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Research Article

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Posted Date: May 24th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-445145/v1>

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Minimizing impact of the urbanization on the physical habitat suitability of downstream river by a multi-objective optimization

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Abstract

Urbanization might considerably change outflow of catchment that might affect physical habitat suitability at downstream river ecosystem. Present study proposes and evaluates an applicable method to minimize impact of urbanization on the suitability of physical habitats in which habitat loss and area of the urban region are optimized. coupled particle swarm optimization- adaptive neuro fuzzy inference system is used to simulate runoff in the structure of a multi-objective metaheuristic optimization. Fuzzy physical habitat simulation was applied to simulate suitability of physical habitats. Different measurement indices including the Nash–Sutcliffe model efficiency coefficient, root means square error and vulnerability index were utilized to measure performance of the simulation-optimization system. Based on the results in the case study, the proposed system is able to mitigate physical habitat impacts by optimizing area of the urban region. Regional government had planned to urbanize 90% of the catchment area. However, it damages physical habitats considerably. The optimal plan reduced the urban area to 56% and minimized physical habitat loss. This method is able to reduce negotiations between regional governments and environmental advocates for development of the new urban areas in terms of minimizing physical habitat loss in river ecosystems.

Key words: Stormwater management, Urbanization, physical habitat loss, ANFIS, MOPSO

1-Introduction

Stormwater is mainly defined as runoff that originates from the rain including snow and ice melt. The most generated runoff is directly conveyed to the rivers or other water bodies (Jefferson et.al, 2017). One of the main tasks for the civil engineers in the urban management is appropriate management of the stormwater. In other words, stormwater management might be defined as controlling the surface runoff to reduce water pollution and restore ecosystem integrity (Shishegar et.al, 2018). Urbanization is one of the main challenges in the stormwater management. Because, the primary effect of the urbanization is increasing impervious surfaces compared with previous surfaces (Kong et.al, 2017). In other words, urbanization increases surface runoff to the river ecosystems. Owing to importance of the stormwater management in the urban areas, different hydrodynamic and hydrologic models have been developed to improve management of the urban areas.

As a review on the used models in the urban water management, two models including SWMM and MUSIC are briefly reviewed. The EPA Storm Water Management Model (SWMM) is one of the applicable models for simulating urban water quality and quantity. This model is mainly applied in the post-development runoff, surface drainage hydraulics, detention pond design, low impact development, runoff water quality, runoff treatment, dual drainage systems, combined sewer overflows and continuous simulations (Gironás et.al, 2010). Moreover, MUSIC is the Model for Urban Stormwater Improvement Conceptualization. In fact, MUSIC is a decision-making system that enables engineers for evaluating conceptual designs of the stormwater management systems. MUSIC applies a risk-based approach in which three main examinations are carried out as follows (eWater, 2011).

- 1) Examination of the treatment system in terms of peak flow reduction, volumetric reduction and frequency of event flows

- 2) Examination of the response of the aquatic ecosystems to pollutant concentrations above a pre-defined threshold level

3) Examination of the long-term mean annual pollutant load delivered to the stream or river as the outflow of the catchment.

These models have been applied in different projects across the world. However, two weakness points should be noted regarding these models and other similar models. First, they could not be used in the structure of the advanced optimization algorithm. In other words, it is required to develop urban water model in the structure of the optimization systems for improving the optimization processes in the stormwater management. Hence, soft computing methods might be an appropriate solution to develop surface runoff models for the optimization applications in the stormwater management. Moreover, these models only addressed the impact of the water quality on the river ecosystem without considering physical habitat impacts that might be important and vital.

Powerful computers provide a huge capacity to use advanced computational methods. Artificial intelligence methods (AI) were the significant step to improve simulation and optimization methods that have been utilized for the engineering applications extensively. Artificial neural networks have widely been used in the hydrologic simulations. For example, they have successfully been applied to forecast stream flow or inflow of the reservoirs (e.g Kisi et.al, 2007; Mehr et.al, 2015; Niu et.al, 2021). Owing to some drawbacks of these methods such as acting as black box, improving neural networks was necessary to increase efficiency and interpretability. Neuro fuzzy inference systems might have advantages of the both fuzzy inference systems and neural networks. Thus, they have been highlighted in the literature to simulate environmental and hydrologic phenomena. Adaptive neuro fuzzy inference system (ANFIS) is an applicable data driven model that applies a fuzzy inference systems in the structure of the neural network. ANFIS based model have been used in the previous studies to predict hydrologic parameters such as stream flow (e.g Riahi-Madvar et.al, 2021; Dalkiliç et.al, 2020; Adnan et.al, 2020). Results indicate that ANFIS based models are effective to improve efficiency of the forecasting systems in the hydrology.

Evolutionary algorithms are one of the advanced methods for optimization processes in the engineering. For example, they have been used in the reservoir operation optimization (e.g Ehteram et.al, 2018; Afshar et.al, 2007; Haddad et.al, 2015; Haddad et.al, 2016). Some algorithms such as the genetic algorithm have been utilized in many problems (Mirjalili et.al, 2020). For example, GA was applied to improve cost-effective methods in the urban water management coupled with MUSIC (Montaseri et.al, 2015). Evolutionary algorithms might be classified in two classes including classic and new generation algorithms (Dokeroglu et.al, 2019). Classic algorithms including GA and particle swarm optimization (PSO) could provide proper response in many engineering problems. New generation algorithms such as bat algorithm (BA) have been developed to improve efficiency of the metaheuristic optimization (Yang et.al, 2013). However, classic algorithms might provide robust response in some cases. The main framework of these algorithms is the same though they use different strategies to search the solution space.

The main impact of increasing stormwater might be on the aquatic habitats in the river ecosystem including two aspects. First, Urbanization might increase water pollutants in the stormwater that might be harmful for the aquatics such as fishes. Another impact that might not be focused in the first glance is on the physical habitats. It is required to review on the concept of the physical habitat to clarify the problem. Initial concept of the physical habitat simulation has been developed by the instream flow incremental methodology (IFIM) (Bovee et.al, 1998). Some methods such as univariate method simulate suitability of the physical habitat parameters including depth, velocity and substrate separately. Then, mathematical models are used to compute combined suitability (Sedighkia et.al, 2021). Owing to importance of improving univariate method, multivariate fuzzy logic approach has been developed (Sedighkia et.al, 2021). Previous studies demonstrated applicability and efficiency of the fuzzy physical habitat simulation to assess physical habitat loss in the river habitats with a focus on fishes as one of the main species in many rivers (Noack et.al, 2013).

Present study proposes a novel framework to minimize impacts of the urbanization on the physical habitat suitability in which an integrated simulation-optimization method is developed. ANFIS based model is applied to simulate runoff in the catchment scale. Fuzzy physical habitat simulation was utilized to assess the physical habitat loss. Multi-objective particle swarm optimization (MOPSO) was utilized to optimize the developing urban area in the catchment. Present study might open a new window to apply novel optimization methods for stormwater management considering advanced concepts of the physical habitats in the development of the urban areas. In fact, the proposed framework might demonstrate how advanced optimization methods can open new windows to solve complex problems in the ecohydrology and ecohydraulics. The proposed framework is upgradable to solve other complex problems in the river basin scale.

2- Application and methodology

2-1- Surface runoff modeling

We applied an ANFIS based model to simulate runoff in the catchment scale. Many factors might be effective to generate surface runoff in the catchments. However, some factors might be considered as the main effective factors in the data driven model. For example, total rainfall, area and slope of the sub-catchment or catchment and land use might be the most important parameters in this regard. Owing to using ANFIS based model, it is necessary to describe the structure of the ANFIS. Figure 1 displays a simple structure of the ANFIS in which two inputs have been considered. Five layers could be seen in the structure of the ANFIS. In the first layer, input membership functions were computed. Fixed nodes in the second layer compute output as product of all incoming signals. Then, normalized firing output as product of all incoming signals is calculated in the third layer. Fourth layer includes adaptive parameters that are tuned during the training process. The overall output as the summation of all incoming signals is finally assessed in the final layer. More details on the formulation of the ANFIS model has been addressed in the literature (Azamathulla et.al, 2009).

Figure 1-Simple structure of ANFIS based data driven model

Using evolutionary algorithms in the training process of the ANFIS based model might improve accuracy of the models. Thus, we utilized PSO to train the data driven model. In other words, surface runoff was simulated using a PSO-ANFIS model. The flowchart of the PSO-ANFIS is displayed in the figure 2.

Figure 2-PSO-ANFIS flowchart

Table 1 displays the main characteristics of the developed ANFIS based model in the proposed framework. Selecting of the inputs is the most important step to develop a correct data driven model. We selected six inputs in the developed method including total rainfall, total area of the catchment or sub-catchment, slope of the catchment or sub-catchment, curve number of the urban areas and curve number of the non-urban areas and percentage of the urbanized area. It should be noted initial assessment of the case study demonstrated that non-urban areas are mainly agricultural lands and mixed forests.

Table 1- Main characteristics of the ANFIS based model

Inputs	Number of MFs (inputs)	Type of MFs (inputs)	Outputs	Number of MFs (Output)	Type of MFs (Output)	Clustering method
Total rainfall (mm)	10	Triangular	Outflow from the catchment or sub-catchment (L/S)	10	Triangular	Subtractive Clustering
Total area of the catchment or sub-catchment (Ha)	10	Triangular				
Average slope of the catchment or sub catchment (%)	10	Triangular				
Curve number (CN) for the urban areas	10	Triangular				
Curve number (CN) for the non-urban areas	10	Triangular				
Percentage of the urbanized area (%)	10					

Each data driven model needs some indices to measure the robustness of the model. Two indices including the Nash–Sutcliffe model efficiency coefficient (NSE) and root mean square error (RMSE) were applied to measure predictive skills of the runoff data driven model as displayed in the following equations. NSE is originally developed for the hydrologic models (Gupta et.al, 2009). Thus, it is applicable in the present study.

$$NSE = 1 - \frac{\sum_{t=1}^T abs(OBS_t - SIM_t)}{\sum_{t=1}^T abs(OBS_t - OBS_m)} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^T (SIM_t - OBS_t)^2}{T}} \quad (2)$$

where OBS_t is observed or recorded data in the time step t , SIM_t is the simulated data by the model and T is total number of time steps.

2-2-Optimization system

The main purpose of the optimization system is to minimize physical habitat loss in which the area of the urban region is optimized. On the one hand, the regional government might aim maximum development of the urban areas. On the other hand, there is a serious concern regarding impacts of the increasing surface runoff on the physical habitat loss in the stream ecosystem. It should be noted that based on the initial survey in the case study, it was demonstrated that current physical habitat suitability is close to the natural flow. The main component of each optimization system is the objective function. Two objective functions were developed including physical habitat loss objective function and urban area objective function as displayed in the following equations. In fact, first objective function is responsible to reduce concerns of the environmental advocators. Conversely, the second objective function would maximize the developing urban area that is aimed by the regional government.

$$Objective\ function\ 1 = \sum_{t=1}^T \left(\frac{NWUAC_t - NWUAF_t}{scc_t} \right)^2 \quad (3)$$

$$Objective\ function\ 2 = \sum_{t=1}^T \left(\frac{MUR - OUR_t}{MUR} \right)^2 \quad (4)$$

where $NWUAC_t$ is normalized weighted useable area in the current condition, $NWUAF_t$ is normalized weighted useable area in the future condition or initial urbanization plan, MUR is maximum percentage of the urban area based on the initial plan in the catchment and OUR_t is optimized percentage of the urbanized area. Figure 3 displays fuzzy physical habitat simulation method that is used in the present study. More details have been addressed in the literature (Noack et.al, 2013)..

Figure 3- flowchart of the physical habitat simulation in the proposed framework

Owing to development of two objective functions in the optimization system, a multi- objective optimization algorithm is required. We selected one of the known multi objective metaheuristic algorithms to optimize surface runoff considering physical habitat impacts. Multi-objective particle swarm optimization (MOPSO) has been applied in the optimization problems successfully. Figure 4 displays flowchart of this algorithm. More details of this optimization algorithm have been addressed in the literature (Coello et.al, 2004). It is essential to apply some indices to measure performance of the optimization system in terms of mitigating physical habitat loss as the main purpose of the optimization

model. Two indices including RMSE and vulnerability index was utilized in this regard. Equations 6 and 7 display these indices.

$$RMSE_{habitat\ loss} = \sqrt{\frac{\sum_{t=1}^T (NWUAC_t - NWUAF_t)^2}{T}} \quad (6)$$

$$Vulnerability\ index_{habitat\ loss} = MAX \frac{(NWUAC_t - NWUAF_t)}{NWUAC_t} \quad (7)$$

Figure 4-mutilobjective Particle swarm optimization (MOPSO) flowchart

2-3-Case study

Tajan River is one of the important rivers in the southern Caspian Sea basin in Iran. This river basin is one of the popular regions for living in the country due to appropriate weather condition. Hence, urbanization is a challenge in this river basin. In other words, increasing population raises needs for more urbanizing areas that mean impervious areas will be increased. Figure 5 displays river network and land use of this river basin. A target sub-basin was selected for the present study as displayed in the figure 5.

183 Target catchment includes some sub-catchments. Main characteristics of the catchment and sub-
 184 catchment are shown in the table 2.

185
 186 Figure 5- Land use, location of the Rajaei reservoir and river network map of Tajan basin

187 Table 2- Main characteristics of the sub-catchments in the target sub-basin

Sub-catchment code	Area (Ha)	Average slope (%)	Main land use in the current condition
1	35.96	4.36	<i>Agriculture</i>

2	47.63	4.48	<i>Agriculture</i>
3	3.58	3.89	<i>Agriculture</i>
4	118.35	3.78	<i>Agriculture</i>
5	227.53	3.73	<i>Agriculture</i>
6	57.54	4.00	<i>Agriculture</i>
7	202.12	3.75	<i>Agriculture</i>
8	71.60	3.43	<i>Urban</i>
9	123.99	3.63	<i>Urban</i>
10	47.19	12.16	<i>Forest</i>
11	108.31	6.62	<i>Agriculture</i>
12	123.74	10.52	<i>Forest</i>
13	20.46	12.15	<i>Forest</i>
14	48.82	14.21	<i>Forest</i>
15	137.61	4.35	<i>Agriculture</i>
16	8.91	2.72	<i>Agriculture</i>
17	313.75	9.86	<i>Forest</i>
18	75.80	9.21	<i>Agriculture</i>
19	9.16	2.98	<i>Agriculture</i>
20	1.07	3.91	<i>Agriculture</i>
21	53.46	8.56	<i>Agriculture</i>
22	54.78	2.90	<i>Agriculture</i>
23	76.62	8.28	<i>Agriculture</i>
24	96.07	5.74	<i>Agriculture</i>
25	136.11	4.70	<i>Agriculture</i>

Recorded data at outflow of the sub-catchments and catchments were utilized to develop the data driven model. Eighty percent of the total recorded data was used to train the model. Testing process was carried out in different sub-catchments and the catchment. It should be noted that it is required to test predictive skills of the model considering changing area of the catchment and land use. Hence, two main sub-catchments including a non-urban and an urban sub-catchment were selected for testing process. Moreover, testing process was carried out in the catchment. Based on the Table 2, urban areas in the catchment are limited in the current condition (close to 9% of the catchment). However, regional government plans to increase urban areas to 90% of the catchment due to increasing population. On the other hand, environmental advocates have serious concerns regarding physical habitats of the downstream river of the catchment. It is an important reproduction habitat for the native fish species. In fact, increasing rate of flow due to urbanization at the downstream river might raise physical habitat loss for the fish species. Hence, there is a challenging conflict between two objectives. In other words, it is necessary to optimize area of the developing urban region considering environmental impacts.

3-Results and Discussion

In the first step, it is necessary to present results of the data driven model to simulate runoff in the scale of the catchment and sub-catchments. Two sub-catchments were selected to demonstrate ability of ANFIS based model to simulate outflow in the simulated period. It should be noted that these sub-catchments were different in terms of land use. In other words, one of them mainly includes non-urban areas. Conversely, second sub-catchment mainly includes urban areas. Figures 6 and 7 display the training and testing processes of the model in these catchments. Two measurement indices including NSE and RMSE are shown on the figures. NSEs demonstrate that data driven model is very robust. Based on the literature, when NSE is more than 0.5, predictive skill of the model is highly robust. Minimum NSE in the sub-catchments is more than 0.9. Thus, model is robust in terms of the NSE. However, using one index might

not be sufficient to authenticate abilities of the data driven model for further applications. RMSEs in the non-urban sub-catchment and urban sub-catchment are 45.2 and 11.7 L/s respectively that demonstrate model might be reliable in the most of time steps. However, model might not reliable to predict outflow in very low rate of flows. It should be noted that stormwater management is the main purpose of the proposed framework that means higher outflow might be noticed. Thus, using the developed model is reliable. Area of the simulated sub-catchments is different. Hence, outflow in the non-urban sub-catchment is much higher than other one. Figure 8 displays training and testing process of the data driven model at the outflow point of the catchment. Based on the computed measurement indices, performance of the model in the catchment is robust as well.

Figure 6- training and testing process of the data driven model in the non-urban sub-catchment

Figure 7- training and testing process of the data driven model in the urban sub-catchment

Figure 8- training and testing process of the data driven model in the catchment

In the next step, it is necessary to present and discuss on the results of the fuzzy physical habitat simulation at the downstream river ecosystem of the simulated catchment. Table 3 displays developed fuzzy rules for the physical habitat simulation based on the expert opinions and field observations in the river habitats of the studied basin for the target species that is the Brown trout. Figure 9 displays NWUA curve for the downstream river ecosystem of the simulated catchment.

Table 3- Physical habitat fuzzy rules (L, M and H mean low, medium and high respectively)

<i>Rule Code</i>	<i>Depth</i>	<i>Velocity</i>	<i>Substrate</i>	<i>Habitat suitability</i>
<i>BR1</i>	<i>M</i>	<i>L</i>	<i>M</i>	<i>M</i>
<i>BR2</i>	<i>H</i>	<i>L</i>	<i>M</i>	<i>M</i>
<i>BR3</i>	<i>L</i>	<i>L</i>	<i>M</i>	<i>L</i>
<i>BR4</i>	<i>H</i>	<i>M</i>	<i>H</i>	<i>H</i>
<i>BR5</i>	<i>L</i>	<i>M</i>	<i>H</i>	<i>H</i>
<i>BR6</i>	<i>M</i>	<i>M</i>	<i>H</i>	<i>H</i>
<i>BR7</i>	<i>H</i>	<i>H</i>	<i>L</i>	<i>L</i>
<i>BR8</i>	<i>M</i>	<i>H</i>	<i>L</i>	<i>L</i>
<i>BR9</i>	<i>L</i>	<i>H</i>	<i>L</i>	<i>L</i>
<i>BR10</i>	<i>M</i>	<i>M</i>	<i>M</i>	<i>M</i>
<i>BR11</i>	<i>L</i>	<i>M</i>	<i>M</i>	<i>M</i>
<i>BR12</i>	<i>H</i>	<i>M</i>	<i>M</i>	<i>M</i>
<i>BR13</i>	<i>M</i>	<i>H</i>	<i>M</i>	<i>L</i>
<i>BR14</i>	<i>L</i>	<i>H</i>	<i>M</i>	<i>L</i>
<i>BR15</i>	<i>H</i>	<i>H</i>	<i>M</i>	<i>L</i>
<i>BR16</i>	<i>L</i>	<i>L</i>	<i>L</i>	<i>L</i>
<i>BR17</i>	<i>M</i>	<i>L</i>	<i>L</i>	<i>L</i>
<i>BR18</i>	<i>H</i>	<i>L</i>	<i>L</i>	<i>M</i>
<i>BR19</i>	<i>L</i>	<i>L</i>	<i>H</i>	<i>M</i>
<i>BR20</i>	<i>M</i>	<i>L</i>	<i>H</i>	<i>M</i>
<i>BR21</i>	<i>H</i>	<i>L</i>	<i>H</i>	<i>H</i>
<i>BR22</i>	<i>M</i>	<i>M</i>	<i>L</i>	<i>H</i>
<i>BR23</i>	<i>H</i>	<i>M</i>	<i>L</i>	<i>H</i>
<i>BR24</i>	<i>L</i>	<i>M</i>	<i>L</i>	<i>M</i>
<i>BR25</i>	<i>L</i>	<i>H</i>	<i>H</i>	<i>L</i>
<i>BR26</i>	<i>M</i>	<i>H</i>	<i>H</i>	<i>L</i>
<i>BR27</i>	<i>H</i>	<i>H</i>	<i>H</i>	<i>L</i>

Figure 9- NWUA curve at the downstream river ecosystem of the simulated catchment based on the output of the physical habitat simulation

Figure 10 displays normalized non-dominated solutions for the optimization problem by the MOPSO. Selecting the best solution is one of the challenges in the application of the multi-objective algorithms. In the proposed framework, optimal solution should provide a balance between urbanization and physical habitat loss for the fish. Thus, least square difference between normalized solutions was considered as the criterion to select the best response. Based on the figure 7, $Z = [46.62 \ 45.82]$ was selected as the best solution in the case study.

Figure 10- Non- dominate solutions by the MOPSO

Figure 11- Direct response by the MOPSO

Figure 12- NWUA in the current condition, initial plan of the urbanization and the optimal plan of the urbanization

Figure 13- Outflows in the current condition, initial plan of the urbanization and the optimal plan of the urbanization

Figure 11 displays urbanizing area (%) in different time steps as direct output of the MOPSO. In fact, optimization algorithm presents different areas for the urban region in each time step to achieve the optimal solution. However, it is not useable practically. Because, area of the urban region could not be changed in different months. Hence, it is essential to apply a statistical index to assess the area of the urban region. Arithmetic mean was considered as an index in this regard as displayed by the dash line in the figure 11. Based on this figure, urban areas should be considered as 56% of the total area of the simulated catchment to minimize physical habitat impacts considering physical habitat loss modeling. In the next step, it is necessary to evaluate optimal plan for the urbanization by the multi-objective optimization.

Figure 12 displays the normalized physical habitat loss in three scenarios including current condition, initial plan for the urbanization and optimal plan for the urbanization proposed by the MOPSO. As presented in the previous section, urban area had been planned up to 90% of the total area in the initial plan. A significant difference between the current condition and the initial plan of the urbanization in

some time steps is a serious threat for the physical habitats. For example, difference between the current condition and the initial plan for the urbanization in the third time step is 20% approximately that increases physical habitat loss for the fish considerably. In contrast, the difference between optimal plan and the current condition is limited. In fact, the performance of the optimization algorithm seems robust to minimize physical habitat loss. However, more discussion needs using measurement indices. Figure 13 displays outflows of the catchment in three scenarios including the current condition, initial plan for the urbanization and optimal plan urbanization. This figure demonstrates that performance of the optimization algorithm is robust as well. Optimal plan reduced surface runoff of the catchment remarkably compared with the initial plan of the urbanization in the case study.

In the next step, it is essential to discuss on the different aspects of the results and the proposed framework. Table 3 displays computed measurement indices regarding the performance of the optimization model. RMSEs for the initial plan and the optimal plan are 4.98 and 0.66 respectively. It seems that 4.98 L/S is not a significant discharge. However, it should be noted that RMSE might not be a good index in our case study. Because, outflow is low in many time steps. Hence, vulnerability index should be noticed in the cases such as our case study. It might be possible RMSE is an appropriate index in other case studies. Thus, we do not recommend excluding RMSE as a measurement index in the future studies. Vulnerability indices for the initial plan and the optimal plan are 71.66% and 5.75% respectively. In fact, vulnerability index demonstrates how the proposed optimization model is able to mitigate physical habitat impacts of the stormwater in the simulated catchment. Vulnerability index in the initial plan indicates that it might be very harmful for the aquatic habitats. Because, maximum physical habitat loss has increased significantly. In fact, it might increase required energy for the fish to swim to the upstream of the river. It might be problematic for the fish to reproduce and search for food when physical habitat loss is high. Conversely, optimal plan is able to decrease physical habitat loss significantly. Because, vulnerability index is 6% approximately that indicates increasing of the physical habitat loss is not remarkable. A point should be noted regarding the optimal plan. It is able to reduce physical habitat

loss and increase urban area simultaneously. In fact, results indicate that 56% for the urbanizing area is more than half of the initial plan that was 90% of the total area. In other words, it might reduce negotiation between regional government and environmental advocates regarding the development of the urban area in the simulated catchment. Hence, we recommend utilizing the proposed framework in the future studies to optimize area of the developing urban region in the catchments considering physical habitat impacts by applying physical habitat loss modeling as an advanced method in this regard

It is necessary to discuss on the different aspects of the proposed framework. First, we should discuss on why the proposed method or mechanism might be appropriate for the practical projects. Using an ANFIS based model to simulate runoff in the catchment and sub-catchment scale is possible to apply the runoff model in the structure of the optimization algorithms. It should be noted available hydrodynamic and hydrologic models to simulate surface runoff in the urban and non-urban catchments are not useable in the structure of the optimization algorithm directly. In fact, in the conventional urban water management, different scenarios might be simulated. Then, they will be analyzed in the structure of a decision-making system. However, the proposed method provides a flexible environment to optimize urban area. Moreover, our method considered the physical habitat impacts by application of one of the most advanced methods in the assessment of physical habitats. It should be noted that the previous models lack the physical habitat component in their structure that might be a significant drawback. Because, not only would the physical habitat loss be important in the streams, but it might also be more sensitive compared with water quality factors in some cases. Thus, the proposed method is able to cover this weakness point for the future studies. Furthermore, using MOPSO is an advantage for the proposed framework. In fact, the developed multi-objective optimization system is able to reduce concerns for the regional governments and environmental advocates simultaneously. MOPSO is a robust algorithm that is able to provide optimal solution for the problem properly. It should be noted limited number of the multi-objective algorithms have been developed in the literature. MOPSO is one of the robust algorithms that has been applied in many engineering branches. It seems that simulation frameworks are not able to cover

complex needs for environmental engineering. In fact, there is a serious conflict between environment and development that might be intensified in the future years due to increasing population. Hence, it is required to use robust simulation-optimization frameworks. Using optimization systems might reduce required time to make decisions. Because, numerous simulations and making decisions based on the result of the simulations might be time consuming. Moreover, absence of using optimization system might weaken accuracy of decisions regarding the development of the urban areas in the catchments.

We discussed on the advantages of the proposed framework in the previous paragraph. However, each new method or model might have some disadvantages and limitations that should be considered in practice. The main limitation of the proposed framework is computational complexities. In the computer science, computational complexities are defined as the needed time or memory for an algorithm. The proposed method is a complex algorithm. Because, it utilizes the ANFIS based model in the structure of the multi-objective optimization. In fact, a multi-objective optimization needs more time and memory compared with single objective optimizations. We added an ANFIS model in the optimization process that might increase computational time significantly. In the case study, we simulated a limited time. However, it needed several hours for simulation. It should be noted that numerous simulations-optimizations or covering a long-term is required in a practical project. Thus, high computational complexities might be a weakness point for the proposed methods. We recommend improving the proposed framework by a focus on the reducing computational complexities in the future studies. The proposed method might open a new window in the urban water management considering complex and unknown environmental aspects such as physical habitat impacts. In fact, the proposed method demonstrates that artificial intelligence or soft computing methods might play a key role in the future of the environmental and water resource engineering.

345

Table 3- Measurement indices for the physical habitat loss

	Initial Plan	Optimal plan
Vulnerability index (%)	71.66	5.75
RMSE	4.98	0.66

346

347 4- Conclusions

348 Present study proposed a novel framework to optimize the area of the developing urban area in a
 349 catchment scale considering physical habitat impacts. We applied PSO-ANFIS framework to simulate
 350 runoff. Testing process of the model was carried out in the sub-catchment and catchment scale. Moreover,
 351 fuzzy physical habitat modeling as one of the novel methods was utilized to model the physical habitat
 352 impacts in the structure of a multi-objective optimization. MOPSO was used to optimize the area of the
 353 developing urban region. Based on the results in the case study, initial plan for the urbanization might
 354 damage physical habitat at downstream river drastically. However, the optimal plan proposed by the new
 355 method is able to minimize impacts of the physical habitat loss. Initial plan considered to increase the
 356 urban area to 90% of the total area. However, the optimal plan proposed 56% as the optimal area for the
 357 urbanization considering environmental impacts in the physical habitats.

358 5- Declarations

359 Funding

360 Not applicable

361 Conflicts of interest/Competing interests

362 None

363 **Availability of data and material**

364 Some or all data used are available from the corresponding author by request.

365 **Code availability**

366 Code is available. However, it is not free of charge

367 **Authors' contributions**

368 Methodology, calculations and draft version by the first author. Field studies and review by the
369 second author

370 **References**

371 Adnan, R.M., Liang, Z., Kuriqi, A., Kisi, O., Malik, A. and Li, B., 2020, October. Streamflow forecasting
372 using heuristic machine learning methods. In 2020 2nd International Conference on Computer and
373 Information Sciences (ICCIS) (pp. 1-6). IEEE.

374 Afshar, A., Haddad, O.B., Mariño, M.A. and Adams, B.J., 2007. Honey-bee mating optimization
375 (HBMO) algorithm for optimal reservoir operation. Journal of the Franklin Institute, 344(5), pp.452-462.

376 Azamathulla, H.M., Chang, C.K., Ghani, A.A., Ariffin, J., Zakaria, N.A. and Hasan, Z.A., 2009. An
377 ANFIS-based approach for predicting the bed load for moderately sized rivers. Journal of Hydro-
378 Environment Research, 3(1), pp.35-44.

379 Bovee, K.D., Lamb, B.L., Bartholow, J.M., Stalnaker, C.B. and Taylor, J., 1998. Stream habitat analysis
380 using the instream flow incremental methodology. GEOLOGICAL SURVEY RESTON VA
381 BIOLOGICALRESOURCES DIV.

382 Coello, C.A.C., Pulido, G.T. and Lechuga, M.S., 2004. Handling multiple objectives with particle swarm
383 optimization. IEEE Transactions on evolutionary computation, 8(3), pp.256-279.

384 Dalkılıç, H.Y. and Hashimi, S.A., 2020. Prediction of daily streamflow using artificial neural networks
385 (ANNs), wavelet neural networks (WNNs), and adaptive neuro-fuzzy inference system (ANFIS) models.
386 Water Supply, 20(4), pp.1396-1408.

387 Dokeroglu, T., Sevinc, E., Kucukyilmaz, T. and Cosar, A., 2019. A survey on new generation
388 metaheuristic algorithms. *Computers & Industrial Engineering*, 137, p.106040.

389 Ehteram, M., Karami, H., Mousavi, S.F., Farzin, S., Celeste, A.B. and Shafie, A.E., 2018. Reservoir
390 operation by a new evolutionary algorithm: Kidney algorithm. *Water resources management*, 32(14),
391 pp.4681-4706.

392 Gironás, J., Roesner, L.A., Rossman, L.A. and Davis, J., 2010. A new applications manual for the Storm
393 Water Management Model (SWMM). *Environmental Modelling & Software*, 25(6), pp.813-814.

394 Gupta, H.V., Kling, H., Yilmaz, K.K. and Martinez, G.F., 2009. Decomposition of the mean squared error
395 and NSE performance criteria: Implications for improving hydrological modelling. *Journal of hydrology*,
396 377(1-2), pp.80-91.

397 Haddad, O.B., Karimirad, I., Seifollahi-Aghmiuni, S. and Loáiciga, H.A., 2015. Development and
398 application of the bat algorithm for optimizing the operation of reservoir systems. *Journal of Water
399 Resources Planning and Management*, 141(8), p.04014097.

400 Haddad, O.B., Hosseini-Moghari, S.M. and Loáiciga, H.A., 2016. Biogeography-based optimization
401 algorithm for optimal operation of reservoir systems. *Journal of Water Resources Planning and
402 Management*, 142(1), p.04015034.

403 Jefferson, A.J., Bhaskar, A.S., Hopkins, K.G., Fanelli, R., Avellaneda, P.M. and McMillan, S.K., 2017.
404 Stormwater management network effectiveness and implications for urban watershed function: A critical
405 review. *Hydrological Processes*, 31(23), pp.4056-4080.

406 Kisi, O. and Kerem Cigizoglu, H., 2007. Comparison of different ANN techniques in river flow
407 prediction. *Civil Engineering and Environmental Systems*, 24(3), pp.211-231.

408 Kong, F., Ban, Y., Yin, H., James, P. and Dronova, I., 2017. Modeling stormwater management at the
409 city district level in response to changes in land use and low impact development. *Environmental
410 Modelling & Software*, 95, pp.132-142.

411 Mehr, A.D., Kahya, E., Şahin, A. and Nazemosadat, M.J., 2015. Successive-station monthly streamflow
 412 prediction using different artificial neural network algorithms. *International Journal of Environmental*
 413 *Science and Technology*, 12(7), pp.2191-2200.

414 Mirjalili, S., Dong, J.S., Sadiq, A.S. and Faris, H., 2020. Genetic algorithm: Theory, literature review, and
 415 application in image reconstruction. *Nature-inspired optimizers*, pp.69-85.

416 Montaseri, M., Afshar, M.H. and Bozorg-Haddad, O., 2015. Development of simulation-optimization
 417 model (MUSIC-GA) for urban stormwater management. *Water resources management*, 29(13), pp.4649-
 418 4665.

419 Noack, M., Schneider, M. and Wieprecht, S., 2013. The Habitat Modelling System CASiMiR: A
 420 Multivariate Fuzzy-Approach and its Applications. *Ecohydraulics: an integrated approach*,
 421 pp.75-91.
 422

423 Niu, W.J. and Feng, Z.K., 2021. Evaluating the performances of several artificial intelligence methods in
 424 forecasting daily streamflow time series for sustainable water resources management. *Sustainable Cities*
 425 *and Society*, 64, p.102562.

426 Riahi-Madvar, H., Dehghani, M., Memarzadeh, R. and Gharabaghi, B., 2021. Short to Long-Term
 427 Forecasting of River Flows by Heuristic Optimization Algorithms Hybridized with ANFIS. *Water*
 428 *Resources Management*, pp.1-18.

429 Sedighkia, M., Abdoli, A. and Datta, B., 2021. Optimizing monthly ecological flow regime by a coupled
 430 fuzzy physical habitat simulation–genetic algorithm method. *Environment Systems and Decisions*, pp.1-
 431 12.

432 Sedighkia, M., Datta, B. and Abdoli, A., 2021. Minimizing physical habitat impacts at downstream of
 433 diversion dams by a multiobjective optimization of environmental flow regime. *Environmental Modelling*
 434 *& Software*, p.105029.

435 Shishegar, S., Duchesne, S. and Pelletier, G., 2018. Optimization methods applied to stormwater
 436 management problems: a review. *Urban Water Journal*, 15(3), pp.276-286.

- 437 Yang, X.S. and He, X., 2013. Bat algorithm: literature review and applications. *International Journal of*
438 *Bio-inspired computation*, 5(3), pp.141-149.

Figures

Figure 1

Simple structure of ANFIS based data driven model

Figure 2

PSO-ANFIS flowchart

Figure 3

flowchart of the physical habitat simulation in the proposed framework

Figure 4

multilobjective Particle swarm optimization (MOPSO) flowchart

Figure 5

Land use, location of the Rajaei reservoir and river network map of Tajan basin Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 6

training and testing process of the data driven model in the non-urban sub-catchment

Figure 7

training and testing process of the data driven model in the urban sub-catchment

Figure 8

training and testing process of the data driven model in the catchment

Figure 9

NWUA curve at the downstream river ecosystem of the simulated catchment based on the output of the physical habitat simulation

Figure 10

Non- dominate solutions by the MOPSO

Figure 11

Direct response by the MOPSO

Figure 12

NWUA in the current condition, initial plan of the urbanization and the optimal plan of the urbanization

Figure 13

Outflows in the current condition, initial plan of the urbanization and the optimal plan of the urbanization