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Water resources carrying capacity to achieve a sustainable ecosystem using support vector regression

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ABSTRACT

Agricultural water resources carrying capacity has been considered an important problem in recent decades. A comparison of the evaluation indicators of water resources indicated the variation levels of the stability. Machine Learning-Support Vector Regression (ML-SVR) was implemented to formulate the agricultural footprints. The obtained statuses of the water resources have always been characterized by agricultural deficit in the Hendijan plain, Khuzestan province, Iran. Experiments performed outperformed the classical model on both fitted values and the validation value. The results showed that the agricultural footprints from 2010 to 2020 in Iran kept steady with higher levels, while from 2014 to 2016 witnessed a significant decline compared with previous years. The predicted agricultural footprint for the recent 10 years continues to decrease in the semi-arid regions. The predicted results via support vector regression (SVR) showed that agricultural footprints from 2017 to 2020 will present a rising trend, meaning the situation of water crisis will be increasingly serious in the eastern parts of the central deserts.

Key words: ecosystem sustainability, Hendijan plain, Khuzestan province, machine learning

HIGHLIGHTS

- In the south of Iran, water management in agriculture can help the sustainability of the ecosystem.
- The agricultural water resources carrying capacity is evaluated using machine learning.

1. INTRODUCTION

The water resources carrying capacity (WRCC) is an important factor for the sustainability of agricultural management. Exceeding the carrying capacity of water resources causes destructive environmental and agricultural effects such as erosion, reduction of water resources, increase in climate change, pollution and health risk, land degradation, reduction of biodiversity, destruction of ecosystem services, and reduction of productivity (Sun *et al.* 2023). In the agricultural sector, the reduction of production efficiency and the increase of planning risk are the most important consequences of the carrying capacity of water resources. Under normal circumstances, these damages will be irreversible or accompanied by environmental destruction and economic failure. Therefore, it is necessary to consider WRCC in planning for long-term agricultural development.

Several planning techniques have been developed to achieve the sustainability of water resources in agriculture including conjunctive exploitation of surface and groundwater, developing the optimal plans for water allocation (Ahmad & Zhang 2022), interbasin water transfer (Cánovas-Molina *et al.* 2023), optimal planning of irrigation (Lalehzari *et al.* 2016), uncertainty modeling, and water resources agricultural footprint analysis (Berger *et al.* 2021). Among these strategies, analyses of carrying capacity and agricultural water resources are widely used to formulate the evaluation systems for developing the sustainability of water resources (Kang *et al.* 2019; He *et al.* 2021; Li *et al.* 2023).

Considering the large spatial difference in water resources, water scarcity, and deterioration of water quality in Northeast China's economic circle, the WRCC was evaluated from the perspective of time and space by Wang *et al.* (2021). Gray correlation analysis and multiple linear regression models were combined to quantitatively predict water supply and demand in different planning years. In the selection of research indicators, the interaction of social economy, water resources, and water environment was also taken into consideration. Song *et al.* (2011) proposed the concept of WRCC to assess the economic and population scale that local water resources can support. In this study, the city of Tianjin, China, is considered as an example and its population size and economic scale were selected as two main indicators. Based on the historical statistical data, the carrying index (CI) and the balance of supply and demand index (IWSD) were evaluated, and then the current WRCC in Tianjin city and its dynamic trend were evaluated using the carrying capacity method. The results showed that the use of water resources in Tianjin is currently inefficient, and rational policies and measures should be established and implemented to ensure the optimal use of water resources in Tianjin city. Qi *et al.* (2021) evaluated the spatiotemporal changes in climatic factors and agricultural water resources carrying capacity (AWRCC) during the crop growing season in the Nenjiang River Basin. Precipitation, evapotranspiration, and meteorological drought were all key driving factors affecting the problem. Wang *et al.* (2023) indicated that the carrying capacity of agricultural water resources in Anhui Province has shown a fluctuating upward trend from 2000 to 2020. Furthermore, the carrying capacity in the southern region of Anhui Province is gradually increasing, while that in the northern region is decreasing. It is recommended that Anhui Province increase the construction of agricultural water resource management and field water conservation facilities to ensure the sustainable use of agricultural water resources.

The basic idea of support vector regression (SVR) is that a non-linear mapping can map the data into a high-dimensional feature space where linear regression is performed. SVR offers a better solution for small sample problems by minimizing the generalization error bound. In recent years, machine learning (ML) has been one of the most significant advances in the field of optimization technology. It is built on the established statistical learning theory (Morshed *et al.* 2024). Support vector machines (SVMs) are learning machines that can achieve better generalization on a limited number of learning patterns. There are two categories: one is support vector classification (SVC) solving classification problems and the other is SVR solving regression problems. In this paper, water resources footprints and carrying capacities are calculated and analyzed. Furthermore, with applying SVR, the prediction of water resources footprints is performed. Moreover, observational data were compared to evaluate the accuracy of SVR.

2. MATERIAL AND METHODS

2.1. Study area

Hendijan plain is located in Khuzestan province in the southwest of Iran, which is located in the north of the Persian Gulf (Figure 1). Hendijan is located at the geographical coordinates of 30.24°N and 49.71°E, and its average height reaches 5 m

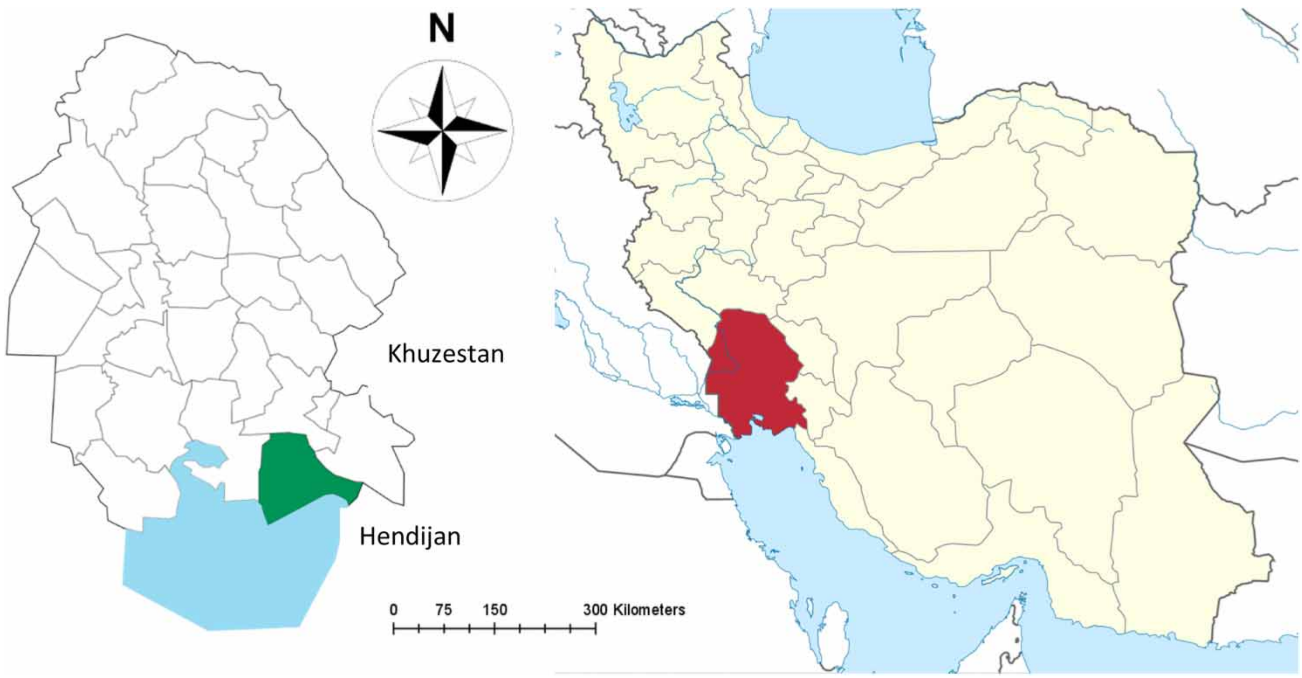

Figure 1 | Hendijan plain in Khuzestan province, southwest of Iran.

above sea level. It has a 90-km water border with the Persian Gulf. The source of agricultural water in Hendijan is the Zahre River, which is located in the southern part of the middle Zagros. The area of Zahre catchment area is 16,033 km^2, of which 10,789 km^2 are mountainous areas and 5,244 km^2 are plains. The extent of the plains is less in the upstream parts of the Abriz Basin, and most of it is located in the Hendijan area of the Khuzestan plain.

2.2. WRCC model

In this study, WRCC refers to the maximum agro-economic development scale that regional water resources can maintain at a certain level of productivity and is a measure of water resources with predetermined spatial and temporal scales. The AWRCC is a key indicator to judge the sustainable development of agriculture and a main factor to quantificationally ensure the safety of regional economic development (Zhang *et al.* 2023). Water resources carrying capacity, EC_w, is given by

$$EC_w = \frac{0.4 \times \beta \times \gamma \times Q}{p} \quad (1)$$

where EC_w is the agricultural carrying capacity of water resources per capita p; β is the water resource yield factor, γ is global equivalence factor of water resources, p is the global water resource average productivity, and Q is total water resource volume.

2.2.1. Water resource footprint model

Water resources considered in the study area are divided into four categories: industry, agriculture, household, and public domestic water consumption. The total agricultural footprint of water resources is formulated as

$$EF_w = N \times EF_w = \sum_{i=1}^{4} N \times \gamma \times \frac{W_i}{p} \quad (2)$$

where EF_w is the agricultural footprint per capita of water resources, N is the population, and W_i represents each of the four categories of water consumption.

2.2.2. Water resource agricultural deficit

Water resources agricultural deficit or plus per capita, ED_w, is given by

$$ED_w = EC_w - EF_w \quad (3)$$

2.2.3. Water resource difference agricultural pressure

In this paper, water resource difference agricultural pressure index, DEPI, was proposed, which is a dimensionless number. It is formulated as

$$DEPI = \frac{EC_w - EF_w}{EC_w} \quad (4)$$

2.2.4. Gross domestic product water resources footprint

Gross domestic product (GDP) water resources footprint, EP_w, is calculated as follows

$$EP_w = \frac{EF_w}{GDP} \quad (5)$$

2.3. Economic output value

To investigate the economic output value of industry water resources consumption (EP), GDP and agricultural water footprint (AF) measures were proposed

$$EP = \frac{AF}{GDP} \tag{6}$$

where AF and GDP are agricultural footprint and gross domestic product, respectively.

2.4. Support vector regression

SVR is built on the established statistical learning theory. The training data have been taken as (Xi, yi), $Xi \in Rn$, $yi \in R$, where $i = 1, 2, \ldots, m$. In the SVR with $\varepsilon - insensitive$ loss function, named ε − SVR, the goal is to try to find a function $f(X)$ in a high-dimensional feature space that has at most ε errors from the actual target values yi for all the training data. Meanwhile, the desired function is required to be as flat as possible. Absolute errors that are less than ε are allowed in ε − SVR, while it will not accept any deviation larger than ε. The linear objective function $f(X)$ is given by

$$f(X) = \langle W.\phi(X)\rangle + b, \ with\ b \in R \tag{7}$$

where $< W \cdot \phi(X) >$ denotes the dot product in the feature space ϕ and W is the direction of the normal vector of the obtained hyperplane.

It is obvious that $f(X)$ may not approximate all pairs (Xi, yi) with ε precision. That is to say, $f(X)$ may not actually exist in some situations. To tackle this problem, conditions can be relaxed. By introducing slack variables $\zeta i, \zeta i*$ and constant $C > 0$ to deal with this case, we can get the following optimization problem

$$\min\left\{2||W|| + C\sum mXi = 1(\zeta i + \zeta i*)\right\} \tag{8}$$

$$\text{subject to} \begin{cases} yi\langle W \cdot \phi(X)\rangle - b \leq \varepsilon + \zeta i \\ \langle W \cdot \phi(X)\rangle + b + yi \leq \varepsilon + \zeta i \\ \zeta(Xi \cdot * \phi i \geq \varepsilon + \zeta i \end{cases} \tag{9}$$

Applying the standard deviation method and the kernel approach, and through a series of derivations and transformations, the final regression estimate function is yielded and given by

$$f(x) = \sum_{i=1}^{nsv} rw^2 \sum_{j=1}^{nf} K(X, Xi) + b - ||W|| + C\sum mXi + 1(\zeta i + \zeta i*) \tag{10}$$

where ζi refers to the Lagrangian multipliers; K is the kernel function; nsv is the number of support vectors; and b is calculated by the Karush–Kuhn–Tucker (KKT) conditions.

Three parameters of SVR should be optimized, that are kernel function, C, and ε. There are various forms of kernel functions, such as Gaussian radial basis function, exponential radial basis function, multilayer perceptron, and additive kernels function. Among these kernel functions, Gaussian radial basis function is usually preferable in practical problems.

The Gaussian radial basis function was developed as the kernel function. To find the optimal parameter combination $(\sigma*, C*, \varepsilon*)$, genetic algorithm can be used with fewer computing overheads. However, due to the greedy search used in the genetic algorithm to find the optimal solution, it may fall into local optimality. To tackle this problem, we repeat the genetic algorithm a given number of times (30 times in our experiment) to find the optimal combination, which has the smallest prediction error on the validation set. This process is finished through Libsvm, an SVM tool box, widely used in the implementation of SVM.

3. RESULTS AND DISCUSSION

3.1. Water resources analysis

Water resources footprints per capita of the four categories in the study area from 2010 to 2020 are calculated (Figure 2). The corresponding evaluation indexes and carrying capacities are calculated in Table 1. As shown in the figure and Table 1, the national average water resources footprint per capita is 1.7 times that of the study area, while the annual mean agricultural carrying capacity in the study area is merely 22.3% of the national level.

3.2. Agricultural footprints

As shown in Figure 3, the change of agricultural footprints per capita in the study area can be roughly divided into two stages: while it has been relatively stable from 2010 to 2020, there has obviously been an overall decline compared with before 2010. As for agricultural carrying capacity per capita, it changes little except in some years such as 2013, 2015, 2017, and 2019, when it was clearly smaller than in the other years.

3.3. Water resource deficit

Water resources analysis from the perspective of water footprint contents in the study area is indicated in Table 2. The agricultural water resources footprint has occupied the highest proportion among four categories. Its proportion is not lower than

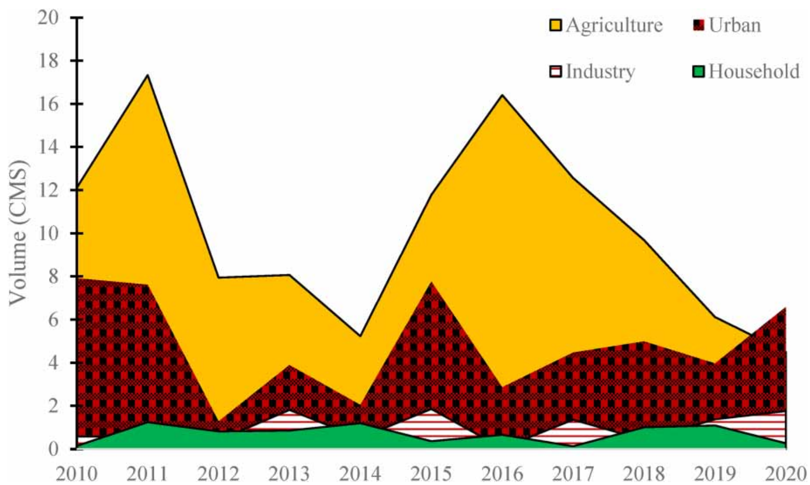

Figure 2 | Water resources footprint per capita in the study period.

Table 1 | Evaluation indexes of the carrying capacities

Year	EF_w	EC_w	ED_w	DEPI	EP_w	EP_i
2010	1.42	0.04	−0.70	−0.14	0.72	0.54
2011	1.17	0.23	−0.51	−0.01	0.84	0.34
2012	1.31	0.31	−0.25	−3.80	0.75	0.92
2013	1.30	0.06	−0.39	−0.48	0.25	0.32
2014	1.59	0.45	−0.83	−3.26	0.32	0.56
2015	1.21	0.50	−0.41	−2.98	0.00	0.68
2016	0.84	0.13	−0.14	−0.17	0.97	0.99
2017	0.37	0.14	−0.50	−3.17	0.84	0.74
2018	0.44	0.16	−0.50	−1.81	0.39	0.11
2019	0.53	0.47	−0.59	−1.25	0.33	0.25
2020	0.22	0.44	−0.24	−3.57	0.30	0.47

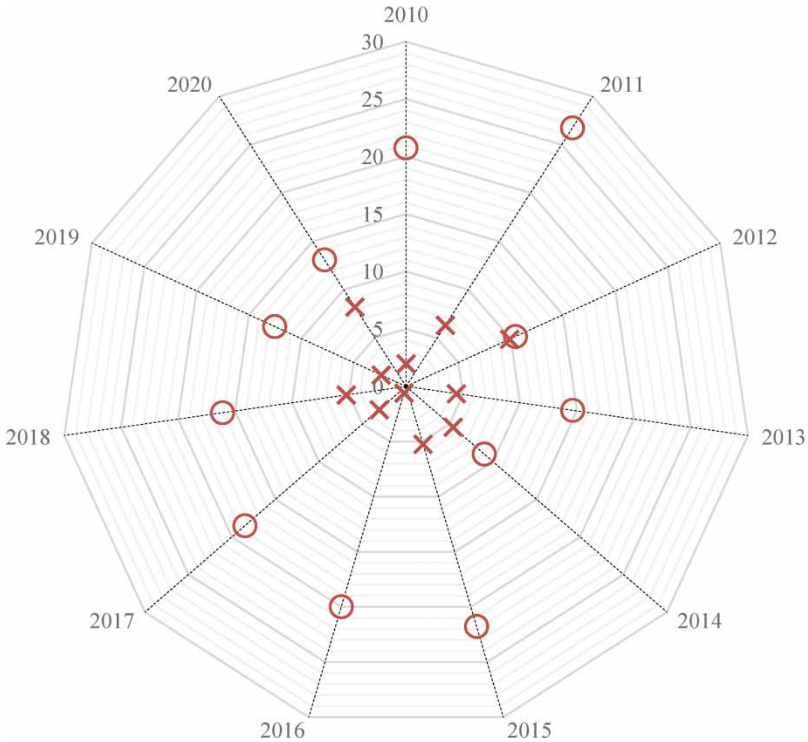

Figure 3 | Comparison of total consumption in the study years.

Table 2 | Water footprint contents in different years

Year	2010	2012	2014	2016	2018	2020
Agriculture	0.48	0.51	0.49	0.56	0.62	0.64
Industry	0.22	0.21	0.25	0.23	0.19	0.18
Urban	0.16	0.15	0.14	0.11	0.1	0.1
Household	0.14	0.13	0.12	0.1	0.09	0.08

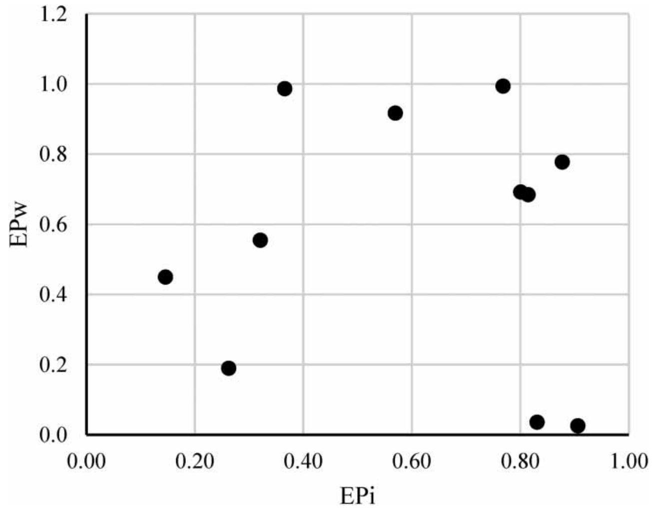

Figure 4 | The longitudinal trend for estimating the EP_i and EP_w.

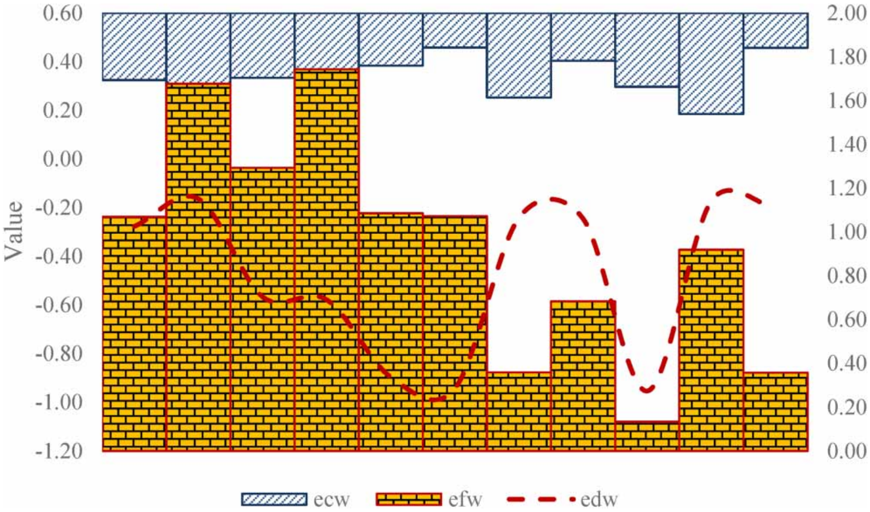

Figure 5 | Comparison of EF_w, EC_w, ED_w based on the time intervals.

0.48. Agricultural footprint per capita has occupied the second highest proportion with a peak value of 0.64. The proportion of urban water resources footprint per capita is nearly equal to the proportion of household water resources footprint per capita every year.

3.4. EP_w and EP_i

Figure 4 shows that EP_w and EP_i have been continuously declining in the study area. EP_i in the study area has always been below the EP_w, which suggests water resources utilization in the study area has become more intensive and economical. Although EP_i in the study area has been continuously declining, it is still greater than the EP_i measuring the mean economic output value of water resources, which means there is room to optimize the industrial structure of the study area.

3.5. EF_w, EC_w, ED_w

Figure 5 shows ED_w in the study area has always been below both 0 and EC_w. In addition, ED_w of the study area has greater fluctuation. The annual mean EC_w of the study area goes up to 0.45. Since EF_w is used to measure the pressure level of the carrying capacity in the study area, we can see that the water resources agricultural carrying capacity of the study area is under significant pressure.

4. CONCLUSION

In this paper, water resources footprints and carrying capacities from 2010 to 2020 in the study area are calculated and analyzed. The same indexes on the level of the whole study area are calculated as a comparison. Furthermore, by introducing SVR, which belongs to the field of ML, water resources footprints per capita from 2010 to 2020 are predicted via the use of a small sample. Experimental results show that SVR has less fitting and prediction errors compared with the classical methods. Although there is no a large sample of water resources, the established SVR model will provide some guidance for the sustainable development of water resources in the study area.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Ahmad, I. & Zhang, F. 2022 Optimal agricultural water allocation for the sustainable development of surface and groundwater resources. *Water Resources Management* **36**, 4219–4236. https://doi.org/10.1007/s11269-022-03249-3.

Berger, M., Campos, J. & Carolli, M. 2021 Advancing the water footprint into an instrument to support achieving the SDGs – recommendations from the 'Water as a global resources' research initiative (GRoW). *Water Resources Management* **35**, 1291–1298. https://doi.org/10.1007/s11269-021-02784-9.

Cánovas-Molina, A., García-Frapolli, E. & Ruggerio, C. A. 2023 A proposal of an Irrigation Sustainability Index for agricultural basins: Application in a semi-arid river basin. *Irrigation Science* **41**, 173–182. https://doi.org/10.1007/s00271-022-00831-w.

He, L., Du, Y., Wu, S. & Zhang, Z. 2021 Evaluation of the agricultural water resource carrying capacity and optimization of a planting-raising structure. *Agricultural Water Management* **243**, 106456. https://doi.org/10.1016/j.agwat.2020.106456.

Kang, J., Zi, X., Wang, S. & He, L. 2019 Evaluation and optimization of agricultural water resources carrying capacity in Haihe River Basin, China. *Water* **11** (5), 999. https://doi.org/10.3390/w11050999.

Lalehzari, R., Boroomand-Nasab, S., Moazed, H. & Haghighi, A. 2016 Multi-objective management of water allocation to sustainable irrigation planning and optimal cropping pattern. *Journal of Irrigation and Drainage Engineering, ASCE* **142** (1), 05015008. doi:10.1061(ASCE) IR.1943-4774.0000933.

Li, X., Pu, X., Wang, W., Dong, X., Zhang, Y., Wang, J., Wang, Y. & Meng, M. 2023 Surface water environmental carrying capacity and surface water quality based on economy-society-environment nexus – Evidence from China. *Water-Energy Nexus* **6**, 231–243. doi.10.1016/j.wen.2023.11.003.

Morshed, S. R., Fattah, A. & Saroar, M. 2024 Assessment of the future environmental carrying capacity using machine learning algorithms. *Ecological Indicators* **158**, 111444. https://doi.org/10.1016/j.ecolind.2023.111444.

Qi, P., Xia, Z., Zhang, G., Zhang, W. & Chang, Z. 2021 Effects of climate change on agricultural water resource carrying capacity in a high-latitude basin. *Journal of Hydrology* **597**, 126328. https://doi.org/10.1016/j.jhydrol.2021.126328.

Song, X., Kong, F. & Zhan, C. 2011 Assessment of water resources carrying capacity in Tianjin City of China. *Water Resources Management* **25**, 857–873. https://doi.org/10.1007/s11269-010-9730-9.

Sun, N., Yao, Z., Xie, Y., Wang, T., Yang, J., Li, X. & Fu, Q. 2023 Sustainability analysis of the water environment carrying capacity of Harbin City based on an optimized set pair analysis posture-deviation coefficient method evaluation model. *Water* **15** (8), 1575. https://doi.org/10.3390/w15081575.

Wang, G., Xiao, C., Qi, Z., Liang, X., Meng, F. & Sun, Y. 2021 Water resource carrying capacity based on water demand prediction in Chang-Ji economic circle. *Water* **13** (1), 16. doi.10.3390/w13010016.

Wang, C., Li, Z., Chen, H. & Wang, M. 2023 Comprehensive evaluation of agricultural water resources' carrying capacity in Anhui Province Based on an improved TOPSIS model. *Sustainability* **15** (18), 13297. https://doi.org/10.3390/su151813297.

Zhang, Y., Gao, Y., Zhang, Y., Liang, Z., Zhang, Z., Zhao, Y. & Li, P. 2023 Assessment of agricultural water resources carrying capacity and analysis of its spatio-temporal variation in Henan Province, China. *Journal of Cleaner Production* **403**, 136869. https://doi.org/10.1016/j.jclepro.2023.136869.

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