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RESEARCH ARTICLE

Development of a smart device Android-based decision support system for controlling non-point source nitrogen and phosphorus pollution in an agricultural catchment

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Highlights

- A smart device Android-based DSS (CNPDSS) is proposed for controlling non-point source N&P pollution.
- The CNPDSS integrates GIS, a Bayesian-based model for predicting N&P loadings, an optimization algorithm, and an interactive interface for smartphones.
- Identified optimal solutions simultaneously minimize N&P loadings and engineering costs.
- Main features of the CNPDSS are tested through its application in the sub-tropical Tuojia catchment, Hunan Province, Central China.

Abstract

Intervention strategies to control non-point source nitrogen (N) and phosphorus (P) pollution in agriculture are expensive and there is a trade-off between engineering cost and treatment effectiveness. Implementing strategies often result in unsatisfactory outcomes and massive engineering costs when managing diffusive pollution in agricultural catchments. To address this issue, this paper proposes a robust, handy, catchment N&P decision support system (CNPDSS), an Android-based smartphone system integrated with a web-based geographic information system (GIS). The CNPDSS aims to provide artificial intelligence-driven decisions that minimize N&P loadings and engineering costs for mitigating pollution in agricultural catchments. It consists of four components: a general user interface (GUI), GIS, N&P pollution modeling (NPPM), and a DSS. The CNPDSS simplifies the GUI and integrates GIS modules to create a user-friendly interface, enabling non-professional users to operate the system easily through intuitive actions. The NPPM uses straightforward empirical models to predict N&P loadings, enhancing efficiency by avoiding excessive parameters. Taking into account the N&P movement pathway in the catchment, the DSS incorporates three control measures: source reduction in farmland (before migration stage), process retention by ecological ditch (midway transport stage), and down-end purification by constructed wetland (waterbody discharge stage), to formulate a comprehensive ternary controlling strategy. To optimize the cost-effectiveness of any proposed N&P control strategies for sub-catchments, a differential evolution algorithm (DEA) is employed in CNPDSS to carry out a dual-objective decision-making optimization computation. In this study, the CNPDSS is applied to a case study in an agricultural catchment in Central China to develop the most cost-effective ternary N&P control strategies that ensure the catchment water quality within Criterion III of the Chinese Surface Water Quality Standard GB3838-2002 is met (total N concentration≤1.0 mg L^{-1} and total P concentration≤0.2 mg L^{-1}). Our results demonstrate that the CNPDSS is feasible and also possesses an adaptive design and flexible architecture to enable its generalization and extension to support strong hands-on applications in other catchments.

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1. Introduction

Excessive discharge of nitrogen (N) and phosphorus (P) from farmlands significantly contributes to non-point source pollution in agricultural catchments (Bryan and Kandulu 2010; Zhang T *et al.* 2019). However, current practices for preventing and controlling non-point source N and P (N&P) pollution in agricultural catchments often focus on specific processes such as discharge, transport, and convergence, without considering the entire process. This narrow approach often leads to limited treatment effectiveness and high costs, as the overall cost-benefit is frequently overlooked (Fan *et al.* 2019; Xia *et al.* 2020). Decision support systems (DSS) help decision-makers systematically address pollution control issues by utilizing data and models (Kochilakis *et al.* 2016; Zhai *et al.* 2020), to provide a more comprehensive understanding of the systematic plan layout, improved decision-making, and enhanced transparency (Courtney 2001; McIntosh *et al.* 2011). Thus, integrating DSS with factors controlling non-point source N&P pollution will hopefully enhance work efficiency, reduce costs, and promote sustainable ecological development in agricultural catchments.

Decision support systems have found broad applications in ecological restoration and environmental protection programs (Navarro-Hellín *et al.* 2016; Udias *et al.* 2018; Karavitis *et al.* 2020; Walling and Vaneeckhaute 2020). For instance, Liao *et al.* (2011) developed a river environment DSS (REDSS) that integrated a user-computer interface, a water quality assessment model, and a water quality database based on GIS, to aid in the recovery of water quality in Suzhou Creek, Shanghai, China. Broad and Corkrey (2011) established a catchment management support system (CMSS) in an Australian river catchment, incorporating a Bayesian model to estimate catchment N&P loadings for water quality management decisions. Zeng *et al.* (2012) designed a web-based water resources management DSS for Daegu City, South Korea, employing artificial neural networks to address water demand issues. Despite their success, these DSSs have certain limitations, such as the complexity of the REDSS for end-users and the lack of GIS modules in the CMSS for easy operation. Furthermore, the rise of smart mobile devices, should allow development of smart mobile device-based DSS with interactive interfaces for non-professionals.

There are three primary challenges facing a DSS developed for managing agricultural non-point source pollution. First, the development of a successful DSS requires a user-friendly human-machine interface enabling non-professional end-users, such as farmers, to easily operate the system. Second, addressing the complex issue of managing non-point source pollution in agriculture requires a comprehensive approach that covers N&P discharge, transport, and convergence processes (Xia *et al.* 2020). This necessitates the inclusion of various measures in the DSS, such as *in-situ* methods to reduce N&P discharge in farmlands (Chilundo *et al.* 2018), ecological ditches to intercept N&P transport (Wu *et al.* 2013), and constructed wetlands to purify converged N&P (Díaz *et al.* 2012). Finally, optimizing the balance between cost and effectiveness is crucial, as the cost of the control plan typically increases with N&P treatment effectiveness (Maringanti *et al.* 2011). To address these challenges, we developed a smart device Android-based DSS for managing catchment non-point source N&P pollution, named CNPDSS.

In this study, the CNPDSS aims to optimize prevention and control strategies for achieving the best possible water quality at the lowest cost in agricultural catchments. It integrates a geographic information system (GIS), a Bayesian-based model for predicting N&P loadings, an optimization algorithm, and an interactive interface for smartphones. To demonstrate the feasibility of the CNPDSS, a case study was conducted in a small subtropical agricultural catchment with severe non-point source N&P pollution (Shen *et al.* 2014; Liu J *et al.* 2020a; Wang *et al.* 2020). A multi-objective decision-making optimization of intervention strategies is proposed using the CNPDSS to ensure that surface water quality at catchment outlets meets Criterion III of the Chinese Surface Water Quality Standard GB3838-2002. Moreover, the CNPDSS is designed to support decision-makers at the basic level including local farmers and government officials.

2. Materials and methods

2.1. System structure

The catchment nitrogen and phosphorus decision support system (CNPDSS) was developed on the Android smartphone platform and oriented towards GIS. Its primary objective is to forecast N&P pollution in stream water and optimize control strategies in agricultural catchments. The CNPDSS comprises four key subsystems: the general user interface (GUI), geographic information system (GIS), N&P pollution modeling (NPPM), and decision support system (DSS). The detailed framework of the CNPDSS is presented in Fig. 1.

(i) The GUI subsystem provides end-users with an intuitive visual interface for easy interaction with the software. Through simple touch-based operations on a smartphone screen, users can delineate catchment areas, select system functions, access graphs, and visualize data and results. The development of the GUI focused on user-friendliness and readability, avoiding complicated dialog boxes to present evaluation and decision outcomes clearly. For GUI programming, it is recommended to utilize ANDROID STUDIO 4.0 and code in JAVA.

(ii) The GIS subsystem displays necessary geographic information data on a visual map. It enables end-users to query and display satellite base maps, local maps, and local map information. Specifically, the GIS facilitates spatial data queries and basic map drawing required for the CNPDSS and

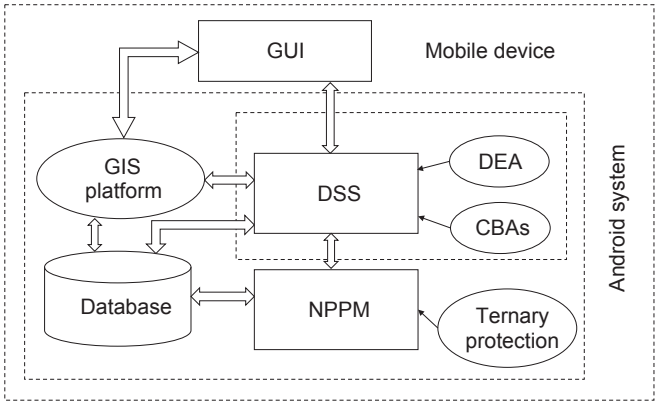


Fig. 1 The methodological framework for the catchment nitrogen and phosphorus decision support system (CNPDSS) development. GUI, general user interface; GIS, geographic information system; DSS, decision support system; NPPM, nitrogen and phosphorus pollution modeling; DEA, differential evolution algorithm; CBAs, cost-benefit analyses.

conveys relevant information to users through the GUI.

(iii) The NPPM subsystem predicts stream water N&P levels and loadings at the outlets of the catchment or sub-catchments. It assumes that N&P discharge from various landscape units (referred to as "sources"), after undergoing transportation and retention by the stream networks (referred to as "retention"), ultimately converges and is exported from sub-catchment or catchment outlets (referred to as "convergence"). By establishing the quantitative relationship between N&P and its sources, retention and convergence, the NPPM effectively predicts N&P levels and loadings at the catchment outlets using linear empirical models. A Bayesian method combined with Markov Chain Monte Carlo (MCMC) sampling is employed to accurately invert the N&P discharge rates of various landscape source units during the process of establishing these linear models.

(iv) The DSS subsystem aims to estimate the net annual costs per unit area (mainly including implementation costs) and optimize the controlling plans for N&P treatment, with a focus on achieving Criterion III of the Chinese Surface Water Quality Standard (EPB 2002) at the sub-catchment or catchment outlets. In this subsystem, the ternary controlling strategies are retrieved and optimized based on the quantitative relationship of "source-retention-converge" in an inverse manner. The resulting output shows the efficiencies of agronomic *in-situ* reduction of farmland, midway interception of ecological ditches, and terminal purification of constructed wetlands, respectively. It should be noted that the CNPDSS in this study conducts static decisions within catchment systems based on average data from multiple years of real-time monitoring.

2.2. Development of GUI subsystem

The widespread adoption of smart mobile devices has revolutionized the traditional office model, simplified information processing, and lowered the learning curve for using specialized software. To accommodate the time and budget constraints of non-professional end-users, the design of the CNPDSS user interface prioritizes simplicity and user-friendliness. End-users can easily select sub-catchment or catchments for agricultural N&P pollution treatment by directly interacting with their phone screens. The system provides clear and customizable output results in the form of excel sheets, tailored to suit the preferences of the end-user.

2.3. Development of GIS subsystem

GIS improves efficiency in spatial data management and analysis, and it has become essential to combine GIS with a DSS. In recent decades, GIS has become more closely integrated with DSS due to technological advancements. In the CNPDSS, the GIS subsystem utilizes the map manipulation function of the open-source library set of Mapbox maps SDKs for Android (https://github.com/mapbox). This allows for the display of maps, interactivity, and customization of the map experience in the mobile smart devices APP. Additionally, it features the implementation of Google tile satellite base map loading, local map loading (catchment, stream network, pond, outlet, etc.), local map query, selection, and display, as well as other basic map processing functions. The local database of the GIS subsystem adopts the GeoJSON data format, which can be converted from ESRI's Shapefile format.

2.4. Development of NPPM subsystem

Linear prediction model for N&P loadings Numerous empirical and physically-based models have been developed to predict catchment N&P pollution loading, such as SWMM (Tu and Smith 2018), ECM (Wang J L *et al.* 2022), HSPF (Bai *et al.* 2020), and ANSWERS (Bouraoui *et al.* 2002). However, the majority of these models are excessively complex and difficult to operate due to the large number of parameters incorporated. In our NPPM subsystem, we opted for the simplest straightforward empirical models to facilitate application. The NPPM model assumed that catchment N&P loadings (F, kg N/P yr^{-1}) result from various landscape source units. To estimate N&P loadings at the sub-catchment or catchment outlet, the discharge rates (R_i, kg N/P ha^{-1} yr^{-1}) of landscape source units (i.e., i=forest, paddy field, tea field, residential area, road, pond) are multiplied by their respective areas (A_i, ha), and then summed within the sub-catchment or catchment (eq. (1)).

$$F=\sum R_i A_i \quad (1)$$

To estimate the R_i, an integrated modelling approach comprising a classical pollutant export coefficient model (Hoos and McMahon 2009) and Bayesian statistics was developed to quantify its variability and uncertainty. Firstly, the riverine N&P pollutant load model was constructed by coupling with an N&P export coefficient model. The prior parameters used in the model were derived from Meng (2019). Secondly, the model was parameterized using Bayesian statistical methods based on the prior distributions of model parameters, resulting in posterior distributions of N&P discharge rates (R_i). Thirdly, the R_i for different landscape source units under various hydrological conditions were determined through the flow duration curve. Notably, the posterior R_i have undergone further validation by comparing them with the monitoring

results of N&P loadings from several sub-catchments or catchments over many years. More detailed methods and calculation formulas are given by Meng *et al.* (2023).

N&P loadings after a ternary controlling strategy Numerous agronomic and ecological measures have been implemented to mitigate agricultural non-point source N&P pollution, including optimizing agronomic practices to reduce *in-situ* farmland N&P discharge, building ecological ditches to intercept stream water N&P transportation, and constructing ecological wetlands to purify N&P in pond/lake water (Yang and Wu 2018; Xue *et al.* 2020). According to the final water quality objectives of the CNPDSS, the NPPM calculated the removal rates of N&P based on the existing N&P loadings within the catchments. To avoid the issue of over-parameterization, the NPPM quantified only the N&P removal rates (p, 0–0.5) resulting from the controlling measures, without considering the number or type of measure settings. The N&P removal rate for *in-situ* farmland measures is denoted as $p1$ (0–0.3), while the N&P removal rates for ecological ditches and constructed wetlands are denoted as $p2$ and $p3$ (0–0.5), respectively. Once N&P controlling measures are applied to a specific sub-catchment or catchment area, the resulting N&P loadings (F', kg N/P yr^{-1}) can be predicted using eqs. (2) and (3):

$$F'=(1.0-p2)\times(1.0-p3)\sum R_i A_i pi \quad (2)$$

where i=forest, paddy, tea, residential area, road, pond, when i=paddy or tea, the pi=(1–$p1$); other case pi=1.

The N&P loadings after implementing specific measures within the catchment (L, kg N/P ha^{-1} yr^{-1}), can be calculated using eq. (3). This equation subtracts the difference in N&P loadings per unit area before and after implementing the measures in the selected sub-catchment from the original N&P loadings of the catchment.

$$L=L_t-\left(L_c-\frac{F'}{S_c}\right) \quad (3)$$

where L_t (kg N/P ha^{-1} yr^{-1}) is the original N&P loading in the catchment, L_c (kg N/P ha^{-1} yr^{-1}) is the N&P loading in the original selected sub-catchment, S_c (ha) is the area of the selected sub-catchment.

2.5. Development of the DSS subsystem

The DSS optimizes the N&P removal efficiency and estimates engineering cost of the ternary controlling strategies to facilitate decision-making. The optimization process consists of two procedures. In the first procedure, the DSS performs a preliminary evaluation of the removal sensitivity of the controlling measures. A touch screen is used to select either sub-catchments or the entire catchment, and smooth bars are utilized to determine the N&P removal efficiencies of farmlands, ecological ditches, and constructed wetlands. This allows for the determination of the specific sub-catchments or the entire catchment where the measures should be implemented. In the second procedure, the DSS intelligently optimizes the ternary controlling strategies to achieve the water quality criterion of the catchment outlet (i.e., Criterion III in the Chinese Surface Water Quality Standard) with the lowest cost. The differential evolution algorithm (DEA) is used to optimize the N&P removal efficiencies of the three controlling plans (including farmland, ecological ditches, and constructed wetlands) while minimizing the cost.

The DEA and the non-dominated sorting genetic algorithm (e.g., NSGA-II) are two widely used multiobjective evolutionary algorithms for optimizing two objectives (Wang S H *et al.* 2022). While NSGA-II has shown strong performance in handling real-valued vectors, the DEA has been demonstrated to be superior to genetic algorithms in optimizing real-valued vectors (Chichakly *et al.* 2013). Specifically, the DEA offers several advantages, including simple implementation, small populations requirement, low computational cost per generation, quick convergence to global optimal solutions in various benchmark problems, and robust performance in the presence of relevant decision variables and noise (Storn and Price 1996; Reddy and Kumar 2007; Charles and Parks 2019). As a result, the DEA has gained considerable attention in the field of evolutionary computation for real-valued optimization. Existing research has shown its great potential in addressing the cost-benefit issue in the decision-making process of controlling non-point source N&P pollution in agricultural catchments.

In this study, the cost of implementing the ternary controlling plans (M, RMB ha^{-1}) is calculated using eq. (4):

$$M=[\textstyle\sum_i^n (B_i\times Y_i\times P_i\times S_c\times p1\times\alpha)+(D_b+H\times D_r\times D_w\times D_p)\times(p2\times\beta)+(W_b+S_c\times W_r\times W_p)\times(p3\times\gamma)]/S_t \quad (4)$$

where M (RMB ha^{-1}) represents the implementation cost per hectare of the catchment; B_i denotes the area ratio (%) of different types of land use in the selected sub-catchment; Y_i (kg ha^{-1}) represents the yield of the crop; P_i (RMB kg^{-1}) is unit cost of the crop; α is weight coefficient of farmland in situ; D_b (RMB) represents the base construction price of ecological ditch; H (m) is the length of the stream; D_r (%) is the ratio of ecological ditch; D_w (m) is the width of ecological ditch; D_p is the construction price (RMB m^{-1}) of ecological ditch; b is the weight coefficient of ecological ditch; W_b (RMB) is the base construction price of ecological wetland; W_r (%) is the ratio of ecological wetland; W_p (RMB ha^{-1}) is the construction price of ecological wetland; g is the weight coefficient of ecological wetlands; S_t (ha) is the area of the catchment.

The DEA was utilized to optimize the parameters, aiming to improve water quality and reduce costs simultaneously. The DEA, a four-step evolutionary algorithm, encompasses the processes of initialization, mutation, crossover, and selection, which are iterated until a termination criteria is met. The fundamental concept underlying the DEA revolves around the generation of trial parameter vectors. Through mutation and crossover, new trial vectors are generated, and subsequent selection determines the survival of vectors into the next generation (Bilal *et al.* 2020). The specific calculations for its four steps are as follows.

Initialization A set of uniformly distributed populations is generated as follows eq. (5):

$$S^G=\{X_j^G: j=1,2,...,NP\}$$
$$X_j^G=X_{low}+(X_{up}-X_{low})\times rand(0,1) \quad (5)$$

where S^G is the population of any generation; X_j^G is a D-dimensional vector, generated using uniformly distributed random number $rand(0,1)$; NP denotes the size of the population; X_{low}, X_{up} are the lower and upper bounds of search space S^G.

Mutation For each target vector X_j^G, a mutant vector V_j^G is generated according to eq. (6):

$$V_j^G=X_{r1}^G+F\times(X_{r2}^G-X_{r3}^G) \quad (6)$$

where F is the scaling factor and its value ranges from 0 to 1, and $r1$, $r2$, $r3 \in \{1,2,...,NP\}$ are vectors that are mutually different and randomly selected.

Crossover After mutation, crossover is done to generate a new vector called the trial vector denoted as U_j^G.

$$U_j^G=\{u_{1,j}^G,u_{2,j}^G,...,u_{D,j}^G\}$$

Crossover is performed between the target vector $X_j^G=\{x_{1,j}^G,x_{2,j}^G,...,x_{D,j}^G\}$ and the mutant vector $V_j^G=\{v_{1,j}^G,v_{2,j}^G,...,v_{D,j}^G\}$ using a crossover probability CR whose value is between 0 and 1. $u_{i,j}^G$ is generated as eq. (7):

$$U_{i,j}^G=\begin{cases}V_{i,j}^G \text{ if } rand_j\le CR\\ X_{i,j}^G \text{ otherwise}\end{cases} \quad (7)$$

where $i \in \{1,2,...,D\}$ and $CR \in [0,1]$.

Selection In this operation, a comparison is done between the target vector and the trial vector according to their fitness value. The one having better fitness survives to the next generation. This operation is performed as eq. (8):

$$X_i^{G+1}=\begin{cases}U_j^G \text{ if } f(U_j^G)\le f(X_j^G)\\ X_j^G \text{ otherwise}\end{cases} \quad (8)$$

In the CNPDSS, the number of iterations is more than 5,000, and the calculation time is less than 5 s. The DEA provides the suboptimal solution that is the closest to the optimal solution, making it the parameter optimization method with the best performance-to-price ratio. As such the algorithm is widely used.

3. Results

3.1. Tuojia catchment

The Tuojia catchment (112°56′–113°36′E, 27°55′–28°40′N, elevation 45–426 m), is a typical subtropical agricultural catchment, covering an area of 50.25 km^2. Located at the Changsha Research Station for Agricultural and Environmental Monitoring of the Chinese Academy of Sciences (CAS), in Hunan Province, China, it was chosen as a catchment for developing and validating the CNPDSS. The catchment has a typical subtropical monsoon climate, with an annual mean air temperature of 17.5°C and a mean annual rainfall of 1,340 mm. The topography consists of low hills with an average slope of 15.4% and average relief ratios of 382. The soil, originating from highly weathered granite parent material, is classified as a Ultisol on hillslopes, with a depth ranging from 1.8 to 2.0 m above the impervious parent materials.

The main land use types within the catchment area are forests and paddy fields. Forested areas are predominantly covered by secondary Masson pine (*Pinus massoniana* Lamb), typically around 30 years old and commonly found on the hillslopes. Alongside masson pine, other vegetation species are present, such as sawtooth oak (*Quercus acutissima* Carr), azaleas (*Rhododendron simsii* Planch), and cape jasmine (*Gardenia jasminoides* Ellis). The dominant agricultural land use in the catchment area is paddy field, which is typically distributed in the valleys and flood plains along streams. Rice is the main crop cultivated in these fields, with planting occurring twice a year, in mid-April and mid-July. The fertilizer application rate for rice cultivation in the catchment is approximately 270 kg N ha^{-1} yr^{-1} and 70 kg P ha^{-1} yr^{-1}. The paddy fields are irrigated using stream water and water management is carried out by intermittent irrigation during the rice growing period. The catchment is also renowned for its flourishing tea industry (Fu *et al.* 2011), with many tea fields established on the terraced hillslopes after the secondary Masson pine woodland was cleared. The tea fields are fertilized at rates of approximately 450 kg N ha^{-1} yr^{-1} and 30 kg P ha^{-1} yr^{-1}. The high fertilization rates and intensive N&P loss from paddy and tea fields contribute to severe non-point source N&P pollution in the catchment.

3.2. Parameterization of Tuojia catchment

To develop the CNPDSS for the Tuojia catchment, it was crucial to establish specific parameters and gather relevant local information. This process involved a comprehensive investigation of the spatial distribution of the stream network. Consequently, we selected 13 stream mouths as outlets for specific sub-catchments. Through the analysis of continuous monitoring results at the outlet of Tuojia catchment spanning a 7-year period (2011–2017), our findings revealed that the average concentrations of N and P in the surface runoff were (1.9±0.3) mg N L^{-1} and (0.5±0.1) mg P L^{-1}, and the corresponding loadings were (10.70±4.10) kg N ha^{-1} yr^{-1} and (0.78±0.38) kg P ha^{-1} yr^{-1}. More detailed information regarding the specific sub-catchments has been reported in our previous research (Liu J *et al.* 2020a; Liu X L *et al.* 2020).

Additionally, the boundaries of each sub-catchment were delineated using the digital elevation model (DEM) obtained from Mapbox (https://www.mapbox.com). The GIS subsystem of the CNPDSS requires the inclusion of local data, including catchment and sub-catchment boundary maps, water network, ponds and reservoirs, water outlets, and other relevant geographic information. The data format used was GeoJSON, and the coordinate system used was EPSG:4326-WGS 84-Geographic, which is consistent with the Google satellite imagery system. In the NPPM subsystem, the parameters used to assess N&P loadings were the N&P discharge rates under different landscape units within the catchment. These discharge rates are provided in Table 1. It is important to note that obtaining these rates required either long-term field observations or accurate estimation from another catchment or using other models. In the DSS subsystem, it was crucial to determine the catchment water quality objective and the pollution controlling parameters, such as base construction price and weight coefficient. According to the Chinese Surface Water Quality Standard, if the concentrations of total-N and total-P in surface water were lower than 1.0 mg N L^{-1} and 0.2 mg P L^{-1}, respectively, (as defined in Criterion III), then no anthropogenic pollution has occurred. In the Tuojia catchment, the average annual runoff is 506 mm yr^{-1}, and total-N and total-P loadings amounted to 5.06 kg N ha^{-1} yr^{-1} and 1.01 kg P ha^{-1} yr^{-1}, respectively.

3.3. Application details and functional display

The CNPDSS was utilized in the Tuojia catchment through

Table 1 Discharge rates of nitrogen and phosphorus under different landscape units in the Tuojia catchment[1)]

Landscape units	Discharge rate of total-N (kg N ha^{-1} yr^{-1})	Discharge rate of total-P (kg P ha^{-1} yr^{-1})
Forest	6.25	0.25
Paddy field	33.50	1.50
Tea field	35.00	2.00
Residential area	73.72	14.84
Road	24.92	2.94
Pond	0.00	0.00

[1)] The prior N&P discharge rates under different landscape units in the Tuojia catchment were determined through a combination of catchment monitoring over the years and socio-economic surveys. To ensure the model's high accuracy, the comparison was made between the integrated model of N&P discharge rates and N&P loadings, and the monitoring of N&P loadings in the river. Subsequently, the posterior discharge rates of N&P, which are provided in the table were obtained using Bayesian statistics in combination with the Markov Chain Monte Carlo sampling.

importing local map data into the designated system catalog within the Android system. The CNPDSS software divides the catchment boundaries, identifies the catchment outlets, and displays catchment information on the interactive interface (Fig. 2). To run the CNPDSS, an Android smartphone with a minimum of 2 GB memory, 16 GB hard disk capacity, and Android 9 operating system is required. Once the package is downloaded onto the smartphone, the interface can be opened, and the system can be directly operated. The user interface, as seen below, shows the 13 sub-catchments of the Tuojia catchment. With the ability to select catchments or water outlets through touch operations, a general assessment of the catchment's N&P levels and loadings can be conducted within the selected area.

The CNPDSS enables a comprehensive evaluation of N&P pollution in the Tuojia catchment. Efforts to prevent and control non-point source N&P pollution in the catchment are approached from three perspectives: "source", "retention", and "converge", corresponding to farmland, ecological ditches, and constructed wetlands, respectively. The removal efficiency of these three-tier preventive and control measures significantly influences the N&P loadings within the catchment. Calculations by the NPPM system display the total N&P loadings in the catchment through a graphical visualization on the user interface. The indicator is color-coded to represent water quality, with green indicating Criterion III or better, yellow indicating Criterion IV, and red indicating Criterion V or worse. Moreover, the number displayed alongside the indicator indicates the achievable reduction in total N&P loadings (Fig. 3). Furthermore, the CNPDSS provides a user-friendly graphical operating system that allows end-users to dynamically observe changes in the removal efficiency of the three-tier measures and N&P loadings by adjusting the sliders.

As shown in Fig. 3, when assessing the total-N loading in the NPPM model, removal efficiencies of 23% for farmland, 43% for ecological ditches, and 34% for constructed wetlands were implemented, resulting in a total-N loading of 5.67 kg N

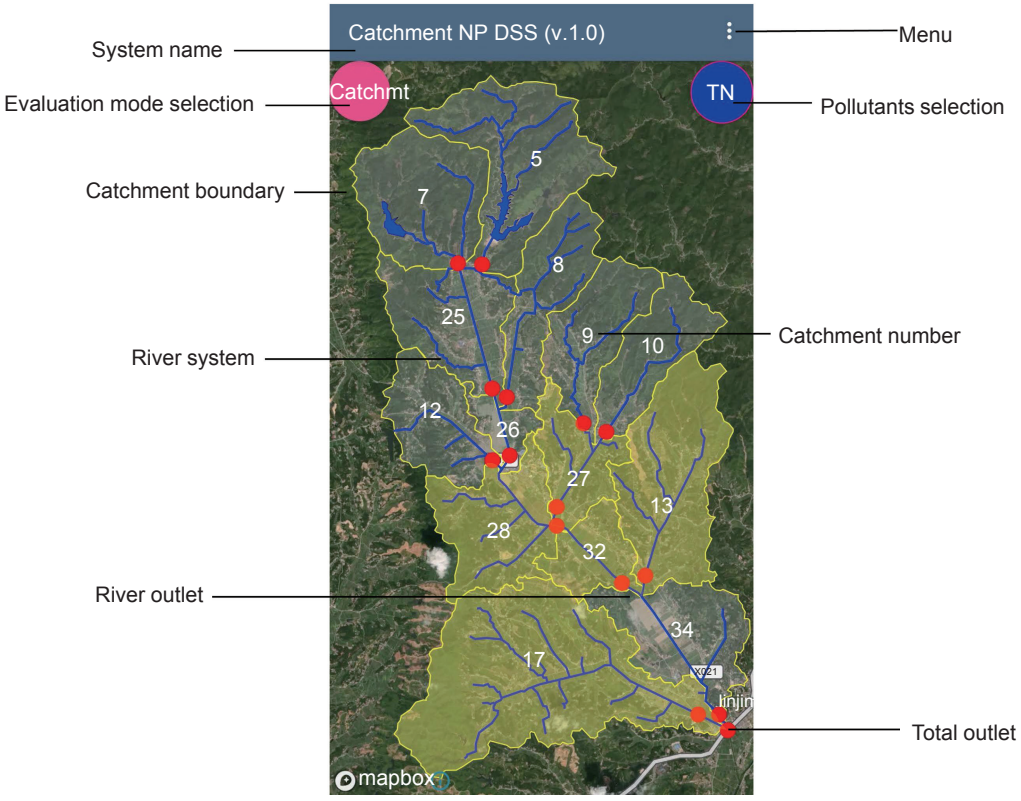


Fig. 2 The general user interface of the catchment nitrogen and phosphorus decision support system (CNPDSS) applied in the Tuojia catchment. TN, total nitrogen. The interface comprised key components such as the system name, menu, evaluation mode selection, pollutants selection, catchment boundary, river system, catchment number, river outlet, and total outlet.

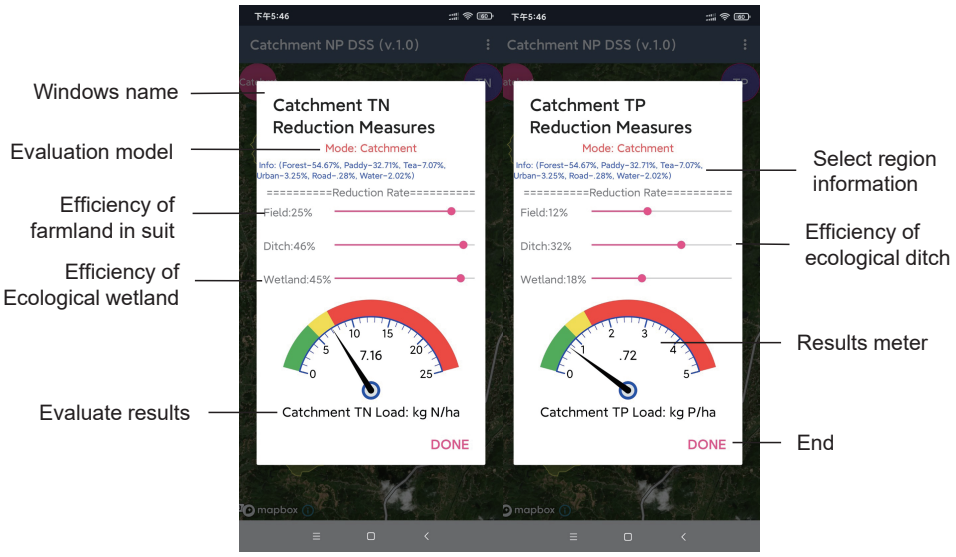


Fig. 3 The information on catchment characteristics and removal measures for nitrogen (N) and phosphorus (P). It includes details such as the percentage of land use types within the catchment, the removal efficiency option indicating the achieved removal rate for each prevention and control measure, and the results meter and evaluation results that demonstrate the total nitrogen (TN) and total phosphorus (TP) loadings from the catchment.

ha^{-1} yr^{-1} in the catchment. Similarly, when assessing Total-P loading in the NPPM model, removal efficiencies of 8% for farmland, 29% for ecological ditches, and 19% for constructed wetlands were deployed, resulting in a total-P loading of 0.64 kg P ha^{-1} yr^{-1} in the catchment.

3.4. Application of CNPDSS

Upon selecting the objective of attaining Criterion III water quality at the catchment outlet, the DSS subsystem carries out cost calculations. As the N&P loadings from the catchment have already been determined, there is no need for recalculating them. The cost of implementing pollution prevention and control measures for N&P loadings in the catchment (M, RMB ha^{-1}) is determined using the following formula eq. (9):

$$M=\{[B_{paddy}\times Y_{paddy}\times P_{paddy}\times(p1\times1.25)+B_{tea}\times Y_{tea}\times P_{tea}\times(p1\times1.25)]\times 0.01\times S_c+(p2\times2)\times[D_b+(H\times D_r)\times D_w\times D_p\times(p2\times2)]+(p3\times 2)\times[W_{base}+(S_c\times10000\times W_r\times W_p)\times(p3\times2)]\}/S_t \quad (9)$$

where B_{paddy} is the area ratio (%) of paddy in the selected sub-catchment; Y_{paddy} (kg ha^{-1}) is a yield of rice grain; P_{paddy} (RMB kg^{-1}) is unit cost of rice grain (default: 2.5 RMB kg^{-1}); B_{tea} is the area ratio (%) of tea field in the selected sub-catchment; Y_{tea} (kg ha^{-1}) is the yield of tea (default: 15,000 kg ha^{-1}); P_{tea} (RMB kg^{-1}) is unit cost of tea (default: 2.5 RMB kg^{-1}); H (m) is length of stream; D_r (%) is ratio of ecological ditch (default: 45%); D_w (m) is width of ecological ditch (default: 3 m); D_p (RMB m^{-1}) is construction price of ecological ditch (default: 150 RMB m^{-1}); D_b (RMB) is base construction price of ecological ditch (default: 100,000 RMB); W_r (%) is ratio of ecological wetland (default: 0.3%); W_p (RMB ha^{-1}) is construction price of ecological wetland (default: 100 RMB ha^{-1}); W_b is base construction price of ecological wetland (default: 100,000 RMB). The numbers 1.25 and 2 denote weights, which serve as parameter settings for the precise calculation of costs. Meanwhile, the numbers 0.01 and 10,000 are utilized for the purpose of unit conversion.

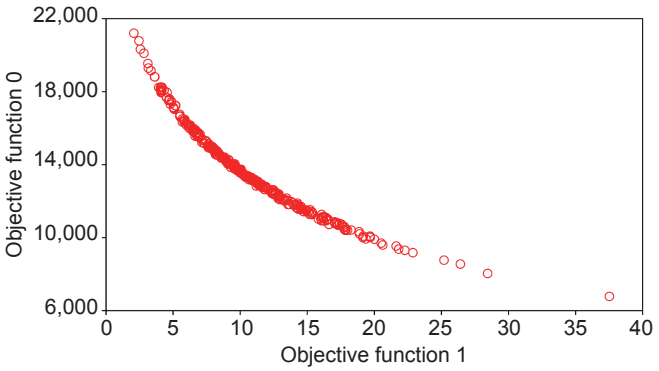


Fig. 4 Pareto front chart of the catchment nitrogen and phosphorus decision support system (CNPDSS) dual-objective optimization. Objective function 1 represents the water quality target, while objective function 0 represents the cost target. The optimal solutions are indicated by the green circle.

Based on the dual goals of enhancing water quality at the catchment outlet while minimizing implementation costs, the optimal solution has been determined through the utilization of the DEA method across 10,000 iterations. The Pareto front chart (Fig. 4) illustrated this optimal solution. The solution, which achieves the best water quality outcome while remaining cost-effective, is highlighted by a red circle.

A range of optimal solutions identified by the CNPDSS using the DEA method is displayed in Fig. 5. These solutions primarily consider the ternary controlling ratio that yields the highest removal efficiency and lowest engineering cost in the Tuojia catchment. The intelligent decision-making for preventing and controlling N&P loadings is based on the entire catchment. By referring to these superior solutions, end-users can select their preferred prevention and control measures for N&P pollutants.

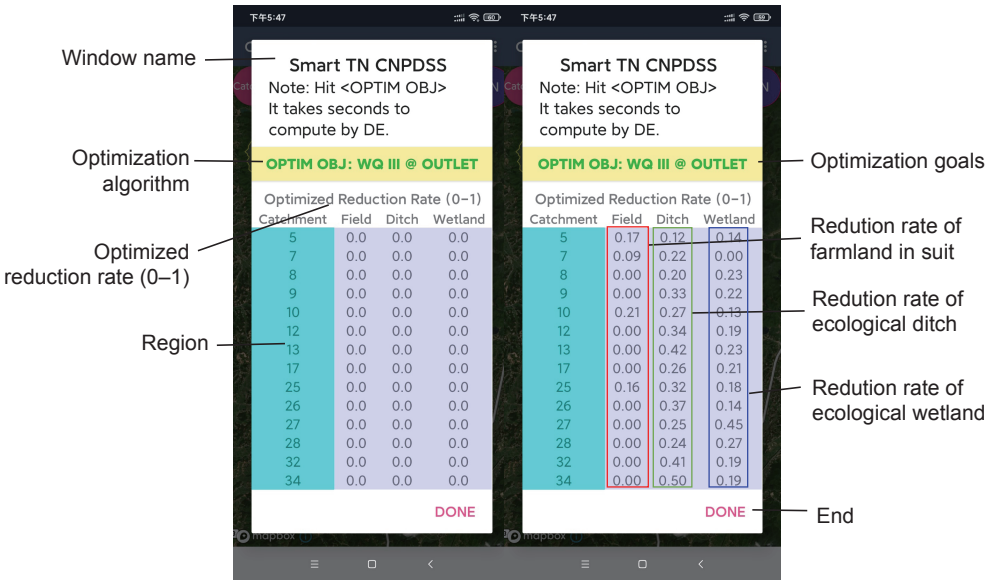


Fig. 5 The catchment nitrogen and phosphorus decision support system (CNPDSS) employs the differential evolution algorithm (DEA) for intelligent decision-making in total-N and total-P controlling in the Tuojia catchment. The algorithm runs for 5,000 iterations, aiming to achieve Criterion III water quality at the catchment outlet while minimizing costs. The interface displays the removal rates of the ternary controlling measures.

4. Discussion

4.1. Easy operation and user-friendly human-machine interface

The CNPDSS system was designed with the aim of being user-friendly for local farmers and government officials, who are the end-users. The literature review regarding DSSs for natural hazard risk reduction conducted by Newman *et al.* (2017) revealed that 22% of the reviewed systems did not clearly define the end-users, which led to a neglect of the analysis of the end-users' requirements. To address this, the CNPDSS incorporated a user-friendly graphical user interface (GUI) to create an intuitive human-machine interface. This GUI sets it apart from the land-use decision support system (LDSS) from Li *et al.* (2020), which lacked an interactive interface. The incorporation of a GUI in the CNPDSS makes it easier for end-users to understand system information. Despite the fact that more than half of the current DSS provide a GUI for data visualization and task management, end-users often face challenges in navigating these interfaces (Zhai *et al.* 2020). For instance, the web-based DSS for managing the food-water-soil-ecosystem nexus in Kolli *et al.* (2022) requires end-users to provide a large number of input parameters through its interactive interfaces. Given that most end-users lack professional knowledge and computer technology skills, it is essential to keep DSS GUIs as simple as possible (Rose *et al.* 2016). In our CNPDSS system, we have simplified the GUI to enable non-professional end-users to perform simple operations such as dragging and clicking, without the need for text input or the display of the calculation process. This simplification ensures that non-professional end-users can quickly start using the CNPDSS system.

The implementation of a simplified and user-friendly GUI is closely linked to the application of GIS technology. GIS is a specialized spatial database system that integrates environmental information and geographic location, which provides an excellent platform for integrating models and databases. In recent years, the development of GIS-based GUI has become a key focus in the development of DSSs as user-friendly interfaces that are vital for successful implementation (Monte *et al.* 2009). The CNPDSS system incorporates well-designed GUI and GIS applications to ensure a user-friendly and seamless experience. It is important to note that end-users are primarily interested in obtaining simple and easily understandable decision support on how to efficiently carry out their measures for N&P pollution prevention and control, rather than the calculation of strategies and solutions. Therefore, the DSS places a strong emphasis on user-friendliness as a central aspect of its design, including helpful tool-tips to guide end-users in performing simple operations, streamlined navigation, and straightforward installation and update processes. This attention to detail and focus on ease of use make the DSS an efficient and reliable tool for decision-making processes.

4.2. Accurate prediction of nitrogen and phosphorus loadings

The NPPM subsystem employed a straightforward empirical model to predict N&P loadings from the catchment and sub-catchments after implementing ternary prevention and controlling measures. While many DSSs rely on complex models, such as the SWAT model (Wang *et al.* 2017; Xu *et al.* 2020) driven by an extensive database encompassing climate, hydrology, vegetation, soil, and human activity, and life cycle assessment (LCA) (Khoshnevisan *et al.* 2020) which evaluates the environmental impact of an element (or product containing this element) throughout its entire lifecycle, these models often suffer from complexity and data-intensive requirements, hindering their predictive effectiveness. In

contrast, our NPPM subsystem adopts a simpler empirical model to avoid the issue of over-parameterization, allowing for easier operation by end-users. Previous research has shown that such straightforward empirical models are sufficient for delivering suitable decision support, and the utilization of more intricate models may impede DSS effectiveness (Janssen 2001; Hajkowicz 2008). Moreover, more complicated methods have been found to pose problems for users (Bojorquez-Tapia *et al.* 2005). Therefore, in designing the CNPDSS system for non-professional end-users, it was crucial to prioritize the use of simpler models that produce high-quality results, enhancing transparency and user efficiency (Hajkowicz 2008). In this regard, the straightforward empirical model employed in the NPPM subsystem is a suitable choice.

The straightforward empirical model used in the NPPM subsystem is rooted in the "source-flow-sink" theory of landscape ecology, which has previously been applied to predict agricultural environmental risk in catchments (Li *et al.* 2015; Zhang L *et al.* 2019; Wang *et al.* 2020). This model is based on a substantial volume of experimental data and tailored to the specific conditions of the catchment, making it adaptable and highly relevant. As a result, it produces more accurate results (Aschonitis *et al.* 2011). For the Tuojia catchment, the empirical model's parameters were derived from field observations and studies conducted between 2011 and 2017. Previous studies confirmed the empirical model's good prediction accuracy for catchment N&P loadings, with R^2 values ranging from 0.46 to 0.90 (Liu J *et al.* 2020; Wang *et al.* 2020; Meng *et al.* 2023). This makes the model a suitable tool for predicting N&P loadings in the Tuojia catchment. In instances where monitoring data is unavailable, alternative sources such as local annual reports or published articles can be consulted. For example, Li *et al.* (2020) obtained relevant parameters or information from Changsha County's statistical yearbook of economic and social development (1996–2016). However, it is necessary to validate the accuracy of these parameters and their corresponding model predictions in the specific catchment when applying the NPPM subsystem.

4.3. Automatically dual-objective decision-making

The CNPDSS system integrates three measures (agronomic practices, ecological ditches, and constructed wetlands) to both prevent and control non-point source N&P pollution in agricultural catchments. Agronomic practices encompass techniques such as fertilization and irrigation control, aimed at reducing N&P discharges from farmlands (Liu J *et al.* 2020b; Qi *et al.* 2020). Ecological ditches intercept N&P migration through processes including sorption, sedimentation, transformation, plant uptake, and microbial metabolic activities (Pierobon *et al.* 2013; Nsenga Kumwimba *et al.* 2018). Constructed wetlands facilitate N&P removal through mechanisms like sedimentation, photolysis, hydrolysis, microbial degradation, adsorption, degradation, and plant uptake (Vymazal 2014). Extensive literature demonstrates the effectiveness of these measures in reducing N&P loadings within catchments. Their combination, particularly when adapted to local conditions, offers a more efficient and cost-effective approach (Müller-Wohlfeil *et al.* 2002; Hesse *et al.* 2008; Chu *et al.* 2013). In the Tuojia catchment, the costs associated with implementing agronomic measures, constructing ditches and wetlands were estimated based on information gathered from previous and ongoing projects.

The CNPDSS, employing water quality and cost as dual-objective optimization criteria, utilizes the smart DEA as its core to determine optimal solutions from an extensive array of alternatives. Previous studies by Vasan and Raju (2006), Reddy and Kumar (2007), Vasan and Simonovic (2010), Chichakly *et al.* (2013), and Gurarslan and Karahan (2015) provide evidence of the efficacy of the DEA in finding optimal solutions for various water management problems. The CNPDSS operates on a goal-oriented approach, first identifying target results and subsequently configuring scenarios accordingly. This diverges from scenario analysis, which involves configuring multiple scenarios for result comparison. By utilizing the DEA, a limited number of scenarios are determined based on user feedback, thus enabling decision-makers to select among them and avoid unnecessary or redundant decisions. The goal-oriented DSS employing the DEA ensures optimized decisions congruent with established goals (Liao *et al.* 2011). Preventing and controlling non-point source pollution presents challenges necessitating comprehensive catchment-scale considerations. The disconnection between prevention and control strategies and decision-making constitutes an urgent issue requiring resolution. The DSS addresses this concern by enhancing transparency in decision-making and assisting decision-makers in comprehensively understanding available options, thereby facilitating informed decision-making.

4.4. Uncertainty

The CNPDSS aims to prevent and control agricultural non-point source N&P pollution in catchments by considering both the cost and effectiveness of prevention and controlling measures. Compared to previous controlling non-point source pollution DSS in the Watts Branch Watershed (Wang *et al.* 2017), the CNPDSS takes into account both the effectiveness and cost of implementation, ensuring that the proposed solutions are practical and can be realistically implemented. The CNPDSS is built on the Android smartphone system, making it more user-friendly than other DSSs such as the Daegu Water Management DSS in Korea (Zeng *et al.* 2012). It features a simpler interface and a wider range of applications than previous models. However, the CNPDSS does have limitations. For instance, it employs a straightforward empirical model to estimate catchment N&P loadings after implementing prevention and control measures. This model overlooks important catchment environmental factors such as climate, topography, soil, and human activities, which are dynamic variables that can impact N&P loadings in the catchment (Zhai *et al.* 2020; Ding *et al.* 2022). For instance, compared with the average of 7-year monitoring results, the accuracy of N&P loadings in the Tuojia catchment estimated using the straightforward empirical model reached 90 and 46% of loadings estimated

from 7-year monitoring (Wang *et al.* 2020; Meng *et al.* 2023), respectively. The larger error in simulating P loading may be attributed to a greater tendency of P to be deposited or adsorbed during transport processes (Mamedov *et al.* 2020), which is not fully accounted for in our predictive model. Furthermore, the parameters used in the NPPM and DEA models rely on a significant amount of experimental data from the catchment, which can change over time due to variations in environmental factors and may also differ across different catchments. Specifically, discharge rates of N&P from residential areas (Table 1) showed a relatively higher level of uncertainty in simulating N&P loadings due to their larger bases. Thus, residential areas could be classified according to population density, household classification, and consumption level. These uncertainties must be taken into account to estimate catchment N&P loadings and make informed decisions in future CNPDSS development.

5. Conclusion

Currently, there is a disconnect between prevention and control practices for catchment N and P losses and implementation of control practices because of the cost of implementation. To address this, a decision support system (CNPDSS) based on the Android smartphone platform was developed to optimize the efficiency and engineering cost of non-point source prevention and control measures in agricultural catchments. The CNPDSS encompasses GUI, GIS, NPPM, and DSS. The GUI subsystem integrates GIS technology to provide an intuitive human-machine interface, offering advantages of high operational efficiency and user-friendliness. In the NPPM subsystem, a straightforward empirical model was adopted to predict N&P loadings in the catchment and sub-catchments after implementing ternary prevention and control measures. This model is adaptable and highly relevant to specific catchments, avoiding unnecessary complexity. The DSS estimates implementation net annual costs per unit area through cost-benefit analysis, and utilizing DEA, it provides optimized decisions that align with the dual objectives of water quality and cost. The goal-oriented DSS resolves the disconnect issue between prevention and control plans and decision-making. When applied in the Tuojia catchment, the CNPDSS identifies the ternary controlling strategies ratios that achieve the highest removal efficiency and lowest engineering cost. The successful application of the CNPDSS in the Tuojia catchment demonstrates its usefulness as a decision-making tool for managing and controlling non-point source N&P pollution. It should be noted that the estimation of N&P loading in the CNPDSS currently disregards the impact of environmental factors, and this consideration will be incorporated in future development.

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Declaration of competing interest

The authors declare that they have no conflict of interest.

Declaration of generative AI and AI-assisted technologies in scientific writing

The authors declare that they did not use AI in the preparation and writing of this manuscript.

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