

Analyzing environmental flow supply in the semi-arid area through integrating drought analysis and optimal operation of reservoir (Postprint)

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Abstract

This study proposes a novel framework for environmental reservoir operation that integrates environmental flow supply, drought analysis, and evolutionary optimization. The results demonstrate that simultaneously supplying downstream environmental flows and meeting water demand presents a significant challenge in semi-arid regions, particularly during dry years. During drought periods, water supply and environmental flow supply achieved only 40% and 30% of target values, respectively. Furthermore, the mean errors in supplying water demand and environmental flow during dry years were $6 \text{ m}^3/\text{s}$ and $9 \text{ m}^3/\text{s}$, respectively. These findings underscore that ecological stress on downstream aquatic habitats and water supply deficits escalate considerably during dry years, indicating that even environmentally optimal operation cannot adequately protect downstream aquatic habitats during severe droughts. Additionally, available reservoir storage decreases substantially (by more than $30 \times 10^6 \text{ m}^3$ on average, compared to the optimal storage of $70 \times 10^6 \text{ m}^3$), suggesting that strategic reservoir storage may be compromised. Among the evolutionary algorithms evaluated, particle swarm optimization (PSO) was identified as the most effective for solving the proposed novel objective function. The primary contribution of this study is the development of a novel objective function for reservoir operation optimization that directly incorporates environmental flow supply integrated with drought analysis. This innovative optimization framework can reduce uncertainties inherent in conventional objective functions by explicitly considering environmental flows and drought analysis within the reservoir operation context, making it particularly applicable to semi-arid regions. The results indicate that utilizing alternative water resources for supply or reducing water demand represents the only viable solution for mitigating downstream ecological impacts on river ecosystems. Consequently, the findings emphasize the necessity for comprehensive water resources replanning in the study area. Adoption of the proposed optimization framework in place of conventional systems for

reservoir operation in semi-arid regions is recommended to minimize conflicts between stakeholders and environmental managers.

Full Text

Preamble

Analyzing Environmental Flow Supply in Semi-Arid Areas Through Integrating Drought Analysis and Optimal Reservoir Operation

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Abstract: This study proposes a novel form of environmental reservoir operation that integrates environmental flow supply, drought analysis, and evolutionary optimization. The results demonstrate that simultaneously supplying downstream environmental flow and meeting water demand is challenging in semi-arid areas, particularly during dry years. In this study, water supply and environmental flow supply achieved only 40% and 30% reliability during droughts, respectively. Moreover, mean errors in supplying water demand and environmental flow in dry years were $6 \text{ m}^3/\text{s}$ and $9 \text{ m}^3/\text{s}$, respectively. These results highlight that ecological stresses on downstream aquatic habitats and water supply losses escalate considerably in dry years, implying that even environmental optimal operation cannot adequately protect downstream aquatic habitats during severe droughts. Furthermore, available reservoir storage is reduced significantly (by more than $30 \times 10^6 \text{ m}^3$ on average compared to the optimal storage of $70 \times 10^6 \text{ m}^3$), suggesting that strategic reservoir storage may be threatened. Among the evolutionary algorithms tested, particle swarm optimization (PSO) was selected as the best algorithm for solving the novel objective function. The significance of this study lies in proposing a new objective function for optimizing reservoir operation that directly addresses environmental flow supply and integrates it with drought analysis. This novel optimization system can overcome uncertainties in conventional objective functions by incorporating environmental flow into the objective function and including drought analysis within the reservoir operation framework, making it especially applicable in semi-arid areas. The results indicate that using alternative water resources for supply or reducing water demand represents the only solution for managing downstream ecological impacts on river ecosystems. In other words, the findings highlight the necessity of replanning water resources in the study area. Replacing conventional reservoir operation optimization systems in semi-arid areas with the proposed system is recommended to minimize negotiations between stakeholders and environmental managers.

Keywords: optimization; reservoir operation; droughts; metaheuristic algorithms; environmental flow regime

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1 Introduction

Water supply and hydropower generation are the primary functions of reservoirs (Altinbilek, 2002; Bilgili et al., 2018; Liersch, 2019). However, river ecosystems are threatened by rising water demand and deteriorating water quality due to population growth (Postel, 1998; Liyanage and Yamada, 2017). Consequently, the concept of environmental flow has been defined to protect river habitats. Basic concepts of the environmental flow regime have been reviewed extensively in the literature (Zeiringer et al., 2018). Several methods have been developed to assess environmental flow regimes, including historic flow methods, hydraulic rating methods, physical habitat methods, and holistic methods (Jowett, 1997; King et al., 2000; Tharme, 2003). Ecological-based methods can assess environmental flow regimes while considering regional ecological values. For example, an applicable model has been developed to assess environmental flow for restoring riparian vegetation (Shafroth et al., 2017). Furthermore, conditional probability networks have been utilized as a tool for assessing environmental flow (Horne et al., 2017). The functional flow approach represents a novel solution for determining environmental flow regimes (Lane et al., 2020). Satisfying environmental flow regimes can be complex for engineers, especially during dry years, as simultaneous supply of water demand and environmental flow presents significant challenges.

Recent studies have highlighted the optimization of environmental flow for improved environmental management of river basins (Dehghanipour et al., 2020; Sedighkia et al., 2021). The application of decision-making models for environmental management of water resources has also been emphasized in the literature (Liu et al., 2008). Integrating water resource management and environmental modeling is required to address environmental challenges (Young et al., 2003; Paredes-Arquiola et al., 2014).

Satisfying downstream environmental flow requirements from reservoirs during droughts is particularly challenging. In conventional reservoir operation, the environmental flow regime is not considered. Optimization of reservoir operation has been reviewed extensively in the literature (Allawi et al., 2018). Previous studies have focused on reservoir management under drought conditions (Spiliotis et al., 2016). Hashimoto et al. (1982) proposed a simple and applicable loss function to optimize reservoir operation that minimizes the difference between target water demand and release from the reservoir. Datta and Burges (1984) highlighted this function as a two-sided loss function and pointed out that storage is another effective parameter for optimal reservoir operation. In other words, loss of storage must be considered in reservoir operation. This loss function has been utilized in many studies (Ehteram et al., 2017, 2018; Zamani et al., 2017).

Optimization methods have improved significantly in recent years, with comprehensive reviews available in the literature (Sun et al., 2019). Linear programming (LP) and non-linear programming (NLP) have been used to optimize reservoir operation (Arunkumar and Jothiprakash, 2012; Zhao et al., 2014). However, advanced evolutionary algorithms are highly effective for increasing optimization efficiency (Ahmad et al., 2014). Evolutionary algorithms have been widely utilized to optimize reservoir operation in recent years (Bozorg-Haddad et al., 2017; Salazar et al., 2017; Yaseen et al., 2019; Zarei et al., 2019). Optimization methods are also applicable for calibration and validation of hydrological models (García-Romero et al., 2019). Recent studies have highlighted the optimization of environmental flow downstream of reservoirs (Yin et al., 2012; Cai et al., 2013; Horne et al., 2017). However, integrating optimal reservoir management with environmental flow supply is needed to minimize negotiations among stakeholders. Water resources engineers have defined environmental flow in water allocation models. Initial systems developed a simulation framework highlighting water flow, water quality, fish habitat quantity and quality, anadromous fish populations, and economics (Flug Bartholow and Campbell, 1999). However, incorporating environmental flow regimes into the structure of water resources optimization models was essential. Thus, water resources management, water quality, and habitat analysis tools were developed within decision support systems (Olden and Naiman, 2010; Paredes-Arquiola et al., 2014). Moreover, some studies used historic flow methods to assess environmental flow downstream of reservoirs (Yin et al., 2012; Payne and Jowett, 2013).

Highlighting the contribution and necessity of this study for addressing the research gap is essential. Several methods have been developed for reservoir operation optimization in recent decades (Dobson et al., 2019). However, considering water supply as the main optimization objective remains challenging. Impacts of climate change on rainfall events and consequent extreme events such as droughts and floods have been highlighted in recent studies (Duan et al., 2016, 2019, 2022). These studies indicate that increasing extreme events such as severe droughts or floods is highly probable due to climate change. Hence, modifying reservoir operation models is essential for addressing environmental challenges such as environmental flow supply during dry years. This study attempts to address this research gap by proposing and evaluating a novel optimization system for reservoirs in semi-arid areas that integrates environmental flow and drought analysis within the objective function and optimization system, respectively.

The present study contributes to improving the optimization process of environmental flow in reservoir operation models by defining a new objective function that links drought analysis to the model for optimizing environmental flow regimes during dry years. Linking drought analysis with reservoir operation models may improve environmental management. This study defines two environmental flow regimes consistent with ecological protection scenarios: the minimum environmental flow regime and the ideal environmental flow regime. The ideal environmental flow regime was defined as the target in the optimization model, while the minimum environmental flow regime was defined using

a penalty function. This novel system can optimally balance environmental requirements and water supply. In summary, the objectives and contributions of the present study are: (1) developing a new objective function for reservoir operation that defines two environmental flow regimes—minimum and target—within the optimization model structure, enabling simultaneous management of environmental flow under different ecological protection scenarios and water supply; and (2) incorporating drought analysis with reservoir operation optimization to manage challenges arising from severe droughts in reservoir operation for satisfying environmental flow regimes.

2 Application and Methodology

[Figure 1: see original paper] displays the workflow of the proposed method. Drought analysis is carried out using the stream drought index (SDI) in the first step. Next, mean monthly flow for dry years is computed based on the drought analysis results. Two defined environmental flows—the minimum environmental flow and ideal environmental flow regimes—are then added to the optimization model, along with other reservoir management constraints. Subsequently, different metaheuristic algorithms are applied to optimize releases from the reservoir. Finally, the best method for optimizing reservoir operation is selected.

2.1 Study Area

The proposed method was applied to the Latian Dam (one of the largest dams in Iran), which is responsible for water supply to the capital territory. This dam has been constructed on the Jajrood River, which originates from the Alborz Mountains and flows toward the Salt Lake in southern Tehran Province, Iran. Satisfying environmental flow during droughts is a serious challenge downstream of the Latian Dam, as environmental flow is necessary to protect valuable downstream habitats. The available flow in some months is inadequate to satisfy both water demand and environmental flow. The reservoir plays a significant role in meeting demands in this basin, as previous studies have corroborated that satisfying water demand and environmental flow is impossible without using the reservoir. Many native aquatic species inhabit the downstream river, requiring sufficient instream flow. Hence, environmental flow regime is highly important in the study area.

In recent years, negotiations between stakeholders and environmental managers have escalated in this river basin, as current environmental challenges threaten regional ecological values drastically. [Figure 2: see original paper] displays the location of the Latian Dam and upstream river basin. The minimum operational storage is $15 \times 10^6 \text{ m}^3$ in this reservoir, and the maximum possible storage is $95 \times 10^6 \text{ m}^3$.

The following datasets were used to implement the proposed method (Table 1).

Table 1. Datasets used in this study

Description	Details
Hydrological data	Historical recorded river flows (inflow) to reservoir for a long-term period (55 years) were available in the data bank of regional water authority
Evaporation data	Average monthly evaporation data from the reservoir surface were available based on long-term data recorded at the regional weather station near the reservoir
Environmental flow time series	A recent regional technical report provided environmental flow analysis data (Abdoli and Sedighkia, 2019)
Water demand time series	Available in the regional water authority dataset

2.2 Drought Analysis

We utilized SDI to analyze droughts in the study area. While the standardized precipitation index (SPI) is usable for analyzing meteorological droughts, it is not applicable for assessing droughts in rivers. Researchers developed SDI based on analogy between meteorological and hydrological drought analysis in rivers (Akbari et al., 2015).

First, cumulative stream flow volume ($V_{i,k}$) is calculated based on Equation 1:

$$V_{i,k} = \sum_{j=1}^k Q_{i,j}$$

where $Q_{i,j}$ is the flow (m^3/s); k is the period ($k=1, 2, 3, 4$) of drought analysis, which might be three to twelve months; and i is the month ($i=1, 2, \dots, 12$). In this study, drought analysis was conducted based on a twelve-month period. Next, Equation 2 is used to calculate SDI:

$$SDI_{i,k} = \frac{V_{i,k} - \bar{V}_k}{S_k}$$

where V is the cumulative stream flow volume (m^3/s); and \bar{V} and S are the mean and standard deviations of cumulative stream flow volume (m^3/s), respectively. More details on SDI have been presented in the literature (Akbari et al.,

2015; Liu et al., 2015). Table 2 displays the criteria used to assess hydrological conditions ranging from non-drought to extreme drought (Akbari et al., 2015).

Table 2. Criteria for definition of SDI

State	Criterion of SDI
Non-drought	$SDI \geq 0.0$
Mild drought	$-1.0 \leq SDI < 0.0$
Moderate drought	$-1.5 \leq SDI < -1.0$
Severe drought	$-2.0 \leq SDI < -1.5$
Extreme drought	$SDI < -2.0$

Note: SDI, stream drought index. The criteria are referenced from Akbari et al. (2015).

2.3 Optimization Model

The objective function (OF) is a key component in any optimization model. Equation 3 shows the OF used in this study:

$$OF = \sum_{t=1}^T [(D_t - RD_t)^2 + (IE_t - OE_t)^2]$$

Equation 3 is a loss function that minimizes differences between defined water demand and release from the reservoir for water supply, as well as differences between the ideal environmental flow regime for the river ecosystem and release for environmental flow from the reservoir. The general form of this loss function is similar to previous studies, with the addition of the environmental flow component.

where IE is the ideal environmental flow (m^3/s); OE is the optimal environmental flow (m^3/s); D is the water demand (m^3/s); RD is the release for demand (m^3/s); t is the time step of the optimization model at monthly scale; and T is the horizon time (months).

Several constraints must be added to the optimization model: (1) storage must not exceed maximum possible storage; (2) storage must not fall below minimum operational storage; (3) release for water demand must not exceed water demand; (4) release for environmental flow must not exceed ideal environmental flow; and (5) release for environmental flow must not be less than minimum environmental flow.

We applied metaheuristic algorithms to optimize reservoir operation and used penalty functions to convert the constrained optimization problem into an unconstrained one for evolutionary algorithms (Baba et al., 2015). This method has been extensively utilized in reservoir operation optimization (Al-Jawad and

Tanyimboh, 2017; Takada et al., 2019). Four penalty functions were added to the optimization system. Equation 4 shows two penalty functions for storage management:

$$P_1 = c_1 \cdot \max(0, S_t - S_{max})^2$$

$$P_2 = c_2 \cdot \max(0, S_{min} - S_t)^2$$

where S is the storage (10^6 m^3); S_{max} is the maximum possible storage or capacity of the reservoir (10^6 m^3); S_{min} is the minimum operational storage (10^6 m^3); c_1 and c_2 are constant coefficients (dimensionless); P_1 is the penalty function related to maximum storage or capacity (dimensionless); and P_2 is the penalty function related to minimum operational storage (dimensionless). These functions increase the OF value as a penalty to maintain storage between minimum operational storage and reservoir capacity. The coefficients c_1 and c_2 were determined through initial sensitivity analysis.

Equation 5 shows two penalty functions for water demand:

$$P_3 = c_3 \cdot \max(0, RD_i - D_i)^2$$

$$P_4 = c_4 \cdot \max(0, D_i - RD_i)^2$$

where RD is the release from the reservoir for water supply (m^3/s).

Equation 6 shows penalty functions for environmental flow:

$$P_5 = c_5 \cdot \max(0, OE_t - IE_t)^2$$

$$P_6 = c_6 \cdot \max(0, ME_t - OE_t)^2$$

Reservoir storage is updated using Equation 7:

$$S_{t+1} = S_t + I_t - OE_t - RD_t - SP_t - V_t \cdot A_t$$

where I is the inflow to reservoir (10^6 m^3); SP is the overflow (10^6 m^3); V is the evaporation (m); and A is the surface area of the reservoir (m^2).

The total release for environmental flow and overflow might be defined as total environmental flow to the downstream river. Overflow was calculated based on maximum storage using Equation 8:

$$SP_t = \max(0, S_t - S_{max})$$

2.4 Metaheuristic Optimization

Three evolutionary algorithms were used: particle swarm optimization (PSO), biogeography-based optimization (BBO), and differential evolution (DE). While the general methodology is similar, different strategies for searching solution spaces are employed.

PSO solves optimization problems using a population of candidate solutions, moving particles in the search space by adjusting their position and velocity (Kennedy and Eberhart, 1995). BBO is inspired by mathematical models of biogeography, simulating speciation and migration of species between islands and extinction of species (Simon, 2008). DE is applicable for multidimensional real-valued functions and does not utilize the gradient of the problem being optimized (Qin et al., 2008). [Figure 3: see original paper], [Figure 4: see original paper], and [Figure 5: see original paper] show flowcharts of the algorithms used. Previous studies have addressed the steps of optimization by evolutionary algorithms (Ebtehaj and Bonakdari, 2016, 2017; Qasem et al., 2017; Ebtehaj et al., 2019). These three algorithms were selected to compare performance and investigate the impact of changing methodology for finding optimal reservoir release.

In the optimization process, the number of iterations was used as termination criteria. Based on experiments with different algorithms, convergence was achieved after 5,000 iterations. Therefore, selecting 10,000 iterations provides a reliable termination criterion.

2.5 Measurement Indices

Two measurement indices were used: reliability index and root mean square error (RMSE). The reliability index measures the robustness of optimization methods in satisfying water demand and environmental flow during the simulated period (Ehteram et al., 2018b; Yaseen et al., 2018). RMSE measures optimization performance in terms of water supply and environmental flow satisfaction, as well as storage benefits compared to optimal storage. Note that the reliability index is not suitable for measuring system performance in terms of storage, where optimal storage at each time step is important for maximizing benefits.

Equations 9 and 10 show the general form of these indices:

$$\text{Reliability index} = \frac{1}{T} \sum_{t=1}^T \delta_t, \quad \text{where } \delta_t = \begin{cases} 1 & \text{if } TR_t \leq R_t \\ 0 & \text{if } TR_t > R_t \end{cases}$$

$$\text{RMSE} = \sqrt{\frac{1}{T} \sum_{t=1}^T (TR_t - R_t)^2}$$

where TR is the target flow (m^3/s).

2.6 Data Analysis

Pre-processing of input data for the optimization model involved analyzing hydrological data (recorded inflow to reservoir) through drought analysis as presented in Section 2.2. Evaporation data were analyzed through monthly averaging to obtain monthly evaporation time series. Environmental flow time series from previous studies (Abdoli and Sedighkia, 2019) were directly applied. Water demand time series were extracted from regional water authority datasets.

Post-processing of optimization model outputs included computing measurement indices (Section 2.5) for water supply, storage, and environmental flow to evaluate reservoir performance.

3 Results and Discussion

[Figure 6: see original paper] displays drought analysis results. Based on this analysis, monthly reservoir inflow was estimated by averaging dry years. Environmental flow regimes were defined based on a previous regional study (Abdoli and Sedighkia, 2019) that used the integrated habitat simulation method. Two environmental flow regimes were defined to maximize flexibility for environmental management: a minimum environmental flow regime providing minimum ecological suitability, and an ideal environmental flow regime providing high ecological suitability.

The minimum regime guarantees 50% of maximum weighted usable area for target fish species, while the ideal regime protects more than 75% of weighted usable area. Details regarding habitat simulation are available in the literature (Bovee et al., 1998; Nalamothu, 2021).

Supplying the ideal environmental flow regime is the best option for environmentalists but may be impossible in dry years due to insufficient river flow. The optimization model helps balance water supply and environmental needs optimally while ensuring flow never falls below the minimum regime. [Figure 7: see original paper] shows time series for water demand, ideal environmental flow, minimum environmental flow, and reservoir inflow (mean monthly flow in dry years). The figure demonstrates that water demand and ideal environmental flow exceed reservoir inflow in several months, potentially increasing conflicts between stakeholders and environmental managers. The optimization system provides a fair balance between water supply and environmental flow, which is necessary for optimal management of the Latian Dam.

[Figure 8: see original paper] shows optimization results for water supply. The performance of different algorithms indicates they can supply only part of water demand. Using alternative water resources in dry years is essential in this region. Results suggest water supply may become a major problem for urban development, as available resources like the Latian Dam cannot meet demands under current conditions. Sustainable urban development should account for these water supply limitations.

Environmental flow supply is particularly challenging during summer. [Figure 9: see original paper] compares optimal environmental releases from different algorithms with ideal and minimum environmental flow regimes. The significant difference between ideal environmental flow and optimal releases indicates that challenges in protecting downstream river habitats must be considered in reservoir operation. However, all algorithms maintain releases above the minimum environmental flow, demonstrating robust penalty function performance.

[Figure 10: see original paper] shows optimal reservoir storage. Algorithm performance varies in terms of storage management. Droughts escalate storage management challenges, making optimal storage inaccessible during dry years and reducing storage benefits inevitable. However, the minimum storage penalty function performed perfectly, maintaining storage above minimum operational levels at all times.

Table 3 shows reliability indices for water supply and environmental flow. Different algorithms exhibit similar performance, with the reservoir supplying only 40% of water demand and 30% of environmental flow during dry years. This diminished reliability reduces downstream river habitat suitability due to insufficient instream flow. The optimization model provides a fair balance between demands, though this reduced reliability is not favorable from an environmental perspective. However, it represents the best solution for challenging periods. Previous studies suggest dry years may increase due to climate change (Rezaee et al., 2013), making the proposed method highly valuable for future drought management. While climate change impacts on streamflow vary by river, extreme events will generally increase. The proposed framework can use climate change model predictions (e.g., 20-year periods like 2020-2040) to evaluate how climate change alters ecological status in optimal reservoir operation.

A new water supply plan is essential due to insufficient water for simultaneous demand and environmental flow satisfaction. Table 3 shows RMSE values for water demand and environmental flow supply. All algorithms perform similarly, though the model shows better performance for water supply ($\text{RMSE} = 6 \text{ m}^3/\text{s}$) than environmental flow ($\text{RMSE} = 10 \text{ m}^3/\text{s}$). Table 3 also shows storage RMSE, with PSO achieving the minimum value, indicating superior performance in optimizing storage loss.

Based on these results, PSO is the best optimization method. Since algorithm performance is similar for water supply and environmental flow, storage optimization performance is the key selection criterion. The proposed method is applicable in two aspects: it balances water supply, environmental flow, and storage to reduce system losses, and it improves water planning to minimize environmental degradation. Water conveyance projects from other sources may reduce losses in some cases.

While PSO is a classic algorithm, its performance is slightly better than newer algorithms. This suggests that changing the objective function affects optimization solution performance more than algorithm selection. Many previous studies

claimed new-generation algorithms improve performance (Bozorg-Haddad et al., 2016), but this study indicates that improving objective functions to consider environmental requirements is more critical.

At first glance, a constraint on maximum environmental release may seem unnecessary. However, this study provides a general framework compatible with various environmental flow assessment methods that do not always consider direct relationships between biological response and river flow. Increasing environmental flow is not always favorable, and it should not exceed the ideal regime. While older hydrological methods may not need this constraint due to linear relationships, the proposed general framework requires it.

Several points warrant clarification. First, different algorithms were applied because metaheuristic algorithms cannot guarantee global optimization, especially for complex objective functions like reservoir operation (Dhiman et al., 2021). Applying multiple algorithms and selecting the best solution is recommended. The different solutions obtained confirm that algorithms cannot guarantee global optimization for the developed objective function. Second, only mean monthly flow in dry years was used, as the study focuses on evaluating environmental flow during critical drought conditions. Third, computational complexity, defined as time and memory required to find solutions (Curry and Dagli, 2014), is low for the proposed method, increasing its applicability.

Regarding uncertainties, inflow data represent a major source, as climate change impacts on future inflow create uncertain results. Climate change models have considerable uncertainties, making reservoir operation analysis potentially unreliable. Changing evaporation represents another uncertainty source, though with minor effects compared to inflow uncertainties. Additionally, environmental flow was assessed based on current conditions without considering climate change impacts. These uncertainty sources must be considered when applying this study's outputs.

4 Conclusions

This study developed a novel reservoir operation model linked with drought analysis to examine challenges in supplying environmental flow and water demand. Results indicate that an integrated optimization framework considering environmental requirements and reservoir losses simultaneously is essential, especially in semi-arid areas prone to severe droughts. Challenges for supplying both water demand and environmental flow are considerable during dry years, with remarkable storage losses. PSO demonstrated superior performance among the tested algorithms.

The study concludes that using the proposed objective function and drought analysis helps overcome uncertainties in reservoir environmental management and minimizes negotiations between stakeholders and environmental managers. Future studies should incorporate other extreme events such as floods into the model.

Conflict of interest: The authors declare no known competing financial interests or personal relationships that could have influenced this work.

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Note: Figure translations are in progress. See original paper for figures.

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