出席國際學術會議報告

報告人姓名	張嘉玲	服務機構及職稱	逢甲大學 水利工程與資源保育學系 教授
會議時間	2014.9.13-2014.9.18	會議地點	德國，柏林
會議名稱	（中文)第十七屆國際水協會擴散污染及優養研討會 （英文）17th IWA International Conference on Diffuse Pollution and Eutrophication		
發表論文題目	（中文）應用倒傳遞類神經網路模式預測集水區污染 （英文）Applying the Back-Propagation Neural Network (BPNN) model to predict pollution concentration in a watershed		

一、　參加會議經過

1. 會議籌備：

國際水協會每年在水環境相關議題舉辦許多大型國際研討會，其中在擴散污染(Diffuse pollution, DIPON)相關的研討會每兩年會舉辦一次大型會議，中間間隔的一年會舉辦區域性的 DIPON 會議；今年在德國柏林所舉辦的 17th IWA International Conference on Diffuse Pollution and Eutrophication 則屬於一般性大型會議。本研討會主軸議題為擴散污染及水質優養，子議題包括：污染傳輸、自來水供給、水質管理策略、水質評估及模式應用等等面向，為相當具有凝聚力及影響力的國際性學術研討會。由於本人長期致力於集水區管理及非點源污染控制之相關研究，因此，接到大會籌備委員會委員 Prof. Sung-Ryong Ha 的邀請，故有幸參與此盛會。

2. 研討會投稿階段：

本人所帶領的研究團隊，應用不同類型的環境模式，預測集水區之水質水量反應，並進而提出相關的管制策略。本次研討會，本人將近期所研究的成果彙整成論文，於本次研討會中發表，論文主題為「應用倒傳遞類神經網路模式預測集水區污染」，為相當新穎的研究議題，也期望在會議中與相關領域的研究所者交流，為本研究後續發展而激發更多想法。經數個月嚴謹的論文審查後，有幸論文被接受，且受邀出席研討會口頭發表論文。

3. 研討會參與期間：

本次研討會會議期間為 9/13-9/18。本人於研討會期間的活動行程如下：

- 第一~三天—9/10：起程，9/11：抵達德國柏林，9/12：研討會準備。
- 第四天—9/13：研討會報到、Welcome Party。
- 第五天—9/14：開幕式、專題演講、分組會議。
- 第六天—9/15：分組會議。
- 第七天—9/16：參觀活動。
- 第八天—9/17：研討會發表(口頭報告)。
- 第九~十天：9/18：回程，9/19：抵達台灣。

4. 研討會會後資料整理階段

本人於會議結束後，將與會資料整理完備，資料包括：研討會手冊、論文發表相關資料、研討會筆記及與會照片等等，並完成「出席國際會議報告」。

二、 與會心得

第十七屆國際水協會擴散污染及優養研討會(17th IWA International Conference on Diffuse Pollution and Eutrophication)為國際水協會所舉辦相當具代表性及重要性的國際性學術研討會，本次會議於 2015 年 9 月 13-18 日，在德國柏林舉行。DIPON 研討會分為一般型及區域型會議，今年屬於一般型會議，但無論是哪一種型式，DIPON 研討會因為主軸相當聚焦，主題以擴散源污染為主，因此，與會的研究學者所做的研究有更多交集，在會議中的交流與互動也更為積極。

本次研討會 Prof. Sung-Ryong Hau 代表籌備委員會致詞，除了祝福大會圓滿成功之外，亦強調擴散污染及水質管理的重要性。在本次研討會「專題演講」的部分，大會很用心安排了許多面向的專題演講，開幕當天上午即安排了四場專題演講，除了專業部分的河川管理及水質與健康風險等等議題，亦安排一場次由 Dr. Brian D’Arcy 演說 DIPON 研討會永續發展之路，他提到 DIPON 研討會傳承的重要性，也期許此未來 DIPON 研討會及相關組織可以更蓬勃發展；各專題演講的提問均相當踴躍，可見大家對於此研討會投入的熱度相當高。

在本次研討會「分組會議」的部分，口頭發表的論文近 100 篇，子議題均是從擴散污染及水質優養主題發展出來的，除了傳統水環境議題中較常見的污染傳輸、污染控制、污染模擬等等議題外，亦有部分研究將水質問題延伸，和人類健康及環境風險作連結，在分組會議中聽聽多元的研究議題，對提升本人研究的廣度與深度均有所助益，國際性學術研討會議是個可以在短時間成長許多的學術活動。

在本次研討會中，本人所發表的論文被安排在 Session 20，這個場次的主題為 Water Quality Assessment and Monitoring，主要的議題著重在水質監測及模擬評估，我口頭發表論文後，有幾位學者在會場上提出相關的問題，會後亦有學者再來找我討論這方面的研究。在水質模擬相關研究上，主要大家較常遇到的問題是資料不足的問題，也有許多人在討論模式模擬的不確定性，透過會議發表及會場上的交流，許多共同的研究問題被拿出來討論，也互相分享克服相關問題的方法，我覺得收穫相當豐碩。

本次會議在德國柏林舉行，有人說柏林就像是一本厚厚的歷史書，第二次世界大戰德國戰敗後，德國被分為東西德，而柏林也按照戰前柏林的行政區界線被分成兩個部分，由蘇聯控制的東柏林，及由美國、英國、與法國控制的西柏林。蘇美冷戰時期，為阻止大量東德居民通過不設防的柏林分界線湧入西柏林和西德，1961 年東德建立柏林圍牆，直到 1989 年柏林圍牆被拆毀，1990 年東西德統一。這次來柏林前，把德國的歷史拿出來好好研讀了一番，我覺得歷

史和地理真的不是看書就能學會的，親身走一遭所有感受都記在心裡了，而柏林是一個必須好好體驗感受的多元城市，可惜這次待的時間不夠久，有機會一定要再去。

三、 考察參觀活動：「德國柏林參觀」

四、 建議

DIPON2015 研討會在德國柏林舉行，到歐美參加研討會需要花費較多的時間、精力和金錢，所以台灣到歐美參加學術研討會的學者，相較於亞洲所舉辦的研討會要來得少了許多。參與國際性學術會議，對於研究學者而言是一個相當重要的學術交流活動，在研討會上可以與各國學者交流，除了可以增加外語能力，提高台灣的曝光度，也可以提升研究能量，激發更多新的研究想法。本人強烈建議未來相關單位可以提供更多機會，提供台灣研究所者專家出席國際性學術研討會的補助，這將會是更為具體的鼓勵。

五、 攜回資料名稱及內容

1. 研討會手冊

2. 研討會論文論文集電子檔

六、　其他—與會照片

	研討會報告處
	Welcome Party --樂團表演
	開幕式 --Prof. Sung-Ryong Ha 致詞

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<tr>
<td>
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<td>Keynote speech

--Dr. Brian D’Arcy 演說 DIPON 研討會永續發展之路</td>
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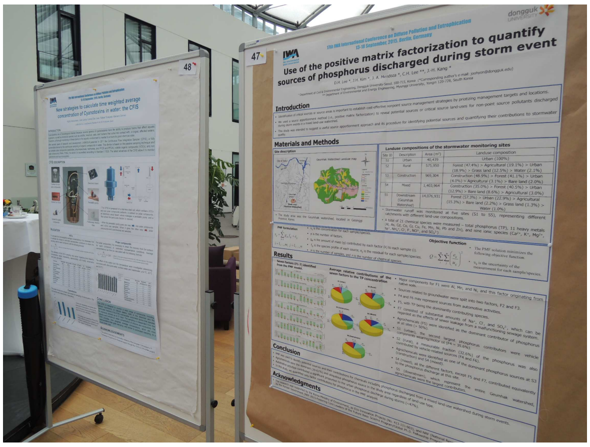
	Poster Session
	分組會議

七、　附件：「研討會論文」

Applying the Back-Propagation Neural Network (BPNN) Model to Predict Pollution Concentration in a Watershed

Chia-Ling Chang *, Meng-Yuan Li **

* Feng Chia University; No. 100 Wenhwa Rd., Seatwen, Taichung, 40724, Taiwan. f89541201@ntu.edu.tw
** Feng Chia University; No. 100 Wenhwa Rd., Seatwen, Taichung, 40724, Taiwan.

Abstract: In order to make a useful watershed management strategy, it is important to utilize deterministic or stochastic models to predict watershed responses to weather patterns. Watershed responses include flows, pollution exports, and water quality conditions. Some models lack a holistic approach to key environmental conditions and, as such, it is difficult to improve the reliability of pollution simulations, particularly when the monitoring records are insufficient. This study applies the Back-Propagation Neural Network (BPNN) model in an attempt to increase the reliability of pollution simulations. As the BPNN is more flexible than many deterministic models, it is more likely to accurately describe the relationship between any two-model factors. The results indicate that the consistent simulation error evident in pollution prediction will decrease when the BPNN neurons are adjusted. For this paper, the neurons in the BPNN output layer constitute pollution concentration. When the average precipitation for the five days prior to the water quality monitoring date are calculated as the neurons in the BPNN input layer, the pollution concentration can be accurately predicted.

Keywords: BPNN; modeling; pollution simulation; watershed management.

Introduction

Climate change increases the difficulty to resolve environmental problems (Bates *et al.*, 2008), and as a result of increased economic development, many natural environments have become over-developed and polluted, and in turn generate a negative impact on local ecologies. Water quality and water quantity problems are usually inter-related and are important factors in the management of water. For example, storms often bring large amounts of precipitation, and in Taiwan particularly, most rainfall cannot be saved and transferred to useful water resources. Heavy storms cause high-turbidity in water and impact the stability of a water supply system as high particle levels in water often lead to water treatment plants shutting down (Jinno *et al.*, 1995; Haimes *et al.*, 1998; Tidwell *et al.*, 2005; Lee *et al.*, 2009). Consequently, floods and suspended water supplies may occur at the same time.

In order to implement a correct environmental management strategy, it is necessary to utilize modeling tools to predict environmental responses (Lung, 2001). As watershed environmental management is critical for decreasing flood damage and maintaining a stable water supply system, the prediction of watershed responses plays an important role in watershed management. Watershed responses, such as water flows, pollution exports, and water quality conditions, are the foundation of a watershed management strategy. Many models have been developed and commonly applied. However, improving the reliability of simulation results has remained elusive.

As pollution exports are influenced by numerous factors, such as rainfall properties, geographic properties, and land-use conditions, it becomes more difficult to decrease the errors in pollution simulation than those in flow simulation. Many studies have demonstrated that the Back-Propagation Neural Network (BPNN) model is more flexible than other models (ASCE, 2000a, b; Philip and Joseph, 2003; Rajurkar *et al.*, 2004; Palani *et al.*, 2008). As the BPNN is a stochastic model, the simulation results may vary even though the input parameters and data are fixed. By adjusting the parameters in the BPNN, there is a high probability that the simulation results will be improved. The objective of this study is to use the BPNN to improve the reliability of pollution simulations.

Material and Methods

BPNN

The BPNN is an Artificial Neural Network (ANN) model that emulates the ability of a biological neural network to create a mathematical system that is able to describe complex relationships within networks in a simplified form; this form can be considered a 'black box' as it translates historical data into predictable outcomes (Huwe and Totsche, 1995; Wu *et al.*, 1997; Calenda *et al.*, 2009). As a result of this advantage, it is often used in many different fields; and it is also common for predicting environmental responses (Maier and Dandy, 2000; Karul *et al.*, 2000; Philip and Joseph, 2003; Rajurkar *et al.*, 2004; Palani *et al.*, 2008; Chang and Liao, 2012).

Many studies describe the relationship between rainfall and runoff. Contrarily, few studies create the relationship between rainfall and pollution concentration; this is the purpose and value of this work. By adjusting the parameters, training times, learning velocity, transfer function, and neurons, it is possible to create a satisfactory BPNN model foundation. This process is called model calibration and validation by using a training set and an internal test set. When the BPNN model foundation is determined, it can be used to predict the output responses of different input data (external set). According to the simulation results by using an external set, it allows us to prove the effectiveness of the BPNN model foundation.

Case study

As shown in Figure 1, the Daiyuku Creek and the Qupoliao Creek located in the Fei-tsui reservoir watershed in northern Taiwan provides the setting for this case study. This site covers an area of 79 km^2. The flow and water quality stations are located near the outlet of this sub-watershed. This study collects precipitation, flow, and pollution concentration data from 2007 to 2010. The data from 2007 (training set) are used for model calibration, and the data from 2008 (internal test set) for model validation. By using the data from 2009 and 2010 (external set), our goal is to judge if the BPNN model foundation-with the parameters determined by careful model calibration and validation-could withstand the rigors of time.

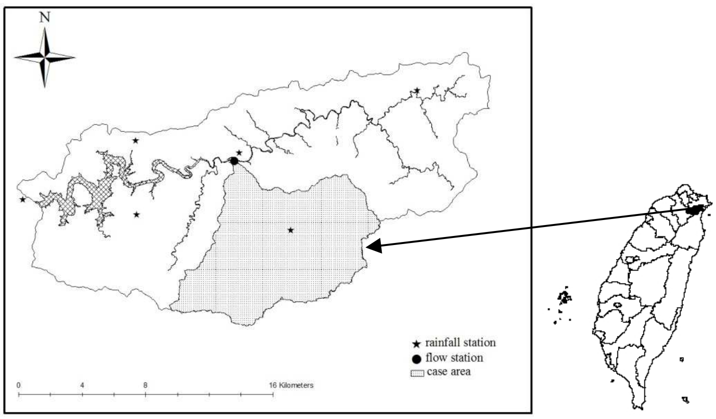


Figure 1 Case area: the Daiyuku Creek and the Qupoliao Creek.

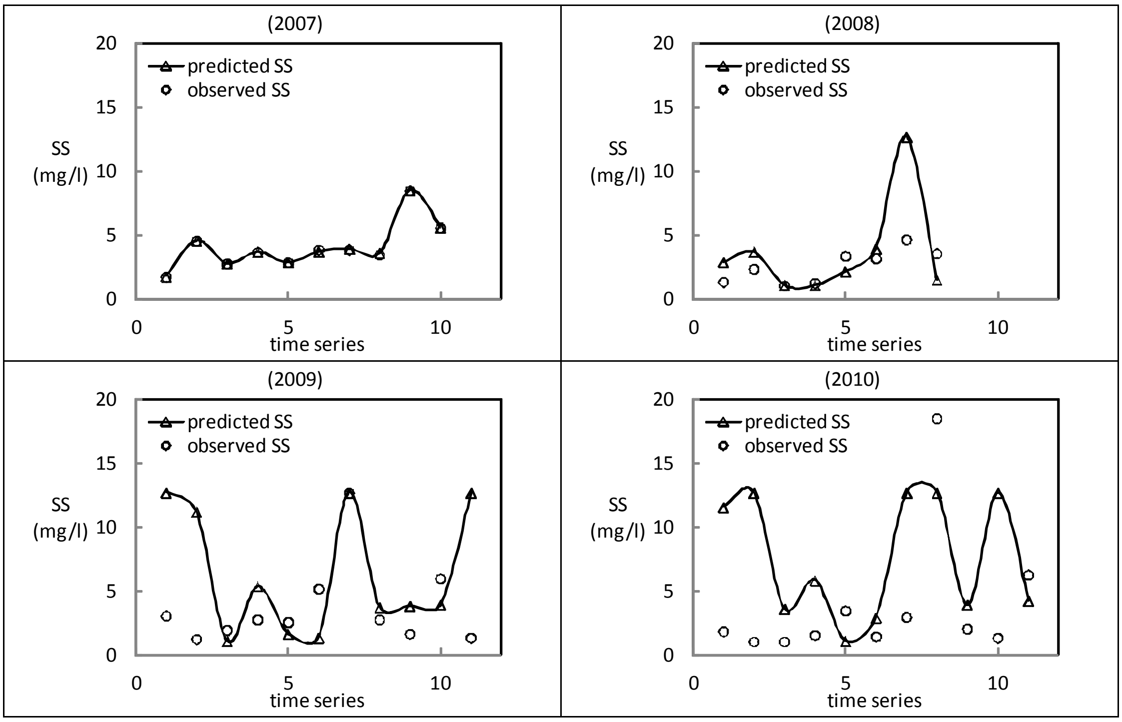
Results and Discussion

A simulation error in pollution prediction may cause false decision-making in watershed management. This study attempts to increase the reliability of pollution simulations by adjusting the BPNN parameters. The training times are calculated as 100 times, and the learning velocity is 1 repetition per 10 seconds. The transfer function is determined as 'Log sigmoid transfer function'. The neurons in the BPNN output layer determine predicted pollution concentration. As the change of the neurons in the BPNN input layer greatly influences the pollution prediction, this study compares the pollution simulation results by varying the neurons in the BPNN input layer.

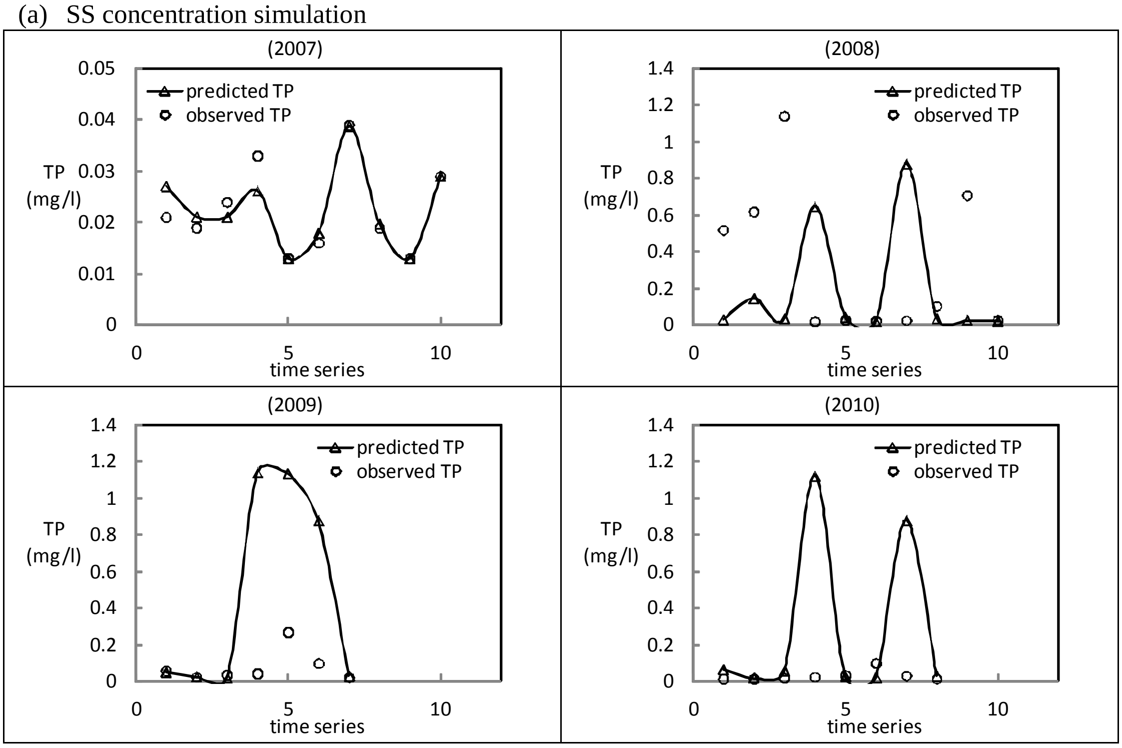
Firstly, the average monthly precipitation is calculated as the neurons in the BPNN input layer. The pollution simulation results are shown in Figure 2. The values for R^2 between predicted and observed SS concentration are 0.99 in model calibration (2007) and 0.47 in model validation (2008). The values for R^2 between predicted and observed TP concentration are 0.85 in model calibration (2007) and 0.12 in model validation (2008). The values for RMSE in SS concentration simulation are 0.069 mg/l in model calibration (2007) and 3.04 mg/l in model validation (2008). The values for RMSE in TP concentration simulation are 0.003 mg/l in model calibration (2007) and 0.63 mg/l in model validation (2008). These results illustrate that the reliability of the pollution simulations is not satisfied, as the simulation results are out of the acceptable range in model validation.

Secondly, the data for model calibration are increased. The average monthly precipitations in 2007-2009 are used for model calibration and the average monthly precipitations in 2010 are used for model validation. The pollution simulation results are shown in Figure 3. The values for R^2 between predicted and observed SS concentration are 0.83 in model calibration (2007-2009) and 0.91 in model validation (2010). The values for R^2 between predicted and observed TP concentration are 0.84 in model calibration (2007-2009) and 0.003 in model validation (2010). The values for RMSE in SS concentration simulation are 0.97 mg/l in model calibration (2007-2009) and 2.28 mg/l in model validation (2010). The values for RMSE in TP concentration simulation are 0.1 mg/l in model calibration (2007-2009) and 0.39 mg/l in model validation (2010). These results show that the reliability of pollution simulations cannot be efficiently improved by increasing the data in model calibration. Although the SS concentration simulation is improved, any improvement in the TP simulation is irrelevant.

Thirdly, this study changes the neurons in the BPNN input layer. Both the average monthly precipitation and average monthly flow are calculated as the neurons in the BPNN input layer; the pollution simulation results are shown in Figure 4. The values for R^2 between predicted and observed SS concentration are 0.99 in model calibration (2007) and 0.008 in model validation (2008). The values for R^2 between predicted and observed TP concentration are 0.99 in model calibration (2007) and 0.06 in model validation (2008). The values for RMSE in SS concentration simulation are 0.21 mg/l in model calibration (2007) and 2.54 mg/l in model validation (2008). The values for RMSE in TP concentration simulation are 0.0005 mg/l in model calibration (2007) and 0.57 mg/l in model validation (2008). These results demonstrate that pollution simulation results cannot be improved when adding the flow records as the neurons in the BPNN input layer.

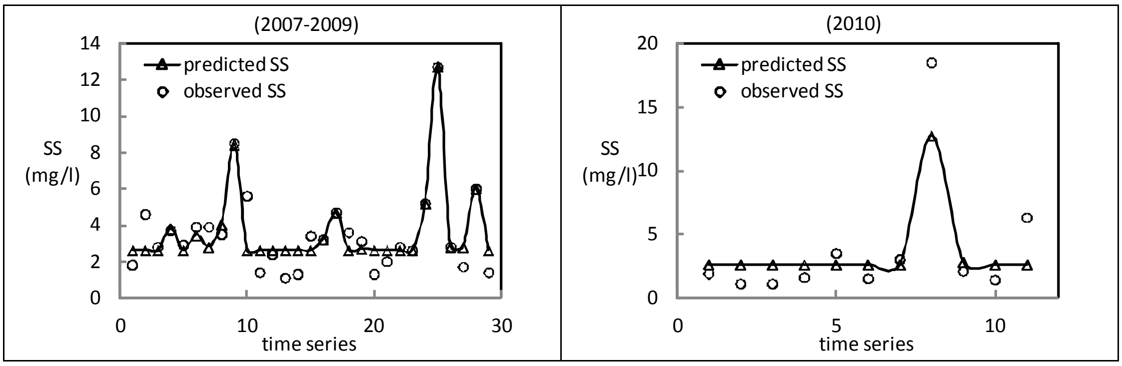


(a) SS concentration simulation

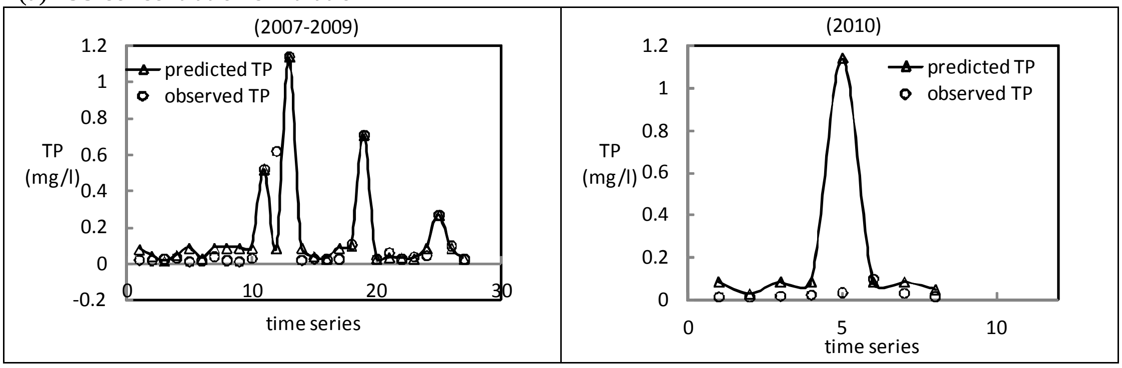


(b) TP concentration simulation

Figure 2 Pollution simulation results when the average monthly precipitation is calculated as the neurons in the BPNN input layer.



(a) SS concentration simulation

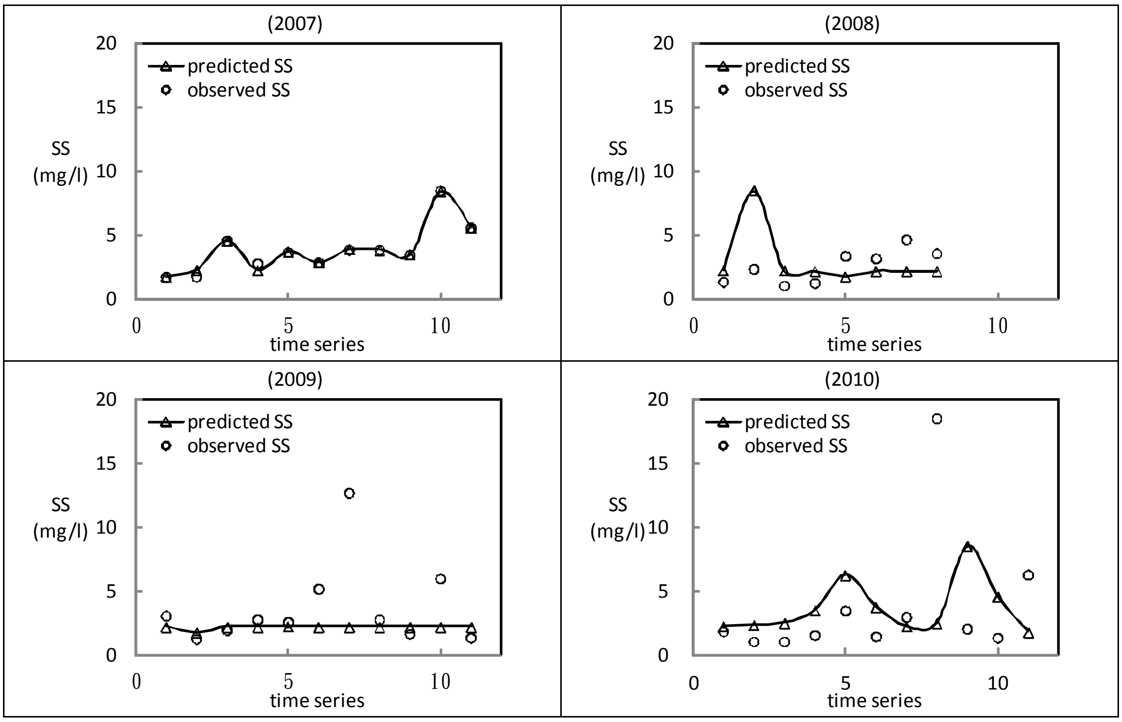


(b) TP concentration simulation

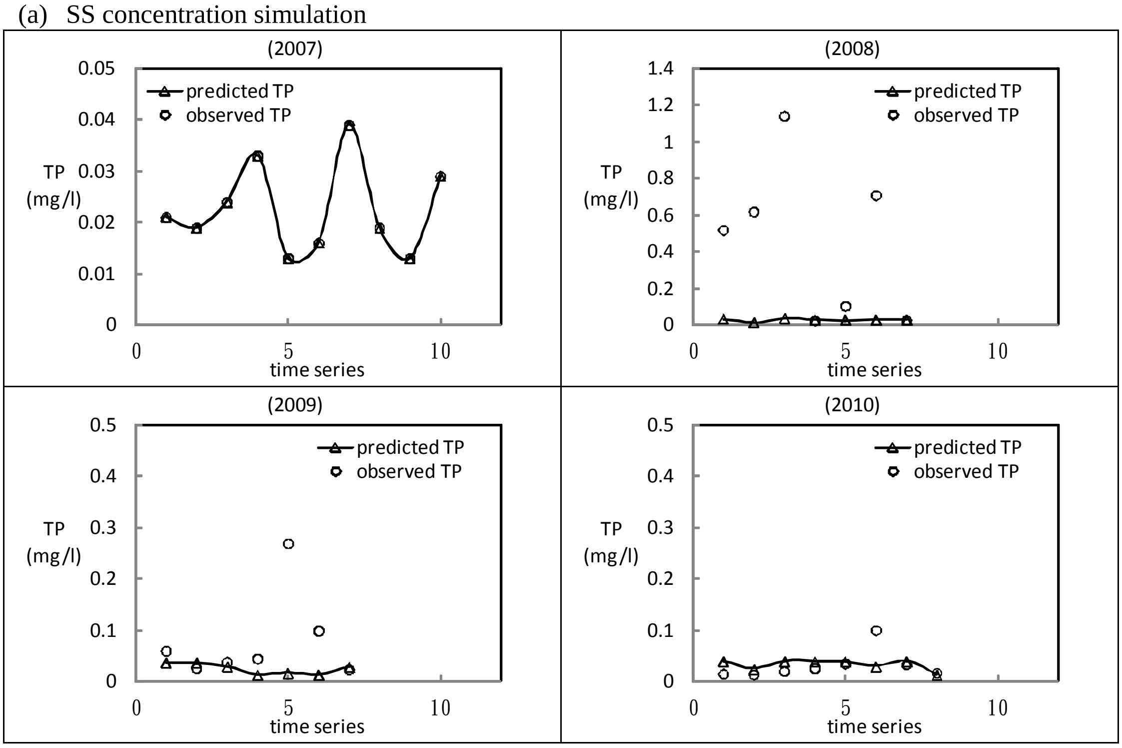
Figure 3 Pollution simulation results when increasing the data for model calibration.

Finally, the average precipitation for the five days prior to the water quality monitoring date are calculated as the neurons in the BPNN input layer; the pollution simulation results are shown in Figure 5. The values for R^2 between predicted and observed SS concentration are 0.76 in model calibration (2007) and 0.53 in model validation (2008). The values for R^2 between predicted and observed TP concentration are 0.81 in model calibration (2007) and 0.66 in model validation (2008). The values for RMSE in SS concentration simulation are 0.85 mg/l in model calibration (2007) and 0.83 mg/l in model validation (2008). The values for RMSE in TP concentration simulation are 0.005 mg/l in model calibration (2007) and 0.22 mg/l in model validation (2008). These results show that both SS and TP concentration simulation can be improved when the average precipitation for the five days prior to the water quality monitoring date are regarded as the neurons in the BPNN input layer.

When the average precipitation for the five days prior to the water quality monitoring date are calculated as the neurons in the BPNN input layer, the effectiveness of the model foundation is acceptable. The values for R^2 between predicted and observed SS concentration are 0.59 in 2009 and 0.91 in 2010. The values for R^2 between predicted and observed TP concentration are 0.59 in 2009 and 0.88 in 2010. The values for RMSE in SS concentration simulation are 2.31 mg/l in 2009 and 3.89 mg/l in 2010. The values for RMSE in TP concentration simulation are 0.04 mg/l in 2009 and 0.009 mg/l in 2010. These results show that the pollution simulation results are satisfied in 2009 and 2010 (external set). Both the reliability and effectiveness of pollution simulations are poor in other scenarios. These findings prove that the BPNN model can work well for the external set when the average precipitation for the five days prior to the water quality monitoring date are calculated as the neurons in the BPNN input layer.

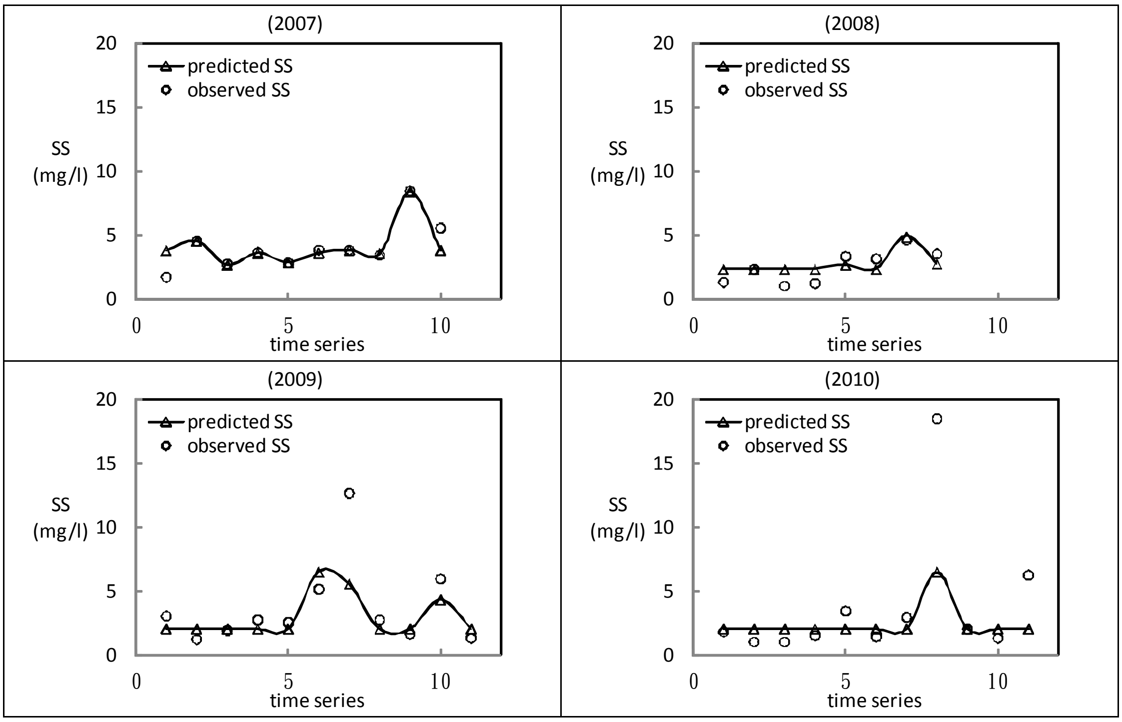


(a) SS concentration simulation

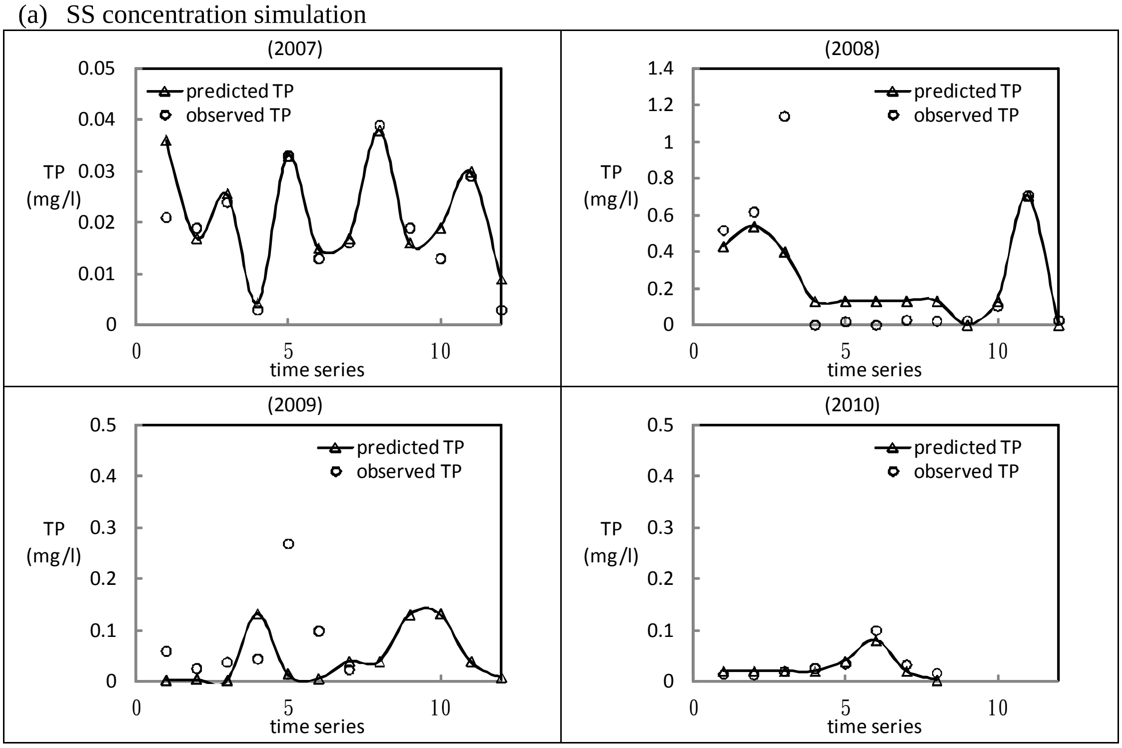


(b) TP concentration simulation

Figure 4 Pollution simulation results when both the average monthly precipitation and average monthly flow are calculated as the neurons in the BPNN input layer.



(a) SS concentration simulation



(b) TP concentration simulation

Figure 5 Pollution simulation results when the average precipitation for the five days prior to the water quality monitoring date are calculated as the neurons in the BPNN input layer.

Conclusions

As the BPNN model is flexible, it is able to improve prediction reliability. This study utilizes the BPNN model to predict SS and TP concentration in a watershed. Several scenarios with different neurons in the BPNN input layer are compared. As pollution concentration in a river system is influenced by numerous factors and, therefore, difficult to predict, most deterministic models cannot efficiently predict pollution concentration. The BPNN, a stochastic model, overcomes this problem. Although water flow is related to pollution concentration, the reliability of pollution simulations cannot be improved when calculating the average monthly flow as the neurons in the BPNN input layer. Similarly, it is impossible to improve pollution simulation results by increasing data in model calibration. When the average precipitation for the five days prior to the water quality monitoring date are calculated as the neurons in the BPNN input layer, both the reliability and effectiveness of pollution simulations can be considered a major improvement over the other scenarios.

Acknowledgment

The authors would like to thank the National Science Council of the Republic of China for financially supporting this research under Contract No. NSC 100-2221-E-035 -072 -MY3.

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