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Detecting and analyzing soil phosphorus loss associated with critical source areas using a remote sensing approach

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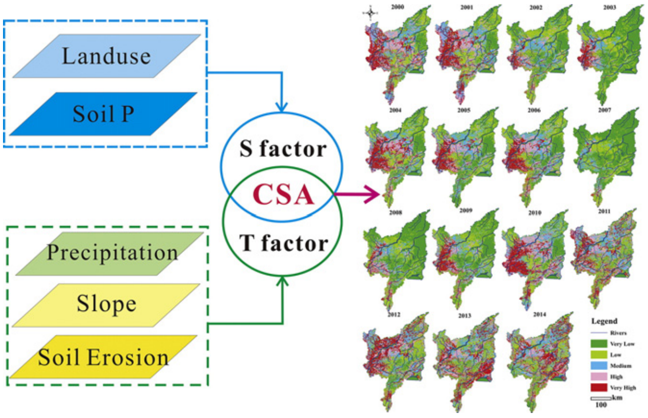
HIGHLIGHTS

- A new approach of detecting CPSAs was created by using three satellite sensors at regional scale.
- We found that the temporal variabilities in the locations of CPSAs are significant, and the spatial distribution are more dispersed over the long term.
- The average proportion of CPSAs is 13.8%, with a range varying from 1.2% to 23.0%.
- Precipitation acts as a key driving factor in the variation of CSAs at the regional scale.

GRAPHICAL ABSTRACT



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ABSTRACT

The detection of critical source areas (CSAs) is a key step in managing soil phosphorus (P) loss and preventing the long-term eutrophication of water bodies at regional scale. Most related studies, however, focus on a local scale, which prevents a clear understanding of the spatial distribution of CSAs for soil P loss at regional scale. Moreover, the continual, long-term variation in CSAs was scarcely reported. It is impossible to identify the factors driving the variation in CSAs, or to collect land surface information essential for CSAs detection, by merely using the conventional methodologies at regional scale. This study proposes a new regional-scale approach, based on three satellite sensors (ASTER, TM/ETM and MODIS), that were implemented successfully to detect CSAs at regional scale over 15 years (2000–2014). The approach incorporated five factors (precipitation, slope, soil erosion, land use, soil total phosphorus) that drive soil P loss from CSAs. Results show that the average area of critical phosphorus source areas (CPSAs) was 15,056 km^2 over the 15-year period, and it occupied 13.8% of the total area, with a range varying from 1.2% to 23.0%, in a representative, intensive agricultural area of China. In contrast to previous studies, we found that the locations of CSAs with P loss are spatially variable, and are more dispersed in their distribution over the long term. We also found that precipitation acts as a key driving factor in the variation of CSAs at regional scale. The regional-scale method can provide scientific guidance for managing soil phosphorus loss

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and preventing the long-term eutrophication of water bodies at regional scale, and shows great potential for exploring factors that drive the variation in CSAs at global scale.

1. Introduction

The global acceleration of the eutrophication of freshwater is primarily driven by phosphorus (P), and a common response has been the management of nonpoint sources based on P (Sharpley et al., 2011; Campbell et al., 2015; Rossel and Bui, 2016). Increasing attention has been focused on P nonpoint sources, with an emphasis on developing tactics to prevent agricultural contributions to surface water P loading (Rivero et al., 2007; Chang et al., 2013; Djodjic and Villa, 2015). Spatially, a majority of P loading to adjacent water bodies from a particular agricultural region (~80%) has been found to derive from small areas (~20%) in the region. These small areas are called critical source areas (CSAs) for P loss (Pionke et al., 2000; Sharpley et al., 2013). While P loss from CSAs has been a subject of research for more than a decade, the formation mechanisms and detection of CSAs remain unclear (Sharpley et al., 2011; Van Dijk et al., 2016). This is because the CSAs are attributed to both internal P concentrations and external environmentally driven factors (e.g., precipitation and soil erosion).

The CSAs define where the areas of high transport potential coincide with high P sources areas on a landscape (Sharpley and Jarvie, 2012; Xie and Zhao, 2016). CSAs generation is defined by the existence of P loss factors. Although there are many factors influence P loss, five major factors can be focused based on previous studies, including precipitation, topography, soil erosion, land use type and P concentration in soil. Precipitation can create surface runoff and soil interflow, and this process can significantly increase resolved dissolved P loss (Weld et al., 2001; Chang, 2010; Liu et al., 2014). Steep topography increases surface runoff and soil erosion, and this also increases both the dissolved P and particulate P loss (Kovacs et al., 2012; Hahn et al., 2014). While the soil erosion process is complex, it directly and powerfully increases particulate P loss (Kronvang et al., 2005; Butler et al., 2006; Kahiluoto et al., 2015). Land-use and land-cover changes are driven by human activity. With the build-up of P levels in the soil, more P loss emerges. At the same time, increases in arable land lead to more and more fertilizer use and consequent soil erosion (McDowell, 2012; Lou et al., 2015). In addition, P concentration is determined by a natural soil matrix and external human P input, and concentration of P in agricultural land is increasing globally, further facilitating P loss (Watson et al., 2007; Withers et al., 2014). Five factors also drive the increase in CSAs, and they can be classified into two groups: P source factors (S factors), which include land-use type and P concentration; and P transport factors (T factors) which include precipitation, topography and soil erosion. These five factors were first identified by P loss studies using in situ experiments; however, different methods are needed to identify critical phosphorus source areas (CPSAs).

Methods to detect CPSAs generally fall into three classes: isotope trace technology, P-index models and ecohydrological models. Isotope trace technology uses radioactive or rare earth elements to trace a P loss path and then find the CPSAs (Zhang and Shan, 2008; Wang et al., 2011a,b). A P-index model integrates transport and source factors to grade how vulnerable an area is to P loss, and thus to identify CPSAs (Lemunyon and Gilbert, 1993; Zhou and Gao, 2011). Ecohydrological models are more frequently used to detect the CPSAs, especially the models that are driven by remote sensing (White et al., 2009; Rivero et al., 2009; Hahn et al., 2014). These methods, however, are often not able to detect the driving factors for spatial and temporal variation in CPSAs. Because isotope trace technology and the P index model generally focus on a fine spatial scale, and the ecohydrological models are skilled in calculating of nutrients load but can't not account for all the major factors driving the increase in CPSAs. Meanwhile, those studies did not take into account the long-term temporal variation in CPSAs. In contrast, remote sensing provides spatially and temporally resolved information, and results from remote sensing models can realize the discretization of P concentration and describe the pathway of P loss; at the same time, the method can extend research at spatio-temporal scale (Liu et al., 2009; Oyama et al., 2015; Shi et al., 2016).

Such research is indispensable to the study of CPSAs, since P-source and P-transport factors at different spatial scales can influence their geographic location and area (Sharpley et al., 2011; Bowes et al., 2015). In this study, the regional scale is defined as an area larger than ten-thousand square kilometers; and at regional scale, land-use type, soil erosion as well as rainfall intensity are more important factors in the generation of CPSAs. Different research methods can best fit particular spatial scales. For example, the isotope trace technology is more proper to plot scale (Wang et al., 2011a,b), the P-index models have good performance at field scale and farm scale (Zhou and Gao, 2011), and the ecohydrological models are more frequently used at watershed scale (Ghebremichael et al., 2013). A study's temporal scale is important at regional scale, but less significant at plot or farm scale. The location and driving factors for CPSAs are stable at fine scale, whereas at regional scale, the generating factors will change over the long term (Sharpley and Jarvie, 2012; He and Silliman, 2015).

There are two issues that have not yet been addressed in research with respect CPSAs. The first is to examine the key factors driving CPSAs at regional scale, which remain unclear. The second is to determine whether the location and area of the CPSAs are stable at regional scale over the long term.

The present study aims to: 1) detect CPSAs at regional scale by incorporating remote sensing with the five factors identified in previous studies; 2) identify the key factors driving these CPSAs; and 3) display the spatial distribution of the CPSAs and their areas at long-term.

2. Methods and materials

2.1. Study domain

The Sanjiang Plain (43°49′55″–48°27′40″N, 129°11′20″–135°05′26″E) (Fig. 1) is a vast area with low relief, located in the northeast of China. It is one of largest producers of commodity crops in China and has a total area of 108,900 km^2 (Yang et al., 2012). Annual precipitation ranges from 500 to 600 mm. The annual average temperature is 1.9 °C, and the climate is humid and mid-humid continental, with an. The north and middle of Sanjiang Plain is flat, which explains the number of large national farms in the area; the mountains are mostly located in the south and west of the area. The main land-use types include dry land, paddy land, wet land, settlement land, grass land, forest land, water body, and unused land. Arable land, forest land and wet land are the three leading land-use types, representing 51.17%, 31.63% and 8.81%, of the area, respectively (Song et al., 2008).

Bawujiu Farm (Fig. 1), is situated in the northeastern of the Sanjiang Plain, served as a typical experimental area for the study. As with the Sanjiang Plain, Bawujiu Farm is smooth and homogenous in geography. Neither the Sanjiang Plain nor the Bawujiu Farm has a history of intensive agriculture development of more than 60 years; the area's massive original wetland is the source of the cultivated land. Two automatic meteorological stations were set up to collect meteorological data that would be used to validate the input of the model. In 2010, soil samples were collected to validate the output of the model.

Naolihe watershed (Fig. 1) is situated in the heart of the Sanjiang Plain. In 2014, soil sampling was conducted in dry land, paddy land,