Inland Water Bodies in China: New Features Discovered in the Long-term Satellite Data

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1 **Inland Water Bodies in China: New Features Discovered in the**

2 **Long-term Satellite Data**

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Water bodies (WBs) - lakes, ponds, and impoundments, provide essential ecosystem services for human society, yet their characteristics and changes over large areas remain elusive. Here we used unprecedented data layers derived from all Landsat images available between 1984 and 2015 to understand the overall characteristics and changes of WBs between two epochs (i.e., 1984-1999 and 2000-2015) in China. Results show that the abundance estimate of WBs greater than 1 km^2 and the total WB surface area were 0.3-1.5 times and 0.2-0.5 times more than the previous estimates, respectively. The size-abundance and shoreline-area relationships of WBs in China conformed to the classic power scaling law, in contradiction to most previous studies. WB changes with various occurrence probabilities show widespread co-existence of disappearance of existent and emergence of new WBs across China driven primarily by human activities and climate change. Our results highlight the importance of using appropriate long-term satellite data to reveal the true properties and dynamics of WBs over large areas, which is essential for developing scaling theories and understanding the relative impacts of human activities and climate change on water resources in the world.

Keywords: inland water bodies; size-abundance; fractal dimension; climate change; land use change

Significance Statement

Inland water bodies (WBs) provide essential ecosystem services for human society, yet their characteristics and changes over large areas remain elusive. We used unprecedented data layers derived from Landsat imagery to quantify and decipher the spatial distributions and contemporary changes of WBs in China. The results shed new light on the characteristics (e.g., abundance, and size-abundance and shoreline-area relationships) and spatiotemporal dynamics of WBs. This study highlights the importance of using appropriate long-term satellite data to reveal the true properties and dynamics of WBs over large areas, which is essential for developing theories and understanding the predominant impacts of human activities and climate change on water resources not only in China but also in other regions of the world.

Introduction

The provisioning of freshwater is an essential ecosystem service for humankind, and such services include water supply, biomass and food production regulation, communication and transportation, wildlife habitats, biogeochemical cycles, and climate regulation (1-3). Fresh water bodies (WBs) are under constant change because of the impacts of anthropogenic activities and climate change (4). Monitoring the dynamic changes of WBs and understanding their causes and consequences have important implications to the resilience of social-ecological systems (5, 6).

The abundance and area of WBs over large regions are critical information for water resource management but remain highly elusive. For example, the number of lakes larger than 0.1 km^2 at the global scale was estimated to range from 246,146 to 4,123,551 (7, 8), more than one order of magnitude difference among them. The estimated area of lakes larger than 0.1 km^2 varied from 2,428,100 km^2 to 4,080,000 km^2 respectively, and the largest difference was 68%. These huge differences among various studies call for innovative investigations to reduce the uncertainties in the number and area of WBs.

Biogeochemical processes in WBs represent major components in the cycle of carbon, nutrients, and other materials at the regional to global scales (9, 10). Estimating biogeochemical processes such as greenhouse gas fluxes from WBs from regional to global scales has been challenging because these processes are size dependent (11). Finding the size-abundance relationship therefore has been a persistent effort for over a century to facilitate the scaling of heterogeneous processes across various WBs (12). Although a power law relationship has been reported in many studies, deviations exist, particularly for small WBs (8, 13-15) and in mountainous regions (16) where topographic relief, geology, and complexity of landscapes are thought to affect the goodness of fit to the power scaling law (14). The existence of the power law and its dependence on topography and geology needs to be evaluated more extensively.

Water-resource management and planning as well as climate change adaptation rely heavily on the knowledge of long-term trends and spatial dynamics of surface WBs (1) . However, progress on characterizing the dynamics of WBs over large

90 regions has been hindered by data availability, dynamic nature of WBs, complexity of

91 driving forces, and geospatial heterogeneity of environments (8). Most previous studies

92 do not have enough data points in time to capture the temporal changes of WBs, and

93 consequently the overall dynamics and size dimensions of the WBs, particularly the

94 intermittent WBs, are not well represented (17, 18). Recently, an unprecedented effort

95 by Pekel *et al*. (2016) has generated a global surface water dataset that describes the

96 changes in WBs from 1984 to 2015 at 30 m resolution (19). Although the overall global

97 patterns of WB changes have been analyzed, more detailed and elaborate analyses are

98 sorely needed at regional and continental scales to better understand the spatial and

99 temporal patterns of WB changes and to test the validity of existing theories such as the

100 controversial power scaling law for the size-abundance relationship (12, 20, 21). China

101 represents an ideal place for such as study because of its vast heterogeneous territories,

102 intensified human activities in recent decades, and large uncertainties in the

103 characterization of its dynamic water resources (22).

Abundance, area, and scaling of WBs

105 Our estimate of WB abundance in China exceeds all previous estimates (*SI*

106 *Appendix,* Table S1 and Table S2). The abundance of WBs (> 1 km^2) is estimated to be

107 6,821 in our study, 1.3 times the previous highest estimate (5,535) and 2.5 times the

108 lowest estimate (2,693) (7, 17, 23, 24). The number of WBs larger than 0.0036 km^2 in

109 China is 688,617 in this study, much higher than 275,029 estimated previously (24).

110 Our estimates of WB area in China are higher than those from previous studies. For

111 example, our estimate of total area of WBs larger than 0.0036 km^2 in China is 134,158

112 km^2, 23% higher than 109,102 km^2 estimated by Yang *et al*. (2014) (24). The total area

113 of WBs larger than 1 km^2 is estimated to be 123,342 km^2 in our study, 22-51% larger

114 than the previous estimates (7, 17, 23, 24). Similar differences can be found across the

115 regions in China as well. For example, the number of medium and large WBs in the

116 YTR (Yangtze River basin, acronyms for the river basins are listed in *SI Appendix,*

117 Table S3) is estimated to be 1952 in this study, much higher than 1395 estimated by

118 Yang *et al*. (2013) (25). The medium and large WBs in the TP amount to 1289 in our

119 study, which is very close to Mao *et al*. (2018) (1291) (26) but higher than Wan *et al*.

120 (2014) (1055) (27) and Lu *et al.* (2011) (1044) (28). We found that the total area of WBs

121 larger than 0.0036 km^2 in the YTR is 36,710.83 km^2, which is 48% higher than Yang *et*

122 *al.* (2013) (24,842 km^2) (25). Our estimate of the WBs larger than 1 km^2 in the TP is

123 56,247.41 km^2, much higher than Mao *et al.* (2018) (46,264.5 km^2) (26) or Wan *et al.*

124 (2014) (41,831 km^2) (27).

125   The overall exceedance of our WB estimates can largely be attributed to the

126 differences in methodology. Conventionally, WBs over large areas are characterized

127 using one or a few snapshots of remotely sensed images, which could not consistently

128 capture intermittent WBs and historical maximum water extents (29). Previous results

129 are therefore contingent to the snapshot-specific climate and hydrological conditions at

130 the time that images were taken.

131   The size-abundance relationships in China conform to the power law with a Pareto

132 coefficient of -0.835 (*SI Appendix,* Fig. S1*F* and Table S4), similar to -0.85 reported for

133 the contiguous United States (CONUS) (30), but higher than that for the world in 2004

134 (-0.992) (7) and in 2016 (-1.054) (17). At a regional scale, the Pareto coefficient in the

135 TP is -0.662, the highest among all regions, signifying a higher fraction of large WBs in

136 the TP compared to other regions (*SI Appendix,* Table S5). In contrast, the scaling

137 exponent in the PR is -0.941, the lowest among all regions, representing a relatively

138 higher share of small lakes. Comparatively, the log-transformed WB size-abundance

139 distribution in China presented a shallower slope or Pareto coefficient than those in the

140 world and CONUS, suggesting that small WBs are relatively more abundant in China

141 than in the CONUS and the world (Fig. 1*C*). Our results showing the power scaling law

142 between abundance and size of WBs in China, despite its complex geography and

143 topographic characteristics, are different from a number of recent studies that have

144 found deviations from the power scaling law, particularly for small WBs (8, 13-15).

145 Seekell *et al.* (2013) show that the size-abundance relationship in a mountainous region

146 (Adirondack, USA) did not follow the power scaling law while it fit well in a flat region

147 (Gotland, Sweden), and argue that the topographic relief, geology, and complexity of

148 the landscapes could impact how well data fits the simple power scaling law (13). It is

149 quite surprising to see that our results fit the power scaling law well in China even

150 though some regions such as the TP, and northwestern and southwestern China are

famous for their high topographic relief and steep slopes that are suspected to cause

deviations from the power scaling law (Fig. 1*B*, *SI Appendix,* Fig. S2).

The shoreline fractal dimension (SFD) derived from dimensional analysis (log

perimeter-log area analysis) is often used to indicate the influences of human

modifications or geology on the shape of WBs (31). The SFD ranges from 1.178 in TP

to 1.321 in PR (Fig. 1*B*, *SI Appendix,* Fig. S3). Theoretically, the fractal dimension of

size-abundance (D) (D = 2 *abs(c), c is the scaling exponent or Pareto coefficient

mentioned above) is supposed to be similar to the SFD (13, 32). We compared the D

and SFD derived from China and found a strong linear relationship between these two

fractal dimensions $(D = 3.13 \times SFD - 2.27, R^2 = 0.73, P < 0.05)$. However, the slope is

significantly different from 1, suggesting that our results do not support the theoretical

equivalency of these two fractal dimensions (Fig. 1*D*). The deviation of D and SFD

from the theoretical equivalency might be caused by increased frequency of smaller

WBs and/or effort in shaping WBs more regularly and reducing the sinuosity of WB

boundaries. Economic growth and aquaculture intensification have propelled the

increase of smaller WBs and geometric regularization of the WBs, particularly in the

southeastern and coastal parts of China (33).

<Fig. 1 roughly here>

Various changes between two epochs

Overall changes of WBs in China between the two epochs (i.e. 1985-1999 and

2000-2015) are shown in Fig. 2, which reveals that 53.9% of the WBs remain

unchanged nationwide, and further shows the various degrees of change between the

epochs. A total of 5197.09 km^2 or 3.92% of the WB area in China disappeared

(absolutely decreased); whereas the very likely (with 75-99% probability), likely (with

25-74% probability), and unlikely (with 1-24% probability) deceases accounted for

1.6%, 6.23%, and 7% of the total WB area, respectively (Fig. 3, *SI Appendix,* Table S6).

A total of 9040.26 km^2 were converted from non-water surfaces into WBs (absolutely

increased), corresponding to 6.81% of the total WB area in China. At the same time,

very likely, likely, and unlikely increase occurred on 3.76%, 8.18%, and 5.71% of the

180   total WB area, respectively. The large WBs (>10 km^2) explain most of the very likely,

181   likely, and unlikely increase or decrease, followed by the small WBs (< 1 km^2) (*SI*

182   *Appendix,* Fig. S4 and Table S7). The WB changes vary widely across regions (Fig. 2).

183   For example, the highest absolute increases in area in percentage (13.72%, 16.41%, and

184   9.69%) are found in the TP, NWR, and SER, respectively. The region changed the most

185   was the HR since only 11.74% of WBs remained unchanged, and the most stable region

186   is the SWR with 75.99% persistently covered by water. The largest absolute decreases

187   in WB occurrence in percentage are found in the HR, SHR, and YTR account for

188   14.26%, 7.83% and 5.47% of their total WB areas, respectively.

189   <Fig. 2 roughly here>

190   Our analysis shows a net gain (absolute change) of 3,843 km^2 in WB between the

191   two epochs. Although some previous studies have quantified an increase (34, 35),

192   decrease (22, 24) or net change of the WB area in China, they are not comparable to our

193   estimate because of the differences in time span and definitions of change. Our change,

194   following Pekel *et al.* (2016), is defined as the difference between two epochs or

195   periods while it is defined as the difference between two time points or years in other

196   studies (19). Consequently, our estimate of change likely represents permanent changes

197   whereas the estimate using other definitions would be more likely influenced by the

198   interannual variability in the climate and hydrologic conditions. Starting with a dry year

199   and ending with a wet year would contain false signals of WB increase, for example,

200   when using the second definition.

201   Driving forces of WB changes

202   WB changes across the country show great divergent trends (Fig. 3), which were

203   most likely driven by multiple compounding drivers such as climate change and direct

204   human land use change activities (22, 35) (Table 1). Climate change has been shown to

205   have a major impact on WB changes, particularly in the TP and NWR regions. Because

206   of the TP's high elevation and sparse population, its WBs are predominantly influenced

207   by climate change. Despite a decline only some areas, the widespread increase of WBs

208   in the TP is primarily entailed by multiple climate-related factors, including the

209 precipitation, temperature, glacier, and permafrost (36, 37). On the one hand, the

210 climate change in the TP is prevalently accelerating, as the mean annual precipitation

211 has increased 20 mm and mean annual air temperature has warmed 1.6°C from 2000 to

212 2014 (26), resulting in the expansion of existing WBs and formation of new WBs by

213 melting glacier and snow in high mountains. On the other hand, permafrost degradation

214 and WB shrinkage have also been observed in some localized areas with drier climate

215 and reduced precipitation, especially in the area between the Himalayas and Tanggula

216 Mountains and in north of the Hengduan Mountains (26). Similarly, increasing WBs are

217 observed in the less populated mountainous areas in the NWR region caused by glacier

218 melting and increase in precipitation (38). The dry climate and drought events in the

219 arid regions (e.g., Inner Mongolia Plateau and part of the Xinjiang Uygur Autonomous

220 Region) have also contributed to WB shrinkage (35, 39).

221   <Fig. 3 roughly here>

222   <Table 1 roughly here>

223   Land use change activities have contributed to the expansion and/or contraction,

224 disappearance, and emergence of WBs at different locations throughout the country.

225 For example, dam constructions can substantially change WB in the upstream and

226 downstream regions (34, 40). Using the YTR basin as an example, both the numbers

227 and surface areas of the reservoirs in the YTR have increased rapidly during past

228 decades, and the impoundment of the great Three Gorges Dam alone formed a new

229 large reservoir with an area of 1,084 km^2 in 2003 when it was put into full operation

230 (41). Intensification of agriculture also brings heavy pressure to WBs (40, 42). For

231 example, the northeast region has experienced a rapid increase (319.0%) in irrigated

232 cropland area in the past three decades (22, 43). Aquacultural change affects the

233 dynamics of WBs in China, particularly in the east, south central, and southeast regions

234 where water resources and climate are suitable for aquaculture (33). Land reclamation,

235 or WB impoldering (i.e., conversion of WBs into other land uses), has resulted in the

236 loss or shrinking of WBs (38, 41). Many natural wetlands and WBs have been drained

237 and transformed into croplands, grasslands, and woodlands (22, 43), resulting in the

238 loss of about 50,360 km^2 or 14.18% of the wetlands across the country from 1990 to

239 2000 alone. Many small WBs are infilled in the process of urban expansion (41).

240 Wuhan, the capital city of Hubei province and once known as the city with thousands of

241 lakes, has lost about 70% of its lakes to reclamation and development between 1994

242 and 2014 (44). Various policies are being put forward by Chinese governments to

243 promote wetland conservation and restoration in recent years (45). After joining the

244 Ramsar Convention in 1992, the Chinese government has implemented the National

245 Wetland Conservation Plan, trying to prevent natural wetlands from further loss and

246 degradation (43). The government had funded more than 200 pilot programs with 20.7

247 billion US$ during 1990-2007 to restore degraded wetlands and create new ones to

248 make amends for lost wetlands (46).

249   Assessing the dynamics of WBs over large regions has been a major challenge

250 because of the constraints in data availability, heterogeneity of environments, and the

251 complexity of driving forces (8). Many studies have mapped WBs with multi-spectral

252 and hyperspectral images and built databases comprising locations, sizes, and

253 distributions of WBs over large regions (17, 47). However, these studies often suffer

254 from two weaknesses. First, they usually do not have enough data points in time to

255 capture the temporal changes of WBs. For instance, results are often generated from

256 subsamples of available remote sensing data at 5-year or longer time intervals (48),

257 representing only snapshots of WB conditions in the sampled years. As a result, the

258 overall dynamics and size dimensions of the WBs, particularly the intermittent WBs,

259 are not well represented (17, 18). Second, the minimal detectable WB size, defined by

260 the resolution of remotely sensed data (e.g., Terra /Aqua MODIS), is usually not fine

261 enough to detect the small WBs that are biologically more active than the large ones

262 (49). Our study shows that the use of dense long-term satellite data at appropriate

263 resolution has the potential to overcome some of the difficulties and reveal

264 unprecedented distributional details and dynamics of WBs over large areas. This

265 capability is essential for validating the relevant theories such as the power scaling

266 relationship between size and abundance and for adequately scaling many hydrological

267 and biogeochemical processes (e.g. the carbon cycle) from individual aquatic systems

268 to regional and global scales (50). It is also important to map the details of WB changes

269 and understand their causes and consequences to improve water resource management

270 and planning.

Materials and Methods

Study area and region boundaries

China (73°33′-135°2′E and 3°52′-53°33′E) is our study area (Fig. 1*A*). To investigate the regional differences of WBs, we delineated China into 11 large regions, primarily following the region boundaries from HydroSHEDS (http://www.hydrosheds.org, last accessed in 2018) (51) and National Lake-Watershed Science Data Center (http://lake.geodata.cn). The abbreviations of the regions are listed in Table S3.

Extraction of lakes, ponds, and impoundments

The Global Surface Water Dataset (GSWD), published by the European Commission's Joint Research Centre, was the basis for our study (https://global-surface-water.appspot.com, last accessed on December 12 in 2018). GSWD was generated using 3,066,102 (1823 terabytes of data) scenes from Landsat 5, 7, and 8 acquired between 16 March 1984 and 31 December 2015 (19). To address the challenges in separating water from other surfaces on the global scale over multiple decades, expert systems, visual analytics, and evidential reasoning techniques were exploited. Details about the implementations of these techniques can be found in Pekel *et al.* (2016). The resultant maps constitute the long-term water history that show the "when and where" of the water presence during the observation period. At the same time, the Water Occurrence, Occurrence Change Intensity, Seasonality, Recurrence, Transitions, Maximum water extent are also shown in the dataset. The accuracy of the water maps was assessed by the developers of GSWD in term of errors of omission and commission at the pixel scale (i.e., 30 m) using a total of 40,124 control points distributed both geographically (globally), temporally (across the 32 years). Overall, errors of commission were less than 1% and omission less than 5%.

The data layer showing the maximum water extent (MWE) (all locations ever mapped as water) during the 32 years was used to extract the locations and maximum extents of WBs in our study. GSWD contains three types of waters: artificial paddy fields, rivers, and others (i.e., lakes, ponds, wetlands, and impoundments). As our goal

was to investigate the characteristics and dynamics of lakes, ponds, wetlands, and

impoundments, rivers and rice paddy fields were removed from the MWE map using

the HydroSHEDS data through overlay operation in ArcGIS v10.2 (ESRI, Redlands,

CA, USA) and manually corrected by visual inspection against Google Earth

high-resolution images. Consequently, the temporal changes of rivers and streams were

also effectively excluded from this analysis (*SI Appendix,* Text S1). Paddy fields in the

MWE were removed by referring to the Global Land Cover dataset (GLCD)

(http://www.globallandcover.com, last accessed in 2018).

WB change between two epochs

GSWD provides water occurrence change intensity (OCI) between two epochs

(i.e., 1984 to 1999, and 2000 to 2015), which was derived from water occurrence

difference between homologous pairs of months (19). Specifically, the water

occurrence difference for each homologous pair of month between epochs was

calculated, and then differences between all homologous pairs of months were

averaged to create the surface water OCI map between the epochs. The OCI map shows

where surface water occurrence increased, decreased, or remained invariant, providing

a summary of the location and persistence of water in space between the two epochs.

The OCI map represents the degree of change as a percentage with values ranging from

-100% to 100%; positive values indicate increase in occurrence while negative ones

show loss of occurrence, and 0% suggests no change in occurrence between the epochs.

To summarize the results, OCI values were grouped into several classes: 75-99% (high

OCI), 25-74% (medium OCI), 1-24% (low OCI), 0% (unchanged), and 100%

(absolutely changed). In essence, these OCI classes effectively represent the

probabilities or likelihoods of conversion from non-water to water (positive OCI) or

from water to other surfaces (negative OCI) between two epochs, which resulted in nine

generalized probability classes of conversion between water and other land covers:

absolutely decreased (OCI= -100%), very likely decreased (OCI= -99% to -75%),

likely decreased (OCI= -74% to -25%), unlikely decreased (OCI= -24% to -1%),

unchanged (OCI= 0%), unlikely increased (OCI= 1% to 24%), likely increased (OCI=

25% to 74%), very likely increased (OCI= 75% to 99%), and absolutely increased

(OCI= 100%).

331   The minimum water surface area detectable is the pixel size of Landsat (0.0009

332 km^2). To facilitate comparison with other studies, whenever necessary, WBs were

333 classified into three categories of small (< 1 km^2), medium (1-100 km^2), and large (>

334 100 km^2) following the classification scheme of most previous studies (35, 39). All data

335 processing and analysis were performed using ARCGIS 10.2 (ESRI, Redlands, CA,

336 USA) and Python 3.6.

337 **Data Availability**

338   All data used in support of this manuscript are available in Figshare

339 (https://figshare.com/s/9e931d6db628e3f96689; DOI: 10.6084/m9.figshare.9959516)

340

Acknowledgments

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479

Figure Legends

Fig. 1. Boundaries of regions, morphological and size-abundance scaling of water bodies in China. (A) locations and boundaries of the 11 regions in China; (B) shoreline fractal dimensions (SFD) of TP. (C) size-abundance distributions of water bodies in China, CONUS, and the world. (D) shoreline fractal dimensions (SFD) and fractal dimension of size-abundance (D) in China and the regions.

Fig. 2. Regional occurrence changes of WBs at various confidence levels. Subsets of four selected cases show WB changes. A, Dongting lake in the YTR, centered at 112.8° E, 29.1°N. B, Hulun lake in the SHR, centered at 117.5°E, 48.9°N. C, Seling Co lake in the TP, centered at 89.1°E, 31.8°N. D, Hongze lake in the HuR, centered at 118.6°E, 33.2°N. E, epochal changes in different regions.

Fig. 3. Epochal changes of water bodies in China and regions at various confidence levels. Changes are classified as Absolutely Decreased (AD), Very Likely Decreased (VLD), Likely Decreased (LD), Unlikely Decreased (ULD), Unchanged (UC), Unlikely Increased (ULI), Likely Increased (LI), Very Likely Increased (VLI), and Absolutely Increased (AI).

Table 1. Summary of main driving forces in different regions.

Region	Main driving forces	References
TP	variations of precipitation; warming-induced glacier-melting and permafrost degradation	Mao et al. 2018b, Zhang et al. 2017a
PR	land reclamation; waterbody impoldering; urbanization	Li et al., 2018; Guo et al., 2015
YTR	dam constructions; aquacultural change; land reclamation or impoldering; urban expansion; sand mining and illegal sand dredging	Cai et al., 2016; Xie et al., 2003
YR	intensification of agriculture; intensified groundwater exploitation	Shi et al., 2011; Zhang et al., 2003
HR	rapid urbanization; land reclamation or waterbody impoldering	Yang et al., 2011; Tian et al. 2016
HuR	dam and floodgate construction; land reclamation	Hu et al., 2008; Zhang et al., 2009
SHR	intensification of agriculture; irrigation; wetland draining or restoration	Xie et al., 2018; Ma et al., 2010
NWR	persistent drought; intensification of agriculture (irrigation); mining	Fang et al., 2018; Tao et al., 2015
SWR	variations of precipitation; warming-induced glacier-melting	Wu et al. 2007; Mao et al., 2018b
SER	aquacultural change; land reclamation or waterbody impoldering;	Lu et al. 2015; Wu et al., 2018
LR	intensification of agriculture (irrigation); wetland conversion	Xie et al. 2018; Ma et al., 2010

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A — Elevation(m)
-
- -272 – 1000
- 1000 – 3000
- >3000

Labels on map: SHR, NWR, LR, HR, YR, TP, HuR, SWR, YTR, SER, PR, South China Sea Islands

B
SFD=1.178
R²= 0.943

TP:Tibet Plateau
— circle A:P, D=1
— SFD

x-axis: log-Area(m²)
y-axis: log-Perimeter(m)

C
World:N=164698*A^{-1.054}

China:N=8155*A^{-0.836}

CONUS:N=13663*A^{-0.908}

Legend: World, China, CONUS

x-axis: Logarithmic size class(km²)
y-axis: N > Area

D
y=3.29x-2.47
R²=0.75

Labels: PR, LR, HuR, YTR, HR, NWR, SHR, China, SWR, YR, TP

x-axis: SFD
y-axis: D

South China Sea Islands

Legend:
- Absolutely decreased
- Very likely decreased
- Likely decreased
- Unlikely decreased
- Unchanged
- Unlikely increased
- Likely increased
- Very likely increased
- Absolutely increased