Reliability of using high-resolution aerial photography (red, green and blue bands) for detecting available soil water in agricultural land

Aditya Nugraha Putra*, Istika Nita
Soil Science Department, Faculty of Agriculture, Brawijaya University, Jl. Veteran Malang No. 1, Malang 65145, Indonesia
*corresponding author: aditya.n.putra@ub.ac.id
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Abstract: The need for irrigation water is influenced by soil water content or more precisely by available water (pF 2.5 and pF 4.2). There is a need for technological breakthroughs in using Unmanned Aerial Vehicle (UAV) to identify water content quickly and broadly and accurately. The study was conducted in an area of ±18 hectares in the Sisim Sub Watershed in September 2019 at 09.00 a.m. Aerial photographs were taken at an altitude of 100 m with DJI Phantom Pro 3.0. The number of observation points was 75 points, where 15 points for validation were calculated based on the map scale. Photo processing was made using Agisoft. The Digital Elevation Model (DEMNAS) with 8.2 m resolution was used to compare the red, green and blue bands. The analysis used was Co-Kriging Geo Statistics Analysis, the compilation of algorithms based on the regression equation and ten index formulations. Validation was done by correlation continued with the regression or paired t-test if the parameter relationship was close. The available water measured in the field ranged from 5.16-48.28%. The results showed that the formulation of soil water content could be run on the Red, Green, and Blue bands, Intensity index, TGI index, ExGreen index and DEMNAS with a weak correlation (below 0.5), where TGI had the highest value (r=0.32). A test of t-pairing was not done because of a weak correlation. The highest estimation of pF 4.2 is DEMNAS (r=0.35), and pF 2.5 was on the TGI index (r=0.4).

Keywords: aerial photography, available soil water, geo statistic, precision agriculture, UAV

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Introduction
The increase in population in Indonesia occurred on a massive scale. The Central Statistics Agency in Indonesia confirmed that there had been an increase of 13.65 in the last five years (2015-2020). This increase in population has an impact on increasing food needs involving the agricultural sector. Therefore, efforts to increase agricultural production continue to be carried out throughout the Indonesian agricultural region. However, in reality, the agricultural practices that have been carried out by most farmers in Indonesia have not yet implemented a precision agriculture technology. For example, in terms of efficient use of agricultural inputs that are still low. The use of irrigation water, farmers generally do not adapt it to the needs of plants or land conditions. Virgawati (2011) that explained that many researchers had conducted agricultural experiments not only to increase the growth rate of food production but also to maintain the soil quality through the PA system approach. The problem is how their successful results in the research area could be implemented and accepted by farmers, along with their local wisdom. In the future, the prospect of developing agriculture in Indonesia to continue by implementing Precision Agriculture.

The principle of this system is the decision to use all agricultural inputs adjusted to the needs per farmer plot so that the output achieved will be optimal. Irrigation water supply is inseparable from

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the actual availability of water in the soil. Water content is very decisive rather than the amount of water that will be provided by farmers. Farmers, in their efforts to distribute and use irrigation water, still do not pay attention to the balance between the amount of water supplied and the crop water requirements. This is compounded by the high rainfall conditions that make it possible to wastewater use or even water deficits. De Clercq et al. (2018) explained that water resources are highly stressed, with more than 40 percent of the world’s rural population living in water-scarce areas. The land has long been recognized as a finite resource, but in earlier times, degraded farmland would be replaced by bringing new, unused land into cultivation. Such lands are rare nowadays, and what remains often cannot be farmed on a sustainable basis. One obstacle faced in ensuring irrigation systems are correct is the need for large and expensive data. In responding to the problem, precision agriculture is an alternative technology that is appropriate and on target that can minimize input costs.

Nowadays, scientific development in precision agriculture is an exciting topic in the world of agriculture. Precision agriculture is one of the smart farming concepts that can be developed. The combination of agricultural practices with the development of digital technology is supporting the realization of Precision. Estimation of water content with precision agriculture has been carried out in the research of Tóth et al. (2012) and De Benedetto et al. (2013) with accurate results. However, the data used are still at a resolution of about 30m even though agricultural lands in Indonesia are generally fragmented and very narrow so that the potential for misalignment in water content is still high. Dane et al. (2002) explained that the understanding of landscape dynamics through remote sensing is challenging. The land-use phenomena with ricefield and settlement like in Indonesia also give an idea on how to understand the fragmentation process of ricefield due to the expansion of more intensive, non-agricultural uses. This study aimed to predict soil water content with more accurate data using Geo Statistical analysis.

Materials and Methods

This study was conducted from June to September 2018. The study location is in one of the upstream sub-watersheds of the Brantas watershed with an area of about 200 to 400 ha with the name of Sisim Sub Watershed. The Sisim Sub-watershed Area is administratively located in Batu City which is topographically a part of the Brantas Hulu Sub Watershed (Figure 1). Only 19 ha is in the Malang Regency administration area of a total area of around 945.63 ha.

This study was carried out with several stages, including aerial photo-taking, pre and post-processing, water content sampling, Geo Statistical analysis, and data reliability testing. In the initial survey, aerial photo recording was carried out using the DJI Phantom 3 Pro Drone, which had been previously set up using a mission planner (Figure 2) so that the flight went well. The flight height was below 110 m or more precisely between 70 to 100 m. The height of 110 m is the area used for helicopters, so flights should not be made in that area. Meanwhile, if the flight is carried out below 70 m, it is feared that the drone will fly unstable. The photos were then processed (mosaic and stacking) using Agisoft software to get images that have become one and geospatial oriented. From this Agisoft Software, aerial photographs were then converted to a high-resolution Digital Elevation Model (DEM). Interviews were conducted with landowners to collect information on water needs and irrigation that are usually carried out as well as the history of the land. Subsequently, formed RGB and DEM maps were used to consider the site plan for soil sampling. In this study, the method chosen was a grid method because the land does not have much variation. The process of creating site points for soil sampling was done with the fishnet tools in ArcGIS 10.3 (Figure 3). Results from the RGB and DEM Maps that have been given a soil sampling point were then displayed as a Field Map.

Determination of the observation points was done by purposive randomized sampling with several sampling points was 75 points with details of 60 points were used to build the model, while 15 points were used to test the validation of the model built. Soil sampling was done on topsoil using the undisturbed soil sampling method. Separation of water was carried out by heating that is usually called as the gravimetric method, and it is a direct measurement method (Dane et al., 2002) to get water content data.

The statistical analysis used was correlation and regression. The correlation coefficient reflects both the magnitude and direction of the relationship between two independent variables (Nathans et al., 2012). Statistical data analysis was performed by a correlation test between soil water content with wavelength levels of red, green, and blue aerial photo recording results. In addition, formulations on the red, green, and blue bands can be used to detect specific characteristics on the surface of the land. This statistical test can simultaneously determine which spectral channels have high contrast between spectral reflections at various soil water contents. The index used in this study is presented in Table 1.

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Figure 1. Sisim sub-sub catchment.

Table 1. Red, green and blue bands combination in various indexes.

| No. | Index                                                | Abbreviation | Formula                                                                 |
|-----|------------------------------------------------------|--------------|-------------------------------------------------------------------------|
| 1   | Colouration Index                                    | CI           | \( R - B \)                                                            |
| 2   | Green leaf index                                     | GLI          | \( \frac{(G - R) + (G - B)}{2G} \) + \( R + B \)                       |
| 3   | Intensity                                            | I            | \( \frac{1 x (R + G + B)}{30.5} \)                                     |
| 4   | Normalized Green Red Difference Index                 | NGRDI        | \( \frac{G - R}{G + R} \)                                            |
| 5   | Normalized Difference Red/Green Redness Index         | RI           | \( \frac{R - G}{R + G} \)                                            |
| 6   | Shape Index                                          | IF           | \( \frac{2R - G - B}{G - B} \)                                        |
| 7   | Simple Ratio Red/Blue Iron Oxide                      | IO           | \( \frac{R}{R} \)                                                   |
| 8   | Simple Ratio Red/Green Red-Green Ratio                | RGR          | \( \frac{R}{G} \)                                                   |
| 9   | Triangular Greeness Index                            | TGI          | \( G - (0.39 \times R) - (0.61 \times B) \)                          |
| 10  | ExGreen                                              | ExGreen      | \( 2 x (G/R+G+B) - (R/R+G+B) - (B/B+G+R) \)                           |

Source: Gitelson et al. (2002).
The Sisim Sub Watershed, with an area of about 945.63 ha, is divided into three subdistricts, namely Bumiaji District, Batu City, and Pujon District, Malang Regency. In Bumiaji District, Sisim Sub-watershed was divided into five villages, namely Gunungsari Village (±594.51 ha), Tuholungrejo Village (±307.33 ha), Punten Village (±15.95 ha), Songkokerlo Village (±5, 51 ha), and Sumberejo Village (±3.54 ha). Some Sisim Sub-watershed areas also enter Pujon Sub-District and are divided into 2 (two) villages, namely Padesari Village (±15.12 ha), and Wiyurejo Village (±3.67 ha). The slope rates are 0-3% (±10.19 ha), 3-8% (±61.02 ha), 8-15% (±94.60 ha), 15-25% (±157, 88 ha), 25-40% (±334.43 ha), 40-60% (±275.73 ha), and> 60% ± 11.79 ha).

Results and Discussion

Land use in the Sisim Sub-watershed consists of fields with an area of ±595.14 ha, irrigated rice fields around ±121.33 ha, which are in the southeast part of the sub-watershed area and are on a gentle slope to a slightly sloping level (0 - 15%). Other areas were divided into shrubs ±93.53 ha, Gardens ±75.29 ha, Settlements ±49.64 ha, and Forest ±10.71 ha. The Digital Elevation Model (DEM) in the Sisim Sub-watershed Area has a resolution of 8 m, meaning that one pixel has an area of about 64 m². Hydrological and geomorphic modeling is an essential application of DEMs (Wilson, 2012). The effect of DEM resolution is especially pronounced for the boundary conditions determining a valid hazard calculation (Claessens et al., 2005). DEM has a range of values between 889 and 1577, which shows elevation points at that location.

At the study location, the digital number range is between 943 and 984, where the range is not too much different. This is because the selection of land used as the same research location is moor with a height variation that is not much different. Purinton and Bookhagen (2017) explained that DEM validation is presented by (i) reporting the vertical accuracy of a number of satellite-derived DEMs at resolutions of 5–30 m from open-access portals, commercial sources, and research agreements, and (ii) carrying out channel profile analysis and geomorphic metric comparisons for a 66 km² catchment with a defined channel knickpoint to assess the quality of these DEMs for tectonic geomorphology. The aerial photograph used was not found in all sub-watersheds, but only around 18 m of land as a primary aerial photo as material for simulating soil water content. Aerial photographs have a red, green, and blue band, as presented in Figure 2 and the observation points in Figure 3. It is known that the available water content from all observation sites varied from 5.16 to 48.28%. Spatial distribution of soil moisture was required for determining hydrological processes, including land–atmospheric interactions, rainfall-runoff response, and erosion processes (Sánchez-Marré et al., 2008). In agriculture, estimation of soil moisture content is important for irrigation scheduling, water management, crop growth, yield forecast modeling, forest dynamics, partitioning of sensible, and latent heat fluxes (i.e., Bowen Ratio), and surface-atmospheric interactions, among others (Petropoulos et al., 2009).

Available water is the amount of water that is between the field capacity (pF 2.5) as the upper limit and the permanent withering point (pF 4.2) as the lower limit (Padarian et al., 2014). Field capacity water is the amount of soil water that is in the soil pore after the soil has been completely saturated or in a condition when drainage water has stopped or almost stopped flowing due to gravity (Dani and Wrath, 2000). Therefore, the provision of water must be given as much as before the plant experiences a permanent wilting point and must not exceed its field capacity. These results were then performed correlation and regression tests to determine the closeness of the relationship and the direction of the relationship of each red, green and blue spectral wavelength recorded by UAV and DEM 8 m as well as the intensity, TGI and ExGreen indexes of water content. Other indices were not displayed because no map output that could be read after the process.

pF 2.5 and pF 4.2, as well as available water, had a low relationship to the 8 m DEM, red, green, and blue bands, intensity index, TGI index, and ExGreen index. This is because the values of the correlation coefficient of each parameter to pF 2,5 and 4.2 pF, as well as available water, were less than 0.5. However, the best relationship between pF 2.5, pF4.2, and available water lies in the TGI index when compared to other indexes or methods. The relationship between pF 2.5 with TGI and ExGreen showed a positive value in the sense that an increase in the value of pF will be followed by an increase in the TGI and ExGreen indexes and comparison shows a negative value with the Intensity index.

Meanwhile, pF 4.2 did not correlate with the Intensity index and TGI index and correlated very low with the ExGreen index. Available water had a positive relationship to the TGI and ExGreen indexes, but it was negatively related to the Intensity index, which means that an increase in available water would be followed by an increase in the value of the TGI and ExGreen indexes as well as a decrease in the intensity index value.
Figure 2. Overview of (a) Red band, (b) Green band, (c) Blue band, (d) ExGreen index, (e) Intensity index, (f) TGI index.
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Sills et al. (2014) explained that Landsat was the primary source of activity data, and about half of the proponents had access to high-resolution (>10 m) satellite imagery. The majority of organizations (70%) showed in-house expertise and used advanced classification and change detection techniques for generating activity data. The filtering can be either at the pixel or image level. In the pixel-based approach, individual pixels are evaluated, and those that meet the quality criteria are selected. Digital value or (Digital Number) is a 1-byte numeric value of a pixel that could be displayed in grey (greyscale). The red line indicates the pH values of 2.5, the blue line indicates the pH value of 4.2, and the green line indicates the available water. The available soil water would decrease along with the increase in height or elevation of an area of 0.2439% (Figure 4). In addition, available soil water would also decrease with an increase in 1 digital number from

![Figure 3. Distribution of research observation points.](image)

**Table 2. Correlation analysis of water content with aerial photography and DEM.**

|        | DEM  | R     | G     | B     | Intensity | TGI   | ExGreen | pF 2.5 | pF 4.2 | Water Available |
|--------|------|-------|-------|-------|-----------|-------|---------|--------|--------|-----------------|
| DEM    | 1.00 |       |       |       |           |       |         |        |        |                 |
| R      | 0.15 | 1.00  |       |       |           |       |         |        |        |                 |
| G      | 0.05 | 0.91  | 1.00  |       |           |       |         |        |        |                 |
| B      | -0.01| 0.85  | 0.80  | 1.00  |           |       |         |        |        |                 |
| Intensity | 0.14 | 0.48  | 0.39  | 0.46  | 1.00      |       |         |        |        |                 |
| TGI    | -0.02| -0.20 | 0.06  | -0.38 | -0.22     | 1.00  |         |        |        |                 |
| ExGreen| 0.31 | 0.05  | 0.03  | -0.27 | -0.09     | 0.58  | 1.00    |        |        |                 |
| pF 2.5 | -0.13| -0.23 | -0.07 | -0.31 | -0.14     | 0.40  | 0.16    | 1.00   |        |                 |
| pF 4.2 | 0.35 | -0.04 | -0.07 | -0.09 | 0.00      | 0.00  | 0.02    | 0.30   | 1.00   |                 |
| Water Available | -0.41 | -0.15 | 0.00  | -0.18 | -0.12     | 0.32  | 0.11    | 0.55   | -0.63  | 1.00            |

*Sills et al. (2014) explained that Landsat was the primary source of activity data, and about half of the proponents had access to high-resolution (>10 m) satellite imagery. The majority of organizations (70%) showed in-house expertise and used advanced classification and change detection techniques for generating activity data. The filtering can be either at the pixel or image level. In the pixel-based approach, individual pixels are evaluated, and those that meet the quality criteria are selected. Digital value or (Digital Number) is a 1-byte numeric value of a pixel that could be displayed in grey (greyscale). The red line indicates the pH values of 2.5, the blue line indicates the pH value of 4.2, and the green line indicates the available water. The available soil water would decrease along with the increase in height or elevation of an area of 0.2439% (Figure 4). In addition, available soil water would also decrease with an increase in 1 digital number from*
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The spectral band of the red band, green band, blue band, and the intensity index would reduce available water by 0.0004%, 0.0323%, 0.2177%, respectively. However, available water would increase along with an increase in the value of the TGI and ExGreen indexes of 0.2171% water content and 0.0128% of the water content each increase in the index value of 1 degree. The relationship of pF 2.5 to elevation was not aligned with very low closeness with an R² value of 0.0179, while the relationship of pF 4.2 to elevation was unidirectional with an R² value of 0.1194 which means it had a low closeness. Moreover, the relationship between available water to elevation was not unidirectional and had a low closeness because it had an R² value of 0.1697. This result did follow the opinion of Nita, et al. (2014), who states that the increasing elevation (altitude) the available water increased by 0.00991% from an increase in 1 m above sea level (asl).

The red digital number was negatively related to low closeness to pF 2.5, pF 4.2, and available water, which means that with an increase in 1 Red digital number would decrease the pF value of 2.5 by 0.0399%, pF 4.2 as much 0.0076% and available water as much as 0.0323%. Low closeness occurred because the value of R² owned by pF 2.5, pF 4.2, and available water was 0.0517; 0.0016; and 0.0226. A small R² value proves that the red spectral band cannot be used in analyzing soil water content singly. The green digital number was negatively associated with a low closeness to pF 2.5, pF 4.2, and available water, which means that with an increase in one green digital number would reduce the value of pF 2.5 by 0.0133%, pF 4.2 as much 0.0129%, and 0.0004% available water. R² owned by pF 2.5, pF 4.2, and available water was 0.0054; 0.0044; and 3E-6, caused a low closeness of the relationship between the green digital number to the water content and proves that the Blue spectral cannot be used singly in describing the water content spatially. The blue digital number was negatively associated with a low closeness to pF 2.5, pF 4.2, and available water, which means that with an increase in one green digital number would reduce the value of pF 2.5 by 0.0464%, pF 4.2 as much 0.0141%, and 0.0323% available water. R² owned by pF 2.5, pF 4.2, and available water was 0.0963; 0.0077; and 0.0311, which caused a low closeness of the relationship between the blue digital number to the water content and proves that the Blue spectral cannot be used singly in describing the water content spatially.

Digital intensity number was negatively associated with a low closeness to pF 2.5, pF 4.2, which means that with an increase in intensity 1 digital number would reduce the value of pF 2.5 by 0.218%, pF 4.2 by 0.0.0013 %. R² intensity digital number between pF 2.5, pF 4.2 is 0.021; 6E-07 which caused a low closeness of the relationship between digital intensity number and water content. Meanwhile, the relationship between the intensity index number and available water was not in the same direction as the low closeness shown by the R² value of 0.0138. This proves that the Intensity Index cannot be used to describe the water content spatially because it only represents 0.1% of water available in the field. TGI digital number was positively related to low closeness to pF 2.5, pF 4.2, which means that with an increase in 1 TGI digital number would increase the value of pF 2.5 by 0.1271 %, pF 4.2 by 0.4E-05%. R² TGI digital number between pF 2.5 and pF 4.2 was 0.1566 and 2E-08, which caused a low closeness of the relationship between TGI digital number and water content.
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Figure 4. Graph of soil water equations available with various bands index combination and DEM.
The relationship between the TGI index number and available water was not in the same direction as the low closeness shown by the $R^2$ value of 0.1042. This proves that the TGI index cannot be used to describe the water content spatially because it only represents as much as 10% of the water available at roomy. ExGreen digital number was positively related to low closeness to pF 2.5 and pF 4.2, which means that with an increase in 1 ExGreen digital number would increase the value of pF 2.5 by 0.0465%, pF 4.2 by 0.006 %. $R^2$ ExGreen digital number between pF 2.5 and pF 4.2 was equal to 0.0253 and 0.0004, which caused a low closeness of the relationship between the ExGreen digital number to pF 2.5 and pF 4.2. The relationship between the ExGreen index number and available water was in the same direction as the low closeness shown by the $R^2$ value of 0.0128. This proves that the ExGreen index cannot be used to describe water content spatially because it only represented 0.01% water available in the field. TGI index which had the highest coefficient of determination ($R^2$) when compared to the spectral red, green and blue bands, intensity and ExGreen index of water available even though it had a value classified as low because it was only able to describe 10% or equal to 0.10 only from the diversity of water available in the field.

Shafian and Maas (2015) state that the coefficient of determination ($R^2$) will be considered good if it has a value of more than 0.5 or it can describe its effect by more than 50%. Therefore, among the various methods or indices used, both the RGB spectral recorded by the UAV, the Intensity Index, the TGI, and the ExGreen cannot be used to describe the water content at this location statistically because the $R^2$ value is below 0.5. Unmanned aerial vehicles (UAVs) and other small unmanned aircraft have a potentially lower cost but also have a significantly lower payload capacity (Hunt et al., 2010).

The available water simulation map (Figure 5) shows the differences in available water, but with a relatively similar pattern in each method used. The 8 m DEM method and the Kriging method yielded available water content having the highest pattern in the east of the study site and the lowest in the west. While among the Red, Green, and Blue methods, the ExGreen index, the Intensity Index, and the TGI Index give results in the high to low available water category with a spread pattern. Based on the results of statistical analysis by comparing various methods including (a) DEM 8 m, DEM analyzed using UAV aerial photographs and intensity index, TGI, ExGreen both DEM 8 m and DEM sourced from UAV aerial imagery still have weaknesses in the resolution. The 8 m DEM is the DEM available at the highest resolution that is only able to represent 64 m² of each pixel. The DEM analyzed from the UAV aerial image results cannot reflect the actual conditions because it is not a DTM but a DSM which means that objects at ground level such as buildings, plants, and objects above the ground level recorded. In addition, DSM recorded by UAVs only capture RGB spectral light. In line with the opinion expressed by Borra-Serrano et al. (2015), who stated that although images captured by UAVs have a very high spatial resolution, the spectral resolution and radiometric resolution captured are relatively low.

The results of the estimation of soil water content might be different if using data recorded by a vehicle that has a multispectral sensor, for example, Landsat. Landsat has been used in predicting soil water content (Zaman et al., 2012). Govender et al. (2009) described multispectral sensors as a parallel array of sensors that detect radiation in a small number of broad wavelengths. High-resolution multispectral imagery with a combination of field sampling can provide information for a model approach in predicting the spatial distribution of surface water content (Hassan-Esfahani et al., 2015). Mutmainna et al. (2017) provided information that a single blue band image from Landsat 8, can be used in estimating soil humidity with a determination coefficient ($R^2$) of 0.653 which results in the equation: $LT = -130.2(B2)^2 + 114.0(B2) + 11.08$. The difficulty of measuring water content directly in steep and dangerous areas, for example, can be solved by using quantitative analysis methods using Geo Statistics, one of which is Kriging which can help the development of remote sensing to identify the distribution of soil water content obtained from satellite imagery (Mello et al., 2011). De Benedetto et al. (2013) showed unclear differences in the results of soil water content analysis using KED (Kriging with External Drift) and OK (Ordinary Kriging). KED is proven to be a potential tool in sensor data fusion, and it can be applied effectively in precision irrigation because KED can explain geophysical information as additional information in the prediction of topsoil water content. The KED method can map soil water content with very few samples at the high spatial resolution, using the best geophysical information. To improve the quality of soil water content mapping results, one can combine orthophoto with small-scale topographic information derived from DEM generated from UAV data (Krenz et al., 2019). Besides the direct use of these maps as variables for biophysical modeling, the uncertainty maps are an exciting source of information that can be used to define future soil sampling schemas (Padarian et al., 2017).
Figure 5. Map of simulation results of water content available using various methods; (a) DEM 8 m, (b) Red Band (c) Green Band, (d) Blue Band, (e) ExGreen Index, (f) Intensity Index, (g) TGI Index, and (h) Kriging.
Conclusion

The available water content in the range of 5.16-48.28% cannot be estimated spatially by DEM 8.25 m, which is indicated by R² for about 16% (low accuracy). These conditions also occur in kriging geo-statistic and bands estimation. However, analysis can still be carried out to determine trends in the spatial distribution of soil water content by comparing it to the Intensity index, TGI index, and ExGreen index. TGI index had a higher coefficient of determination (R²) compared to the spectral red band, green band, blue band, intensity, and ExGreen index of water available. Even though it had a value classified as low because it was only able to describe 10% or equal to 0.10 only from the diversity of water available in the field.

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