Method Article

A rule-based method to downscale provincial level power sector projection results to plant level

Haoran Li\textsuperscript{a,b}, Xueqin Cui\textsuperscript{a}, Yuwei Weng\textsuperscript{a}, Wenjia Cai\textsuperscript{a,b,*}

\textsuperscript{a} Ministry of Education Key Laboratory for Earth System Modeling, Department of Earth System Science, Tsinghua University, Beijing 100084, China
\textsuperscript{b} Tsinghua-Rio Tinto Joint Research Centre for Resources, Energy and Sustainable Development, International Joint Laboratory on Low Carbon Clean Energy Innovation, Laboratory for Low Carbon Energy, Tsinghua University, Beijing 100084, China

\textbf{A B S T R A C T}

Usually, previous studies on the future development pathway of coal power are based on the economic models to provide the administrative pathways, or the coal-fired power plants dataset to provide bottom-up pathways with the multi-scenario hypothesis. However, these two methods above are difficult to be combined: there is a gap between the comprehensive consideration of economic, policy, and environmental factors, with the high spatial resolution of technology and space. This study narrows the gap between regional projection and unit data, and also considers the uncertainty of the operating units with the Monte Carlo Method. Firstly, we evaluate the score of each unit according to its technical parameters and other attribute information, which is based on a sufficient dataset of coal-fired power units with their geographical spatial coordinates. And next, the probability distribution function is built according to the scores of the candidate units. Then, we do sampling from the candidate units until the total capacity reaches the regional projection of the coal power development goal. Based on this method, we could identify the spatial distribution probability of coal-fired power units in the future, and therefore it can help us explore the environmental impacts in high-resolution space.

- The method calculates the probability of operating status of candidate units using technical and attribute information-base scores with Monte Carlo method.
- This paper describes the uncertainties in determining the spatial distribution of future power plants, and verifies the robustness of the results.
- This method narrows the scale gap between regional projection and unit-level data.

© 2021 The Author(s). Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

DOI of original article: 10.1016/j.apenergy.2021.116986
* Corresponding author at: Ministry of Education Key Laboratory for Earth System Modeling, Department of Earth System Science, Tsinghua University, Beijing 100084, China.
E-mail address: wcai@tsinghua.edu.cn (W. Cai).
Specifications table

| Subject Area                      | Environmental Science                  |
|-----------------------------------|----------------------------------------|
| More specific subject area        | Environmental System Analysis; Energy System Modeling; |
| Method name                       | Downscaling method from macroscopic projection of coal power to plant-level considering uncertainty with Monte Carlo Method |
| Name and reference of original method | Haoran Li, Cui Xueqin, Hui Jingxuan, et al. Catchment-level water stress risk of coal power transition in China under 2°C/1.5°C targets[J]. Applied Energy, 2021, 294: 116986. |
| Resource availability             | No                                      |

Background

In the context of the continuous refinement of carbon emission reduction in various countries, many researchers and policymakers are paying more attention to the regional impacts of the national carbon emission targets and actions [1–3], which is key for identifying the exact location of emitters and its environmental impacts, like power plants. In some countries, such as China [4] and India [5], coal power is the main power supply and carbon dioxide emission source now and is facing fast and important transformation pressure under the carbon emission reduction targets. The development of coal power is influenced by many factors, such as energy policies, environmental impacts, technology and cost progress, and carbon emission reduction targets, which will be much uncertain in the future. Thus, most previous studies on future development pathways are usually conducted with macroeconomic models, for example, Computable General Equilibrium (CGE) model [6,7], Multiregional Input-Output (MRIO) model [8–11], technology-economic model of energy system [12–16], or accounting model [17]. However, these studies have usually been carried out on national, provincial or other large scales in China [6,12,15,18–20] or other countries [10,21], which might filter out regional environmental impacts or others associated with smaller geographical scales. These studies could hardly answer the questions below due to their scale limits: Where will the coal-fired power plants locate? How will the regional technical structure of the power plants change in the future? What regional environmental impacts may arise from future coal power development?

In addition, some other studies try to identify the regional impacts of the power sector, like the emission or water withdrawal, based on power unit data with geographical information at the sub-provincial [22,23] or grid-level scale [24,25]. However, these studies could only consider limited technical factors or spatial distribution changes without multiple socioeconomic impacts on power sector development. Therefore, it is difficult for the studies above to comprehensively combine various environmental, energy, economic policies, as well as technological progress [23], such as the constraint of carbon dioxide emission reduction, renewable energy incentives, and generation technology progress. In other words, there exists a gap between the administration-scale management of power development pathways affected by multiple factors and the high-resolution impacts in geographical space, which is difficult to integrate the socio-economic impacts of power development at high spatial resolution.

This study proposed a rule-based method that combines the projection at national or provincial scale and coal-fired power unit data with spatial coordinates, which could span the gap between the two types of methodologies mentioned above. Also, we give an uncertainty analysis of the coal power plant distribution with Monte Carlo Methods. This method has been applied in a water resources impact study discussing future power sector development under the influence of multiple factors [26], which helps us to achieve high spatial resolution risk analysis while integrating the impact of macro policies, and avoid the neglect of regional water resources issues due to coarse spatial scale.
Fig. 1. The provincial projection of coal power installed capacity in 2050 by MESEIC [26].

Data

The regional coal power installed capacity projection and a sufficient dataset of coal-fired power units are two essential input data before the downscaling process. In this study, the provincial capacity \( \text{CA}_{pr} \) of China’s power sector in the future is obtained from a technology-economic model of power system (MESEIC) we developed (Fig. 1). The MESEIC model is a bottom-up, technology, optimization model, in which Mainland China is divided into 32 provincial areas [26]. This model takes into account the considered factors of macroeconomic models mentioned in paragraph 1 to give the future pathways of China’s power development. Of course, the regional projection could be derived from other models. It depends on the model tools and the designs of power sector development pathways.

The dataset of coal-fired power units built by us contains more than 7800 units (including retired, operational, and planned units) and covers more than 98% of the total operational capacity in 2015 [26]. What needs to be emphasized is that the dataset includes sufficient potential plants choice and will provide a more reliable basis for the determination of the spatial distribution of coal power plants in the future. Except for the total 894GW operating units in 2015 (Fig. 2a) there are also additional 837GW planned units (actually they could be divided into announced, permitted, or others status) (Fig. 2b). The dataset covers various attributes of each unit such as the current status, nameplate capacity, commissioning year, boiler type, heating or not, fuel source, cooling technology, permitted water withdrawal, water source. Each unit owns its current or planned geographical location, which can help determine the spatial distribution of the units operating in the future.

Method

The downscaling process combines the provincial coal power installed capacity and the total available coal-fired power units in the province from the dataset, which is generally divided into three steps: (1) Grading to the units according to the technical rules; (2) Constructing probability distribution function (PDF) based on the quantification from step(1); (3) Do sampling from the dataset to meet the regional projection of the coal power installed capacity.

Step 1: Quantify each unit’s score based on its technical and attribute information

Firstly, the projection year should be confirmed, such as 2050, and all units are divided into three statuses of “operating”, “planned” and “retired” in that year. For the current units of operating (in
projection year), once the units exceed their operating lives, they will be eliminated and classified as “retired” units. Meanwhile, we give each coal-fired power unit a “P-value” (no matter whether they have been put into operation or not) according to its technical parameters and other factors, including the capacity, boiler types, cooling types, combined heat and power (CHP) or not, and fuel sources (Eq. (1)). The P-value determines the relative advancement, suitability and advantages of the unit compared to others, which indicates the relative priority of different units within the same status. Units with a higher P-value will have a relatively higher probability of being retained or put into
operation. Because all units are divided into three states of “operating”, “planned” and “retired”, there does not exist interference among the units in different statuses.

\[ P_{\text{unit}} = f(\text{capacity, boiler, cooling type, heating, fuel source}) \]  

Next, we quantify the technological attributes of each unit. Since there are many influencing factors in reality, we only consider some factors such as technology attributes here, so the quantification of the \(P\)-value is relatively simplified compared with reality. The quantitative value of each attribute reflects the weight of its influence on unit selection. Quantification of the factors (\(i\) denotes the unit):

(1) Unit capacity (\(UC_i\)). \(UC_i\) is equal to the ratio of unit capacity value and “100MW”. Since there may still be an application for small capacity units, the lower limit of the small unit is not lower than it for the unit of 300MW to avoid being “ignored” by their capacity.

(2) Boiler type \((B_i)\). \(B_i\) is equal to 3 (ultra-supercritical boiler), 2 (supercritical boiler), and 1 (subcritical and other boilers).

(3) Cooling types \((CT_i)\). \(CT_i\) is equal to 5 (air cooling and recycle cooling unit) and 1 (once-through cooling unit). The unit quantification is mainly determined by the relative value of the water withdrawal quota efficiency (Table 1). The values of air cooling units and recycle cooling units are similar.

(4) CHP or not \((H_i)\). \(H_i\) is equal to 2 (the CHP units) and 1 (only generating).

(5) Fuel source \((F_i)\). \(F_i\) is equal to 2 (pithead power plant) and 1 (others).

In addition, there is another variable of Lifetime \((L_i)\) to be considered for those operating units besides \(P\)-value (Eq. (2)). \(L_i\) is equal to the remaining service life of the existing units. It is considered when the units are decommissioned.

And in the end, \(P\)-value is determined by Eq. (2). The quantization results distinguish the corresponding priorities of units at different stages. For example, for the planned units in the same province, the probability of putting into operation of a 600MW ultra-supercritical and CHP unit that adopts air cooling and is close to coal mines, is 60 times that of a 300MW supercritical and non-heating unit that adopts once-through cooling and is far away from the coal mine.

\[ P_i = UC_i \cdot B_i \cdot CT_i \cdot H_i \cdot F_i \]  

**Step 2: Construct the probability distribution function of the units**

A sample-based probability distribution function (PDF) is required before sampling in the Monte Carlo method. The PDF of the planned and retired units will mainly rely on the \(P\)-value while the operating units will combine the \(P\)-value and its operating lifetime (Eq. (3)). It is important to note that the PDF will be rebuilt each time after one unit is picked up from the operating units or planned units. If the total capacity of these “operating” units is larger than the projection of provincial coal power capacity from MESEIC, the retained operating units will be determined by \(PDF_{\text{operating}}\). On the contrary, if the total capacity of these “operating” units is lower than the projected provincial capacity, the whole “operating” units will be preserved and the demand for new units will be met by the “planned” units according to \(PDF_{\text{reserved}}\). If there is still a shortage of planned units (although might be unlikely), “retired” units will also be considered as planned units and put into operation according to \(PDF_{\text{retired}}\).

\[
\begin{align*}
PDF_{\text{operating}} &= g_1(P_{\text{unit}} \cdot \text{operating life}) \\
PDF_{\text{reserved}} &= g_2(P_{\text{unit}}) \\
PDF_{\text{retired}} &= g_3(P_{\text{unit}})
\end{align*}
\]
Fig. 3. The flow chart of units confirmation of Monte Carlo sampling [26].

where $C_A$: capacity of the province by MESEIC model; $U$: units in someone province; unit: the coal-fired power units; op: operating; pl: planned; rt: retired.

$$
\begin{align*}
\text{PDF}_\text{operating,i} &= \frac{P_i \cdot L_i}{\sum (P_{\text{reserved,i}} \cdot L_{\text{reserved,i}})} \\
\text{PDF}_\text{reserved,i} &= \frac{P_i}{\sum P_{\text{reserved,i}}} \\
\text{PDF}_\text{retired,i} &= \frac{P_i}{\sum P_{\text{retired,i}}}
\end{align*}
$$

(4)

**Step 3: Monte Carlo Sampling**

The process of once sampling according to the Monte Carlo method in this study is shown below (Fig 3). Firstly, the units in operation in a certain year will be eliminated and classified as retired units once the units exceed their operating life. If the total capacity of the rest existing units is greater than the future projection ($C_A_p$), the retired units will be selected by sampling from the existing units. If not, the newly constructed units will be obtained from the planned units. It should be noted that the $P$-value of each unit represents its relative probability of being sampled and selected. And after each sampling, the PDF will change.

After each sampling, since the geographic coordinates of each candidate unit are known, we will get a spatial map of coal-fired power plants, as well as the coordinate-based water withdrawal or other environmental factors. We performed 5000 samples to ensure the stability of the probabilities. In fact, the results of some catchment reached stability quickly, and in this study doing sampling for 3000 times is sufficient.

**Result**

This downscaling approach was applied to discuss the water stress risk of future coal power development in China [26]. The catchment-level water stress risk of coal-fired power is measured by Exceed Probability (EP), which is obtained by the water withdrawal of total coal-fired power units according to the downscaling method in this study and the available water resources under the RCP4.5 scenario from World Resources Institute [27] (Fig 4a). In each sampling we could get the total water
Fig. 4. Catchment-level water stress by the coal-fired power unit (a) and the distribution of the total water withdrawal under 3000 Monte Carlo sampling (b) in 2050. (a) Exceeding Probability (EP) for catchment-level water stress of 0.05, which represents the water stress risk of each catchment by the coal-fired power units; (b) Distribution of total water withdrawals in the catchment (basin ID is 6436) that is marked by the blue lines in the figure(a). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
withdrawn by all coal-fired power units on the catchment scale. And through enough sampling, we could get the distribution of water withdrawal (Fig 4b) so as to get the water stress risk based on the future available water.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study was financially supported by the National Key R&D Program of China (2017YFA0603602), National Natural Science Foundation of China (71773061 and 71673165), Tsinghua-Rio Tinto Joint Research Centre for Resources, Energy and Sustainable Development, and Tsinghua University Tutor Research Fund. The authors of this study would like to thank Jingxuan Hui, Gang He, Yaoyu Nie, Can Wang, Fang Guo, Yidan Chen, and Jiachen Wang for their work on the original research paper. The authors are thankful to the reviewers for their constructive suggestions that helped to improve this manuscript and the original research paper.

References

[1] W. Cai, C. Clapp, I. Das, S. Perkins-Kirpatrick, A. Thomas, J.E. Tierney, Reflections on weather and climate research, Nat. Rev. Earth Environ. 2 (2021) 9–14.
[2] M. Chang, J.Z. Thellufsen, B. Zakeri, B. Pickering, S. Pfenninger, H. Lund, et al., Trends in tools and approaches for modeling the energy transition, Appl. Energy 290 (2021) 116731.
[3] W. Schakel, S. Pfister, A. Ramirez, Exploring the potential impact of implementing carbon capture technologies in fossil fuel power plants on regional European water stress index levels, Int. J. Greenhouse Gas Control 39 (2015) 318–328.
[4] G. He, J. Lin, F. Sifuentes, X. Liu, N. Abhyankar, A. Phadke, Rapid cost decrease of renewables and storage accelerates the decarbonization of China’s power system, Nat. Commun. 11 (2020) 1–9.
[5] C. Shearer, R. Fofrich, S.J. Davis, Future CO2 emissions and electricity generation from proposed coal-fired power plants in India, Earth’s Future 5 (2017) 408–416.
[6] M. Li, H. Dai, Y. Xie, Y. Tao, L. Bregnbæk, K. Sandholt, Water conservation from power generation in China: a provincial level scenario towards 2030, Appl. Energy 208 (2017) 580–591.
[7] Q. Zhou, H. Naota, F. Shinichiro, Economic consequences of cooling water insufficiency in the thermal power Sector under climate change scenarios, Energies 11 (2018) 1–11.
[8] C. Zhang, L.D. Anadon, Life cycle water use of energy production and its environmental impacts in China, Environ. Sci. Technol. 47 (2013) 14459–14467.
[9] L. Chai, X. Liao, L. Yang, X. Yan, Assessing life cycle water use and pollution of coal-fired power generation in China using input-output analysis, Appl. Energy 231 (2018) 951–958.
[10] N. Dilekli, F. Duchin, I. Cazcarro, Restricting water withdrawals of the thermal power sector: an input-output analysis for the northeast of the United States, J. Clean. Prod. 198 (2018) 258–268.
[11] L. Liu, Z. Yin, P. Wang, Y. Gan, X. Liao, Water-carbon trade-off for inter-provincial electricity transmissions in China, J. Environ. Manag. 268 (2020) 110719.
[12] B. Cai, B. Zhang, J. Bi, W. Zhang, Energy’s thirst for water in China, Environ. Sci. Technol. 48 (2014) 11760–11768.
[13] M.I. Hejazi, J. Edmonds, L. Clarke, P. Kyle, E. Davies, V. Chaturvedi, et al., Integrated assessment of global water scarcity over the 21st century under multiple climate change mitigation policies, Hydrol. Earth Syst. Sci. 18 (2014) 2859–2883.
[14] M. Hejazi, J. Edmonds, L. Clarke, P. Kyle, E. Davies, V. Chaturvedi, et al., Long-term global water projections using six socioeconomic scenarios in an integrated assessment modeling framework, Technol. Forecast. Soc. Change 81 (2014) 205–226.
[15] W. Huang, D. Ma, W. Chen, Connecting water and energy: assessing the impacts of carbon and water constraints on China’s power sector, Appl. Energy 185 (2017) 1497–1505.
[16] J. Liu, K. Wang, J. Zou, Y. Kong, The implications of coal consumption in the power sector for China’s CO2 peaking target, Appl. Energy 253 (2019) 1–14.
[17] B. Pan, A. Gu, D. Jiang, Emission-water nexus: China’s future power scenarios (in Chinese), Ecol. Econ. 32 (2016) 37–41.
[18] Y. Hao, Z.Y. Zhang, H. Liao, Y.M. Wei, China’s farewell to coal- a forecast of coal consumption through 2020, Energy Policy 86 (2015) 444–455.
[19] Y. Shang, P. Hei, S. Lu, L. Shang, X. Li, Y. Wei, et al., China’s energy-water nexus: assessing water conservation synergies of the total coal consumption cap strategy until 2050, Appl. Energy 210 (2018) 643–660.
[20] X. Liao, J.W. Hall, N. Eyre, Water use in China’s thermoelectric power sector, Glob. Environ. Change 41 (2016) 142–152.
[21] L. Liu, H. Mohamad, I. Gokul, A.F. Barton, Implications of water constraints on electricity capacity expansion in the United States, Nat. Sustain. 2 (2019) 206–213.
[22] C. Zhang, L. Zhong, J. Wang, Decoupling between water use and thermoelectric power generation growth in China, Nat. Energy 3 (2018) 792–799.
[23] D. Tong, Q. Zhang, F. Liu, G. Geng, Y. Zheng, T. Xue, et al., Current emissions and future mitigation pathways of coal-fired power plants in China from 2010 to 2030, Environ. Sci. Technol. 52 (2018) 12905–12914.

[24] C. Zhang, L. Zhong, X. Fu, J. Wang, Z. Wu, Revealing water stress by the thermal power industry in China based on a high spatial resolution water withdrawal and consumption inventory, Environ. Sci. Technol. 50 (2016) 1642–1652.

[25] X. Zhang, J. Liu, Y. Tang, X. Zhao, H. Yang, P.W. Gerbens-Leenes, et al., China’s coal-fired power plants impose pressure on water resources, J. Clean. Prod. 161 (2017) 1171–1179.

[26] L. Haoran, X. Cui, J. Hui, G. He, Y. Weng, Y. Nie, et al., Catchment-level water stress risk of coal power transition in China under 2°C/1.5°C targets, Appl. Energy 294 (2021) 116986.

[27] F. Gassert, M. Landis, M. Luck, P. Reig, T. Shiao, Aqueduct Global Maps 2.1, World Resources Institute, Washington, DC, 2014 Working PaperAvailable online athttp://www.wri.org/publication/aqueduct-metadata-global.