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Correction

Correction: Sibanda et al. Application of Drone Technologies in Surface Water Resources Monitoring and Assessment: A Systematic Review of Progress, Challenges, and Opportunities in the Global South. *Drones* 2021, *5*, 84

Mbulisi Sibanda [1,*], Onisimo Mutanga [2], Vimbayi G. P. Chimonyo [3,4], Alistair D. Clulow [5], Cletah Shoko [6], Dominic Mazvimavi [7], Timothy Dube [7] and Tafadzwanashe Mabhaudhi [3]

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Missing Citation

In the original publication [1], "Fahad Alawadi. Detection of surface algal blooms using the newly developed algorithm surface algal bloom index (SABI)", "Proc. SPIE 7825, Remote Sensing of the Ocean, Sea Ice, and Large Water Regions 2010, 782506 (18 October 2010); https://doi.org/10.1117/12.862096" [2] was not cited. The citation has now been inserted in "*3.5. The Role of Drone Data Derived Vegetation Indices and Machine Algorithms in Remote Sensing Water Quality and Quantity*" as reference [60] and should read: "Numerous vegetation indices were derived from drone remotely sensed data for characterising surface water quality and quantity. The most widely used sections of the electromagnetic spectrum in detecting water quality parameters were the visible section (blue and green) and the NIR wavebands. In this regard, vegetation indices such as the red and near-infrared (NIR), Surface Algal Bloom Index (SABI) [60], two-band algorithm (2BDA) [26], NDVI, and Green NDV [33], as well as band combinations and differencing such as (R+NIR/G) were used mostly in characterising chlorophyll content as well as TSS. As was suggested in many studies, the combination of sensitive spectral variables with robust and efficient algorithms produce accurate models. This study noted that algorithms such as linear regression (LR), image differencing, matching pixel-by-pixel (mpp), artificial neural networks (ANN), and the Manning–Strickler and adaptive cosine estimator were utilised in characterising mostly water quality parameters (Figure 9). The mpp-based algorithms were also detected during the bibliometric analysis illustrated in Figure 3 (red cluster). Despite being a parametric estimator, LR was the most widely used algorithm because it is simple to implement [61] across various statistical platforms ranging from Microsoft Excel to R statistics. Since LR is a parametric statistic, it requires the data to suit specific assumptions such as normality that are often a challenge to attain. In this regard, there is a need for more efforts in assessing the utility of robust machine learning algorithms such as stochastic gradient boosting, random forest, and the ANN in mapping water quality based on drone remotely sensed data (Figure 10)."

For the references after 60, should be revised like below:

Original 60 change to 61;
Original 61 change to 62;
Original 62 change to 63;
Original 63 change to 64;
Original 64 change to 65;
Original 65 change to 66;
Original 66 change to 67;
Original 67 change to 68;
Original 68 change to 69;
Original 69 change to 70;
Original 70 change to 71;
Original 71 change to 72;
Original 72 change to 73;
Original 73 change to 74;
Original 74 change to 75;
Original 75 change to 76;
Original 76 change to 77;
Original 77 change to 78;
Original 78 change to 79.

Which the corresponding citations in the main text should be changed like below:

"*4.1. Evolution of Drone Technology Applications in Remote Sensing Water Quality and Quantity, the second paragraph*."

Meanwhile, results showed that more efforts from the community of practice were widely exerted towards mapping water quality in relation to water quantity. Specifically, only fourteen studies assessed the level of water, whereas thirty-seven studies assessed water quality parameters based on drone remotely sensed data [44,47–49,62–72]. A few examples of studies that mapped water levels included Ridolfi and Manciola [63], who used a method that was based on the Ground Control Points (GCPs) to detect water levels, where water level values were measured using drone-derived data. Meanwhile, Adongo et al. [64] assessed the utility of undertaking bathymetric surveys combined with geographic information systems (GIS) functionalities in remotely determining the reservoir volume of nine irrigation dams in three northern regions of Ghana. On the other hand, the majority of water quality-related studies that were conducted based on drone remotely sensed data, principally mapped and monitored the chlorophyll content [30,32,33,37,38] and turbidity in lakes, ponds, and dams (Figure 5b) [34–36]. This trend was also revealed through the bibliometric analysis illustrated in Figure 3. Other water quality parameters that were of interest include the chemical oxygen demand (COD) [26,35,73], Secchi disk depth (ZSD) [26,34,74], total nitrogen [35], total phosphorous [35,73], conductivity [24–26,73], water quality index [73], pH [27,75], total suspended solids (TSS) [28,29,76], dissolved Oxygen (DO) [75,77], and turbidity [35,48], in order of importance illustrated by their frequency in the literature.

"*4.2. Challenges in the Application of Drone Technologies with Special Reference to the Global South, the first paragraph*."

The major challenge associated with many regions is the statutory regulations that govern the operation of UAVs [77–79]. In many countries, there are still stringent restrictions regarding where and how UAVs are supposed to be operated [16]. In some countries of the global south, the take-off mass, the maximum altitude of flight, and the operational areas of drones tend to be regulated [16]. For instance, the South African Civil Aviation Authority (SACAA) stipulates that remotely piloted aircraft or toy aircraft should not be operated at 50 m or closer to any person or group of persons. It states that remotely piloted aircraft or toy aircraft must not be operated at an altitude higher than 45.72 m (150 ft) from the ground unless approved by the Director of Civil Aviation of the SACAA. Remotely piloted aircraft or toy aircraft weighing more than 7 kg should be operated only if approved by the SACAA (http://www.caa.co.za/pages/rpas/remotely%20piloted%20aircraft%20systems.aspx, accessed on 19 July 2021). The size of the UAV which is often associated with its batteries, engine efficiency, load, and type of UAV (fixed-wing or multi-rotor) tends to determine the length of time it can spend on a single flight plan and the size of the area it can cover [46,79]. In this regard, the regulation on the mass of UAV at taking off tends to indirectly restrict the areal extent that can be covered as well as the size of the camera to be mounted for research purposes, amongst other uses [16,68].

Added References

Alawadi, F. Detection of surface algal blooms using the newly developed algorithm surface algal bloom index (SABI). In *Remote Sensing of the Ocean, Sea Ice, and Large Water Regions 2010*; International Society for Optics and Photonics: Bellingham, WA, USA, 2010; p. 782506. https://doi.org/10.1117/12.862096.

The authors apologize for any inconvenience caused and state that the scientific conclusions are unaffected. The original publication has also been updated.

References

1. Sibanda, M.; Mutanga, O.; Chimonyo, V.G.P.; Clulow, A.D.; Shoko, C.; Mazvimavi, D.; Dube, T.; Mabhaudhi, T. Application of Drone Technologies in Surface Water Resources Monitoring and Assessment: A Systematic Review of Progress, Challenges, and Opportunities in the Global South. *Drones* **2021**, *5*, 84. [CrossRef]
2. Alawadi, F. Detection of surface algal blooms using the newly developed algorithm surface algal bloom index (SABI). In *Remote Sensing of the Ocean, Sea Ice, and Large Water Regions 2010*; International Society for Optics and Photonics: Bellingham, WA, USA, 2010; p. 782506. [CrossRef]