Chapter

Water Sustainability through Drainage Reuse in Agriculture – A Case for Collaborative Wireless Sensor Networks

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Abstract

With increasing prevalence of wireless sensor networks (WSNs) and internet of things (IoT) in agriculture and hydrology, there exists an opportunity for providing a technologically viable solution for the conservation of already scarce freshwater resources. In this chapter, a novel framework is proposed for enabling a proactive management of agricultural drainage and nutrient losses at farm scale where complex models are replaced by *in situ* sensing, communication, and low complexity predictive models suited to an autonomous operation. This is achieved through the development of the proposed Water Quality Management using Collaborative Monitoring (WQMCM) framework that combines local farm-scale WSNs through an information sharing mechanism. In this chapter, we present the design of a framework for facilitating real-time utilization or disposal of agricultural drainage among farms using collaboration among prevalent farm networks. The basic system architecture comprises modules for environmental learning, prediction of the impact of neighboring events in terms of drainage and nutrients losses, and a local decision support mechanism. The overall functionality of the framework is explored in terms of stages of learning, training, and testing. A network learning model is required to identify flow links of a network with neighboring networks.

Keywords: wireless sensor networks, internet of things, collaborative networks, water quality management

1. Introduction

Owing to the coupled impact of traditional farming practices and inherent inefficiency of nutrient uptake by crops (up to 60%), there is an inevitable release of drainage water (35–60% of surface irrigation water) rich in nutrients [1]. For example, in a watershed (190,000 ha) in Western Australia, facing high nutrient fluxes, phosphorous losses are measured to be 140 tonnes per annum (tpa) that is twice its target. It is expected to rise to 1300 tpa in the next 100 years if current practices continue [2]. In another study on the North China Plain, the recovery of fertilizer N by the crop at the conventional N fertilizer rate (300 $KgNha^{-1}$) was approximately 25%, while 30–50% of the applied N was lost [3].

In order to avoid exacerbating the water crisis and to prevent food shortages, an advantageous strategy is the conservation and reuse of agricultural drainage (and the dissolved nutrients) before it ends up in freshwater system [4]. Reusing drainage water and nutrients emanating from one farm in another farm, before they enter the water system, can have huge environmental as well as economic benefits. In particular, reuse reduces the amount of freshwater extracted from the environment, thus lowering its diversion from sensitive ecosystems. In regions where irrigation water supplies are limited, drainage water can be used to supplement them [5, 6]. In addition, agricultural drainage reuse can benefit the farmers (or any stakeholders) by saving cost on not using fresh irrigation water and fertilizer inputs.

The only concern about drainage water reuse is whether or not the water is safe for reuse, that is, does not contain high concentration of salts and pesticides. Highly saline water cannot be used for salt-sensitive crops. However, it can successfully be used for salt-tolerant crops, trees, fodder, and natural wetland and even for salt-sensitive crops at later growth stages [4, 7]. Conjunctive use of saline water with freshwater increases the suitability of drainage water. With regard to pesticides, in areas where strong environmental safeguards exist for pesticide usage, there is little risk associated with the reuse of surface runoff or tail water drainage [7–9]. Hence, drainage water can safely be used if appropriate considerations are taken into account.

Drainage water and dissolved nutrients have been globally utilized for crops and greenhouses. In some intensive farming areas, farmers have begun to test their groundwater for nitrate concentrations and therefore change their nutrient budgets accordingly [10]. In another case, reapplication of N-rich runoff waters provided more than the annual nutrient requirements for that land [11]. In one study, reuse of saline water for salt-tolerant forages has been investigated under varying salinity-level treatments (between 15 and 25 dS/m). For this experiment, sand tanks were used in a greenhouse. Almost all forages showed promise with regard to biomass production, whereas wheatgrass, Bermuda-grass, and paspalum performed particularly well [12].

Some work in local drainage reuse is reported for hydroponic systems maintained in a greenhouse (in which plants are grown in water instead of soil). In one application, high-quality tomato was grown with drainage reuse [13]. During seedling stage, fresh nutrients were supplied with irrigation of which 20–30% overflowed as drainage. At the final stage of ripening, the preserved drainage was reused with no wastage being drained out from the greenhouse. In a similar work based on greenhouses in Australia, drainage reuse was used for growing cucumber and tomato [14]. The study was aimed at investigating the use of drainage water of the greenhouse to increase water and nutrient use efficiency and reduce the environmental impact. Flow meters were installed to gauge the volumes of water applied to the crops. Water samples were taken five times a day for inflows and outflows, and were analyzed for pH, salinity, and concentrations of nutrients. The results indicated 33% reduction in freshwater usage for irrigation. Furthermore, it was determined that drainage water collected from the greenhouse contained 59% of applied N and 25% of applied P. These studies, though small scale and based on local drainage reuse, are very encouraging.

Existing work though promising is based on spatially and temporally limited manual sampling of soils and waters and on hypothetical guesses as to the processes involved in the N cycling. Furthermore, various resource constraints and farmer's concerns regarding real time availability of information on volumes, timings, and quality of discharges that will be delivered to the farms [15, 16] restricts wide adoption of this mechanism in agriculture. Despite tremendous promise of the benefits of drainage water reuse and technological advancements, implementation of an intelligent and autonomous management mechanism has not kept pace with the deteriorating water situation. Some of the reasons as outlined in a detailed study [17] are as follows: (i) insufficient awareness of available technology, (ii) unavailability of soil, weather, and crop data, (iii) inappropriate model selection which inadequately capture the system details, and (iv) gap between decision makers and scientists. The integration of useful and relevant scientific information is necessary and critical to enabling informed decision making for drainage reuse or disposal [18]. Recent adoption of WSNs in agriculture and hydrology presents huge promise for improving water management, and the next section discusses the applications of WSNs for water quality monitoring and agriculture and identifies huge opportunities available with real time, dense, and remote data availability.

This chapter presents the architecture of water quality management using collaborative monitoring (WQMCM), which uses existing networked farms and water systems and low-complexity predictive models to enable real-time drainage water management [19–21]. The functional overview of the WQMCM framework with the design of a modified drainage network is discussed.

2. Function overview of WQMCM

WQMCM is an integrated control and management strategy, which requires that individually targeted monitoring units or local networks, representing different stakeholders in a catchment, for example, a farm, should be able to share information with each other about runoff, drainage, or nutrient fluxes. These events may be intense but are short-lived and so information sharing becomes important as they may be very fast, and so may normally be missed with the usual sampling rate. Allowing event information to be transmitted across multiple networks as they are detected will allow prediction of when the repercussions of that event might be seen downstream, allowing other stakeholder networks in the vicinity to adjust their monitoring and management strategy. This will include taking decisions about reusing or disposing the drainages, or increasing their sample rate to catch transient events. As emphasized in the literature, drainage reuse strategy reduces the overall stress of nutrient losses to the water system and provides economic benefit as well by reducing fertilizer usage. The proposed framework enables stakeholders to manage and benefit from this reutilization by sharing information about their availability and presence. Such a de-centralized approach comprising autonomous networks presents a flexible methodology where independent networks, in addition to local monitoring objectives, seek to opportunistically utilize neighboring events.

To demonstrate the mechanism of the proposed framework with respect to agricultural drainage reuse, a modified drainage network is designed. **Figure 1** illustrates an example irrigation and drainage system in which various farms and drainage regions are linked with each other through water flow paths. The figure shows an additional bay, drainage reuse bay, linked with individual farm's irrigation and drainage bay to implement the drainage reuse mechanism. Each farm would have the option to either use drainage from another farm or fresh irrigation water for irrigation. As mentioned earlier, the WQMCM framework aims to combine local individual networks into an integrated mechanism; therefore, it is assumed that these farms are monitored by individual networks with local application objectives. These objectives are to facilitate farming decisions with regard to, for example, irrigation or pesticides scheduling by monitoring microclimate (soil moisture, crop cover, and soil temperature) of the field. For implementing the framework, an additional network on the water system, the drainage reuse bay in this case, is required to monitor drainage and nutrient contributions by each farm. As shown in **Figure 1**, individual sensors in the drainage network are deployed at the outlet of each farm to monitor its drainage outflow. Other nodes monitor base flow in the drainage bay. This network will be either deployed by an official governing body working toward maintaining water quality or by local farmers for a collaborative cause.

These networks, under the proposed WQMCM framework, share information about the start of a daily event with each other, for example, an irrigation event in a farm or high pollutant drainage discharge from drainage bay. When event information is received from a farm network (e.g., farm A), the drainage network node associated with that farm uses on-node predictive models to forecast the values for expected drainage and nutrient dynamics as a result of that event. The forecasting of drainage dynamics is undertaken by the drainage network for the following reasons.

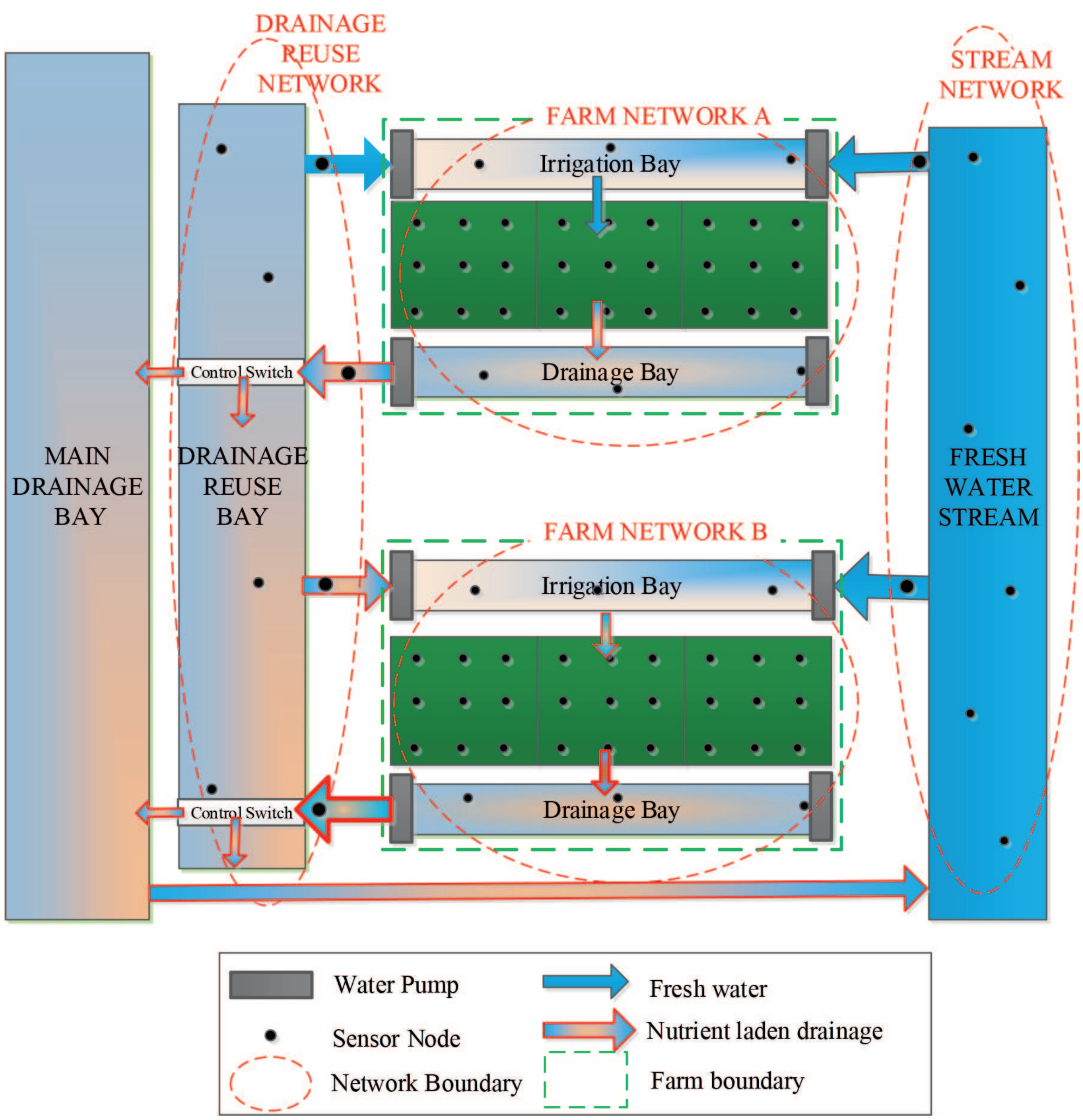

Figure 1.
A modified drainage network design to implement drainage reuse for the WQMCM framework.

Firstly, because drainage network links all the farms and the stream networks, it is ideal to have the drainage network disseminate the predicted information about drainage to all the other farms and stream network for reuse, treatment, or disposal. Secondly, the main drainage bay could be distantly located from the drainage ditch of a farm; hence, volumes of actual drainage outflows received by a drainage bay from a farm may change owing to evapotranspiration and absorption during its transport. Additionally, running predictive models is a computational overhead, which should naturally be taken up by the network responsible for decision making.

Figure 2 illustrates the format of information shared by a farm and the parameters predicted by a drainage network. The shared event information packet from a farm includes network and event details. To identify a network, information such as network id, type, and location is included. Network type is related to whether it is a farm, drainage, or a stream network, which helps filter out received messages. For instance, a farm network may only want to receive information from drainage or stream network, or a drainage network may only be interested in information coming from farms for obvious reasons. Network location filters out geographically dislocated networks or the ones located downstream, which are unlikely to impact upstream networks. Further to that, event detail in the information packet includes event depth/volume, event duration, fertilizer quantity applied. Any additional event information will be governed by the requirements of a predictive model, which is discussed in the next chapter. As far as the predicted parameters for expected drainage are concerned, as discussed in chapter 1, the relevant information necessary to implement a proactive monitoring and management system is drainage depth/volume (Q), fertilizer loads in the drainage (TON), start time (t_1), and duration (t_d) of the drainage.

Predicted values of drainage and nutrient dynamics by the sensor node are transmitted to the gateway of drainage network, from where it is relayed to the neighboring farm and stream networks. The farm networks (e.g., farm B) uses the predicted information and local decision support model to decide whether to reuse the drainage or not, and transmit a reuse acknowledgement to the drainage network. In the former case in which network B intends to reuse the drainage, the drainage water, once available from farm A, is allowed to drain into the drainage reuse bay (through a control pump) instead of the main drainage bay. From the reuse bay, the drainage is then pumped into the irrigation bay of farm B. In case none of the networks send reuse acknowledgements, the drainage would be drained into the main drainage bay. The stream network can then decide, based on the predicted values for nutrients, whether

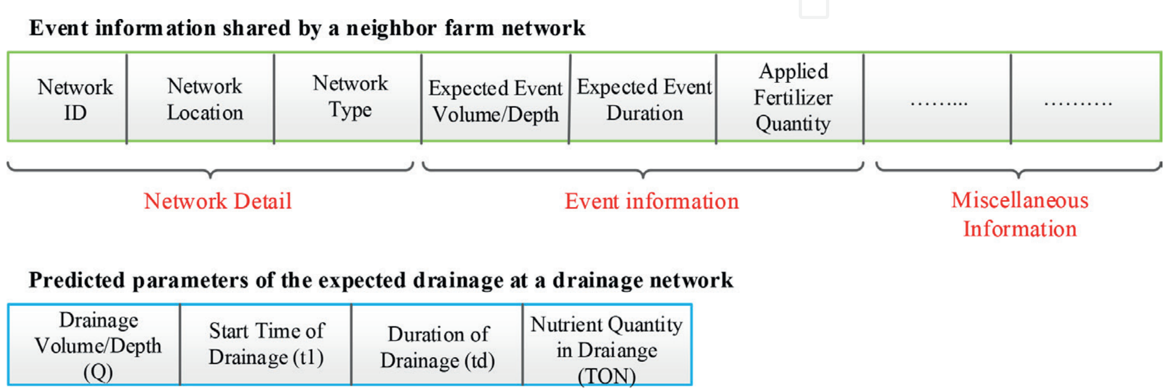

Figure 2.
Parameters related to upcoming event shared by neighbor networks and the predicted variables for the resulting drainage event.

to divert the flow in case of high-nutrient outflows or to otherwise allow it to enter the stream.

3. Architectural detail

The fundamental part of the WQMCM framework is that individual networks learn their environment to predict the impact of events elsewhere in the catchment on their own zone of influence. The predicted drainage information can be beneficial for adjusting management strategy in a farm or in a stream network accordingly, by adopting drainage reuse, disposal, or treatment. For managing agricultural reuse, the overall architectural detail comprises of various modules encompassing drainage, farm, and stream networks, as illustrated in **Figure 3**. For enabling forecasting of drainage dynamics expected as a result of an event in a neighboring farm, two key modules are developed in the drainage network: neighbor linking model, and drainage and pollutant dynamics module. The neighbor linking model uses neighbor event information and sensed drainage data to link the impactful neighbors. The predictive module further comprises individual models to predict Q, t_1, t_d, and TON. The predicted drainage information is used by decision support models in farm and stream network to enable decision making about its reuse or disposal. Furthermore, this information is further used to adjust sampling rate of the sensors, to capture the approaching drainage flow, at the predicted response time.

It has been emphasized in this chapter that due to inevitable drainage and nutrient losses despite adopting BMPs, it is important to enable mechanism for their reutilization. Therefore, a simplified decision support model is developed just as an example to illustrate the utilization of predicted information for enabling reuse mechanism. The modules of

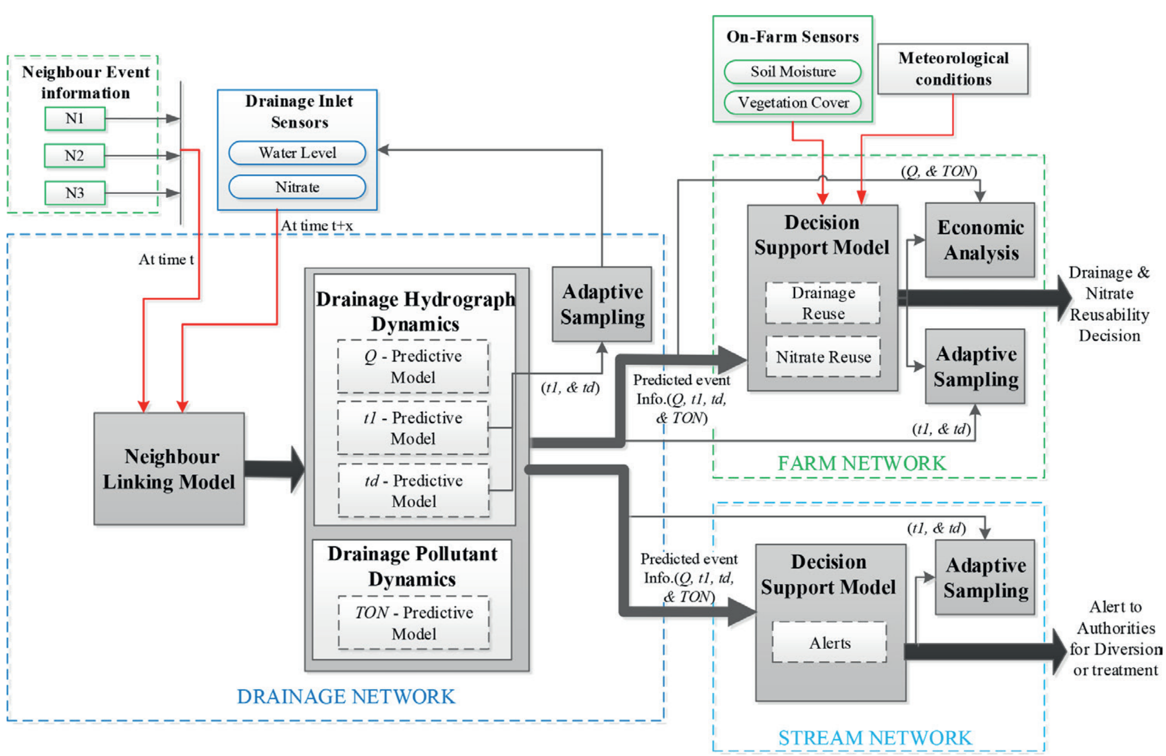

Figure 3.
Block diagram of the WQMCM framework architecture.

drainage network and farm network blocks are briefly introduced. **Figures 4** and **5** found illustrates the functional flow of these modules for both the blocks.

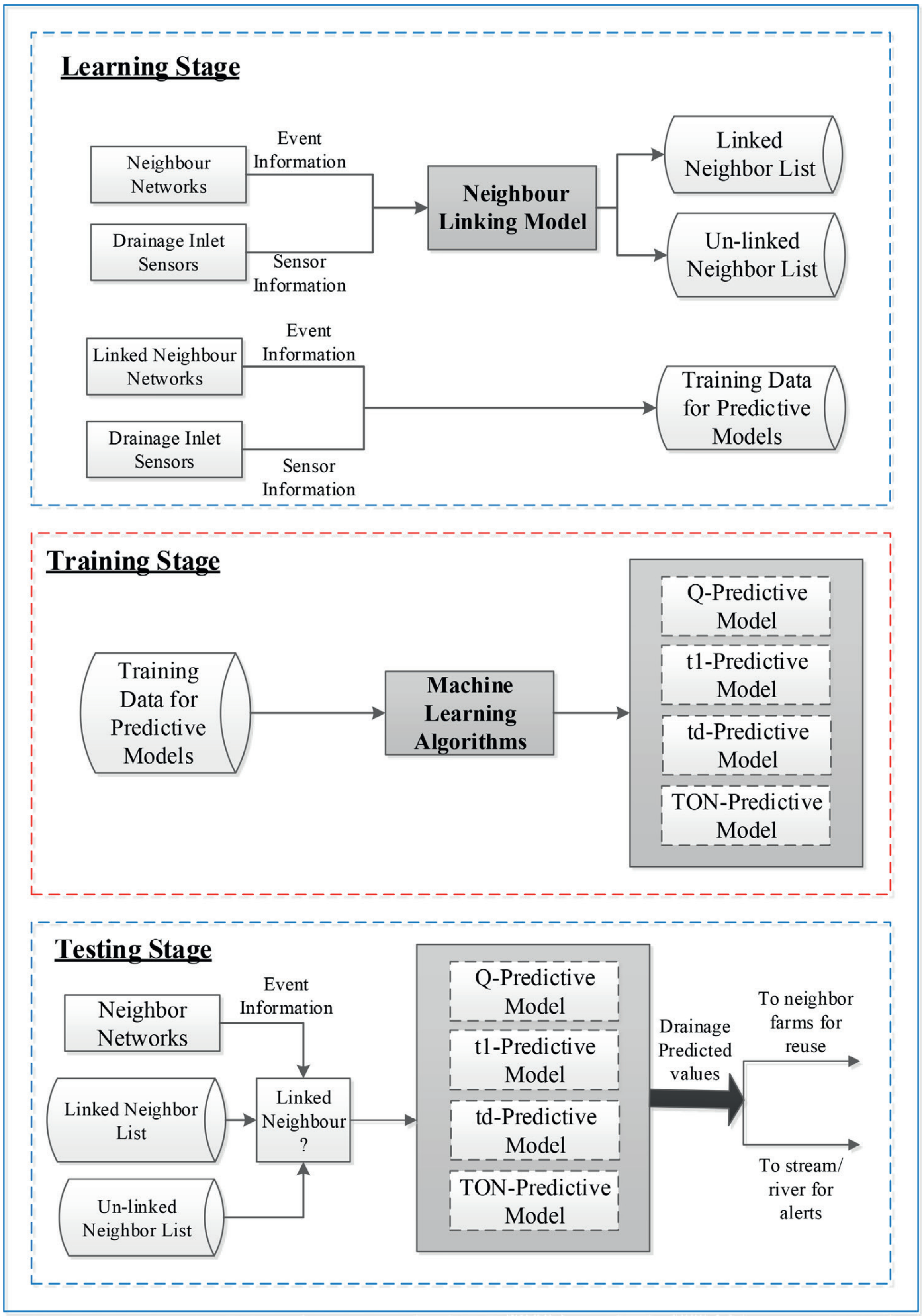

Figure 4.
Functional stages of the drainage network modules, under the WQMCM framework, such as "Learning," "Training," and "Testing."

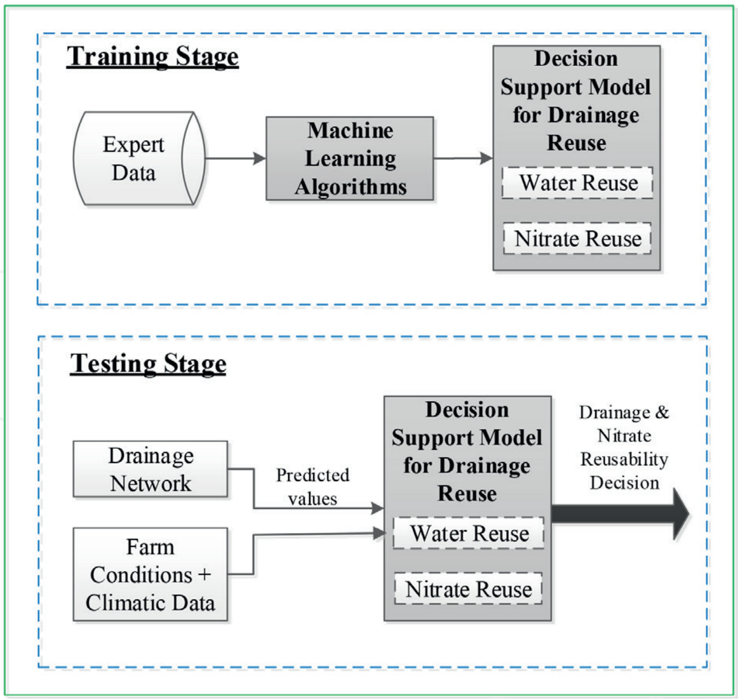

Figure 5.
Functional stages of a decision support model at a farm network, which intends to reuse drainage water, under the WQMCM framework.

3.1 Neighbor linking model

The main purpose of this module in the drainage network is to identify the farm networks that drain into this drainage network. These links are identified over a period of time using a learning process. Firstly, dislocated networks (e.g., located at lower altitudes of the catchment) are filtered out using network location in the shared information packet by the neighbors. Secondly, for the filtered neighbors, training dataset is acquired over a period of time, as respective event information is received from these individual neighbors. Training data consists of (i) the event information packets that were received that particular day, for example, at time t, and (ii) the sensed values of the received drainage and nutrients at the drainage bay at time $t + x$. Here, x refers to the time it takes for drainage to appear in the drainage bay from the time event information is received, and t is ranged between 00 hrs and (x-1) hrs.

For each set of the acquired training data for a particular neighbor, a linear regression model is used to identify the relationship between the sensed drainage and the received event details. This process divides the neighbors, which sent information over the learning phase, into two lists: linked neighbors and un-linked neighbors. Later, for the linked neighbors, sufficient training data are acquired to provide for the development of the predictive models. **Figure 4** illustrates the mechanism of the neighbor linking model in the learning stage section.

3.2 Drainage hydrograph and nutrient dynamics predictive models

Once training dataset is acquired for the linked neighbors, the next step is to develop the models for predicting the drainage hydrograph and nutrient dynamics. Constraints on network nodes (battery life, computing power, availability of sensors, etc.) require a simplified underlying physical model, and a simple machine learning model based on fewer and, ideally, real-time field parameters acquired autonomously and shareable across neighboring farms. Ideally, the model should be based on minimal training samples so that the model can be implementable soon after the deployment of the network. Such models are local in the sense of being valid for a given site (farm in this case). Once developed at the gateway, these models are deployed on the relevant node associated with the particular farm. This facilitates distributed computing where individual nodes of the drainage network, deployed at the outlets of farms, run the learned predictive models for forecasting drainage from those farms. These models can then generate expected drainage hydrograph and nutrients dynamics, which are transmitted to the gateway for further action regarding transmission to neighboring networks.

These models intrinsically self-calibrate because the evolving record of the observations allows them to adapt to the latest condition. This creates portability from one season to the next and from one climate regime to the next. With new data regarding a farm, the models are calibrated at the gateway and re-deployed at the relevant node. However, it is important that a model must maintain a balance between the complexity of the model and the predictive accuracy of the model.

Existing state-of-the-art predictive models are used as a basis to derive low-complexity models for Q, t_1, t_d, and *TON.* A machine learning algorithm, M5 tree, is then used to train the individual models as shown in the training stage of **Figure 4**. Once the models are trained with acceptable prediction performance, the drainage network progresses to the testing stage. In the testing stage, neighbor event information is firstly interpreted using developed neighbor linking lists and then used to predict drainage dynamics using the predictive models, in case of a linked neighbor as illustrated in the testing stage of **Figure 4**. As mentioned earlier, the model accuracy can be continuously improved by learning the evolving instances in the testing stage.

The algorithmic flow of these stages for a drainage network is illustrated using a flow diagram in **Figure 6**. When information is received at the data sink of the drainage network by either a drainage network sensor or a neighbor farm, firstly it is checked whether the network is in the learning stage or not. In such a case, the information is passed on to the neighbor linking model. If the model is in testing stage, then in case the received data packet is from a neighbor, it is checked if the neighbor ID is in the linked neighbor list. If it is an already linked neighbor, then the relevant trained predictive models for that particular neighbor are used to predict the event values. Otherwise, it is determined if the neighbor is an un-linked neighbor, in which case the event packet information is disregarded. In case the received data packet is from the drainage sensor, then the data within the packet are linked with the relevant neighbor information and saved for improving the models later.

3.3 Decision support model (for drainage reuse in a farm)

For the decision support model, the challenge lies in designing a model which takes into account local field conditions, predicted dynamics, and expert knowledge. Unlike the predictive models in the drainage network, this model essentially runs on the gateway of the farm network. The model complexity can substantially vary depending upon the requirements set by the farmer. For example, the farmer may want the model to advice on the possible repercussions of drainage reuse on crop. Furthermore, in case the available drainage is not enough or high in N, the model may also advise on mixing drainage and freshwater for irrigation to fulfill its requirements or to disregard the excess nutrients in the drainage which the farm may not want to reuse. These complexities are highly scenario dependent and require sufficient expert knowledge and data to address. In this chapter, a simplified decision support model is

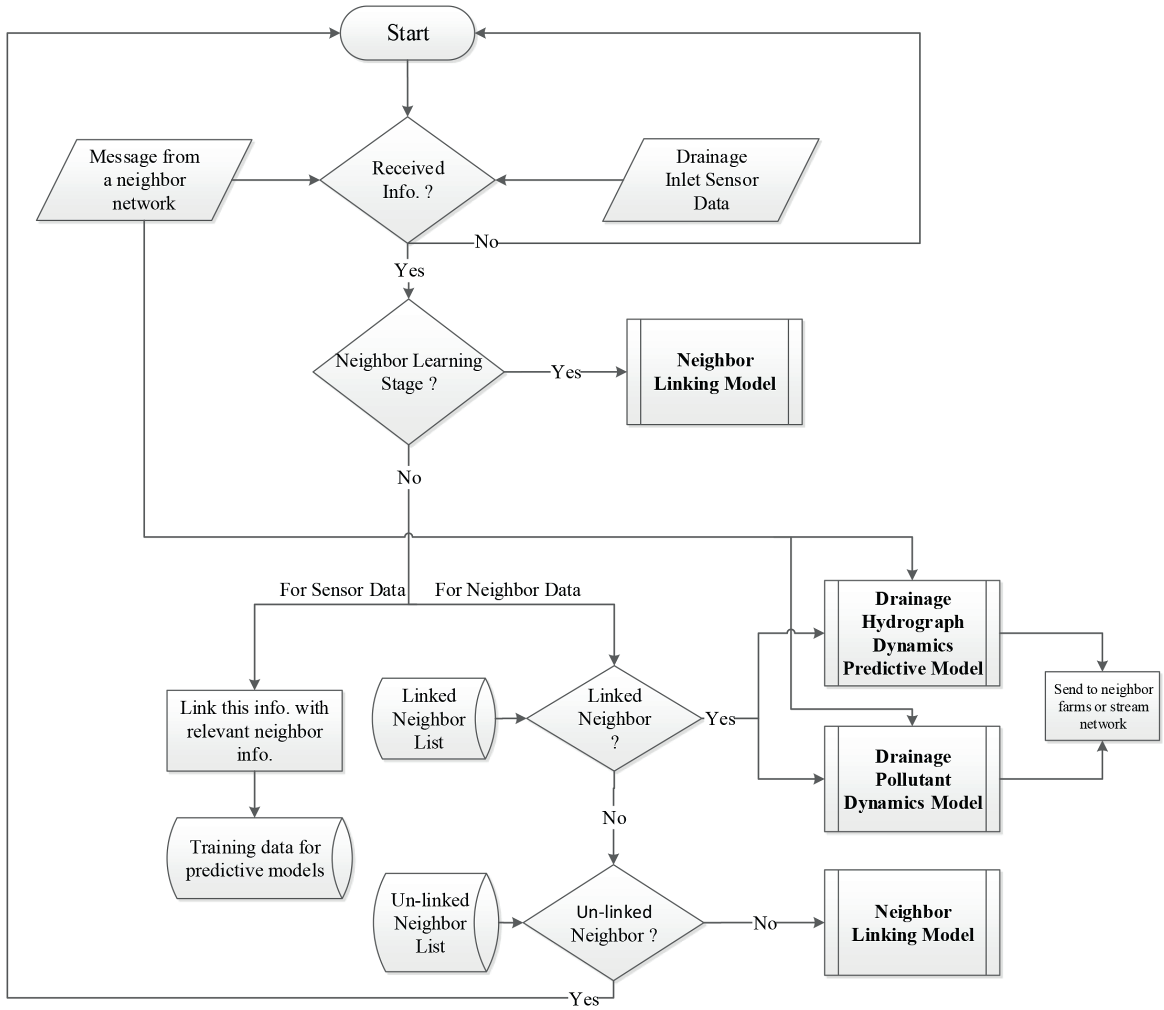

Figure 6.
Basic algorithm running at a sensor node of a drainage network under WQMCM framework.

developed as an example to demonstrate the utilization of predicted information for enabling the reuse mechanism.

Figure 6 illustrates the functional stages of the development and use of the decision model for drainage reuse in a farm. In the training stage, expert knowledge and machine learning algorithms are used to implement simplified models for drainage and nutrient reuse. Once the model is trained, predicted drainage information received from a drainage network, and local field conditions and climatic data are used to classify the usability of the drainage water and nutrients (as shown in the testing stage of **Figure 6**).

4. Conclusions

This chapter presented the water quality monitoring, control, and management framework for a collaborative control and management of agricultural drainage water for addressing the issue of prevalent water crisis. The framework leverages individual networked farms and streams into an integrated water management mechanism. Such a monitoring system should enable each farm to share information about its drainage flow with neighbor networks, for example, with a drainage bay network, which can then process the information for timely treatment, disposal, or reuse of the drainage.

To implement the drainage management, the architecture of the WQMCM framework comprises various modules. Modules for a drainage bay network include neighbor linking model, and predictive models for drainage and pollutant dynamics, whereas, for a farm network, a decision support model is used to ascertain the reusability of the predicted drainage event. The overall functionality of the framework is explored in terms of stages of learning, training, and testing. In the learning stage, neighbor linking model is used to determine the correlation of events in various farm networks with the events received in the drainage bay by the drainage network. The model results in identifying linked and un-linked farm networks by using a combination of geographical filtering and linear regression methods. For the linked networks, training dataset is acquired to provide for the development of the predictive models for drainage dynamics and nitrate losses. When the drainage network has learned the environment and the predictive models for individual farms, it is brought into a testing stage. In this stage, neighbor event information is firstly interpreted using developed neighbor linking lists and then, in case of a linked neighbor, used to predict drainage dynamics. These predicted values are transmitted by a drainage network to other farms and stream networks so that they can take a decision for the reuse, disposal, or conservation of the expected drainage.

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