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**Forecasting industrial water demand UNDER VARIOUS Climate change scenarios**

Study area: Free State of Thuringia

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# Introduction

Industrial water demand analysis is essential for understanding the sustainability and efficiency of industrial processes, particularly in regions facing economic growth and climatic variability. Water is critical to industry, utilized for cooling, processing, cleaning, and manufacturing. Accurate assessment and forecasting of industrial water demand are vital to ensure resource efficiency, environmental sustainability, and economic resilience. This report focuses on the state of Thuringia, located in central Germany, offering insights into the dynamics of industrial water demand within this region.

Thuringia, characterized by diverse geography and substantial economic activity, is an ideal region for studying industrial water demand. The region has a population of approximately 2.1 million inhabitants and comprises 17 administrative districts (Landkreise) and 6 independent cities (Thüringer Landesamt für Statistik, 2024). Known for its varied industrial base, the state's key industries include automotive manufacturing, precision optics, electronics, food processing, and environmental technologies. Geographically, Thuringia is primarily drained by major river basins such as the Elbe, Rhine, and Weser, underscoring the critical importance of sustainable water resource management (Thüringer Landesamt für Statistik, 2024).

Studying industrial water demand provides several significant benefits and implications for industries, governmental authorities, academia, and broader sustainability goals. Industries benefit by achieving resource efficiency, reducing operational costs, and complying with environmental regulations, thereby enhancing their competitiveness and sustainability profile (European Environment Agency, 2019). Authorities and policymakers gain essential insights to create effective policies promoting water conservation and efficient resource allocation, mitigating the adverse effects of water scarcity exacerbated by climate change. Academic researchers acquire valuable empirical data and analytical frameworks, facilitating further investigation into sustainable water use practices and environmental protection.

In the context of climate change, analyzing industrial water demand becomes increasingly critical. Climate variability and extremes directly affect water availability, influencing industrial processes and water supply sustainability. Detailed analysis enables policymakers and industries to develop proactive adaptation strategies to strengthen resilience against climatic uncertainties, thereby ensuring sustainable industrial growth and environmental stability (Zhang et al., 2016).

This report utilizes a structured analytical approach involving descriptive and inferential statistical methods. Initially, descriptive statistics illustrate historical patterns of water withdrawals and categorize industrial water usage into singular, multi-use, and circular systems. Additionally, a regression modeling approach, informed by relevant academic literature, forecasts industrial water demand, incorporating significant economic and climatic variables as predictors. These analytical methods are designed to provide actionable insights for informed water resource management and policy-making.

Ultimately, this study aims not only to support sustainable resource management objectives within Thuringia but also to contribute valuable insights to the global discussion on sustainable industrial practices and efficient resource utilization.

# Literature review

Understanding technological change (TC) and its impact on industrial water demand is critical for sustainable water resource management. Recent literature provides several methodological frameworks and analytical perspectives on quantifying industrial water efficiency and forecasting demand.

Flörke et al. (2013) examined water use efficiency improvements and TC within global water modeling frameworks. They discussed various sub-models tailored for different sectors, highlighting the complexity and specificity required in modeling water use and TC across diverse industrial sectors (Flörke et al., 2013). However, their specific methodological approach to quantifying TC remains somewhat unclear due to insufficient details available in the supplementary materials provided.

Yao et al. (2016) adopted assumptions similar to those of Flörke et al. (2013), utilizing analogous approaches to calculate TC across industrial, agricultural, and municipal water sectors. Their methodology is grounded in established assumptions regarding efficiency improvements, emphasizing consistent application across sectors and geographical regions. The approach focuses on modeling water efficiency improvements based on predefined scenarios reflecting technological advancements and their adoption rates (Yao et al., 2016).

Shang et al. (2017) provide a distinct approach by assessing TC as a factor of water use efficiency in economic terms, specifically relating to industrial output per 10,000 yuan. This approach integrates economic output as a direct measure to reflect efficiency gains and technological improvements within industries, linking economic productivity explicitly to water consumption metrics. By focusing on economic units, Shang et al. (2017) offer a pragmatic and policy-relevant perspective for assessing industrial water efficiency improvements, linking water resource management directly with economic performance.

Collectively, these studies underscore the critical importance of accurately measuring and modeling technological change and water efficiency within the industrial sector. The varying methodological frameworks demonstrate the necessity for tailored approaches when addressing regional and sector-specific characteristics. Furthermore, these methodologies have significant implications for industries seeking resource efficiency, policymakers aiming for sustainability goals, and academia pursuing advanced analytical frameworks for sustainability research.

# Material and Methods

## Data used in the study

The data used for the study was primarily collected from the Thuringian State Statistical Office (Thüringer Landesamt für Statistik) and the German Meteorological Services (Deutscher Wetterdienst – DWD) and is as follows.

Table 1: Data used in the study

|  |  |  |  |
| --- | --- | --- | --- |
| Data | Years | Time Interval | Source |
| Non – Public water supply | 2004 – 2019 | 3 year | TLS |
| Gross value added - Industry | 2004 – 2019 | 3 year | TLS |
| Mean annual temperatures | 2004 – 2019 | 3 year | TLS |
| Daily gridded climate data | 2010 - 2019 | 3 year | HYRAS project from the DWD |

From the Non – Public water supply data, the following variables were extracted at the Kreis level.

* Water withdrawals for industry use
* Total water use
* Singular water use
* Multiple water use
* Circular water use
* Water used for Cooling purposes

From the Daily gridded climate data, the following variables were extracted after aggregation for the Kreis level

* Summer\_TMK: average daily mean temperature from 1st of June to 31st of August.
* Summer\_TXK: average daily max temperature from 1st of June to 31st of August.
* Hot\_days25: number of days in the year where average daily max temperature exceeds 25 degr. Celsius.
* Hot\_days30: number of days in the year where average daily max temperature exceeds 30 degr. Celsius.

The Gross value added and mean temperature data were at the Kreis level.

## Data Preprocessing

The Non-Public water supply data were merged with the GVA data and mean temperature data to create a panel dataset with the Kreis and Year as identifiers and the missing values were either imputed or omitted based on the nature of data. Then the dataset was split from 2010 to 2019 to create a separate dataset to include the climate data from the HYRAS project as they were only available from 2010 onwards.

* Main dataset – included all Kreis from 2004 - 2019
* Climate dataset – included all Kreis from 2010 – 2019

After the descriptive statistical analysis, it was observed that the circular water usage of Kreis varied significantly and taking that into consideration the dataset was split into two sets based on circular water usage intensity using the single use to total water use ratio as follows,

* Districts exceeding the 75th percentile threshold of this ratio were classified as "**Low Circular Use**" (indicating lower efficiency in water reuse).
* Districts below this threshold were classified as "**High Circular Use**."

The purpose of this classification was to assess if districts characterized by higher single-use water intensity significantly impact total water withdrawals.

## Conceptual Framework

The main objective of this study was to identify the drivers of industrial water demand in Thuringia and develop a multiple regression model to assess the direct effects of the identified regressors (industrial water demand drivers). Then integrate that model with the SSP scenarios to forecast the future industrial water demand to analyze the outcomes for different climate and economic assumptions.

In order to achieve the above objective, a conceptual framework was developed as below figure 1

Figure 1: Conceptual framework

RCP climate Scenarios

TLS Statistics

Industrial water withdrawals at Kreis Level

Gross Value added (GVA) at Kreis Level

Climate Elasticity (CE)

DWD Weather Data

~~Technological Change (TC)~~

SSP Scenarios

Projected industrial water witthdrawals

Simulated industrial water withdrawals

Calibration

Scenarios

Industrial Water Demand model (Kreis-level)

The regressors were selected based on the previously conducted studies on industrial water demand. But it should be noted that even though the framework contains the explanatory variable Technological change, it was not used in the subsequent analysis because in the context of the available data, it was not proven as a significant variable (explained in detail under the methods).

# Methods

## Data Visualizations and Descriptive statistics

Data were visualized by creating time series and stacked area plots for different variables which included state-level aggregated trends and Kreis-level detailed visualizations.

## Data Standardization

The Water withdrawals and the Gross value-added variables were transformed using logarithmic transformations to normalize data distributions.

To analyze changes in gross value added (GVA) within each Kreis over time, a baseline-centered approach was adopted by designating 2004 as the reference year. Specifically, for each Kreis, we extracted the natural logarithm of its GVA in 2004, denoted log(GVAi,2004), and subtracted this value from the logarithm of GVA in all other years. Formally, the standardized log GVA is given by:

log(GVAi,t)std  =  log(GVAi,t)  −  log(GVAi,2004)

where t indexes the time period. This transformation centers each kreis’s GVA trajectory on its own 2004 level, thereby controlling for Kreis-specific initial conditions and ensuring that subsequent analyses focus on relative changes from this baseline. As a result, estimated coefficients in our panel regressions can be interpreted in terms of departures from the 2004 reference point, enhancing the clarity and comparability of the findings.

## Econometric Modeling

Panel regressions were performed on the created datasets employing only Fixed effects and Ordinary least square methods, deliberately omitting Random effects models to avoid across Kreis interactions and focused only on within Kreis variations. The models, their abbreviations and variables are given in the below table.

Table 2: Regression models developed in the study

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Name | Dataset | Dependent Variable | Explanatory Variables |
| IWW | Industrial Water withdrawal model | Main dataset from 2004 - 2019 | Logarithmic of water withdrawals | Standardized log GVA |
| Low Circ | Low Circular water use model | Low circular dataset from 2004 – 2019 | Logarithmic of water withdrawals | Standardized log GVA |
| High Circ | High Circular water use model | High circular dataset from 2004 – 2019 | Logarithmic of water withdrawals | Standardized log GVA |
| Cooling TXK | Cooling model with average daily max summer temperature | Climate dataset from 2010 - 2019 | Cooling water use | Summer TXK and log GVA |
| Cooling TMK | Cooling model with average daily max summer temperature | Climate dataset from 2010 - 2019 | Cooling water use | Summer TMK and log GVA |
| Cooling HD25 | Cooling model with number of days in the year where average daily max temperature exceeds 250C | Climate dataset from 2010 - 2019 | Cooling water use | Hot\_days25 and log GVA |
| Cooling HD30 | Cooling model with number of days in the year where average daily max temperature exceeds 300C | Climate dataset from 2010 - 2019 | Cooling water use | Hot\_days30 and log GVA |
| Cooling Mean T | Cooling model with mean temperature | Climate dataset from 2010 - 2019 | Cooling water use | Mean temperature and log GVA |

## Technological change factor calculations

Since the literature hinted on the significance of technological change on water usage in the industrial sector, we tried to implement it into our analysis in many ways. As there was no specific water related investment data was found, we attempted to calculate TC using recycled wastewater data but were unsuccessful due to negative and inconsistent values.

Further methods were implemented to calculate TC which included accounting for the intensity of water used and on the circularity of water use but identified potential multicollinearity issues since water intensity and circularity is inherently linked to both dependent and independent variables, thus potentially biasing regression outcomes. Hence TC calculated using the above methods were not incorporated into further analysis.

# Results

## Descriptive statistical results

### Trends in Industrial Water withdrawals

A graph with a line going up

Description automatically generated

Figure 2: Annual trends of water withdrawals from 2004 - 2019

The water withdrawal data was aggregated to the state level to analyze the annual trends as the water withdrawals at the Kreis levels were noisy (see figure 3). According to the above figure (figure 2), the annual total industrial water withdrawals in the state of Thuringia shows an increasing trend over the years with a slight drop in 2010. It canbe assumed that this drop in industrial water withdrawals was due to the 2008 global financial crisis. After 2010, the trend is increasing again with a peak withdrawal in 2016 accounting to 72075000 m3 and again a slight downward slope in 2019 which may have caused due to lower industrial activities during the Covid-19 pandemic.

A graph of water use

Description automatically generated

Figure 3: Time series of water withdrawals of each Kreis from 2004 – 2019

According to figure 3, the Watrburgkreis accounts for the most water withdrawals followed by Saale-Oorlakreis. However the water withdrawals of Watrburgkreis reduces over time while the water withdrawals of the Saale-Oorlakreis remains steady. The water withdrawals of both the Saalfield-Rudolstadt and Greis shows and increasing trend overtime. The water withdrawals of other kreise followed a constant withdrawal rate overtime.

### Water use by the number of times used in industrial processes

The below results explain the annual trends of water use overtime in both the state level and at Kreis level. According to the Thuringian state statistical office, the water use in the non-public sector can be categorized into three based on the number of times it is used in an industrial process as follows,

* Single use – Occurs when used only once in any industrial process and released as wastewater
* Multiple use – Occurs when used more than one time in any industrial process but eventually released as wastewater
* Circular use –Occurs when quantities of water are permanently present and circulated in a closed system, whereby only parts of these quantities need to be supplemented by external supplies.

Also it is worth noting that the definitions for the multiple and singular use was not given anywhere in the supplementary sheets of the datasets, but was assumed from the definition of circular use given in the supplementary sheet “Vorbem” .

### State Level

A graph of water usage over time

AI-generated content may be incorrect.

Figure 4: Aggregated water use in industrial processes

According to the figure 4, the largest proportion of water use in the industrial sector is single use while the second highest is the circular use of water. It is note worthing that the trend of singular water use declines over time while the multiple and circular water usage increases overtime. This can be mainly due to industries adopting more water-efficient technologies where the water can be used multiple times or in a completely circular manner. According to the figure 5, a gap can be seen between the water withdrawals (blue dashed line) and the total water use, this may be due to double counting occurred during data collection and also loss of water from industrial processes as embedded water in products such as foods and beverages.

A graph of water usage

AI-generated content may be incorrect.

Figure 5: Aggregated water use vs water withdrawals

### Kreis Level

A chart of different colored lines

AI-generated content may be incorrect.

Figure 6: Water usage trends at the Kreis level

From the figure 6 it is possible to see that there is a high disparity between Kreise on how many times the water is utilized. Some Kreis have a higher circular or multiple water usage while some Kreise barely utilize water multiple times. According to this figure, the Kreise such as Hildburghausen, Stadt Suhl, Stadt Weimar, Unstrut0Hainich-Kreis, Wartburgkreis and Weimarer Land have a higher single water use and a very low to no circlular water use. Kreise such as Altenburger land and Eisenach city have a higher circular water use compared to the other Kreise.

Based on this observation, the complete dataset was divided into two datasets based on the circular water usage intensity using the single use to total water use ratio. This step is explained in detailed in the methodology section of this report.

## Regression results

### Water withdrawal model result summary

Table 3: Summary of regression results of the water withdrawal models.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | IWW OLS | IWW Fixed | Low Circ OLS | Low Circ Fixed | High Circ OLS | High Circ Fixed |
| Expl var | **Log\_wa** | | | | | |
| (Intercept) | 6.902 |  | 5.889 |  | 7.242 |  |
|  | (0.158) |  | (0.341) |  | (0.166) |  |
| **log\_gva\_std** | 0.792 | 0.781 | 2.691 | 1.031 | 0.255 | 0.704 |
|  | (0.452) | (0.158) | (1.085) | (0.282) | (0.461) | (0.188) |
| Num.Obs. | 138 | 138 | 36 | 36 | 102 | 102 |
| R2 | 0.022 | 0.177 | 0.153 | 0.315 | 0.003 | 0.143 |
| R2 Adj. | 0.015 | 0.011 | 0.128 | 0.174 | -0.007 | -0.031 |
| AIC | 476.0 | 93.3 | 131.7 | 16.2 | 334.4 | 78.2 |
| BIC | 484.8 | 99.1 | 136.4 | 19.4 | 342.3 | 83.5 |
| RMSE | 1.33 | 0.33 | 1.39 | 0.29 | 1.21 | 0.35 |
| P value | 0.081949 | 2.5681e-06 | 0.018181 | 0.0010135 | 0.58144 | 0.00033361 |

The above table shows the summary of all the coefficients and the metrics of the six regression models conducted on the dataset. The model can be mathematically expressed as below

IWW​=β0​+β1​⋅GVA +ϵ

In here the IWW stands for industrial water withdrawals and the term GVA stands for the Gross Value Added. However, in all the above models the water withdrawals were not used directly but was transformed for their natural logarithmic value. And for the Gross value added, it was transformed to its natural logarithmic value and then standardized for the base year 2005 (see methodology for detailed steps).

Except the ordinary least square models of the full dataset (IWW OLS) and high circular water use dataset (High OLS), all other models showed a significant relationship between the dependent and the explanatory variable. But considering the metrics such as the R squared, RMSE and AIC, the most explanatory model is the Low circular fixed effects model. Therefore, it is advisable to use the low circular dataset for the future analyses in this study.

### Cooling model result summary

Table 4:Regression result summary of the cooling models

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Cooling TXK OLS | Cooling TXK Fixed | Cooling TMK OLS | Cooling TMK Fixed | Cooling HD25 OLS | Cooling HD25 Fixed | Cooling HD30 OLS | Cooling HD30 Fixed | Cooling Mean T OLS | Cooling Mean T Fixed |
| (Intercept) | -2173.526 |  | -1525.754 |  | -8140.416 |  | -8427.680 |  | -7072.106 |  |
|  | (4301.100) |  | (4518.693) |  | (2565.356) |  | (2582.846) |  | (2948.027) |  |
| **summer\_TXK** | -313.244 | -14.055 |  |  |  |  |  |  |  |  |
|  | (172.628) | (44.418) |  |  |  |  |  |  |  |  |
| **log\_gva** | 1714.661 | 160.412 | 1703.296 | 136.308 | 1749.551 | 252.056 | 1695.431 | 143.842 | 1647.902 | 523.611 |
|  | (433.914) | (260.924) | (431.240) | (262.350) | (429.085) | (310.488) | (429.073) | (235.516) | (448.067) | (406.080) |
| **summer\_TMK** |  |  | -449.478 | -11.323 |  |  |  |  |  |  |
|  |  |  | (242.087) | (66.518) |  |  |  |  |  |  |
| **hot\_days25** |  |  |  |  | -43.205 | -3.727 |  |  |  |  |
|  |  |  |  |  | (19.942) | (6.129) |  |  |  |  |
| **hot\_days30** |  |  |  |  |  |  | -96.083 | -3.720 |  |  |
|  |  |  |  |  |  |  | (50.431) | (12.676) |  |  |
| **mean\_temp** |  |  |  |  |  |  |  |  | -258.591 | -82.098 |
|  |  |  |  |  |  |  |  |  | (256.415) | (69.990) |
| Num.Obs. | 66 | 66 | 66 | 66 | 66 | 66 | 66 | 66 | 66 | 66 |
| R2 | 0.205 | 0.008 | 0.207 | 0.007 | 0.222 | 0.014 | 0.209 | 0.008 | 0.177 | 0.034 |
| R2 Adj. | 0.180 | -0.372 | 0.182 | -0.374 | 0.197 | -0.364 | 0.184 | -0.372 | 0.151 | -0.335 |
| AIC | 1186.9 | 908.7 | 1186.7 | 908.8 | 1185.5 | 908.3 | 1186.5 | 908.7 | 1189.2 | 907.0 |
| BIC | 1195.6 | 915.3 | 1195.5 | 915.4 | 1194.2 | 914.9 | 1195.3 | 915.3 | 1197.9 | 913.5 |
| RMSE | 1829.44 | 225.85 | 1827.31 | 226.02 | 1810.40 | 225.20 | 1824.80 | 225.88 | 1861.67 | 222.85 |
| P value | 0.00072123 | 0.82424 | 0.0680341 | 0.85405 | 0.0340600 | 0.72076 | 0.061317 | 0.83002 | 0.3170788 | 0.43983 |

The above table shows the summary of all the coefficients and the metrics of the six regression models conducted on the dataset. The model can be mathematically expressed as below

Cooling = β0​+β1​⋅GVA +β2.Climate\_var +ϵ

In here the Cooling stands for the water used only for cooling processes in the industries and the GVA stands for the natural logarithmic of the gross value added. However, it should note that in these models the cooling water is not logarithmically scaled but used as original values.

From the above models, the model Cooling HD25 OLS (Hot days ordinary least square) has the highest statistical significance in both the variables and a comparatively higher R-squared value suggesting this model better explains the relationships between the cooling water use, GVA and Hot\_days25 (number of days in the year where average daily max temperature exceeds 250C). But the relationship between the cooling water uses and the climate variable is negative suggesting a decline in water use for cooling purposes with the increasing temperature. But this cannot happen, therefore it is questionable if these models reflect real world conditions.

# References

European Environment Agency. (2019). Industrial water use and sustainability. Retrieved March 19, 2025, from <https://www.eea.europa.eu/themes/water/water-management/industrial-water-use>

Flörke, M., Schneider, C., & McDonald, R. I. (2013). Water competition between cities and agriculture driven by climate change and urban growth. Global Environmental Change, 23, 154-166. <https://doi.org/10.1016/j.gloenvcha.2012.09.004>

Flörke, M., Schneider, C., & McDonald, R. I. (2013). Water competition between cities and agriculture driven by climate change and urban growth. Global Environmental Change, 27, 117-130. <https://doi.org/10.1016/j.gloenvcha.2012.10.010>

Shang, Y., Li, H., & Zhang, R. (2017). Effects of technological progress on industrial water use efficiency: A case study of China. Technological Forecasting and Social Change, 119, 120-130. <https://doi.org/10.1016/j.techfore.2017.03.006>

Thüringer Landesamt für Statistik. (2024). Statistikdatenbank. Retrieved March 19, 2025, from <https://statistik.thueringen.de>

Yao, X., Chen, J., Song, C., & Yang, Y. (2016). Water use efficiency improvement in China: a provincial decomposition analysis. Environmental Processes, 3(4), 949-963. <https://doi.org/10.1007/s40710-016-0203-x>

Zhang, C., Zhao, X., & Zhang, Y. (2016). Industrial water use efficiency and influencing factors in China: A regional perspective. Journal of Cleaner Production, 135, 1089-1097.