Dear Dr. Shukla,

Thank you for conveying the second round of referee comments and major revisions to us. We have again made improvements to the manuscript in response to the referee comments. On the next page, we list the most relevant changes to the manuscript and supplementary material, followed by a point-by-point response to the referee comments, followed by a marked-up version of the revised manuscript that highlights (in blue) the changes that we made.

In particular, we have addressed the concerns of the reviewers that precipitation variability could be affecting the estimated trends in tank water extent, and that there was insufficient justification for associating trends in tank inflow to land use change. Following your advice, we believe that much of the reviewer concern arose from lack of clarity around the presentation of the statistical methods in the manuscript. Consequently, we have extensively revised the methods section which now:

(1) Provides an overview of the remote sensing analysis, but has moved many of the specific details to Supplemental Material, considerably shortening this section;
(2) Starting with a tank water balance, presents a detailed rationale for terms that were included or excluded from the linear model, and the justification for modeling the present terms in the way that they have been addressed;
(3) Presents the linear model as the outcome of this water balance argument; and
(4) Provides additional analysis to confirm the importance of accounting for the existence of a trend in tank water extent that derives from drivers other than rainfall. We show that excluding this trend from the model reduces the model performance significantly (F-test $p<3.1\times10^{-11}$) and by a meaningful margin ($r^2=0.68$ when B is included, is 0.58 when B is excluded).

We have also added several new results to the text and figures to the Supplemental Material to address the questions of:

(1) Trends (or, in practice, the lack thereof) in precipitation at basin and smaller scales during the study period (Fig. S11 and S12)
(2) The relative effect sizes of precipitation variability versus a non-precipitation related time trend in tank water extent (Fig. S15).

Several other updates, corrections, and clarifications are provided to address the referees' suggestions. We thank the referees for their consideration of this manuscript, and we look forward to hearing back regarding the revised manuscript.

Best regards,

Gopal Penny
Veena Srinivasan
Iryna Dronova
Sharad Lele
Sally Thompson

List of relevant changes

- Moved detailed information about remote sensing from the methods section to Supplemental Material. Similarly, moved detailed information about pixel-scale model validation results to the Supplemental Material.
- Extensively rewrote the methods section to show how water balance reasoning at the tank scale informed the design of the statistical model, and clarifying the focus on and interpretation of the *Year* effect term (B) – and why we interpret this term as a proxy for changes in hydrological processes.
- Using an F-test, we compared the statistical model with a restricted version of the model omitting the *Year* effect term (B). The model including B performed significantly better ($p<3.1\times10^{-11}$) than the restricted model, with better R^2 (0.68 with the time trend, 0.58 excluding the time trend) (sections 2.5 and 3.2). This helps confirm the importance of non-precipitation-related changes in explaining the variations in tank areal extents over time.
- Added multiple figures to the supplementary material, demonstrating that we were unable to detect any statistically significant long-term trends in precipitation (at the watershed or tank cluster scales) (Figs. S11 and S12). Showed the variability in tank water extent due to precipitation (holding time constant) and due to the non-rainfall-related temporal trend for each of the tank clusters (Fig. S15).
- Added figure S16, plotting the *Year* effect term B against the time averaged land-use fraction for irrigated crops and eucalyptus plantations.
- Clarified nomenclature referring to different time periods in the year with respect to the monsoon season (section 2.1), including renaming the "post-monsoon" to the "end-of-monsoon" period to be consistent with official definitions of the monsoon season.
- Updated our count of the number of end-of-monsoon (previously "post-monsoon") Landsat images from 18 to 16. The statistical analysis is unchanged (18 years was a miscount of the total number of years input into the original model).
- Fixed inconsistencies in the use of the terms *surface water*, *surface area*, and *tank water extent* – the latter is now used preferably throughout the manuscript.
- In the abstract, noted the how much of the variability in the model is attributed to variability in precipitation.

Point by point response to referees

Please note, when we reference text in the manuscript, we refer to the new locations in the updated manuscript (while leaving the referee comments and references unmodified). Whenever including text from the manuscript, previously-written text is reproduced in blue, and revisions are shown in red.

Reviewer 1

This version of the article is much improved, particularly in terms of the description of how the change in relationship between rainfall and streamflow, B, is interpreted and in the additional background providing context on the relationship between Arkavathy and water resources in India more broadly.

Thank you.

I appreciate the authors' attempt to look at the land use change data in a different way; however, I still struggle with the analysis of the relationship between land use and B (change in relationship between rainfall and streamflow). Relating a trend (B) to a time-averaged land use fraction is not intuitive to me. I expect that the authors want to use the trend rather than the time series because the trend, as calculated, excludes interannual variability in precipitation and dry season days. Given the limitations on data availability, I think the approach, with the given caveat of not inferring causation, is acceptable. The number of land use fraction measurements (4) would not support a direct comparison of trends, which I suspect is why the authors use the time-average land use fraction.

Thank you for this query. There were two motivations for focusing on the time averaged land use fraction. Firstly, as the reviewer notes, the land use maps are not highly resolved in time. Secondly, there is considerable uncertainty in the time needed for a land use change to result in a hydrologic change. Many of the causal connections hypothesized to exist between land use and surface water flow in the Arkavathy Watershed are mediated by groundwater depletion. This is a process associated with non-trivial time lags, meaning that a hydrologic change might significantly lag a land use change, complicating trend analysis. Both of these factors suggest a space-for-time approach, in which the variations in mean land use fraction across all 17 tank clusters for which this information is available are related to the time-trends in tank water level, might be the most straightforward way to initially diagnose the effect of different land uses. We completely agree that a more temporally resolved analysis would be desirable, but is not necessarily straightforward to achieve.

It is unclear how many points are used in the regression (are all 13 tank clusters used or just 3 (see line 25, p. 9)? Are unique values of land use fraction used for each tank cluster?). I'd like to see the plot of average irrigated area vs. B in the supplementary materials. It would be good if the authors could clarify exactly what data went into the *regression analysis and also give further justification for this choice of method.*

We apologize for this lack of clarity. The three subwatersheds upstream of the TG Halli reservoir are used, within which there are a total of 17 tank clusters. We have added a supplementary Figure S16 showing $B_{1,j}$ versus land use fraction for both irrigated crops and Eucalyptus plantations. Text is amended as follows (page 8, line 14-32):

We used four land use maps developed for 1973-74, 1991-92, 2001-02, and 2013-14 (Lele and Sowmyashree, 2016) encompassing the TG Halli watershed, which contains the three subwatersheds upstream of the TG Halli reservoir (TG Halli East, Kumudavathy, and Hesaraghatta) and includes a total of 17 tank clusters. The maps differentiate agricultural land use classes into rainfed crops, irrigated agriculture, and Eucalyptus plantations. Irrigated agriculture in this region is supplied almost exclusively by groundwater, allowing us to test whether groundwater irrigated agriculture, increased water utilization by Eucalyptus plantations (Srinivasan et al., 2015), both, or neither, are associated with the trends in surface flows.

In the early 1970s, rainfed agriculture was the primary land use in the TG Halli watershed. Over the study period, many farmers adopted groundwater irrigation and others converted their fields to *Eucalyptus* plantations, which have the potential to mine shallow groundwater or to significantly reduce deep recharge. These land use changes have the potential to reduce surface water flows by depleting subsurface water availability and baseflow over time, likely resulting in a non-stationary streamflow response. This non-stationarity, in conjunction with the relatively sparse availability of land cover data over time, complicated a direct analysis of land use against tank water level. Instead, a space-for-time approach was used to compare the differences in time-averaged land use across each tank cluster to the differences in tank water level trends inferred for each cluster. We therefore calculate the time-average land use fraction corresponding to irrigated crops $A_{irrigated,avg}$ and *Eucalyptus* plantations $A_{Eucs,avg}$ for each of the 17 tank cluster watersheds and regress $B_{1,j}$ against these land fractions:

$$B_{1,j} = C_{Eucs}\, A_{Eucs,j} + C_{irrigated}\, A_{irrigated,j}$$

The coefficients, C_{Eucs} and $C_{irrigated}$, correspond to the sensitivity of hydrological change to time average *Eucalyptus* land cover and irrigated agriculture land cover, across all 17 tank clusters. This analysis is not designed to directly infer causation, but rather to understand associations between streamflow decline and agricultural practices.

Reviewer 2

Authors argued about trends in tank water extent that could not be explained by precipitation (page 7 line 28-29) without providing any evidences.

Respectfully, this statement is a misinterpretation of what was written, which is not an argument, but a description of the statistical method employed. However, we hope that the intent of the statistical model has been clarified by the reworked methods section. The introduction to the statistical modeling section (page 6 lines 2-4) now states:

The aim of the statistical model is to identify changes in tank water extent that could be attributed to changes in streamflow production in the Arkavathy watershed. To achieve this, the model should control for drivers of water extent variability other than streamflow.

The section then elaborates on how such controls can be put in place by consideration of a tank water balance.

1. The manuscript does not provide any time series plot of summarized tank water extent extracted from LS by the tank cluster in comparison with rainfall. A quick search reveals a paper by Suresh et al., 2010 that discussed inter-annual variability in rainfall around the Arkavathy watershed. If we assume a similar rainfall regime over Arkavathy, it resembles the tank water extent shown for at least 2 tanks in supplemental figure 4 and 5 for 1994, 2002, 2007 and 2008. Rainfall was well below the mean in 1994 and 2002 corresponding to the lowest water extent while the 2007 and 2008 had good rainfall also reflected in the increased water extent for those tanks compared to 1994 and 2002. It is possible that human activities are playing major role in declining tank water extent, but the temporal patterns also need to be evaluated with respect to changes in precipitation. Here is another example by Subash et al., 2014 where it shows rainfall is declining in Karnataka.

The original manuscript did not include such a discussion because the linear model controlled for variability in precipitation, and the goal of the study was not to explain all sources of variability in tank water extent, but to isolate a signature of non-stationarity in tank water extent that could be attributed to anthropogenic drivers. While we continue to emphasize the importance of isolating such a signature and understanding its spatial variations, we have now also incorporated precipitation trend analyses.

Results quoted in the main text and figures presented in the Supplemental Material confirm that there are no statistically significant trends in precipitation occurring at whole-of-basin, subwatershed or tank cluster scales (see <u>page 6 line 26 – 31</u> for discussion of data sources and methods, <u>page 9 lines 22-25</u> for written results, and <u>Figures S11 and S12</u> for graphical results).

2. In validation: adding analysis with respect to google earth images is good, however it provides some confusion, the max water extent shown in supplemental figure 6 does not in line with max extent shown in figure 6 in the main text. So are two sets of tanks presented in these two figures totally different? Speaking of water extent area, unlike what is mentioned in page 10 ln 19 and 22, 25 ha and 2.5 ha are equivalent to 276 and 26 pixels according to 30 m pixel size as suggested in Table 1 and section 2.2. Which one is correct? 25 ha or 27.8 pixels? if latter is true then i think it requires finer resolution than 30 m to effectively identify tanks of that size from the satellite image.

The tanks validated using Google Earth (Figure S8) are a subset of tanks validated using the LISS image (manuscript Fig. 4). Although it is true that the max water extent of the tanks from the Google Earth validation (2004, 2005, 2009) is greater than the max water extent of tanks from the LISS validation (2014), this is not surprising given the variability of tank water extent.

Thank you for catching the error regarding tank area and pixel count. The corrected manuscript reads (page 9, lines 5-6):

A regression of Landsat extent versus reference extent (Figure 6) for tanks less than 25 hectares (~~27.8~~ 278 pixels) had a slope of 0.98 and coefficient of determination (R^2) of 0.95.

3. Why the image water extents were not compared against the tank area computed from the shapefile of KSRSAC or tank area from the topographic maps where possible? I would expect, the post-monsoon tank water extent would resemble the maximum water extent possible for each tank as it can be expected to be full after monsoon period.

There are two primary reasons why we have not conducted such an analysis. (1) We do not have information about the quality of the surveyed boundaries with respect to maximum tank water extent. (2) The tanks do not fill up every year. For any given year, the maximum tank water extent at the end of the monsoon can be substantially different than what might be assessed from mapped tank boundaries.

With these considerations in mind, validating against high resolution imagery allows control on the timing of the observations, the actual water extent in image, and constrains uncertainty in the validation dataset.

4. The manuscript did not provide proper definition of what they mean by pre-monsoon, monsoon, post-monsoon, wet-monsoon, normal-monsoon (fig S6), dry season, monsoon year (page 8 line 18), normal year, wet year (page 10 line 26-27). In southern India there are two different monsoon seasons; southwest and northeast with two rainfall peaks june-july for southwest monsoon and October for northeast monsoon. The above mentioned terms are inconsistently used throughout the manuscript.

Thank you for noting these nomenclature issues. We have now added some definitions for clarity, particularly with respect to terms used to define discrete time periods and ensuring we follow the official end of the northeast monsoon in December (instead of November), requiring a change in nomenclature from "post-monsoon" period to "end-of-monsoon" period for the Landsat images used in the study. Even though the official wet season ends in December, little precipitation (<5%) arrives that month.

We have expanded the discussion of climate in the study site description as follows (page 4, lines 17-22):

It has a monsoonal climate and mean annual rainfall of 820 mm. The monsoon season includes the southwest monsoon from June to September and the northeast monsoon from October to December. We therefore refer to several discrete periods of time within the year as the pre-monsoon period, taken as April–May, the wet season or monsoon season, between June and December, the end-of-monsoon period, taken as December–January, and the dry season, January–May. We also refer to the “monsoon year”, analogous to the usual concept of the water year, spanning the period from April to March of the following year.

Next, we have added some clarification about use of terms such as normal and wet at the time of use (page 5 lines 27-30):

We also used Digital Globe imagery available from Google Earth (Google Earth, 2016) to assess the validity of the classification in normal (680-955 mm) and wet (>955 mm) precipitation years during the study period. Given the limited availability of these images, we were unable to find a dry-year image (< 680 mm) within the study period that was suitable for comparison with a mostly cloud-free Landsat image.

The thresholds for wet and dry years correspond to the upper (955 mm) and lower quartiles (680 mm) of annual precipitation. We have removed mention of wet and normal monsoons, and now refer to these same periods as normal and wet years.

5. In the entire manuscript it was never mentioned what was the total water extent derived from images, all the tanks or by tank cluster for each year. Seems like it would be really very small.

We have included the max water extent for each of the clusters in Table S2 of the supplementary material. The total area is not relevant to the analysis at hand, and thus is not discussed.

6. Page 4 line 16-17 suggest study focus on Dec and Jan tank water extent estimates, however it is not clear how many data points were used in running the trend analysis. If only Dec and Jan estimates were considered then there would be only 18 data points between 1973 and 2010. Is it enough for a trend analysis? I do not think so.

The study does focus on a single image for each year. Usable end-of-monsoon images were only available in 16 (rather than 18) years out of the 38 years total in the study period. We update the text on page 5, line 5-9 as follows:

A detailed description of the remote sensing methods employed is provided in the Supplemental Material, Section S1, and the main steps are summarized below. Landsat imagery was used for analyses. Sixteen (16) images taken in December or January between 1973 and 2010 were classified to provide information about end-of-monsoon tank water extent. An additional 32 images were also classified to assist in validation, and to provide information about tank water extent variations during the 10 dry season (see Supplemental Material Fig. S1 and Table S1 for imagery dates).

Naturally, more data would be preferable for developing and testing a model. We have, however, provided confidence intervals (which account for sample size) for each of the model coefficients as well as model performance statistics, which show that the model explains 68% of the variation in the observed tank water extents.

We have also run the regression with and without the presence of the non-rainfall-derived time trend ($B_{1,j}$), and confirmed that the model performance increased meaningfully in terms of the R^2 and F statistics when the time trend was included. The differences in the resulting models were statistically significant via the F-test, with the null hypothesis that $B_{1,j}=0$, and alternative hypothesis $B_{1,j} \neq 0$, for at least one value of j. The results of the F-test reject the null hypothesis ($p < 3.1 \times 10^{-11}$). The confidence intervals then allow us to determine for which clusters $B_{1,j} \neq 0$.

Thus, we are confident that the trend identified in this study is a meaningful component of the time variation in the tank water extent.

We have now added the following text page 8, lines 1-2:

Model performance was assessed using multiple R^2 statistics and significance of the trend slope $B_{1,j}$.

And on page 8, lines 9-12:

Because the value of $B_{1,j}$ is the key result of interest, additional analyses were performed to confirm its importance. Specifically, the model was refit while omitting the *Year* effect $B_{1,j}$. The performance of the two models (with and without $B_{1,j}$) was compared via R^2 metrics. The significance of deviations between the two model predictions was tested using an F-test ($H_0 : B_{1,j} = 0$, $H_A : B_{1,j}$ 6= 0, for at least one value of j).

At page 10, line 10-13 we have added the following:

We confirmed that the *Year* effect $B_{1,j}$ was important for understanding the variations in tank water extent. Omitting the *Year* effect from the tank water extent model lowered the R^2 from 0.68 to 0.58. Furthermore, the model predictions with and without the *Year* effect were significantly different according to the F-test ($p < 3{:}1 \mathrm{x} 10^{-11}$). These results allow us to reject the null hypothesis that $B_{1,j} = 0$, meaning that the *Year* effects could be ignored.

7. Page 8 line 11-12, surface water extent was strongly related to precipitation metrics, what does this mean?

This statement simply identifies the period of time over which antecedent precipitation best explained the variations in tank water level (September 1 to the date of the Landsat image). The statement is rephrased in the rewritten methods section on page 6, lines 26-31, as:

Variations in P (ii) were accounted for using daily rainfall data from 62 gauges operated by the Karnataka State Natural Disaster Monitoring Centre (KSNDMC). Precipitation trends were analyzed using Mann-Kendall non-parameteric tests. Exploratory analysis at the whole-basin scale indicated that tank water extents were most related to precipitation totals from September 1 to to the date of Landsat image acquisition. Contemporary observations in the Arkavathy watershed suggest that only the largest or most intense storms generate runoff. The average depth of large storms (>10 mm/day) from September 1 to the date of the Landsat image was used as a metric of extreme rainfall occurrence to account for these observations.

8. Page 8 line 31-34, how could the authors confirm tank water storage which is the volume of water dynamics from surface water extent which is an area.

Thank you for picking up this loose use of language. Of course, throughout the paper we interpret the surface area (tank water extent) of the tanks as a proxy for storage, but we should be more explicit.

Firstly, we address this use of the proxy by referring to bathymetric surveys currently in publication at *Water* journal (page 6 lines 4-6):

Bathymetric surveys in the Arkavathy watershed indicate that tank surface area is a function of tank volumetric storage (Young et al., 2017). Thus, a volumetric water balance for a tank can be used to consider the drivers of water extent variability.

Throughout the paper we now take care to refer to "tank water extent" rather than storage. Finally, we used the results from the bathymetric survey papers to associate scaling of storage volumes in tanks to the scaling of surface area, as follows (page 6 lines 20-23):

Carry-over water extent from 2013 monsoon to the start of the 2014 monsoon was > 25% or approximately >12.5% of post monsoon storage for more than 50% of tank clusters, and >50% or approximately >35% of storage for more than 75% of clusters (storage to volume conversions are based on bathymetric data reported in Young et al., 2017).

9. Page 11 line 25-26, another example of no evidence. No observed streamflow data or analysis was conducted, but conclusion was drawn for observed streamflow. Throughout the manuscript the satellite derived extracted water extent is used vaguely as proxy to tank water storage and streamflow, which to me is inappropriate and incorrect.

With respect, the link between the rainfall-controlled trend in tank water extent and non-stationary streamflow is not a vague proxy, but a core inference drawn from the results of the analysis.

However, we appreciate that the way the paper was written asked the reader to draw the threads behind this inference together independently, and that we can clarify the logic by making it explicit. We have focused our re-writing of the methods section around this clarification.

The methods section now starts with a tank water balance, asks where data are available to directly control for variations in the drivers of this water balance, explores how observations can be used to infer stationarity or non-stationarity in other terms, and explains the logic behind converting the water balance and stationarity observations into a suitable linear model. The linear model is then presented. The interpretation of the *Year* effect, $B_{1,j}$ as an indicator of non-stationarity in streamflow production is explained explicitly, and additional analysis to confirm the importance of this effect outlined.

Please see the new text on pages 6-8.

10. Again out of context discussion of water table and drilling of wells in Page 11 line 26-30.

With respect, this statement is not out of context.

Rather, it again concerns key inferences made in the study.

The land use change analysis explicitly considers irrigated agriculture and eucalyptus plantation area. The hypothesized link between these land uses and declining trends in tank water area as a proxy for streamflow is described in the Methods section, page 8 line 20 – 23:

In the early 1970s, rainfed agriculture was the primary land use in the TG Halli watershed. Over the study period, many farmers adopted groundwater irrigation and others converted their fields to Eucalyptus plantations, which have the potential to mine shallow groundwater or to significantly reduce deep recharge. These land use changes have the potential to reduce surface water flows by depleting subsurface water availability and baseflow over time.

The information provided about the depth to which groundwater wells are now drilled is consistent with this hypothesized link: deep well depths imply a deep water table, which is consistent with the hypothesis above. It is consistent with the finding that negative non-precipitation-related trends in tank surface area are greatest in those basins where groundwater irrigation practices are more extensive.

11. Page 12 line 4-7, no supporting evidence provided.

Thank you, we failed to cross reference the figure that provides this evidence (Figure 6). The results quoted refer to the output of the model described in Section 2.5.

We have clarified this section by making these cross references explicit (page 10 lines 22-25):

The regression of the *Year* effect $B_{1,j}$ on irrigated agriculture and *Eucalyptus* land use areas explained most of the differences in $B_{1,j}$ between tank clusters (R2 = 0.68). The relationship between irrigated crops and $B_{1,j}$ was statistically significant (95% confidence intervals of $C_{irrigated}$ excluded zero), and the relationship with *Eucalyptus* plantations was not statistically significant (Fig. 6).

12. Page 12 line 19-25, if I understand correctly, what was done is, extract tank surface water extent area from satellite images over time and analyze the change that is present in the surface water extent area, then try to correlate these changes with changes in land use. There were no analyses done with streamflow or tank storage, now the authors started discussing about streamflow and tank storage.

Please see our responses to point 1 and point 9. Our response to this question is covered by these previous responses.

13. I find the discussion section 4.1 incoherent given the analyses done. The discussion is all about streamflow while the analyses was on tank surface water extent extraction.

Please see our responses to point 1 and point 9 which justify why our discussion focuses on streamflow.

14. Figure 6 last line, that is why more than one index/method is needed to accurately identify tanks from multi-date satellite images.

This issue is covered extensively in the discussion of validation and quality control for the remote sensing analysis.

15. The entire conclusion is incoherent and not supported by circumstantial evidence.

We understand this comment to again refer to the fact that the conclusion discusses an interpretation of the study findings in terms of streamflow. We refer to our responses to questions 1 and 9 to cover this and do not propose any modifications to the conclusions.

16. What is this supplemental figure 9 for? How do the lines drawn? Why the data points for the available images for December not shown in this plot?

This figure (now Fig. S10) presents the data referred to in Section 2.4 (page 6 lines 19-25 and page 7 lines 1-7). The figure is cross referenced there in the main text. We were unable to obtain any usable images from December 2013. The lines in (a) are lines of best fit, showing the trajectory of tank water extent late into the dry season. Furthermore, they represent some of the uncertainty in determining drying rates for the end-of-monsoon period, simply because there are limited images within these months over the course of the study period.

17. Again what is this supplemental figure 7, 8 and 10 for? No mention of this figure in the main text. Graphs show the data and circumstantial evidence needed to support any conclusion or statement made in the text.

Supplemental Figure 7 (now Figure S14) is needed to enable Table S3 (which is referred to in the main text) to be interpreted. It offers the key to relate the cluster identifiers to their location in the watershed. We now clarify this in the caption as follows:

Figure S14: Subwatershed names and cluster IDs used in the multiple regression. These identifiers are needed to associate the results in Table S3 with their spatial locations, shown in this figure. The Manchanabele and Harobele subwatersheds here are named for reservoirs within the watershed, which are not located at the subwatershed outlet.

Supplemental Figure 8 (now Fig. S13) provides a standard component of QA/QC for a linear model, namely verification that residuals of the model are distributed normally. We now add brief reference to it in the results section (Page 9, line 26-27):

Model residuals were normally distributed (Figure S13).

Supplemental Figure 10 (now Fig. S9), and shows data that are discussed in the main text in the Results Section 3.1. We now cross reference Figure S9 as follows (page 9 lines 16-20):

Although the time variation in most tanks have not been reported as ground data, trends in water storage over time are widely known for some of the major reservoirs. The TG Halli and Hesaraghatta reservoirs declined from a peak storage in the 1970s to much lower contemporary storage. Large increases in water extent were observed in Manchanabele reservoir, which was constructed in 1993, and Harobele reservoir which was constructed in 2004. These anecdotal trends corroborate our findings for these specific structures (Figure S9).

18. Very poor figures and maps, especially Figure 1, 4 and 7, no coordinates/index maps.

We respectfully disagree, but are happy to entertain any changes to these figures as requested by the editor or HESS guidelines.

Spatial characterization of long-term hydrological change in the Arkavathy watershed adjacent to Bangalore, India

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Abstract. The complexity and heterogeneity of human water use over large spatial areas and decadal timescales can impede the understanding of hydrological change, particularly in regions with sparse monitoring of the water cycle. In the Arkavathy watershed in south India, surface water inflows to major reservoirs decreased over a 40 year period during which urbanization, groundwater depletion, modification of the river network, and changes in agricultural practices also occurred. These multiple, interacting drivers combined with limited hydrological monitoring make attribution of the causes of diminishing water resources in the watershed challenging and impede effective policy responses. To mitigate these challenges, we develop a novel, spatially distributed dataset to understand hydrological change by characterizing the residual trends in surface water extent that remain after controlling for precipitation variations and comparing the trends with historical land use maps to assess human drivers of change. Using an automated classification approach with subpixel unmixing, we classified water extent in nearly 1700 man-made lakes, or tanks, in Landsat images from 1973 to 2010. The classification results compared well with a reference dataset of water extent of tanks (R^2 = 0.95). We modeled water extent of 42 clusters of tanks in a multiple regression on simple hydrological covariates (including precipitation) and time. Interannual variability in precipitation accounted for 63% of the predicted variability in water extent. However, precipitation did not exhibit statistically significant trends in any part of the watershed. After controlling for precipitation variability, we found statistically significant temporal trends in water extent, both positive and negative, in 13 of the clusters. Based on a water balance argument, we inferred that these trends likely reflect a non-stationary relationship between precipitation and watershed runoff. Independently of precipitation, water extent increased in a region downstream of Bangalore, likely due to increased urban effluents, and declined in the northern portion of the Arkavathy. Comparison of the drying trends with land use indicated that they were most strongly associated with irrigated agriculture, sourced almost exclusively by groundwater. This suggests that groundwater abstraction was a major driver of hydrological change in this watershed. Disaggregating the watershed-scale hydrological response via remote sensing of surface water bodies over multiple decades yielded a spatially resolved characterization of hydrological change in an otherwise poorly monitored watershed. This approach presents an opportunity for understanding hydrological change in heavily managed watersheds where surface water bodies integrate upstream runoff and can be delineated using satellite imagery.

1 Introduction

Human water consumption is straining water resources worldwide (Vogel et al., 2015; Gleick, 2014; Wada et al., 2012; Lall et al., 2008), with developing nations particularly vulnerable to water scarcity (Vörösmarty et al., 2010). The causes of water scarcity are complex (Srinivasan et al., 2012) and in south India have been associated with urbanization (Srinivasan et al., 2013), groundwater depletion (Reddy, 2005), degradation of rainwater harvesting structures (Gunnell and Krishnamurthy, 2003), and interstate water disputes (Anand, 2004).

Effective management of water resources in south India requires better characterization of nonstationary water resources (Kumar et al., 2005; Milly et al., 2008) and associated human drivers of change (Venot et al., 2007; Falkenmark et al., 2007; Wagener et al., 2010). Human interventions in the water cycle often occur due to decisions made at local scales, and therefore exhibit considerable spatial heterogeneity when considered at larger scales. This is problematic in this region because most research linking human drivers to hydrological responses focuses on either the local scale (Perrin et al., 2012; Van Meter et al., 2016), or regional to national scales (Gosain et al., 2011; Devineni et al., 2013; Tiwari et al., 2009). There is little research that addresses the emergent effects and heterogeneity of human-driven hydrological change across the watershed scales at which management decisions must typically be made. The gap in scientific understanding at management-relevant scales is strongly associated with lack of data resolution at these scales, and forces water managers to make decisions without sufficient information about cause and effect within watersheds (Batchelor et al., 2003; Glendenning et al., 2012; Lele et al., 2013; Srinivasan et al., 2015).

The data scarcity that challenges understanding of human-driven hydrological change in south India is a common challenge in hydrology and has been extensively explored through the lens of “predictions in ungauged basins” (PUB) over the past two decades (Bonell et al., 2006; Hrachowitz et al., 2013). The methodologies developed through the PUB initiative focused strongly on near-“natural” basins, where proxies for flow behavior (whether climatic, geographic or geomorphic) could be used to form a space in which to extrapolate flows observed in gauged basins to those in the ungauged site (Blöschl, 2013). Extending these techniques to heavily managed catchments presents numerous challenges, including the identification of suitable proxies to define the effects of human intervention and non-stationarity of the water cycle (Thompson et al., 2013). Given the complexity of these managed systems, hydrological reconstruction to infer or reproduce the history of hydrological change can help identify the predominant processes that relate human water use and management with the hydrological response.

Here we present such a hydrological reconstruction covering four decades of extensive hydrological change in the Arkavathy watershed near Bangalore, India (Fig. 1). Concern about water scarcity in the Arkavathy watershed has grown with the loss of historical monsoon-season river flow and reduced inflows to the TG Halli reservoir, which was the primary water supply reservoir for Bangalore between the 1930s and 1970s. These inflows have declined by nearly 80% since the late 1970s, a time period that also included groundwater depletion and loss of storage in surface reservoirs. Analysis by Srinivasan et al. (2015) showed that neither trends in precipitation nor evaporative demand could explain the observed changes in river flow. Instead, reductions in river channel flow were probably caused by human drivers of change such as expansion of *Eucalyptus* plantations, groundwater depletion associated with irrigated agriculture, and the construction of in-stream check dams (Srinivasan et al., 2015).

Groundwater irrigation grew in popularity in India in the 1960s (Briscoe and Malik, 2006), supplanting tank irrigation in south India in the following decades with the widespread adoption of borewells for groundwater pumping (Janakarajan, 1993a). Groundwater is now the dominant source of irrigation water in the Arkavathy watershed (Lele et al., 2013; Srinivasan et al., 2015). The availability of year-round reliable water supplies led to increases in the extent and intensity of agricultural production, and thus further demand for water. Replacement of traditional crops with *Eucalyptus* plantations, and population growth and urbanization around the periphery of Bangalore, the road network, and other urban hubs have also likely increased water demand. As villages and farmers became more reliant on groundwater, they attempted to augment groundwater recharge by constructing hundreds, if not thousands, of in-stream check dams which impound a portion of streamflow which is then removed from the channel via groundwater recharge or evaporation (Srinivasan et al., 2015). These decentralized land and water management decisions are spatially heterogeneous and characterizing their effects on surface water is hindered by the lack of hydrological records in the Arkavathy. However, spatially explicit characterization of variations in these drivers and hydrological change across the watershed could offer a basis for drawing conclusions about the likely causes of change, thus assisting in the development of management approaches. To date, such analysis has been limited to anecdotal stakeholder accounts (Lele et al., 2013).

Our reconstruction relies on developing a history of change in the end-of-monsoon-season water storage in widely distributed surface rainwater harvesting structures known as tanks (Vaidyanathan et al., 2001; Van Meter et al., 2014). Agriculture in south India was historically sustained by a series of reservoirs known collectively as the "cascading irrigation tank system". Nearly 1700 tanks have been constructed in the Arkavathy watershed. Tanks typically consist of a long, shallow dam bund constructed across a river to harvest surface runoff during the monsoon and supply irrigation water during the dry season. The bund impedes streamflow until the tank fills, overflows, and "cascades" into downstream tanks. Although the dam bunds remain in place, village-level water managers report that the tanks rarely fill up or overflow in large portions of the Arkavathy (ATREE et al., 2015), similar to other watersheds in south India (Janakarajan, 1993b; Gunnell and Krishnamurthy, 2003; Kumar et al., 2016). This decline of tank water is a cause of concern in the Arkavathy and much of the region, and multiple efforts have been initiated to rejuvenate tanks, often without clear understanding of the drivers of degradation of the system (Kumar et al., 2016; Srinivasan et al., 2015).

Other studies have also used small surface reservoirs as aggregators of upstream discharge. For instance, *In situ* measurements of tank water storage have been successfully used to calibrate and validate hydrological models in Andhra Pradesh (Perrin et al., 2012) and Tamil Nadu (Van Meter et al., 2016). Other studies in south India (Mialhe et al., 2008), the USA (Halabisky et al., 2016), Africa (Meigh, 1995; Liebe et al., 2005; Sawunyama et al., 2006; Liebe et al., 2009; Gardelle et al., 2010) and South America (Rodrigues et al., 2012) also use surface water bodies as aggregators of streamflow.

An illustrative example of one of the tanks in the Arkavathy watershed is shown in Fig. 2 for two conditions: one prior to a runoff event, and another following a runoff event in August 2014. This tank, like all tanks in the watershed, is directly connected to surface flow in the river channel network. Consequently changes in the water surface area within tanks (tank water extent), such as the changes occurring between the two images shown in Figure 2, provide a proxy for surface flow generation over the upstream catchment area.

Hydrological changes in the Arkavathy watershed should be apparent in historical satellite imagery, as the period of reported hydrological change in the Arkavathy (from the late 1970s onward) coincides with the initial image collection by Landsat satellites in 1972. We develop an automated approach for estimating tank water extent in the Arkavathy watershed using Landsat imagery and apply this approach to reconstruct a timeseries of water extent in tanks from 1973 to 2010. We then undertake a statistical analysis that identifies temporal trends in water extent while controlling for variability in precipitation over the study period. We interpret long-term trends in tank water extent that remain after controlling for precipitation variations as an indication of spatially-variable hydrologic nonstationarity. Specifically, we hypothesize that declines in tank water extent derive from human activities associated with groundwater depletion, such as groundwater abstraction for irrigation or groundwater mining by *Eucalyptus* plantations. To explore this hypothesis, we compare the non-precipitation-related temporal trends of tank water extent against land use profiles developed by Lele and Sowmyashree (2016). These analyses, including remote sensing, modeling of tank water extent, and land use–trend comparison, are outlined in the methods section below.

2 Methods

2.1 Study site

The Arkavathy watershed spans 4,253 km^2 on the western edge of the city of Bangalore in Karnataka, south India (Fig. 1). It has a monsoonal climate and mean annual rainfall of 820 mm. The monsoon season includes the southwest monsoon from June to September and the northeast monsoon from October to December. We therefore refer to several discrete periods of time within the year as the pre-monsoon period, taken as April–May, the wet season or monsoon season, between June and December, the end-of-monsoon period, taken as December–January, and the dry season, January–May. We also refer to the "monsoon year", analogous to the usual concept of the water year, spanning the period from April to March of the following year. The watershed has a relatively stable daily maximum temperature of 27°C, which a peak near the end of the dry season in April around 34°C, before pre-monsoon rainfall arrives sporadically in April and May. The river is gauged at TG Halli reservoir (Location 2, Fig. 1b) and upstream of Harobele reservoir (Location 5, Fig. 1b).

The watershed contains a mix of urban, natural, and agricultural land uses. Agricultural land can be divided into rainfed grain crops, irrigated vegetable crops, *Eucalyptus* plantations, and other irrigated tree plantations (e.g., areca nut). Most present-day irrigation water in the Arkavathy is sourced from a deep, fractured rock aquifer. Irrigation from tanks is now significant in only a few locations, mostly located downstream of Bangalore. The city of Bangalore imports water from the regional Cauvery river and returns some urban wastewater to the Arkavathy system. Although many tanks are no longer in use, the tank structures remain intact and continue to capture inflow.

2.2 Remote sensing analysis

The aim of the remote sensing analysis was to generate a timeseries of the surface area of water stored in each tank (referred to from now on as the 'tank water extent') in the Arkavathy watershed. There is minimal rainfall or flow outside the monsoon period, and analysis of tank areas within the monsoon period is inhibited by extensive cloud cover. The analysis therefore focuses on end-of-monsoon images from the months of December and January (<5% of rainfall arrives in December).

A detailed description of the remote sensing methods employed is provided in the Supplemental Material, Section S1, and the main steps are summarized below. Landsat satellite imagery was used for analyses. Sixteen (16) images taken in December or January between 1973 and 2010 were classified to provide information about end-of-monsoon tank water extent. An additional 32 images were also classified to assist in validation, and to provide information about tank water extent variations during the dry season (see Supplemental Material Fig. S1 and Table S1 for imagery dates).

A range of pre-processing and quality assurance/quality control procedures were performed on the imagery, including converting all Landsat imagery to top-of-atmosphere reflectance (Chander et al., 2009), correcting for scan-line error in Landsat 7 ETM+ images (Scaramuzza et al., 2005; Chen et al., 2011; Catts et al., 1985), and masking of cloud shadows (Zhu and Woodcock, 2012; Irish, 2000; Craven et al., 2002). The location of tanks within the resulting images was determined using a shapefile of tank boundaries obtained from the Karnataka State Remote Sensing Application Centre (KSRSAC, karnataka.gov.in/ksrsac), supplemented by 1970s topographic maps (surveyofindia.gov.in) for the beginning of the study period (see Table S2 for all data sources used in this study). Within each identified tank boundary, a two-stage approach for estimating water extent was followed (see Section S1.2 for further details). First, pixels having definitive spectral properties of water were identified and classified as "apparent" water pixels. Second, spectral unmixing was used to estimate the water fraction in all pixels within 60 m of any apparent water pixels. Tanks were excluded from the analysis if their boundaries intersected with a cloud or cloud shadow, if $\geq$25% of their area overlapped with missing pixels due to the SLC error in Landsat 7, or if $\geq$25% of their area overlapped with the edge of the scene.

2.3 Validation of classification method

Classification results were validated against a 5 m resolution LISS IV satellite image from 26 February 2014 using a classified Landsat image from 27 February 2014. The classifications were compared at the pixel scale and tank scale. Pixel level validation details are described in the Supplemental Material, Section S1.3. Tank scale Landsat results were compared directly to the results from the reference (LISS) classification, ignoring tanks in which there were obvious differences due to the incongruous image capture dates (e.g., cloud cover). We also used Digital Globe imagery available from Google Earth (Google Earth, 2016) to assess the validity of the classification in normal (680–955 mm) versus wet (>955 mm) precipitation years during the study period. Given the limited availability of these images, we were unable to find a dry-year image (<680 mm) within the study period that was suitable for comparison with a mostly cloud-free Landsat image. We manually delineated 18 tanks in the normal year (2009) and 34 tanks in wet years (2004 and 2005), and compared the manual delineation with classification of Landsat images from the same time period using a linear regression.

2.4 Statistical model of tank water extent

The aim of the statistical model is to identify changes in tank water extent that could be attributed to changes in streamflow production in the Arkavathy watershed. To achieve this, the model should control for drivers of water extent variability other than streamflow. Bathymetric surveys in the Arkavathy watershed indicate that tank water extent is a function of tank volumetric storage (Young et al., 2017). Thus, a volumetric water balance for a tank can be used to consider the drivers of water extent variability, as follows:

$$S(t_2) = S(t_1) + \sum_{t_1}^{t_2} (P - Drainage - ET) A_{tank} + \sum_{t_1}^{t_2} Q_{in} - \sum_{t_1}^{t_2} Q_{out} - \sum_{t_1}^{t_2} Withdrawals, \quad (1)$$

where S indicates tank storage at time t_2 when the Landsat image was taken, $S(t_1)$ is the storage in the tank at some prior time t_1, P is the precipitation depth over the tank area, $Drainage$ the drainage from the tank floor, ET evaporation from the tank surface area, A_{tank} is the tank surface area, Q_{in} the streamflow entering the tank, Q_{out} the overflows leaving the tank, $Withdrawals$ any anthropogenic withdrawal from the tank itself, and sums are taken from t_1 to t_2. The statistical model we developed addressed the above sources of variation by (i) approximating $S(t_1)$ with zero, (ii) directly accounting for variations in P (and thus their contribution to variations in Q_{in}), (iii) neglecting variations in Q_{out}, for two reasons: first, because watershed managers report that tanks rarely overflow, so Q_{out} can reasonably be approximated as ≈ 0, and second because any overflow that does occur implies that S is equal to its maximum S_{max}, so that variations in overflow cannot contribute to changes in observed S, (iv) treating the sum of $Drainage$, ET and $Withdrawal$ fluxes as a stationary cumulative loss term, and (v) accounting for time trends in tank water extent that remain having accounted for (i)–(iv). Such time trends, if present, would indicate the presence of non-stationarity in tank water extents that could not be explained by variability in precipitation.

We confirmed that (i) is reasonable by analyzing carry-over storage across the dry season using 2014 imagery (selected because of high image availability). Carry-over water extent from 2013 monsoon to the start of the 2014 monsoon was $\leq 25\%$ or approximately $\leq 12.5\%$ of end-of-monsoon storage for more than 50% of tank clusters, and $\leq 50\%$ or approximately $\leq 35\%$ of storage for more than 75% of clusters (water extent to volume conversions are based on bathymetric data reported in Young et al., 2017). Tank clusters with the highest carryover storage (as inferred from water extent) were found in urban subwatersheds or hilly sub watersheds in the southern part of the Arkavathy watershed (see Fig. S10). These results suggest that carry-over storage is minimal in most parts of the watershed and that neglecting its effect on tank water extent variability is reasonable.

Variations in P (ii) were accounted for using daily rainfall data from 62 gauges operated by the Karnataka State Natural Disaster Monitoring Centre (KSNDMC). Precipitation trends were analyzed using Mann-Kendall non-parameteric tests. Exploratory analysis at the whole-basin scale indicated that tank water extents were most related to precipitation totals from September 1 to to the date of Landsat image acquisition. Contemporary observations in the Arkavathy watershed suggest that only the largest or most intense storms generate runoff. The average depth of large storms (>10 mm/day) from September 1 to the date of the Landsat image was used as a metric of extreme rainfall occurrence to account for these observations.

Finally, we accounted for losses by treating the sum of $Drainage$, ET and $Withdrawal$ fluxes as a lumped linear loss term focusing on the end-of-monsoon and early dry season. Previous analysis of monitored locations shows that since the early 1970s, no streamflow occurred in the Arkavathy watershed other than in months when rainfall occurred (Srinivasan et al., 2015), and rainfall was minimal from December 1 onward. Changes in tank water extent from December 1 into the early dry season are therefore dominated by loss terms. We confirmed that these losses were stationary in 6 of the 8 watersheds analyzed by bootstrapping the non-parameteric Mann–Kendall trend tests using classified tank water extents obtained from 27 dry season Landsat images (see Fig. S10).

All analyses proceeded by considering two spatial scales: 8 subwatersheds, which represent regions of relatively homogeneous climatic forcing, and 42 smaller hydrologically-connected subwatershed units, which are referred to as tank "clusters", each containing at least 15 tanks having non-zero water extent in at least 4 end-of-monsoon images (Fig. 3). Aggregated tank water extents for each cluster form the basis for statistical analysis. Aggregating data in this way overcomes some of the challenges associated with a relatively short record and frequently dry tanks, while offering enough spatial resolution to identify variability in trends across the Arkavathy watershed. The analysis excluded reservoirs, because the water extent in a reservoir is also influenced by active management and water transfers. Some tanks were constructed during the study period, and these tanks were excluded from the analysis in any years prior to their construction.

These model features (i) – (v) were incorporated into a multivariate regression with interactions between continuous covariates and categorical variables (e.g., see Jaccard et al., 1990; Cohen et al., 2003). The covariates used were cumulative monsoon season rainfall (from September 1 onward), denoted P_{total}; average depth of large storms during the monsoon season (from September 1 onward), denoted $P_{extreme}$; time delay from the beginning of the end-of-monsoon period (December 1) to the date of Landsat image acquisition, denoted DSD; and the year in which the observation was made, denoted $Year$.

The P_{total}, $P_{extreme}$, and DSD covariates were modeled as fixed effects which interact with the subwatersheds. In other words, the response of the tank water extent to these variables was allowed to vary for each subwatershed, but was assumed to be consistent for the tank clusters within the subwatershed. The year effect was estimated separately for each tank cluster.

The model can be written as follows:

$$A_{cluster,ij} = C_0 + C_{1,k} P_{total,ij} + C_{2,k} P_{extreme,ij} + C_{3,k} DSD_i + B_{1,j} Year_i + e_{ij} \tag{2}$$

The subscripts refer to the Landsat scene (i), tank clusters (j), and subwatersheds (k). Other than the intercept (C_0), the fixed effects differ for each subwatershed ($C_{1,k}$, $C_{2,k}$, and $C_{3,k}$) or tank cluster ($B_{1,j}$). The errors for each observation are included as e_{ij}.

The model predicts the tank water extent per cluster ($A_{cluster,ij}$), normalized by its maximum. Tank clusters were only analyzed for any given scene if $\leq 30\%$ of the total cluster tank area was missing (due to tanks being omitted for QA/QC purposes in classification, or not having been constructed by the date of analysis). All covariates were centered by subtracting the mean before being input into the model. We confirmed that collinearity between covariates was minimal and did not impact interpretation of confidence intervals or model output using Generalized Variance Inflation Factors (Fox, 2008; Fox and

Monette, 1992) (see Supplemental Material Section S2.2 for details). The model performance was assessed using multiple R^2 statistics and significance of all effects.

The primary result of interest is the $Year$ effect on tank water extent for each cluster, $B_{1,j}$. This effect represents a temporal trend in total tank water storage over time (as a percent change over time), after controlling for a stationary relationship between tank water storage and the covariates (P_{total}, $P_{extreme}$, DSD). In the 6 watersheds where dry season losses were stationary, we attribute this change to changing inflows, as all other sources of non-stationarity are controlled for. In the two subwatersheds where a change in the effect of dry season water loss on tank storage was detected, $B_{1,j}$ captures the combined effect of hydrological change and non-stationarity in dry-season tank water losses.

Because the value of $B_{1,j}$ is the key result of interest, additional analyses were performed to confirm its importance. Specifically the model was refit while omitting the $Year$ effect $B_{1,j}$. The performance of the two models (with and without $B_{1,j}$) was compared via R^2 metrics. The significance of deviations between the two model predictions was tested using an F-test ($H_0 : B_{1,j} = 0$, $H_A : B_{1,j} \neq 0$, for at least one value of j).

2.5 Linear regression of streamflow trend against land use

We used four land use maps developed for 1973-74, 1991-92, 2001-02, and 2013-14 (Lele and Sowmyashree, 2016) encompassing the TG Halli watershed, which contains the three subwatersheds upstream of the TG Halli reservoir (TG Halli East, Kumudavathy, and Hesaraghatta) and includes a total of 17 tank clusters. The maps differentiate agricultural land use classes into rainfed crops, irrigated crops, and *Eucalyptus* plantations. Irrigated agriculture in this region is supplied almost exclusively by groundwater, allowing us to test whether groundwater irrigated crops, increased water utilization by *Eucalyptus* plantations (Srinivasan et al., 2015), both, or neither, are associated with the identified streamflow trend.

In the early 1970s, rainfed agriculture was the primary land use in the TG Halli watershed. Over the study period, many farmers adopted groundwater irrigation and others converted their fields to *Eucalyptus* plantations, which have the potential to mine shallow groundwater or to significantly reduce deep recharge. These land use changes have the potential to reduce surface water flows by depleting subsurface water availability and baseflow over time, likely resulting in a non-stationary streamflow response. This non-stationarity, in conjunction with the relatively sparse availability of land cover data over time, complicated a direct analysis of land use against tank water level. Instead, a space-for-time approach was used to compare the differences in time-averaged land use across each tank cluster to the differences in the $Year$ effect $B_{1,j}$ found for each cluster. We therefore calculate the time-average land use fraction corresponding to irrigated crops ($A_{irrigated,avg}$) and *Eucalyptus* plantations ($A_{Eucs,avg}$) for each of the 17 tank cluster watersheds and regress ($B_{1,j}$) against these these land fractions:

$$B_{1,j} = C_{Eucs} A_{Eucs,j} + C_{irrigated} A_{irrigated,j} \tag{3}$$

The coefficients, C_{Eucs} and $C_{irrigated}$, correspond to the sensitivity of hydrological change to time average *Eucalyptus* land cover and irrigated agriculture land cover, across all 17 tank clusters. This analysis is not designed to directly infer causation, but rather to understand associations between streamflow decline and agricultural practices.

3 Results

3.1 Accuracy assessment

The Landsat classification yielded timeseries of water extent in each of the tanks throughout the watershed (e.g., see Figs. S5 & S6). The Landsat classification agreed well with the reference LISS classification at the tank scale, and accuracy improved with increasing tank size. A regression of Landsat extent versus reference extent (Figure 4) for tanks less than 25 hectares (278 pixels) had a slope of 0.98 and coefficient of determination (R^2) of 0.95. When all tanks and reservoirs were included, the regression line had a slope of 1.02 and coefficient of determination of 0.99. Over 99% of dry tanks were correctly classified as dry, but error was considerably large for small tanks with non-zero water extent less than 2.5 ha (28 pixels), due to false positives in the reference classification as well as errors the Landsat classification. For tanks between 2.5 and 10 ha the classification performed considerably better. The mean absolute error increased as the extent of the water body increased, but mean percent error decreased with water body size. Pixel scale accuracy assessment (see Supplemental Material, Section S1.3) indicated that classification at pixel scales was accurate for completely wet or completely dry pixels (producer's accuracies of 84% and 99% respectively), and lower for mixed pixels (producer's accuracy 41–82%) (see Fig. S7). Comparison of our automated Landsat classification similarly compared well with the Google Earth manual delineation of tanks in both normal years (R^2 = 0.97) and wet years (R^2 = 0.97) (see Fig. S8).

Although the time-variation in most tanks have not been reported via *in situ* measurements, trends in water storage over time are widely known for some of the major reservoirs. The TG Halli and Hesaraghatta reservoirs declined from a peak storage in the 1970s to much lower contemporary storage. Large increases in water extent were observed in Manchanabele reservoir, which was constructed in 1993, and Harobele reservoir which was constructed in 2004. These anecdotal trends corroborate our findings for these specific structures (Figure S9).

3.2 Statistical analysis

Trend analysis of the 62 rain gauges in the watershed showed that there were no statistically significant trends in rainfall at whole watershed (see Fig. S11), subwatershed (not shown), or tank cluster scales (see Fig. S12). Precipitation has thus been stationary, although exhibiting considerable inter-annual variability, during the period of analysis, and any identified trends in tank water extent over time can exclude consideration of precipitation change as a driver.

The multivariate analysis explained nearly 70% of the variation in tank cluster water extent (R^2 = 0.68). Model residuals were normally distributed (Figure S13). The effects of both precipitation covariates (P_{total} and $P_{extreme}$) were significant (the 95% confidence interval of the slopes excluded zero) in nearly all subwatersheds, and the effect of dry-season water loss was significant in the two subwatersheds that flow into TG Halli reservoir. Inter-annual variability in precipitation (P_{total} and $P_{extreme}$) explained 63% of the total predicted variability in tank water extent over the study period, while the DSD term explained 10% of the variability.

The multivariate analysis also identified significant $Year$ effects $B_{1,j}$ (Table S3, Fig. S14) in 13 tank clusters. $B_{1,j}$ varied in its sign and statistical significance among tank clusters, and explained 27% of the total variation in tank water extent (see

Fig. S15 for a comparison of the effects of precipitation and $B_{1,j}$ across each cluster.). In the two subwatersheds flowing directly into the TG Halli reservoir, $B_{1,j}$ captured the combined effect of non-stationarity in streamflow generation and non-stationarity in dry-season tank water losses (lower tank losses increase $B_{1,j}$). If the sign of $B_{1,j}$ is negative in these tanks, it implies that the effect of non-stationarity in streamflow generation must both be negative and exceed the effects of reduced tank water losses. We converted the units of $B_{1,j}$ to an areal rate of change over time per 10 km^2 of catchment area (Figure 5). In the three subwatersheds upstream of TG Halli reservoir, most tank clusters exhibit negative $B_{i,j}$ values, implying reductions in streamflow generation. Tanks within Bangalore generally exhibited negative $Year$ effects, and tanks at the city periphery and immediately downstream of the city had positive effects. Other regions of the watershed exhibited mixed values of $B_{i,j}$, but none were statistically significant at the 95% confidence level.

We confirmed that the $Year$ effect $B_{1,j}$ was important for understanding the variations in tank water extent. Omitting the $Year$ effect from the tank water extent model lowered the R^2 from 0.68 to 0.58. Furthermore, the model predictions with and without the $Year$ effect were significantly different according to the F-test ($p < 3.1 \times 10^{-11}$). These results allow us to reject the null hypothesis that $B_{1,j} = 0$, meaning that the $Year$ effects could not be ignored.

Overall, the results indicate that while (unsurprisingly), interannual variations in rainfall totals and extremes explain the majority of interannual variation in tank water level, that a trend in tank water level is present in several regions of the Arkavathy watershed that is independent of rainfall variability. This trend cannot be explained by trends in rainfall, which were negligible, by trends in dry season tank water loss rates, which, where they existed, had the opposite sign to the identified trend in water level, or by changes in outflows, which are constrained to occur when tank storage is at its peak. The results suggest that changes in streamflow production independent of rainfall are occurring in discrete locations in the Arkavathy watershed, and that the sign of these changes varies through space.

3.3 Streamflow decline and agricultural practices

The regression of the $Year$ effect $B_{1,j}$ on irrigated agriculture and *Eucalyptus* land use areas explained most of the differences in $B_{1,j}$ between tank clusters (R^2 = 0.68). The relationship between irrigated crops and $B_{1,j}$ was statistically significant (95% confidence intervals of $C_{irrigated}$ excluded zero), and the relationship with *Eucalyptus* plantations was not statistically significant (Fig. 6).

4 Discussion

4.1 Long-term hydrological trends and human drivers of change

Tank water extent at the end of the monsoon season can be primarily attributed to the storage of monsoon season streamflow, given that tanks in the Arkavathy watershed rarely overflow, there is little carry-over storage year to year, and loss processes do not extensively deplete the tanks from the end of the monsoon period to the time when tank water extents were observed by Landsat. Thus, storage of water in tanks offers an integrated measure of tank inflows during the previous wet season.

Statistical analysis of the tank water extents suggests that while inter-annual variability in tank water extent is largely explained by precipitation, this variability is superimposed on a longer-term trend in tank water extent that is independent of precipitation, representing a non-stationarity in inflows. Analysis of rain gauges indicated that precipitation has been stationary within the watershed during the study period. Non-stationarity in inflows, coupled with stationarity in precipitation, indicate changes in the runoff ratio (defined as flow production per unit precipitation), a common indicator of changing hydrological processes (Hughes et al., 2012).

Historical land use maps for the TG Halli watershed indicate that there is an association between the inferred streamflow generation trends (particularly streamflow declines) and human drivers of change. We hypothesized that the inferred decline in streamflow would correspond with agricultural practices associated with groundwater depletion. Although little data exist to describe historical declines of the water table, contemporary farmers typically have to drill new borewells to depths exceeding 100 m to reach any groundwater. If a loss of baseflow due to groundwater depletion and the disconnection of the water table from the stream channel is a primary driver of streamflow decline, we would expect the negative trends in streamflow to correspond with irrigated agriculture, which is supplied almost entirely by groundwater in the TG Halli watershed.

In the linear model relating the $Year$ effect $B_{1,j}$ to land use in the TG Halli watershed (Equation 2, Section 1), the time-averaged irrigated crop land use area is a clearer and stronger predictor of declines in tank water extent than *Eucalyptus* land use (Fig. 6). Moreover, other exploratory analyses showed that irrigated crop land-use is more correlated with $B_{1,j}$ ($R^2 = 0.68$, see Fig. S16) than rainfed crops ($R^2 = 0.5$) and all other land-use types ($R^2 < 0.38$). Areas retaining mostly rainfed crops exhibit higher (less-negative) values of $B_{1,j}$, and lower (more-negative) values of $B_{1,j}$ are associated with areas with higher conversion of rainfed crops to irrigated crops. The finding that *Eucalyptus* plantations do not play a major role in streamflow decline is consistent with field experiments, which show that that *Eucalyptus* plantations tend to reduce soil infiltration capacity and therefore would increase infiltration excess runoff (Penny et al., 2015). There could be some relationship between *Eucalyptus* plantations and non-stationary hydrologic processes, but if so it is secondary to that of irrigated crops.

Areas with a high fraction of irrigated agriculture are also likely to contain relatively higher densities of check dams than other land use types, given the desire to recharge diminished groundwater resources. In the absence of datasets describing the spatial distribution and hydrological properties of check dams (or a viable way to develop such a dataset), this analysis is unable to separate the effect of loss of baseflow due to groundwater pumping from the in-stream losses due to check dams. Both processes likely play a role in observed hydrological changes. Recession analyses indicate that the loss of the shallow water table could plausibly explain the observed magnitude of streamflow declines (Srinivasan et al., 2015), and check dams exacerbate the loss of streamflow by converting water in the stream channel to groundwater recharge (Jeremiah et al., 2014).

The most negative values of $B_{1,j}$ and thus the largest inferred reductions in streamflow production occurred in the northernmost regions of the Arkavathy where elevation is higher than other areas of the watershed. Although it may appear that the pattern of decline could be related to upstream-downstream processes and the presence or absence of irrigation return flows (Van Meter et al., 2016, e.g., see), we are doubtful that this effect is important in the Arkavathy today. Indirect evidence (e.g., surveys) indicates that the water table is hundreds of meters below the surface in northern parts of the Arkavathy watershed

(Srinivasan et al., 2015). Furthermore, the relief in the watershed is $\approx$ 100 m over a distance of 50 km in the TG Halli watershed, meaning that system-wide return flows connecting upstream to downstream are unlikely.

Urbanization could result in increased streamflow being routed to downstream tanks, due to increases in impervious surfaces, the fallowing of agricultural land in anticipation of urbanization, and reduced consumptive water use. Increased urban water use produces increased urban effluent, which is discharged to the surface channel network where it can contribute to increases in tank water storage downstream. The observed positive $Year$ trends downstream and on the periphery of the Bangalore urban area are consistent with the substantial increases in Bangalore's imports from the Cauvery river, from 185 million liters per day (MLD) in 1974 to 1350 MLD currently (BWSSB, 2017). Additionally, as the city has grown, groundwater pumping for urban areas has increased to an estimated 600 MLD (Lele et al., 2013). About 40% of Bangalore's sewage of 1400 MLD flows to Byramangala reservoir (Jamwal et al., 2015). This has contributed to additional inflows to Byramangala reservoir and more irrigated agriculture directly downstream of the reservoir. Tanks within urban areas can also exhibit drying trends. For instance, tanks may be encroached upon as residential areas expand. Additional urban wastewater inflow can lead to expansion of algae blooms covering the tank water surface, which can appear as a "drying" of the tank in this analysis.

4.2 Assessing the classification and model uncertainty

The classification of small tanks in the Arkavathy watershed poses challenges associated with harmonization of different Landsat sensors and the variability in the spectral properties of "wet" tanks due to variations in water quality and vegetation extent. The classification tends to overestimate the amount of water in dry pixels and underestimate the amount of water in wet and mixed pixels. Because our classification scheme is designed to avoid bias between images taken with different Landsat sensors, we likely sacrifice some precision with sensors from Landsat missions 5–8.

Because these mixed pixels lie at the boundary of the wetted tank area, classification error would be sensitive to geo-registration error in one or both of the Landsat and LISS images. Error could also arise from our specification that water pixels must lie within 60 m of clearly identifiable water bodies, or the assumptions made during spectral unmixing. Although the classification scheme accounted for only two classes, the spectral properties of the land class varied among dry soil, wet soil, sparse vegetation, and irrigated agriculture. Classification of water was complicated by vegetation in tanks, varying degrees of turbidity, and algae blooms in tanks with considerable wastewater inflow.

Errors at the pixel and tank scales are likely unavoidable given the spectral heterogeneity of both land and water pixels. In particular, tanks containing water of variable turbidity, excessive vegetation, or algae blooms are prone to classification errors. Because pixel-scale errors are unbiased, accuracy at the tank scale improves as tank size increases. Error is further mitigated by grouping tanks into clusters in the statistical model.

The uncertainty of the classification (R^2 = 0.99 when all water bodies are included) is small compared with the uncertainty of the statistical model (R^2 = 0.68). Although the results of our statistical model imply a non-trivial amount of unexplained variation, Gardelle et al. (2010) reported similar performance (R^2 = 0.78) for a model relating precipitation and water extent in a single lake, and noted that the correlation was valid only for a nine-year subset of the five-decade study period. The sources of uncertainty include the complex hydrological processes that relate precipitation, streamflow, and tank water storage, as well as the nonlinear and heterogeneous relationship between water extent and water storage, the neglect of pre-monsoon tank water extent in the model, and the non-stationary behavior of dry-season losses in the two northernmost watersheds. Given this uncertainty, results of our analysis are reasonable given the simplicity of the model and the complexity and heterogeneity of the watershed hydrological response.

5 Conclusions

The Arkavathy watershed embodies many of the water security challenges confronting southern India. With data limitations hampering the characterization of changing water supplies in the watershed, remote sensing tools provide insights into the history and spatial pattern of change in water availability and hydrological function. We were able to take advantage of a pre-existing "sensing network" provided by the irrigation tank system throughout the Arkavathy watershed. The high number of tanks in this watershed allowed for a comparison of hydrological change with land use at spatial scales appropriate for a first-order analysis.

The analysis reveals that while inter-annual variations in tank water extent are dominated by inter-annual variation in precipitation, an independent time trend in tank water extent occurs for a subset of the watershed. This trend is not spatially homogeneous, but varies in its magnitude and sign among different regions of the watershed. These differences appear to be associated with differing patterns of land use across the watershed. A comparison of the hydrological trends with agricultural practices within the TG Halli watershed showed that declines in tank water extent over time, controlling for precipitation, are more closely associated with groundwater irrigated agriculture than other kinds of land use, including *Eucalyptus* plantations. This association is consistent with hypothesized effects of groundwater depletion on streamflow generation in the Arkavathy, and with the potential influence of check-dams in fragmenting the surface flow network (Srinivasan et al., 2015). Further investigation could attempt to attribute the cause of the inferred streamflow decline, either via a more sophisticated statistical analysis considering the many potential drivers of change or via a mechanistic model of catchment hydrological functioning. Ideally such analysis would also separate the relative effects of loss of baseflow due to groundwater pumping and conversion of surface flows to groundwater recharge via check dams.

Surface networks of rainwater harvesting structures are employed in seasonal climates worldwide, whether in cascading tank systems in southern India and Sri Lanka, or hillslope farm dams in Australia (Callow and Smettem, 2009; Roohi and Webb, 2012), North-East Brazil (Lima Neto et al., 2011; Malveira et al., 2012; de Araújo and Medeiros, 2013; de Toledo et al., 2014), South Africa (Hughes and Mantel, 2010), the US Great Plains (Womack et al., 2012) and China (Xiankun, 2014; Xu et al., 2013). Capitalizing on these networks as proxy indicators of rainfall and streamflow variation, as in the Arkavathy, could prove a valuable approach to circumventing problems of data scarcity and characterizing changing hydrological conditions.

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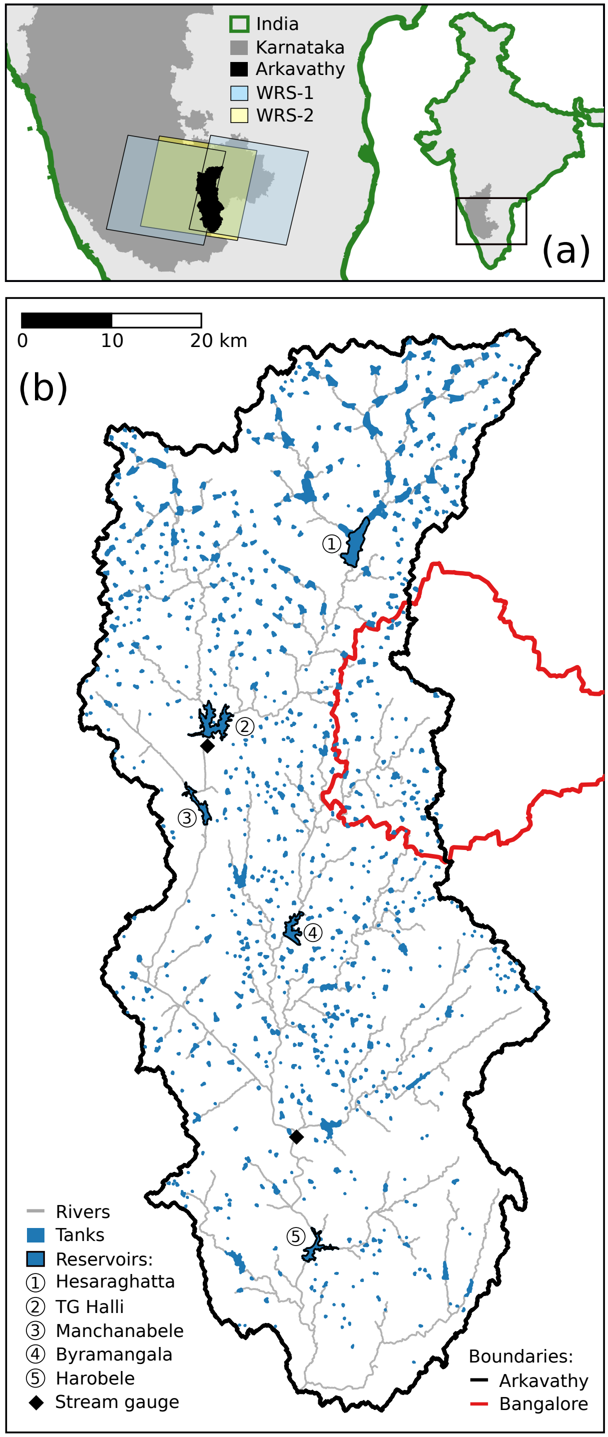

Figure 1. Site map. (a) Location of the Arkavathy watershed within the state of Karnataka, India, and scene boundaries for Landsat 1–3 (WRS-1) and Landsat 4–8 (WRS-2). (b) Map of the watershed including tanks, reservoirs including the stream gauge locations, river network, and municipal boundary of Bangalore. Lower-order streams and a number of small, generally dry tanks are excluded.

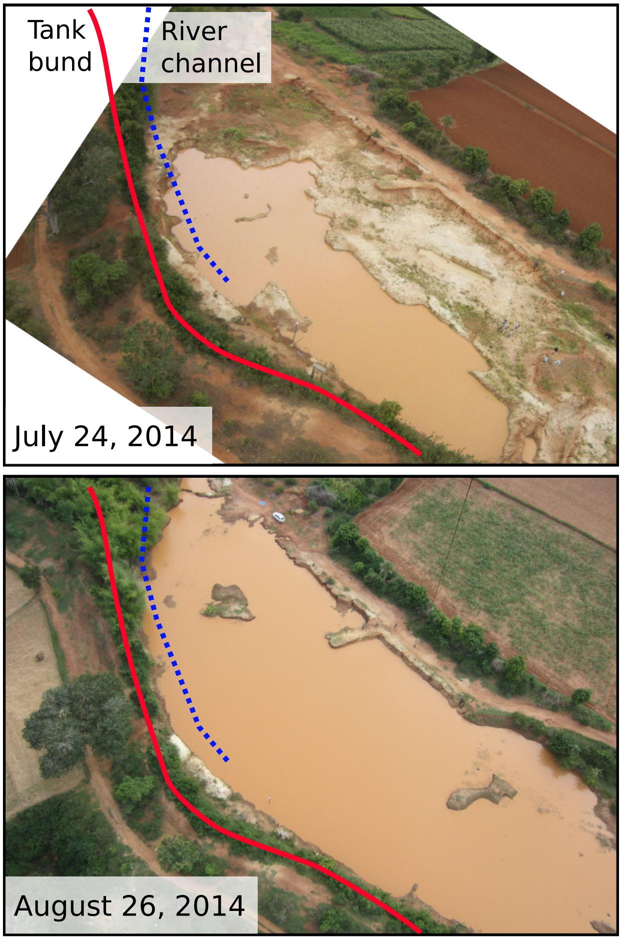

Figure 2. Aerial photos of a small tank containing turbid water in the Arkavathy watershed before and after runoff events in August 2014. The tank receives water from the channel and directly from adjacent agricultural plots, and water extent increases with storage.

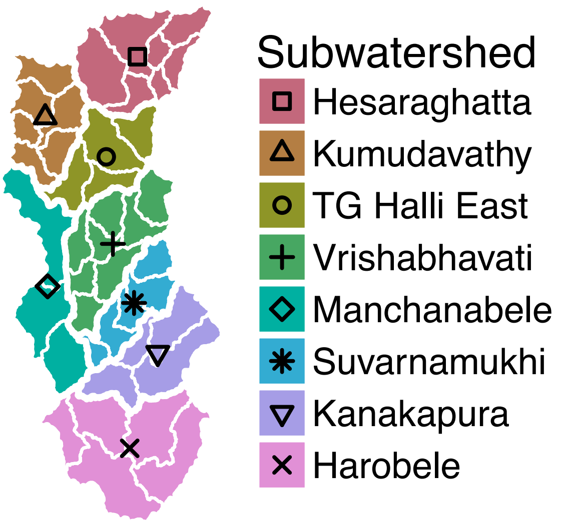

Figure 3. Subwatersheds and tank cluster watersheds. Each tank cluster contained at least 15 tanks.

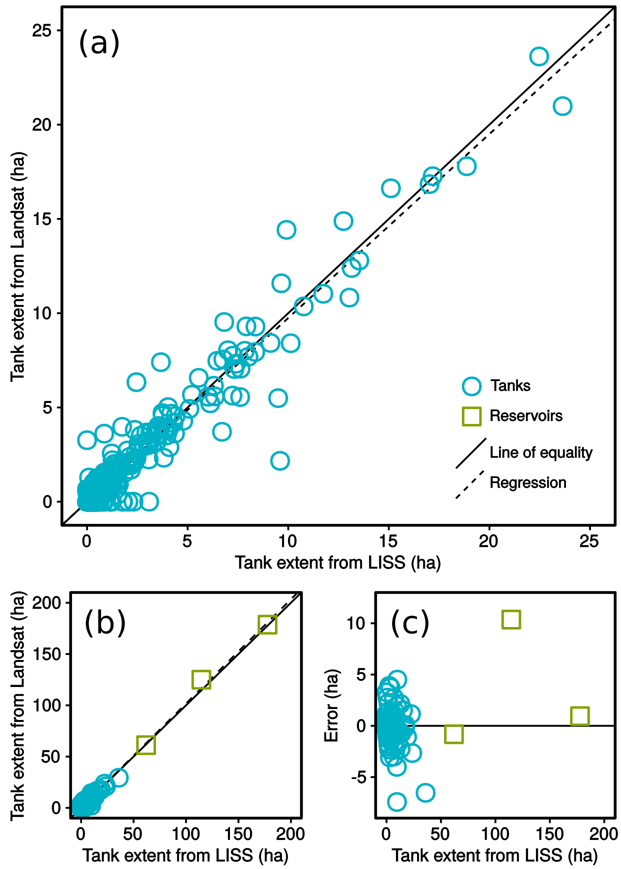

Figure 4. Comparison of Landsat and reference (LISS) classification from February 2014 images. (a) Water extent in tanks less than 25 ha. (b) Water extent in all tanks and reservoirs. (c) Error in the Landsat classification for tanks and reservoirs. Relative error decreases with increasing tank size. Only three of the five reservoirs are included because the LISS image excluded the Harobele reservoir and there was considerable change in an algae bloom in the Byramangala reservoir in the time between the acquisition of the LISS and Landsat images.

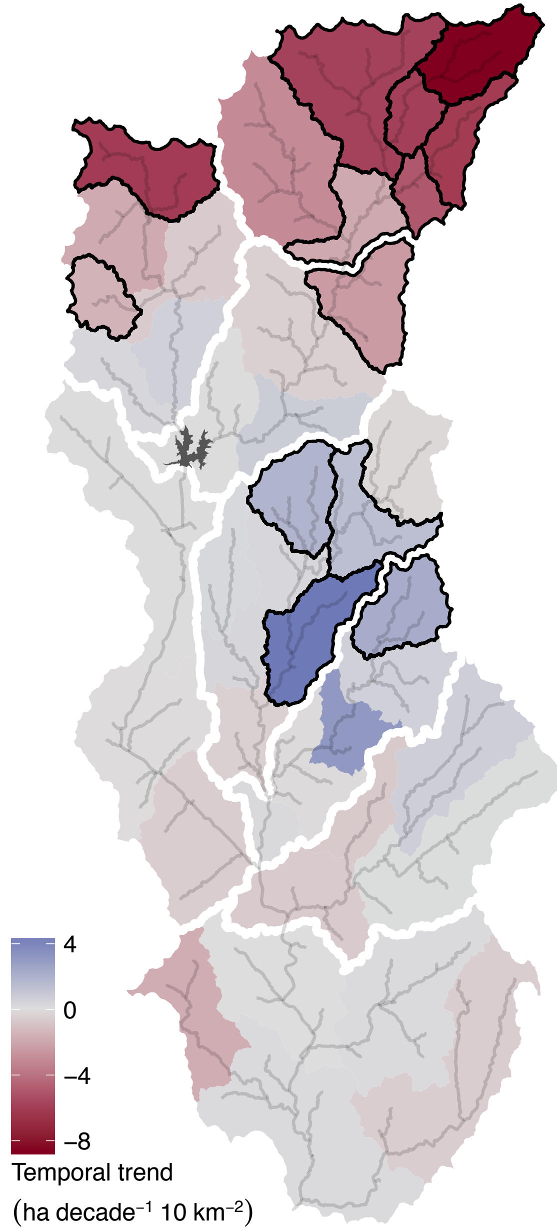

Figure 5. Values of $B_{i,j}$, the $Year$ effect on cluster water extent, 1973–2010, given as change in water surface area (ha) per decade per 10 km^2 of watershed area. White space indicates subwatershed boundaries, and black lines indicate statistical significance of the cluster trend. Based on analysis of a tank water balance, the sign of $B_{i,j}$ offers insight into likely trends in runoff ratio (streamflow generated within each tank cluster per unit incident rainfall).

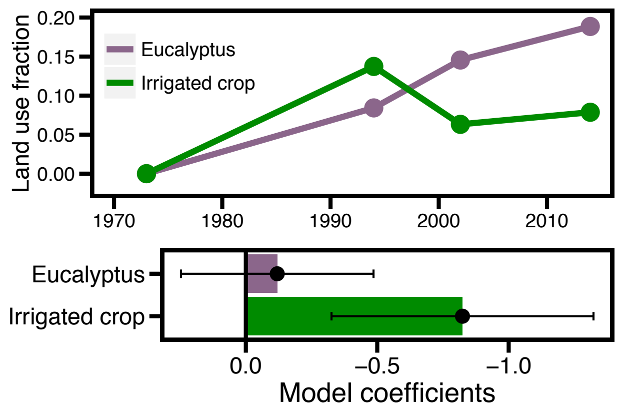

Figure 6. Agricultural land use and hydrological change. (Top) Land use fraction of *Eucalyptus* plantations and irrigated crops in four land use maps. (Bottom) Model coefficients (C_{Eucs}, $C_{irrigated}$)relating hydrological change to *Eucalyptus* and irrigated crops based from the multivariate linear regression. Horizontal lines indicate 95% confidence intervals.