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Methods for Direct Load Calculations in Agricultural Watersheds

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List of Acronyms

BOD	Biochemical Oxygen Demand
C	concentration
chl	chlorophyll a
DO	dissolved oxygen
DWR	Department of Water Resources
ITRC	Irrigation Training and Research Center
JMP	statistical software
kg	kilograms
l	liters
L	load
l/s	liters per second
mg/L	milligrams per liter
mL	milliliter
N	number of continuous samples
n	number of grab samples
NIST	National Institute of Standards and Technology
TAN	Ammonia as nitrogen (Total ammonia + ammonium nitrogen)
NO_3	Nitrate
PO_4	Dissolved Orthophosphate as Phosphorus
ppb	parts per billion
Q	flow
QA	quality assurance
QC	quality control
SpC	specific conductivity
t	time
TDS	Total Dissolved Solids
TMDL	Total Maximum Daily Load
TN	total nitrogen
TP	total phosphorus
TSS	total suspended solids
V	volume
YSI	Yellow Springs International
µS/cm	micro seimens per centimeter

Abstract

Measuring the discharge of diffuse pollution from agricultural watersheds as part of implementing total maximum daily load (TMDL) programs presents unique challenges. Flows in agricultural watersheds, particularly in Mediterranean climates, can be predominately irrigation runoff and exhibit large diurnal fluctuation in both volume and concentration. Flow and pollutant concentrations in these smaller watersheds dominated by human activity do not conform to a normal distribution and it is not clear if parametric methods are appropriate or accurate for TMDL calculations. The objective of this study was to compare the accuracy of five load estimation methods to calculate pollutant loads from agricultural watersheds. Calculation of loads using results from discrete (grab) samples was compared with the true-load computed using *in situ* continuous monitoring measurements. A new method is introduced that uses a non-parametric measure of central tendency (the median) to calculate loads (median-load). The median-load method was compared to a more commonly used parametric estimation methods which rely on using the mean as a measure of central tendency (mean-load and daily-load), a method that utilizes the total flow volume (volume-load), and a method that uses measure of flow at the time of sampling (instantaneous-load). Using measurements from ten watersheds in the San Joaquin Valley of California, the average percent error compared to the true-load for total dissolved solids (TDS) were 4.9% for the median-load, 6.4% for the mean-load, 6.3% for the volume-load, 12.3% for the instantaneous-load, and 17.3% for the daily-load methods of calculation. The results of this study show that parametric methods are surprisingly accurate, even for data that have starkly non-normal distributions and are highly skewed.

The volume-load method is recommended for the calculation of diffuse pollution loads from agricultural watersheds when complete or nearly complete continuous flow data sets are available. If there are significant missing flow data, then the mean-load or median-load estimates should be used. Where pollutant concentrations and flows do not conform to the normal distribution or where the data distribution is unknown, the median-load method is most appropriate, but the mean-load method is accurate. In the absence of flow monitoring, instantaneous measures can be used, but using average daily flow is not recommended.

Introduction

In the United States, under section 303(d) of the Clean Water Act, waterbodies that are too polluted or otherwise degraded to meet established water quality standards must be identified (listed) and the maximum amount of a pollutant that a listed waterbody can receive and still safely meet designated uses must be specified (United States Environmental Protection Agency, 2012b). Since the 1970s, the National Pollutant Discharge Elimination System (NPDES) and other programs have been used successfully to regulate point source discharges in the United States by defining the concentrations of pollutants that can be discharged by individual emitters (United States Environmental Protection Agency, 2000). For a number of reasons, including population growth, merely limiting the concentration of pollutants from point sources has not been sufficiently protective of many waterbodies and beneficial uses such as fishing and swimming must be restricted (United States Environmental Protection Agency, 2012b, a). Regulations based on a total maximal daily load (TMDL), which restrict the total mass of pollutant that can be discharged into surface waterbodies, have been implemented since approximately 1996, but enforcement is difficult because sources of diffuse pollution are difficult to identify and measure (Drolc et al., 2007; Stringfellow et al., 2008a; Stringfellow, 2008; Tiemeyer et al., 2010). Since 1996, over 49,000 TMDLs have been approved for impaired water bodies, but only 1,926 of these waterbodies have been improved to the extent that they have attained all water quality uses (United States Environmental Protection Agency, 2012a).
Agricultural activities are identified as a major cause of water quality impairment that result in listing a water body for TMDL development. Approximately 200,000 kilometers of river and streams and 15,000 square-kilometers of lakes, reservoirs, ponds, bays, and estuaries are listed as impaired by pollution from agricultural activities (United States Environmental Protection Agency, 2012a). Determining loads of pollutants entering surface waters is challenging, particularly from irrigated farmlands, where flows may be intermittent and concentrations of pollutants highly variable (Kratzer et al., 2004; Drolc et al., 2007; Stringfellow, 2008; Stringfellow et al., 2008b; Tiemeyer et al., 2010; Kratzer et al., 2011). As a result of these technical challenges, run-off from farmlands is only beginning to be regulated and initial efforts have focused on monitoring and characterization of agricultural run-off (e.g. Kratzer et al., 2004; Drolc et al., 2007; Stringfellow et al., 2008a; Stringfellow, 2008; Stringfellow et al., 2008b; Kratzer et al., 2011).

Accurate quantification of loads is critical to assessing compliance with TMDL programs and appropriate methods for monitoring agricultural drainage must be developed. For load estimation, a monitoring method must be deployed that is suitable for the expected flow behaviors of the watershed. Common water quality monitoring methods are discrete (grab) sampling, where samples are collected infrequently, and *in situ* continuous monitoring, where sensors are deployed to collect data continuously (Richards and Holloway, 1987; Kot et al., 2000; Vrana et al., 2005; Hildebrandt et al., 2006; Stringfellow et al., 2008a; Stringfellow, 2008; Stringfellow et al., 2008b). If a pollutant can be measured continuously, then the continuous measurement of concentration and flow can be combined to calculate the actual load of the pollutant in the stream (true-load). Constituents that can be measured by continuous sampling, however, are limited and therefore most constituent sampling data is collected periodically as grab samples. For these constituents that can only be periodically sampled, it is necessary to

determine if the data being collected can be used to accurately estimate the true-load of the system.
Previous studies have investigated methods for estimating the pollutant loads in large rivers and in smaller streams dominated by precipitation driven events (storm flows) (Richards and Holloway, 1987; Preston et al., 1989; Robertson and Roerish, 1999; Fogle et al., 2003; Domagalski et al., 2008; Henjum et al., 2010; Lebo et al., 2012). Methods broadly fall into three categories: averaging, ratio, and regression methods (Preston et al., 1989). Averaging methods combine parametric estimates of central tendency for concentration and flow to estimate stream and river loads (Richards and Holloway, 1987; Preston et al., 1989; Fogle et al., 2003; Henjum et al., 2010; Lebo et al., 2012). Averaging methods are widely used and have been applied to watersheds with flows over 200 m^3/s to flows less than 0.1 m^3/s (Fogle et al., 2003; Lebo et al., 2012). Ratio methods combine averaging methods with statistical estimates of error to calculate loads (Richards and Holloway, 1987; Preston et al., 1989). Ratio methods have been applied to larger rivers and are considered most accurate when supplemented with data from high flow events (Richards and Holloway, 1987; Preston et al., 1989; Preston et al., 1992). Their applicability to smaller, less frequently sampled systems has not been established. Regression based methods, also known as rating curves, are based on regression models and are only applicable to systems where concentrations are dependent on flow (Preston et al., 1989; Robertson and Roerish, 1999; Domagalski et al., 2008). Regression methods are not appropriate for many agricultural streams, where pollutant concentrations and flows are not correlated (Kratzer et al., 2004; Domagalski et al., 2008; Kratzer et al., 2011).

In this study, we investigated a novel method for calculating loads using non-parametric estimations of central tendency (median) in addition to other previously reported methods (by averaging flow, using total flow volume, using daily average flow, and taking the instantaneous flow) and the true-load as determined by continuous monitoring. Previous studies have examined the question of how much sampling is required to estimate load accurately (Richards and Holloway, 1987; Robertson and Roerish, 1999; Fogle et al., 2003; Henjum et al., 2010; Melwani et al., 2010). In this study we ask the question: given a typical sampling frequency determined by regulatory and logistic considerations, how accurate are estimates of loading made from routinely scheduled monitoring data collected in agricultural streams as part of TMDL programs? We compare the true-load of total dissolved solids (TDS) as determined by continuous measurement of specific conductance (SpC) and flow, with the loading of TDS calculated from independent measurements determined from grab samples collected as part of a TMDL implementation program.

Flow and pollutant concentrations in agricultural ecosystems dominated by irrigated agriculture do not conform to a normal distribution and it is not clear if parametric methods are appropriate or accurate for TMDL calculations. The objective of this study was to compare the accuracy of five load estimation methods to calculate pollutant loads from agricultural watersheds. We tested the hypothesis that non-parametric estimates of central tendency would be more appropriate for measuring pollutant loads from irrigated agriculture. Calculation of loads using results from discrete (grab) samples was compared with the true-load computed using *in situ* continuous monitoring measurements. A new method is introduced that uses a non-parametric measure of central tendency (the median) to calculate loads (median-load). The median-load method was compared to a more commonly used parametric estimation methods which rely on using the mean as a measure of central tendency (mean-load and daily-load), a method that utilizes the total flow volume (volume-load), and a method that uses measure of flow at the time of sampling (instantaneous-load). The objective of this study is to evaluate which measure of flow produces the best estimations of TDS load (*i.e.* the lowest magnitude of percent error) for all sites, irrespective of the sampling frequency and data distribution shapes.

Methods

Site descriptions and characterizations

The sample site locations and predominate characteristics for each watershed are given in Table 1 and Figure 1. All sample sites are located on the western side of the San Joaquin Valley in central California, with the exception of MID Miller Lake, which is located on the eastern side of the valley. The western side of the valley drains the Coastal Range, which does not accumulate a snow-pack. The valley has a semi-arid Mediterranean climate and receives precipitation mostly between October and March and has a distinct dry-season. In areas that are not farmed in this region, dry-season flows are non-existent, whereas in farmed areas, creeks fill with agricultural return flows even in the dry-season (Figure 2). Land use in the San Joaquin Valley is dominated by agriculture. Ingram, Orestimba, and Del Puerto Creeks originate in the Coast Range and follow historical creek beds until they reach the valley floor. Due to the low relief in the valley, all of the creek beds have been channelized to improve their function for drainage conveyance. These creeks represent typical farm drains for the west side of the Central Valley. Marshall Road Drain, Spanish Grant Drain, and San Luis Drain End receive agricultural runoff which is collected and transported via open canal or ditch and eventually piped through large concrete drains. BCID-New Jerusalem Drain is a part of a tile drainage system where agricultural runoff is collected and transported completely by underground pipeline. MID Miller Lake, Mud Slough, and Salt Slough are channels which receive both agricultural runoff and wetland drainage.

Soils on the west side of the San Joaquin River are predominantly derived from alluvial deposits originating in the Coast Range which is composed of marine and continental sedimentary rocks (Panshin et al., 1998). West side soils have a fine texture with high clay content and lower permeability compared to east side soils. The dominant soils in the region have Revised Universal Soil Loss Equation erodibility factors (K) between 0.24 and 0.42, are considered moderately erodible, and may produce high rates of runoff (Renard et al., 1991; U.S. Department of Agriculture, 2008). Agricultural runoff from this region can have high concentrations of suspended sediments in addition to soluble reactive phosphate, nitrate, and other pollutants (Kratzer et al., 2004; Stringfellow, 2008). In poorly drained agricultural landscapes, tile drains and drainage ditches are constructed to convey surface water and groundwater away from fields for the purpose of improving crop production (Needelman et al., 2007). This region is characterized by slopes of 0 to 0.7 percent. Runoff and groundwater is managed using a network of artificial and modified natural drainages.

Sampling and Field Water Quality Measurements

All sample collection, data evaluation, and analysis in the project was collected in accordance with rigorous QA/QC procedures (Borglin et al., 2006; California Department of Fish and Game, 2007; Stringfellow et al., 2008a; Stringfellow, 2008). Field sampling consisted of collecting water samples, measuring water quality with a sonde, and recording field conditions at sites within the study area. The day before sample collection, a YSI 6600 Sonde connected to YSI 650 MDS handset was calibrated following procedures in the YSI 6-Series Environmental Monitoring Systems Handbook (Yellow Springs Instrument Co. Inc., 2002). Specific conductance (SpC) was measured with a temperature compensated electrical conductivity probe and calibrated using a 1408 µS/cm conductivity standard (Radiometer Analytical SAS, Lyon, France). This measurement of SpC was used for grab-sample based load calculations (eq. iii and iv). Total dissolved solids (TDS) is determined from the SpC measurement by the following relationship,

$$\text{TDS [mg/l]} = 0.64 * \text{SpC } [\mu\text{S/cm}] \qquad \text{(i)}$$

Temperature calibration is checked against a NIST certified thermometer.

At most sites, field samples were typically collected weekly or biweekly during the 2007 irrigation year from April to September. However, a few study sites were sampled less frequently. Marshall Road and Spanish Grant Drains were only sampled three times between May and June and New Jerusalem Drain was sampled four times between June and September. The total number of grab samples for each site is listed in Table 2.

Continuous monitoring stations were used to measure flow and SpC every fifteen minutes, except for MID Miller Lake which was measured in hourly intervals. The total number of flow measurements as well as the mean and median flow and TDS values for each site are listed in Table 2 (TDS values are calculated from continuous SpC values using equation i). Stations were visited monthly for instrument maintenance, cleaning, QA checks, downloading data, and clearing debris and sediments from weirs and other flow measuring structures. Continuous measurements of SpC were made with YSI 600 Sondes (Yellow Springs Instruments, Yellow Springs, OH). This measurement of SpC was used for true-load calculations (eq.ii). H355 bubblers equipped with H350-XL data loggers (Design Analysis Associates Inc., Logan, UT) were used to measure stage. QA on the SpC probe was conducted by cleaning the probe with a small brush then comparing SpC measurements with that of an independently calibrated sonde. Stage QA was conducted by measuring a sharp crested weir structure with a weir stick (Cal Poly ITRC, San Luis Obispo, CA).

Data is missed on occasion during continuous monitoring measurements due to equipment malfunction and other factors, including vandalism. For the load calculation methods that required a complete data set (true-load or array method), an average value of the previous and subsequent values was used to fill gaps in continuous flow data. For the remaining load calculation methods (mean-, median-, daily-, and instantaneous-load methods), the unmodified flow data set is used for load calculations and these short and infrequent gaps in continuous data have only a small effect on load calculations. The total number of missing flow measurements for each site is listed in Table 2. More than half of the sites have either one or no missing continuous measurements, and the remaining sites have less than 6% missing continuous data. Values of SpC lower than 100 µS/cm are below the detection limit of the sensors and the load is assumed to be 0 kg.

All distribution and statistical analyses of flow and TDS concentration from continuous monitoring are conducted using JMP 9 software (SAS Institute Inc). Skewness is calculated in JMP using the adjusted Fisher-Pearson standardized moment coefficient (Esralew et al., 2012).

Mass load estimations

The true-load is computed by integration of concentration versus time plots from continuous monitoring measurements during the irrigation season. This is done by summing the product of the measured flow and corresponding TDS concentration, given in the following equation,

$$\text{True-load}\,[\text{mass}] = \sum_{i=1}^{N} C_i Q_i \Delta t_i \qquad \text{(ii)}$$

where C_i is the concentration of sample i [mass/volume], Q_i is the flow rate at the time of continuous sample i [volume/time], and Δt_i is the time between the ith and (i+1)th continuous measurement (here, Δt_i = 15 min for all sites except for MID Miller Lake where Δt_i = 60 min). The number of continuous measurement samples is N.

Grab sampling data collected during the irrigation season was used to estimate TDS load by five methods. Load estimates by the flow volume method are calculated by summing the product of the grab sample concentration and the total flow volume over each calculation interval (determined by the intervals between grab-sampling events), given by the following equation,

$$\text{Volume-load}_{\text{grab}}[\text{mass}] = \sum_{k=1}^{n} C_k V_k \qquad \text{(iii)}$$

where C_k is the concentration of grab sample k [mass/volume], n is the number of calculation intervals, and V_k is the total flow volume over the kth calculation interval. The flow volume V_k is found from the time-integration of the continuous flow measurements over the calculation interval k, or $V = \sum_{j=1}^{N} Q_j \Delta t_j$, where Q_j is the flow rate at the time of continuous measurement j [volume/time], Δt_j is the time between the jth and the $(j+1)$th continuous measurement (all Δt_j = 15 min for all sites except for MID Miller Lake where Δt_j = 60 min for a portion of the season), and N is the number of continuous measurements over the time interval.

Load estimates by mean, median, daily mean, and instantaneous methods are calculated by summing the products of the grab sample concentrations and one of four corresponding representative measures of flow $\overline{Q}_k$ during the calculation interval, given by the following equation,

$$\text{Load}_{\text{grab}}[\text{mass}] = \sum_{k=1}^{n} C_k \overline{Q}_k \Delta t_k \qquad \text{(iv)}$$

where C_k is the concentration of grab sample k [mass/volume], Δt_k is half the time between the (k-1)th and ($k+1$)th measurement or the duration of the calculation interval, and n is the number of calculation intervals. The median and the mean flow from continuous monitoring measurements over each calculation interval are used as flow $\overline{Q_k}$ for the "median-load" and "mean-load" calculations, respectively. The mean flow for the day the grab sample k is taken is used as the measure of flow $\overline{Q_k}$ for the "daily-load" calculation. The instantaneous flow at the exact time of sampling is used as $\overline{Q_k}$ to compute "instantaneous-load." The median-load method is unique to this paper, the volume-load, mean-load, instantaneous-load and the mean-daily-load methods have been used in previous studies (Preston et al., 1989; Fogle et al., 2003; Henjum et al., 2010; Lebo et al., 2012).

Total flow volumes corresponding to the five methods were also calculated for each site over the irrigation season in order to isolate the influence of the different measures of flow on the overall mass load estimations. The total volume using the true-load method or the "true-volume" is calculated by a time-integration of flow over the irrigation season, given by the following equation,

$$\text{True - volume} = \sum_{i=1}^{N} Q_i \Delta t_i \qquad \text{(v)}$$

where Q_i is the flow rate at the time of continuous sample i [volume/time], and Δt_i is the time between the ith and (i+1)th continuous measurement (here, Δt_i = 15 min for all sites except for Miller Lake where Δt_i = 60 min for a portion of the season). The number of continuous measurement samples is N. Total volume using the volume-load method is an identical calculation and hence is equal to the true-volume.

Total volumes estimated by mean, median, daily mean, and instantaneous methods are computed by summing the corresponding representative measures of flow over the time interval, given by the following equation,

$$\text{Volume}_{\text{grab}}[\text{mass}] = \sum_{k=1}^{n} \overline{Q_k} \Delta t_k \qquad \text{(vi)}$$

where Δt_k is the calculation interval and n is the number of calculation intervals. The corresponding representative measures of flow $\overline{Q_k}$ are found in the same manner as in equation iv.

To illustrate the methods, a summary of TDS load calculations computed using the load estimation methods (equations ii-iv) for Ingram Creek are given as an example in Table 3. Over the study period, a total of 20 grab samples were taken in Ingram Creek. The grab sample date defines the middle of the calculation interval. The grab sample date, grab sample concentration, and start and end dates of each calculation interval are shown in Table 3. The grab sampling-based load estimations and the true-load are computed over identical calculation intervals to aid comparisons between the true-load and the load estimates across each interval in the study period. From these values (using equation iv), the grab sampling volume-load, mean-load, median-load, daily-load, and instantaneous-load are computed for each calculation interval. The loads from each calculation interval are summed to give the total load over the study period.

Percent error for each load estimate is computed as a comparison with the true-load from continuous data, by the following equation,

$$\%\,\text{error} = 100 * \left(\frac{\text{load estimate - true-load}}{\text{true-load}} \right) \qquad \text{(vii)}$$

Hence, a negative percent error indicates an underestimate of the true-load and a positive percent error is an overestimate. The absolute value of percent error is used to compare the accuracy of the estimations across sites and for computation of average percent errors for each estimation method.

All load calculation analyses were conducted using the Microsoft Excel spreadsheet package. Distribution and box-plot analysis were calculated using JMP software.

Results and discussion

Flows in artificial ecosystems

The San Joaquin River and its tributaries have implemented TMDLs for a number of constituents, including mercury, a variety of pesticides and herbicides, dissolved oxygen, and salts, including boron, nitrate, and selenium (Quinn and Hanna, 2003; Stringfellow, 2008; Stringfellow et al., 2008b). The San Joaquin River Valley has a semi-arid Mediterranean climate and is the location of four of the top ten agricultural counties in the United States (San Joaquin, Stanislaus, Merced and Fresno Counties). The mountains of the Coastal Range on the western portion of the San Joaquin Valley do not accumulate snow-pack and do not receive significant precipitation in the dry-season (April through September). The watersheds included in this study are hydrologically modified and the streams experience dry-season flows that consist entirely of irrigation return flow (Stringfellow and Jain, 2010). In the dry season, these flows have strong diurnal fluctuations as a result of irrigation patterns (Figure 3). Irrigation return flows are a major source of flow and nutrients to the San Joaquin River (Kratzer et al., 2004; Stringfellow et al., 2008a).

Data from ten watersheds (Table 1), where flow and specific conductance were measured continuously, were included in this study. Grab sampling and continuous monitoring of water quality and flow was carried out in these watersheds as part of various regulatory compliance efforts. Flows as a function of time over representative two week periods for three of the sites, Ingram Creek, Marshall Road Drain, and Del Puerto Creek, are shown in Figure 3. The artificial nature of flows in these drainages is apparent. For example, in Ingram Creek between April 5 to 18, 2007, each day the maximum flow occurred between 5:00 and 7:30 AM, as a result of morning irrigation, and the daily minimum flow occurs between 10:30 AM and 6:15 PM after irrigation is completed. The daily swing in flow is as large as 250 l/s. TDS concentrations are also varied, but did not exhibit a regular diurnal pattern (Figure 3). Similar temporal fluctuations due to irrigation were observed at all sites.

The artificial nature of flows in watersheds dominated by irrigated agriculture present unique challenges for evaluating diffuse pollution loads as part of TMDL programs. Moreover, the variability in the temporal behavior also underscores the need to identify a load estimation method that accuracy predicts true-load for agricultural watersheds that can be applied irrespective of flow and concentration patterns. This is important particularly for watersheds where the data distribution is not known *a priori* or if irrigation patterns change or flows are not predictable.

Distribution of flow & water quality data

Histograms and boxplots for flow and TDS at three representative sites (Ingram Creek, Marshall Road Drain, and Del Puerto Creek) are given in Figure 4. Flow and TDS distributions for all sites do not fit a normal, log-normal, or Weibull distribution (α = 0.05). The normal approximation is shown for each flow and TDS distribution in Figure 4 to illustrate the relationship of this data to a normal distribution. The flow distributions for the sites in this study vary from symmetric, but non-Normal, to moderately skewed, to highly skewed and are listed in Table 2. Mean and median flow and TDS concentration values for each site are also given in Table 2. Since the flow and water quality data do not fit a normal distribution and most of the sites have some degree of skewness, the use of mean as a measure of central tendency may be misleading. Previous studies have not reported distribution histograms or box-plots, but most data were reported as fitting normal or log-normal distributions.

Sampling frequency

Typically for urban water pollutant monitoring, sampling is conducted in response to storm events, and high frequency sampling is conducted during first flush or peak-flow events (Melwani et al., 2010). Studies have been conducted on storm-flows in urban watersheds to compare loads calculated from grab sampling and true-loads calculated from continuous concentration and flow monitoring. In some studies, “sampling” was simulated by selecting individual measurements from the continuous monitoring record. In highly event responsive systems, sub-daily sampling frequencies, ranging from as few as four samples per day (Richards and Holloway, 1987) to sampling every ten minutes (Fogle et al., 2003) or even every minute (Henjum et al., 2010), were recommended. Other studies suggest that loads from non-event responsive systems are accurately estimated using a daily sampling frequency (Preston et al., 1989). Sampling with high frequency in agricultural watersheds is not practical. Flows are highly variable in agricultural watersheds (Figure 3) with flows varying daily and therefore peak-flow monitoring is not practical (Kratzer et al., 2004; Stringfellow et al., 2008a).

Generally, precision and accuracy of load estimates improve with sampling frequency (Richards and Holloway, 1987). Development of an appropriate sampling strategy is particularly difficult for streams where flow and pollutant concentration trends have not previously been characterized or are inconsistent and for streams with strong diurnal variations in flow and water quality (Richards and Holloway, 1987; Preston et al., 1989; Fogle et al., 2003). Robertson and Roerish (1999) conducted one year studies in small flashy streams (eight sites in agricultural areas with drainage areas of 14 – 110 km^2) and utilized a regression-based approach with daily average stream flow to estimate loads. They found monthly grab sampling with supplementary sampling after storms tends to overestimate loads by 25 to 50% as compared with the true-load, determined from continuous monitoring data of concentration and flow. Notably, biweekly sampling (*i.e.* every other week) with additional sampling after storms only gave slightly smaller error and Robertson and Roerish (1999) conclude that the modest improvement is not worth the doubled sampling effort.

Although ideally monitoring programs for TMDL management should be designed based on statistical certainty, in reality there are significant limits on the frequency of sampling that can be conducted in agricultural areas as part of any TMDL or other monitoring program. The frequency of sampling is typically determined by regulatory requirements (which are typically monthly or quarterly) and tight budgets. Logistical constraints, including the large distances between sampling stations and the number of stations to be sampled in order to accurately characterize an agriculturally impacted river, do not allow sampling to occur as frequently as prior studies suggest is optimal.

Previous studies have suggested time of day of sampling is important because pollutant concentrations can fluctuate diurnally (Fogle et al., 2003). Thus, they recommend collecting grab samples at the time of day nearest the daily mean. However, this is not practical for agricultural discharges, as the sampling data required to determine the time of the daily mean may not be available or even feasible to collect. Additionally, the time of day of the daily mean may fluctuate over the season or occur at a time of day that is impractical to collect grab samples. In our data sets, we found large variations in TDS (Figure 3), but not a daily pattern that would indicate a specific bias associated with sampling times.

Grab samples were collected in these watersheds as part of a TMDL research program (Stringfellow et al., 2008a). Samples were collected on a regular schedule, or in the case of Marshall Road, New Jerusalem, and Spanish Grant Drains, as part of a special sampling program to determine water quality in agricultural drainages that were not included in the regular sampling program. As for many monitoring programs, the sampling schedule was determined by program objectives and resource limitations (Stringfellow et al., 2008a). In this study we investigated how accurate the load estimation can be, using data typically available for agricultural ecosystems. How accurate and useful is grab sampling data for estimating true-load and what are the factors affecting accuracy? Furthermore, what are the most appropriate statistical approaches for analysis of this data?

Regression and rating curve methods

There was either a weak or not significant relationship between TDS and flow for these watersheds ($0.0001<R^2 < 0.34$; see Table 2), so regression methods, such as the LOADEST model, are not appropriate for calculating loads. LOADEST is unable to compute loads if less than 25 water quality samples are available over a period of 2 years and the correlation between flow and sample concentration is poor (Runkel et al., 2004). These requirements make regression methods of limited use for load analysis in many agricultural watersheds.

Other studies have also found that pollutant concentration is not a function of flow in agricultural watersheds dominated by artificial hydrology. The US Geological Survey has tracked the trends in nutrient concentrations (nitrate, ammonia, total nitrogen, orthophosphate, and total phosphorus) and flows from point and nonpoint sources between 1975–2004 in the Sacramento, San Joaquin, and Santa Ana River basins in California and reported that LOADEST had a high standard error of prediction compared to the true load for watersheds dominated by irrigated agriculture (Kratzer et al., 2011).

Domagalski et al. (2008) compared nutrient and organo-nitrogen transport in five agricultural watersheds in Washington, Nebraska, Indiana, Maryland, and California with varying climatic, land-use, and irrigation patterns. In the first four sites there was a strong relationship between stream flow and concentration and annual load estimation for those sites was conducted using the multiple regression estimator LOADEST. The remaining site, Mustang Creek in the lower Merced River basin of San Joaquin Valley, has an ephemeral nature with the majority of flow a result of rainfall during the winter and dry-season irrigation flow. This watershed has a poor correlation between flow and concentration and hence LOADEST was not used. Instead, annual load estimates for Mustang Creek were made by summing the storm-driven loads calculated from concentration and water volume measurements after each storm (Domagalski et al., 2008). This approach is similar to the volume-load method used in this paper.

Load calculations and errors

The true TDS load in these watersheds was determined using sub-hourly continuous TDS and flow data (Table 4), as described above. In Table 4, the true-load is compared to the estimated loads using grab sampling data and the error is reported (eq. vii). Overall, using measurements from the ten watersheds, the average percent error compared to the true-load for TDS were 4.9% for the median-load, 6.4% for the mean-load, 6.3% for the volume-load, 12.3% for the instantaneous-load, and 17.3% for the daily-load methods of calculation. Grab samples were taken at irregular intervals at all sites and the number of samples varied from 3 to 30 (Table 4). Surprisingly, an increase in numbers of grab samples did not consistently reduce the magnitude of the percent error for load estimation.

The median-load method does not appear to universally improve accuracy for sites with skewed flow distributions, however, when considered in aggregate across all sites median-load does perform slightly better than mean-load (4.9% error for the median-load and 6.4% error for the mean-load). The mean-load and median-load absolute differences are within 5% for all sites, except Marshall Road Drain which was infrequently and irregularly sampled (n = 3). These results show that mean-load can be considered a robust estimation method, even for highly skewed flow distributions.

In order to explore sources of error in estimating loads for agricultural watersheds, the estimates of flow using the different methods were compared. The total volumes computed for each of the estimation methods are presented in Table 5. The flow volume estimates also help to explain why the flow-volume method generally has a lower percent error as compared with the mean-load and median-load estimation methods for each site; volume-load estimates eliminate flow measurements as a source of contributing error since the flow volumes are identical to the true-volume. For mean- and median-load methods, the total volume is instead estimated by its measure of central tendency for each calculation interval, which mostly has small error, under 2%, but are as large as 23% (Table 5). Overall, errors in flow estimation do not account for errors in load estimation, probably due to the large number of flow measurements in comparison to grab sample measurements.

Our results are consistent with previous studies. Henjum et al. (2010) made a comparison of mean-load with true-loads for chloride, nitrate, and total suspended solids (TSS) and found that the mean-load calculation could estimate loads accurately (< 10% error) if pollutant concentrations are normally distributed, the pollutant concentration is not correlated with stream flow, and sampling was biweekly or monthly. For watersheds that had non-normally distributed concentration data, weak correlation between concentration and flow, and biweekly or monthly sampling, the mean-load was greater than 50% and often over 100% different from the true-load (Henjum et al., 2010). They did not comment on the distribution fit for flow in their watersheds. These errors are much higher than our findings which may be due to their short study time of one month and their flashy, well-drained watersheds. Fogle et al. (2003) applied the instantaneous-load and volume-load approaches to a watershed with flashy flow conditions (high flow rates and rapid rises and falls in water level) sampled daily, weekly, and biweekly to estimate loads of total solutes and nitrate nitrogen. The instantaneous-load method yielded load estimations with errors up to 22% and the volume-load approach had errors up to 10%, in comparisons with true-load. These results are consistent with our findings.

Since uniformity in analysis is an important factor when considering how loads are calculated in a TMDL program, our results indicate that calculating loads of diffuse pollution using volume-load methods will be a more accurate and uniform approach to determining loads from agricultural watersheds, many of which are infrequently sampled or poorly characterized. However, our results also suggest that loads calculated by different methods are generally comparable, and there is no absolute requirement to use only one method in a regional TMDL allocation. If there are large numbers of missing data from continuous flow monitoring sensors, representative estimates of the missing data need to be input in order to use the flow-volume method. This can be a time and resource consuming activity unless it can be automated by a software program. Additionally, if there are gaps in the data (*e.g.* a few partial or full days over the study period) the replacement data may no longer correctly estimate the flow and may bias the flow volume estimate and hence the volume-load estimate. In those instances, the mean- and median-loads can both be computed, compared, and used to determine a range for the estimated load. If there are longer gaps of missing data (*e.g.* for multiple days or a week over the study period), the daily-load may then be a better choice for load estimation, since the mean and median may no longer accurately describe the central tendency of flow for the calculation intervals. A decision flow chart for selecting a load estimation method is given in Figure 5.

Application to other water quality parameters

For the purposes of TMDL allocations, estimates of load will be calculated for water quality parameters that can only be measured by grab-sampling and for which there can be no true-load determined. The estimated loads for nine different analytes, total dissolved solids (TDS), biochemical oxygen demand (BOD), chlorophyll-a (chl), total nitrogen (TN), nitrate (NO_3), ammonia as nitrogen (NH_3), total phosphorous (TP), phosphate (PO_4), and total suspended solids (TSS), for Ingram Creek from April 1 to Sept 30, 2007 are summarized in Table 6, as an example. In those cases, determination of TDS true-load can provide a reference as to how accurate grab-sample data are for each location. Additionally, calculation of load from grab sample data by multiple methods and comparing the consistency of results can provide information on precision, if not accuracy, of the load estimate.

Conclusions

In this study we investigated how accurately loads of diffuse pollution from agricultural ecosystems could be estimated using typical water quality monitoring data. TDS loads were estimated for ten agriculturally-dominated watersheds in the San Joaquin Valley during the irrigation season (April 1 to September 30) using grab sampling data in comparison with the true-loads, as measured by continuous monitoring. These watersheds have widely varying values of concentration and flow, differing temporal flow patterns, non-normal flow and TDS distributions, and poor correlation between flow and concentration. Additionally, different grab sampling strategies were employed. The number of samples n varied from 3 to 30, and some sites were sampled throughout the irrigation season, while other sites were sampled for only portions of the irrigation season. These watersheds provide diverse model systems for assessing the viability and accuracy of the five load estimation methods utilizing grab sample data and representative measures of flow from continuous measurements: (i) the median flow, (ii) the mean flow, (iii) flow volume, (iv) the instantaneous flow at the time of measurement, and (v) the mean flow on the sampling day.

The volume-load method was the best method for estimating loads in these watersheds as it gives consistently low percent errors across all the sites irrespective of the degree of skewness in their flow distributions or the duration and frequency of the calculation interval as compared with the accuracy of the mean- and median-load. The volume-load method, however, requires a complete flow data set. If many data are missing (over a day or days or longer) and replaced with estimates of the flow, this will bias the results. In this case the mean- and median-load may be better choices for load estimation. The mean- and median-load methods had comparable error, generally within 5% of each other, for these sites. While, the mean-load method appears to be robust and not influenced by skew of the flow distribution, we recommend computing both median- and mean-load as a check for precision. The instantaneous-load and daily-load methods are both poor estimators of true-load and should not be used if continuous flow data is available to measure central tendency.

The volume-load method is particularly a good choice for load estimation in agricultural ecosystems since it is typically not known in advance what type of flow and concentration distribution is to be expected in a watershed and discrete sampling may be limited or conducted infrequently due to cost or other constraints. Additionally, the close agreement between the volume-load and the true-load in this study of TDS (the average error magnitude for all the sites is less than 7%) gives us confidence to apply this combination sampling method using continuous flow measurements together with grab samples for load estimates of other relevant water quality parameters for TMDL reporting.

We recommend continuous flow monitoring be added to critical watersheds. The success or accuracy of any diffuse pollution TMDL calculation is dependent on accurate measurement of flow, and continuous monitoring is highly recommended in critical watersheds. Continuous flow monitoring stations represent a significant investment of time and capital, but less expensive, pressure based monitoring devices can be installed temporarily during critical periods, such as during irrigation season or during the rainy season, to capture storm events.

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Table 1. Site locations for collection of flow and water quality data**.**

Site name	Station Number	Longitude	Latitude	Predominate drainage
Del Puerto Creek	36	37.540	-121.122	Agricultural
Ingram Creek	34	37.600	-121.225	Agricultural
Marshall Road Drain	38	37.436	-121.036	Agricultural
MID Miller Lake	25	37.542	-121.094	Agricultural and wetland
Mud Slough	18	37.263	-120.906	Agricultural and wetland
New Jerusalem Drain	31	37.727	-121.300	Agricultural
Orestimba Creek	21	37.414	-121.015	Agricultural
Salt Slough	19	37.248	-120.852	Agricultural and seasonal wetland
San Luis Drain End	44	37.261	-120.905	Agricultural
Spanish Grant Drain	65	37.436	-121.036	Agricultural

Table 2. Continuous and grab sampling characteristics and statistical summary of continuous flow and TDS data for each site.

	Del Puerto Creek	**Ingram Creek**	**Marshall Road Drain**	**MID Miller Lake**	**Mud Slough**
Sampling start date	April-13	April-13	April-13	April-13	April-13
Sampling end date	September-13	September-13	September-13	September-13	September-13
Number of grab samples, *n*	20	20	3	15	26
Number of continuous flow samples, *N*	17567	17568	17568	6576	17364
Number of missing continuous flow samples	1	0	0	21	204
Stage to flow relationship quality	Poor	Good	Good	Good	Good
Mean flow (l/s)	661.7	279.9	105.2	352	1,096.8
Median flow (l/s)	526.7	285	82.4	325.5	962.8
Shape of flow distribution*	Moderately skewed	Symmetric	Highly skewed	Moderately skewed	Moderately skewed
Mean TDS (mg/l)	723.5	716.2	642.4	190	2,055.2
Median TDS (mg/l)	701.4	713.6	690.2	191.2	2,144.0
Correlation coefficient, R^2	0.1	0.23	0.04	0.007	0.003

* Shape of distribution determined by calculation of skew where: -0.5 <skew < +0.5 is symmetric, -1 < skew < -0.5 or +0.5 > skew > +1 is moderately skewed, and skew < -1 or > +1 is highly skewed. None of the sites have a flow distribution that conforms to the normal distribution

Table 2 cont. Continuous and grab sampling characteristics and statistical summary of continuous flow and TDS data for each site.

	New Jerusalem Drain	Orestimba Creek	Salt Slough	San Luis Drain End	Spanish Grant Drain
Sampling start date	April 1	April 1	April 1	April 1	April 1
Sampling end date	September 30	September 30	September 30	September 30	September 30
Number of grab samples, *n*	4	18	30	19	3
Number of continuous flow samples, *N*	17568	16628	17387	17567	17568
Number of missing continuous flow samples	1	940	181	1	0
Stage to flow relationship quality	Good	Good	Fair	Good	Fair
Mean flow (l/s)	213.5	153.3	3,556.60	645.7	347.3
Median flow (l/s)	223.4	141.6	3,681.20	600.3	342.1
Shape of flow distribution*	Symmetric	Highly skewed	Symmetric	Symmetric	Highly skewed
Mean TDS (mg/l)	1,521.90	626.4	758	2,751.30	751.2
Median TDS (mg/l)	1,529.60	615	738.6	2,726.40	730.2
Correlation coefficient, R^2	0.0001	0.22	0.34	0.28	0.11

* Shape of distribution determined by calculation of skew where: -0.5 <skew < +0.5 is symmetric, -1 < skew < -0.5 or +0.5 > skew > +1 is moderately skewed, and skew < -1 or > +1 is highly skewed. None of the sites have a flow distribution that conforms to the normal distribution

Table 3. TDS loads for Ingram Creek from April 1 to Sept 30, 2007, presented as an example for each load estimation method.

Calculation Interval			True-Load[1,b] (kg)	Grab Sampling										
Grab Sample Date	Start Date	End Date		TDS[a] (mg/l)	Volume-load[2,b] (kg)	Mean		Median		Daily		Instantaneous	
						Flow (l/s)	Load[3,b] (kg)	Flow (l/s)	Load[4,b] (kg)	Flow (l/s)	Load[5,b] (kg)	Flow (l/s)	Load[6,b] (kg)
04/12/07	04/01/07	04/18/07	329,947	683.9	305,850	287.5	305,850	282.0	299,985	402.8	428,407	282.0	299,985
04/26/07	04/19/07	05/02/07	205,869	703.4	212,104	249.3	212,104	245.2	208,646	223.5	190,205	103.6	88,181
05/10/07	05/03/07	05/16/07	160,366	637.4	174,170	225.9	174,170	218.6	168,542	158.4	122,133	144.1	111,124
05/24/07	05/17/07	05/30/07	205,103	703.0	212,445	249.8	212,445	252.0	214,290	270.8	230,274	234.7	199,603
06/07/07	05/31/07	06/13/07	159,292	936.4	197,252	174.1	197,252	163.1	184,746	138.4	156,819	124.3	140,805
06/21/07	06/14/07	06/27/07	282,319	546.9	263,323	398.0	263,323	391.1	258,712	471.7	312,047	400.1	264,707
07/05/07	06/28/07	07/07/07	244,021	709.1	226,085	369.0	237,389	360.8	232,069	354.3	227,904	253.4	163,031
07/12/07	07/08/07	07/13/07	122,409	690.9	122,913	411.8	147,495	407.2	145,850	447.9	160,425	487.3	174,553
07/17/07	07/14/07	07/17/07	78,510	795.8	87,304	423.2	101,854	408.8	98,368	409.0	98,432	337.0	81,093
07/19/07	07/18/07	07/20/07	76,473	785.0	82,155	403.8	95,848	388.6	92,261	397.7	94,414	273.0	64,801
07/24/07	07/21/07	07/24/07	90,036	756.2	93,064	474.8	108,575	459.9	105,155	503.7	115,170	489.9	112,018
07/26/07	07/25/07	07/27/07	65,126	663.3	67,536	392.8	78,792	377.0	75,630	389.2	78,074	370.4	74,295
07/31/07	07/28/07	07/31/07	75,840	803.1	93,256	448.0	108,798	452.8	109,956	447.7	108,714	389.4	94,552
08/02/07	08/01/07	08/03/07	82,045	715.1	82,211	443.6	95,913	435.5	94,173	474.8	102,669	428.4	92,642
08/07/07	08/04/07	08/07/07	83,531	658.4	81,148	475.5	94,672	465.4	92,662	458.7	91,324	344.6	68,616
08/09/07	08/08/07	08/11/07	91,870	694.3	98,481	410.4	110,791	411.9	111,174	388.0	104,743	315.7	85,225
08/16/07	08/12/07	08/22/07	244,475	733.0	254,144	401.3	266,852	397.7	264,457	423.9	281,860	406.6	270,388
08/30/07	08/23/07	09/05/07	210,857	762.5	224,558	243.5	224,558	255.4	235,577	306.4	282,563	319.7	294,863
09/13/07	09/06/07	09/19/07	64,153	792.4	64,033	66.8	64,033	58.3	55,913	70.7	67,748	44.7	42,884
09/27/07	09/20/07	09/30/07	32,725	770.4	29,676	40.5	29,676	21.0	15,343	136.8	100,171	186.3	136,427
Total[c] (kg)			**2,904,967**		**2,971,706**		**3,130,388**		**3,063,508**		**3,354,095**		**2,859,793**

[1] Load calculated by integration method from continuous monitoring data using equation (ii).
[2] Load calculated from grab sampling data using equation (iii)
[3] Load calculated from grab sampling data using equation (iv), where the measure of flow is the mean flow over the calculation interval.
[4] Load calculated from grab sampling data using equation (iv), where the measure of flow is the median flow over the calculation interval.
[5] Load calculated from grab sampling data using equation (iv), where the measure of flow is the mean flow on the day of grab sampling.
[6] Load calculated from grab sampling data using equation (iv), where the measure of flow is the instantaneous flow at time of sampling.
[a] Total dissolved solids (TDS) measured during grab sampling event.
[b] TDS load for the calculation interval beginning midway between the current and previous grab sample date and ending midway between the current and subsequent grab sample date.
[c] Total load for study period calculated by summing all calculation interval loads.

Table 4. Comparison of total TDS load and percentage error over study period at each site.

Site	n[a]	True-load[1] (kg)	Grab sampling Volume-load[2] (kg)	Mean-load[3] (kg)	Median-load[4] (kg)	Daily-load[5] (kg)	Instantaneous-load[6] (kg)
Del Puerto Creek	20						
Total TDS load[b] (kg)		7,345,877	7,989,131	7,989,278	8,025,019	7,842,771	8,562,925
% error[7]		-	8.8	8.8	9.2	6.8	16.6
Ingram Creek	20						
Total TDS load[b] (kg)		3,050,474	3,131,478	3,131,478	3,062,322	3,354,095	2,859,793
% error[7]		-	2.7	2.7	0.4	10.0	-6.3
Marshall Road Drain	3						
Total TDS load[b] (kg)		1,015,733	1,227,881	1,227,881	948,814	1,812,062	996,853
% error[7]		-	20.9	20.9	-6.6	78.4	-1.9
MID Miller Lake	15						
Total TDS load[b] (kg)		974,129	988,763	992,468	909,811	701,378	679,392
% error[7]		-	1.5	1.9	-6.6	-28.0	-30.3
Mud Slough	26						
Total TDS load[b] (kg)		35,355,002	37,894,025	37,878,316	37,294,065	38,974,559	38,775,583
% error[7]		-	7.2	7.1	5.5	10.2	9.7
New Jerusalem Drain	4						
Total TDS load[b] (kg)		5,136,196	5,411,364	5,411,086	5,501,868	5,107,215	5,094,412
% error[6]		-	5.4	5.4	7.1	-0.6	-0.8
Orestimba Creek	18						
Total TDS load[b] (kg)		1,295,371	1,369,868	1,381,411	1,338,940	1,591,803	1,709,549
% error[6]		-	5.8	6.6	3.4	22.9	32.0
Salt Slough	30						
Total TDS load[b] (kg)		41,531,589	45,509,574	45,498,720	45,182,954	45,354,498	45,551,310
% error[6]		-	9.6	9.6	8.8	22.9	9.7
San Luis Drain End	19						
Total TDS load[b] (kg)		28,868,621	28,706,223	28,706,380	28,925,308	29,158,503	28,138,229
% error[6]		-	-0.6	-0.6	0.2	9.2	-2.5
Spanish Grant Drain	3						
Total TDS load[b] (kg)		4,043,855	4,073,910	4,073,910	3,999,786	4,297,952	4,598,105
% error[6]		-	0.7	0.7	-1.1	6.3	13.7

[1] Load calculated by integration method from continuous monitoring data using equation (ii).
[2] Load calculated from grab sampling data using equation (iii)
[3] Load calculated from grab sampling data using equation (iv), where the measure of flow is the mean flow over the calculation interval.
[4] Load calculated from grab sampling data using equation (iv), where the measure of flow is the median flow over the calculation interval.
[5] Load calculated from grab sampling data using equation (iv), where the measure of flow is the mean flow on the day of grab sampling.
[6] Load calculated from grab sampling data using equation (iv), where the measure of flow is the instantaneous flow at time of sampling.
[7] Percent error calculated using equation (v).
[a] Number of grab samples and calculation intervals.
[b] Total load for study period calculated by summing all calculation interval loads.

Table 5. Comparison of total volume and percentage error over study period at each site.

Site	N[a]	True-volume[1]	Mean-volume[2]	Median-volume[3]	Daily-volume[4]	Instantaneous-volume[5]
Del Puerto Creek	17567					
Total volume[b] (10^6 l)		10,462	10,462	10,524	10,276	11,189
% error[6]		-	0.0	0.6	-1.8	7.0
Ingram Creek	17568					
Total volume[b] (10^6 l)		4,425	4,425	4,332	4,761	4,045
% error[6]		-	0.0	-2.1	7.6	-6.7
Marshall Road Drain	17568					
Total volume[b] (10^6 l)		1,664	1,664	1,279	2,354	1,306
% error[6]		-	0.0	-23.1	41.5	2.1
MID Miller Lake	6576					
Total volume[b] (10^6 l)		5,086	5,019	4,669	3,641	3,576
% error[6]		-	0.5	-8.2	-28.4	-19.4
Mud Slough	17364					
Total volume[b] (10^6 l)		17,339	17,331	17,053	18,046	18,012
% error[6]		-	0.0	-1.7	4.1	5.4
New Jerusalem Drain	17568					
Total volume[b] (10^6 l)		3,375	3,375	3,432	3,180	3,172
% error[6]		-	0.0	1.7	-5.8	-7.6
Orestimba Creek	16628					
Total volume[b] (10^6 l)		2,170	2,188	2,126	2,526	2,732
% error[6]		-	0.8	-2.0	16.4	24.1
Salt Slough	17387					
Total volume[b] (10^6 l)		56,237	56,222	55,801	56,624	56,954
% error[6]		-	0.0	-0.8	0.7	2.5
San Luis Drain End	17567					
Total volume[b] (10^6 l)		10,210	10,210	10,285	10,378	10,019
% error[6]		-	0.0	0.7	1.7	-2.2
Spanish Grant Drain	17568					
Total volume[b] (10^6 l)		5,491	5,491	5,386	5,913	6,317
% error[6]		-	0.0	-1.9	7.7	17.2

[1] Volume calculated by integration method from continuous monitoring data using equation (v).
[2] Volume calculated using equation (vi), where the measure of flow is the mean flow over the calculation interval.
[3] Volume calculated using equation (vi), where the measure of flow is the median flow over the calculation interval.
[4] Volume calculated using equation (vi), where the measure of flow is the mean flow on the day of grab sampling.
[5] Volume calculated using equation (vi), where the measure of flow is the instantaneous flow at time of sampling.
[6] Percent error calculated using equation (vii).
[a] Number of continuous flow measurements.
[b] Total volume of flow for study period calculated by summing all calculation interval volumes.

Table 6. Load estimates of nine different analytes for Ingram Creek from April 1 to Sept 30, 2007.

	n	Mean concentration (mg/L)	Volume-load (kg)	Mean-load (kg)	Median-load (kg)	Daily-load (kg)	Instantaneous-load (kg)
TDS	20	727	3,131,478	3,131,478	3,062,322	3,354,095	2,859,793
BOD	14	11.218	48,839	48,839	47,902	48,945	41,886
Chl	20	0.0822	373	373	364	311	274
TN	20	7.93	32,667	32,667	32,011	34,086	29,137
NO_3	20	5.88	24,255	24,255	23,727	25,334	21,380
TAN	20	0.589	2,295	2,295	2,253	2,317	2,033
TP	20	0.3468	1,532	1,532	1,491	1,648	1,417
PO_4	20	0.2011	896	896	876	958	799
TSS	19	654.8	2,960,715	2,960,715	2,873,097	3,166,996	2,930,365

Figure 1. Map of the study area and each of the sites included in the study. Station numbers correspond to Table 1.

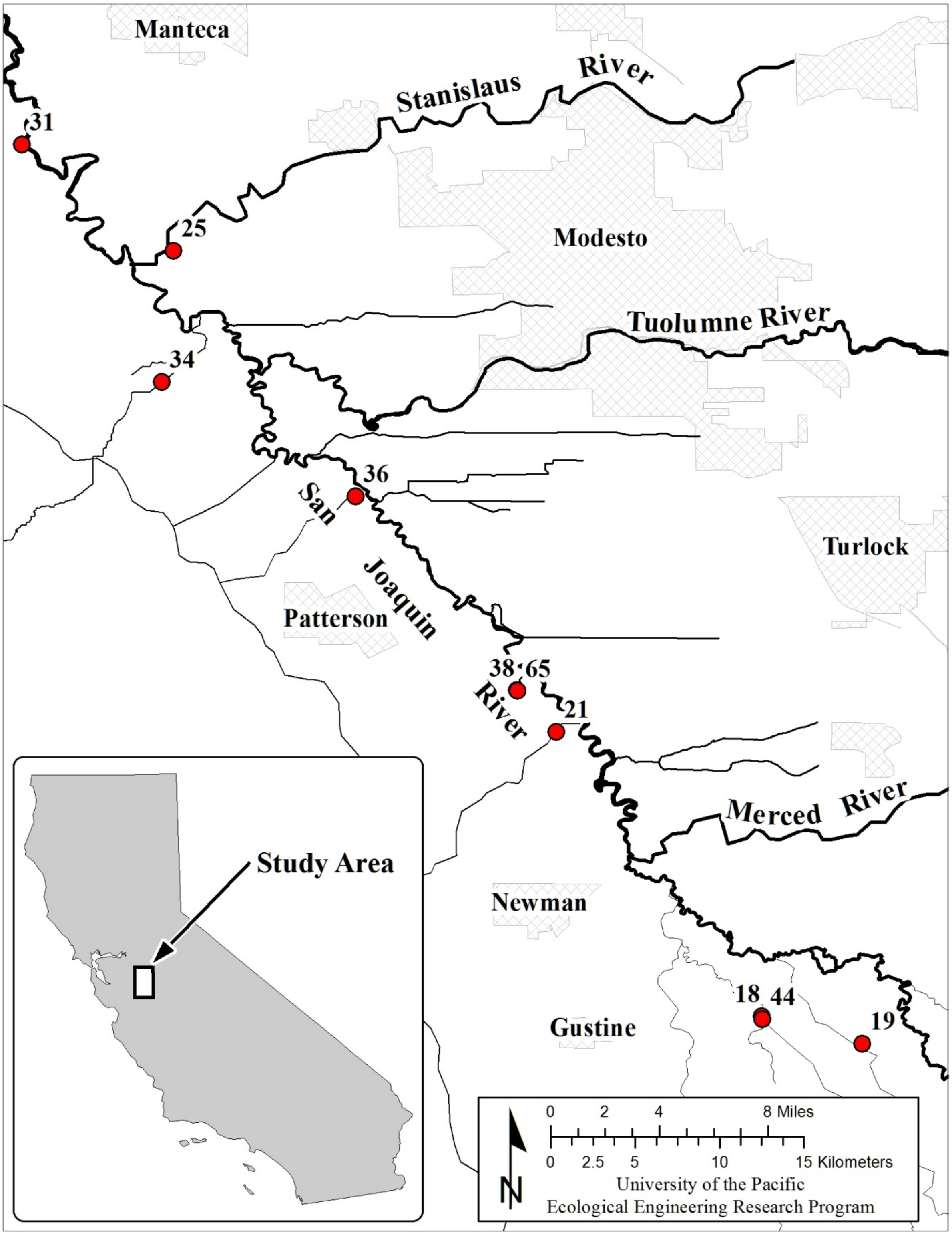

Figure 2. Surface flows at long-term monitoring sites on the western side of the San Joaquin Valley. Mean monthly average flows for 2000 to 2010 for Orestimba Creek up-gradient (USGS station 11274500) and down-gradient (USGS station 11274538) of agricultural regions. Results show the influence of irrigated agriculture on surface flows in the western San Joaquin Valley.

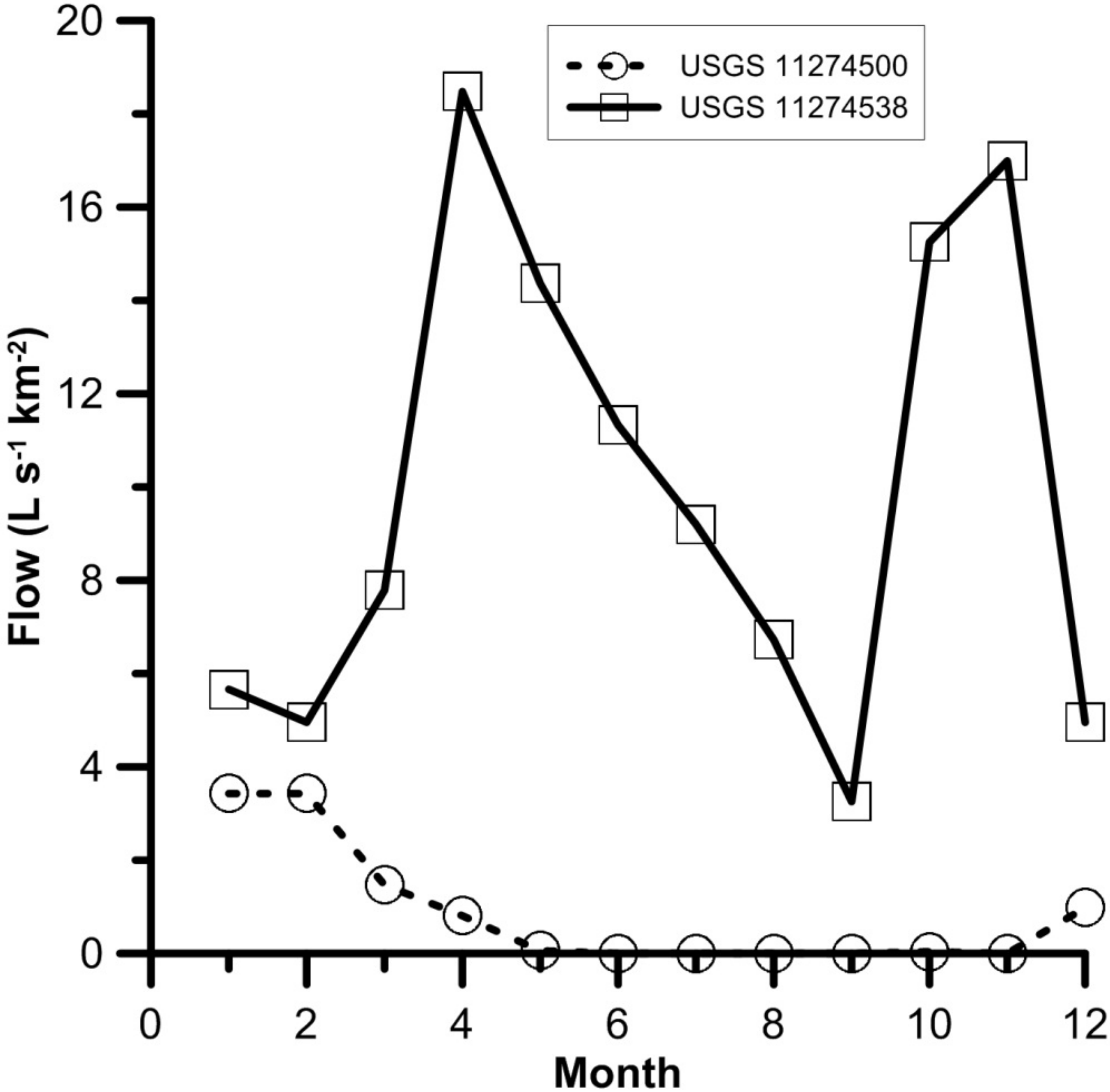

Figure 3. Temporal plots of flow and TDS over two week sampling periods for (a) Ingram Creek from April 5 to 18, 2007, (b) Marshall from May 10 to 23, 2007, and (c) Del Puerto Creek from April 5 to 18, 2007.

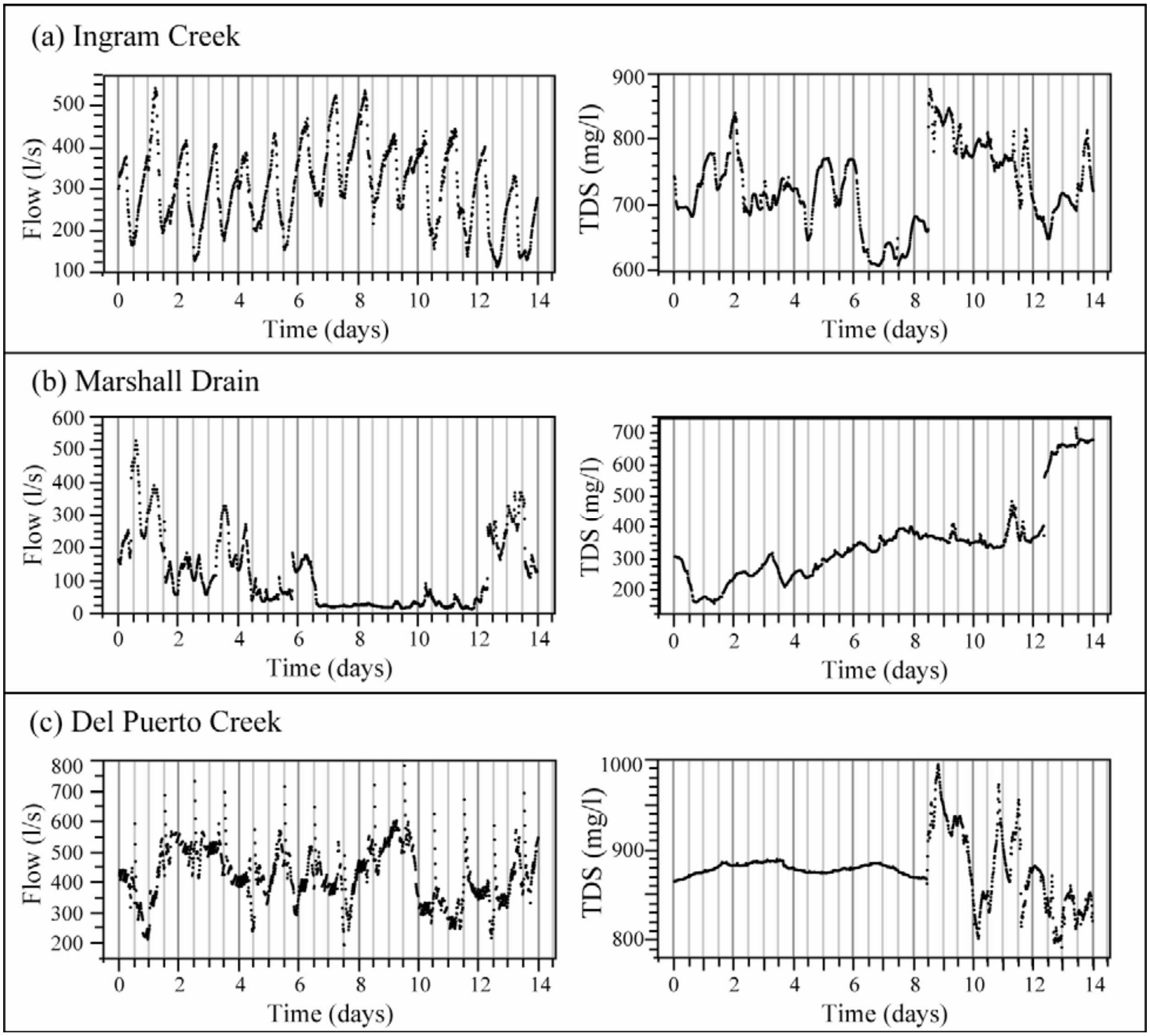

Figure 4. Histograms and boxplots of flow and TDS over irrigation season (April 1 to Sept 30) for (a) Ingram Creek in 2007, (b) Marshall in 2007, and (c) Del Puerto Creek in 2007. The curves are a Normal approximation to the data.

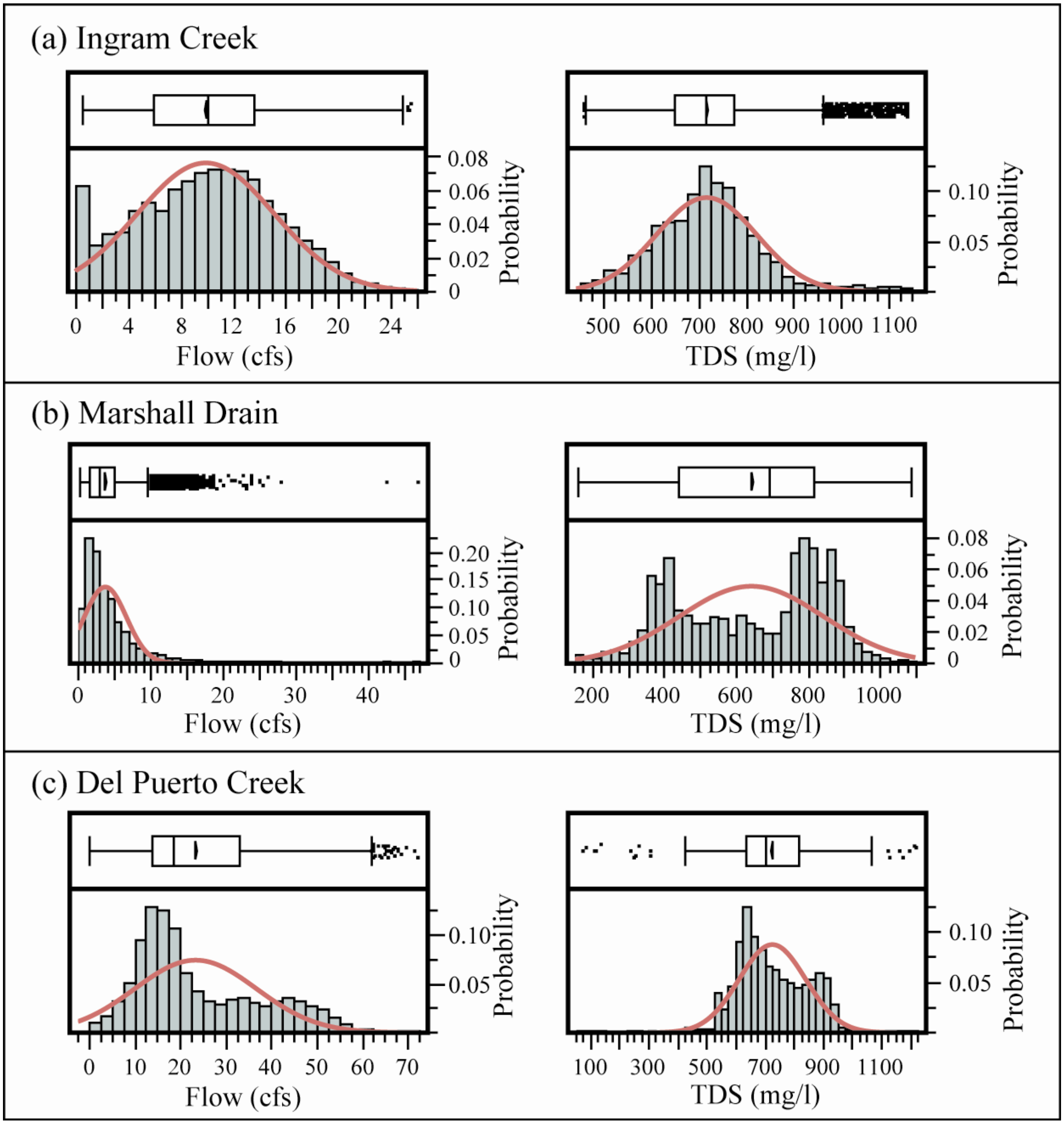

Figure 5. Decision flow chart for selecting a load estimation method.