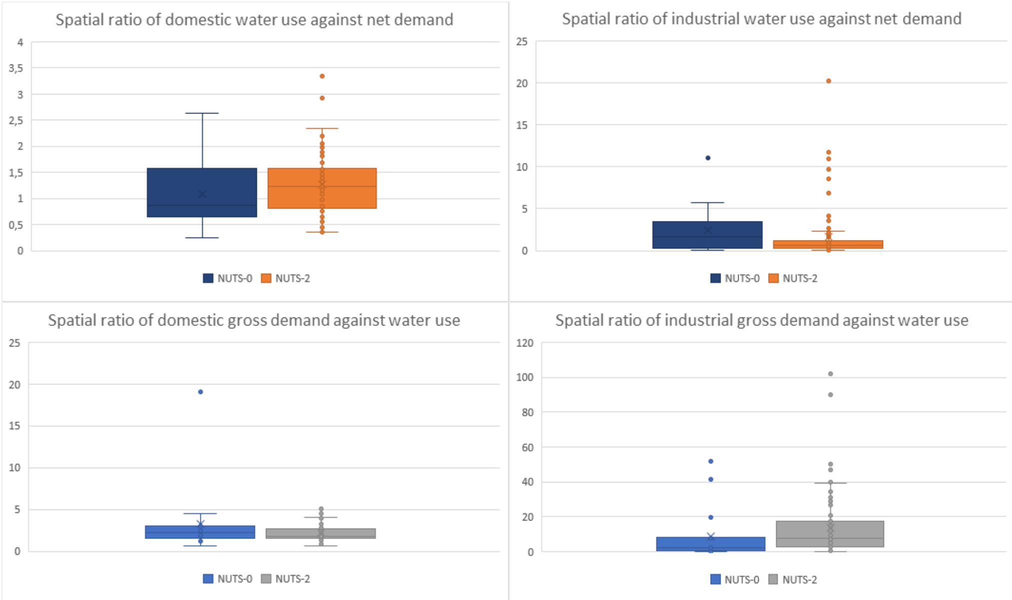

Figure 3.2: Spatial ratio in a box and whisker plot for households (left) and industries (right) between water use and net demand (top) and gross demand and water use (bottom).

3.2. Reference dataset

Wada's method is used as a foundation to create a high-resolution water demand method, for the domestic and industrial sector at a 5 arcmin resolution. Wada's method will be recreated to the best ability of this study using the same equations, datasets and downscaling techniques as mentioned in the previous chapter. By recreating Wada's method to calculate sectoral water demand, this research can (1.) get an idea to what extent the method is already matching the validation set, and thus where it stands within global hydrological resource modelling; (2.) find how sensitive the method is by comparing it to the original outcome; (3.) give this research a reference dataset against which component changes can be measured.

The reference dataset for households and industry will be built up on 3 years of data with 10 years interval. To have data on the past, 1990 was used; as 2000 is the benchmark year it can be regarded as the present, while data from 2010 was used to create a future reference set. Both gross and net demand are calculated as on the one hand this research wants to include all information possible i.e. the recycling ratio too, for which net demand is needed and on the other hand using bot gross and net demand gives an insight in differences with the validation set and if they are of the same order, i.e. which role does the recycling ratio play.

3.2.1. Results of original outcome

Sutanudjaja et al. [2018] compared total country (surface, ground and combined) water withdrawals measured in PCR-GLOBWB with a validation set on water withdrawals from AQUASTAT. In this GHM, water withdrawal is set equal to gross water demand over all sectors (unless sufficient water is not available). The total combined water withdrawals have a R^2 of 0.89 for both 1968-1992 and 1993-2015. Sub-dividing it in sectors shows that industrial water demand decreases from R^2 is 0.95 to 0.83 between in this time-series, while domestic water withdrawals decrease less from 0.94 to 0.91. Total water withdrawal is therefore simulated reasonably well by Wada's method, while domestic water withdrawals does even better and industrial water withdrawals do it better at first, but then decrease a bit in performance. It is shown that gross water demand allocation can still be further improved. These outcomes support the selection of Wada's method as the foundation of this research.

3.2.2. Domestic water demand

Recreating the method to calculate domestic water demand is done as explained in the previous chapter, except for the fact that two datasets were not retrievable and have therefore been subject to change, see Table 3.1. An extended version of the Table used to recreate the domestic water demand method, including the URLs for retrieving the data can be found in Appendix A, Figure A.3.

Additionally, as no information exists that could be used as a validation set to test the monthly domestic water demand method, the choice has been made to look at annual totals. This means that for domestic water demand, the step that dis-aggregates from yearly to monthly values is skipped, and instead using equation 2.6, 2.7 and 2.9 subsequently. If a monthly assessments needs to be created, it should be known that as data on temperature variables is extracted from the CRU, version TS 3.24 should be used instead of TS 2.1. TS 2.1 was released in 2005 and covers temperature data at 50 km resolution for the period 1901-2002, while the period should cover climatic data till 2015 which TS 3.24 does (see Appendix B, Figure B.4).

The downscaling technique that was used by Wada [Wada, 2020] was a population density map based on nighttime light as part of HYDE 3.1 [Klein Goldewijk et al., 2010]. This research assumed the downscaling map was from the benchmark year (2000) whereas actually the 2010 population density map was applied, this also concerns industrial water demand explained below (see Appendix B, Figure B.5).

Variable	**Definition Wada**	**Source**	**Definition Reference**	**Source**
POP_{xxx}	downscaling map population	IMAGE26 2010	downscaling map population	HYDE 3.1 2000 (1)
T, T_{avg} T_{max}, T_{min}	Temperature	CRU TS 2.1 (2)	Temperature	CRU TS 3.24 (3)

Table 3.1: Adapted variables for calculating the reference dataset for domestic water demand. (1) Klein Goldewijk et al. [2010] (2) Mitchell and Jones [2005] (3) Harris et al. [2014]

3.2.3. Industrial water demand

Recreating the industrial water demand method is done in the same way as in the previous chapter, except for the fact that three dataset were not retrievable, thus these variables have been subject to change, see Table 3.2. An extended version of the Table, including the URLs for retrieving the data can be found in Appendix A, Figure A.4.

Three of the four socio-economic variables used to calculate economic development are retrieved from different sources, causing the change in definition of the data. Electricity production (EL), energy consumption (EN) and household consumption (HC) were retrieved by Wada from the United Nations Environment Programme (UNEP), but now they are inaccessible. All three variables where accessible through the World Bank.

Electricity production at UNEP has the International Energy Agency (IEA) as data source. Through the World Bank, electric power consumption in kWh per capita was retrieved which calculates the production of power plants and combined heat and is also originally retrieved from the IEA. Energy use from the World Bank is in the unit kilotonnes of oil equivalent (KTOE) per capita and it refers to use of primary energy before transformation to other end-use fuels. Both the data from the World Bank and UNEP have the IEA listed as data source. Household consumption could still be retrieved at the World Bank. Since the UNEP dataset used by Wada concerned the year 2000, it was considered to be dated and replaced by data expressed in US dollars and indexed for the year 2010.

3.3. Sensitivity analysis

While Wada's method is used as a starting point for reaching a high-resolution water demand method, other water resource approaches should be considered as they can give ideas on which components to adapt, add or concepts to change. A sensitivity analysis is conducted and is driven by deficiencies in the original method of Wada, categorized in concepts, parameter resolution and downscaling techniques.

The sensitivity analyses will help this research to achieve the main aim and is conducted in the following way. The variables are adapted one by one in the reference dataset for 2010, subsequently the expected overlap in gross and net water demand on the one side and water use on the other side is measured (at country and NUTS-2 level). This is corroborated by scatter plots, the regression slope and R^2, as well as visualized in absolute water demand and relative differences compared to the reference dataset.

Explaining the (absent) overlap will give information on the relation between gross and net water demand on the one hand and observational water use on the other for all changed components.

The scatter plots, the R^2 and the regression slope measure the effect of adaptations made and will help in finding dominant, robust and essential parameters. R-squared is a statistical measure that represents to what extent the variance of one dependent variable can be attributed by the variance of a second independent

Variable	Definition Wada	Source	Definition Reference	Source
EL	Electricity production	UNEP	Electric power consumption	World Bank
EN	Energy consumption	UNEP	Energy use (kg of oil equivalent)	World Bank
HC	Household consumption	UNEP	Households and NPISHs final consumption expenditure / total population	World Bank
POP_{xxx}	downscaling map population	IMAGE26 2010	downscaling map population	HYDE 3.1 (1)

Table 3.2: Adapted variables for calculating the reference dataset for industrial water demand (1) Klein Goldewijk et al. [2010].

variable, i.e. it will tell something about the amount of variability in gross/net water that is explained by the model. Additionally, R^2 is the square of the correlation. Gross water demand will be better comparison material, but net water demand contains more information, therefore both are compared at country and NUTS-2 level with water use. NUTS-2 will be included to examine to what extent the method can resemble observational data at higher resolution. Two assumptions are made: (1) as gross water demand should be higher than water use, the regression slope is expected to be above the 1:1 line while net water demand should be lower and thus below the 1:1 line; (2) R-squared should be higher for gross demand than for net demand.

Absolute net water demand is shown as this also includes information on the return flow, while absolute values can give an idea on the spatial distribution of water demand, informing which parameters play an important role. Only net water demand will be shown as the return flow is considered an important variable, which is reflected in this demand. It is expected that especially population density will play a large role in distributing water demand, with high intensities in urban areas.

Relative difference between net water demand of the sensitivity analyses and the reference dataset in cell and country data may give an insight in the strength of adapted variables. Relative differences over the country are given as cell data might be prone to large errors.

3.3.1. Adjusted variables

One by one variables in the created reference dataset for domestic water demand will be adapted using better defined concepts, methods from other approaches [Bernhard et al., 2017, 2018] or higher resolution variables and updated data. Where the adapted variables also influence industrial water demand, this will also be updated. the following subsection is ordered by type of change applied.

Conceptual change

Wastewater treatment Wada's concept on the recycling ratio in equation 2.9 assumed that the difference between gross water demand, which is the water withdrawals and net water demand which is the potential water consumption, were only dependent on the urban population and the recycling ratio of the country. Elaborating on the assumptions made, it can be concluded that this concept is weak since (1.) It assumes only urban population is connected to the sewage system; and (2.) the recycling ratio of a country is categorized in three stages only related to income and subsequent development which not does justice to the complex dynamics between income, water management, health and environmental policies and culture [Koop and van Leeuwen, 2017; Van Puijenbroek et al., 2019].

Sewage connection and the treatment of wastewater are important indicators in differentiating between gross and net water demand. By changing the waste water concept to individual values at country level, it is expected that more spatial variability will occur between countries for net water demand. The dataset compiled by Van Puijenbroek et al. [2019], provides information for sewage connections and waste water treatment at country level for 1990, 2000 and 2010 for 200 countries.

In equation 2.9 the return flow of gross domestic water demand is defined by the product of $F_{urban} \times R_{industry}$. This return flow was replaced by one variable, F_{sewage} for 2010 in equation 2.9.

Downscaling techniques

Population density maps and industrial land cover Population variables as distribution and density, on a global, national and local level are important components to calculate domestic water demand [Bernhard et al., 2017; Bijl et al., 2016; Flörke et al., 2013; Martin, 1999]. In Wada's assessment, population density is the only contributor to a 5 arcmin resolution domestic water demand grid as its weighed form is used to dis-aggregate all variables from national level to 5 arcmin, as global covering variables for his assessment were only available at national level. For industry the downscaling map and the gross industrial water demand retrieved at 30 arcmin (50km) resolution were the two contributors to the resolution of 5 arcmin, as for other variables only data at country level is available. Enabling the method to calculate water demand at a 30 arcsec (1x1 km) resolution has to be done by including a downscaling map with the preferred 1km resolution. Using a higher resolution population density map should generate a spatially higher variable water demand model.

The assumptions made and concepts these equations are based on, should be reconsidered for this study to create a high-resolution water demand dataset which resembles observational data, as both domestic and industry are downscaled using population maps, while industry is not necessarily distributed according to population distribution and more near important transit points for transport. However, more studies disaggregate industrial water use/demand with population maps [Bijl et al., 2016; Flörke et al., 2013; Vassolo and Döll, 2005] which therefore still shall be assessed too.

For domestic water demand, the downscaling method is replaced by a weighed population map at 30 arcsec map from Worldpop for 2000 and 2010 to dis-aggregate to a 1 km resolution [Tatem, 2017] as population density is an major indicator for spatially variability in water demand [Flörke et al., 2013; Rathnayaka et al., 2014].

For industrial water demand, two downscaling techniques are applied and by analysing them the one that captures observational data the best will be implemented in the high-resolution water demand method. The gross industrial water demand map (WWDR-II) at 50 km is added per country and redistributed using the weight of the population density map from Worldpop at 1km. Secondly, another downscaling technique is used based on a method Bernhard applied on his industrial water use [Bernhard et al., 2018]. He assessed land use fraction downscaling techniques from LUISA. This study will use land cover data from the CORINE inventory in 2000, which indicates the areas that include industrial regions, to calculate industrial water demand at 0.5 arcmin resolution [Feranec et al., 2016].

Increasing resolution of variables

Bernhard et al. [2017] focused on high resolution GDP and population numbers, which both have been indicated as important drivers in domestic (both) and industrial (mostly GDP) water resource modeling. Both parameters are used in an early stage in the method of Wada, respectively equation 2.1 and 2.6, indicating that increasing their resolution would support the method to dis-aggregated to a high-resolution scale from the beginning. This research expects that including these two variables at a higher resolution will increase the explained variance R^2 with the validation set. It is also expected that having multiple variables at high-resolution will increase the spatial variability on a regional level.

Gross domestic product Gross domestic product is often considered as a proxy for income and represents economic development making it a major driver for domestic and industrial water demand [Babel and Shinde, 2011; Bernhard et al., 2017; Flörke et al., 2013; Vassolo and Döll, 2005; Vörösmarty et al., 2000a]. Income and the related GDP will influence water demand in a positive way where higher incomes come with increase in living standards which often are associated with the use of more water-using applications and machines to some extent. Wada considers GDP as one of the four components for estimating economic development at national level. National data will not capture income differences within a country while this component is highly spatially variable across countries. In Figure 2.2 it can be seen that there are within-country differences where there are low income regions in high income countries (the Netherlands, Germany and Belgium) and high income regions in low income countries (Hungary, Poland and Czechia). There is a general pattern with high income areas concentrating in urban areas.

Bernhard used GDP as well in Bernhard et al. [2017] and retrieved it through EUROSTAT at NUTS-3 level. GDP is increased in resolution from national to NUTS-3 level by using the data captured and simulated by Bernhard for two reasons: (1.) Data on GDP at NUTS-3 level is not retrievable for France, parts of the United Kingdom, Iceland, Poland, Norway, Turkey, Serbia, Montenegro, North Macedonia, Bosnia and Herzegovina and Albania, and (2.) Bernhard's assessment simulated GDP where no data was observed at NUTS-3 level, and as his assessment to estimate water use has the same magnitude and generally differed less than $5m^3/year$ from EUROSTAT values, we will assume the simulated GDP is usable for this research.

The other three socio-economic factors, household consumption, energy consumption and electricity production, influencing the economic development are still retrieved at national level as higher resolution does not (yet) exist. In domestic and industrial water demand the same variable will be adapted.

Population Population density is seen as an important driver and indicator of water demand [Arbués et al., 2010; Bernhard et al., 2017; Flörke et al., 2013; Martin, 1999]. Population has a positive relation with water demand, where higher population ratios in a grid cell of a model will increase the water demand of that grid cell. Wada considers population at national level, and neglects in this way spatial differences within countries of potentially dense populated areas. As the NUTS levels are selected based on population total with a minimum of 150.000 and a maximum of 800.000 people in the NUTS-3 category, meaning that locations with high population density will have smaller NUTS-3 areas. Both this aspect and the resolution increase of this variable will cause higher spatial variability of population within a country and thus higher spatial variability in water demand is expected for households.

Bernhard used population numbers as well in Bernhard et al. [2017] and retrieved population at NUTS-3 level from EUROSTAT [EUROSTAT, 2020]. The population in this assessment is increased in resolution from national level to NUTS-3 using population data from Bernhard and EUROSTAT, because EUROSTAT is updated regularly and data is removed, which was present in Bernhard dataset.

3.4. high-resolution water demand dataset

The main aim is to set up a flexible framework to define and test high-resolution water demand for households and industries in Europe, using existing downscaling concepts and datasets with the final objective to develop and improve high-resolution global water demand estimates that may benefit from forthcoming data sources. This means that the reference dataset is used as a starting point and the adapted components mentioned above that improve the method will be implemented.

Creating a high-resolution water demand dataset for the domestic and industrial sector, should take into account the following pitfalls, points of improvements and dated variables of Wada's method:

- The base year of 2000 should be updated to a year for which plenty of data is available, so that data can be retrieved when the year of consideration is compared to the base year. A recent year for which enough data on socio-economic, population and climatic data is available is 2010. Adaptations will be made for:
  - Domestic water use intensity (DWUI), from 2000 to 2010 data.
  - The downscaling population map will be updated from 2000 to 2010.
  - The denominators in the equation for economic and technological development (eq. 2.1 and 2.2) are updated from 2000 to 2010. In short this means that $T0$ is updated from 2000 to 2010.
- Where possible, national data should be increased to a higher level resolution using NUTS levels. This can be done for the following component:
  - GDP from country level to NUTS-3 level.
  - Population numbers can be increased from country level to NUTS-3 level.
- To optimize the method to a high-resolution water demand dataset at 30 arcsec resolution, it is needed to increase the resolution of the downscaling technique and assess differences between sectors, using:
  - Population map at 0.5 arcmin from Worldpop.
  - CORINE land cover fraction map for industrial areas.
- Updating equations and variables which are essential and constitute to the understanding of water demand, meaning the conceptual part of the method:
  - Change the recycle ratio from three stages to country statistics to better represent the complexity of water management on wastewater systems within countries.

4
Results

This chapter starts by comparing existing water resource approaches with each other and with observational data for both sectors. The outcome of the reference dataset is then given in absolute values and compared to the original outcome of Wada and to the validation set. Subsequently, a sensitivity analysis is conducted testing the influence and dominance of all adapted variables, concepts and downscaling techniques. With the gained knowledge, the high-resolution water demand dataset is created, and its performance is also measured.

4.1. Comparing existing approaches

The original method of Wada is first compared to existing data on water use (validation set) on different temporal and spatial scales to conclude on the possibility to use Wada's conceptual method for a higher resolution compared to the existing NUTS levels. This is done by calculating the expected overlap between gross and net water demand on the one hand and water use on the other. Additionally, Sutanudjaja et al. [2018] tested the method by comparing it to national data from AQUASTAT, which will also be mentioned.

4.1.1. Domestic water demand

In Table 4.1 the results of Wada's method for domestic water demand are compared with EUROSTAT data on NUTS-0 and NUTS-2 level and with Bernhard's outcome on NUTS-3 level, all are the retrievable NUTS levels.

Bernhard's water use data had 882 data points on NUTS-3 level and is expected to be sandwiched between the gross and net demand of Wada as terminology differs, which was the case around 45% of the time while overlap decreased from 2010-2013.

Data from EUROSTAT is compared in the same way as Bernhard but then at country (NUTS-0) and NUTS-2 level [EUROSTAT, 2020]. For country level, there are only 20 countries with data for Wada and EUROSTAT in 2010 of which only 20% overlap. The most data at EUROSTAT for NUTS-2 water use is retrievable for 2010 with 107 data points, and data points decrease towards 2013 with only 28 data points. The overlap in data was for 2010 and 2011 around 38% but 2012 and 2013 only had 18% overlap.

The overlap of data between EUROSTAT and Bernhard is in the same range as mentioned in Bernhard et al. [2017], with around $< 5m^3/year$ of water use difference, implying that comparing to him would almost equal comparing to EUROSTAT when no data is available. This can be explained by the fact that they measure the same phenomenon and include the same sub-sectors within households. Bernhard mentions there are much larger discrepancies between his outcome and the method of Wada.

In conclusion, as expected overlap increases between domestic water demand and water use on higher spatial resolutions, which implies that the ability of the method to resemble observational data increases on higher resolutions, it can be assumed that Wada's method can be used as a starting point for developing a high-resolution water demand model with a higher resolution than NUTS-3 level.

Households			
Spatial resolution: NUTS-0			
Year	**Data points**	**Wada vs. EUROSTAT Points**	**[%]**
2010	20	4	20.0
Spatial resolution: NUTS-2			
Year	**Data points**	**Wada vs. EUROSTAT Points**	**[%]**
2010	107	41	38.3
2011	46	18	39.1
2012	54	10	18.5
2013	28	5	18.0
Spatial resolution: NUTS-3			
Year	**Data points**	**Wada vs. Bernhard Points**	**[%]**
2010	882	408	46.3
2011	882	400	45.4
2012	882	402	45.6
2013	882	381	43.2

Table 4.1: Comparison of values for domestic water demand and domestic water use and how they overlap for Wada's method, EUROSTAT and Bernhard's method. NUTS-0; country level, NUTS-2; regions, states or provinces, NUTS-3; provinces or counties.

4.1.2. Industrial water demand

In Table 4.2 the results of Wada's method for estimating industrial water demand are at country level (NUTS-0) compared with historical to almost present data of EUROSTAT [EUROSTAT, 2020] and with Bernhard [Bernhard et al., 2018] for the overlapping examined years, 2010-2014.

Comparing Bernhard to Wada can only be done for the overlapping years of their assessments on country scale, 2010-2014. There are 26 countries that can be compared, water use of Bernhard lays in between gross and net industrial water demand by Wada in 27% of the countries for all years, while it is expected all water use data would fall between gross and net demand.

When evaluating the overlap between data from Wada and EUROSTAT on country level the amount of data points increases from 4 in 1970 to 23 in 2014. Water use from EUROSTAT overlaps with Wada's range for 45% or more in 2000, 2011 and 2012, while no overlap occurred from 1985 to 1995. From 2010-2014 the factor of difference increased to 6.16, while before 2010 there is no trend between consecutive years on how much the factor differs and the overlap matches.

On NUTS-2 level, the amount of data point decreased from 109 in 2010 to 30 in 2013 while there seems to be no coherence between the amount of overlap in data and the amount of data points.

Bernhard compared his work to data from EUROSTAT and found that his calculated sectoral, regional water use was almost equal to the national values from EUROSTAT with only small relative differences [Bernhard et al., 2018; EUROSTAT, 2020].

In conclusion, the expected overlap between industrial water demand and water use shows no spatial or temporal pattern when the resolution level is increased. This would imply that the method for calculating industrial water demand is less suitable as a starting point for a high-resolution water demand method, but as no comparison at NUTS-3 level was possible, this assumption cannot be fully substantiated. The industrial water demand method is therefore also used as a starting point for a higher resolution method, but more emphasize will be put on domestic water demand.

Industry							
Spatial resolution: NUTS-0							
Year	**Data points**	**Wada vs. EUROSTAT**		**Data points**	**Wada vs. Bernhard**		
		Points	**[%]**		**Points**	**[%]**	
1970	4	1	25.0				
1975	4	1	25.0				
1980	6	1	16.7				
1985	8	0	0.00				
1990	9	0	0.00				
1995	9	0	0.00				
2000	15	7	46.7				
2005	20	8	40.0				
2010	21	8	38.1	26	7	26.9	
2011	20	9	45.0	26	7	26.9	
2012	25	12	48.0	26	7	26.9	
2013	22	8	36.4	26	7	26.9	
2014	23	8	34.8	26	7	26.9	
Spatial resolution: NUTS-2							
Year	**Data points**	**Wada vs. EUROSTAT**					
		Points	**[%]**				
2010	109	26	23.9				
2011	48	7	14.6				
2012	57	17	30.0				
2013	30	2	6.67				

Table 4.2: Comparison of values for industrial water demand and industrial water use and how they overlap for Wada's method and EUROSTAT and Wada's method and Bernhard's method. NUTS-0; country level, NUTS-2; regions, states or provinces, NUTS-3; provinces or counties.

4.2. The reference dataset

As Wada's method is used as a starting point to generate a high-resolution water demand method it was recreated to serve as reference dataset. The created reference datasets are given in absolute net and gross water demand for both industry and households, and are displayed at a 5 arcmin European level. The created reference datasets for domestic and industrial water are compared to the outcome of water demand as assessed by Wada, as the methods used differ on a couple of data sources it is important to point out the relative differences in net domestic and industrial water demand. Since individual points can give a misrepresentation due to data errors or lost data, country averages are given as well. The bluer a country is the higher the underestimation of domestic water demand of the created reference dataset compared to Wada's outcome, whereas an overestimation corresponds to a red color. Additionally, the reference datasets were also compared observational data on water use from EUROSTAT.

4.2.1. Absolute outcome of the reference dataset

Domestic water demand

The outcome of the reference dataset for gross and net domestic water demand at European level can be found in Figure 4.1.

Gross domestic water demand is spatially heterogeneous and highest in densely populated urban areas, as population number is an important factor in determining water demand for a grid cell. Demands over $2500 \cdot 10^3 m^3/year$ per grid cell are reached in Madrid, the south coast of Spain, the Netherlands, Italy, the United Kingdom, the Ruhr area, Berlin, Moscow, Saint Petersburg and Albania. Between 1990 and 2010, gross domestic water demand shows a pattern of gradual increase in rural areas, e.g. Poland, Baltic States and the perimeter of high water demand increases in urban areas. Russia and Ukraine show decreasing values for gross water demand through time in rural areas and an increase of water demand in urban areas.

Net domestic water demand, displayed in the bottom row of Figure 4.1, takes the difference between gross water demand and what is supposedly returned to the river network into account by including urban population and the recycling ratio, thus representing a fraction of gross demand. Net water demand is spatially heterogeneous and has the same trend as gross demand but differences between lowest and highest demand are less pronounced and more spread. Between 1990 and 2000, net domestic water demand increases significantly in Poland, Hungary, Czechia, Slovakia, Balkan countries, Bulgaria, Ukraine and Russia, whereas western Europe shows no large visual difference between gross and net demand. Between 2000 and 2010, the perimeter of >2500 $10^3 \cdot m^3/year$ water demand grid cells decreases around urban areas in the United Kingdom, the Netherlands, Germany, Greece and Hungary. Rural net water demand increases in the rest of Europe, e.g. Poland, Romania, Ukraine, Belarus, Latvia, Switzerland, Italy, Norway and Sweden.

As the development of countries continued from 1990 to 2010, their recycling ratio and thus the part of water that returns to the river network increases, possibly being an important factor in determining net domestic water demand.

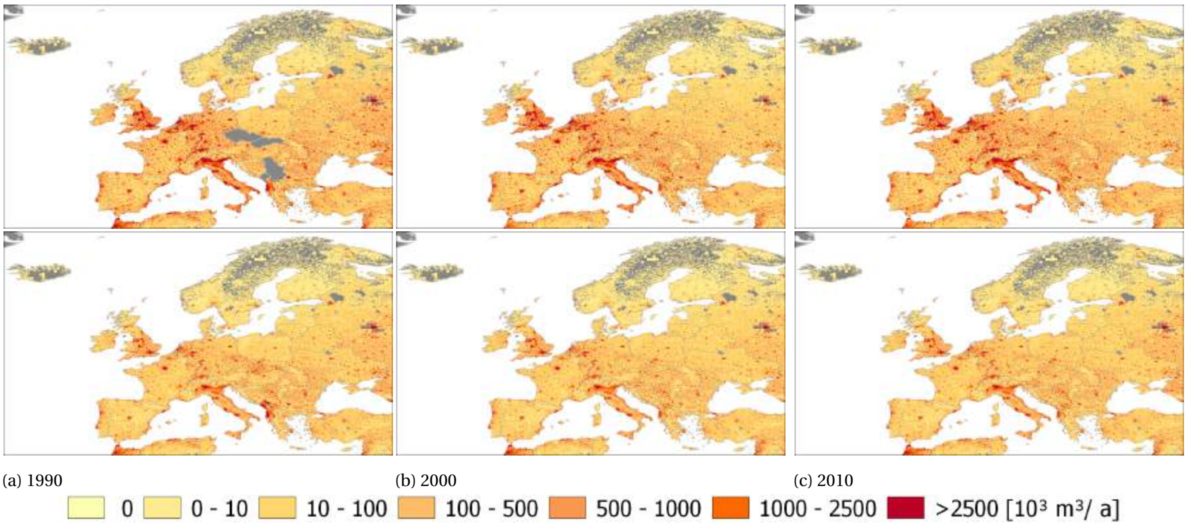

Figure 4.1: Gross (top) and net (bottom) European domestic water demand at 5 arcmin for 1990, 2000 and 2010 for the reference dataset.

Industrial water demand

The outcome of the reference dataset for industrial water demand at European level can be found in Figure 4.2.

Gross industrial water demand is spatially heterogeneous across Europe and of a higher order than gross domestic water demand. A large portion of total water demand in developed regions is contributed by industry, e.g. in Europe, industry contributes up to 57% to industrial water demand whereas domestic water demand contributes for 22% [FAO, 2010]. In general, gross industrial water demand over 2500 $10^3 m^3/year$ is achieved in large parts of Europe showing a pattern of higher water demands where population density is highest, e.g. the Netherlands, Belgium, the Ruhr area, middle England, Paris, northern Italy, Rome, Milan, Madrid, the coast of Portugal, southern Poland, Moldova, Romania and Bulgaria. A temporal pattern can be detected where high intensity gross industrial water demand relocates from western Europe to eastern Europe and Russia. Industrial water demand decrease in western Europe between 1990 and 2010, e.g. the United Kingdom, The Netherlands, France, Belgium, Germany, Spain and Switzerland, but increases in eastern Europe, the Baltic states, Balkan countries and Russia. As the latter have experienced most economic and technological development compared to 1990, big changes may have occurred in gross industrial water demand because of this.

As net industrial demand is a fraction of gross industrial demand depending on the development of the country, with high developed countries presumably returning 80% of the gross industrial demand, the spatial differences for net water demand (bottom Figure 4.2) decrease in comparison to the gross water demand. High net industrial water demand is located in densely populated areas with the same spatial pattern as gross industrial demand but less pronounced, the highest spatial demand is located in the polygon between London, Paris, Amsterdam and Frankfurt. On a temporal level, between 1990 and 2010, net industrial water demand decreases in Portugal and western Europe, but increases through the years to the east with higher demands in Poland, Czechia, Slovakia and Hungary in 2000 than in 1990. Subsequently, higher demands in

Russia, Belarus, Baltic states, the Balkan, Romania, Moldova, Ukraine and Bulgaria are noticed in 2010 compared to 2000 and compared to the previous mentioned countries with high demands in 2000. As the fraction of what is net industrial water demand depends solemnly on the recycling rate, the increase in development of eastern Europe has played a major role here.

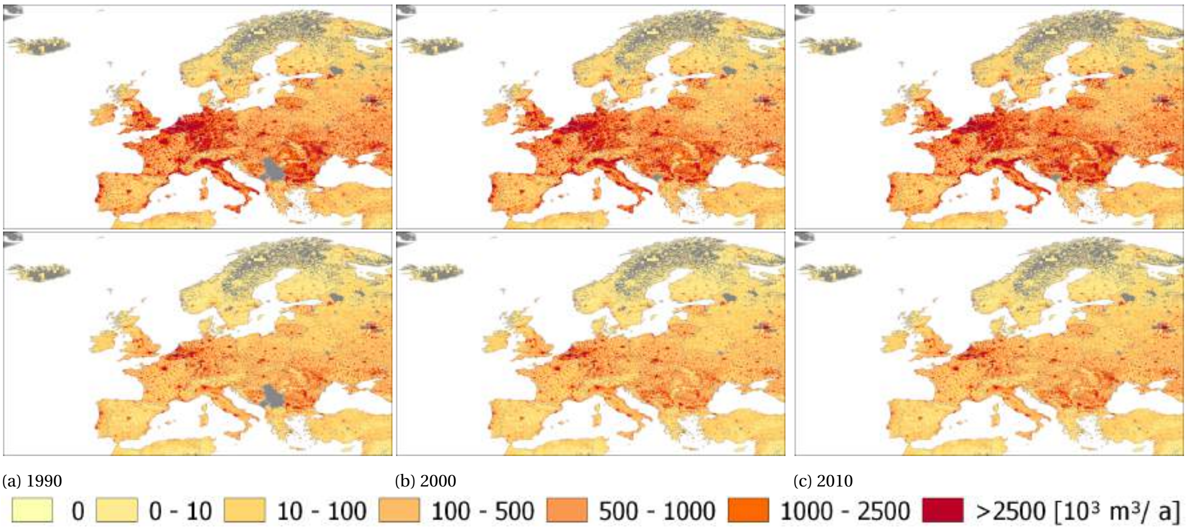

Figure 4.2: Gross (top) and net (bottom) European industrial water demand at 5 arcmin for 1990, 2000 and 2010 for the reference dataset.

4.2.2. Comparing reference dataset to Wada's outcome

Domestic water demand

Figure 4.3 shows the relative difference in domestic water demand for 1990 to 2010 in cell data and country averages.

Focusing on cell data, it can be seen that there is a general pattern of the reference dataset estimating higher water demand values in urban areas than the original outcome of Wada's method, while lower values are measured by the reference dataset than the original outcome in rural areas. The United Kingdom, Ireland, Iceland, the Netherlands, Russia, Slovakia and the Balkan countries have much higher values for domestic water demand in the reference set than the original outcome, which country averages confirm. Russia shows at cell data constantly higher water demand for the reference dataset than for the original outcome, indicating a chance in parameter at country level. At a temporal scale it can be seen that the outcome for water demand in the reference set decreases in value compared to the outcome of the original dataset, i.e. red becomes less prevalent, between 1990 and 2010. Most countries are within a -50 to +50% range compared to the original outcome.

As 2000 is the benchmark in the method from which other years of water demand are derived by inclusion of technological and economic development, the least noise is expected in this year. As this is not the case, other explanations should be considered for the relative differences between the reference dataset and the original outcome. The differences might be a result of different downscaling techniques, gap-filling techniques, or parameter differences in population numbers, recycling ratios, water use intensity or urban population ratio (see equation 2.6 and 2.9). Figure C.1 in Appendix C illustrates compared gross domestic water demand in 2000 which has higher positive values in relative differences. As gross water demand is not affected by urban population and the recycling ratio, it would imply that these two factors do not play a role in the difference between the original and the recreated outcome.

Industrial water demand

Figure 4.4 shows the relative difference in industrial water demand for 1990 to 2010 in cell data and country averages.

In general, cell data shows that the outcome of the reference dataset for industrial water demand is lower than the original outcome, except for middle England, the Netherlands, Paris, Frankfurt, parts of the Balkan towards Moldova and Russia, and is supported by country averages. Differences in general are more negative

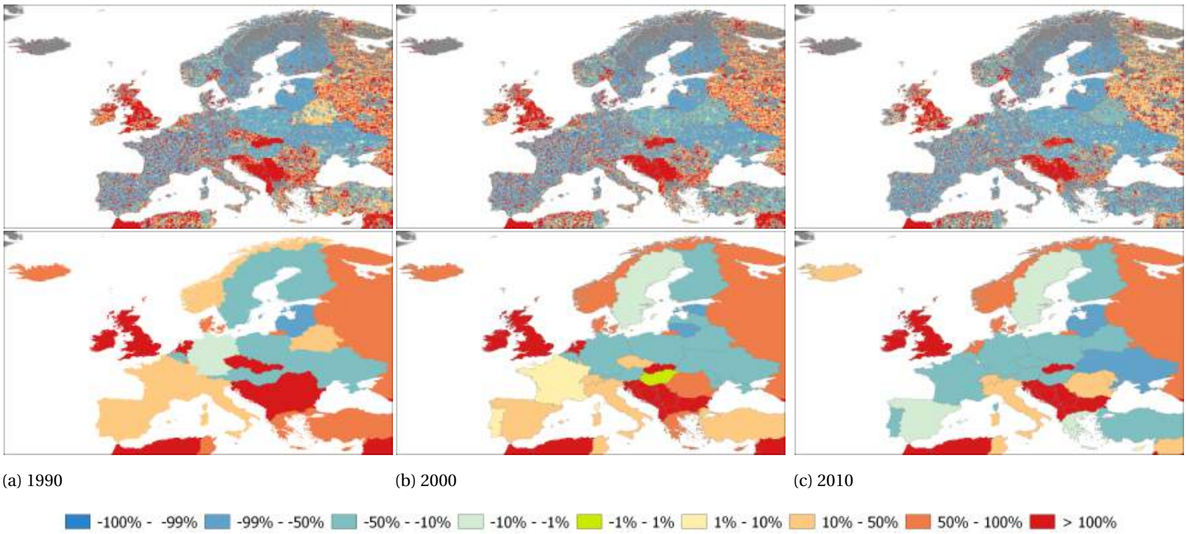

Figure 4.3: Relative difference between the reference dataset for net domestic water demand and the original outcome of Wada's method as point data (top) and averaged over the country (bottom) at 5 arcmin European scale for 1990, 2000 and 2010.

than for domestic water demand mostly in the range that the original outcome is around 10-50% higher than the reference dataset. Between 1990 and 2010 the same temporal pattern as for domestic water demand can be found where the relative differences decreases from a high positive value to a less high negative value around urban areas.

Noise between relative differences in net and gross water demand of 2000 do not change in the western part of Europe, including the United Kingdom, Ireland, Iceland, Spain, France, Italy, the Netherlands, Belgium, Germany, Norway, Sweden, Finland, Denmark and Switzerland (see Figure C.2 in Appendix C. Furthermore, gross industrial demand has lower relative difference in the Balkan countries than net demand, which would indicate that the data on development stage and subsequently the recycling ratio has changed between the method of Wada and the reference dataset in this research, or the gap-filling technique when no data was available is different.

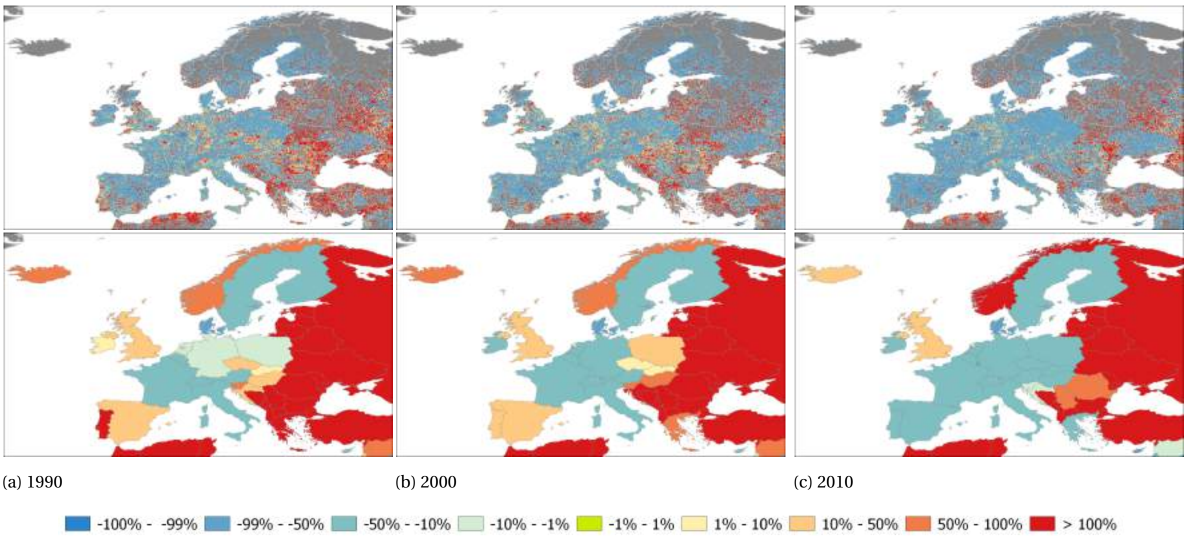

Figure 4.4: Relative difference between the reference dataset for net industrial water demand and the original outcome of Wada's method as point data (top) and averaged over the country (bottom) at 5 arcmin European scale for 1990, 2000 and 2010.

4.2.3. Compare reference dataset to observational data

Domestic water demand

The regression slope of gross and net domestic water demand against EUROSTAT's water use are 0.600 and 1.35 at country level, while decreasing to 0.49 and 0.96 respectively at NUTS-2 level, as can be seen in Figure 4.5. At both spatial levels gross demand is below the 1:1 line, while net domestic demand is at country level above and on NUTS-2 level slightly below the 1:1 line. As for both gross and net demand the opposite is expected, an explanation could be the discrepancy between the demand and use.

The square of the Pearson correlation coefficient, R^2, increases from country level to NUTS-2 level and decreases from gross to net demand. From gross to net demand at country level, R^2 decreases from 0.565 to 0.486 while at NUTS-2 level this decrease is from 0.629 to 0.510. The decrease in R-squared between gross and net demand is expected and the increase of R^2 with increase in resolution adds to the conclusion that the domestic water demand method can be used as a starting point for a high-resolution water demand method which can be further improved.

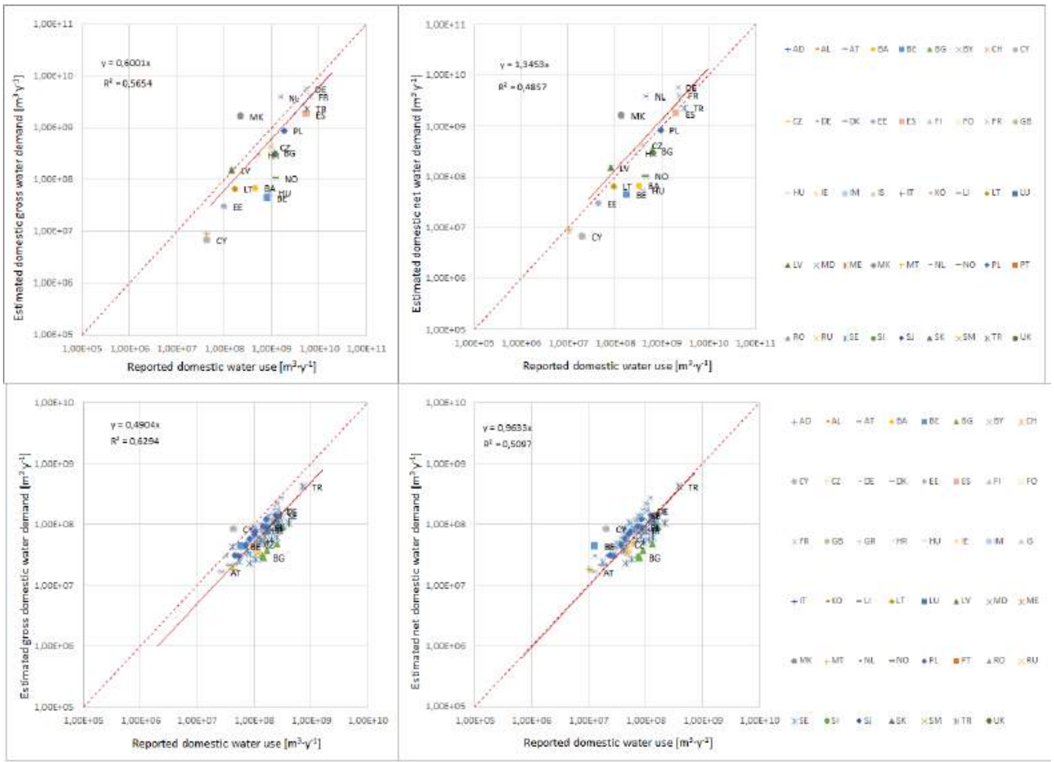

Figure 4.5: Gross (left) and net (right) domestic water demand ($m^3/year$) from the reference dataset compared to the outcome of water use by EUROSTAT at country level (top) and NUTS-2 level (bottom). The regression coefficient is forced through the zero intercept.

Industrial water demand

The regression slope of gross and net industrial water demand against EUROSTAT's water use are 0.498 and 2.22 at country level, while decreasing to 0.115 and 0.359 at NUTS-2 level, respectively (see Figure 4.6. It seems that Macedonia and Cyprus are the main data points that are out of line. At both spatial levels gross demand is below the 1:1, which is the opposite of what is expected. Meanwhile, net water demand is above (as expected) the 1:1 line at country level but falls below this line when resolution is increased. This might indicate a larger discrepancy for industrial compared to domestic between water demand and use.

The R^2 decreases from gross to net as expected and decreases from country resolution to NUTS-2 resolution, which is not expected. At country level, gross and net R^2 are 0.440 and 0.378, while at NUTS-2 they are respectively 0.005 and 0.0006. Such a low R-squared at NUTS-2 level actually indicates that almost none of variability in water demand data can be explained by observational water use. This supports the fact that the industrial water demand method is not as suited as the method for households to increase in resolution, showing there is a lot of improvement possible.

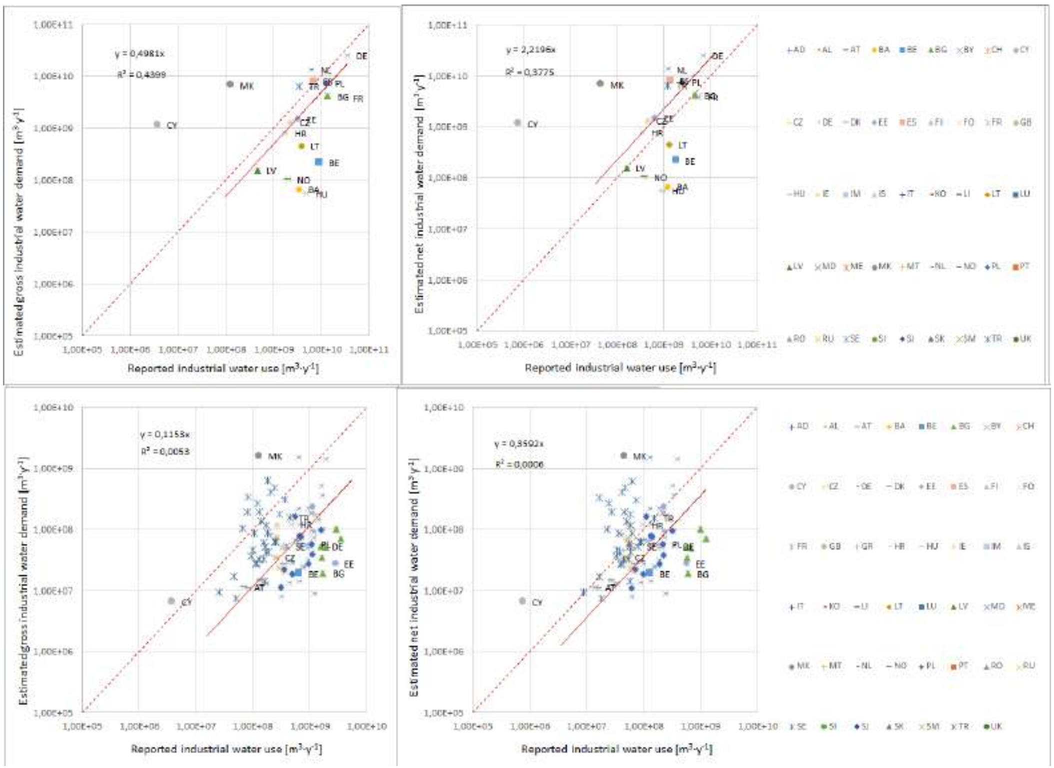

Figure 4.6: Gross (left) and net (right) industrial water demand ($m^3/year$) from the reference dataset compared to the outcome of water use by EUROSTAT at country level (top) and NUTS-2 level (bottom). The regression coefficient is forced through the zero intercept.

4.3. Sensitivity analyses by adjusting variables

The sensitivity analysis conducted is controlled by deficiencies in Wada's original method. These deficiencies are categorized in concepts, parameter resolution and downscaling technique used. The variables are adapted one by one in the reference dataset for 2010, and their performance is measured and visualized in different manners.

4.3.1. Sectoral comparison

In Table 4.3 an overview is given for the all adapted variables and their influence on improving the method in terms of overlap. The analyses consists of the reference dataset, followed by variables that caused the highest overlap between observed and modelled data to lowest percentage overlap.

It can be seen that overlap between water use from EUROSTAT and gross and net water demand for households for the reference dataset is higher for NUTS-2 than for country data in general, whereas for industries overlap is higher at country level. The overlap between the domestic reference dataset differs from the original outcome on both levels, respectively 15.8% and 20.0% at NUTS-0, against 63.8% and 38.3% at NUTS-2 (see Table 4.1). Both the reference dataset and the original outcome increase in relative overlap with higher resolution, the reference dataset seems to resemble observational data better at NUTS-2 level whereas the original outcome resembles observational data better at country level. The relative overlap for the industrial reference dataset is lower than the original outcome when compared to the observational data, respectively 27.8% and 38.1% at country level, and 22.6% and 23.9% at NUTS-2 level (see Table 4.2. The original outcome seems to resemble observations better at country level, but there is almost no relative difference at NUTS-2 level between the reference dataset and the original outcome.

For domestic water demand, relative overlap only changes on country level to 55.6% by changing the concept on wastewater. At NUTS-2 level, the relative overlap increases again for changing the concept of wastewater (to 94.2%), implying this has a major positive effect in recreating observational data. The concept of wastewater influences the recycling ratio directly and as this ratio defines the fraction of gross domestic demand which will become net water demand, i.e. the gap between gross and net demand will become larger, increasing the chance of water use to be sandwiched by them which is subsequently measured. Other resolution and downscaling changes of the method yield a 1-2% decrease in overlap. This difference is too small to draw a conclusion on the influence of these parameters by a table only, as values might be distorted by the difference in definition of water demand and use, which could emphasize the bias of this study.

For industrial water demand, relative overlap at country level only increases by changing the resolution of GDP from national data to NUTS-3 data (from 27.8% to 33.3%), but as the amount of data points are low a conclusion cannot be drawn without further research. At NUTS-2 level, using the CORINE industrial land cover fraction at 30 arcsec results in the same relative overlap between industrial demand and observed data, whereas a 30 arcsec population map from Worldpop results in a 2.8% (20.6%) overlap. Increasing the resolution of GDP decreases the overlap 1%, but as here are also not that many data points it is important to explore this further.

Spatial resolution: NUTS-0							**Year: 2010**
		Households			**Industry**		
Adapted component	**Sort change**	**Data points**	**Wada vs. EUROSTAT**		**Data points**	**Wada vs. EUROSTAT**	
			Points	**[%]**		**Points**	**[%]**
Reference dataset		19	3	15.8	18	5	27.8
Wastewater	Concept	18	10	55.6			
GDP to NUTS-3	Resolution	19	3	15.8	18	6	33.3
POP to NUTS-3	Resolution	19	3	15.8			
Population 1km 2000	Downscaling	19	3	15.8	18	5	27.8
Population 1km 2010	Downscaling	19	3	15.8			
CORINE 1km	Downscaling				18	5	27.8
Spatial resolution: NUTS-2							
		Households			**Industry**		
Adapted component	**Sort change**	**Data points**	**Wada vs. EUROSTAT**		**Data points**	**Wada vs. EUROSTAT**	
			Points	**[%]**		**Points**	**[%]**
Reference dataset		105	67	63.8	106	25	23.6
Wastewater	Concept	104	98	94.2			
POP to NUTS-3	Resolution	105	67	63.8			
CORINE 1km	Downscaling				106	25	23.6
GDP to NUTS-3	Resolution	105	65	61.9	106	24	22.6
Population 1km 2000	Downscaling	105	66	62.9	106	22	20.8
Population 1km 2010	Downscaling	105	65	61.9			

Table 4.3: Result of the sensitivity analyses for households and industry, effect of adapting individual components on relative overlap between water demand and observed water use. The outcome for national and regional data.

4.3.2. Comparing adapted components

For clarity, tables with information on regression slopes and the explained proportion of variation (R^2) will be given here, but the scatter plots (visual inspection of scatter plots is essential) and maps of visualized absolute and relative water demand can mostly be viewed in Appendix D except for downscaling techniques, as maps visually change to the desired high resolution which is considered important.

Conceptual change

Adapting the concept of wastewater treatment to detailed national data collected by Van Puijenbroek et al. [2019], has given more overlap between observed data on water use on the one hand an gross and net water demand on the other hand. A side note has already been made that his is probably because the difference between gross and net water demand becomes larger, increasing the chance that water use indeed falls in between gross and net demand. Changing the wastewater component will not yield differences for gross domestic water demand as is only influences net domestic water demand.

In Figure D.2 in Appendix D changed regression slopes and R^2 compared to the reference dataset for net demand can be seen on the right part of the image, and in Table 4.4 it is stated as well. For net domestic water demand with the changed conceptual approach of the recycling ratio, the regression slope at country and

NUTS-2 level almost double, which is unexpected. Net water demand is in theory lower than water use and is therefor expected to lay below the 1:1 line. For net water demand, the R^2 decreases a lot but still has a better fit at a higher resolution level. This implies that with changing the recycling ratio concept, the ability of the method to recreate observational data stays the same for gross demand compared to the reference dataset and decreases for net water demand. Wada assumed that the recycling ratio was the part of the water that was still usable, which does not depend on F_{sewage} (eq. 2.9) but on the treatment given, i.e. 100% sewage does not mean 0% net water demand.

As the change of this concept in the present form does not improve the method, the maps are visualized in Figure D.1 in Appendix D, where spatial variability and comparison to the reference dataset for net domestic water demand can be found. Spatial variability within countries does not change as the component of wastewater is at national level. It does decrease net water demand to a lower fraction of gross domestic water demand, which also explains why most countries experience a negative relative difference compared to the reference dataset.

Conceptual change				R^2 **(Regression slope)**
	Country		NUTS-2	
Data set:	Gross	Net	Gross	Net
Reference households	0.565(0.600)	0.486(1.35)	0.629(0.490)	0.510(0.963)
Concept on waste water	0.565(0.600)	0.152(2.60)	0.629(0.490)	0.206(2.01)

Table 4.4: R^2 and regression slope in brackets for the reference datasets and the change in concept of recycling ratio for gross and net water demand at country and NUTS-2 level for households and industry.

Change variable resolution

Changing resolution for gross domestic product and population in equations 2.1 and 2.6 from data at country level to NUTS-3 level enables the water demand method to implement variables at a higher resolution than national level. GDP and population are variables that are used early on in the method which would mean that a higher resolution is established from the beginning. Increasing their resolutions should result in higher spatial variability within countries, visible at gross and net water demand. Regression slopes and R^2 values, and their change by changing the resolution of these variables are written out in Table 4.5.

Gross domestic product Figure D.4 and D.5 in Appendix D show the scatter plots, regression slopes and R^2 when changing the variable of gross domestic product to NUTS-3 level in the method and how it affects gross and net demand at country and NUTS-2 level for households and industries.

For households, the R^2 decreases slightly at country level and increases slightly at NUTS-2 level (Table 4.5), while the regression slopes stay almost equal to the reference dataset. Water demand is visualized in Appendix D in Figure D.3 and there is not a general different spatial pattern then in the reference dataset. Relative differences shows that when adapting GDP at NUTS-3 level, most countries increase or decrease in water demand with no spatial variability within a country arising (except for Ireland, Finland and Turkey), which was not expected. Adapting the resolution of GDP shows that most countries experience a lower water demand (blue areas), while Norway, Sweden, Ireland, Denmark, Poland and the Balkan countries increase in water demand. As the reference dataset used a different data source than the adapted variable, this could be a cause. Additionally, as GDP is measured against the benchmark year, relative difference is important and within-country differences on GDP can be evened out as economic growth may be constant over a country.

For industry, changing GDP to a higher resolution level yields higher R^2 and regression slopes for gross and net water demand at country level and gross demand at NUTS-2 level, net demand at this level does not change. This indicates a better fit, which could be the result of the relocation of water demand within the country. Changing GDP to a higher resolution also shows no visual change in spatial variability of water demand (Figure D.6, Appendix D). Comparing to the reference dataset it can be seen that there is higher spatial variability within countries (e.g. Poland, Romania, Portugal, Hungary, Croatia and Sweden), indicating that changing the resolution of GDP relocates water demand within countries. Scandinavia, the Baltic states, Poland and a part of the Balkan have higher water demand at country level than the reference dataset, which could be the cause by the use of different data sources.

Population For households, increasing the resolution of population data in the variable POP in equation 2.6, increases the R^2 at country slightly and much more at NUTS-2 level while the regression slopes do not change that much compared to the reference dataset. The regression slopes are expected to be above the 1:1 line for gross demand and below it for net demand, while it is the opposite. Including spatial variability on population within countries improves the method in its ability to resemble observational data on water use. The scatter plots can be seen in Figure D.8 in Appendix D.

Visualization of this data leads to Figure D.7 in Appendix D, which shows that there is a spatial change when increasing population resolution; urban areas become smaller with a higher intensity net water demand in them (Portugal and Italy) or their highest intensity area relocates (in the Netherlands from the area of the Hague to north Holland). Relative differences show that adapting population resolution lowers water demand in most countries in comparison to the reference dataset, while water demand increases in Scandinavia (except Iceland), Poland, Croatia and Bosnia and Herzegovina. At NUTS-3 level (point data) there is a lot of within-country variation, indicating that population and thus water demand are relocated, as expected. Higher water demand would indicate a larger population in these areas than calculated for the reference dataset. A cause could be that there is a difference in data source used between this variable and the reference dataset.

Increasing variable resolution				**R^2 (Regression slope)**
	Country		NUTS-2	
Data set:	Gross	Net	Gross	Net
Reference households	0.565(0.600)	0.486(1.35)	0.629(0.490)	0.510(0.963)
Population to NUTS-3: households	0.586(0.631)	0.516(1.44)	0.751(0.493)	0.638(0.969)
GDP to NUTS-3: households	0.548(0.618)	0.456(1.35)	0.633(0.484)	0.520(0.935)
Reference industry	0.440(0.498)	0.378(2.22)	0.005(0.115)	0.001(0.359)
GDP to NUTS-3: industries	0.454(0.537)	0.394(2.40)	0.006(0.124)	0.001(0.359)

Table 4.5: R^2 and regression slope in brackets for the reference datasets and the change in variable resolution for gross and net water demand at country and NUTS-2 level for households and industry.

Different downscaling techniques

The downscaling technique applied is changed in two ways for both domestic and industrial water demand. Domestic demand is downscaled with a 2000 and 2010 population density map from Worldpop, whereas industrial water demand is downscaled using the 2010 population map and the CORINE land cover map with industrial areas covered. The increased resolution of the downscaling technique will be the factor that enables the increase of the method from NUTS-3 or country level to a 30 arcsec level. Emphasize should be put on changing these techniques to find the impact it has on water demand allocation. Downscaling is done in the method in equation 2.7 and 2.3. Regression slope and R^2 can be compared to the reference dataset in Table 4.6, extra maps may be visualized in Appendix D.

Changing downscaling techniques				**R^2 (Regression slope)**
	Country		NUTS-2	
Data set:	Gross	Net	Gross	Net
Reference households	0.565(0.600)	0.486(1.35)	0.629(0.490)	0.510(0.963)
30 arcsec population 2000: households	0.565(0.600)	0.486(1.35)	0.713(0.481)	0.593(0.940)
30 arcsec population 2010: households	0.612(0.598)	0.526(1.34)	0.732(0.471)	0.617(0.916)
Reference industry	0.440(0.498)	0.378(2.22)	0.005(0.115)	0.001(0.359)
30 arcsec population 2000: industries	0.439(0.499)	0.377(2.22)	0.011(0.118)	0.002(0.371)
30 arcsec CORINE land cover: industries	0.439(0.499)	0.377(2.22)	0.006(0.113)	0.001(0.367)

Table 4.6: R^2 and regression slope in brackets for the reference datasets and the change in downscaling technique and year for gross and net water demand at country and NUTS-2 level for households and industry.

Downscaling for households Coming to a high-resolution water demand model for households, a population density map from Worldpop is used at 30 arcsec, which creates grid cells of 1x1km, for 2000 (same year as the reference dataset used) and 2010. Both R^2 and the regression slope do not change at country level for downscaling to 1km with a 2000 map, implying that both the 0.5 and 5 arcmin map have the same country population totals (see Appendix D, Figure D.9 for 2010). However, at NUTS-2 level R^2 increases while

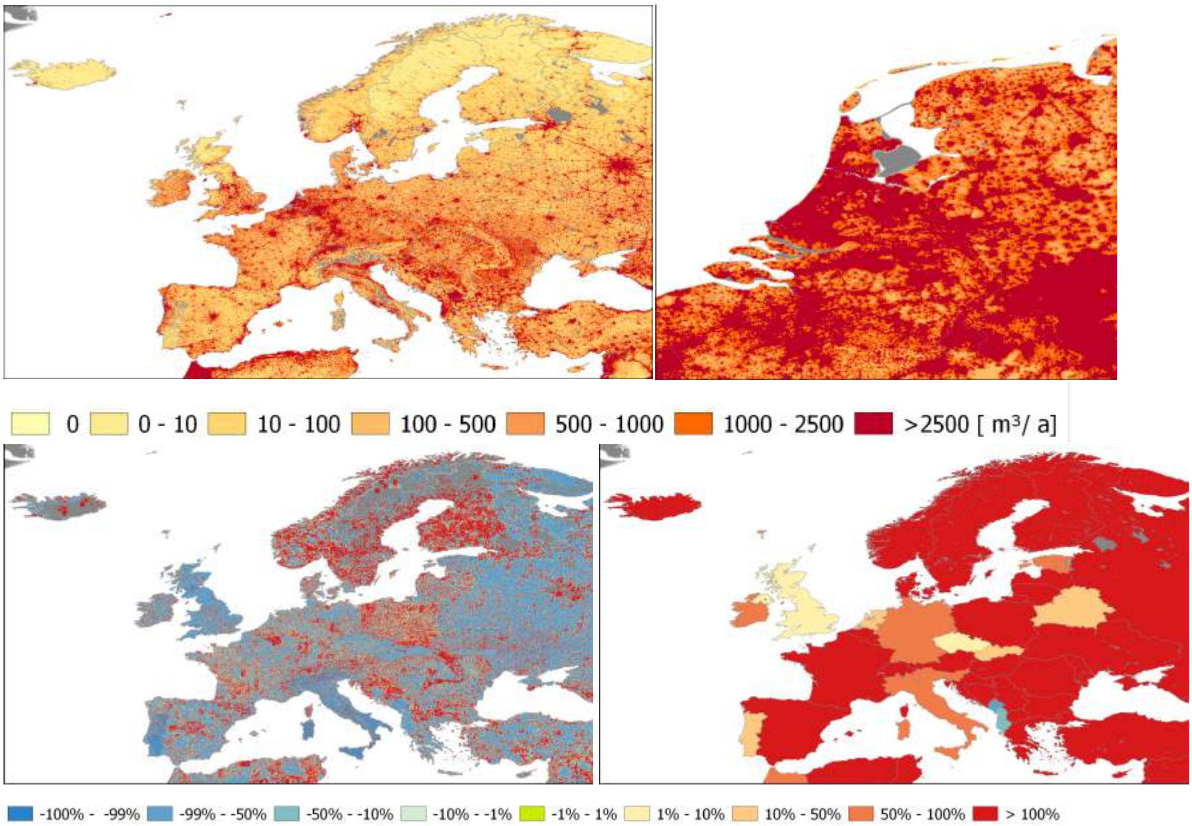

Figure 4.7: Net demand (top) when adapting the downscaling technique to a 2010 population map for domestic water demand and zoomed in on the Netherlands to show the fine resolution and the spatial allocation of water demand, and the relative difference between the outcome of the sensitivity analyses and the reference data set in cell data (bottom left) and as country average (bottom right) at 30 arcsec for 2010 at European scale.

the regression slope slightly decreases, which could be explained by a change in water allocation as the resolution has become finer. The downscaling technique with the 2010 map shows little variation in regression slope with the reference dataset, but R^2 increases significantly for both country and NUTS-2, as well as gross and net demand. This implies that a finer resolution downscaling technique allocates water in a better way, especially when comparing it at NUTS-2 levels.

At European scale, in Figure 4.7, spatial variability of water demand allocation at 1 kilometer resolution is visible. Zooming in on the Netherlands shows how a 30 arcsec resolution captures the outline better than at 5 arcmin, including the Wadden islands. Spatial allocation of water demand has a pattern with high demands near urban areas and towns (e.g. small towns in Flevoland also show a difference with the rural parts) but it should be noted that the legend scale has been adapted compared to the reference dataset. Relative difference in cell data does not show a spatial pattern, but water demand seems to be higher in Scandinavia compared to the reference dataset, which is supported by country averages.

Downscaling for industries Coming to a high-resolution water demand model for industries, a population density map from Worldpop is used at 30 arcsec, which creates grid cells of 1x1km for 2000 (same year as the reference dataset used), and a land fraction map from CORINE for industries is used at 30 arcsec for 2000 as well. At country level there is no change visible between R^2 of the reference dataset and for the two downscaling techniques (see Table 4.6). This can be explained by the fact that the gross industrial water demand from WWDR-II is used for all three methods, before being added to a country total and redistributed, generating the same values for R^2. However, at NUTS-2 level, different water allocation takes place and R^2 doubles with the population map, whereas slightly increases with the CORINE land cover fraction. The R^2 shows for all three a weak connection, which makes it hard to draw a conclusion of which downscaling technique works best for industries, although population maps seem to give a better fit.

Visualization with the two downscaling techniques gives completely different spatial variability of industrial water demand as the population map uses downscaling with population density, whereas CORINE only takes areas which are allocated as industrial areas in consideration (Figure 4.8 for CORINE, Figure 4.9 for 2000 population). The relative difference between CORINE and the reference dataset is difficult to read as all industrial water demand is now focused on the small areas where all industries are located instead of across the country, intensifying total industrial water demand where there is industrial area. The downscaling with the population map shows the same spatial variability as for households (mind the legend has a factor 10 applied to the scale), with higher industrial water demand in more densely populated areas. This results in the same relative differences with the reference dataset.

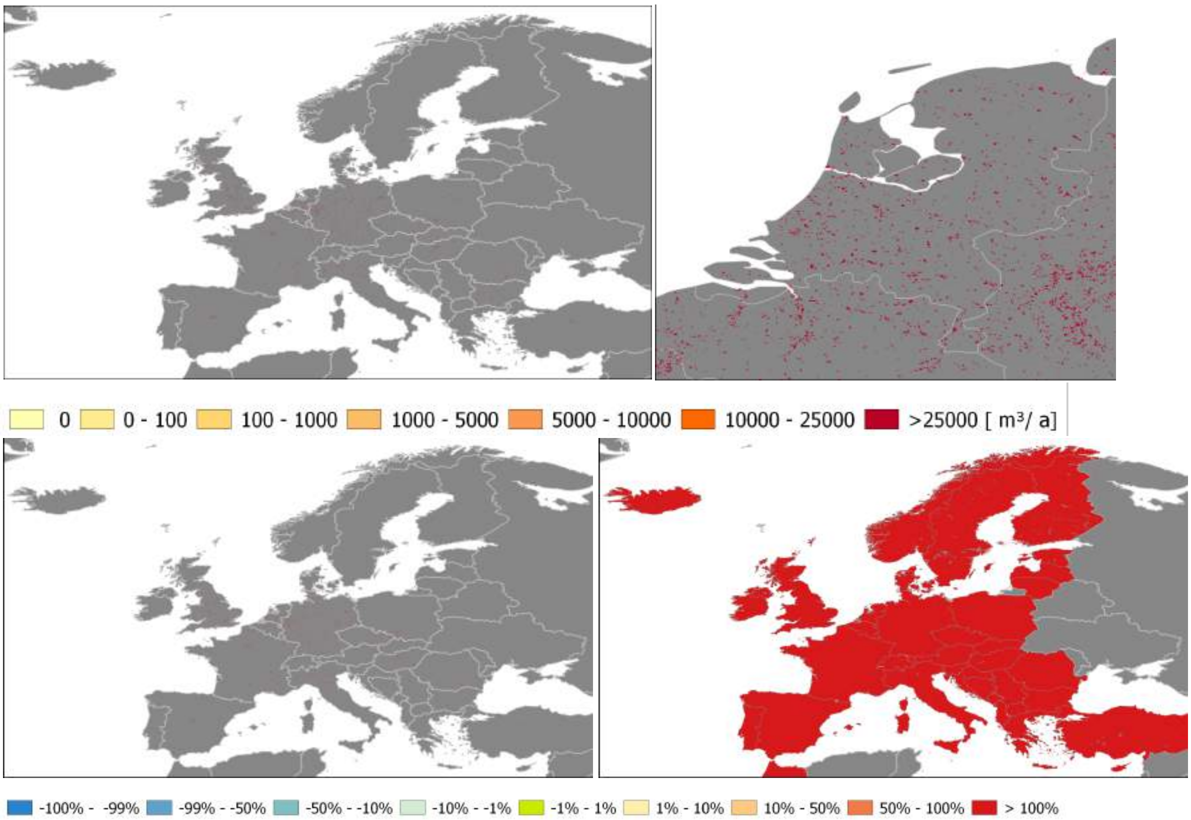

Figure 4.8: Net demand (top) when adapting the downscaling technique to a CORINE land cover fraction map for industrial water demand and zoomed in on the Netherlands to show the fine resolution and the spatial allocation of water demand, and the relative difference between the outcome of the sensitivity analyses and the reference data set in cell data (bottom left) and as country average (bottom right) at 30 arcsec for 2010 at European scale.

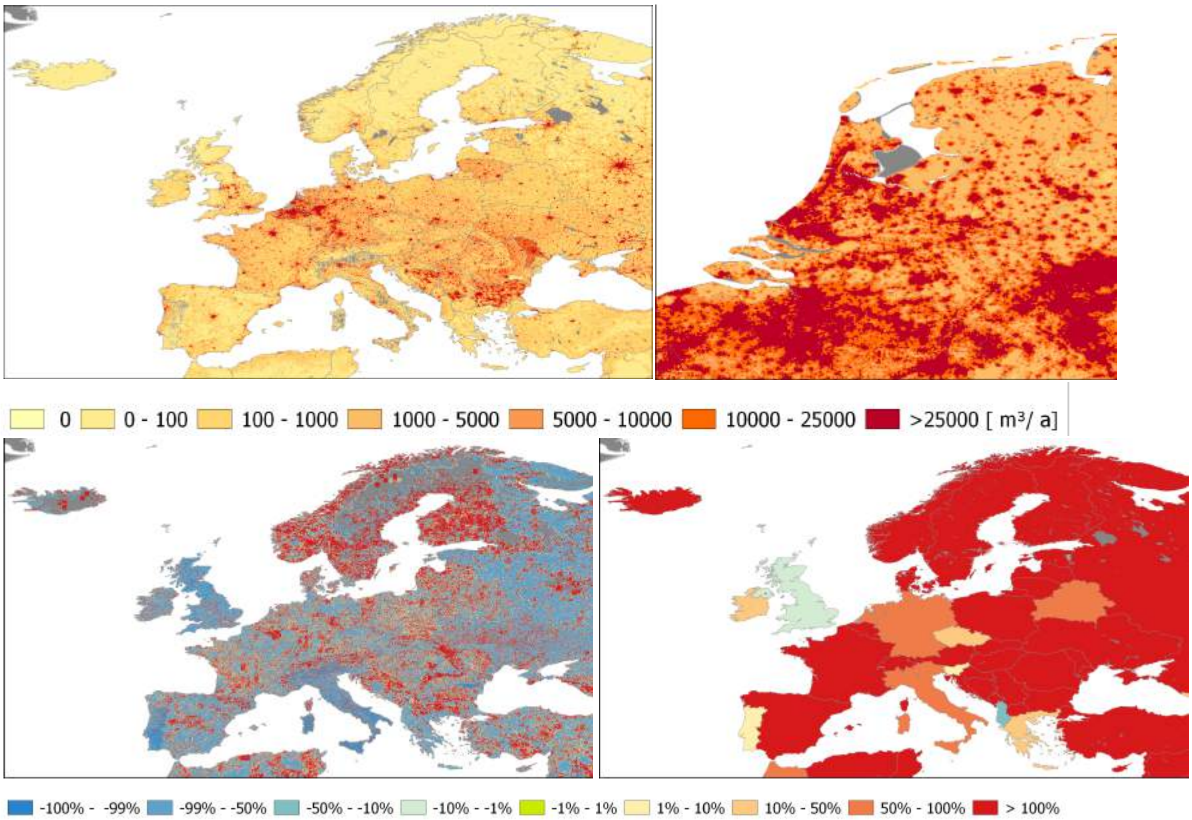

Figure 4.9: Net demand (top) when adapting the downscaling technique to a 2000 population map for industrial water demand and zoomed in on the Netherlands to show the fine resolution and the spatial allocation of water demand, and the relative difference between the outcome of the sensitivity analyses and the reference data set in cell data (bottom left) and as country average (bottom right) at 30 arcsec for 2010 at European scale.

4.4. High-resolution water demand method and dataset

The aim of this research is to create a high-resolution method and dataset which are able to define high-resolution water demand for households and industry in Europe and which in the future could be implemented on a global scale. To achieve this aim it is important to conduct a final assessment where dominant and essential components, evaluated in the previous section are included to improve the existing method. The effect of data quality on the method for the purpose of global applications is determined. The domestic and industrial water demand method are changed in the following way:

- The benchmark year defined as $T0$ is updated from 2000 to 2010, meaning that domestic water use intensity (DWUI) is now implemented using 2010 data and the denominators of the four socio-economic variables in the economic development equation (eq. 2.1) are all updated as well, as are the $T0$ variables in technological development (eq. 2.2);
- Downscaling to 30 arcsec is done for households by using a population settlement map at 30 arcsec and is updated from 2000, to 2010 for households. For industry, both the population settlement map at 30 arcsec from 2010 and the CORINE land cover technique are applied as R^2 for both did not show a clear distinction;
- The variable of gross domestic product (GDP in economic development) and population (POP in eq. 2.6) are increased in resolution from national data to data at NUTS-3 level for both households and industry where possible;
- The concept of the recycling ratio is changed to a parameter that is reported by Van Puijenbroek et al. [2019], but will take into account urban population as Wada did in equation 2.9. Wada does not assume that all water that is treated returns to the hydrological cycle, so neither will this study do that. The sensitivity analysis showed that by doing that the R^2 decreases to a really low value.

The method is applied to the year 2013 as this is the most recent year for which water use data at NUTS-2 level is retrievable from EUROSTAT. Information on adapted variables can be found in Appendix A in Figure A.5. The calculated overlap in gross and net water demand from this method and from observed data on water use are stated in Table 4.8, R^2 and regression slopes are stated in Table 4.7.

High-resolution water demand dataset				R^2 **(Regression slope)**
Data set:	Country Gross	Net	NUTS-2 Gross	Net
Reference households	0.565(0.600)	0.486(1.35)	0.629(0.490)	0.510(0.963)
30 arcsec population 2010: households	0.946(0.205)	0.890(0.541)	0.665(0.457)	0.822(0.907)
Reference industry	0.440(0.498)	0.378(2.22)	0.005(0.115)	0.001(0.359)
30 arcsec population 2010: industries	0.615(0.530)	0.012(1.41)	0.019(0.038)	0.020(0.162)
30 arcsec CORINE land cover: industries	0.604(0.531)	0.012(1.41)	0.019(0.038)	0.020(0.162)

Table 4.7: R^2 and regression slope in brackets for the reference datasets and final method with different downscaling techniques for gross and net water demand at country and NUTS-2 level for households and industry at 30 arcsec in 2013.

Spatial resolution: NUTS-0						**Year: 2010**
	Households			**Industry**		
Adapted component	**Data points**	**Wada vs. EUROSTAT**		**Data points**	**Wada vs. EUROSTAT**	
		Points	**[%]**		**Points**	**[%]**
Reference dataset	19	3	15.8	18	5	27.8
30 arcsec population 2010	9	5	55.6	18	7	38.9
30 arcsec CORINE land cover				17	7	41.2
Spatial resolution: NUTS-2						
	Households			**Industry**		
Adapted component	**Data points**	**Wada vs. EUROSTAT**		**Data points**	**Wada vs. EUROSTAT**	
		Points	**[%]**		**Points**	**[%]**
Reference dataset	105	67	63.8	106	25	23.6
30 arcsec population 2010	28	12	42.9	29	6	20.7
30 arcsec CORINE land cover				29	6	20.7

Table 4.8: Relative overlap for water demand of households and industry with observational water use when implementing the full high-resolution water demand dataset and method at country and NUTS-2 level for 2013.

4.4.1. Domestic high-resolution water demand

The final created method for domestic water demand used the 2010 population downscaling map at 30 arcsec from Worldpop and when compared to observational data on water use of 2013, strong correlations and R^2 are found, much stronger than for the reference dataset (see Table 4.7, or for the plots see Appendix D Figure D.10), while the regression slope decreases for all. At country level especially, R^2 increases to 0.946 and to 0.890 for gross and net demand (but N=9). At NUTS-2 level R^2 increases only slightly for gross demand from 0.629 to 0.665, but for net water demand R^2 reaches 0.822 compared to 0.510 in the reference dataset (N=28).

Visualizing the spatial variability in water demand gives Figure 4.10, with a fine resolution for water demand allocation. Water demand is highest where population density is highest, highlighting urban areas in red. Using this method causes data gaps for Iceland, Bosnia and Herzegovina and Kosovo. The outcome of the final method is also compared to the reference dataset to find relative differences (see Figure D.11 in Appendix D). In general, domestic water demand in the improved high-resolution water demand method calculates lower water demand per grid cell than the reference dataset. The R^2 shows a really strong explained variation for this method implying that the original method of Wada overestimated net domestic water demand. Cell averages show no spatial pattern between urban and rural areas.

4.4.2. Industrial high-resolution water demand

The final created method for industrial water demand used the 2010 population downscaling map at 30 arcsec from Worldpop and the CORINE land cover fraction for industrial areas. Both show an increase in reported

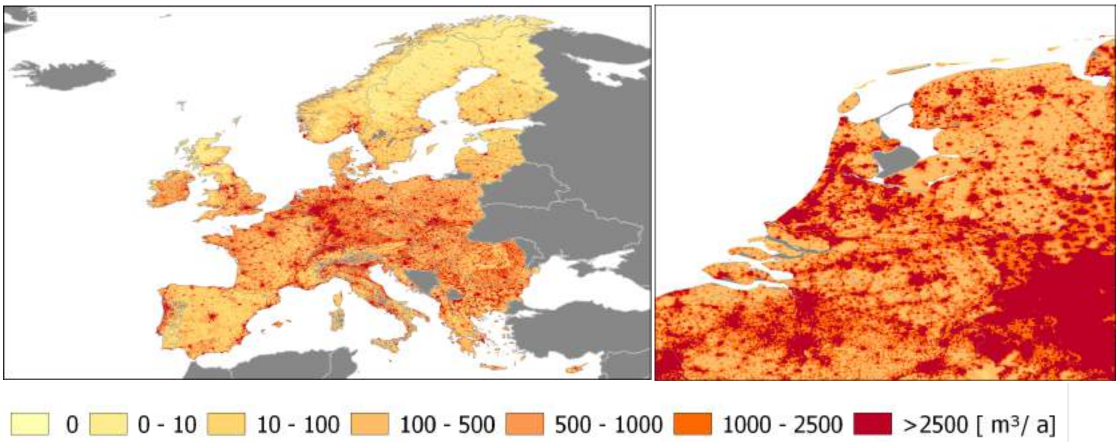

Figure 4.10: Net domestic water demand with the high-resolution water demand method and dataset focused on Europe and the Netherlands to show the fine resolution and the spatial allocation of water demand,

R^2 (see Table 4.7), but at NUTS-2 level these values are still low and indicate a weak explained variation between water demand and observational water use from EUROSTAT (extra plots can be found in Appendix D Figure D.13 and D.15). Gross water demand increases from 0.378 (reference dataset) to 0.615 and 0.604 for the population downscaling map and the CORINE land cover map respectively.

The spatial variation of industrial water demand according to distribution by population and CORINE land cover fraction can be seen in Figure 4.11, respectively at the top and at the bottom. The outcome of the high-resolution industrial water demand method is also compared to the reference dataset to find relative differences (see Figure D.12 and D.14 in Appendix D). For the population downscaling map, spatial distribution in relative differences is almost the same as for domestic water demand which implies that the population map at 30 arcsec has a large influence in the difference with the reference dataset. For the CORINE downscaling map, industrial water demand is focused in areas with industrial cover, intensifying the demand in these locations and showing as if total country industrial demand are much higher, giving a distorted image. As both maps increase the explained variation to the same extent, neither will be left out this study.

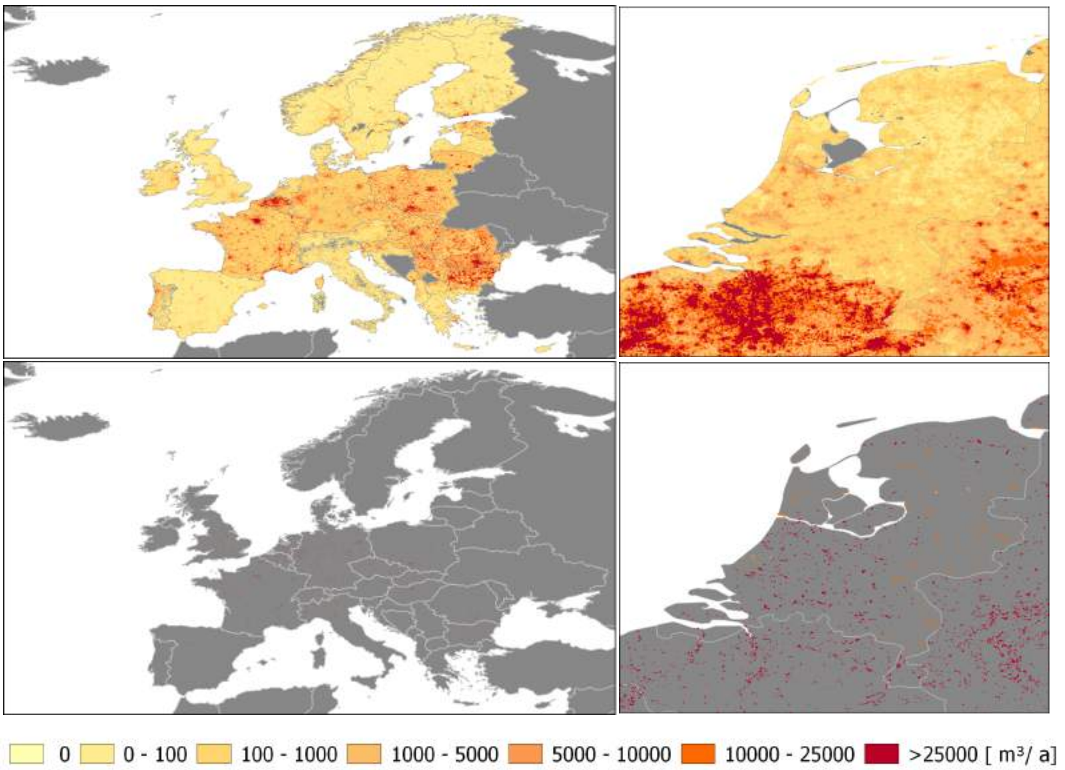

Figure 4.11: Net industrial water demand with the high-resolution water demand method and dataset focused on Europe and the Netherlands to show the fine resolution and the spatial allocation of water demand,

5
Discussion

The development of water resource models requires reliable projections of gross and net water demand into the past for validation purposes and into the future to explore mitigation and adaptation strategies. The ambition to bring these models to hyper-resolution makes this requirement all the more pressing. Yet, the problem arises that high-resolution water demand data are universally missing resulting in absence of relevant studies that assess global water demand at high spatial resolution. On the one hand, global studies estimating water demand often use data at national level and have a resolution of 10 or 50 kilometer grid cells which neglect the impact of local characteristics, making it hard to distinguish related patterns and trends. Furthermore, limited availability and accuracy of data sources contributed to a more basic portrayal of water demand in global scale water demand modelling assessments. At the same time, studies on water demand with high spatial resolution containing variables at regional scale use more refined methods, but they cover only a specified study area and do not consider global water demand or processes. These models can simulate more, yet the same method cannot be applied on a different area since data sources for other areas have often lower data densities.

This study is conducted to track down the possibilities and the restrictions of existing downscaling techniques in context of a high-resolution water demand method and to determine the effect of data quality. The approach is to set up a flexible framework to define high-resolution water demand for households and industries in Europe, using existing downscaling concepts and datasets with the final objective to develop and improve high-resolution global water demand estimates that may benefit from forthcoming data sources.

This chapter will be organised in a way that the four research objectives, which contribute to achieving the aim of this research will be discussed in order. The potential improvements of a conceptual top-down approach and the implementation by Wada are considered first before emphasizing on components which improve sectoral water demand methods using other approaches. The individual parameters and concepts that contribute to the needed improvements and their quality are analysed. Subsequently, the outcome of the high-resolution water demand method is discussed. Finally, the uncertainties of this research are explained and advice for future research is given.

5.1. Water resource modelling: implementation of different approaches

This section will emphasize on the strengths and potential improvements of Wada's water demand method first before giving the general structure of existing water resource approaches and emphasizing how their structures can benefit the method of Wada with recommended potential improvements. The section is build up in a way that enables the first research objective to be achieved: *Identifying the potential improvements on the existing water demand method by Wada and analysing other water resource approaches.*

5.1.1. Strengths and potential improvements: analysing Wada's method

Wada's method for calculating sectoral water demand has a major advantage as it was set up using simple rules [Wada et al., 2011a, 2016]. His goal was to reconstruct water demand in the past and project it to the present as he was driven to assess global water stress. A high temporal scale was included to capture the out of phase manner in which water availability and demand are related. He included variables that considered socio-economic status, economic and technological development of a country, climate components and population, and thus capturing multiple complex drivers of water demand. The data he used is freely derivable from global databases, and he used a top-down conceptual approach when he considered water demand. This approach calculated water demand by implementing parameters at national level and disaggregating to 5 arcmin grid cells at a global scale through population distribution maps. His method was not perfect in resembling reported water withdrawal values at 5 arcmin, but still reports good representation of observed data with a R^2 of 0.89 for total water withdrawals when compared to observational data [Sutanudjaja et al., 2018] at country level. For these reasons, the method of Wada Wada et al. [2011a, 2016] can therefore be used as a foundation water demand method to achieve high-resolution in this research, while focusing on the European Union.

Additionally, the overlap between gross and net water demand on the one hand and water use observations EUROSTAT [2020] and simulations Bernhard et al. [2017, 2018] on the other were compared. The expected overlap increased between domestic water demand and water use increases when compared at higher spatial resolutions, this implies that the ability of the method to resemble observational data increases with higher spatial resolution. For industrial water demand there is no relation found between the increase in spatial resolution and the expected overlap, but as NUTS-3 level was not included, a final conclusion is not yet made.

The potential improvements of Wada's method can be categorized in shortcomings in the description, data source limitations and obsoloteness, the resolution and the variables used.

- Recreating Wada's method is complex and limited by the lack of elaboration and explanation in the published papers [Wada et al., 2011a, 2014; Wada and Bierkens, 2014; Wada et al., 2016]. Not one paper has fully described the method for calculating global water demand at 5 arcmin and recreation asked for combining multiple equations from published papers between 2011-2016 and a conversation with the creator [Wada, 2020].

- For both industrial and domestic water demand modelling, all variables are on national level except the downscaling technique (5 arc minute), the climate ratio (30 arc minute) and the gross industrial water demand (30 arc minute). Data on national level will not capture spatial variability in a country, see figure 2.2 that GDP already differs on a NUTS-3 level. As the aim of this research is to establish a high resolution water demand dataset, it is important to incorporate data at high resolution level, where possible. Hyper-resolution GHMs are required for modelling future water problems, as low resolution models highly underestimate the number of people living under water scarcity [Vörösmarty et al., 2000a; Wood et al., 2011]. Wada is actually using parameters in his method which can be retrieved at a higher resolution level if applied on Europe.

- Conceptual approaches are limited by the strength of the arguments and the foundation on which it is based. As Wada explored water demand for the domestic sector he, on the one hand took into account the influence of socio-economic variables, and included four of them, but on the other hand did not include any variable on demographics. Demographic data as household size, age and distribution are important factors in determining water demand Arbués et al. [2010]; Bernhard et al. [2017]; Martin [1999]; Rathnayaka et al. [2014]; Reynaud [2015].

  Additionally, another conceptual approach that has not been developed properly is the inclusion of the recycling ratio. On the one hand this enables to differentiate between total water withdrawals (gross demand) and total water consumption (net demand), but as it is the only component adding to the difference between gross and net water demand it should have a solid foundation. Wada based the recycling ratio on the development status of Japan over time, subdividing development and GDP in three stages and recycling, with higher recycling ratios in more developed countries. The recycling ratio of water is a complex parameter reflecting a society's dynamics between income, water management, health and environmental policies and culture [Koop and van Leeuwen, 2017; Van Puijenbroek et al., 2019]. Narrowing the recycling ratio of a country down to three possible values does therefor not do justice to the complexity behind this concept.

5.1.2. Identifying improvements and implementing other water resource approaches

Domestic water resource modelling has population density and per capita water use as most important drivers, and in most assessments economic development measured often with GDP, demographics, climate, technological development and water price play a major role too [Bernhard et al., 2017; Bijl et al., 2016; Flörke et al., 2013; Wada et al., 2011a]. Downscaling techniques applied all are based on population distribution.

Industrial water resource methods often differentiate between sectors of manufacturing and thermo-electric cooling, which both have their own independent drivers: industry/gross value added for the manufacturing industry, while thermo-electric cooling water has electricity production or excess amount of heat as drivers. Other important components of industrial water resource models are structural change, technological development and economic development. Dis-aggregation is done mostly by (urban) population density maps, night time light or power station locations [Flörke et al., 2013; Vassolo and Döll, 2005; Wada et al., 2011a], while Bernhard et al. [2018] dis-aggregates to 5 arcmin grid cell level by using pollutant densities and their link to individual industries, and industrial land cover fraction. Even though the other methods still can resemble observational data to a good extent, the main driver of spatial distribution of industry is not necessarily population although it is an influence.

Using the general structure of other methods, the potential gaps of Wada's method that can be improved can be classified in three categories: concepts, downscaling techniques and the increase of resolution of included variables. The concept of the recycling was adapted as there was data available at country level by Van Puijenbroek et al. [2019]; the downscaling techniques was increased in resolution to 30 arc sec, and while population density remained the method to dis-aggregate domestic water demand, both population density and industrial land cover fraction are included in downscaling industrial water demand to 30 arc sec.

5.2. Quality of the reference dataset

This section will evaluate the outcome of the recreated method and dataset of Wada, which itself will be compared to the original outcome and to the validation dataset. The second objective of this research can be achieved in this way: *Analysing the quality of and interpreting the recreated method and datasets of Wada to estimate European water demand for households and industry.*

5.2.1. Interpreting the reference dataset

The created reference dataset follows a spatial distribution along the contours of population density for domestic water demand, this is expected as this is on of the two main drivers (together with water use per capita). From 1990 to 2010, gross and net water demand in eastern Europe and the east part of southern Europe: (1.) increase in the perimeters of urban areas; (2.) increase, without increasing spatial heterogeneity, within these countries, and; (3.) net water demand decreases through time compared to gross water demand. The rest of Europe experiences in the same time period a decrease in high water demand around urban areas or a stagnation of water demand distribution.

These demographic changes could explain the temporal and spatial distribution of water demand as (1.) Flörke et al. [2013] observed that water use intensifies when the average income increases in the beginning and after a maximum level is reach, per capita use either stabilizes or declines; (2.) Eastern Europe and the eastern part of southern Europe experienced an increase in urbanisation levels from the 1990's onwards and an increase in GDP per capita while on the other hand total population decreased [Bank, 2020]; (3.) The rest of Europe experienced in the same time period a relative lower increase in GDPm and urbanisation levels are lower [Bank, 2020].

Combining these spatial and temporal changes would indicate that eastern Europe and the east part of southern Europe have an increase in total water demand because the per capita water use increase due to increase in GDP plays a larger role than the decline in total population, while spatial distribution intensifies in urban areas through both increase in per capita use and the high urbanisation level. The decrease in net water demand through time here is then linked to the increase in recycling ratio, declining the part of gross water demand that is appointed as net water demand. The rest of Europe experiences relative lower increases in GDP and a low increase in population, which could indicate a stagnation or decline of per capita water use while total water demand could increase only slightly, not affecting the spatial distribution within a country as urbanisation levels stay relatively equal. Additionally, as they already reached the highest development stage in or before the 1990's, their recycling ratio does not change anymore which therefore does not show a temporal difference in water use intensity in time.

For industrial water demand, partly the same explanation can hold as the reference dataset assumed industrial water demand is downscaled according to population as well. As industrial demand takes up a higher portion of total water demand (57% against 22% for domestic water demand [FAO, 2010]), total water demand is much higher. The relocation of gross water demand through time from western to eastern Europe may be explained by the effect that the relative high economic development in eastern Europe has a larger influence than the relative high technological development (which decreases water demand) in western Europe.

5.2.2. Quality of the reference dataset

As the original method was established in 2011, a problem was encountered in obtaining the data needed for the equations. Data from statistic offices is updated and changed regularly, which means that data is possibly adapted or even withdrawn from a particular source (UNEP, World Bank, FAO AQUASTAT). This would partially explain why the recreated method, acting as a reference dataset in this assessment, differed from the original outcome of Wada's water demand assessment. For the year 2000, which is the benchmark year, economical and technological development are not considered (as these make temporal distribution possible), while there is still a large relative difference in spatial distribution for water demand. As this is the case for both domestic and gross water demand, inconsistencies probably are sourced in underlying processes such as the downscaling or gap-filling technique.

It is not possible to generate the same results with the recreated method as Wada did (see Figure 4.3 and 4.4). Taking into account that local variances might show misconceptions of differences between the recreated dataset and the outcome of Wada's water demand, average relative difference over countries are also taken into account, and no consistency in the recreated method compared to Wada's outcome is found. This could be classified as a consistency problem.

Additionally, Wada et al. [2016] showed that slight differences in methodological approaches when modelling water resources and the use of different water use datasets cause a lack in agreement between the outcome for PCR-GLOBWB [van Beek and Bierkens, 2009], H08 [Hanasaki et al., 2008] and WaterGAP [Flörke et al., 2013]. This reinforces the idea that using updated or different datasets could have caused the conflict between the outcome of Wada's method and the created reference dataset.

Data is updated and extended through the years, which already was noticed in the scope of this research, let alone in 9 years time. The reference dataset covers more area for water demand in Africa (not focused on in this research, but was calculated) than the original outcome as data could have been made available only recently.

Wada's outcome and the reference dataset were both compared using expected overlap with observed data on water use [EUROSTAT, 2020], as these outcome differed, it is indicated that the reference dataset and the original outcome differ. Wada's original showed more expected overlap between water demand and water use for both industry and domestic water demand at both country and NUTS-2 level, except for domestic demand at NUTS-2 level which showed twice as much overlap compared to the original outcome. Unavailable data or data that was outdated in 2011 now exists or is updated which is expected to contribute to constructing European water demand by increasing the overlap, but this is not the case.

The non-existing relation in expected overlap between net and gross water demand on the one hand and water use on the other hand and the increase in existing data quality, implies that a critical note should be made on only measuring overlap, as this does not give a good enough representation on how well the method is performing.

The reference dataset is therefore also compared to observational data by using scatter plots and interpreting the portion of variation that is explained (R^2). For domestic water demand, the explained variation is higher for gross demand at both spatial resolutions as expected, because there is less distortion generated by the recycling ratio. NUTS-2 resolution has a better performance (0.629 and 0.510) than country level (0.565 gross and 0.486 net), indicating that at higher spatial levels this method performs better. Next to the fact that R^2 for industrial water demand, is lower in general, it still shows the expected decrease between gross and net demand at country level (0.440 to 0.378), and at NUTS-2 level there is almost no explained variation for gross and net demand (0.005 to 0.0006). Domestic water demand already performs better than industrial water demand, and the inclusion of the recycling ratio adds a factor of uncertainty to the model, the most for industrial water demand.

Moreover, these findings indicate a misconception of the recycling ratio, while also underpinning the effect it has and therefore its influence. The recycling ratio should not just be the portion of water withdrawals that flows back to the hydrological system, but should also be subject to sewage connection and waste water treatment. For domestic water demand, Wada inserted an extra factor (urban population), which provided this did not happen, consequently net water demand performs reasonably. In contrast, for industrial water demand, $net = (1 - RC) \times gross$ this is not taken into account Sutanudjaja et al. [2018]; Wada et al. [2011a], and the method performs poorly. Wrongly interpreting the recycling ratio gives high uncertainties in the performance, resulting in that this could also have added to the noise in relative difference between the reference dataset and the original outcome.

5.3. Dominant components in modelling sectoral water demand

This section will focus on discussing and interpreting the results from the sensitivity analysis by classifying the change of the methods. This allows to achieve the third research goals of this assessment: (3.) *Adapting the individual parameters and concepts that contribute to the improvements of the domestic and industrial water demand method and analysing their quality.*

5.3.1. Conceptual change

The concept of waste water treatment is changed for domestic water demand to national level values based on Van Puijenbroek et al. [2019]. Data on wastewater possesses a lot of information on the corresponding society and is therefore an enormous improvement as it allows for more spatial variable differences between gross and net water demand. An assumption is made that no information on urban population is needed anymore (eq. 2.9) as all information on waste water treatment is included in the data withdrawn, so the portion of water that is recycled is corresponding to the wastewater treatment connection. This changes the equation to $net = (1 - F_{sewage}) \times gross$. Doing this enables to do a final test on the dominance and influence of the recycling ratio.

Measuring the overlap between net water demand (notice gross demand remains unchanged) and water use, shows an increase at country level (15.8 to 55.6%) and at NUTS-2 level (63.8 to 94.2%). Contradictory, the R^2 is also expected to increase if overlap increases, but instead the explained variance decreases at both spatial resolutions from 0.486 to 0.152 (countries) and from 0.510 to 0.206 (NUTS-2).

These outcomes, when analysed together and individually, imply two things: (1.) The difference between gross and net water demand is not just the recycling ratio but also should take into account that not everything is treated or connected to the sewage system by adding an extra factor (e.g. urban population). This can also explain why the R^2 for net industrial demand is so low as it only consists of the industrial recycling ratio without an extra factor. This could mean that before net industrial water demand has been underestimated by only including the industrial recycling ratio instead of also taking treatment into account; (2.) measuring the overlap between gross and net demand that sandwich water use, which was expected at the beginning of this research actually shows the relation between the water demand and water use instead of indicating the performance of the method. In this case, countries such as the Netherlands have a 99% wastewater connection which would mean that the actual consumption is 99% lower than the total water withdrawal, therefor the range between gross and net demand enlarges and chances increase that water use will fall within this range. This is not possible as in the original method, Wada assumed there was an upper limit to the amount of water that can return, as 100% sewage connection would never mean 0% net water demand.

The outcome for changing the component of connection to the sewage system is a dominant factor and should be applied with caution in the method. It is essential in differentiating between gross and net water demand but should include another factor (e.g. urban population) as not all water that comes into the sewage systems, will be returned to the hydrological system because of e.g. quality reasons.

The fit of the scatter plots should in principle be the same for gross an net demand, as the recycling ratio does not change, but gross demand performs marginally better. Not only for the sensitivity analyses of waste water treatment but for all tested variables. This implies two things: (1.) the gross water demand is closer to the water use and differences are due to variations in the reported values. This mostly arises because of observation error, the fat that the definition or what is measured is inconsistent across countries, (2.) the recycling ratio adds additional error as it is more variable between countries and smaller areas (NUTS-2).

5.3.2. Increasing variable resolution

Changing resolution for gross domestic product and population in equations 2.1 and 2.6 from data at country level to NUTS-3 level enables the water demand method to implement variables at a higher resolution than national level, increasing spatial variability of water demand within countries. This is needed in order to define a well-performing water demand method. As GDP and population are variables that are used early on in the method, a higher resolution is established from the beginning.

Implementing GDP at NUTS-3 level in domestic and industrial water demand showed that the explained variation remained nearly the same both at country and NUTS-2 level and for gross and net demand, although it slightly increased for industrial demand. The expected spatial re-allocation of water demand within countries happens for industrial water demand but does not happen for domestic water demand. Additionally, the expected overlap for GDP stays constant (country) or decreases (NUTS-2) for households, while it increases (country) and decreases (NUTS-2) for industries. As this study demonstrated that overlap more so explains the relation between gross and net water demand and water use, instead of the performance of the method, no conclusion will be drawn.

The main driver for industrial water demand is considered to be gross value added which is related to GDP, therefore industrial water demand is relocated when increasing resolution level of GDP, directly demonstrating that the main driver is defined correctly [Bernhard et al., 2017; Bijl et al., 2016; Flörke et al., 2013; Vassolo and Döll, 2005]. Additionally, industrial water demand can only be spatially relocated by either economic or technological development, which consists of four socio-economic factors including GDP. Changing one component will thus have a large influence on the spatial distribution of water demand. A side note should be made, as there is no distinction made between GDP for industry and GDP for households, which is done in the WaterGAP model albeit on national level, but with a proper downscaling method this might improve the method [Flörke et al., 2013].

Domestic water demand, which is dependent on more variables than industrial water demand, such as population distribution and per capita water use, which both are the main drivers [Bernhard et al., 2017; Bijl et al., 2016; Flörke et al., 2013]. The fact that domestic water demand is not redistributed within countries when implementing high-resolution GDP data could be explained that its influence is just much lower than for industrial water demand.

Implementing population at NUTS-3 level for domestic water demand increased R^2 when measured at both country and NUTS-2 level. The expected overlap between water demand and water use remains constant for both resolution level. As population is identified as one of the two main drivers, it is expected that an increase in population distribution increases the performance of the method. It is therefore an important factor as large within-country urban areas such as metropolises can in this way be taken into account.

Depending on the main drivers of the sectoral water demand, increasing the resolution of GDP is an important factor in re-allocating industrial water demand but does only slightly increase the performance of the method, and it does not improve the method for domestic water demand. Increasing the resolution of the population variable is an important component in estimating high-resolution domestic water demand.

5.3.3. Downscaling technique

Changing the downscaling technique to a population density map and industrial land cover through CORINE [Feranec et al., 2016] at 30 arc sec are the components that will enable this method to estimate high-resolution water demand, and are therefore important.

For domestic water demand, implementing the higher resolution population density map increases explained variation the most at NUTS-2 level and also increases at country level to values indicating a reasonably well performance of resembling observational data. The high-resolution population distribution map therefore cannot only be used as a downscaling technique, but it also better allocates water demand than the 5 arcmin map. A 30 arcsec downscaling technique enables distinction between rural areas and small towns, which was not possible with a 5 arcmin map. The fact that population distribution is one of the two main drivers for domestic water demand allocation can be seen here, as the model is very sensitive to this parameter. The relative difference compared to the reference dataset might be explained by the fact that both population density maps have different data sources.

Downscaling industrial water resource modelling with population distribution maps and with industrial areas by the CORINE land cover does not change the performance of the model at country level as the total gross demand of all countries remains unchanged (calculated through WWDR-II), but the performance at NUTS-2 level becomes slightly better for both downscaling techniques. A side note should be made, as the R^2 increased for gross industrial demand from 0.005 (reference dataset) to 0.011 (population map) and 0.006 (CORINE), and changed for net water demand from 0.001 (reference dataset) to 0.002 (population map) and 0.001 (CORINE). The method in general does not perform well for computing net industrial water demand, and it seems to be a consistent underestimation that is at play.

Both downscaling processes will be applied in the high-resolution water demand method and dataset to find the final performance under different circumstances, enabling to better discuss the methods.

5.4. Defining high-resolution water demand for households and industries

This section will discuss which variables are chosen for implementation in the high-resolution water demand method before going into how this method performs in distributing water demand for households and industries in Europe. Finally, the desired flexibility of the method is discussed. This is done in a way so that the fourth and last research goal is achieved, alongside the main aim: *Measure to what extent the improved high-resolution method and dataset are applicable for construction of a European water demand dataset.*

Dominant components in domestic water demand can be classified under three headings. First, conceptual change has proven - by a wrong inclusion of the component in the sensitivity analyses - how strongly it can affect the net water demand and it has shown a high level of dominance in net water demand. Additionally, the wrong inclusion shows directly how inadequate the performance of the model becomes. Therefore, the wastewater component is chosen to be included in the method but should be supported by the fraction of urban population as in equation 2.9. Secondly, increasing the resolution of variables helps to dis-aggregate the model outside of the downscaling technique. Population is the most essential factor influencing spatial distribution of domestic water demand and as GDP does not decrease the performance of the model, both are included in the final method. Finally, the downscaling technique applied will be the 2010 population map as it both enables to reach the high-resolution method and it best allocates water demand.

In industrial water demand, none of the changed components performed as well as for calculating domestic water demand, indicating it is prone to large uncertainties. Thermo-electric cooling is indirectly taken into account, while other approaches calculate this directly, which might indicate a source of uncertainty as cooling water may take up to 90% of industrial water withdrawals [Förster, 2014]. The components that did increase the performance of the industrial water demand method are the increase of the resolution of variables that are available. GDP is the most dominant factor affecting industrial water demand, as it is a main driver, so this variable is incorporated. Finally, the downscaling technique applied will be both the 2010 population map and the CORINE land cover map as the individual performances could not be distinguished from each other, therefor an extra test is needed to see how they perform in the bigger image.

For both methods, the high-resolution water demand dataset is calculated for the year 2013 as this was the most recent year on which all required data was available. There are years with more reported data, 2010 is one of those years, while the amount of data points decrease when taking 2009 or 2011, and thus when calculating 2013 we should take into account that there are only a few data point available to compare against. Additionally, 2010 is taken as the new benchmark year.

The final created method for domestic water demand found that the performance of the method to resemble high-resolution water demand seems outstanding with a R^2 of 0.946 and 0.890 at country level, and of 0.665 and 0.822 at NUTS-2 level for gross and net demand respectively. The small data sample of N=9 should be taken into account at country level, but at NUTS-2 level the data sample had the same N of 18 as the reference dataset. Additionally, the expected overlap between water demand and water use increases, too. Spatially, water demand is allocated according to the population distribution, and in general shows a lower demand than for the reference dataset.

The choice to incorporate the concept of wastewater treatment alongside the factor of urbanisation seems to improve the model as R^2 increases significantly for net water demand, especially at NUTS-2 level. This is against the expectations, as more uncertainty is included through the recycling ratio in the net water demand method. This is also the first analyses of this research showing a regression slope below the 1:1 line for net water demand which is expected as it should be lower than the observational water use. The high level of explained variation at NUTS-2, indicate that this method can be used to construct a domestic water demand method at high-resolution.

The final created method for industrial water demand using increased significantly for gross water demand at country level to 0.615 (population) and 0.604 (CORINE) from 0.440 (reference dataset), but decreased to almost zero explained variation for net water demand at country level. Both gross and net demand increased at NUTS-2 levels, but as these values were already close to zero they still do not explain variation of the method. The overlap between industrial water demand and water use increases at country level but decreases at NUTS-2 level.

The combination of both the individual downscaling techniques and GDP at high-resolution level improve the method for gross water demand to resemble observational data and increase therefore the performance of the method. In contrast, the performance of net water demand has decreased so much that the uncertainty in this template - i.e. the combination of dis-aggregating to NUTS-3 level in the beginning and downscaling to 30 arc sec in the end - seems to be reinforced by the recycling ratio. The recycling ratio for industrial water demand is assumed to be the part of gross water demand that is returned to the river network and has no upper limit included like the domestic water demand, which might explain the uncertainty and contribute to an underestimation of net industrial water demand. Increasing the resolution level when comparing the method against observational data shows a small improvement but still almost no variation is explained. There are improvements possible for industrial water demand, but within the scope of this research it is found that the improvements only apply when calculating gross industrial water demand at country level. Spatial variation using the population map is explained by the population distribution and spatial variation when using the CORINE land cover is according to locations of industrial area. It was expected that CORINE land cover would show a higher explained variation, but this is not the case. This could be due to the fact that there is a high uncertainty level in estimating industrial water demand, which neglects the differences between the two downscaling techniques.

As the method uses a top-down approach it is possible to extend this method from covering only Europe to a global water demand dataset, as its flexibility allows for increasing resolution of variables were possible. The code used is visible in Appendix E, and if the *clonemap* is adapted the spatial resolution can be adapted too. The approach should be flexible so when forthcoming high-resolution data sources become available its effect can be determined and it can be implemented without changing the model. Finally, for now this method is only usable to project high-resolution water demand for Europe, but updated data are for many countries available through World bank, FAO AQUASTAT and UNEP [Bank, 2020; FAO, 2010; UNEP, 2012]. Additionally, the data by Van Puijenbroek et al. [2019] on wastewater treatment has data for 200 countries for 1990, 2000 and 2010, which can be included.

5.5. Uncertainties and future research

As this research was conducted, uncertainties were found as the timescale was limited and the developing aspect of this assessment required assumptions. Those uncertainties should be accompanied by critical remarks and possible solutions, and are important to be kept in mind when interpreting the results of this assessment. Possible solutions may be used in future research. The items will be given in order of different sub-categories.

5.5.1. Methods

- The most important uncertainty lays within the quality of testing this method. As available observational data on water use, withdrawal and consumption is limited and does not consist of water demand [EUROSTAT, 2020], the adapted method can only to some extent be compared to existing data. If there was to be a trend between comparing net and gross water demand and the observed water use, it would have been more helpful. Additionally, the definition of water demand and use is defined differently in all found datasets and established methods, with the in- and exclusion of some sectors, resulting in a higher uncertainty when comparing to observational data.

- Increasing the resolution of the method is feasible when using enough computer power [Sood and Smakhtin, 2015]. Mapping net and gross water demand in Europe at a 0.5 arcmin resolution scale resulted in maps of 150MB each, which would increase to 3GB per image for a global high resolution map. Not only the results, but also the input, as more spatially diverse data is needed which requires a high demand on the processing power of the used computer.

- The foundation to project it for the past and present demand was done by using a benchmark year (2000). Consequently, the base for calculating industrial water demand is a map of global industrial water demand at 30 arc minute resolution for 2000 which is adapted by taking into account economical and technological development. I.e. two countries may have different initial gross water demand values but even with the same economic and technological development, their water demand will never be equal. This method is thus extremely sensitive to which year is chosen as the base year. Additionally, the domestic water use intensity (DWUIT0 in eq. 2.6) used to calculate domestic water demand is also extracted from 2000, also causing uncertainty. This uncertainty may be counteracted in future research by taking both DWUIT0 for the benchmark year and a DWUIT into account.

- As the method is a conceptual approach, it is only as solid as the concepts behind it are. Dependencies, included variables and assumptions all add to the uncertainty when not carried out correctly. An example is the differences between the three mentioned global water use models by Flörke et al. [2013]; Hanasaki et al. [2008]; van Beek and Bierkens [2009] as they all use different input and find different outcomes for local water demand. Wada et al. [2013] finds high uncertainty when projecting industrial water demand as a consequence of changing temperature and precipitation variability, working through in arising uncertainties in GHMs and global climate models (GCMs).

- While implementing the method in Python and choosing the cell-length, high inaccuracy was found of a maximum of around 1% when cell-length was adjusted from 0.00833333 to 0.0083333 (8 or 7 digits behind the decimal point).

- It was assumed that the thermo-electricity was included in the water use dataset by WWDR-II, although it was nowhere explicitly stated (in the sources of WWDR-II nor by Wada et al. [2011a]). Wada et al. [2016] states that the GHM PCR-GLOBWB uses GDP, total electricity production, and total energy consumption. As thermo-electricity can make up a major part in industrial water demand, it is important to find more ground for this assumption.

- This method relies on a benchmark year being used against which the growth or the decline of socio-economic factors was measured. This contributes to the problem that a developing and a developed could go through the same economic development generating the same ratios without ever coming to the same water use if the base years have different values.

- Relative differences are measured as point data, and as country averages. Country averages are calculated by measuring the average relative difference of a country. It could also have been calculated as summing the country totals for water demand for both the reference data set and the to be measured dataset, and taking their relative difference, which probably would yield different results.

- A deliberate choice was made to only include net water demand for the sensitivity analyses, as this captures also the recycling ratio or waste water treatment component. But as it probably adds noise to the method, a strong basis could have been to also compare it to gross water demand.

5.5.2. Downscaling

- Downscaling techniques were not explicitly mentioned but a population distribution map was used in this research. According to Wada et al. [2016], downscaling for industrial water demand was done using urban areas only, which deviates from the method in this study.

5.5.3. Data sets

- The most recent year for which all data was retrievable was 2013, which is still seven years ago when this research was conducted. As the method is dependent on different data sources, problems arise to recreate this method for the near past.

- R_{dom} is representing the amplitude of the difference in seasonal water demand. A value of 0.1 would mean that water demand in summer is 5% than the average while it is 5% lower in winter, depending the time T is near T_{min} or T_{max}. This value contributes highly to a seasonal variability in water demand but cannot be measured against an observational dataset as these have all lower (often annual) temporal resolution. Accordingly, as this study assessed annual water demand values, R_{dom} was not taken into account.

- Data sets from EUROSTAT at NUTS-level sometimes contain bugs which complicates matching them to the existing data set used for the method. When retrieving these data sets, this should be taken into account.

- Data sets on water withdrawals and use at NUTS-2 level from EUROSTAT have been removed as per mid April 2020, which left this research with data that was retrieved in time up to 2013, complicating the research.

- Bierkens et al. [2015] mentioned that global covering high-resolution data for estimating water demand are not yet available.

- Wada and this research defined net water demand as the volume of water (m^3) required by users to satisfy their needs. Domestic water demand also included small businesses and hotels, whereas Bernhard and EUROSTAT only considered households [EUROSTAT, 2020]. Additionally, both Bernhard and EUROSTAT do not measure water demand but water use, which differs as it measures the volume of water supplied by the network to households, causing it to range between water consumption and water withdrawals. The differences in definitions and assessments of water use, consumption and withdrawal inherently imply that the results of the validation set and the observed data will not be exactly equal.

FAO AQUASTAT has another observational dataset but this covers only water withdrawals, which could be measured against gross water demand but not net.

5.5.4. Concepts

- By using the data of Van Puijenbroek et al. [2019] on sewage connection, it was assumed that the type of waste water treatment (primary, secondary, tertiary treatment) had no influence on the amount of water that is brought back into the stream. This is an effect of data quality as the amount of water that is flushed through the toilet does not change.

5.5.5. Recommendations

- When observational data becomes available on sectoral water demand it should be used in future research to calibrate this flexible method for water demand.
- A more guiding analyses that is driven by water use being sandwiched by gross and net water demand (if water availability is not limiting) could have been linked to a forecasting model. It can be tested in time and related to the components of change that are introduced here, to get a better idea of consistency and give more concrete points for improving.
- Even as the outcome of water use by Bernhard et al. [2017] is simulated at NUTS-3 level and not observed data, his outcome is in close proximity and of the same magnitude as the data from EUROSTAT. Future research can assume his dataset as a validation set as is simulated water use for every NUTS-3 region between 2000 and 2013 which could be a solution to counteract the limiting amount of data points and also for data sets at NUTS-2 level cannot longer be retrieved from EUROSTAT.
- This research used data from EUROSTAT as it was available at multiple resolution scales at a yearly interval, but previous research used AQUASTAT country data which might give more information if the sensitivity analyses was compared with this as well.
- This research could be extended on a temporal scale as for this research only 2010 and 2013 have been compared.
- Not all data at NUTS-3 level were accessible, based on the method of Bernhard et al. [2017], a recommendation can be made on the collection of data. Water demand data could be collected at individual statistical offices or governing bodies, which brings along that they may not capture the exact same thing, e.g. including/excluding losses or evaporation. The fact that he mentions that values reported by national statistics offices did often not match exactly with the values from EUROSTAT, adds to the idea that not the exact same thing is captured.
- Some studies on domestic water demand include factors on demographics, e.g. Bernhard et al. [2017], which is not done in this study. An attempt has been made an the data for the Netherlands is present, but it yielded corresponding problems. Future research may take this into account as an extra variable influencing the per capita water demand, but it would increase uncertainty when reconstructing to the past and projecting to the future.

6 Conclusion

The development of water resource models requires reliable projections of gross and net water demand, and the ambition to bring these models to hyper-resolution makes this requirement even more important. Yet, the problem arises that high-resolution water demand data are universally missing resulting in absence of relevant studies that assess global water demand at high spatial resolution.

This study is conducted to track down the possibilities and the restrictions of existing downscaling techniques in context of a high-resolution water demand method and to determine the effect of data quality. The main aim is to set up a flexible framework to define high-resolution water demand for households and industries in Europe, using existing downscaling concepts and datasets with the final objective to develop and improve high-resolution global water demand estimates that may benefit from forthcoming data sources. The aim is reached by achieving the following research goals: (1.) Identifying the potential improvements on the existing water demand method by Wada and analysing other water resource approaches; (2.) Analysing the quality of interpreting the recreated method and datasets of Wada to estimate European water demand for households and industry; (3.) Adapting the individual parameters and concepts that contribute to the improvements of the domestic and industrial water demand method and analysing their quality; (4.) Measure to what extent the improved high-resolution method and dataset are applicable for construction of a European water demand dataset.

Wada defined water demand as the net water demand, i.e. the water withdrawal minus the return flow from fresh surface water or blue water. Net blue water demand is the potential consumptive use from available resources and is lower than gross blue water demand, as part of the industrial and domestic water demand is recycled and returned. Wada's method is a conceptual, top-down approach assessing global water demand at 5 arcmin, as he was driven to project water demand in the past and present, using a method which consisted of general rules that could be applied everywhere. Bernhard assessed water use, which is defined as the demand that can be satisfied when taking supply constraints into account. He focused on determining the relation between predictors per area (DDA, AGE15, IP) and water use as predictand. Wada was looking for driving factors which he assumed did not change, while Bernhard assumed that the correlations will always change.

Domestic water resource approaches in general have population density and water use intensity per capita as main drivers, while economic (especially GDP) and technological development, demographics, water price (and thus water management policies), climate and recycling variables also play a major role. Industrial water resource models differentiate between manufacturing and cooling water, capturing the large differences between the purpose of water within industry. Wada has the only method that does not actively differentiate in cooling water, as it is already included in the WWDR-II dataset. Main drivers for the thermoelectric cooling assessments are electricity production and excess amount of heat, while for manufacturing use industry/gross value added are seen as main drivers. Other important components are structural change, technological and economical development. Downscaling is mostly done by (urban) population density instead of industrial land cover fraction.

Wada's method can be used as a foundation for this research and possible improvements to construct a high-resolution water demand method are: increasing resolution of included variables as the downscaling technique is the only component that dis-aggregates from national level to 5 arcmin; improve the concept of wastewater treatment; increase and adapt the downscaling technique applied.

The recreated method for domestic water demand follows a spatial distribution along the contours of population density and through the years follows the demographic changes of Europe: urbanisation and development of eastern Europe cause increased water demand patterns, while the water use intensity and urbanisation stagnate in developed regions. For industrial water demand the same patterns are found, but total water demand is higher. Due to a higher increase in economic development in eastern Europe through time than technological development, industrial water demand relocates through the years with higher intensities in eastern Europe.

It is not possible to generate the same results with the recreated method as for the original outcome of Wada's method, which is a consistency problem. The explained variation of the reference dataset performs reasonably well. The higher R^2 for gross demand is a consequence of the additional error added in net water demand by the recycling ratio. The higher R^2 at NUTS-2 level shows that this method is better able to estimate water demand at higher resolution levels. The performance of industrial water demand is usable at country level although explained variation is low, but increasing the resolution decreases R^2 to zero. The recycling ratio adds more noise to industrial water demand than to domestic water demand, which can cause these uncertainty levels.

The possible improvements of the reference dataset are classified in three groups: conceptual change, increase in variable resolution and downscaling techniques. For domestic water demand, the conceptual change of waste water treatment has proven - by a wrong inclusion of the component in the sensitivity analyses - how strongly it can affect the net water demand and it has shown a high level of dominance in net water demand. The wrong inclusion showed directly how inadequate the performance of the model becomes by decreasing the explained variation. Increasing the variable resolution of population in the domestic water demand method, a main driver, increases the performance of the model and spatially redistributes water demand within a country in accordance with the urbanisation level. GDP does not alter the performance in a significant way, and as it is not a main driver, this can be explained. Adapting the downscaling technique to a high-resolution population map increases the performance of the domestic water demand allocation. A high-resolution population map redistributes water in a way that a distinction is made between small town and rural areas.

The final high-resolution water demand method for households performs outstanding with a R^2 of 0.946 and 0.890 at country level and 0.665 and 0.822 at NUTS-2 level. Spatial distribution of domestic water demand is at a more detailed level and shows in general lower net water demand compared to the reference dataset. This is a consequence of the inclusion of the recycling ratio, which increases the difference between gross and net water demand. Including waste water along with urbanisation in the model shows both how this component improves the method a lot when incorporated correctly, but can it other cases cause high uncertainty for net water demand. The limiting factor when constructing a high-resolution dataset would be the data quality and not necessarily our understanding of the system.

For industrial water demand, the increase in variable resolution is an important aspect. The main driver for industrial water demand is considered to be gross value added which is related to GDP, and industrial water demand is relocated when increasing resolution level of GDP, confirming this component to be the main driver. The performance of the method is not increased with this inclusion, which counteracts its importance. But as the main driver for industrial water demand distribution, it will still be included in the final high-resolution water demand method. Including information on the distribution of industrial areas in the spatial downscaling of the industrial water demand using CORINE dataset compared to a downscaling technique based on population, did not lead to a preferred method. The low resemblance of net industrial water demand with observational data is linked to the additional error within in the recycling ratio.

The performance of the final high-resolution industrial water demand method increases at country level to 0.615 (population) and 0.604 (CORINE) from 0.440 (reference dataset), but decreased to almost zero explained variation for net water demand at country level. At NUTS-2 level explained variation decreases towards zero which can be linked to the additional error of recycling ratio, as a consequence net industrial water demand is underestimated. Spatial variability of industrial water demand using the population map is explained by the population distribution, but this makes population density involuntarily a main driver in estimating industrial water demand. Spatial variation of industrial water demand when using the CORINE land cover is according to locations of industrial area. Downscaling with land cover fraction did not show a higher explained variation, as the high uncertainty level in estimating industrial water demand neglects improvements of the downscaling techniques. The limiting factor when constructing a high-resolution industrial water demand dataset, seems to be our understanding of the system, as the same data does improve the method for domestic water demand.

As the method uses a top-down approach it is possible to extend this method from covering Europe to a global water demand dataset, as its flexibility allows for increasing resolution of variables were possible. The approach is flexible so when forthcoming high-resolution data sources become available its effect can be determined and it can be implemented without changing the model.

Due to uncertainties in the framework, methods, datasets and concepts of this method it is important to include recommendations for future research. The concept of waste water treatment both adds large improvements in the method when added correctly, but also may cause the largest uncertainty to net water demand by adding additional errors. Future research may take into account gross demand better so to determine whether the noise comes from the additional error of the waste water conception. The created high-resolution water demand method should especially be tested for multiple years against an observational dataset. NUTS-2 level data are at this moment not retrievable anymore from EUROSTAT, and it could be recommended to use the simulated dataset from Bernhard as an observational dataset as he simulated water use at NUTS-3 level for 2000-2013.

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A

Original and reference datasets

A.1. Domestic water demand: Wada's original dataset

Variable	**Definition**	**URL**	**Note**
POP	National population	`http://www.fao.org/nr/water/aquastat/data/query/index.html`	Geography & population - Population - Total population
DWUI	Domestic water use intensity	`http://www.fao.org/nr/water/aquastat/data/query/index.html`	Water use - Water withdrawal by sector - Municipal water withdrawal
T, T_{avg} T_{max}, T_{min}	Temperature	`https://crudata.uea.ac.uk/cru/data/hrg/`	Withdrawn, but other climatological data is still retrievable
F_{urban}	Fraction urban/total population	`http://ede.grid.unep.ch//`	Search: 'urban population total'. Select: Urban population - total (national level)
$R_{industry}$	Recycling rate	`https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups`	Select hyperlink: historical classification by income in XLS format

Table A.1: Variables for creating Wada's method for domestic water demand with extended information on URLs.

A.2. Industrial water demand: Wada's original dataset

Variable	**Definition**	**URL**	**Note**
GDP	Gross Domestic Product	`https://data.worldbank.org/indicator/NY.GDP.MKTP.KD`	Make sure to use per capita
EL	Electricity production	`http://ede.grid.unep.ch//`	search: 'electricity production'. select: 'electricity - production' (national)
EN	Energy consumption	`http://ede.grid.unep.ch//`	search: 'energy consumption'. select: 'Total Final Energy Consumption - Total (IEA)' (national)
HC	Household consumption	`http://ede.grid.unep.ch//`	search: 'household consumption'. select: 'Household Final Consumption Expenditure - Total' (national)
$IWD_{gr_{t0}}$	Gross industrial water demand	`http://wwdrii.sr.unh.edu/download.html`	H. Domestic and industrial water use, and their proportional use - (H1) Industrial water use, year 2000 (millions of m3/year per grid cell)
POP_{xxx}	weighed population downscaling	`https://themasites.pbl.nl/tridion/en/themasites/hyde/basicdrivingfactors/population/index-2.html`	I have gotten the maps directly from R. van Beek, have not used this site
$R_{industry}$	Recycling rate	`https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups`	Select hyperlink: historical classification by income in XLS format

Table A.2: Variables for creating Wada's method for industrial water demand with extended information on URLs.

A.3. Domestic water demand: reference dataset

Variable	**Definition**	**URL**	**Note**
POP	National population	`http://www.fao.org/nr/water/aquastat/data/query/index.html`	Geography & population - Population - Total population
DWUI	Domestic water use intensity	`http://www.fao.org/nr/water/aquastat/data/query/index.html`	Water use - Water withdrawal by sector - Municipal water withdrawal
T, T_{avg} T_{max}, T_{min}	Temperature	`https://crudata.uea.ac.uk/cru/data/hrg/`	Withdrawn, but other climatoligical data is still retrievable
F_{urban}	Fraction urban/total population	`http://ede.grid.unep.ch//`	Search: 'urban population total'. Select: Urban population - total (national level)
$R_{industry}$	Recycling rate	`https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups`	Select hyperlink: historical classification by income in XLS format

Table A.3: Variables for calculating the reference dataset for domestic water demand with extended information on URLs.

A.4. Industrial water demand: reference dataset

Variable	Definition	URL	Note
GDP	Gross Domestic Product	https://data.worldbank.org/indicator/NY.GDP.MKTP.KD	Make sure to use per capita
EL	Electric power consumption	https://data.worldbank.org/indicator/EG.USE.ELEC.KH.PC	Make sure to use per capita
EN	Energy use (kg of oil equivalent)	https://data.worldbank.org/indicator/EG.USE.COMM.GD.PP.KD	Make sure to use per capita
HC	Households and NPISHs final consumption expenditure	https://data.worldbank.org/indicator/NE.CON.PRVT.PC.KD	Make sure to use per capita
$IWD_{gr_{t0}}$	Gross industrial water demand	http://wwdrii.sr.unh.edu/download.html	H. Domestic and industrial water use, and their proportional use - (H1) Industrial water use, year 2000 (millions of m3/year per grid cell)
$R_{industry}$	Recycling rate	https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups	Select hyperlink: historical classification by income in XLS format

Table A.4: Variables for calculating the reference dataset for industrial water demand with extended information on URLs.

A.5. Adapted variables

Variable	Definition	URL	Note
F_{sewage}	Wastewater connection	https://www.sciencedirect.com/science/article/pii/S0301479718311824#mmc1	Download PDF multimedia component 1, go to last section
Downscaling technique (population)		https://www.worldpop.org/geodata/listing?id=64	Check the year and resolution
Downscaling technique (CORINE)		https://land.copernicus.eu/pan-european/corine-land-cover/clc2018	Check the year and resolution
GDP	Gross domestic product	https://ec.europa.eu/eurostat/web/products-datasets/-/nama_10r_3gdp	Data on EUROSTAT often changes location or by defintion, make sure you have 'Gross domestic product (GDP) at current market prices by NUTS 3 regions'

Table A.5: Variables for calculating with the adjusted variables for water demand with extended information on URLs.

B

Downscaling concepts

This Appendix contains visual material on the NUTS regions and downscaling concepts.

B.1. NUTS regions

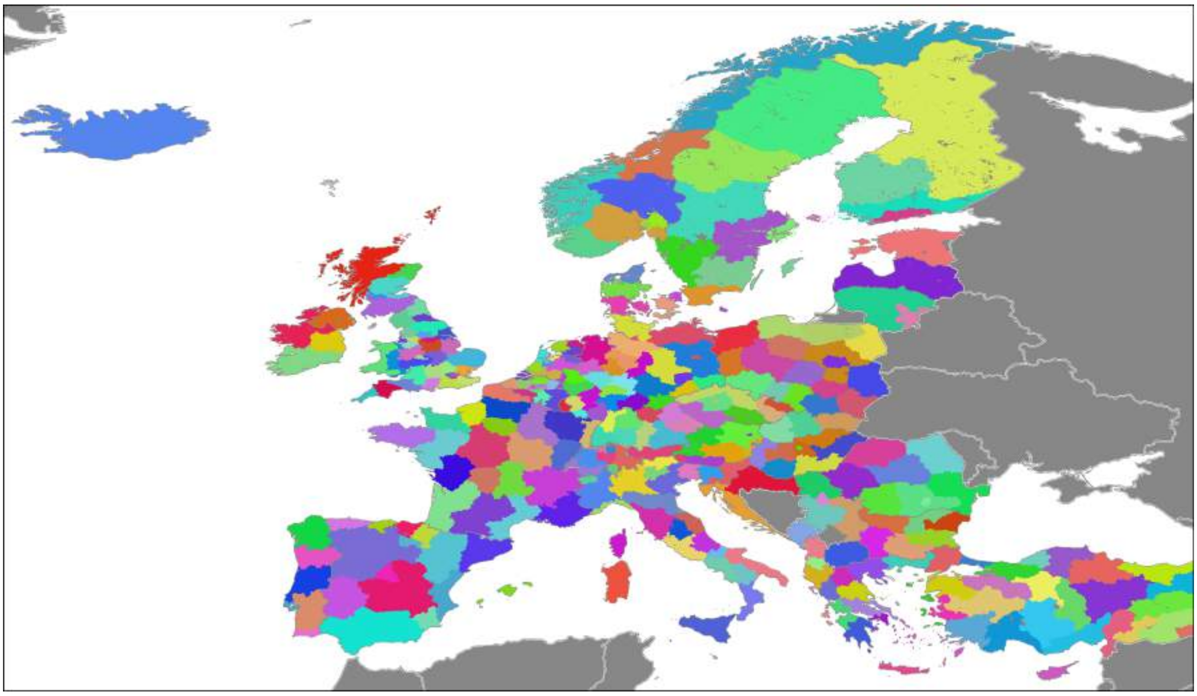

Figure B.1: Division of Europe into regions on NUTS-3 level from EUROSTAT [EUROSTAT, 2020].

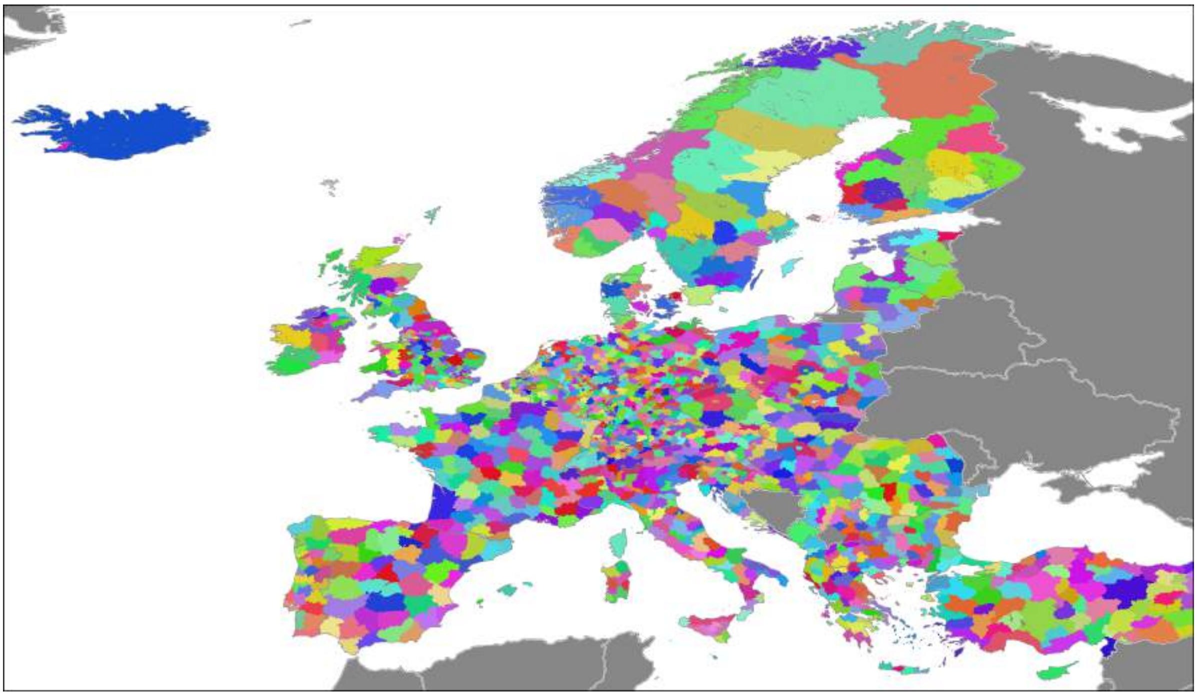

Figure B.2: Division of Europe into regions on NUTS-3 level from EUROSTAT [EUROSTAT, 2020].

B.2. Maps for reference dataset

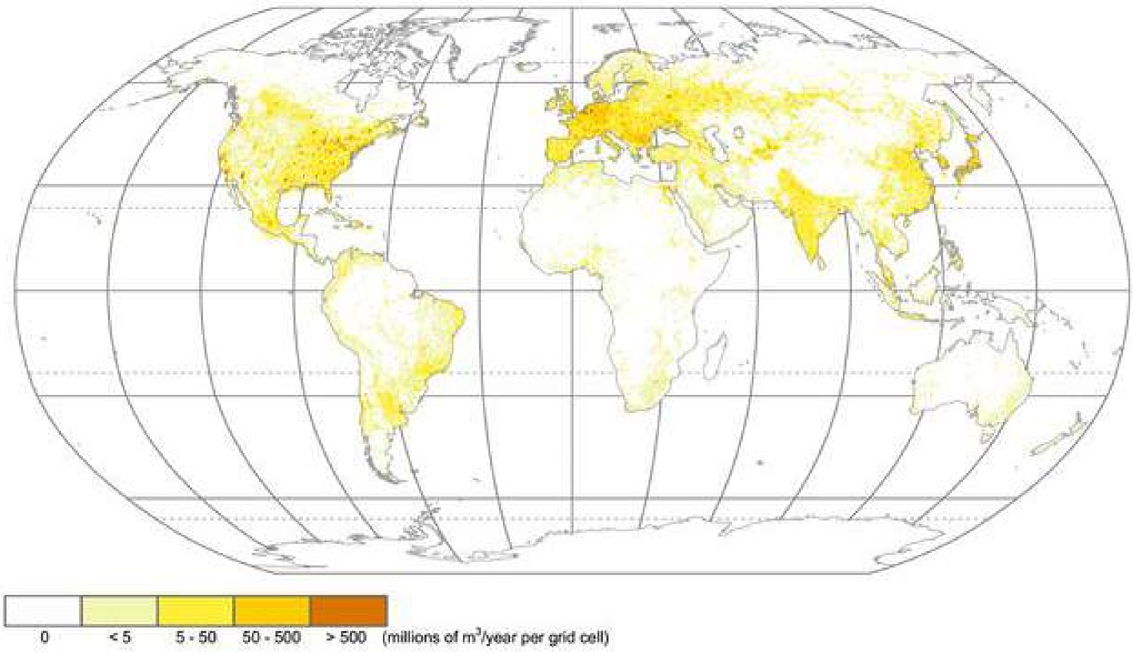

Figure B.3: Global industrial water use, year 2000 (millions of $m^3/year$ per grid cell). retrieved from World Resources Institute et al. [1998].

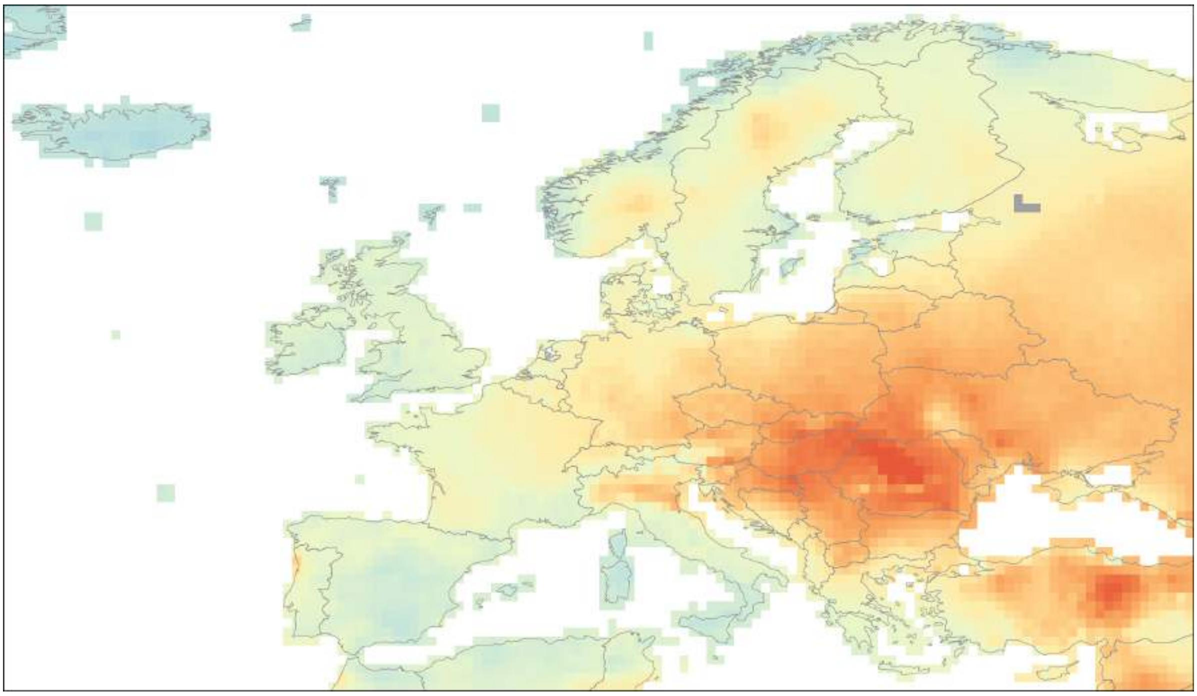

Figure B.4: Climatic variable factor for Europe for January, long-term average 1961-2014, recreated from Mitchell and Jones [2005]

.

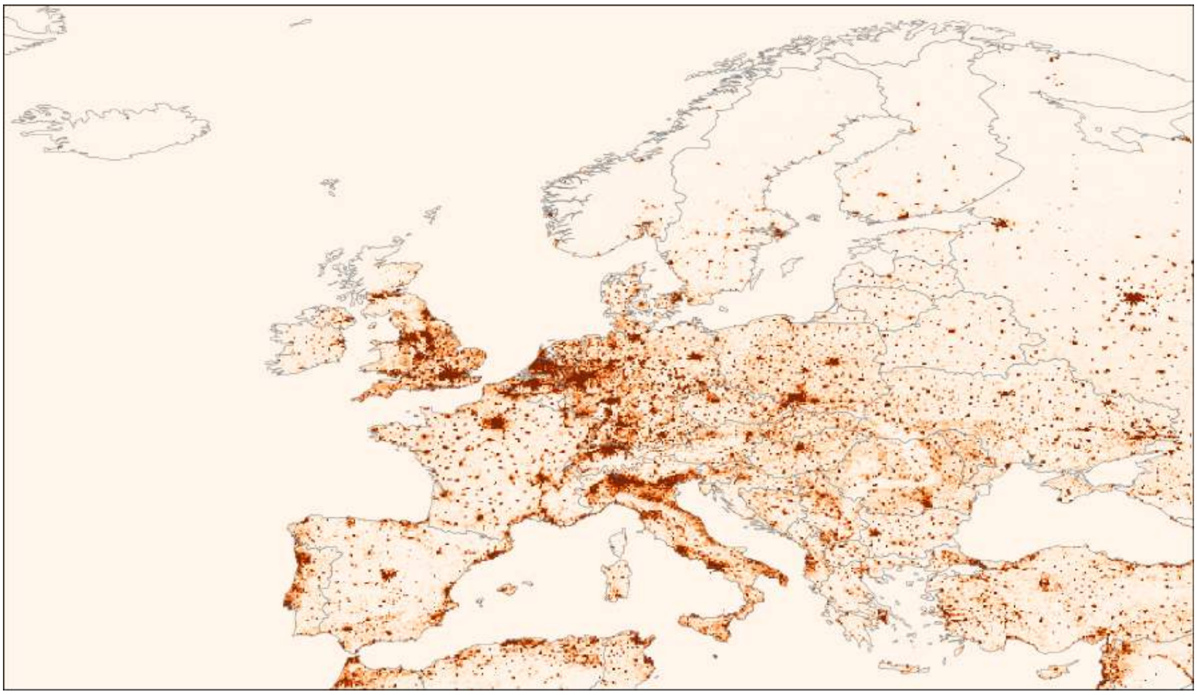

Figure B.5: Downscaling map based on population density through night-time light intensity for the year 2000 at 5 arcmin.

B.3. Maps for sensitivity analysis

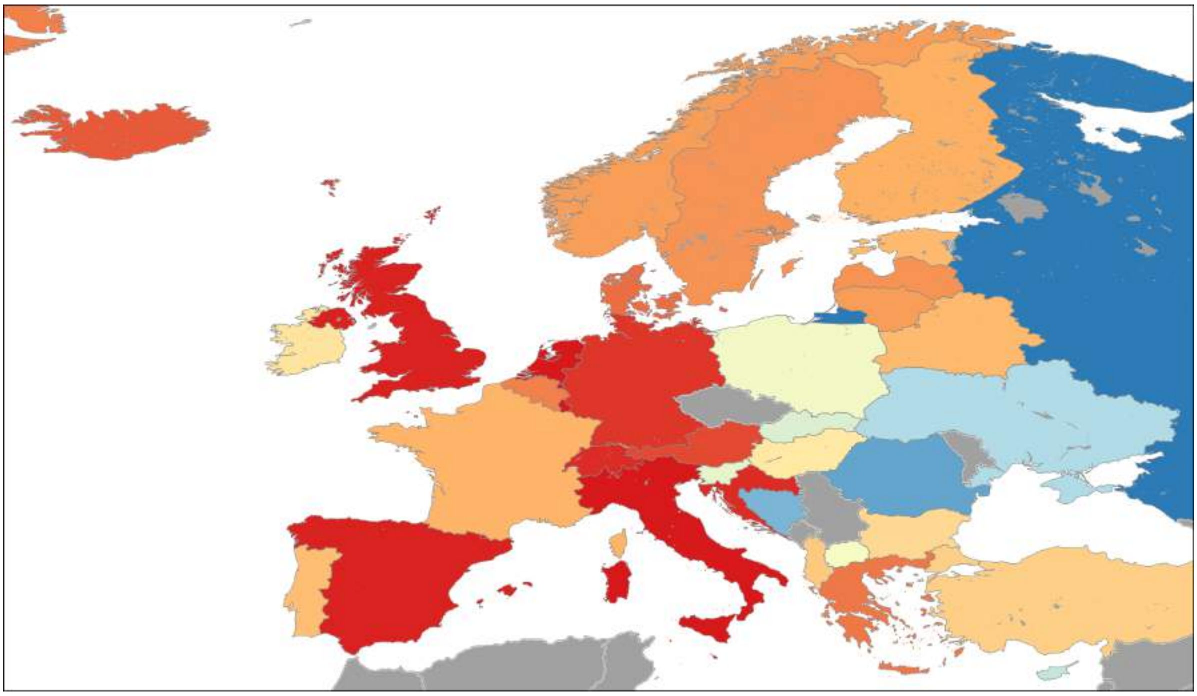

Figure B.6: Ratio of sewage connection and waste water treatment, where 0.99 is red (the Netherlands) and 0.36 is deep blue (Russia) [Van Puijenbroek et al., 2019].

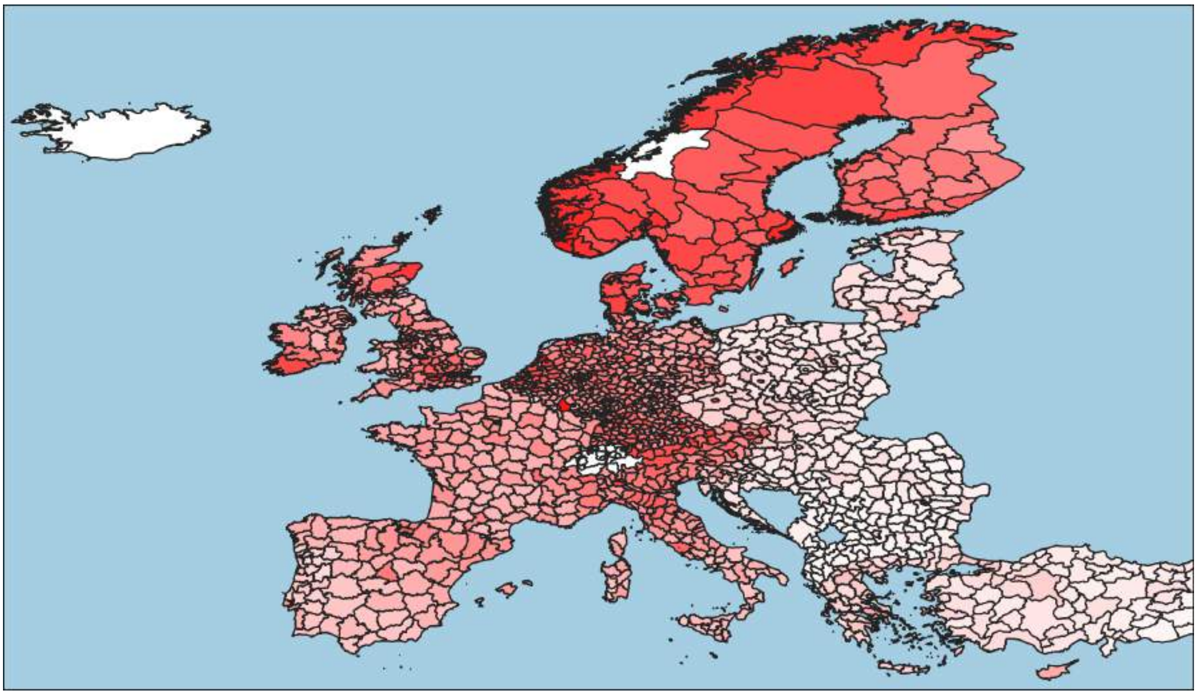

Figure B.7: GDP per NUTS-3 area in Europe in 2013, red areas have the highest GDP and blue area the lowest [EUROSTAT, 2020].

Figure B.8: Downscaling map based on population density for the year 2010 at 0.5 arcmin from World pop.

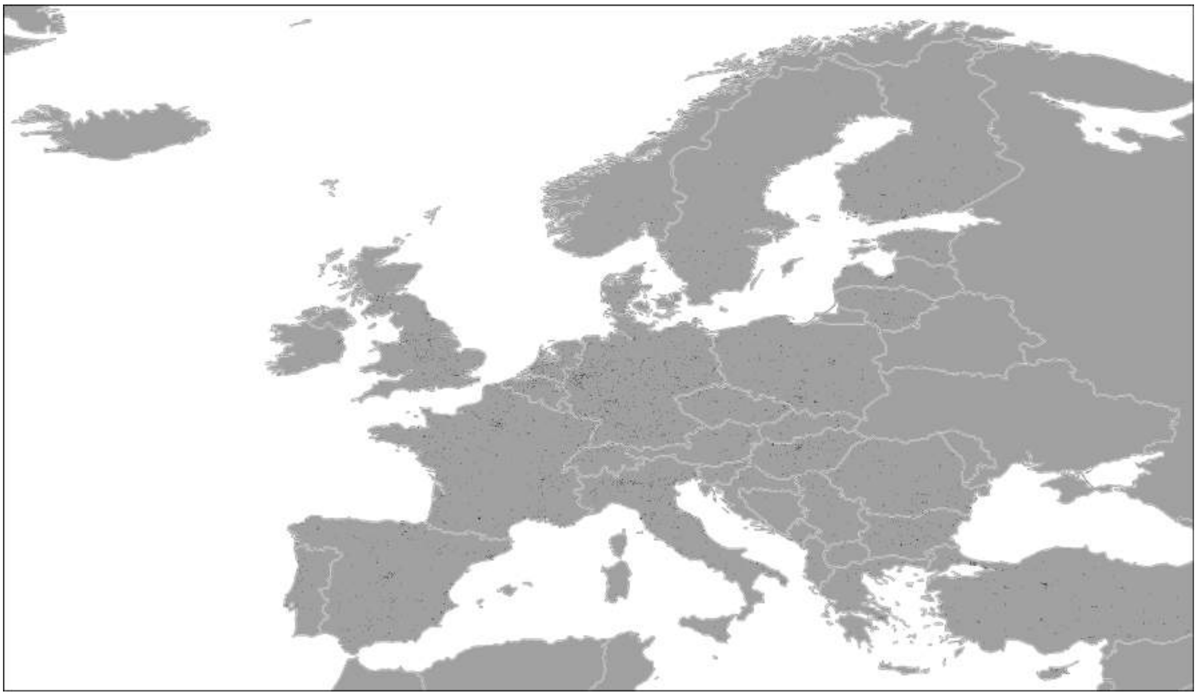

Figure B.9: Downscaling map based on population density for the year 2010 at 0.5 arcmin based on European land cover of industry by CORINE.

C

Reference dataset against original outcome

C.1. Comparing reference dataset

C.1.1. Domestic water demand against Wada's original outcome

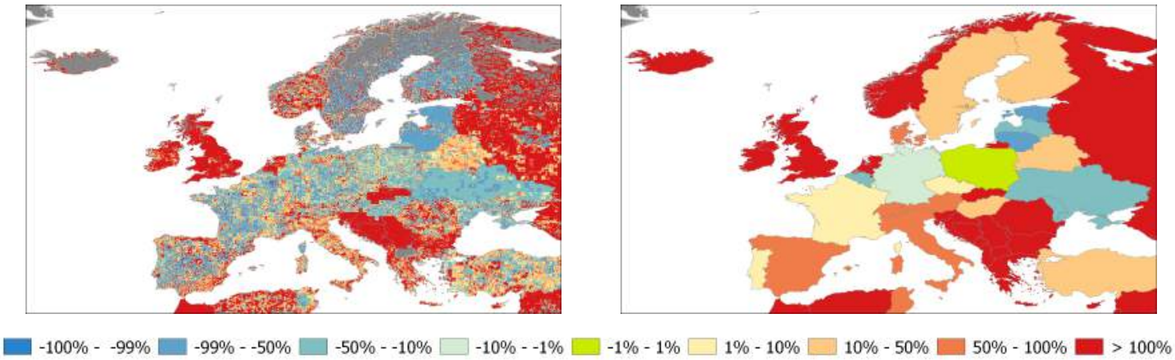

Figure C.1: Relative difference between the reference dataset for gross domestic water demand and the original outcome of Wada's method as point data (top) and averaged over the country (bottom) at 5 arcmin European scale for 2000.

C.1.2. Industrial water demand against Wada's original outcome

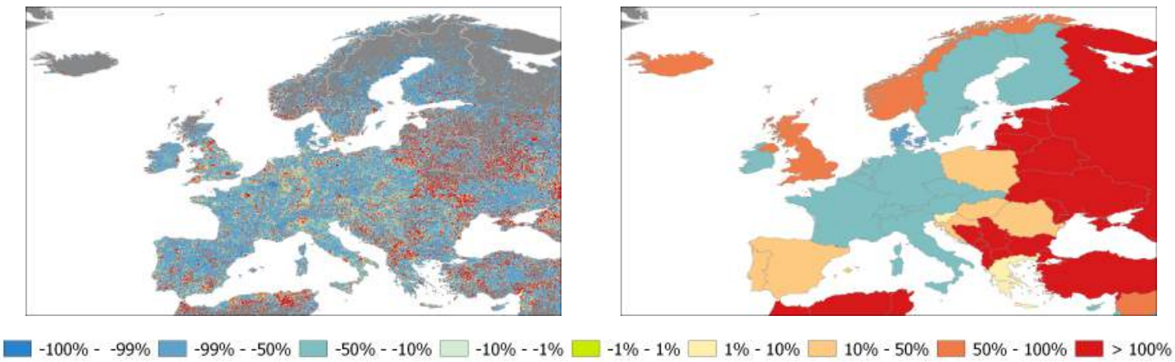

Figure C.2: Relative difference between the reference dataset for gross domestic water demand and the original outcome of Wada's method as point data (top) and averaged over the country (bottom) at 5 arcmin European scale for 2000.

D

Extra visualisation of results

This Appendix contains extra visualisation on the results.

D.1. Outcome sensitivity analyses

D.1.1. Conceptual change

Wastewater treatment

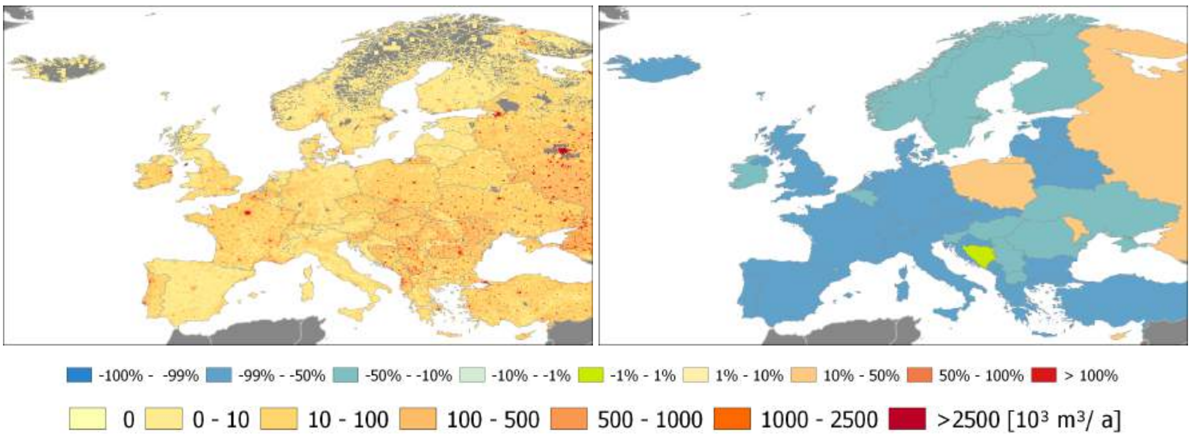

Figure D.1: Net water demand with changed wastewater component (left) and the relative difference between changed component and the reference dataset as country average at 5 arcmin for 2010 at European scale. Note: as wastewater changes relative for the complete country, point and country averages will look the same.

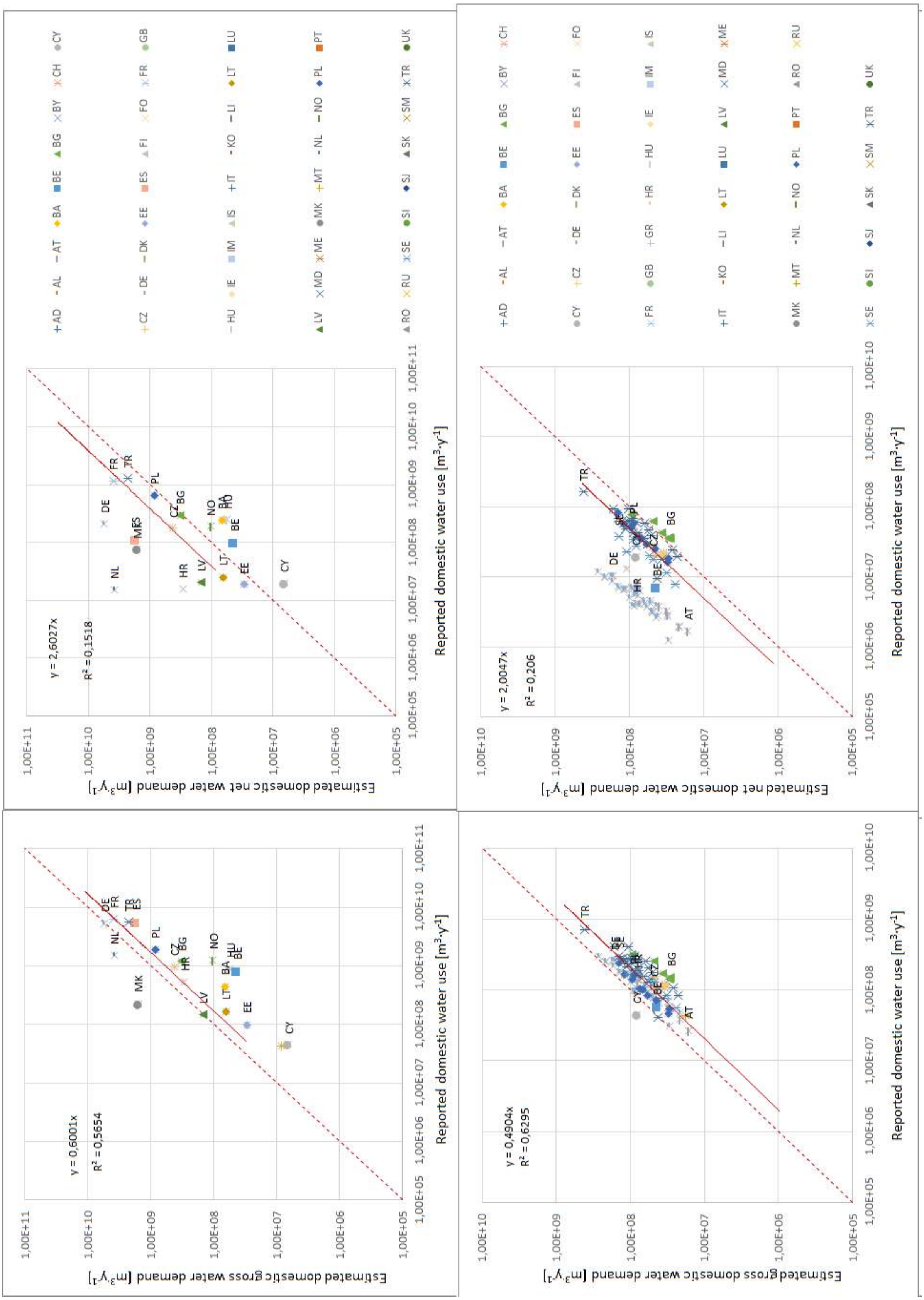

Figure D.2: Gross (left) and net (right) domestic water demand ($m^3/year$) with a changed wastewater concept compared to the outcome of water use by EUROSTAT at country level (top) and NUTS-2 level (bottom). The regression coefficient is forced through the zero intercept.

D.1.2. Changing variable resolution

Gross domestic product

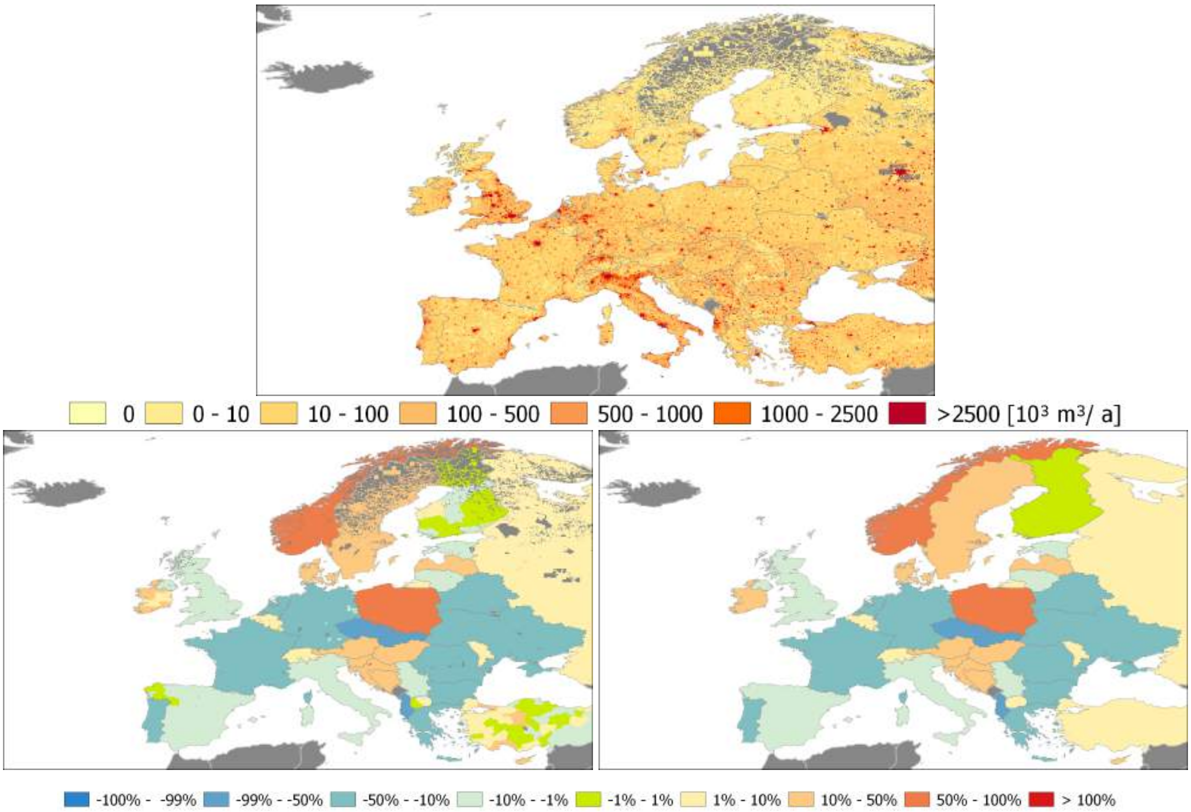

Figure D.3: Net demand (top) when adapting the resolution of GDP for domestic water demand and the relative difference between the outcome of the sensitivity analyses and the reference data set in point data (bottom left) and as country average (bottom right) at 5 arcmin for 2010 at European scale.

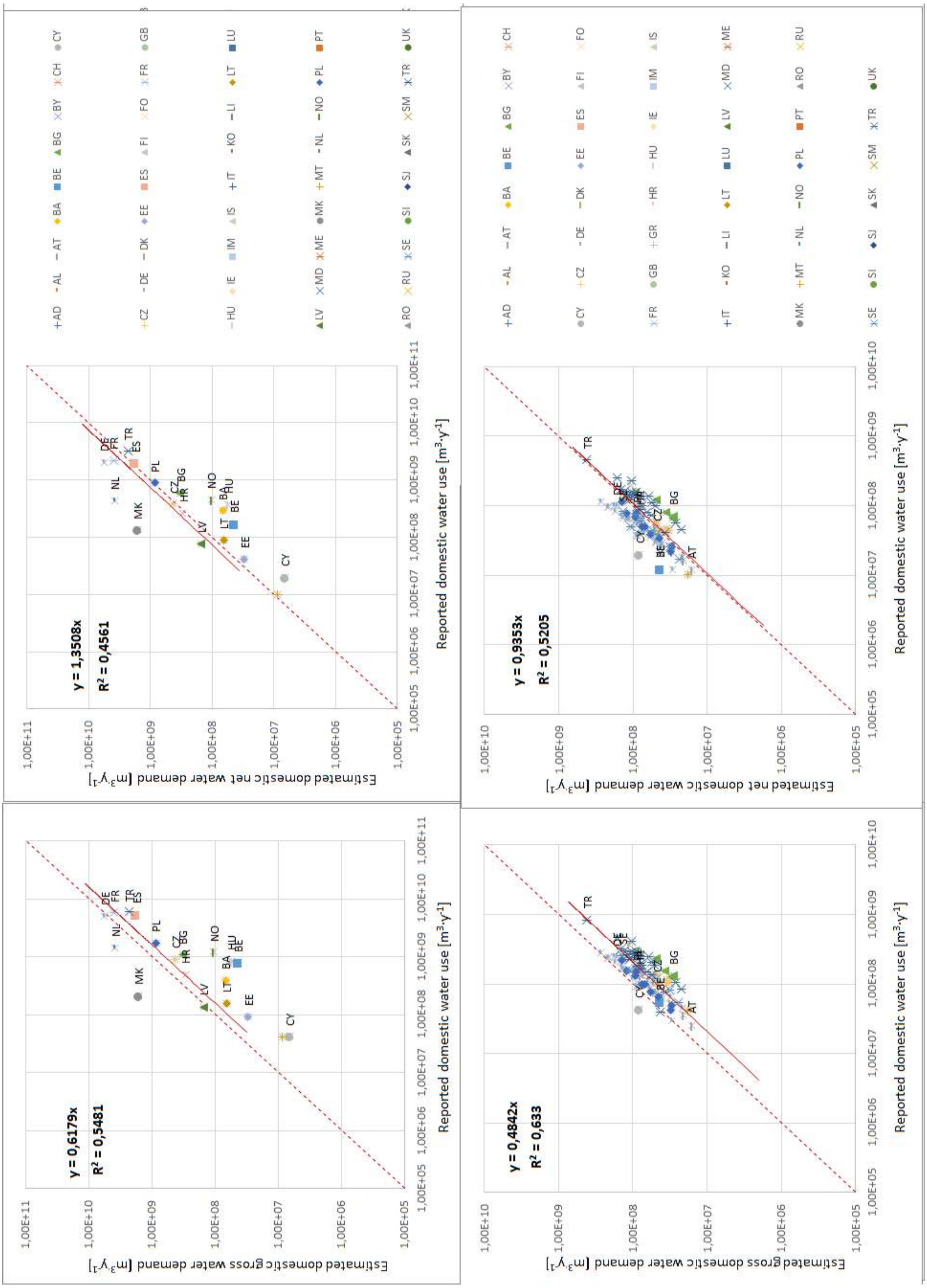

Figure D.4: Gross (left) and net (right) domestic water demand ($m^3/year$) with increased GDP variable resolution compared to the outcome of water use by EUROSTAT at country level (top) and NUTS-2 level (bottom). The regression coefficient is forced through the zero intercept.

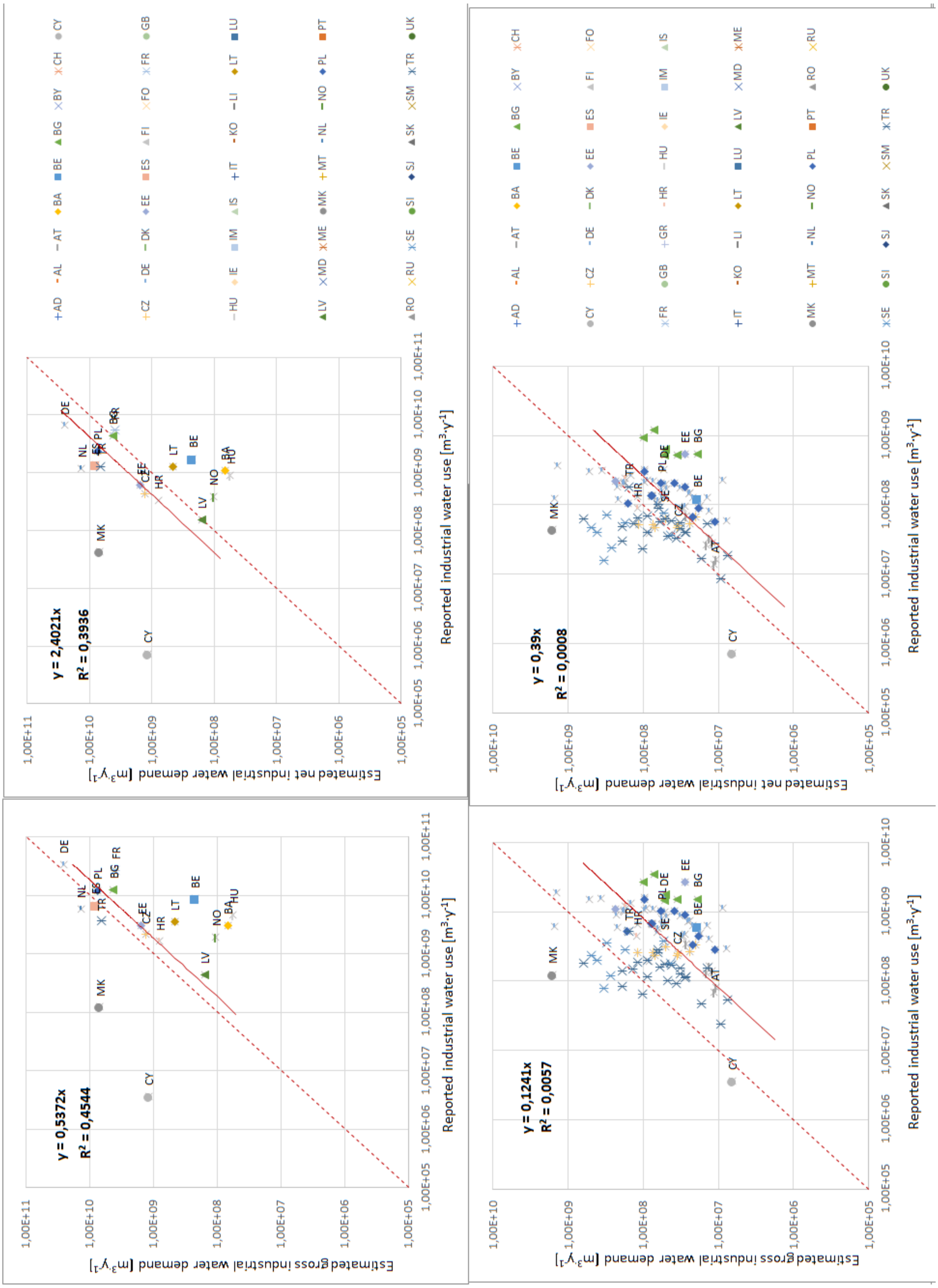

Figure D.5: Gross (left) and net (right) industrial water demand ($m^3/year$) with increased GDP variable resolution compared to the outcome of water use by EUROSTAT at country level (top) and NUTS-2 level (bottom). The regression coefficient is forced through the zero intercept.

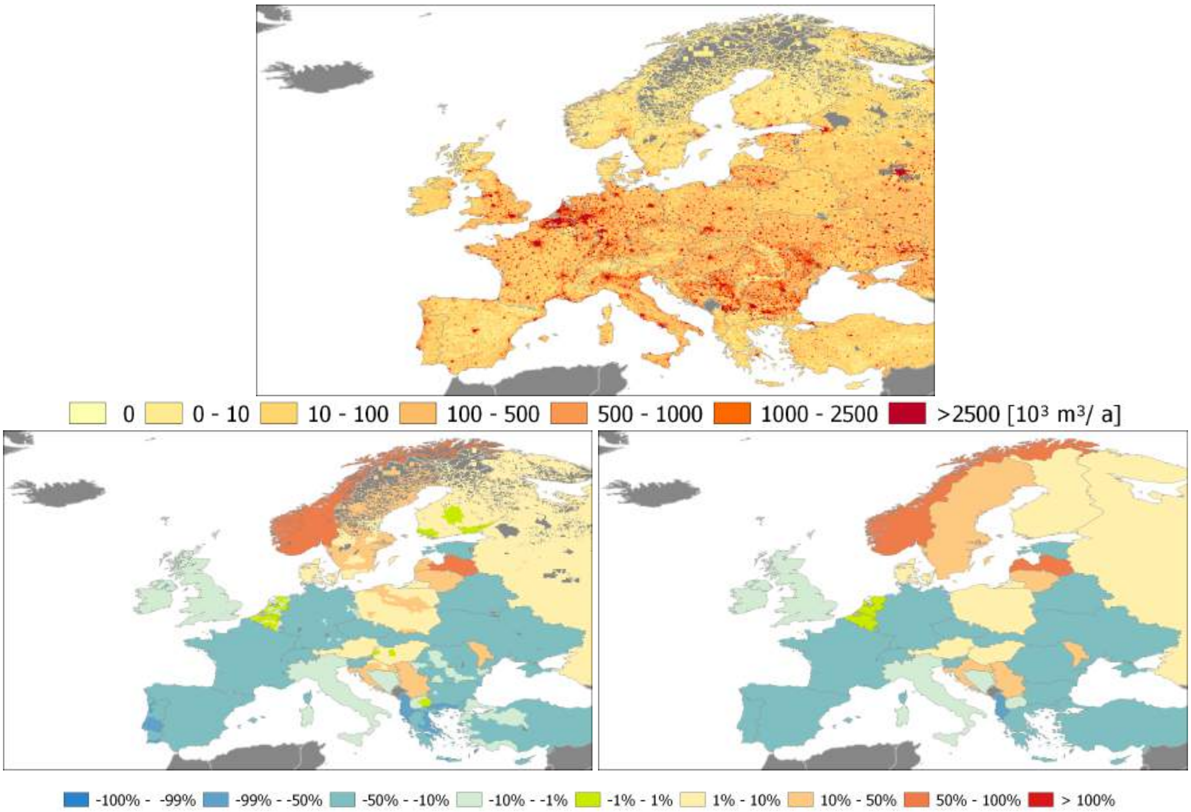

Figure D.6: Net demand (top) when adapting the resolution of GDP for industrial water demand and the relative difference between the outcome of the sensitivity analyses and the reference data set in point data (bottom left) and as country average (bottom right) at 5 arcmin for 2010 at European scale.

Population

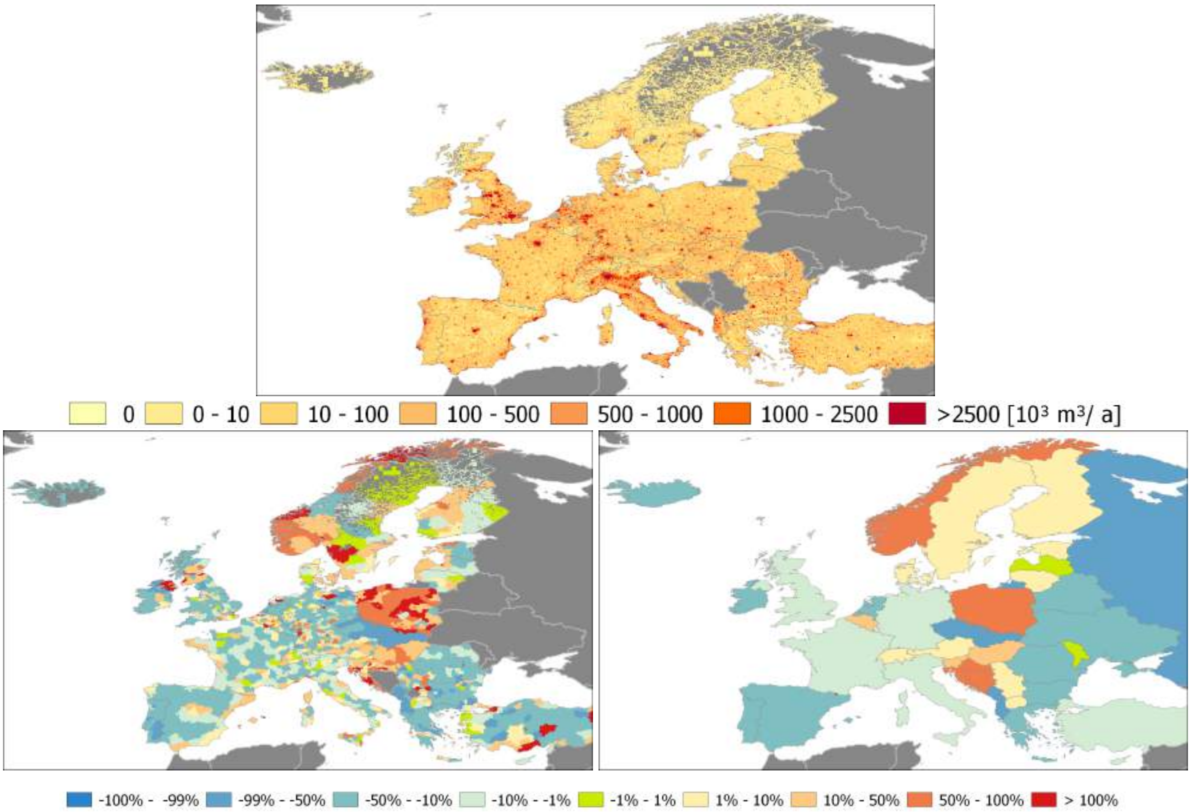

Figure D.7: Net demand (top) when adapting the resolution of population for domestic water demand and the relative difference between the outcome of the sensitivity analyses and the reference data set in point data (bottom left) and as country average (bottom right) at 5 arcmin for 2010 at European scale.

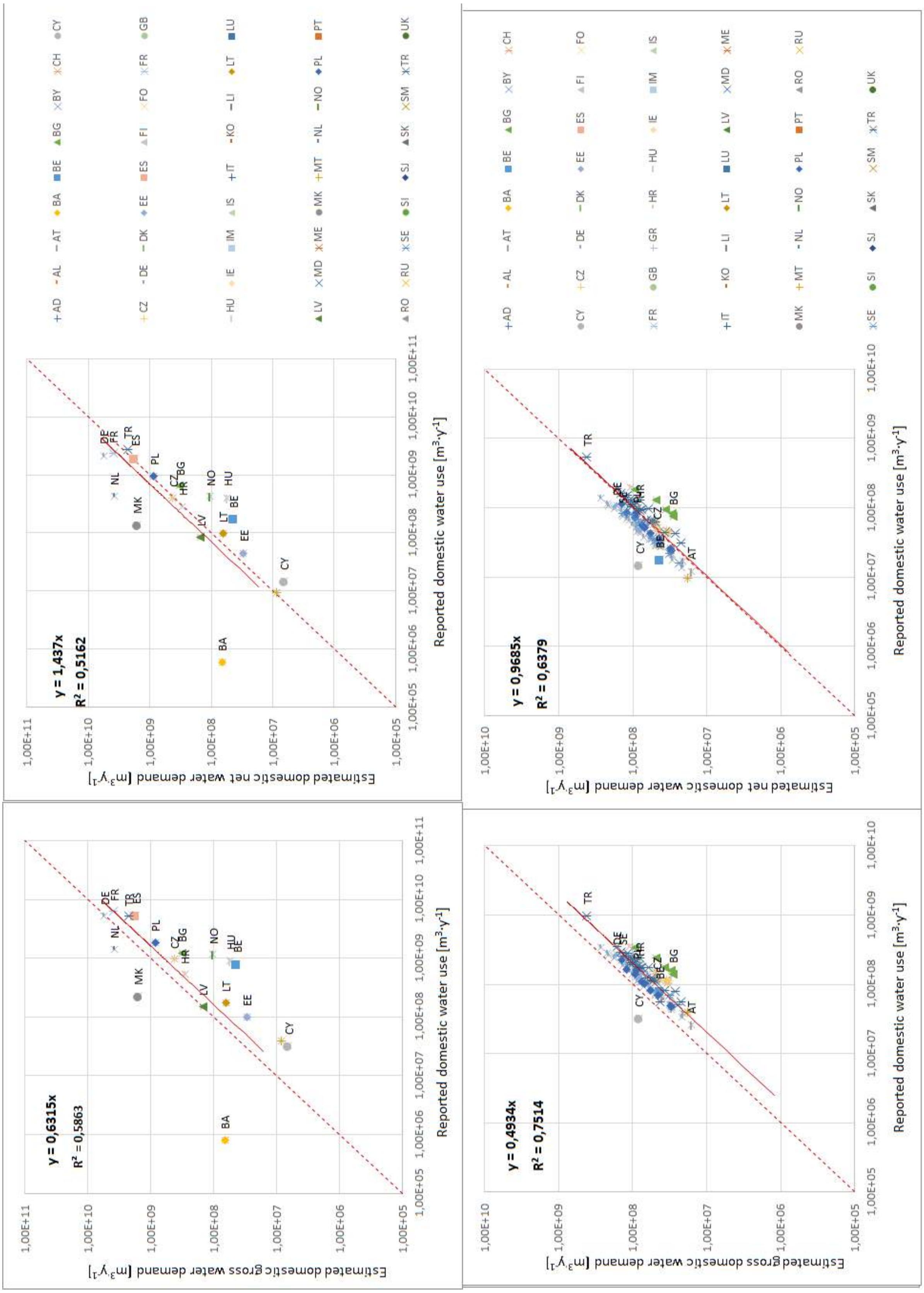

Figure D.8: Gross (left) and net (right) domestic water demand ($m^3/year$) with increased population variable resolution compared to the outcome of water use by EUROSTAT at country level (top) and NUTS-2 level (bottom). The regression coefficient is forced through the zero intercept.

D.2. Downscaling techniques

D.2.1. Downscaling for households

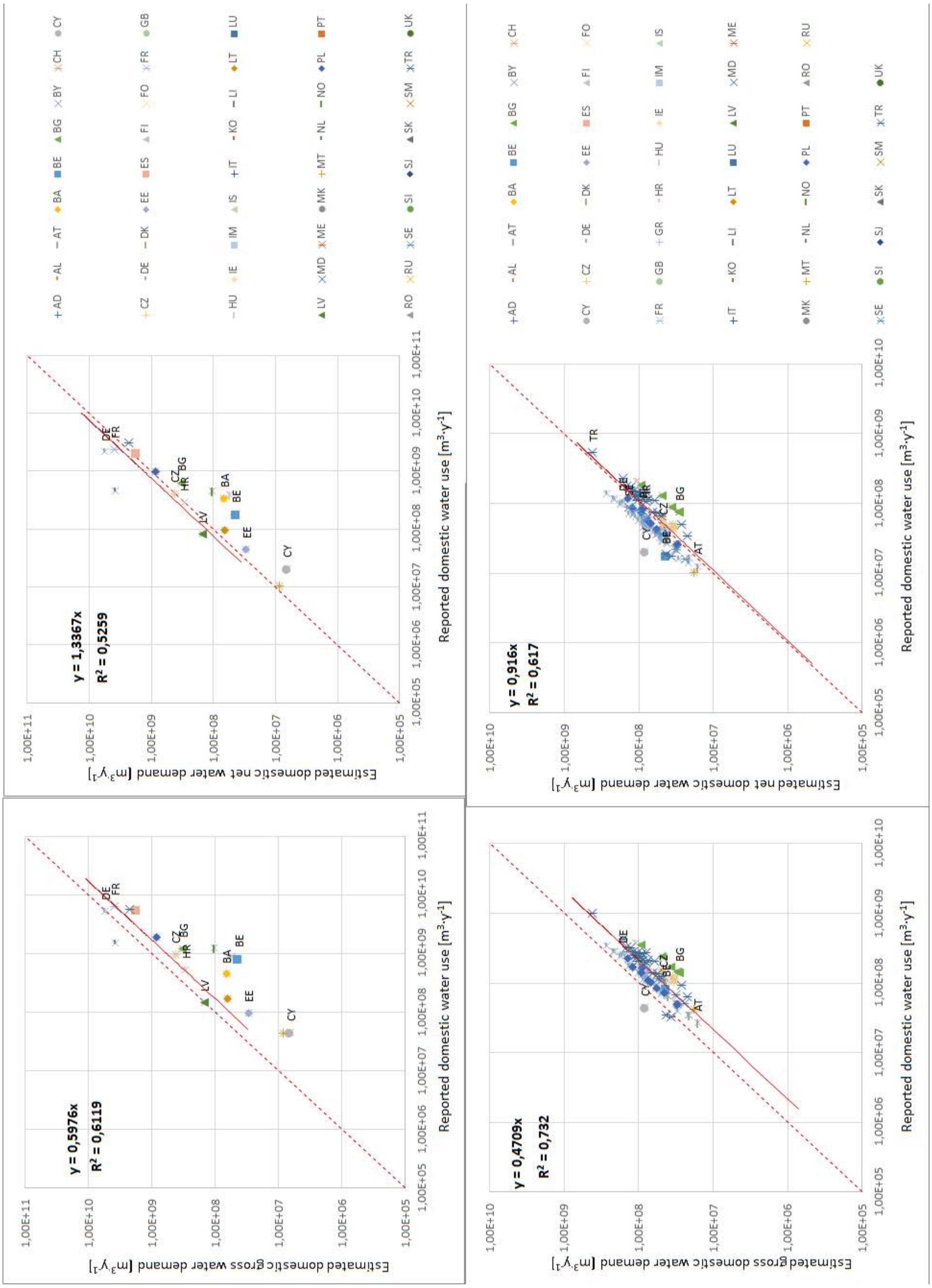

Figure D.9: Gross (left) and net (right) domestic water demand ($m^3/year$) with a 2010 population density map at 0.5 arcmin compared to the outcome of water use by EUROSTAT at country level (top) and NUTS-2 level (bottom). The regression coefficient is forced through the zero intercept.

D.3. Outcome final method and dataset

D.3.1. Domestic water demand

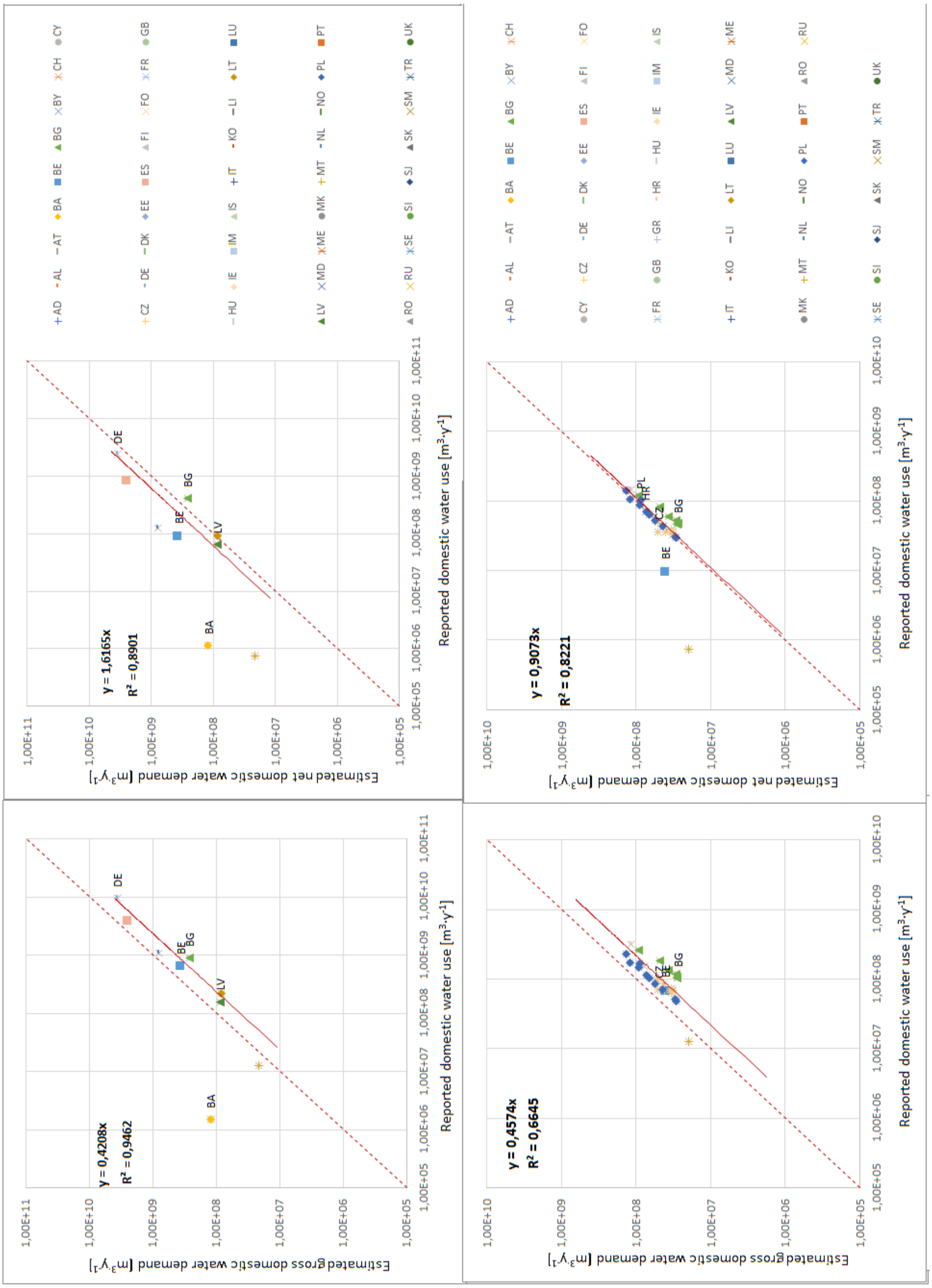

Figure D.10: Gross (left) and net (right) domestic water demand ($m^3/year$) of the final method and dataset compared to the outcome of water use by EUROSTAT at country level (top) and NUTS-2 level (bottom). The regression coefficient is forced through the zero intercept.

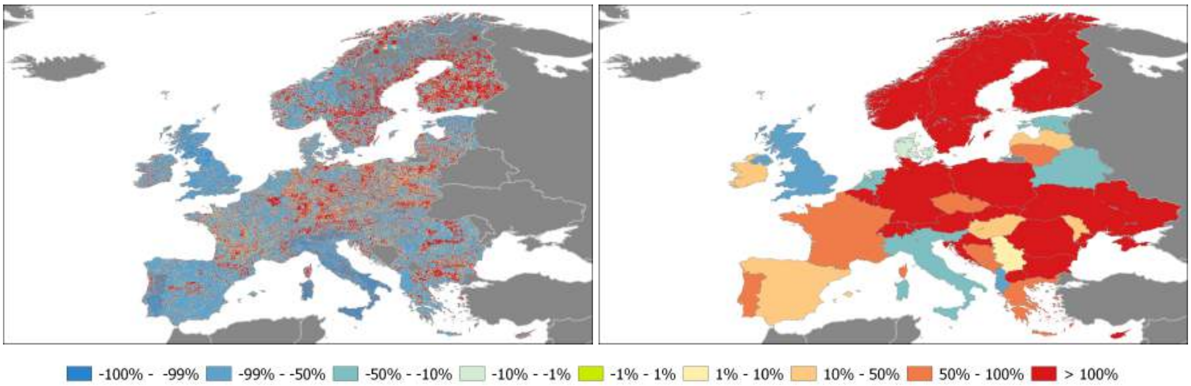

Figure D.11: Net domestic water demand for the final method and dataset compared to the reference dataset as point and country averages at 30 arcsec for 2013/2010.

D.3.2. Industrial water demand

Population downscaling technique

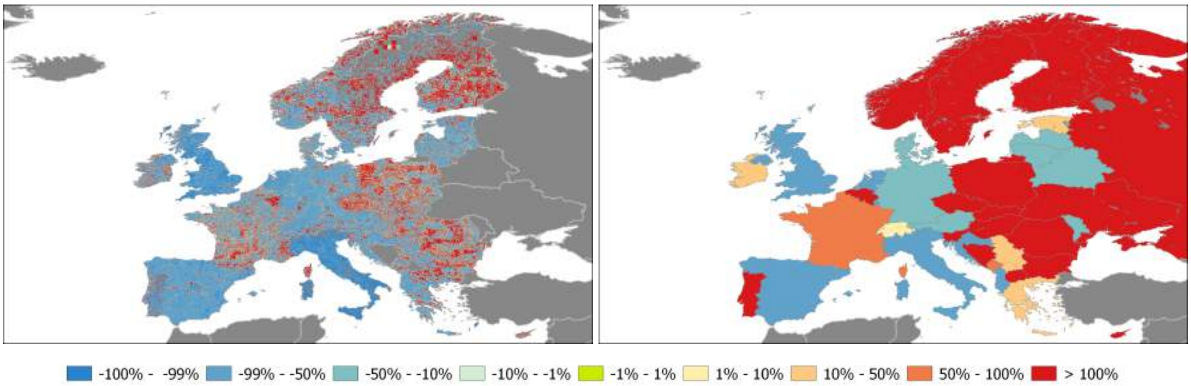

Figure D.12: Net industrial water demand for the final method with population downscaling maps and dataset compared to the reference dataset as point and country averages at 30 arcsec for 2013/2010.

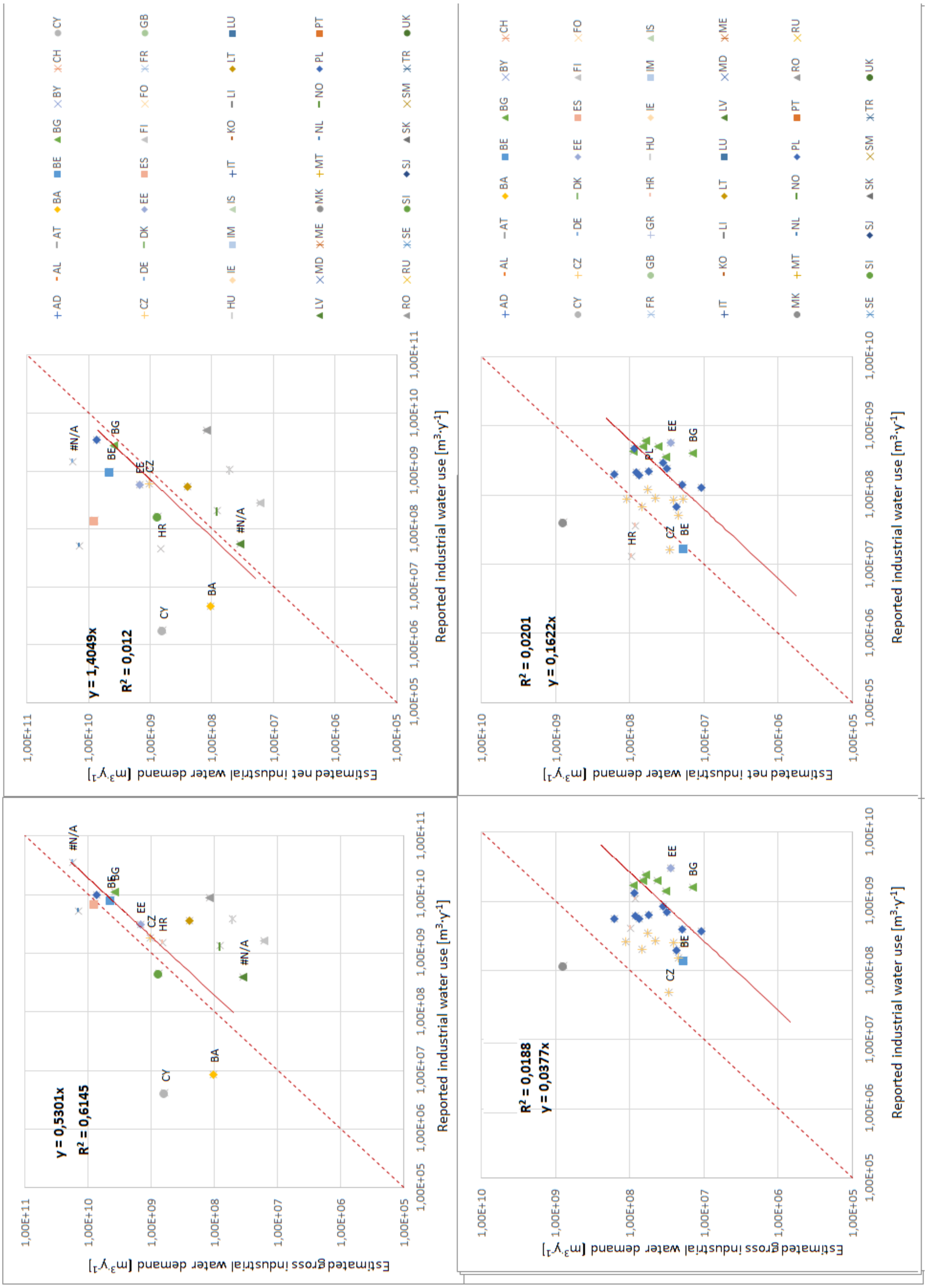

Figure D.13: Gross (left) and net (right) industrial water demand ($m^3/year$) of the final method with population downscaling technique and dataset compared to the outcome of water use by EUROSTAT at country level (top) and NUTS-2 level (bottom). The regression coefficient is forced through the zero intercept.

CORINE downscaling technique

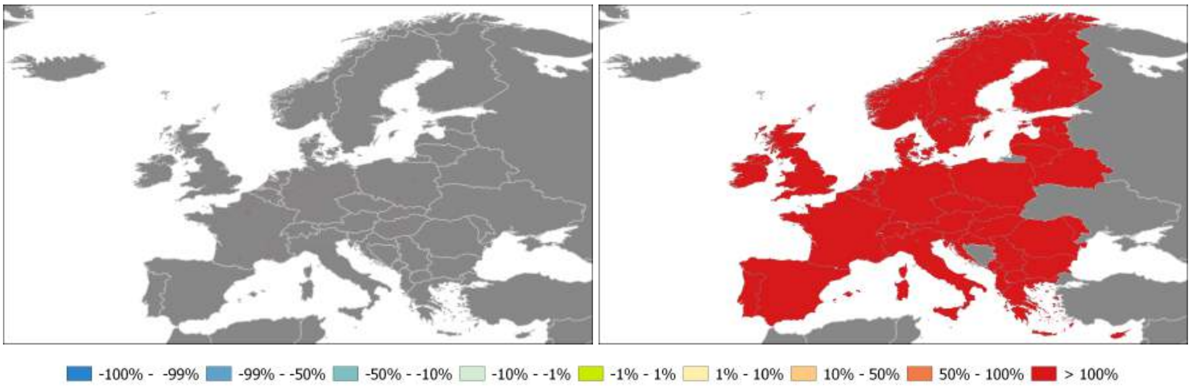

Figure D.14: Net domestic water demand for the final method and dataset with CORINE land cover downscaling maps compared to the reference dataset as point and country averages at 30 arcsec for 2013/2010.

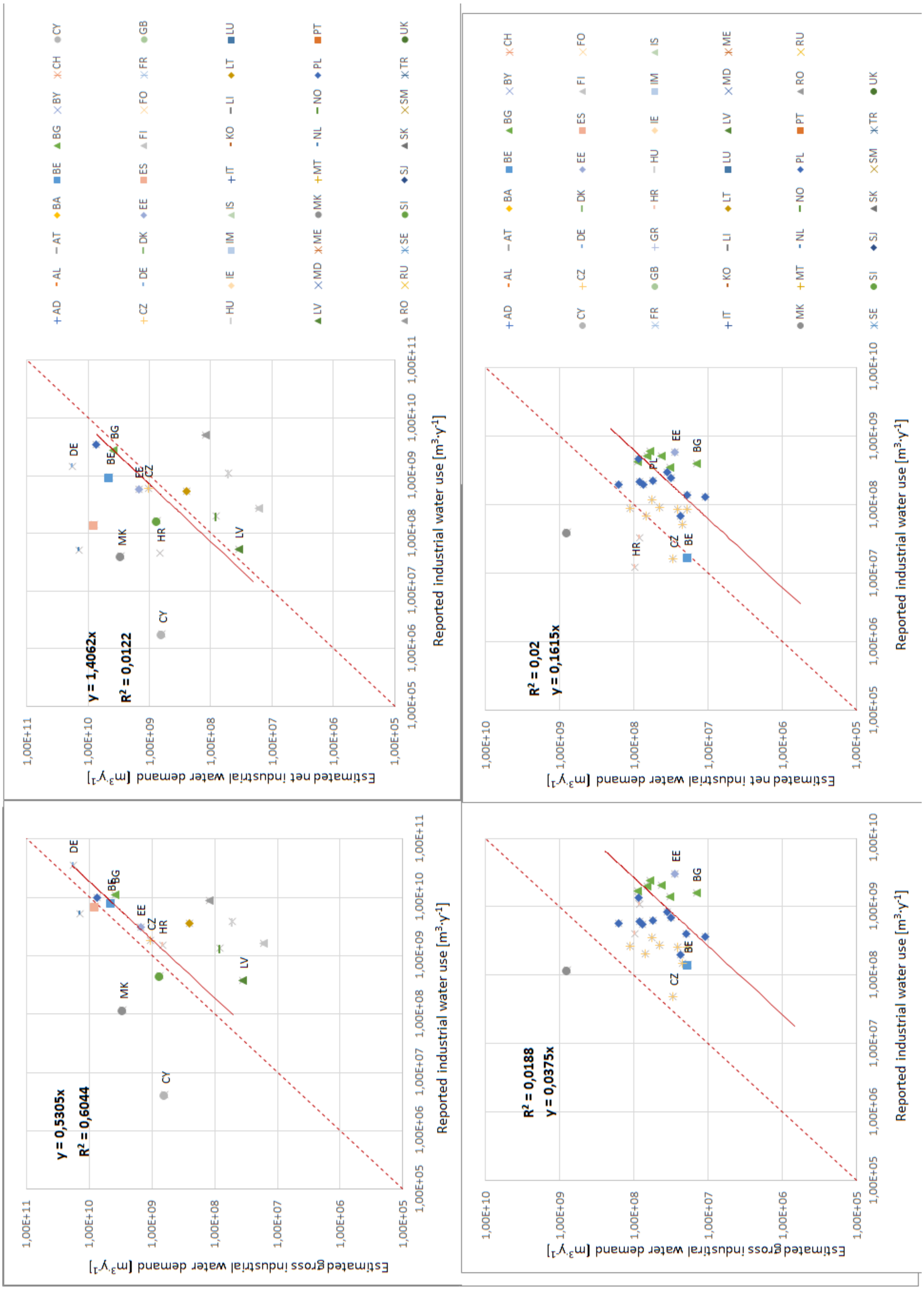

Figure D.15: Gross (left) and net (right) industrial water demand ($m^3/year$) of the final method with CORINE land cover downscaling technique and dataset compared to the outcome of water use by EUROSTAT at country level (top) and NUTS-2 level (bottom). The regression coefficient is forced through the zero intercept.

E

High-resolution method code

```
import os
import sys

import numpy as np
import pcraster as pcr
import pcraster.framework as pcrm, generateNameT

from zonalStatistics import zonal_statistics_pcr
from spatialDataSet2PCR import spatialAttributes, spatialDataSet, setClone
from functions_water_demand import *

def main():

    # initialization
    missing_value = -999.9
    dummyvariablename = 'dummy'
    resample_method = 'near'

    # set the ldd as land mask
    lddfilename = 'clonemap/Europe_outline_1km.map'

    # set the countries
    countryfilename = 'data_input/countries_pbl.shp'
    country_attribute = 'ISO1'

    #These are the downscaling maps used
    total_population_30sec = 'Downscalingmaps/ppp_2010_1km_Europe.map'
    Spatial_industry_distribution = 'Downscalingmaps/EuropeIndustrieCor1km.map'

    # If the trend between urban and rural areas needs to be analysed, this is a map
                                            covereing all urban areas.
    urban_population = pcr.readmap('data_input/urban_population_boolean.map')

    grossindustrialfilename='data_input/ind_2000_mlnm3.asc'

    nuts2_filename =  'EuropeShape/NUTS2_code.shp'
    nuts2_id_attribute = 'NUTS_code'

    #GDP ratios at NUTS3 with 2010 as a base year and a different year as t are
                                            included below
    nuts3_filename = 'EuropeShape/NUTS3_combi_JEROENEUROSTAT_gdp_pop_ID.shp'
    nuts3_id_attribute = 'nuts3_id'
    GDP2000 = "2000GDP"
    GDP2010 = "2010GDP"
    GDP2013 = "2013GDP"
    POP2000 = "2000pop"
    POP2010 = "2010pop"
    POP2013 = "2013pop"
```

```
#Only import if you want to compare to the original method from Wada for domestic
                                            water demand, this is net demand
#Reference at 1 km
Europe_demand_reference_1990_domestic_netto_1km = pcr.readmap('Uitkomsten/
                                            Referentiedata/
                                            Reference_dataset_netto_domestic_1990_Europe_1km
                                            .map')
Europe_demand_reference_2000_domestic_netto_1km = pcr.readmap('Uitkomsten/
                                            Referentiedata/
                                            Reference_dataset_netto_domestic_2000_Europe_1km
                                            .map')
Europe_demand_reference_2010_domestic_netto_1km = pcr.readmap('Uitkomsten/
                                            Referentiedata/
                                            Reference_dataset_netto_domestic_2010_Europe_1km
                                            .map')
Europe_reference_dom_netto_1kmlist = [
                                            Europe_demand_reference_1990_domestic_netto_1km
                                            ,
                                            Europe_demand_reference_2000_domestic_netto_1km
                                            ,
                                            Europe_demand_reference_2010_domestic_netto_1km
                                            ]

Europe_demand_reference_1990_industrial_netto_1km = pcr.readmap('Uitkomsten/
                                            Referentiedata/
                                            Reference_dataset_netto_industrial_1990_Europe_1km
                                            .map')
Europe_demand_reference_2000_industrial_netto_1km = pcr.readmap('Uitkomsten/
                                            Referentiedata/
                                            Reference_dataset_netto_industrial_2000_Europe_1km
                                            .map')
Europe_demand_reference_2010_industrial_netto_1km = pcr.readmap('Uitkomsten/
                                            Referentiedata/
                                            Reference_dataset_netto_industrial_2010_Europe_1km
                                            .map')
Europe_reference_ind_netto_1kmlist = [
                                            Europe_demand_reference_1990_industrial_netto_1km
                                            ,
                                            Europe_demand_reference_2000_industrial_netto_1km
                                            ,
                                            Europe_demand_reference_2010_industrial_netto_1km
                                            ]

# country information: table with various information organized per coun-
# try and the entries provided per row. country_table_column_start: this
# is the last column of those columns identifying the different information
# on country and region IDs as contained by the country-specfic tables:
# FID   ISO1    ISO2    ISO3    Name    IMAGE26 IMAGE26_name    data
# Countries_data_040220202.txt contains all data to recreate Wada's method
country_data_tbl_filename = 'data_input/Final_method_with_urban.txt'
table_country_key      = 1
table_country_name_key = 4
table_regions_key      = 5
DWUITO                 = 20
table_column_start     = 6
country_data_tbl_columns = {\
                            'country_id':            table_country_key, \
                            'TDev13':                table_column_start +  9, \
                            'EDev13':                table_column_start +  10, \
                            'Recycle13':             table_column_start +  11, \
                            'Urban%13':              table_column_start +  15, \
                            }

# set the clone and create the land mask
cloneattributes = spatialAttributes(lddfilename)
setClone(cloneattributes)
landmask = pcr.defined(pcr.readmap(lddfilename))

# read in the countries, NUTS2, NUTS3, regions and total population at 5 arcmin
# read in with unique ID's make sure only countries are covered and waterbodies are
                                             left blank
```

```
# sort the id low to high
countries = pcr.cover(getattr(spatialDataSet(dummyvariablename,\
    countryfilename, 'INT32', 'Nominal',\
    cloneattributes.xLL, cloneattributes.xUR, cloneattributes.yLL, cloneattributes.
                                                yUR,\
    cloneattributes.xResolution, cloneattributes.yResolution,\
    pixels= cloneattributes.numberCols, lines= cloneattributes.numberRows,
                                                attribute= country_attribute),
                                                dummyvariablename), 0)
countries = pcr.ifthen(landmask, countries)
countries = pcr.ifthen(countries != 0, countries)
country_ids = np.unique(pcr.pcr2numpy(countries,0))
country_ids = (country_ids[country_ids != 0]).tolist()
country_ids.sort()

#read in regions through IMAGE26 number, sort every unique region from low to high
regions = map_table_info_to_pcr(\
                datafile      = country_data_tbl_filename, \
                key_map       = countries, \
                key_column    = table_country_key, \
                data_column   = table_regions_key, \
                pcr_data_type = pcr.nominal, \
                testverbose   = False)
region_ids = np.unique(pcr.pcr2numpy(regions,0))
region_ids = (region_ids[region_ids != 0]).tolist()
region_ids.sort()

nuts2 = pcr.cover(getattr(spatialDataSet(dummyvariablename,\
    nuts2_filename, 'INT32', 'Nominal',\
    cloneattributes.xLL, cloneattributes.xUR, cloneattributes.yLL, cloneattributes.
                                                yUR,\
    cloneattributes.xResolution, cloneattributes.yResolution,\
    pixels= cloneattributes.numberCols, lines= cloneattributes.numberRows,
                                                attribute= nuts2_id_attribute),
                                                dummyvariablename), 0)
nuts2 = pcr.ifthen(landmask, nuts2)
nuts2 = pcr.ifthen(nuts2 != 0, nuts2)
nuts2_ids = np.unique(pcr.pcr2numpy(nuts2,0))
nuts2_ids = (nuts2_ids[nuts2_ids != 0]).tolist()
nuts2_ids.sort()

nuts3 = pcr.cover(getattr(spatialDataSet(dummyvariablename,\
    nuts3_filename, 'INT32', 'Nominal',\
    cloneattributes.xLL, cloneattributes.xUR, cloneattributes.yLL, cloneattributes.
                                                yUR,\
    cloneattributes.xResolution, cloneattributes.yResolution,\
    pixels= cloneattributes.numberCols, lines= cloneattributes.numberRows,
                                                attribute= nuts3_id_attribute),
                                                dummyvariablename), 0)
nuts3 = pcr.ifthen(landmask, nuts3)
nuts3 = pcr.ifthen(nuts3 != 0, nuts3)
nuts3_ids = np.unique(pcr.pcr2numpy(nuts3,0))
nuts3_ids = (nuts3_ids[nuts3_ids != 0]).tolist()
nuts3_ids.sort()

total_population_30sec = pcr.cover(getattr(spatialDataSet(dummyvariablename,\
    total_population_30sec, 'FLOAT32', 'Scalar',\
    cloneattributes.xLL, cloneattributes.xUR, cloneattributes.yLL, cloneattributes.
                                                yUR,\
    cloneattributes.xResolution, cloneattributes.yResolution,\
    pixels= cloneattributes.numberCols, lines= cloneattributes.numberRows,
                                                attribute= country_attribute),
                                                dummyvariablename), 0)
total_population_30sec = pcr.ifthen(landmask, total_population_30sec)
total_population_30sec = pcr.ifthen(total_population_30sec !=0,
                                            total_population_30sec)

#Read in the GDP at NUTS3 level, which year do you want to compare to 2010, now
                                            2013 is used.
nuts3_gdp2010 = pcr.cover(getattr(spatialDataSet(dummyvariablename, nuts3_filename
                                            ,\
```

```
    'FLOAT32', 'Scalar', cloneattributes.xLL, cloneattributes.xUR, cloneattributes.
                                            yLL, cloneattributes.yUR,\
    cloneattributes.xResolution, cloneattributes.yResolution, pixels=
                                            cloneattributes.numberCols, \
    lines= cloneattributes.numberRows, resampleMethod= resample_method, attribute=
                                            GDP2010), \
    dummyvariablename), 0)
nuts3_gdp2010 = pcr.ifthen(landmask, nuts3_gdp2010)
nuts3_gdp2010 = pcr.ifthen(nuts3_gdp2010 !=0, nuts3_gdp2010)

nuts3_gdp2013 = pcr.cover(getattr(spatialDataSet(dummyvariablename, nuts3_filename
                                            ,\
    'FLOAT32', 'Scalar', cloneattributes.xLL, cloneattributes.xUR, cloneattributes.
                                            yLL, cloneattributes.yUR,\
    cloneattributes.xResolution, cloneattributes.yResolution, pixels=
                                            cloneattributes.numberCols, \
    lines= cloneattributes.numberRows, resampleMethod= resample_method, attribute=
                                            GDP2013), \
    dummyvariablename), 0)
nuts3_gdp2013 = pcr.ifthen(landmask, nuts3_gdp2013)
nuts3_gdp2013 = pcr.ifthen(nuts3_gdp2013 !=0, nuts3_gdp2013)

nuts3_pop2013 = pcr.cover(getattr(spatialDataSet(dummyvariablename, nuts3_filename,
                                            \
   'FLOAT32', 'Scalar', cloneattributes.xLL, cloneattributes.xUR, cloneattributes.
                                           yLL, cloneattributes.yUR,\
    cloneattributes.xResolution, cloneattributes.yResolution, pixels=
                                            cloneattributes.numberCols, \
    lines= cloneattributes.numberRows, resampleMethod= resample_method, attribute=
                                            POP2013), \
    dummyvariablename), 0)
nuts3_pop2013 = pcr.ifthen(landmask, nuts3_pop2013)
nuts3_pop2013 = pcr.ifthen(nuts3_pop2013 !=0, nuts3_pop2013)

#Read in the CORINE spatial cover for industrial land use
Industry_spatially = pcr.cover(getattr(spatialDataSet(dummyvariablename,\
    Spatial_industry_distribution, 'INT32', 'Nominal',\
    cloneattributes.xLL, cloneattributes.xUR, cloneattributes.yLL, cloneattributes.
                                            yUR,\
    cloneattributes.xResolution, cloneattributes.yResolution,\
    pixels= cloneattributes.numberCols, lines= cloneattributes.numberRows,
                                            attribute= country_attribute),
                                            dummyvariablename), 0)
Industry_spatially = pcr.ifthen(landmask, Industry_spatially)
Industry_spatially = pcr.ifthen(Industry_spatially !=0, Industry_spatially)
Industry_spatially = pcr.ifthen(Industry_spatially == 121, pcr.scalar(1))

# read in gross industrial water demand from 2000 in million cubic meters at 0.5
                                            resolution (30 arcmin)
# cover only countries ignore water bodies
grossindustrialdemandT0 = pcr.cover(getattr(spatialDataSet(dummyvariablename,\
    grossindustrialfilename, 'Float32', 'Scalar',\
    cloneattributes.xLL, cloneattributes.xUR, cloneattributes.yLL, cloneattributes.
                                            yUR,\
    cloneattributes.xResolution, cloneattributes.yResolution,\
    pixels= cloneattributes.numberCols, lines= cloneattributes.numberRows,
                                            attribute= country_attribute),
                                            dummyvariablename), 0)
# ATTENTION: as the file is at 30 arcmin/0.5 resolution - 50 km, create
                                            convert_WWDR_to_wanted_resolution
# multiply change in resolution from y with change in resolution from x
# e.g. if clone map has resolution of 0.083 (10km) convertion = 0.5/0.083 * 0.5/0.
                                            083 = 6*6 = 36
convert_WWDR_to_wanted_resolution = (0.5 / cloneattributes.yResolution) * (0.5 /
                                            cloneattributes.xResolution)
grossindustrialdemandT0 = grossindustrialdemandT0 * 1000000 /
                                            convert_WWDR_to_wanted_resolution
grossindustrialdemandT0 = pcr.ifthen(landmask, grossindustrialdemandT0)
grossindustrialdemandT0 = pcr.ifthen(grossindustrialdemandT0 != 0,
                                            grossindustrialdemandT0)
```

```
#The two below downscaling techniques are for industry using CORINE(above) and
                                             domestic or industry by population(
                                             below)
# this function redistributes the total industrial water demand per country and
                                             gives weight for domestic water demand
# on the basis of the population for the reference year
total_population_country_30sec_nut3 = pcr.areatotal(total_population_30sec , nuts3)
weight_population_30sec_nuts3 = total_population_30sec /
                                             total_population_country_30sec_nut3
grossindustrialdemandT0_distributed_30sec_nuts3 =  weight_population_30sec_nuts3 *
                                             pcr.areatotal(grossindustrialdemandT0,
                                             nuts3)

total_industry_country_nuts3 = pcr.areatotal(Industry_spatially, nuts3)
weight_industry_nuts3 = Industry_spatially / total_industry_country_nuts3
grossindustrialdemandT0_distributedCORINE_nuts3 = weight_industry_nuts3 * pcr.
                                             areatotal(grossindustrialdemandT0,nuts3
                                             )

#Convert domestic water use intensity from table to pcr map
DWUIT0 = map_table_info_to_pcr(\
                datafile       = country_data_tbl_filename, \
                key_map        = countries, \
                key_column     = table_country_key, \
                data_column    = DWUIT0, \
                pcr_data_type  = pcr.scalar, \
                testverbose    = False)
DWUIT0 = pcr.ifthen(landmask, DWUIT0)
DWUIT0 = pcr.ifthen(DWUIT0 != 0, DWUIT0)

# identify unique cells per country and get their maximum number per region
# Get the maximum number of countries
country_seed = pcr.ifthenelse(pcr.areaorder(pcr.spatial(pcr.scalar(1)),countries) =
                                             = 1,pcr.scalar(1),0)
max_number_countries = zonal_statistics_pcr(country_seed, regions, region_ids, np.
                                             sum)

#As industrial water demand is calculated for 1990 to 2010, create a list and read
                                             in the variable_names for available
                                             data
#As only 2010 data is available
years = list(range(2013,2015,5))
variable_names_ind = ['EDev', 'TDev','Recycle','POP']
yearcnt = 0

for year in years:
    #Read in Wada's outcome if you would like to compare to the original method
    industryNettoDemandReference1km = Europe_reference_ind_netto_1kmlist[yearcnt]
    domesticNettoDemandReference1km = Europe_reference_dom_netto_1kmlist[yearcnt]

    #Read in all variables depending on what year you are in within the for-loop
    mapped_country_info_ind = {}
    for variable_root_ind in variable_names_ind:
        variable_name_ind = str.join('', (variable_root_ind, str(year)[2:]))
        data_column = country_data_tbl_columns[variable_name_ind]
        mapped_country_info_ind[variable_root_ind] = map_table_info_to_pcr(\
                datafile       = country_data_tbl_filename, \
                key_map        = countries, \
                key_column     = table_country_key, \
                data_column    = data_column, \
                pcr_data_type  = pcr.scalar, \
                testverbose    = False)
        # If data in the table is non-zero it can be used.
        mapped_country_info_ind[variable_root_ind] = pcr.ifthen(
                                                     mapped_country_info_ind[
                                                     variable_root_ind] != 0,\
                          mapped_country_info_ind[variable_root_ind])

    mapped_region_info = {}
    for key,value in mapped_country_info_ind.items():
```

```
        # print number of countries
        actual_number_countries = zonal_statistics_pcr( \
                 pcr.ifthen(pcr.defined(mapped_country_info_ind[key]), country_seed
                                                         ), \
                 regions, region_ids, np.sum)

        print ('%s' % key)
        for region_id in region_ids:
            print ('%3d: %3d out of %3d countries present' % \
                   (region_id, \
                    actual_number_countries[region_ids.index(region_id)],\
                    max_number_countries[region_ids.index(region_id)]))

        # get the mean and fill missing values, this is the gap-filling technique
        mapped_region_info[key] = pcr.areaaverage(value, regions)
        mapped_country_info_ind[key] = pcr.cover(mapped_country_info_ind[key],
                                                 mapped_region_info[key])

        DWUIT0_regions = pcr.areaaverage(DWUIT0, regions)
        DWUIT0 = pcr.cover(DWUIT0, DWUIT0_regions)

        nuts3_gdp2010_country = pcr.areaaverage(nuts3_gdp2010, countries)
        nuts3_gdp2010 = pcr.cover(nuts3_gdp2010,nuts3_gdp2010_country)

        nuts3_gdp2013_country = pcr.areaaverage(nuts3_gdp2013, countries)
        nuts3_gdp2013 = pcr.cover(nuts3_gdp2013,nuts3_gdp2013_country)

        nuts3_pop2013_country = pcr.areaaverage(nuts3_pop2013, countries)
        nuts3_pop2013 = pcr.cover(nuts3_pop2013,nuts3_pop2013_country)

        #Calculate net industrial water demand as explained in the research.
        #EDev and TDev are economical and technological development, Recycle is the
                                                  recycle ratio.
        #In the final method, GDP is extracted at NUTS3 level and thus needs to be
                                                 added to the other three parts
                                                 of EDev
        #and divided by 4 to get the average EDev.
        Total_EDev = (mapped_country_info_ind['EDev'] + pcr.sqrt(nuts3_gdp2013/
                                                 nuts3_gdp2010)) / 4.0

        #Choose downscaling technique and adapt first variable in equation below:
                                                 add CORINE_nuts3 or
                                                 population_nuts3 as a suffix
        grossindustrialdemand = grossindustrialdemandT0_distributedCORINE_nuts3 *
                                                 Total_EDev *
                                                 mapped_country_info_ind['TDev']
        grossindustrialdemand = pcr.ifthen(grossindustrialdemand != 0,
                                                 grossindustrialdemand)
        netindustrialdemand = grossindustrialdemand * (1.0 -
                                                 mapped_country_info_ind['
                                                 Recycle'])
        netindustrialdemand = pcr.ifthen(netindustrialdemand!=0,netindustrialdemand
                                                 )

        #If you want to compare to outcome Wada use the following lines to get the
                                                 relative difference for point
                                                 data and country averages:
        compare_validation_Wada_indn_point = ((netindustrialdemand -
                                                 industryNettoDemandReference1km
                                                  ) /
                                                 industryNettoDemandReference1km
                                                 )*100.0
        compare_validation_Wada_indn_point = pcr.ifthen(
                                                 compare_validation_Wada_indn_point
                                                  != -100,
                                                 compare_validation_Wada_indn_point
                                                 )
        compare_validation_Wada_indn_countries = pcr.areaaverage(
                                                 compare_validation_Wada_indn_point
                                                 ,countries)
```

```
    pcr.report(compare_validation_Wada_indn_point, generateNameT("pointin",year
                                                    ))
    pcr.report(compare_validation_Wada_indn_countries, generateNameT("countin",
                                                    year))

    #HOUSEHOLDS
    #Domestic water demand in m3 for total population in a year using the
                                                    equations from the research
    Gross_domestic_water_demand_country = Total_EDev * mapped_country_info_ind[
                                                    'TDev'] * nuts3_pop2013 *
                                                    DWUIT0

    #Downscaling to required population using population weight and thus
                                                    distribution
    Gross_domestic_water_demand_country_downscaled =
                                                    weight_population_30sec_nuts3 *

                                                    Gross_domestic_water_demand_country


    #Gross to net is retrieved by considering the population that is connected
                                                    to a sewage system and applying
                                                     wastewater treatment.
    Ratio_gross_to_net = 1.0 - ((mapped_country_info_ind['Urban%']/100.0)*
                                                    mapped_country_info_ind['
                                                    Recycle'] )

    Net_domestic_water_demand_yearly =
                                                    Gross_domestic_water_demand_country_downscaled
                                                     * Ratio_gross_to_net
    Net_domestic_water_demand_yearly = pcr.ifthen(
                                                    Net_domestic_water_demand_yearly
                                                     != 0,
                                                    Net_domestic_water_demand_yearly
                                                    )

     #If you want to compare to outcome Wada use the following lines to get the
                                                      relative difference for point
                                                      data and country averages:
    compare_validation_Wada_domn_point = ((Net_domestic_water_demand_yearly -
                                                    domesticNettoDemandReference1km
                                                    ) /
                                                    domesticNettoDemandReference1km
                                                    )*100.0
    compare_validation_Wada_domn_point = pcr.ifthen(
                                                    compare_validation_Wada_domn_point
                                                     != -100,
                                                    compare_validation_Wada_domn_point
                                                    )
    compare_validation_Wada_domn_countries = pcr.areaaverage(
                                                    compare_validation_Wada_domn_point
                                                    ,countries)
    pcr.report(compare_validation_Wada_domn_point, generateNameT("pointdn",year
                                                    ))
    pcr.report(compare_validation_Wada_domn_countries, generateNameT("countdn",
                                                    year))

# If you would like to write the results to a textfile use the following part.
                                                Remember industry is in
# years whereas households is in months, so if you'd like dom to be in years as
                                                 well you should adapt it.
# Write to textfile nuts2 level
# Use: yearly_gross_dom or grossindustrialdemand and yearly_net_dom or
                                                netindustrialdemand
yearly_gross_dom_nuts2 = pcr.areatotal(grossindustrialdemand ,nuts2)
yearly_net_dom_nuts2 = pcr.areatotal(netindustrialdemand ,nuts2)
gross_demand_list_nuts2 = zonal_statistics_pcr(yearly_gross_dom_nuts2, nuts2,
                                                nuts2_ids, np.mean)
net_demand_list_nuts2 = zonal_statistics_pcr(yearly_net_dom_nuts2, nuts2,
                                                nuts2_ids, np.mean)
```

```
        with open('Water_demand_written_to_text\\
                                                    write_nuts2_industry_finalmethod_cordownscale_na
                                                    .txt', 'w') as f:
        # iterate over the countries and the corresponding mean
            w_str = 'Data on nuts2 id, gross demand\n'
            f.write(w_str)

            for nuts2_id in nuts2_ids:

                # get the index
                ix = nuts2_ids.index(nuts2_id)

                # get the values

                f.write('%d: %g' % (nuts2_id, gross_demand_list_nuts2[ix]) + '\n')

            w_str = '\nData on nuts2 id, net demand\n'
            f.write(w_str)

            for nuts2_id in nuts2_ids:
                # get the index
                ix = nuts2_ids.index(nuts2_id)

                # get the values
                f.write('%d: %g' % (nuts2_id, net_demand_list_nuts2[ix]) + '\n')

        #Write to textfile for countries
        # Use: yearly_gross_dom or grossindustrialdemand and yearly_net_dom or
                                                    netindustrialdemand
        yearly_gross_dom_country = pcr.areatotal(grossindustrialdemand,countries)
        yearly_net_dom_country = pcr.areatotal(netindustrialdemand,countries)
        gross_demand_list_country = zonal_statistics_pcr(yearly_gross_dom_country,
                                                    countries, country_ids, np.mean)
        net_demand_list_country = zonal_statistics_pcr(yearly_net_dom_country,
                                                    countries, country_ids, np.mean)

        with open('Water_demand_written_to_text\\
                                                    write_country_industry_finalmethod_cordownscale_
                                                    .txt', 'w') as f:
        # iterate over the countries and the corresponding mean
            w_str = 'Data on country id, gross demand\n'
            f.write(w_str)

            for country_id in country_ids:

                # get the index
                ix = country_ids.index(country_id)

                # get the values
                f.write('%d: %g' % (country_id, gross_demand_list_country[ix]) + '\n')

            w_str = '\nData on nuts2 id, net demand\n'
            f.write(w_str)

            for country_id in country_ids:
                # get the index
                ix = country_ids.index(country_id)

                # get the values
                f.write('%d: %g' % (country_id, net_demand_list_country[ix]) + '\n')

#
                                            ############################################################

        yearly_gross_dom_nuts2 = pcr.areatotal(
                                                    Gross_domestic_water_demand_country_downscaled
                                                    ,nuts2)
        yearly_net_dom_nuts2 = pcr.areatotal(Net_domestic_water_demand_yearly,nuts2)
        gross_demand_list_nuts2 = zonal_statistics_pcr(yearly_gross_dom_nuts2, nuts2,
                                                    nuts2_ids, np.mean)
```

```
        net_demand_list_nuts2 = zonal_statistics_pcr(yearly_net_dom_nuts2, nuts2,
                                                    nuts2_ids, np.mean)

        with open('Water_demand_written_to_text\\
                                                    write_nuts2_domestic_finalmethod_popdownscale_nuts3
                                                    .txt', 'w') as f:
        # iterate over the countries and the corresponding mean
            w_str = 'Data on nuts2 id, gross demand\n'
            f.write(w_str)

            for nuts2_id in nuts2_ids:

                # get the index
                ix = nuts2_ids.index(nuts2_id)

                # get the values

                f.write('%d: %g' % (nuts2_id, gross_demand_list_nuts2[ix]) + '\n')

            w_str = '\nData on nuts2 id, net demand\n'
            f.write(w_str)

            for nuts2_id in nuts2_ids:
                # get the index
                ix = nuts2_ids.index(nuts2_id)

                # get the values
                f.write('%d: %g' % (nuts2_id, net_demand_list_nuts2[ix]) + '\n')

        #Write to textfile for countries
        # Use: yearly_gross_dom or grossindustrialdemand and yearly_net_dom or
                                                    netindustrialdemand
        yearly_gross_dom_country = pcr.areatotal(
                                                    Gross_domestic_water_demand_country_downscaled
                                                    ,countries)
        yearly_net_dom_country = pcr.areatotal(Net_domestic_water_demand_yearly,
                                                    countries)
        gross_demand_list_country = zonal_statistics_pcr(yearly_gross_dom_country,
                                                    countries, country_ids, np.mean)
        net_demand_list_country = zonal_statistics_pcr(yearly_net_dom_country,
                                                    countries, country_ids, np.mean)

        with open('Water_demand_written_to_text\\
                                                    write_country_domestic_finalmethod_popdownscale_nuts3
                                                    .txt', 'w') as f:
        # iterate over the countries and the corresponding mean
            w_str = 'Data on country id, gross demand\n'
            f.write(w_str)

            for country_id in country_ids:

                # get the index
                ix = country_ids.index(country_id)

                # get the values
                f.write('%d: %g' % (country_id, gross_demand_list_country[ix]) + '\n')

            w_str = '\nData on nuts2 id, net demand\n'
            f.write(w_str)

            for country_id in country_ids:
                # get the index
                ix = country_ids.index(country_id)

                # get the values
                f.write('%d: %g' % (country_id, net_demand_list_country[ix]) + '\n')

        yearcnt = yearcnt + 1
if __name__ == "__main__":
    main()
    sys.exit('done')
```