Response to Reviewer #1

We are very grateful to the reviewer for the insightful and careful review. These comments are very helpful to improve the quality of the manuscript. All comments were answered in below, and the manuscript was revised according to these comments. The comments from the reviewers are kept in regular font with underlines and our responses in blue color. Please note that the line numbers refer to the marked-up version of the revision.

Referee 1

<u>Interesting paper with an approach to surface water detection globally. In general, the method works and generates results that are compelling enough to consider.</u> (1) <u>However there are many significant holes in the logic that were not tested (or not proven) by the authors which could have significant impacts on their results and conclusions. Overall, much more detail is needed in the descriptions of how conditions (I noted several specific things in my comments below) were handled and tested for validity.</u> (2) <u>While I accept the premise that frequent MODIS observations are an advantage compared to frequency products using Landsat, which was stated by the authors in the introduction, it is still necessary to compare the frequency results from GLOBMAP to one or more of the frequency maps from Landsat (Pekel or Pickens at the very least). The comparisons that were done were with other MODIS derived products. This is ok for a first look but if you are trying to claim that you have a better approach than the Landsat products you must test this and show the results so the reader can decide for themselves. For this paper to be published in context these evaluations must be performed and reported. Beyond that it is important to clarify for the reader how the following things were handled so that the reader can trust the results.</u> (3) <u>How did you delineate the oceans? Where did you cut off rivers where they meet the oceans?</u> (4) <u>How did you handle extensive burned areas globally which would effect your low NIR values?</u>

Response:

(1) We carefully revised the paper according to the reviewer's comments, such as analyzing the global distribution of available clear-sky snow-free observations, adding comparison with high-resolution surface water datasets and validation at high-mid latitudes, clarifying the definitions of permanent and intermittent surface water, supplementing descriptions of post-processing procedures, and discussing the effects of noise such as burned areas. Please refer to the reply of the relevant comments for details.

(2) We added the comparison with two high-resolution surface water datasets derived from Landsat observations, including Global Land Analysis & Discovery (GLAD) Global surface water dynamics dataset from Pickens et al. (2020) and global surface water dataset from Pekel et al. (2016). The areas of global maximum, permanent and intermittent surface water were compared (lines 274-282 in Section 4.1 in the revision). The generated SWF maps were also compared with the annual water percent dataset of GLAD and seasonality dataset of GSW in three demonstration regions, including Taihu Lake, lakes in northeastern Tibetan Plateau and Qarhan Salt Lake. Considering the time of available data for the five datasets (GLOBMAP, GLAD, GSW, GSWCD and ISWDC), the year for the comparison of the three regions was changed to 2015, and the results was similar to that in 2016. Figure 3-5 and the relevant description in Section 4.2 were revised (lines 296-363), and description about the two datasets were added in Section 2.3 (lines 114-118, 139-156). In general, the spatial pattern of GLOBMAP SWF maps agrees with that of the two high resolution datasets in three comparison regions. The two Landsat-based products can represent more small water bodies and extract larger area of permanent and maximum surface water with their fine spatial resolution, while our dataset captures more intermittent surface water and successfully reduces the influence of clouds and frozen water. Please see details in Section 4.1 and 4.2.

(3) The oceans were delineated using the ocean label in the state QA flags of MOD09A1 products (sur_refl_state_500m). This dataset provides the distribution of

oceans around the globe, but ocean pixels may be not fully connected with the land in some areas. And the data are not updated annually, so some pixels marked as ocean may become land due to human activities or natural factors. In this paper, we first used the flag of MOD09A1 as the initial ocean flag. Those pixels detected as land by the proposed method were labeled as land, and those water pixels between the land and the ocean flagged by MOD09A1 were labeled as ocean. For water bodies that were not marked as oceans in state flag of MOD09A1, we extended the land boundary toward the water. If the extended land boundaries meet with each other, the water bodies were marked as inland surface water; if the extended land boundaries meet the ocean pixels, the adjacent water pixels were labeled as ocean. Since the river estuary may be labeled as ocean in MOD09A1 state flag, this method may result in some areas of the river estuary to be labeled as ocean. This should have little effects at large scale. The post-processing procedures were supplemented in lines 237-243 in the revision.

(4) As you suggested, burned area greatly reduces the reflectance in the NIR band, thus burned area observations may be included in the selected six observations with the lowest NIR reflectance for the maximum surface water extent mapping. It may be hard to separate water from some burned areas, especially for those that has just occurred serous fires and accumulated with a lot of black carbon on the ground. But black carbon is usually easy to be removed by wind and water, and then its spectrum will be different from that of water, making it can be differentiated from water. Additionally, the maximum surface water extent was mapped with pixels with water count $\geq$ 3, which can exclude 1-2 false detections caused by burned area and other noise.

Line Comment

50 “Surface water was also mapping” needs revision for English grammar

Response: The sentence has been revised to "Surface water was also mapped" (line 52 in Section 1 in the revision). Thanks for your careful review.

99 determinate should be determine

Response: The word was edited according to your suggestion (line 101 in the revision).

101 why did you not use the finer resolution GMTED which was designed for use with MODIS data?

Response: In this paper, the DEM data was mainly used to exclude large areas mountain shadows, such as shadows in the margin of the Tibetan Plateau. The GTOPO30 data with approximately 900 m resolution can meet this demand. For mountain shadows with a small range, since the local time when MODIS passes changes among days, the distribution of shadows will change due to different solar and viewing geometry. MOD09A1 selects the best possible observation during an 8-day composition period, and its spatial resolution is coarse (500 m), which help to reduce the effects of mountain shadows with a small range. As you suggested, the fine resolution GMTED2010 DEM data would help to improve the identification of terrain shadows. Related discussions were added in lines 589-595 in Section 5 in the revision, and better DEM data will be considered in future work. Thank you for your suggestion.

116 the sentence starting with "The cloud, ice…" appears to end abruptly or otherwise be an incomplete sentence

Response: The sentence has been revised and moved to lines 127-129 in Section 2.3 as follows: "The cloud, ice/snow and no valid data were labeled with MODIS State

QA layer and land surface temperature data, and cloud and no valid pixels were filled with temporal-spatial interpolation to produce a gap-free time series."

136 all of your validation sites are in the tropics, this is not a best practice. For a global product you need to have validation from northern latitudes as well as mid latitudes to assess performance everywhere.

Response: We added four validation sites to demonstrate the performance of the dataset at middle and high latitudes, including Lake Winnipegosis in Canada (99.91° W, 52.61° N), lakes in western Russia (31.00° E, 64.10° N), Lake Maggiore in Italy (8.65° E, 45.90° N), and Lake Wakatipu in New Zealand (168.55° E, 45.10° S). The first two sites are located in high latitudes of the Northern Hemisphere, where concentrated a large number of small water bodies. The last two sites are located in the mid-latitudes of the northern and southern Hemispheres, respectively. Lake Maggiore is surrounded by mountains in the Alps in northern Italy, which shows an example in mountainous regions. Figure 6 and the relevant description were revised (lines 160-187 and lines 366-400). It is complex and requires a lot of work to validate a global product. Here we selected eight sites as examples to demonstrate the performance of our dataset for different surface water types, permanent and seasonal waters, different latitudes, as well as with presence of frequent cloud cover. We will further analyze the dataset in future work.

173 If you use MOD09A1 you have a total of 46 possible observations in a year. In most cases at least half (probably more) are not usable due to clouds or other data problems. Using the "six lowest NIR" values, could be that you only have six total observations for a pixel. This is a questionable method for a global product.

Response: The number of available clear-sky observations in a year (N_{Clear}) was counted during the period 2001-2020 over global terrestrial surface. In this paper, clear-sky observation refers to the valid MOD09A1 observation that not covered with clouds and snow/ice. There are averagely 4,285 pixels with $N_{Clear} \leq 6$, accounting for 0.0008% of the total terrestrial surface pixels (550,215,315). This percentage is 0.02% (460 pixels out of total 1,901,338 water pixels) for the inland water bodies. The proportion of pixels with extreme sparse clear-sky observation is very small, and its influences should be limited at global scale.

Figure 1.1 shows the global map of N_{Clear} in 2020. Fortunately, N_{Clear} is generally above 40 in arid and semi-arid areas, where water bodies may show significant seasonal variation in their extent. The low N_{Clear} values are concentrated in the tropics and subtropics, such as the Gulf of Guinea, the Amazon, the Southeast Asia, and the Sichuan Basin in southwestern China, where N_{Clear} is mostly ranging from 25 to 35. Since surface water generally shows relatively small seasonal changes in the tropics and subtropics, the available clear-sky observations should be able to capture the distribution of surface water. In high latitudes in the northern hemisphere, N_{Clear} is generally reduced to 10-25 due to long period of snow/ice cover and the polar night in winter. The proposed algorithm excludes snow/ice observations and uses the observations in unfrozen period to estimate the surface water cover frequency. In the glacial areas, such as Greenland and glacial areas of the Tibetan Plateau, N_{Clear} is less than 10 as snow and ice observations are excluded in counting of clear-sky observations, but it should have little impacts on the dataset due to limited water bodies in these regions. In some areas in the central part of huge lakes (e.g., Caspian Sea), since they are far away from the land pixels on the shore and their clear-sky observations may be different from that of the adjacent reliable land pixels, N_{Clear} are set to fill value to reduce the uncertainties in N_{Clear} estimation. The SWF of these regions is usually estimated to be 100%, as its N_{land} is usually less than 15.

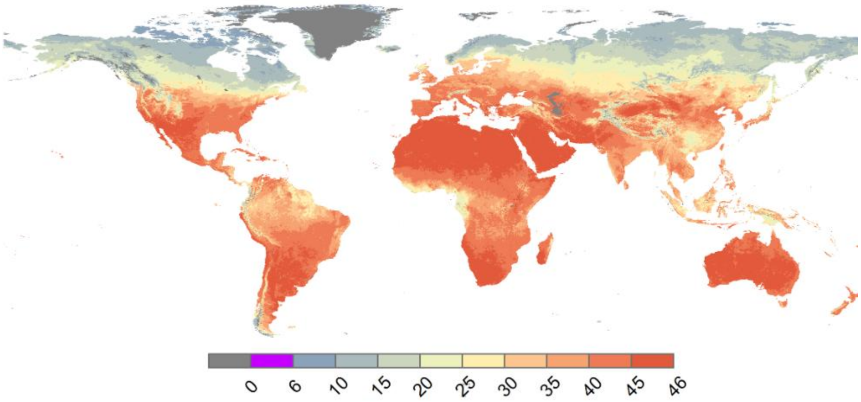

Figure 1.1. Global map of the number of clear-sky snow-free MOD09A1 observation in 2020

The limited number of valid observations is a common problem for optical remote sensing. The MODIS onboard Terra and Aqua satellites observe the Earth's surface every 1 to 2 days. Their dense time series can be acquired to generate more clear-sky observations. Since MOD09A1 contains the best possible clear-sky observation during 8-day composition period, clear-sky observations can be available as long as there is one clear sky in 8 days. Most regions of the world have six clear-sky observations during a year. Additionally, in the proposed method, all pixels with water count ≥ 3 among six observations with the lowest NIR reflectance were used to create the maximum surface water extent map. This means that the algorithm can be implemented with three valid observations during a year, which helps to improve the global applicability of the algorithm.

The discussion about the clear-sky observations were supplemented in lines 561-585 in Section 5. The definition of clear-sky observation was added in lines 217-218 in Section 3.1.

194 less than 15 percent or less than 15 count? What do you do in the frequent case where N_{Land} is < 15? In northern latitudes you won't get that many snow free observations, the method seems to ignore the typical case of snow surrounding ice covered lakes.

Response: It is less than 15 count. For the largest 100 inland water bodies around the globe excluding rivers and water bodies with great seasonal variation in water extent, we set the SWF to 100% for those pixels with N_{Land} < 15 count to eliminate the effects of uncertainty in N_{Clear} estimations. For large inland water bodies, the adjacent reliable land pixels that used to estimate N_{Clear} over the maximum surface water extent may be far away from the water pixels, which may result in uncertainties in N_{Clear} estimation of water pixels and SWF consequently. The above processing can reduce the influence of uncertainty in N_{Clear} on SWF dataset. The relevant description was revised to make it clear (lines 229-235 in Section 3.1 in the revision).

Figure 1.1 in this file shows that the areas with less than 15 snow-free clear-sky observations are mainly concentrated in the glacial areas and the far high latitudes of the northern hemisphere where distributed lots of small lakes. The post-processing was only implemented for the global 100 largest inland water bodies excluding rivers and lakes/ wetlands with great seasonal variation in water extent. It should not affect the performance of the dataset for ice covered lakes at high latitudes.

230 does your definition of intermittent include the fact that high latitude lakes are frozen for a large part of the year? Much more clarity is needed on your definitions.

Response: In this paper, the intermittent surface water refers to the areas covered by water for part of a year. As you pointed out, some lakes freeze for part of the year. Since snow and ice observations are excluded in estimation of the SWF in the proposed method, the observations in unfrozen period are used to estimate the surface water cover frequency for the year. If area is underwater for part of the observation period (i.e., the unfrozen period), it is considered to be the intermittent surface water; while if water is present throughout the unfrozen period, the water body is considered to be a permanent surface water. Generally, water is still present under the ice layer during the frozen period. This simplification can represent the spatial and seasonal patterns of lakes at high latitudes and high altitudes which are frozen for a part of the year. The definitions of intermittent and permanent surface water are clarified in lines 261-267 in Section 4.1 in the revision.

308 this statement confirms my earlier comments. Many of your assumptions about the availability of clear sky observations are invalid for many places in the world. Unless you provide a companion product describing the per pixel reliability (based on the number of observations available) users are likely to draw incorrect conclusions in many cases.

Response: According to your suggestion, we have uploaded the number of MOD09A1 clear-sky snow/ice-free observations (N_{Clear}) data on the Zenodo repository at https://doi.org/10.5281/zenodo.6462883 (Liu and Liu, 2022) as a quality dataset. The description about the N_{Clear} dataset was supplemented in lines 610-615 in Section 6 in the revision. The global map of N_{Clear} and relevant discussion were also supplemented in Section 5. Thank you very much for your insightful comment.

352 should be Carroll not Carrell.

Response: The name has been corrected (line 438 in the revision). Sorry for the mistake.

378 for these evaluations to be understood it is essential to know how many clear observations there were in each year. How can the reader know that the variation you are reporting is not simply due to differences in the number of observations for a given year?

Response: The available clear-sky observations count (N_{Clear}) was averaged over the maximum surface water extent in the Poyang Lake region for each year during 2001-2020 (purple line in Fig. 1.2). The average N_{Clear} in this region was between 33 and 39 during this 20-year period. Correlation was observed between the area of maximum surface water extent and the N_{Clear}. More clear-sky observations mean less precipitation, which may lead to smaller lake area. While less clear-sky observations mean more precipitation, and the lake area should be larger. However, these two variables do not correspond exactly. For example, in 2003, 2004, 2013 and 2017, the average N_{Clear} reached the maximum (39), but the annual maximum surface water extent presented notable variations with the area ranging from 3544 km^2 to 4589 km^2. Less clear-sky observations were available in 2005, 2010 and 2016 (35), but the maximum surface water area in 2010 reached the second largest value (5239 km^2) in 20 years, while it was only about 4300 km^2 in the other two years. This indicates that the maximum surface water area does not depend on the N_{Clear}. The minimum surface water area shows no obvious correlation with N_{Clear}, and its interannual fluctuation should be related to precipitation and the amount of water entering the lake in the dry season. We supplemented the interannual fluctuations of N_{Clear} in Fig. 9b and revised the relevant description in lines 480-493 in Section 4.5.1 in the revision.

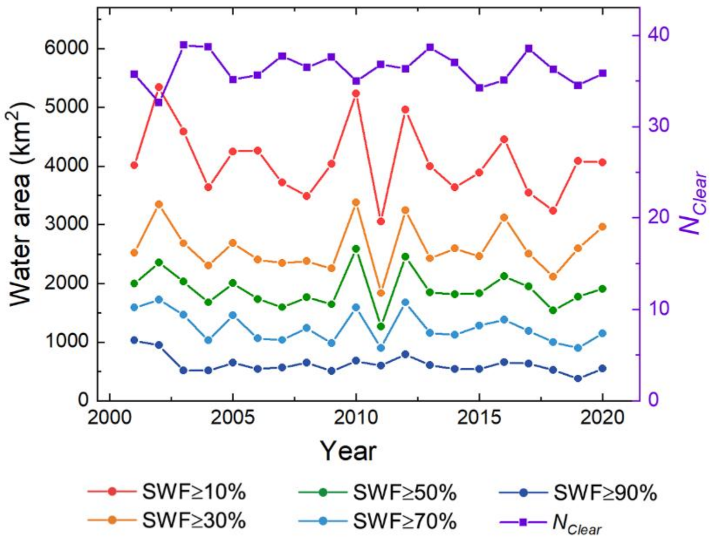

Figure 1.2. The interannual variation of the area of Poyang Lake with different inundation frequency and mean value of available clear-sky observations count (N_{Clear}) over the maximum surface water extent from 2001 to 2020.

395 largest variation by total area or by percent change? Total area would limit this to only very large lakes…

Response: We agree with your comment. Here, the ten lakes with the largest seasonal variation were identified by percent change, which is the proportion of the intermittent water area to the annual maximum water extent. The relevant description was revised in lines 496-497 in the revision to make it clearer.

Reference:

Pekel, J. F., Cottam, A., Gorelick, N., and Belward, A. S.: High-resolution mapping of global surface water and its long-term changes, Nature, 540, 418-+, 10.1038/nature20584, 2016.

Pickens, A. H., Hansen, M. C., Hancher, M., Stehman, S. V., Tyukavina, A., Potapov, P., Marroquin, B., and Sherani, Z.: Mapping and sampling to characterize global inland water dynamics from 1999 to 2018 with full Landsat time-series, Remote Sens. Environ., 243, 10.1016/j.rse.2020.111792, 2020.

Response to Reviewer #2

We are very grateful to the reviewer for the insightful and careful review. These comments are very helpful to improve the quality of the manuscript. All comments were answered in below, and the manuscript was revised according to these comments. The comments from the reviewers are kept in regular font with underlines and our responses in blue color. Please note that the line numbers refer to the marked-up version of the revision.

Referee 2

The dataset provides a MODIS-derived annual surface water frequency dataset, which can help analyze the dynamics of surface water. The manuscript is well structured and written! My major comments are:

(1) I agree with the authors that the daily MODIS observations have value in capturing the variations of surface water; however, its limitation is also obvious. The 500-m resolution is too coarse for capturing the abundant small water bodies as well as the subtle changes of surface water. Moreover, the Sinusoidal projection of MODIS caused a considerable distortion in high latitudes, worsening this omission, particularly in North America and Eastern Russia, where a large portion of the global small water bodies are located. (2) It seems that the authors have been mainly focused on China and a few low-mid latitudes, but did not assess the performance in high latitudes, which seems to require more attention during validation.

Response: (1) As you pointed out, it is difficult for the dataset to capture small water bodies and the subtle changes of surface water due to the coarse spatial resolution of MODIS, especially in high latitudes in the Northern Hemisphere where a large number of small water bodies are located. The Sinusoidal projection of MODIS distorts shape and angles, but it can preserve the size of features true to their real area as an equal area projection. We think that the main problem at high latitudes is the limitation of coarse resolution of MODIS in the identification of small water bodies. Satellite data often has certain advantages in terms of temporal or spatial resolution, time coverage, etc., but it is difficult to take into account all of these aspects. MODIS provides daily spectral measurements of the Earth surface since 2000. Its long-term high-frequency observations have unique advantages in monitoring of the seasonal and interannual changes in surface water. The relevant discussion has been added in lines 601-606 in Section 5 in the revision.

(2) We added four validation sites to demonstrate the performance of the dataset at high and mid latitudes, including Lake Winnipegosis in Canada (99.91° W, 52.61° N), lakes in western Russia (31.00° E, 64.10° N), Lake Maggiore in Italy (8.65° E, 45.90° N), and Lake Wakatipu in New Zealand (168.55° E, 45.10° S). The first two sites are located in high latitudes of the Northern Hemisphere, where concentrated a large number of small water bodies. The last two sites are located in the middle latitudes of the northern and southern Hemispheres, respectively. Figure 6 and the relevant description were revised (lines 160-187 in Section 2.4 and lines 366-400 in Section 4.3). It is complex and requires a lot of work to validate a global product. We selected eight sites as examples to demonstrate the performance of the dataset for different surface water types, permanent and seasonal waters, different latitudes, as well as with presence of frequent cloud cover. We will further analyze the dataset in future work.

<u>The authors reported the areas of global inland surface water, including permanent and maximum areas; however, I think the numbers could be biased by failing to capture the small water bodies as commented in the above paragraph. As many much finer surface water datasets have already been produced, I would suggest the authors clarify the conditions of these reported areas, such as water bodies larger than a certain size; otherwise, the areas would not be valid.</u>

Response: Since the spatial resolution of MODIS is 500 meters, only water bodies with a spatial range greater than 500 m×500 m can be detected. In addition, to reduce the influence of noise, the water bodies with an area less than 2×2 pixels were removed for the generated SWF maps. Thus, the dataset provides maps of inland water bodies larger than 1 km×1 km open to the sky. The relevant description was edited in lines 278-280 in Section 4.1, and the post-processing procedures were supplemented in lines 237-238 in Section 3.1 in the revision.

<u>I am not convinced why the authors did not compare the results to the global water dataset produced by Pekel et al. and the GLAD (Pickens et al., 2020), which all provide permanent and seasonable water cover that can be comparable to this dataset.</u>

Response: We added the comparison with two high-resolution surface water products derived from Landsat observations, including Global Land Analysis & Discovery (GLAD) global surface water dynamics dataset from Pickens et al. (2020) and global surface water dataset from Pekel et al. (2016). The areas of global maximum, permanent and intermittent surface water were compared (lines 236-243 in Section 4.1 in the revision). The generated SWF maps were also compared with the annual water percent dataset of GLAD and seasonality dataset of GSW in three demonstration regions, including Taihu Lake, lakes in northeastern Tibetan Plateau and Qarhan Salt Lake. Considering the time of available data for the five datasets (GLOBMAP, GLAD, GSW, GSWCD and ISWDC), the year for the comparison of the three regions was changed to 2015, and the results was similar to that in 2016. Figure 3-5 and the relevant description in Section 4.2 were revised (lines 296-363), and description about the two datasets were added in Section 2.3 (lines 114-118, 139-156). In general, the spatial pattern of GLOBMAP SWF maps agrees with that of the two high-resolution products in the three comparison regions. The two Landsat-based products can represent more spatial details and extract larger area of permanent and maximum surface water with their fine spatial resolution, while our dataset captures more intermittent surface water and successfully reduces the influence of clouds and frozen water. Please see details in Section 4.1 and 4.2.

Specific comments:

I would suggest removing “for change analysis of inland water bodies” in the title.

Response: The title has been edited according to your suggestion. This product can not only be used to analyze the changes of inland water bodies, but also can characterize their spatial distribution and seasonal characteristics.

Line 172, why six observations?

Response: We selected six observations by weighing available clear-sky observations and possible noise observations, such as shadows, burned areas and occasional water cover. In the tropics, subtropics, and high latitudes of the northern hemisphere, the number of available clear-sky snow-free observations is usually limited due to frequent cloud and snow/ice covers as well as the polar night in winter (see details in discussion about available clear-sky observations in lines 561-585 in Section 5 in the revision). On one hand, selecting too many observations may include cloud or snow/ice observations in the determination of the maximum surface water extent. On the other hand, choosing too few observations may be interfered by possible noises in maximum surface water mapping. For example, shadows and burned areas greatly reduce the reflectance in the NIR band, and heavy rain and flood would cause occasional water cover, which may be included in the selected observations with the lowest NIR reflectance. Through extensive tests across the globe, we selected six observations with the lowest NIR reflectance during a year to map the maximum surface water extent. There are more than six clear-sky snow-free observations for 99.9992% (99.98%) of the total terrestrial surface (inland water bodies), which can ensure to obtain reliable clear-sky observations in most regions of the world. Those pixels with water count ≥ 3 were used to create the maximum surface water extent map to exclude the occasional water cover and residual shadows and burned areas. The relevant description was edited in lines 209-214 in Section 3.1 to make it clearer.

<u>Line 179, does the slope criteria also remove water in a sloppy area that is outside of shadow? Also, did the variation of solar angles along latitudes and seasons considered in estimating shadows?</u>

Response: The variation of solar angle along latitudes and seasons was not considered in the slope criteria for shadows estimation, which may cause water that is outside of shadow to be removed in mountainous areas. Here, the slope criteria was mainly used to exclude large areas mountain shadows, such as shadows in the margin of the Tibetan Plateau. Underestimation of lakes in these regions should have limited impacts on large scale. For mountain shadows with a small range, since the local time when MODIS passes changes among days, the distribution of shadows will change due to different solar and viewing geometry. MOD09A1 selects the best possible observation during an 8-day composition period, and its spatial resolution is coarse (500 m), which helps to reduce the effects of mountain shadows with a small range. As you suggested, consideration of solar angle variation would help to improve the identification of terrain shadows. We supplement the related discussion in Section 5 (lines 587-595 in the revision).

<u>Line 200, please clarify what resample method was adopted.</u>

Response: The Sentinel-1 SWF maps were resampled to 500 m resolution by averaging the valid SWF estimations from Sentinel-1 data within the MODIS 500 m grid. The resample method has been revised in lines 247-248 in the revision to make it clearer.

Line 427-448, I am not fully agreeing with the novelty of the method as mentioned here. The method still identifies water cover as explained in the methodology, so the statement of the advancement here does not seem to be a valid point. Also, the method seems to be a very simple one without considering calculating water index or machine learning-based models. I am honestly surprised that it was robust enough for producing a reasonable global result.

Response: We mean that the algorithm does not directly identify water cover to estimate surface water cover frequency (SWF). The water observations count was estimated by subtracting the land observations count from clear-sky observations (land and water) count, and then divided clear-sky observations count to estimate the SWF. As you pointed out, we identified water pixels in mapping the maximum surface water extent. But this procedure used six observations with the lowest reflectance in the NIR band (R_{NIR}). Since cloud and snow/ice generally show much higher R_{NIR} than that of land and water, cloud and snow/ice observations should be excluded in these six observations, thus water can be separated from land reliably. The relevant description has been edited to make it clearer (lines 527-527 in Section 5).

In generation of global water datasets, it is not only needed to propose good water cover extraction algorithm, but also need to consider data quality, noise and applicability of the algorithm in different regions. Indeed, we also tried various methods such as water index and classification. But it is difficult to distinguish water from clouds and snow/ice in some cases, and variation of characteristics of water body and surface background may also result in confusion in water extraction, making it challenging to establish a globally applicable algorithm.

We found a reliable and robust method to separate land from water, cloud and snow/ice. The reflectivity of the red band (R_{Red}) of the former is generally lower than that of the SWIR band (R_{SWIR}), while it is opposite for the latter three. If the SWF were estimated indirectly by identifying land, the interference of cloud and snow/ice in water identification would be avoided. Here, three procedures were implemented to extract the SWF indirectly. (1) In mapping of the maximum surface water extent, cloud and snow/ice observations were excluded automatically through selecting several observations with the lowest R_{NIR} during a year, which helps to determine the possible surface water extent reliably. (2) The land identification method ($R_{Red} < R_{SWIR}$) was robust and applicable for major types of water bodies and surface background, and can exclude cloud and snow/ice observations. (3) The water count was estimated by subtracting the land observations count from clear-sky observations count, which avoids directly distinguishing water from cloud and snow/ice. The above methods are ubiquitous for various water bodies and surface background types, and reduce the interference of cloud and snow/ice, which helps to improve the applicability of the algorithm across the globe. The relevant description was revised (lines 539-555 in Section 5).

Figure 8 is hard to interpret because most of the pixels showing positive trends also show negative trends. I think that the authors need to come up with a better way of presenting the results.

Response: Figure 8 was revised to present the fraction and rate of the dominant change trend of surface water cover frequency in 10 km resolution (Fig. 2.1 in this file). For visualization, the linear trend of surface water cover frequency was aggregated to 10 km resolution and selected to display the fraction of positive slopes or negative slopes ($p < 0.05$), whichever is larger in each 10 km grid, to represent the dominant monotonic change type of surface water. Grids with dominantly positive (negative) slopes were labeled as inundation frequency increasing (decreasing) areas (positive (negative) fraction). Similarly, we compared the average rate of positive slopes and negative slopes within each 10 km grid, and chose the faster change rate to represent the intensity of surface water changes. Grids with positive (negative) slope rate mean that the water occurrence is increasing (decreasing) rapidly. Figure 8 and related descriptions have been revised (lines 427-453 in Section 4.4 in the revision).

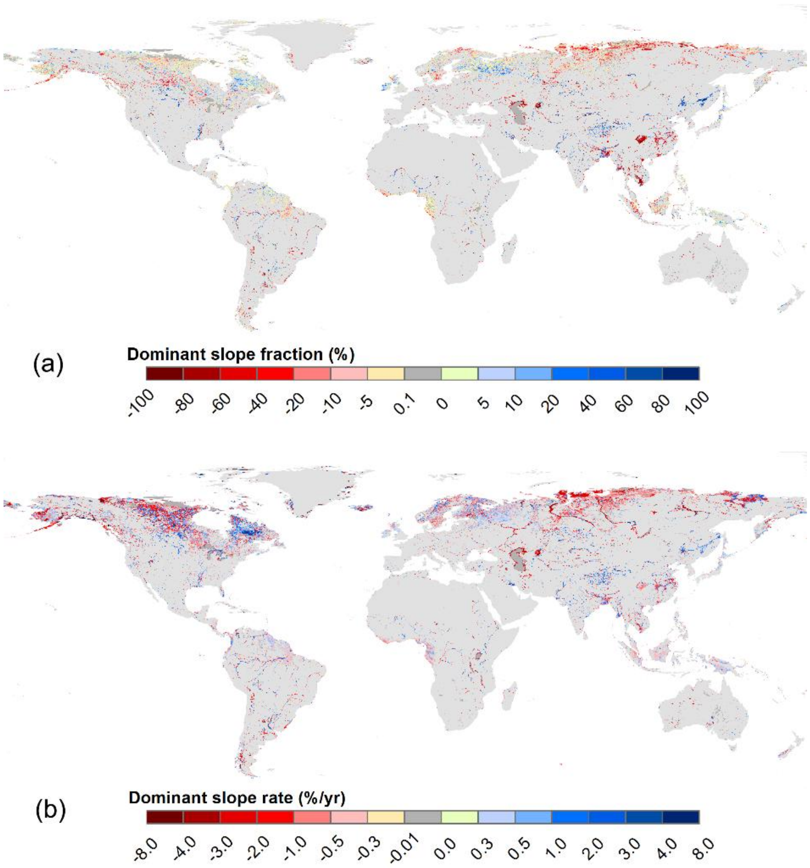

Figure 2.1. Linear trends of surface water cover frequency (SWF) during 2001 and 2020. The trend maps were aggregated to 10 km resolution for visualization. (a) Dominant SWF slope fraction (%). The positive (negative) fraction means that the fraction of pixels with increasing (decreasing) SWF ($p < 0.05$) in each 10 km grid, indicating whether the inundation frequency is dominantly increasing (decreasing). (b) Dominant SWF change rate (%/yr). The positive (negative) slope rate means that the mean linear slope rate of pixels with increasing (decreasing) SWF ($p < 0.05$) in each 10 km grid, whichever is faster, indicating whether the inundation frequency is increasing (decreasing) rapidly. The light grey refers to non-water covered areas.

Reference:

Pekel, J. F., Cottam, A., Gorelick, N., and Belward, A. S.: High-resolution mapping of global surface water and its long-term changes, Nature, 540, 418-+, 10.1038/nature20584, 2016.

Pickens, A. H., Hansen, M. C., Hancher, M., Stehman, S. V., Tyukavina, A., Potapov, P., Marroquin, B., and Sherani, Z.: Mapping and sampling to characterize global inland water dynamics from 1999 to 2018 with full Landsat time-series, Remote Sens. Environ., 243, 10.1016/j.rse.2020.111792, 2020.