

Article Spatio-Temporal Change Monitoring of Outside Manure Piles Using Unmanned Aerial Vehicle Images

Geonung Park ¹, Kyunghun Park ² and Bonggeun Song ³,*

- ¹ Department of Smart Ocean Environmental Energy, Changwon National University, Changwon 51140, Korea; ubps0380@changwon.ac.kr
- ² School of Civil, Environmental and Chemical Engineering, Changwon National University, Changwon 51140, Korea; landpkh@changwon.ac.kr
- ³ Industrial Technology Research Institute, Changwon National University, Changwon 51140, Korea
- * Correspondence: envsong@changwon.ac.kr; Tel.: +82-10-2880-3299; Fax: +82-55-281-3011

Abstract: Water quality deterioration due to outdoor loading of livestock manure requires efficient management of outside manure piles (OMPs). This study was designed to investigate OMPs using unmanned aerial vehicles (UAVs) for efficient management of non-point source pollution in agricultural areas. A UAV was used to acquire image data, and the distribution and cover installation status of OMPs were identified through ortho-images; the volumes of OMP were calculated using digital surface model (DSM). UAV- and terrestrial laser scanning (TLS)-derived DSMs were compared for identifying the accuracy of calculated volumes. The average volume accuracy was 92.45%. From April to October, excluding July, the monthly average volumes of OMPs in the study site ranged from 64.89 m³ to 149.69 m³. Among the 28 OMPs investigated, 18 were located near streams or agricultural waterways. Establishing priority management areas among the OMP sites distributed in a basin is possible using spatial analysis, and it is expected that the application of UAV technology will contribute to the efficient management of OMPs and other non-point source pollutants.

Keywords: UAV; terrestrial laser scanning; digital surface model; agriculture area; non-point source pollutants; livestock waste, outside manure piles

1. Introduction

Composted livestock waste in agricultural areas is actively used as fertilizer to improve crop cultivation [1,2]. Livestock waste that enters water systems is a major concern because of factors such as nutrients, suspended solids, oxygen depletion, and bacteriological quality [3]. Particularly, phosphorus, one of the main components of livestock waste, acts as a non-point source pollutant because it primarily exists as inorganic phosphorus, and its content in manure ranges from 2600 to 40,000 mg/kg. Because 80% of livestock waste is water-soluble, it is likely to flow as leachate or surface runoff during rains [4–6]. As of 2014, 80% of the total volume of the livestock waste generated was used as a resource by converting it to manure and liquid manure [7]. In case of small livestock facilities, however, a large volume of livestock waste is stacked outdoors, to be used as a resource in the form of an outside manure pile (OMP) because it is difficult to access the livestock waste treatment facility. Hence, water quality is deteriorating due to livestock manure loaded outdoors, requiring efficient management of OMPs.

In South Korea, release of nutrients into the water system during rainfall is a concern because here, OMPs are usually located on the edges of agricultural land, near stream embankments, and agricultural waterways. Hence, a cover such as a plastic sheet is used to prevent the release of pollutants during rainfall, and local government managers are continuously conducting surveys as a temporary measure for the management of OMPs. However, local government managers are limited in their ability to investigate the distribution locations and volumes of OMPs quickly and accurately [8]. This is because the



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spatial distribution of OMPs is extensive, making it difficult for investigators to conduct a direct full-scale investigation. For this reason, the behavior of OMPs which is a prerequisite for efficient management has not been confirmed, and thus OMP investigation is necessary.

Recently, technology for the detection of various ground surface information using image data obtained from satellites and unmanned aerial vehicles (UAVs) has been developed that obviates the need for direct on-site investigation. Remote sensing tools have also been actively used in the management of non-point source pollutants [9–13]. Satellite images can provide information on the ground surface covering a wide area. They are also effective in identifying temporal changes in the characteristics of the ground surface because they capture images of the same area at regular intervals [14–16]. However, it is difficult to precisely identify the characteristics of the ground surface with satellite images as most of these images exhibit mid to low resolution, and it is particularly difficult to detect objects, such as OMP sites, that occupy small areas [17–19]. Therefore, it is necessary to use alternative remote sensing tools to identify the characteristics of small pollution sources such as OMPs. UAVs capable of acquiring high-resolution images in space and time are attracting attention because of their ability to overcome the limitations of satellite images [20,21]. They can collect data rapidly, and facilitate precise identification of ground surface characteristics by collecting images at low altitudes [22–26]. Because of these advantages, UAVs have been utilized in various areas, including photogrammetry [27–30], agriculture [31,32], rescue missions [33], vegetation monitoring [34,35], and construction [20], and the range of applications is continually expanding. In the field of management of non-point source pollution in agricultural areas, UAV images have been used in many studies to overcome the limitations of satellite images [8,36,37]. Therefore, it is expected that UAV image data can be used for investigating and monitoring pollutants such as OMPs that are difficult to detect in satellite images, allowing for efficient management of non-point source pollution.

In this study, a UAV was applied to investigate the spatio-temporal changes of OMP in agricultural areas. this is previous step to efficiently manage non-point source pollution caused by OMPs in agricultural areas. To this end, (1) UAV images were acquired, and the OMP locations were identified, and (2) a digital surface model (DSM) was created and compared with terrestrial laser scanning (TLS) to verify the reliability of OMP volumes calculated using UAV images. Finally, (3) the spatio-temporal distribution and volume changes of OMP were analyzed.

2. Materials and Methods

2.1. Study Area

Samga township, Hapcheon county, Gyeongsangnam province (35° 24′48″ N, 128° 6′17″ E) in South Korea, with a total area of 1.5 km², was selected as the study site for investigating spatiotemporal changes in OMPs (Figure 1). In the study area, which is a flat area between mountainous terrain, streams flow around the farmland and provide agricultural water. As the agricultural waterway that supplies agricultural water between farmland is connected to the stream, non-point pollutants on the ground are likely to flow as surface runoff during rainfall into the stream. The agricultural areas in the study site operate as double-cropping; in winter, upland crops are cultivated, while in summer, paddy rice is grown as the main crop, with livestock manure used to grow crops throughout the four seasons. As OMPs are used for crop growth, the selected area is considered to be a suitable study site for investigating spatiotemporal changes in OMP sites.

2.2. UAV Image and OMP Information Collection

The DJI Phantom 4 UAV was used for image acquisition. The standard camera and other equipment were not modified, and it was possible to use automatic flight modes [38]. The digital camera (1" CMOS sensor) installed on the gimbal had a resolution of 20 megapixels and a shutter speed of 1:8000 [39]. The data collection used automatic flight mode to collect images of the study site once a month from March to October 2019, excluding July. In July, UAV flights were not possible due to the rainy season in South

Korea. In March, only four acquisitions of OMP data were collected for comparison with TLS-based DSMs and volumes. In the UAV image collection, detailed 3D modeling was not possible because the ground sample distance was 4.09 cm; however, images were captured by setting the image overlap ratio to 75% at an altitude of 150 m (legally specified as the highest altitude in South Korea) to rapidly collect information over the entire study site. In addition, real-time kinematic (RTK) global navigation satellite system (GNSS) equipment was used for correcting the positions of the images, and 25 ground control points (GCPs) were acquired as terrain features at about 500 m intervals (Figure 1).



Figure 1. Location of the study area in Samga township, Hapcheon county, Gyeongsangnam province, South Korea, is indicated with a red dot. The study site is in. The yellow circles and red X marks indicate the location of the outside manure piles (OMPs) and ground control points (GCPs), respectively.

Ortho-images and DSMs were produced using the collected UAV images and GCPs by PIX4D MAPPER S/W. The distribution and cover installation status of OMPs were then identified using ortho-images. As shown in Figure 2, the cover installation status of the OMPs was classified as one of three types because the amount of rainwater that penetrates the OMP during rainfall depends on this status. The volume of OMP was calculated using the Surface Volume tool after setting the outline in the ortho-image along the boundary of the OMP and then clipping the outline from the DSM using the Extract by Mask tool by ESRI ArcGIS 10.6 S/W.



Figure 2. Cover installation status of OMP is classified into three types: (**a**) type A, OMP that is completely covered by a cover; (**b**) type B, OMP that is partially covered; and (**c**) type C, OMP without a cover.

2.3. Comparison of UAV-Derived DSM Accuracy of OMP Volumes

The OMP volume produced by the UAV-derived DSM was compared and analyzed with TLS-derived DSM to determine the accuracy of the OMP volume; this method was obtained from existing literature [40,41]. TLS is considered a trustworthy and accurate measurement method and has been used in many studies to generate terrain data [40–47]. However, TLS measurement is more time consuming than UAV-imaging-based measurements due to the requirement for several scan positions, along with manual transportation, and the measuring time; in particular, the TLS instrument is more difficult to transport because of its heavier mass as compared with that of a UAV [40]. Therefore, OMP sites with various sizes were selected for the smooth TLS data collection, and a total of four OMP sites were collected.

TLS was performed simultaneously with UAV imaging and from at least four directions relative to the OMP. The equipment used was a RIEGL VZ 400i, for which the scan range and error were 800 m \pm 5 mm [48]. The RiSCAN PRO S/W was used to match the 3D point clouds acquired from the ground [49]. DSMs and ortho-images were then created by extracting the point clouds and using the Las Dataset to Raster tool of ArcGIS 10.6 S/W. The resolution of all DSMs was set to 5 cm, and the DSMs were produced after removing the point clouds of the trees adjacent to the OMP. Next, the TLS images were subjected to geometric correction based on the UAV ortho-images. To compare the form of the OMPs, the TLS-derived DSM was adjusted to the same Z value based on the average of Z value of the UAV-derived DSM for each OMP. The spatial difference between UAV- and TLS-derived DSMs was estimated using the raster calculator tool, and the accuracy of the volume of the OMP calculated from TLS-derived DSM and is the volume of the OMP calculated from TLS-derived DSM and is the volume of the OMP calculated from TLS-derived DSM and is the volume of the OMP calculated from TLS-derived DSM and is the volume of the OMP calculated from TLS-derived DSM and is the volume of the OMP calculated from TLS-derived DSM and is the volume of the OMP calculated volume calculations.

Volume Accuracy (%) =
$$\left(1 - \left|\frac{V_{TLS} - V_{UAV}}{V_{TLS}}\right|\right) \times 100$$
 (1)

3. Results

3.1. Results of UAV Flight Data

Table 1 and Figure A1 (which is in the Appendix A at the end of the manuscript) show the results of the distribution of the OMPs and the cover installation status from April to October 2019 using the ortho-images of the UAV; the OMPs were identified in a total of 28 sites. Between April and May, four OMP sites were created, the largest number compared to other periods, indicating that OMPs were actively created. Between September and October, seven OMP sites disappeared and three OMP sites were created, which had the largest number of disappearing OMP sites compared to other periods. Furthermore, the type A (covered with plastic sheets) OMPs accounted for only 22.2% of the OMPs in October, which was much lower than other months. October is the harvest period of paddy rice in south Korea; this indicates that several OMPs were scattered after the harvest. In June, the cover installation status type A had the largest percentage compared with other months. From June to August, it is a rainy season causing more than a week of rain in Korea [50,51]. Thus, farmers covered OMPs with plastic sheets to prevent loss of the OMPs during the rainy season. After the rainy season, it was confirmed that traces of leachate had flowed out despite extensive type A coverage in August. Despite limitations in determining which variable acted on the OMPs during the rainy season, type A OMPs, which were expected to prevent rain penetration, could also act as a non-point source pollutant. In addition, from April to October, 80% of the newly created OMPs in each month were the type C, and 10% were confirmed as type B; three of the four OMPs created in May appeared as type C; the one OMP created in August appeared as type B; the two OMPs created in September appeared as type C, and the three OMPs created in October

appeared as type C. This indicates there was no immediate management of newly created OMPs.

Table 1. Monthly data for number of OMP sites and their cover installation status through the ortho-images of the unmanned aerial vehicle (UAV).

Month		April	May	June	August	September	October
Number of OMP Sites	Total	19	23	22	21	22	18
	Disappeared	-	-	1	2	1	7
	Created	-	4	-	1	2	3
Cover	Type A	68.40%	69.60%	86.40%	81.00%	81.80%	22.20%
Installation Status	Туре В	15.80%	8.70%	13.60%	9.50%	9.10%	33.30%
	Type C	15.80%	21.70%	0.00%	9.50%	9.10%	44.40%

3.2. Accuracy Analysis of OMP Volume from UAV Data

The OMPs numbered 5, 6, 7, and 8 (which refer to Figure A1 (a) for their location) were used to analyze the accuracy of UAV-derived DSM and volume using TLS-derived DSM; as a result of georeferencing TLS images based on UAV images, the RMS error was 2.57 cm. The cover installation status of OMPs Nos. 6, 7, and 8 was type A, and OMP No. 5 was type B. Table 2 and Figure 3 show the results obtained by comparing the UAV-derived DSMs with those of the TLS-derived DSMs. To examine sections that exhibit significant differences from the geometry obtained with TLS, the class of each image was divided by the standard deviation (σ) interval based on the mean; the standard deviation value was 0.086 m, with three of the four OMPs, and the mean value was -0.001 m; red indicates higher TLS-derived DSM, and blue indicates higher UAV-derived DSM. The mean residual errors of UAV- and TLS-derived DSMs were -0.002 m and -0.001 m, and the standard deviations were 0.078 m and 0.086 m, respectively. Comparing the volume of the OMPs, the results showed that volume accuracy of OMPs from UAV-derived DSMs had an accuracy range of 86.67% to 96.97%, with an average of 92.45%. In addition, it was found that the smaller the OMP volume, the lower the accuracy. It is considered that the smaller the OMP volume, the greater the volume ratio of the irregular curved surface of the part that could not account for the use of tires used to secure the cover of the OMP, so that the difference is greater.

Overall, the UAV- and TLS-derived DSM show noticeable differences in areas where tires were used. As shown in Figure 3b, the sections where the red area is visible are generally observed in the areas with tires, and as shown in Figure 3a, the section where the blue area is visible between the tires is mainly found at the edge of the OMP. OMP is a pile of livestock manure with various and irregular curves along the perimeter. When it has a cover, such as plastic sheets, tires or ropes are installed on its periphery to hold the cover in place. According to Ouédraogo et al. [41], UAV better reconstructs the individual ridges and furrows, whereas TLS shows a succession of mounds and depressions. Therefore, the TLS-derived DSM expresses the irregular curves or tires; however, the UAV-derived DSM appears to produce differences as it reconstructs them into smooth curves. In addition to the tire areas, red or blue areas, as shown in Figure 3c, were identified. There were apparent differences between TLS- and UAV-derived DSM because most of the covers were plastic sheets which could be swollen, depending on the wind conditions.

Table 2. Digital surface model (DSM) comparison results for each OMP.

OMP ID	F	Residual Error	Volume (m ³)		
	Mean (m)	Standard Deviation (m)	TLS	UAV	
5	-0.001	0.086	238.19	228.69	
6	-0.002	0.078	79.92	77.5	
7	-0.001	0.086	18.16	16.37	
8	-0.001	0.086	8.748	7.61	



Figure 3. DSM comparison result images for each OMP. (**a**) White boxes where the blue area is visible between the tires are mainly found at the edge of the OMP; (**b**) yellow-green boxes where the red area is visible are generally seen in the areas with tires, and (**c**) red boxes where red or blue areas are visible without tires.

3.3. Spatio-Temporal Changes of OMPs

From April to October 2019, the volume of OMPs for each month was calculated using ortho-images and DSMs, as shown in Table 3. The spatial distribution of monthly OMP volume changes is shown in Figure 4; a considerable decrease is indicated by a blue region, while a considerable increase is indicated by a red region compared to the previous month. The average volume of OMPs per month tended to increase from 89.73 m³ to 108.70 m³ from April to May. Twelve OMPs showed volume increases in the range of 0–25 m³, the largest in the number of small increases compared to other months, while there were also four OMPs that showed increases of over 100 m³, the largest in the number of large increases. In June, the average volume of OMPs decreased from May to 94.77 m³; twelve OMPs showed volume decreases, the largest in the number of small decreases compared to other months. This is because the OMPs were stored while growing upland crops such as garlic and onions until May and were used for planting paddy rice in June [52]. In August, the average volume of OMPs tended to increase from June to 149.69 m³, which was the

highest compared to other months; there were eight OMPs that showed increases in the range of 50–100 m³, and three OMPs that showed increases over 100 m³. In September and October, the average volume of OMPs, 103.58 m³ and 64.89 m³, respectively, showed a tendency to continuously decrease from the previous month; there were six OMPs that decreased in the range of -100 to -50 m³ in both months, and there were two and four OMPs that decreased over -100 m³. The reason for this trend is that livestock waste was stored and composted in advance to produce good quality OMPs in August [3,53], because OMPs were scattered over the agricultural ground to improve soil fertility and productivity by increasing nutrient supply, water retention, and microbial activity after harvesting was completed in September and October [54–56].

OMP ID	Volume (m ³)							
	12 April	10 May	25 June	10 August	29 September	26 October	Mean	
1	228.14	490.07	251.21	355.39	227.43	68.87	270.19	
2	5.43	35.45	-	13.05	14.71	-	11.44	
3	152.33	168.95	146.61	194.67	125.91	-	131.41	
4	-	33.22	25.03	12.98	14.15	-	14.23	
5	230.8	239.03	207.39	282.82	201.7	111.58	212.22	
6	83.37	89.34	79.13	102.38	67.67	-	70.32	
7	4.54	4.94	4.25	79.3	89.89	-	30.49	
8	4.42	5.24	5.29	-	-	-	2.49	
9	164.02	156.62	165.6	259.83	170.84	134.01	175.15	
10	38.49	36.61	33.36	44.32	115.33	110.83	63.16	
11	89.88	106.19	189.72	254.77	176.37	-	136.16	
12	271.26	290.69	244.26	345.34	253.92	103.34	251.47	
13	130.43	133.82	108.93	155.08	111.37	104.44	124.01	
14	21.24	20.08	18.94	174.45	117.01	109.81	76.92	
15	-	102.79	133.35	191.13	120.68	110.36	109.72	
16	43.18	43.76	44.97	78.51	64.66	17.5	48.76	
17	22.59	55.69	46.63	109.04	153.97	93.48	80.23	
18	-	117.1	96.07	182.36	-	-	65.92	
19	87.17	101.4	89.32	65.16	60.37	38.58	73.67	
20	48.45	56.33	51.67	73.52	51.99	-	46.99	
21	40.13	140.16	69.02	134.2	74.19	34.13	81.97	
22	38.99	40.4	56.77	-	-	-	22.69	
23	-	32.18	17.52	35.27	12.67	15.1	18.79	
24	-	-	-	-	7.84	4.04	1.98	
25	-	-	-	-	45.98	17.68	10.61	
26	-	-	-	-	-	21.11	3.52	
27	-	-	-	-	-	45.54	7.59	
28	-	-	-	-	-	27.68	4.61	
Mean	89.73	108.7	94.77	149.69	103.58	64.89		

Fable 3. V	′olume o	f OMPs	in	the	study	/ site.
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The average volumes of individual OMPs numbered 1 to 28 were identified. As in the case of OMP No. 22, a total of ten OMPs with an average volume of less than 23 m³ were confirmed. These small-scale OMPs were not identified more than twice during the investigation period, confirming that five OMPs were especially produced in September and October. The small-scale OMPs created in September and October were created to scatter OMPs over agriculture areas. In addition, considering both these OMPs and the cover installation status suggested in Section 3.1, these OMPs were consistent with type C as no cover was used in October after harvest. Therefore, if it rains during these months, which is the harvesting period, it is highly likely that a substantial amount of nutrients will be released into water systems as rainwater will directly penetrate the OMP. Thus, inspection of the cover installation status is required during rainfall. On the contrary, it was confirmed that 16 of 18 OMPs with an average volume exceeding 23 m³ were always observed from April to September, except in October, when OMPs were heavily

scattered. Among them, OMPs Nos. 1, 5, and 12 with average volume of 270.19, 212.22, and 251.47 m³, respectively, were always observed from April to October. The location of such bulky OMPs was constant despite fluctuations in volume. Thus, it is necessary to check the OMP locations because, if they are close to the water systems, it is highly likely that leachate will be released into the water systems during rainfall.



Figure 4. Spatial distribution of volume changes for each OMP in the study site (**a**) April–May, (**b**) May–June (**c**) June–August (**d**) August–Septemper (**e**) Septemper–October.

OMPs Nos. 9–14 in the study site were located near the stream without the presence of embankments or other management facilities; their leachate or surface runoff would flow directly into the stream during rainfall. Among them, OMPs Nos. 9, 12, 13 and 14 were located near the stream at a distance of 3.9–6.9 m. Furthermore, all OMPs, except Nos. 9–14, were located near the agricultural waterway within the embankment; their leachate or surface runoff would be possible to flow into the stream through the agricultural waterway during rainfall. Eleven of twenty-two OMPs were located within 6.9 m of agricultural waterways; these were Nos. 1, 2, 3, 6, 15, 16, 18, 19, 23, 25, and 28. This confirmed that many OMPs were located near streams or agricultural waterways. In addition, as discussed above, once OMPs are created, they tend to remain at their locations. Hence, there is a possibility that nutrients will enter the water system during each rainfall event throughout the crop cultivation period.

Finally, the range of increase or decrease in the volume of OMPs was confirmed. OMP No. 1 showed the largest range of increase or decrease in volume with an average of 178.30 m³, whereas OMP Nos. 3, 5, 11, 12, 15, 18, and 22 showed an average change

of more than 50 m³. Except for OMP No. 22, the average volumes of these OMPs were large, and their locations were mostly consistent with OMPs that were close to streams or agricultural waterways. Loading or use of OMPs in agricultural areas is usually carried out even during rainfall according to the agricultural work schedule for composting. Thus, inspecting OMPs with a large average volume and high fluctuation require continuous monitoring and review of the OMP sites or management facilities.

4. Discussion

Non-point sources such as livestock waste have been considered as a major cause of water quality [57]. It is important to acquire information such as the location and type of pollutants to manage the water quality because it is difficult to determine the status of non-point pollutants that are widely distributed in the watershed [58,59]. The basic water quality investigation has a limitation in that it is difficult to confirm the spatial and quantitative distribution of pollutants; the pollutant information is filled in survey tables at the judgment of the field investigator. In this respect, UAVs can provide quantitative data, which can be an alternative way to investigate pollutants.

UAVs have been used for many applications, including reconnaissance, rescue, and monitoring. In particular, small fixed-wing and rotary-wing UAVs have been popular because of their moderate cost [60–63]. Many UAV applications, however, exhibit problems covering large areas; these problems are caused by battery life, obstacles such as buildings and mountains, and communication connection [64,65]. These challenges must also be considered in similar studies in the future. Therefore, it is difficult to manage a large basin, including those containing several cities, when investigating non-point source pollutants. Thus, areas around small rivers are judged to be appropriate for the investigation of non-point source pollutants. UAVs must be used after selecting priority survey areas with large influences from non-point source pollutants, and in conjunction with existing survey methods such as water sampling and satellite imaging. In addition, methods for making appropriate connections must be considered.

Despite the challenges encountered with the use of UAVs, investigations of OMP sites using UAVs can reduce time and cost compared to the existing survey methods in which investigators perform on-site measurements to calculate OMP volumes. UAVs can also gather quantitative data from surrounding areas, in addition to those for the OMP sites. Furthermore, it was confirmed that UAVs can be used to identify the spatial distribution, cover installation status, and volumes of OMP sites. These can be used as necessary data for developing effective OMP management methods. For example, it is possible to identify the location of OMP sites with insufficient management to prevent the inflow of OMP into streams, which is caused by rainfall in the rainy season. In addition, it will be possible to establish priority management areas among the OMP sites distributed in a basin, provided that spatial analysis is conducted using conditions under which OMP can release more non-point source pollutants.

The OMP volume was calculated using a UAV, and an average accuracy of 92% or higher was confirmed by comparison with TLS results. However, there were several other considerations involved in calculating the actual OMP volume. First, there were cases in which vegetation grew on the OMP over time, or when the covers of the OMP were swollen by wind or the gas generated from the livestock waste, which may lead to errors. As the magnitudes of the errors generated by natural phenomena have not yet been investigated, further research is required. Moreover, because it was difficult to identify the geometry of the ground surface under the OMP, the volume of the OMP located on a slope could be different from the actual volume because the former was calculated by including the volume of the slope. Therefore, it was difficult to calculate the actual OMP volume; however, the results were adequate for examining temporal changes in OMP volume.

5. Conclusions

This study was designed to apply the unmanned aerial vehicle (UAV) for investigating the spatio-temporal changes of outside manure piles (OMPs) in agricultural areas. To this end, UAV images were compared with terrestrial laser scanning (TLS) measurements. Then, a UAV was used to acquire image data, and the distribution and cover installation status of OMPs were identified through ortho-images, and the OMP volumes were calculated using digital surface model (DSM).

UAV- and TLS-derived DSMs were compared for identifying the cause of the error in calculating the volume. While it was difficult to express the detailed texture, it was confirmed that the overall shapes were similar; the average volume calculation accuracy was 92.45%. According to that finding, an application of UAV images was quite successful in investigation of OMP volumes.

According to the results of the monthly OMP volume changes from April to October, the volume of OMPs tended to increase before crops were harvested; thus, the tendency to change according to the condition of the crops was confirmed. The small-scale OMPs with an average monthly volume of 23 m³ or less were identified as OMPs created in September and October and were consistent with the type C (uncovered) in October after harvest. In addition, from April to October, 80% of the newly created OMPs in each month were the type C, and 10% were confirmed as type B. This indicates that there is no immediate management of small-scale OMPs or newly created OMPs. Loading or use of OMPs in agricultural areas is usually performed even during rainfall according to the agricultural work schedule for composting. Thus, OMPs with a large average volume and high fluctuation require continuous inspection and review of the OMP sites or management facility. The results above could be used as basic data to efficiently manage non-point source pollution caused by OMPs in agricultural areas.

This study has demonstrated that UAV imagery is sufficiently applicable for investigating the distribution and volume of OMPs. Of course, it is still necessary to develop methods to efficiently investigate OMP. Future research directions will include studies of automatic OMP detection technology that uses data analysis methods such as machine learning and deep learning to improve the efficiency of surveys done with UAVs. In addition, as information on various non-point source pollutants can be collected from images using UAVs, research can be extended to include analysis of non-point source pollutants other than OMPs.

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Data Availability Statement: The data are not available due to ethical restrictions.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A



(a)



(b)







(**d**)



(e)



Figure A1. Monthly distribution of OMPs in the study site. The symbol with a yellow green circle and letter A is type A that indicates OMP completely covered by cover. The symbol with a blue circle and letter B is type B that indicates OMP to be not completely covered. The symbol with a red circle and letter C is type C that indicates OMP without a cover. (a) 12 April 2019, (b) 10 May 2019, (c) 25 June 2019, (d) 10 August 2019, (e) 29 September 2019, (f) 25 October 2019.

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