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1 **Detection and attribution of nitrogen runoff**
2 **trend in China's croplands**

3

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23 Acronyms and Abbreviations

| | | | |
|------------|--|--------|--|
| R_{TN} | Cropland N runoff | RR | R_{TN} per unit N fertilizer additions |
| R^0 | Background N runoff | pH | Soil pH value |
| SOM | Soil organic matter | $Clay$ | Soil clay content |
| TN | Soil total nitrogen | $Temp$ | Mean air temperature |
| N_{rate} | Nitrogen (N) fertilizer application rate per unit sowing area | W | Sum of precipitation and irrigation within observation period |
| x_k | Environmental variables | CE | Correction coefficient |

25 **Abstract**

26 Reliable detection and attribution of changes in nitrogen (N) runoff from croplands are
27 essential for designing efficient, sustainable N management strategies for future.
28 Despite the recognition that excess N runoff poses a risk of aquatic eutrophication,
29 large-scale, spatially detailed N runoff trends and their drivers remain poorly
30 understood in China. Based on data comprising 535 site-years from 100 sites across
31 China's croplands, we developed a data-driven upscaling model and a new simplified
32 attribution approach to detect and attribute N runoff trends during the period of 1990-
33 2012. Our results show that N runoff has increased by 46% for rice paddy fields and
34 31% for upland areas since 1990. However, we acknowledge that the upscaling model
35 is subject to large uncertainties (20% and 40% as coefficient of variation of N runoff,
36 respectively). At national scale, increased fertilizer application was identified as the
37 most likely driver of the N runoff trend, while decreased irrigation levels offset to some
38 extent the impact of fertilization increases. In southern China, the increasing trend of
39 upland N runoff can be attributed to the growth in N runoff rates. Our results suggested
40 that increased SOM led to the N runoff rate growth for uplands, but led to a decline for
41 rice paddy fields. In combination, these results imply that improving management
42 approaches for both N fertilizer use and irrigation is urgently required for mitigating
43 agricultural N runoff in China.

44 **Keywords:** Nitrogen runoff; temporal trend; spatial pattern; attribution analysis;
45 Bayesian inference

46 **Capsule**

47 Cropland N runoff in China increased by 30% over the past two decades mainly due to
48 increased fertilization and decreased irrigation.

49

50 **Highlights**

- 51 • A data-driven upscaling model can effectively and reliably detect N runoff trends
- 52 • N runoff has increased by 46% for rice paddy fields and 31% for uplands since
53 1990
- 54 • SOM change results in inverse trend of N runoff rates between upland and rice
55 fields

56

57 **1. Introduction**

58 Meeting food security targets while simultaneously reducing reactive nitrogen losses
59 has drawn attention from both scientists and the public ([Chen et al., 2014](#); [Mueller et](#)
60 [al., 2012](#); [Tilman et al., 2011](#); [Zhang et al., 2015](#)). Large amounts of anthropogenic
61 nitrogen (N) inputs have resulted in excess N being lost in runoff from croplands to
62 water bodies and the atmosphere worldwide ([Cui et al., 2014](#); [Leip et al., 2011](#);
63 [Seitzinger et al., 2010](#)). As one of the consequences, increased occurrences of aquatic
64 eutrophication and ecosystem degradation were observed, particularly in China and
65 South Asia ([Paerl et al., 2014](#)). Reliable detection and attribution of cropland N runoff
66 are crucial for policy makers and farmers to develop site-specific N management
67 strategies ([Cherry et al., 2008](#)). Although cropland N runoff is substantial in China (e.g.,
68 2.1 ± 0.2 or 0.8 Tg N yr^{-1} estimated by [Gu et al., \(2015\)](#) and [Wang et al., \(2014\)](#),
69 respectively), large-scale, spatially detailed N runoff trends and its attribution remain
70 poorly understood.

71

72 Cropland N runoff, defined as a generation process of N loss via surface runoff, depends
73 on environmental conditions and agricultural management practices ([Zhang et al.,](#)
74 [2016](#)). This complexity makes large-scale N runoff difficult to estimate using empirical
75 models. Plot-scale N runoff flux data from croplands are also difficult to scale up into
76 spatially detailed maps because of spatio-temporally varying results ([Shen et al., 2012](#)).
77 Currently, an export coefficient approach has been widely used to estimate cropland N

78 runoff (Hao, 2006; Liu et al., 2010; Velthof et al., 2009; Wang et al., 2014). For example,
79 the first National Pollution Census Program of China (NPCP) provided a collection of
80 N runoff flux coefficients for different geographical regions in China, determined by
81 fitting cross-sectional site data to an export-coefficient model (Wang et al., 2014).
82 Nevertheless, substantial evidence gathered from field observations indicates that linear
83 and homogeneous models are rarely capable of capturing the spatial variability of N
84 runoff at regional scale (Schaefer and Alber, 2007; Sobota et al., 2009; Hou et al., 2016).
85 This highlights the difficulty of accurately predicting its future evolution as well as
86 quantifying the impacts on aquatic ecosystems.

87

88 While it is still challenging to attribute contributions of each individual driving factor
89 (e.g., climate condition, agricultural management practices) to the cropland N runoff
90 trend assessment, statistical correlation or regression analyses have been widely applied
91 (Korsaeth and Eltun, 2000; Stalnacke et al., 2015) over past decades. However, this
92 approach has two potential limitations. Firstly, statistical analyses of historical R_{TN}
93 generally characterizes the related major drivers, thus includes the signals not only from
94 the temporal trends, but also from inter-annual or decadal variability. Secondly, the use
95 of statistical analysis generally assumes that the effects of drivers on N runoff are linear
96 and independent of each other (Piao et al., 2015). However, a growing number of
97 studies based on both data from field experiments and theoretical analyses indicated
98 non-linear responses of N runoff to changes in driving factors as a consequence of

99 complex interactions (Hou et al., 2016). Although these limitations in attribution
100 analysis could be overcome through the application of process-based models (Hao,
101 2006; Abbaspour et al., 2015, Liu et al. 2016), core limitations of such simulation
102 models are the large uncertainties arising from model structure and parameter choice
103 (Schulz et al., 1999). One way to separate the contribution of natural and anthropogenic
104 controls is to use the Kaya Identity concept developed in economics (Raupach et al.,
105 2007), which is adopted when studying climate change and hydrological science
106 (Streimikiene and Balezentis, 2016; Wang et al., 2015b).

107

108 To quantify and attribute cropland N runoff trends during past decades, we analyzed the
109 data in this study is based on a upscaling model following a new simple attribution
110 approach. Synthesized field measurements were used for model calibration and cross-
111 validation based on the Bayesian Recursive Regression Tree algorithm version 2.0
112 (BRRT v2, Zhou et al., 2015), utilizing high-resolution gridded datasets including
113 climate conditions, soil attributes, and agricultural management practices. First, we
114 assessed inter-annual dynamics of cropland N runoff derived from the data-driven
115 upscaling model to detect trends for the period from 1990 to 2012. Second, we
116 compared the proportional change rate of each driver to upscaling results of R_{TN} , which
117 allowed us to diagnose the contributions of different drivers. Finally, we discussed how
118 each driver modulates the temporal trend of R_{TN} and the implications for site-specific
119 N management.

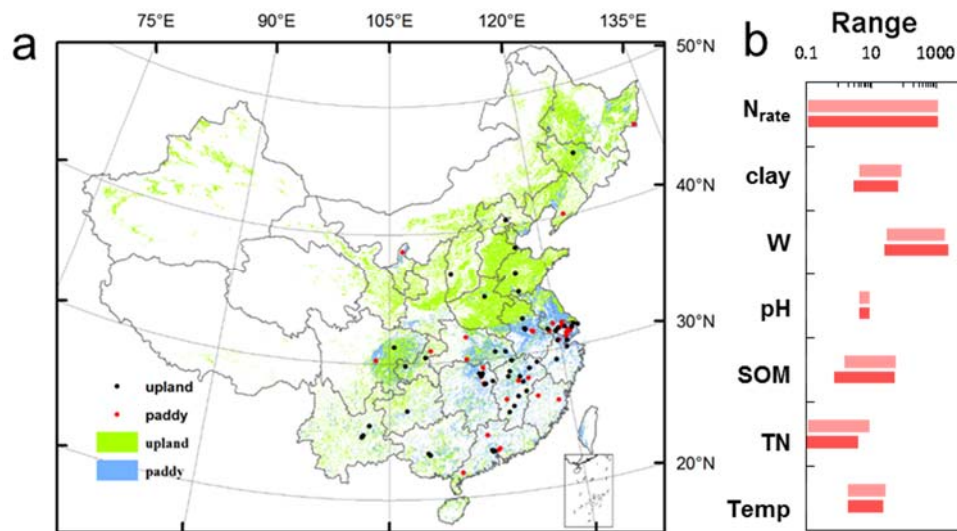
120

121 **2. Data and methodology**

122 **2.1 Dataset**

123 Based on the National Pollution Census Program of China (NPCP) and datasets
124 published by the scientific community, *in situ* measurements of N runoff and associated
125 variables in each plot were collated from 100 experimental sites for both rice paddy and
126 upland fields (i.e., as a flooded parcel of arable land used for growing rice and non-rice
127 crops, respectively). Water samples were collected in the drainage outlet for each
128 rainfall event in most of the measurements, where the runoff volume was consecutively
129 measured within the observation period. N concentrations in water samples were
130 analyzed using ultraviolet spectrophotometric methods, following the Standard
131 Methods for the Examination of Water and Wastewater approach for China (SEPA,
132 2002). Precipitation within the observation period and soil properties (0-20 cm depth)
133 at the beginning of the experiment were synchronously monitored. Missing values of
134 soil properties or climatic factors at a few sites were supplemented with data from the
135 China Soil Scientific Database (<http://vdb3.soil.csdb.cn/>) based on the corresponding
136 soil type of the county or from the 0.1-degree China Meteorological Forcing Dataset
137 (CMFD) v0106 (<http://data.cma.cn/>) depending on its geographic coordinates.
138 Information on agricultural management practices including N fertilizer application
139 rate, irrigation amount, fertilizer types, and crop types were recorded, including the
140 timing of the application. The dataset comprised 535 site-years data (293 for upland

141 and 242 for rice paddy fields) (Fig. 1a and Supplementary Data S1), and can be
142 considered representative of most major cropping areas except northwestern China (Fig.
143 1).



144
145 **Figure 1. Location of experimental sites on cropland N runoff in China.** Sixty-two
146 experimental sites for upland are illustrated as black solid circles, whereas thirty-eight
147 sites for paddy field are indicated as red solid circles. The ranges of each individual
148 variable is illustrated as a light red bar for observational datasets and a dark red bar for
149 croplands for the whole of China in panel b. The variables are N_{rate} (kg N ha^{-1}), clay
150 content (Clay, %), water input (W, mm), soil pH, soil organic matter (SOM, g kg^{-1}),
151 soil TN (g kg^{-1}) and air temperature (Temp, $^{\circ}\text{C}$).

152

153 2.2 Data-driven upscaling model

154 We developed an upscaling model which accounts for the effects of environmental
155 conditions and agricultural management (Eq. 1). Specifically, N fertilizer application
156 rate (N_{rate}) and environmental conditions (x_k) are directly included as independent

157 variables, whereas fertilizer application and crop types are considered as correction
158 terms in the model:

$$159 \quad R_{TNl} = RR_l(x_k) \cdot N_{rate} + R^0_l(x_k) + \varepsilon, \quad \forall l=1,2,\dots,L, \quad x_k \in \Omega_l \quad (1a)$$

160 where

$$161 \quad RR_l = RR_l^*(x_k) \times CE_i(RR) \times CE_j(RR), \quad (1b)$$

$$162 \quad R^0_l = R^{0,*}(x_k) \times CE_j(R^0), \quad (1c)$$

$$163 \quad RR_l^*(x_k) = f(x_k) \cdot N_{rate} + g(x_k), \quad R^{0,*}(x_k) = h(x_k), \quad (1d)$$

164 and i and j represent the index of fertilizer types and crop types, respectively; l and L
165 are the index and number of piecewise functions. x_k is climatic condition or soil attribute.

166 Observations (Fig. S1) of air temperature, water input and soil clay content can be used

167 as proxies to reflect the variations of soil temperature and water content within the

168 observation period, respectively. RR^* and $R^{0,*}$ are the reference values when urea is

169 applied and where wheat or rice are cultivated on experimental sites. Both are then

170 adjusted to reflect different fertilizer and crop types to develop a specific RR and R^0 for

171 a given scenario. The details of correction coefficients (CEs) can be found in Table S1.

172 It should be noted that fertilizer types considered include urea, compound fertilizers,

173 manure and/or crop residues, and ammonium bicarbonate. In addition, crop types

174 distinguish between rice, wheat, maize, soybean, cotton, and other crops.

175

176 The Bayesian Recursive Regression Tree version 2 (Zhou et al., 2015), was

177 subsequently used with observational data to determine optimal L , $f(x_k)$, $g(x_k)$, and $h(x_k)$.

178 The detailed methodological approach of the BRRT v2 is described by Zhou et al. (2015)

179 and [Text S2 in the Suppl. Mat.](#). The resulting calibrated model was applied to simulate
180 spatial patterns of N runoff over Chinese croplands from 1990 to 2012 at a spatial
181 resolution of 1 km. The details on input data used in this model, including N_{rate} by
182 fertilizer and crop types, water input, clay content, air temperature, soil pH, soil organic
183 matter (SOM), and soil N, are described in [Table S2](#) and [Fig. S2](#). Due to the lack of
184 detailed information on the spatio-temporal changes in fertilization methods, timing,
185 and cultivation practices in China, this information was not included in the data-driven
186 upscaling model simulation presented here.

187

188 **2.3 Structural decomposition analysis**

189 We further applied a simplified attribution approach, ‘Runoff Identity’ (analogous to
190 the Kaya Identity in economics), to assess the contribution of water input changes (W ,
191 the sum of precipitation and irrigation amounts), the fertilizer-to-water ratio (the ratio
192 of fertilizer used to water input) and N runoff rate (i.e., the ratio of annual N runoff flux
193 to fertilizer addition) to the relative rate of change of R_{TN} in China. The Runoff Identity
194 combines the variables of regional averaged water inputs and fertilizer addition in a
195 causal relationship to cropland N runoff (R_{TN}). R_{TN} is therefore regarded as the
196 integration of the three variables:

$$197 \quad R_{TN} = W \left(\frac{N_{rate}}{W} \right) \left(\frac{R_{TN}}{N_{rate}} \right) = w \cdot f \cdot e \quad (2)$$

198 We then defined the proportional change rate of a quantity $X(t)$ as $r(X) = X^{-1}dX/dt$ (with
199 units $[\text{time}]^{-1}$). Because $((dR_{TN}/dt)/R_{TN}) = ((dR_{TN}/dt)/(wfe)) = ((dw/dt)/w) + ((df/dt)/f) +$

200 $((de/dt)/e)$, the Runoff Identity for proportional change rate can be rewritten as

$$201 \quad r(R_{TN}) = r(w) + r(f) + r(e) \quad (3)$$

202 Using time-series data of w , f and e , we applied this approach to quantify the role of
203 each driver in relation to changes of the R_{TN} trend. The theoretical proportional change
204 rate, which was a sum of factors w , f and e , closely approximates the rate of R_{TN} that
205 actually occurred. We calculate their rates of change over the whole period from 1990
206 to 2012 using a linear regression method, and normalized them by corresponding mean
207 values, respectively. The relative contribution of each factor is the ratio of its
208 proportional change rate to the proportional change rate of R_{TN} during the same period.

209

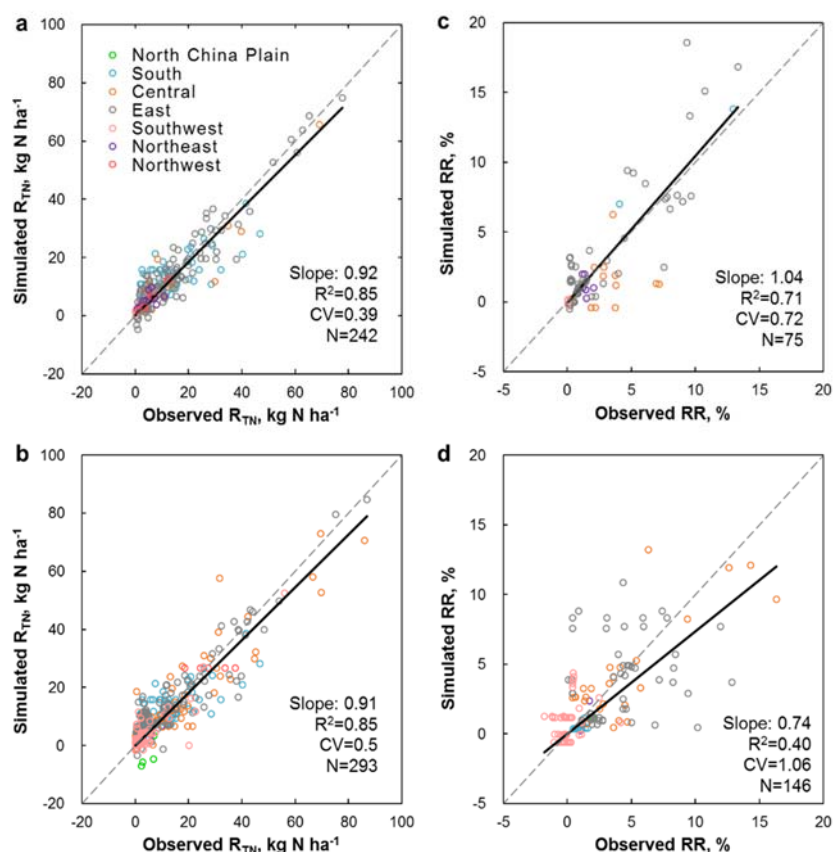
210 **3. Results**

211 **3.1 Model performance**

212 The data-driven upscaling model (Table S3) was evaluated by reviewing the coefficient
213 of determination (R^2) and coefficient of variation (CV, calculated as the ratio of root-
214 mean-squared error to mean value), which were 0.85 and 39% for rice paddy fields
215 (n=242, Fig. 2a), and 0.85 and 50% for upland grain crops (n=293, Fig. 2b), respectively.

216 The evaluation results suggest that most of the variance of R_{TN} could be explained by
217 the model with acceptable bias. Model performance for R_{TN} per unit N fertilizer
218 additions (RR) ($R^2 = 0.71$ and n=75 for rice paddy fields, Fig. 2c; $R^2 = 0.40$ and n =
219 146 for uplands, Fig. 2d) further indicate that our model is able to capture the sensitivity
220 of R_{TN} to N inputs. Regionally, there are no evident differences in model performance

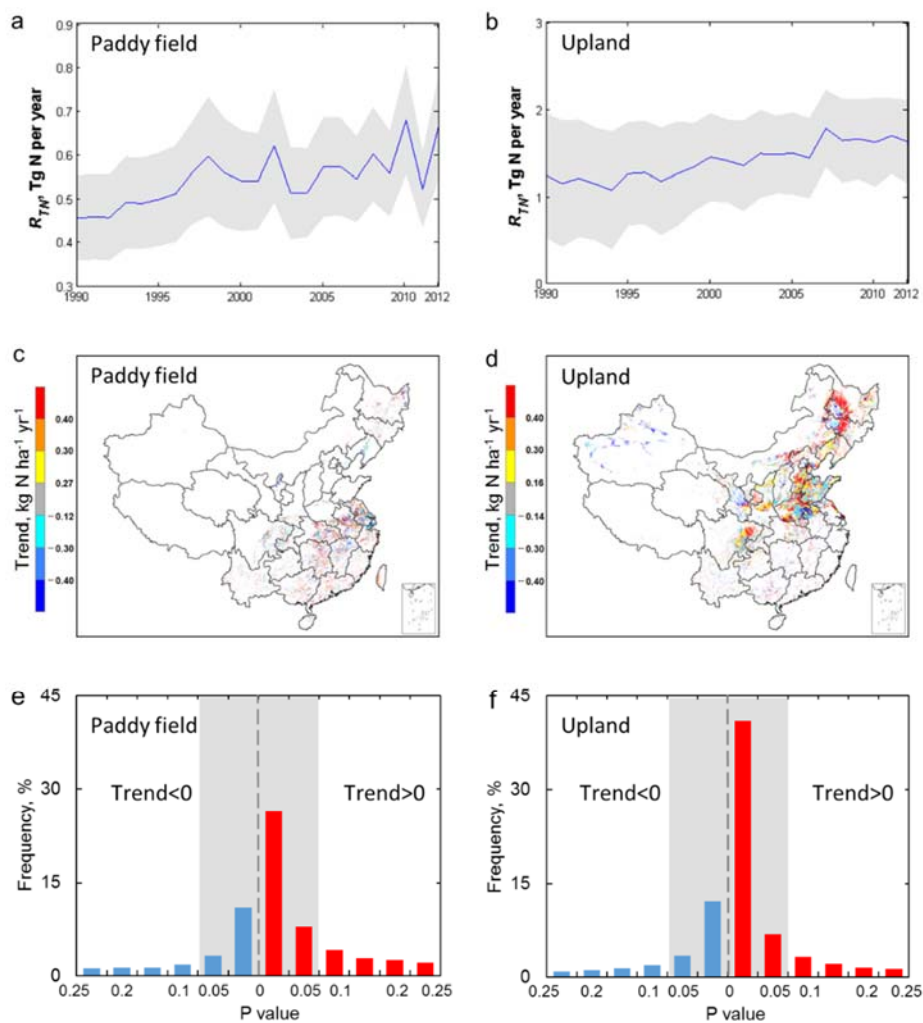
221 of R_{TN} across the 7 regions (Fig. 2), but RR simulated by our model shows differences
 222 compared to observations in East China in particular. Additionally, a few simulated RR
 223 were different from the observations (Fig. 2), mainly due to the lack of spatially detailed
 224 data on specific fertilization methods, cultivation practices, or rainfall intensity in our
 225 models (Liu et al., 2016; Miyazato et al., 2010; Wang et al., 2015a; Xu et al., 2013).



226
 227 **Figure 2. Calibration of R_{TN} , RR for paddy fields (panels a and c) and upland**
 228 **(panels b and d).** The slope, R^2 , and coefficient of variation (CV) are indicated in the
 229 insets at the bottom right of each panel. Dots are colored in Fig. 2 to indicate model
 230 performances in different regions in China.
 231

232 **3.2 N runoff trends and their spatial patterns**

233 [Figures 3a](#) and [3b](#) show the annual N runoff or runoff rate from China's rice paddy and
234 upland soils from 1990 to 2012, respectively. In 1990, R_{TN} was $1.69 \pm 0.80 \text{ Tg N yr}^{-1}$
235 in China (σ is the standard deviation of N runoff due to the uncertainties of input data
236 and model parameters), splitting into $0.46 \pm 0.08 \text{ Tg N yr}^{-1}$ for paddy field and $1.23 \pm$
237 $0.51 \text{ Tg N yr}^{-1}$ for upland ([Fig. 3](#)). More details of uncertainty estimation approach
238 using Monte Carlo ensemble simulations can be found in [Text S3](#). R_{TN} had increased
239 by $46 \pm 11\%$ for rice paddy fields and $31 \pm 14\%$ for uplands (σ is the standard
240 deviation of N runoff changes occurring over a 23-year period; [Fig. 3a and 3b](#)).



242 **Figure 3. Temporal trend of cropland N runoff during 1990-2012.** (a) paddy field;
243 (b) upland; (c) spatial pattern of N runoff trend for paddy field; (d) the same as for c but
244 for upland; (e) frequency distribution of the significance level (P-value) of N runoff
245 trend for paddy field; (f) the same as for e but for upland. The P -value of N runoff
246 trends for each pixel is estimated based on T test. The gray shaded areas in panels (a)
247 and (b) reflect standard deviations based on uncertainty assessments (see [Text S2](#)).

248

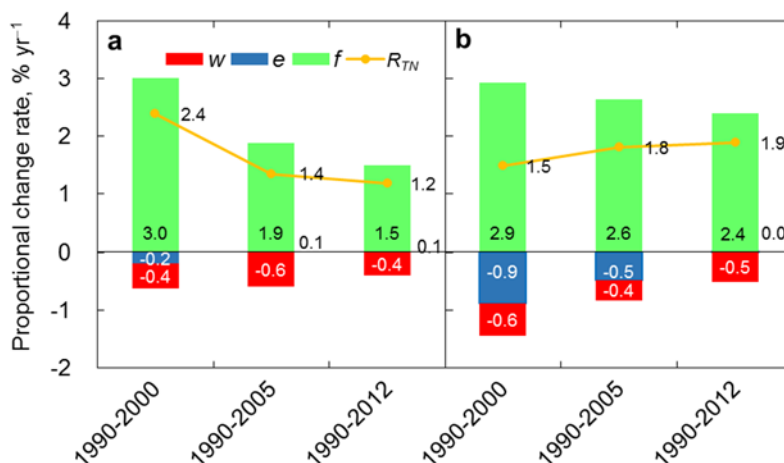
249 Spatial patterns of the N runoff trends across China for the period from 1990 to 2012
250 were for the land area of China by applying the upscaling model are displayed in [Figs.](#)
251 [3c and 3d](#). Both simulation results for rice paddy fields and uplands consistently showed
252 that N runoff trend increased in most regions of China ($P < 0.01$ according to the Mann–
253 Kendall test), while the magnitude of the R_{TN} trend varied for different croplands in
254 China. For rice paddy soils, regions with the largest R_{TN} trend are generally found in
255 southern China and parts of northeastern China (i.e., Amour-Ussuri-Songhua River
256 Plain, defined in [Fig. S3](#)), where the trend of R_{TN} is generally larger than 0.4 kg N ha^{-1}
257 yr^{-2} . However, regions that experienced a decreasing trend (14% of croplands) were
258 located in the lower reaches of the Yangtze River Basin, Ningxia Plain, and part of the
259 Sichuan Basin ([Fig. S3](#)), where the trend of R_{TN} is $-0.12 \text{ kg N ha}^{-1} \text{ yr}^{-2}$. For uplands,
260 the highest values of the R_{TN} trend ($>0.4 \text{ kg N ha}^{-1} \text{ yr}^{-2}$) are found in northeast China,
261 the Guanzhong Plain, and parts of the North China Plain and Sichuan Basin. In contrast,
262 regions with a decreasing R_{TN} trend (16% of croplands) include the Shandong Peninsula,

263 upper reaches of the Huaihe River Basin, and northwest China ($-0.14 \text{ kg N ha}^{-1} \text{ yr}^{-2}$).
264 The R_{TN} trend is statistically insignificant ($P>0.05$) in less than 40% of croplands,
265 mainly in the Yangtze River Basin, Shandong Peninsula and Shanxi province (Fig. 3e
266 and 3f).

267

268 3.3 Attribution of N runoff trends at national scale

269 For rice paddy fields (Fig. 4a), the relative rate of change of R_{TN} at national scale was
270 $1.2 \% \text{ yr}^{-1}$ over the last 23 years, which was primarily driven by a growing fertilizer-
271 to-water ratio, but partly offset by the decline of water input (28%). For upland, the
272 trend of R_{TN} also showed an increase ($1.9\% \text{ yr}^{-1}$; Fig. 4b) during the period 1990-2012,
273 with the largest attributable contribution of fertilizer-to-water ratio and a positive
274 proportional change rate of $2.4 \% \text{ yr}^{-1}$ which was partially offset by the decreased water
275 input ($-0.5 \% \text{ yr}^{-1}$). Fig. 4 also illustrates the trend of each identity for rice paddy fields
276 and uplands during different periods. The relative R_{TN} change rate for rice paddy field
277 was $2.4 \% \text{ yr}^{-1}$ prior to the year 2000, but gradually reduced to $1.4 \% \text{ yr}^{-1}$ during the
278 period of 1990-2005 and then less than $1.2 \% \text{ yr}^{-1}$ during 1990-2012, primarily due to
279 the decreased growth rate of fertilizer-to-water ratio (3.0 to $1.5\% \text{ yr}^{-1}$). However, the
280 trend of R_{TN} for uplands increased from $0.15 \% \text{ yr}^{-1}$ before 2000 to $0.19 \% \text{ yr}^{-1}$ during
281 the whole period. This could primarily be explained by the fact that the decrease of
282 growing fertilizer-to-water ratio (from 2.9 to $2.4 \% \text{ yr}^{-1}$) was totally offset by the change
283 in the N runoff rate (from -0.9 to $0.01 \% \text{ yr}^{-1}$).



285

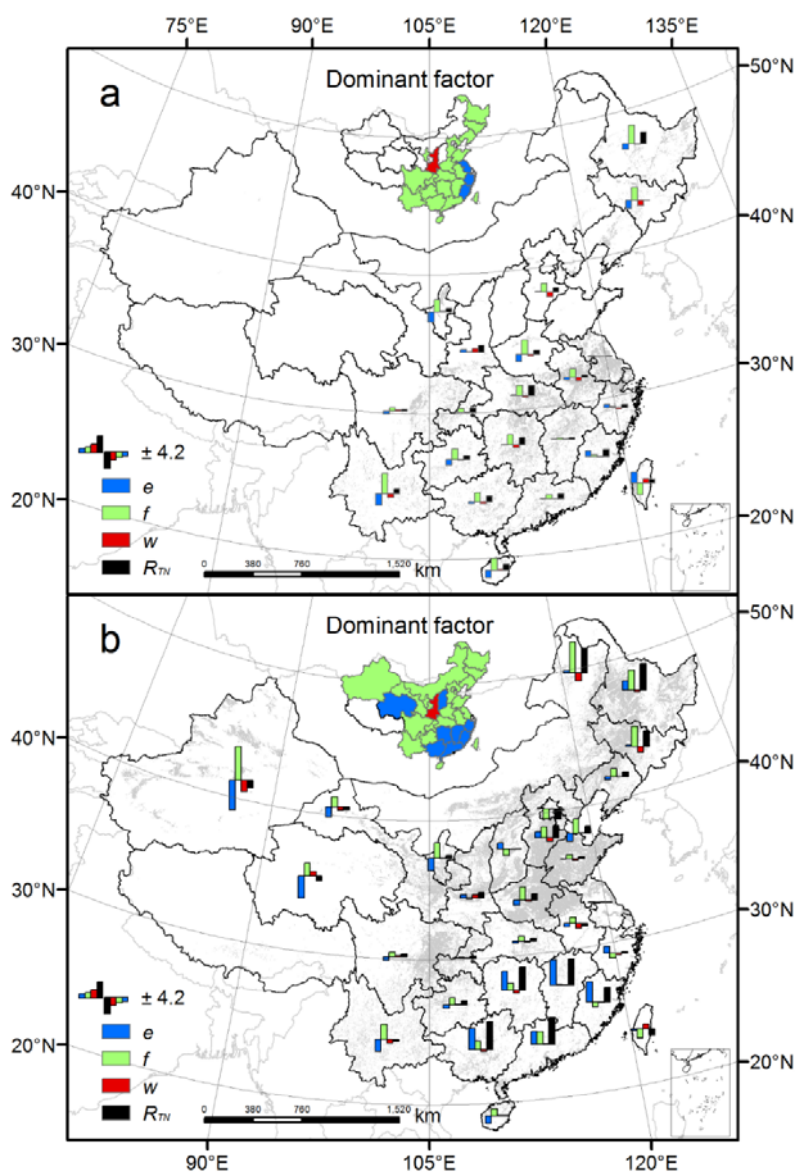
286 **Figure 4. Proportional change rate of cropland N runoff and its drivers.** (a) Paddy
 287 field; (b) upland. Contributions of the N runoff identity factors during the years 1990-
 288 2000, 1990-2005 and 1990-2012, including the water input of precipitation and
 289 irrigation (*w*), N runoff rate (*e*) and fertilizer-to-water ratio (*f*).

290

291 3.4 Spatial patterns of N runoff trend attributed to different drivers

292 As demonstrated in Fig. 5, the contributions from three main driving factors to the trend
 293 of R_{TN} were highly spatially heterogeneous across different provinces. For rice paddy
 294 fields, fertilizer-to-water ratio was the dominant factor for R_{TN} trends in most regions
 295 in China, whereas N runoff rate and water input could be attributed to drive the trends
 296 in N runoff in eastern coastal regions, and Weihe River Basin (inset plot of Fig. 5a).
 297 More specifically, fertilizer-to-water ratio factor alone increased N runoff at a rate of
 298 $1.14 \pm 1.05 \text{ \% yr}^{-1}$ in most rice-cropping areas in southeastern China (Fig. 5a) while N
 299 runoff rate had a positive effect on the R_{TN} trend in most regions in southern China at
 300 an average of change rate of $1.32 \pm 0.98 \text{ \% yr}^{-1}$. However, N runoff rate had a more

301 substantial negative effect on the R_{TN} trend in the other regions and the average trend
 302 of R_{TN} attributed to N runoff rate is $-1.12 \pm 1.07 \text{ \% yr}^{-1}$. In contrast to those two driving
 303 factors, the relative contribution of water input to the R_{TN} trend was minor, but remained
 304 consistently negative for rice paddy fields across the whole country ($< -0.14 \text{ \% yr}^{-1}$),
 305 except for Taiwan (1.06 \% yr^{-1}), Shaanxi (0.99 \% yr^{-1}), and Ningxia provinces (0.31 \% yr^{-1}).
 306 yr^{-1}).



307
 308 **Figure 5. Trends in N runoff and its drivers during the period 1990-2012 at**
 309 **provincial scale. (a) Paddy fields; (b) upland. The dominant driving factors for the R_{TN}**

310 trend in each province are shown in the insets above the maps. The grey area shows the
311 spatial pattern of upland or paddy fields in China.

312

313 Fertilizer-to-water ratio contributed more to the R_{TN} trend for uplands than for rice
314 paddy fields in the North China Plain and northeast Plain only. A positive effect of
315 fertilizer-to-water ratio on the R_{TN} trend was largely offset by N runoff rate changes
316 across southern China and western China, where the trends of R_{TN} attributed to N runoff
317 rate averaged at $4.36 \pm 1.67 \% \text{ yr}^{-1}$ and $-3.08 \pm 2.40 \% \text{ yr}^{-1}$, respectively. On the other
318 hand, the model estimates indicate that N runoff rate changes may result in R_{TN}
319 increases in southern China (except for Hainan and Taiwan), which were one-fold
320 higher than the negative effect found across most of northern China. Although there
321 was no apparent difference in spatial patterns as to water input trends between upland
322 and paddy field (Fig. 5), the relative contribution of water input to the R_{TN} trend for
323 upland was less than that for paddy field. In contrast to other regions, water input in
324 Shaanxi, Taiwan and Hainan provinces has significantly increase ($P < 0.01$). The
325 increase in trend of R_{TN} due to water input change in Shanxi was larger than due to N
326 runoff rate and fertilizer-to-water ratio for both crop types. The observations in Taiwan
327 and Qinghai show that water input change played an important role in R_{TN} increase,
328 albeit less than the other two driving factors, accounting for $1.2 \% \text{ yr}^{-1}$ and $1.1 \% \text{ yr}^{-1}$
329 of the trend of R_{TN} . In summary, the effects of agricultural management practices,
330 including fertilization and irrigation schemes, outweigh the influence of current climate

331 change on model-derived R_{TN} trend increase for both paddy field and upland.

332

333 **4. Discussion**

334 Our findings generally agree well with most prior works, with a few exceptions. For
335 example, [Gu et al. \(2015\)](#) applied an integrated N budget model to constrain the
336 magnitude and trend of N runoff from China's croplands, with an estimate of R_{TN} of
337 $2.1 \pm 0.2 \text{ Tg yr}^{-1}$ with a relative change rate of $1.8 \% \text{ yr}^{-1}$ during the period 1990-2010.
338 In our study, we explicitly incorporated the non-linear and spatially varied responses of
339 an R_{TN} model at multiple N input levels and reached very similar estimates of total N
340 runoff ($1.7 \pm 0.2 \text{ Tg yr}^{-1}$) and trend ($1.7 \% \text{ yr}^{-1}$) while explicitly accounting for spatial
341 variability during the same period ([Fig. S4](#)). In addition, [Ti and Yan \(2013\)](#) indicated
342 that the fertilizer-induced N runoff in the Huanghe River Basin, the Yangtze River Basin,
343 and the Paerl River Basin was 1.06 Tg yr^{-1} in 2010 with a relative change rate of $1.4 \% \text{ yr}^{-1}$
344 during the period from 1990-2010, which is also comparable to our results (0.72
345 Tg yr^{-1} in 2010 and $1.7 \% \text{ yr}^{-1}$). In general, using a new data-driven upscaling model,
346 our estimates derived from a large network of cropland N runoff observations, provide
347 novel insights into the spatially detailed N runoff trend for China's croplands.

348

349 By developing a novel structured decomposition approach for a 'Runoff Identity' (see
350 section 2.3), we are able to accurately identify and quantify the contribution from each
351 individual driver including climatic and human-induced variables to R_{TN} trend. Our

352 results suggest that fertilization (or fertilizer-to-water ratio) is the dominant driver of
353 R_{TN} trends for both rice paddy fields and uplands across most of the country, which is
354 consistent with experimental results at multiple N input levels (Liang et al., 2005; Shi
355 et al., 2010; Yu, 2011). Indeed, over the last two decades, China experienced a growth
356 rate in N fertilizer application of more than $4.0 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ on average in response
357 to a continuous increase in crop production (Fig. S5a). Previous studies suggest that
358 this high rate of N additions to agricultural systems resulted in an increase in soil
359 residual N (Yan et al., 2014). Such accumulated residual N was eventually transferred
360 into aquatic ecosystems (Rasouli et al., 2014). Conversely, eastern and southern coastal
361 regions in Mainland China remained largely unchanged with regard to N application
362 rates and even rates even decreased in Taiwan (Fig. S5a). The N runoff rate in these
363 regions therefore becomes the primary driving force for R_{TN} trends.

364

365 Likewise, we quantified the contribution of water input to the R_{TN} trend increase in
366 China. For rice paddy fields, our model suggests that the decreasing water input offsets
367 27% of the impact of fertilization on the increasing R_{TN} trend at the national scale, and
368 this offset effect is more clearly observed in northern China than in south (Fig. 5).
369 Previous studies indicated that R_{TN} tends to increase with water input (Gao et al., 2016;
370 Hou et al., 2016), because high precipitation and irrigation events in turn resulted in
371 large runoff pulses (Sorooshian et al., 2014). As we illustrated, the decline in water
372 input mainly occurred due to the decrease in irrigation inputs, rather than a marked

373 change in precipitation patterns, except in Taiwan, Hainan and parts of northwestern
374 China (Fig. S6a). Improving the irrigation efficiency could be an effective measure to
375 reduce the overall amount of water used for irrigation in most provinces, whereas the
376 expansion of irrigated area dominates the growth of irrigation mainly in the Northeast
377 Plain, Sichuan Basin, and Yunnan-Guizhou Plateau. Similar drivers and patterns of
378 irrigation trends are found for upland all over the country (Fig. S6b). It should be noted
379 that our per-area irrigation dataset was compiled based on total values at municipal
380 level, rather than on crop-specific amounts (Fig. S5b). Therefore, it would be valuable
381 if future research focused on surveys to address this issue by gathering data per-area
382 irrigation among different crops in each municipal area.

383

384 Our results attributing the contribution by different factors also indicate that the N
385 runoff rate positively affected the R_{TN} trend for uplands across most of southern China,
386 but in general had a negative effect for rice paddy fields (Fig. 5). To interpret such
387 distinct effects on N runoff rates, we conducted two types of scenario assessments to
388 separate the impact of changes in environmental conditions or agricultural management
389 practices: a control simulation with all conditions and practices varying from 1990 to
390 2012 and an experimental simulation with one condition or practice fixed at year 1990
391 levels. The difference was considered as the response to one change in conditions or
392 practices. SOM was identified as the dominant factor for the trends of N runoff rate for
393 both uplands and rice paddy fields nationwide, followed by N_{rate} and water input (Fig.

394 [S7](#)). Increased SOM led to N runoff rate growth for uplands, but a decline for rice paddy
395 fields at provincial level during the period 1990-2012 ([Fig. S8](#)). This result was also
396 confirmed by observations from 63 field sites across China ([Fig. S9](#)), and could be
397 explained by the difference in the generation process of N runoff. Upland N runoff
398 begins when raindrops hit the ground and detach soil particles by splash. The sediments
399 eroded from upland fields carry adsorbed N that is subsequently transported
400 downstream. Therefore, high SOM may increase the risk of upland N runoff during
401 rainfall events ([Liu et al., 2014](#)). In contrast, N runoff from paddy fields increases when
402 rainfall input exceeds its storage capacity. Overflow through the paddy field levee
403 carries dissolved N into ponding water and rainfall-driven interstitial runoff of nitrate
404 at the soil-water interface to the surrounding water bodies ([Huang et al., 2014](#);
405 [Higashino and Stefan, 2014](#)). High SOM improves the adsorption of soil N in ponding
406 water thus lowers the magnitude of N runoff from paddy fields. Additionally, high SOM
407 benefits upland N mineralization under aerobic environment, resulting in increases in
408 soil inorganic N availability and hence N runoff. Little inorganic N, however, will be
409 released from SOM in paddy field under anaerobic environment, which helps reducing
410 N runoff ([Wu et al., 2017](#)).

411

412 In this study, we comprehensively quantified and analyzed the attribution factors for N
413 runoff trends in China's croplands. However, we found that some results for simulated
414 N runoff were significantly different from observations ([Fig. 2](#)). Previous experiments

415 showed that N runoff or N runoff rate were also changed following different fertilization
416 (e.g., methods, timing), irrigation schemes, or rainfall intensity (Liu et al., 2016;
417 Miyazato et al., 2010; Wang et al., 2015a; Xu et al., 2013). For example, field trials
418 highlighted that the application of controlled release N fertilizers significantly reduced
419 N runoff by 48-72% compared to top-dressing fertilization for paddy fields. Similarly,
420 the application of optimized irrigation methods significantly reduced N runoff by 24%
421 compared to flooding irrigation (Yang et al., 2015); N runoff from paddy fields was not
422 only passively generated by monsoon rain in China, but also a consequence of human-
423 induced drainage before transplanting (Yan et al., 2016). However, the current
424 upscaling model did not fully consider such management practices. Meanwhile, air
425 temperature and clay content were used in this study as proxies for soil temperature and
426 soil water content within the experimental period, respectively, due to the lack of long-
427 term observations across China. Although previous works have found a significant
428 linear relationship between air and soil temperatures or between clay and water contents
429 (Zheng et al., 1993; Wäldchen et al., 2012), more robust estimations of soil temperature
430 and water content become another question to be undertaken by future studies. In
431 addition, *in situ* measurements of N runoff are scarce in Northwest China (e.g., Xinjiang
432 province), leading to large uncertainty in R_{TN} estimates in this regions. Previous studies
433 indicated that the dominant pathways of N losses would be ammonia volatilization to
434 the atmosphere and N leaching to aquifers (Gao et al., 2016; Van Damme et al., 2017),
435 rather than surface N runoff. More importantly, this region accounts for only 8.6% of

436 N fertilizer application and 11% of the sowing area in China and has a low N runoff
437 rate observed in the NPCP ($0.34 \pm 0.26\%$). Therefore, N runoff in Northwest China
438 makes a small overall contribution to the total N runoff of Chinese croplands. To
439 confirm the contribution from Northwest China, more observations should be
440 conducted in the future to verify R_{TN} estimates. Furthermore, data from field
441 manipulation experiments on the response of R_{TN} to environmental conditions (e.g.,
442 SOM) is lacking and would be useful to constrain our upscaling model. Therefore,
443 further efforts to make widespread measurements and to carry out field manipulation
444 experiments for R_{TN} are necessary to improve the reliability of such model simulations.

445

446 In summary, cropland N runoff has been increasing significantly in China for the period
447 1990-2012. At a national scale, increases in fertilizer application and decreases in
448 irrigation amounts were identified as the most likely causes for the N runoff trend. The
449 positive contribution of N runoff rate to the R_{TN} trend is more evident in southern China
450 than in the north. We expect a continuously decreasing trend in irrigation amounts into
451 the future, and fertilizer application rates likely to plateau, since China aims to improve
452 water use as well as fertilizer N application efficiencies through the action plans like
453 clean water and “zero-increase fertilizer use” (Ju et al., 2016). However, current
454 projections on climate change suggest that precipitation, particularly extreme rainfall
455 events, will increase. This might further lead to N runoff and N runoff rate increase in
456 the future. In addition to the expected improvements on N use efficiency and water use

457 efficiency in China's croplands, applying effective management approaches that
458 generate benefits for both N runoff and crop yields are urgently required to design more
459 efficient and sustainable agricultural N management. Improving the representations
460 associated with the effects of agricultural management practices and understanding the
461 response of N runoff to environmental conditions should be the priorities for the
462 agricultural modeling.

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470 **Appendix A. Supplementary data**

471 Supplementary information related to this article can be found online, including
472 Supplementary Data S1, Text S1 to S3, Tables S1 to S4, and Figures S1 to S9.

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