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Correlating sentinel-2-derived NDVI with the amount of visible color changes and seed fall of Glasswort (*Salicornia herbacea* L.) during it's ripening stage

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Abstract

Glasswort (*Salicornia herbacea*) is a succulent plant that grows widely around intertidal zone of Gomishan Lagoon in eastern boarders of the Caspian Sea in Iran. Due to its medicinal, industrial, and economic values, tendency of local people to utilize it from natural habitats, and thus its plantation is growing in recent years. One of the challenges to managing a glasswort farm is to know the appropriate date to harvest since glasswort seeds ripe quickly and seedfall happens considerably by little shake. An effective way of defining appropriate harvesting dates should be correlated mostly with visual characteristics of the plant; like its color change. If NDVI values derived from remote sensing imageries show a meaningful correlation with the amount of visible greenness of the plant, and its ripening stage, then the qualitative estimation of the color of the field can be substituted with the quantitative estimating the amount of filed reflectance and consequently defining appropriate harvesting time of the plant. Experimental research was therefore conducted to answer this problem by relating the changes in Glasswort color classes and its amount of seedfall to the amount of Normalized Difference Vegetation Index (NDVI) values that were obtained from SENTINEL 2 remotely sensed imagery. Field sampling was started from 2019.11.8 to 2019.12.21. The proportion of greenness, redness and brownness of the plants within each sample plots were estimated. The amount of falling seeds were also collected and weighed within each sample plots. The maximum NDVI values of 41 Sentinel-2 images during 2018-2020 within Glasswort phenological period were extracted and were correlated with the color class of the plant and the weight of seedfall in sample plots. Results showed a strong correlation between NDVI and brownness color class (R^2=0.80) and a strong negative correlation with amount of seedfall of the plant (R^2=-0.83). When the brownness color class of the Glasswort filed exceeds 50 percent, the seeds have reached to their highest maturity and are ready to be harvested. This strong but negative correlation between maximum NDVI values and Glasswort seedfall supports the findings of the correlation of the filed data. Our findings therefore can help filed workers to have an observable phenomenon of the plant to decide when to start harvesting Glasswort in the study area.

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Introduction

Glasswort (*Salicornia herbacea*) is a succulent plant that grows naturally in the salt marshes along the coastline of the Caspian Sea. It has been prescribed in traditional medicines for the treatment of intestinal ailments, nephropathy, and hepatitis. In addition, *S. herbacea* has recently been reported to be effective on atherosclerosis, hyperlipidemia, and diabetes (Rhee et al., 2009). A variety of pharmacological experiments have revealed that a solvent-extracted fraction of *S. herbacea* exhibits anti-oxidative, anti-microbial, anti-proliferative, and anti-inflammatory activities (Rhee et al., 2009). Due to the easy collection of the plant and remarkable biological activities, this plant has become the food and medicine in seashore areas (Bibi et al., 2018). An array of functional nutrients as fibers, polyphenols, and flavonoids has been detected in *Salicornia*. Though high salt, oxalate, and saponin content in the plants are anti-nutrients, they can be removed to justify the usage of *Salicornia* as a 'sea vegetable' (Patel, 2016). Due to its high protein content, it is used in feeding animals. For its saltiness and crunchiness, it is also used as a green salad. Even in some cultures, it is considered a delicacy. Research conducted on *Salicornia* cultivation in Kuwait revealed that lambs had the best growth rate when fed a traditional alfalfa diet incorporated with 12.5% *Salicornia* (Abdal, 2009). A study found that *Salicornia* not only stimulates the fermenting microbe propagation but also improves the quality of vinegar (Seo et al., 2010). Apart from direct consumption, these plants have been found fitting as a source of dietary salt. *Salicornia herbacea* powder was transformed into spherical granules, which showed the potential to be used like NaCl (Shin and Lee, 2013). A study found that 1.5% of Salicornia salt as a partial substitute for NaCl can be added to frankfurters for texture improvement without any perceivable side effects (Patel, 2016; Rahman et al., 2018).

In the 16th century, the word "glasswort" was coined to describe plants (wild or cultivated) that could be used for making soda-based glass (Simpson and Weiner, 1989). Glasswort is high in soda (sodium carbonate) and the burning of this plant releases sodium more easily than common salt. In medieval and early post-medieval centuries, glasswort was gathered and burned in heaps, and the ash fused with sand to make glass. When a better quality glass was required, the ash was leached with limewater to make a solution of caustic soda, which was evaporated and added to the silica. Glasswort ash was also mixed with animal fats for its use in soap production (Kristine and Seth, 2015).

Glasswort grows widely around intertidal zone of Gomishan Lagoon in eastern boarders of the Caspian Sea in Iran. Due to its medicinal, industrial, and economic values, tendency of local people to utilize it from natural habitats, and thus its plantation is growing in recent years. Newly an area of about 15 hectares near the Gomishan shrimp farm was devoted to cultivating glasswort for seed collection purposes. It is newly decided to expand the cultivation of Glasswort to 1000 hectares in the area. Defining exact harvesting time is, therefore, becoming economically crucial for managers. Multiple studies have shown the interest of remote sensing images for field management (Acevedo-Opazo et al., 2008; Bégué et al., 2018; Carrillo et al., 2016; Hall et al., 2011; Johnson, 2003; Veloso et al., 2017;). However, the current limitation of most remote sensing acquisition platforms is their low temporal resolution (16 days for the Landsat 8 platform) and their cost. It is acknowledged that unmanned aerial vehicle (UAV) and airborne platforms can be used intensively over time to monitor the temporal dynamics of plants growth or plants water status either at the field or at the within-field level (Hall et al., 2011), but such monitoring approach is quickly limited by acquisition costs, making any commercial services unrealistic (Matese et al., 2015). The recent availability of Sentinel-2 images might be seen as an interesting opportunity to provide an affordable service to monitor the plant's growth over time. Indeed, the two satellites (2a and 2b) have particularly valuable features (Drusch et al., 2012). A revisit period of 5 days that could enable the observation of significant changes in plants canopy growth within plant phenological stages; 13 different spectral bands, 10 of which is particularly interesting for the computation of vegetation indices [e.g. normalized difference vegetation index (NDVI) or soil-adjusted vegetation index (SAVI)] (Sepehry and Hassanzadeh, 2004) or soil-related indicators; and free diffusion of the images, with multiple levels of correction (e.g. atmospheric correction, orthorectification, cloud masks, etc.) (Drusch et al, 2012; Hakimzadeh et al., 2017).

One of the cropping practices which is of high interest to various institutions and agencies is collecting information on the most up to date status of the crops in individual fields, including the approximate date of harvest (Veloso et al., 2017). The Tuszynska et al., (2018) research proved the applicability of Sentinel-2 satellite data for detecting the approximate date of harvest of the following crops: wheat, barley, and rapeseed along with their winter varieties. The possibility to use SWIR bands with high repetition provides a tool for recognition of the date of harvest. They also mentioned there are two drawbacks resulting from the application of optical data: issues with obtaining cloudless images insufficient frequency of images, which impact the estimated length of the period in which harvest was performed (the approximate period of harvest).

Despite these advantages, Sentinel-2 images also present some drawbacks which, in Glasswort growing regions, may limit the use of this new information source. First, the images' spatial resolution ranges from 10 to 20 m according to the wavebands, which may be limiting to record relevant information in small fields or in fields with complex boundaries (Devaux et al., 2019). Another limitation of this resolution lies in the impossibility of obtaining pure pixels of Glasswort. Indeed, Sentinel-2 images are necessarily made up of mixed pixels (Glasswort/soil or Glasswort/water when water is rising in intertidal sequences). Second, depending on the location under study, cloudy weather conditions can be of great concern as they limit the number of usable images (as the Glasswort maturity stage happens in mid-December when finding could free images is a rarity) (Devaux et al., 2019). In their study, Nasrallah et al., (2018) examined the ability of the Sentinel-2 to accurately map winter wheat in the Bekaa plain of Lebanon based on the NDVI values that are able to overcome the major challenges of achieving high accuracy classification before the end of the cropping cycle. Their proposed method has proven to be successful in predicting wheat spatial distribution using Sentinel-2 data. Data have a finest spatial resolution of 10 m which is ideal for monitoring crops at parcel level. Crop type mapping with Sentinels has already been demonstrated in various recent studies (Belgiu and Csillik, 2018; Defourny et al., 2019; Immitzer et al., 2016; Van Tricht et al., 2018) using vegetation indices or backscattering. Similarly, several studies (e.g. Veloso et al., 2017, Vrieling et al., 2018) have shown that Sentinel data could be used for studying phenology. A methodology was proposed by d'Andrimont et al., (2020) to map oil seed rape (OSR) flowering phenology from time series generated from the Copernicus Sentinel-1 (S1) and Sentinel-2 (S2) sensors. They showed Sentinel-based parcel-level flowering parameters can be combined with weather data to support in-season predictions of OSR yield. Khilola et al., (2022) used time-series analysis of Sentinel-2 satellite images for sunflower yield estimation. They showed the possibility of predicting sunflower grain yield at the pixel or field level, 3–4 months before the harvest, which is crucial for planning food policy. Boori et al., (2020) used monthly crop phenology from January to December 2018 by using the NDVI time series derived from moderate to high Spatio-temporal resolution Sentinel and Landsat data in cropland field at Samara airport area, Russia. Their results support the potential of Sentinel and Landsat data derived NDVI time series for accurate crop phenological monitoring with all crop growth stages such as active tillering, jointing, maturity and harvesting according to crop calendar with reasonable thematic accuracy. Narin and Abdikan, (2022) investigated suitability of Sentinel-2 data for the phenological stage analysis and yield estimation of sunflower plant in Turkey. they used ten Vegetation Indices (VIs) using multi-temporal Sentinel-2 data obtained during the growth stages of sunflower plant and yield estimation was obtained. As their result, the indices obtained on 30 June, at the stage of inflorescence emergence, provided coefficient of determination (R2) higher than 0.67. Among the VIs, the best forecast obtained by NDVI (R2 = 0.74) approximately three months before the harvest of sunflower.

The work of Parra et al., (2020) presented the use of satellite imagery for the monitoring of different varieties of Camelina sativa. According to the results of the spectral signatures, they identified a different phenology in different varieties. they calculated NDWI, NDMI, and EVI indices to find a possible correlation between indices and harvest. Their results showed that none of the typical vegetation indices tested presented a correlation. The southern beech forest in New Zealand periodically has “mast” years, during which very large volumes of seeds are produced. This excessive seed production results in a population explosion of rodents and mustelids. To plan pest control and keep it cost-effective, Jolly et al., (2022) developed a remote sensing method for the creation of a national beech flowering map. It used a temporal sequence of Sentinel-2 satellite imagery to determine areas in which a yellow index, which was based on red and green reflectance (red-green)/ (red + green), was higher than normal in spring. The overall classification accuracy of the map was 90.8%. they claimed that the method is fully automated and could be used to help to identify areas of potentially excessive seed fall across the whole of New Zealand.

Khoirunnisa et al., (2020) used Sentinel-2A imagery with NDVI equation to explain the correlation between the Normalised Difference Vegetation Index (NDVI) values and rice productivity and then to estimate the rice productivity. Their results indicated that a Linear R Correlation best described the correlation between the NDVI value and rice productivity and an R2 value of 0.88 was obtained.

Due to claims of many studies correlating harvest detection with the spectral bands or vegetation indices, it was decided to correlate the spectral reflectance of glasswort natural grown population using NDVI available on Sentinel-2 satellite data with the amount of visible greenness of the plant, and its ripening stage hoping to define appropriate harvesting time of the plant.

One of the challenges to managing a glasswort farm is to know the appropriate date to harvest since glasswort seeds ripe quickly and seedfall happens considerably by little shake due to wind or any vehicle movement. Seed ripening is a physiological process that is considerably under the combined effect of environmental factors such as temperature, and air humidity (Probert, 2000). Defining when seeds are ready to harvest needs laboratory examination that is costly and time-consuming. An effective way of defining appropriate harvesting dates should be correlated mostly with visual characteristics of the plant; like its color change, so that field workers can easily observe and recognize the appropriate time of the harvest. If electromagnetic reflectance of Glasswort in its different phonological period that is quantified in vegetation indices show a meaningful correlation with the amount of visible greenness of the plant, and its ripening stage (Figure 1), then the qualitative estimation of the color of the field can be substituted with the quantitative estimating the amount of filed reflectance and consequently defining appropriate harvesting time of the plant. Therefore, the experimental research was conducted to answer this problem by relating the changes in Glasswort color classes to the amount of Normalized Difference Vegetation Index (NDVI) values that are obtained from SENTINEL 2 remotely sensed imagery, and the falling seeds of the plant that can be harvested during plant phonological period.

Material and Methods

Study Area

Study area was selected on natural habitat of Glasswort in Gomishan lagoon that spread widely around the outlet of canal that discharges extra water of shrimp farms that have been established in the area to the lagoon (Figure 1). The Glasswort habitat is submerged periodically by discharged brackish water of the canal. This area is located in the western part of Golestan province and lies between the longitude of 2′ 54˚ to 15′ 54˚ E and latitude of 10′ 37˚ to 18′ 37˚ N on the eastern edge of the Caspian Sea, at 20 km from Bandar Turkman city Golestan province, Iran. The minimum and maximum elevation of the region ranges from -24 to -11 m.a.s.l. The average annual rainfall is 343 mm, and the average annual temperature is 17°C (Kam *et al.*, 2014). Halophyte species in the area are *Halocnemum strobilaceum*, *Salsola rigida*, *Halostachys caspica*, *Tamarix galica*, *Salicornia herbacea*, *Tamarix ramosissima*, which grow on the north and east coasts of Caspian Sea (Karimi, 2010).

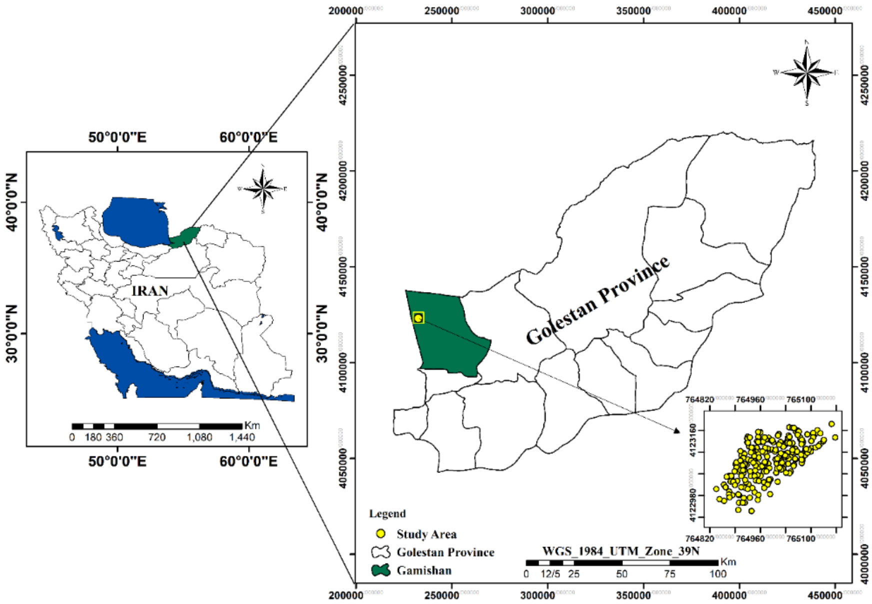

Figure 1. Study area is located in the South East coast of Caspian Sea in the bank of Gomishan lagoon. Sample plots were shown on the bottom left corner of the map.

Satellite Data

The launching of Sentinel-2A and Sentinel-2B was in June 2015 and March 2017, respectively, as an integral part of Europe's Copernicus program aiming at independent and continued global observation capacities (Immitzer et al., 2016). Sentinel-2 offers fine spectral, spatial and temporal resolutions (i.e., 13 bands ranging from 10 m to 60 m with a revisit time of five days). Datasets produced by this satellite could be downloaded free of charge from Europe's Copernicus website (Europe's Copernicus Website, 2018). Total of 41 Sentinel-2 images that had cloud cover of less than 10 percent were collected within 2018–2020-time range for which filed data had been collected. These images covered the main Glasswort phenological stages of the study area. The pre-processing of L1C (Top of Atmosphere or TOA reflectance) Sentinel-2 images, which includes orthorectification, cloud removal (using cloud mask produced by Sen2Cor/SNAP), radiometric calibration and atmospheric correction, was performed using SNAP/Sentinel-2 toolbox. The output of the preprocessing corresponds to L2A Bottom of Atmosphere (BOA) reflectance.

The choice of images was dictated by cloudless condition and the time proximity to field measurements. Ground truth data were collected and their database was established. Then, the images were processed and Normalized Difference vegetation index (NDVI) images of 41 available images were generated using the following equation:

Equation 1: $\frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}} = \frac{\mathrm{BAND8-BAND\ 4}}{\mathrm{BAND8+BAND4}}$

Finally, maximum NDVI data values of the pixels that correspond to the ground sample points of all images were extracted (Shuang, et al., 2021; Taddei, 2010; Xueying et al., 2021).

Field Data

The habitat was visited regularly within the phenological stage of Glasswort to estimate the period when the Glasswort seeds ripe and start to fall (Figure 2). This period is changing due to the climate condition of the year. Field sampling was started from 8.11.2019 to 21.12.2019. Samplings were performed 12 times started with one-week intervals and preceded with two days' intervals depending on the speed of seed maturity. In each sampling period, 20 sample plots of 1 square meter were randomly spread within the study area so that samples were at least 30 meters apart from each other to minimize the chance of plots overlap when their corresponding NDVI data values were extracted from 10 by 10 pixels in the images. The proportion of greenness, redness and brownness of the plants within each sample plots were estimated visually by accounting the proportion of shoots that were green, red or dry (brown). The amount of falling seeds were also collected and weighed by shaking plants within each sample plots.

A. *Salicornia* cultivation green field

B. *Salicornia* cultivation field in initial growth stage

C.*Salicornia* cultivation field in middle growth stage

D. *Salicornia* cultivation field ready to harvest

Figure 2. *Salicornia* cultivation field representing changes in plant color during its phenological stages.

The position coordinates of each sample plots were recorded using GPS. Vector file of sample points were generated and then maximum NDVI data values of the pixels that correspond to the ground sample points of all images were extracted. Since the date of samplings did not match with date of available image acquisition, extracted NDVI values of images were interpolated to estimate closest NDVI values that correspond to the date of field data sampling. In order to do so, the dates of image acquisitions were converted to Julian days. The curve of maximum NDVI values was drawn to have visual impression of NDVI fluctuation within full phenological period of Glasswort community (Figure 4). To estimate the maximum NDVI values of each day, moving average was performed on each three consecutive dates. The associated NDVI values of each sampling dates were then graphed for the period of samplings (Figure 5). Since the curve of maximum NDVI values within the period of filed sampling dates was unimodal, it was divided into upward and downward curves that could best be estimated with linear regression model (Figure 6). To graph maximum NDVI values within the period of filed sampling and the percentage of brownness color class and the weight of seedfall of Glasswort simultaneously, the data were normalized by range (Figure 8). The regression equation model was performed between normalized maximum NDVI values by range as an independent variable and normalized brownness color class percentage and the normalized weight of seedfall as dependent variables (Figures 6, 7, and 8, and Tables 1 and 2).

Results and Discussion

Simultaneous graphing the percentage of glasswort color class changes and the change of its seedfall percentage during its phenology period within which we expected the seed ripening stage has reached and the probable seed fall starts(Figure 3) (Nodehi, et al., 2021). During its maturity, the percentage of greenness declines and the percentage of redness increases. When the maturity of the plant gets complete, brownness prevails. As it can be seen in figure 3, seedfall starts when the percentage of brownness color class rises over 42.50 percent on Julian day of (2019338) . within ten days, Seedfall reaches to its maximum level (more than 74.27 percent on Julian day of (2019348)) when brownness color class reaches to more than 70 percent. Till that time, there is positive correlation between brownness color class and seedfall. After that time, brownness continues to rise but seedfall declines rapidly.

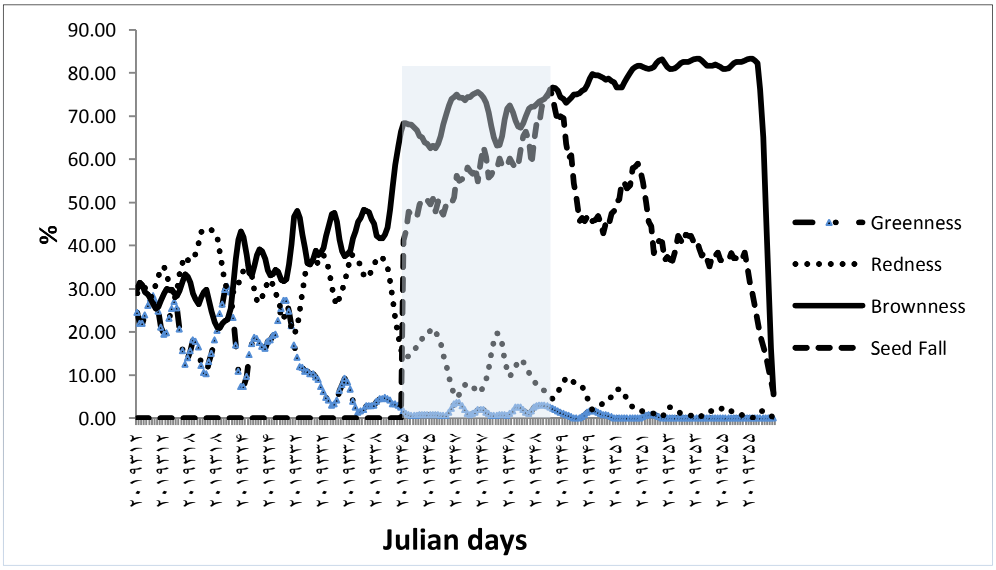

Figure 3. The percentage of changes in color classes before and after seed maturity of Glasswort in the study area (Nodehi, et al., 2021).

It is therefore logical to conclude that there is a period in Glasswort maturity stage that maximum of positive correlation can be observed between brownness and the amount of seedfall. To maximize the support for this correlation, this correlation should be defined within the context of the proportion of different pigments in the leaf of the plant that can best be quantified by Normalized Difference Vegetation Index (NDVI). The curve of maximum NDVI values within full phenological period of Glasswort community was shown in Figure 4. As it can be seen, the NDVI value that has been quantified by Sentinel 2 images start to rise sharply from 0.16 to 0.66 (range between 0-1) in the period of April to August 2019. It stays relatively constant within 50 days and starts to decline sharply to 0.25 from October to December. It should be noted that theoretically NDVI should rise and decline in a steady manner. Random fluctuation in the curve is due to changes in the background reflectance that happens due to the periodical inundation of the study area with brackish water of the canal and/or due to rainfall and cloudy condition of the area during image acquisition which is inevitable and it should be minimized as much as possible. It is therefore decided to smooth the curve by running moving average. A moving average is used to smooth out short-term fluctuations and highlight longer-term trends in a time series data ("Moving average" 2020).

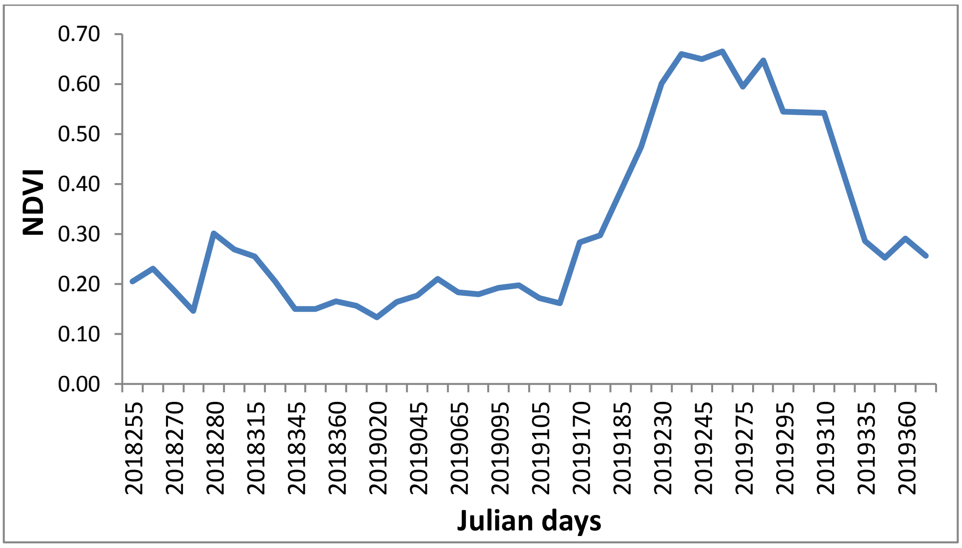

Figure 4. The curve of maximum NDVI values within full phenological period of Glasswort community.

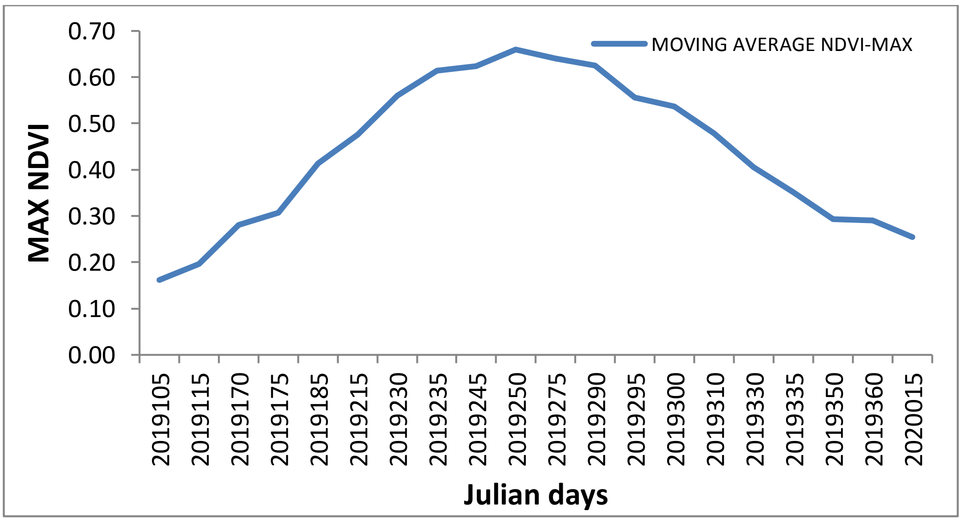

Figure 5. The curve of maximum NDVI values within the period of April to December 2019.

As the curve of maximum NDVI values within the period of field sampling dates is unimodal, it can be divided into upward and downward curves that can best be estimated with linear regression model (Figure 6 a and b).

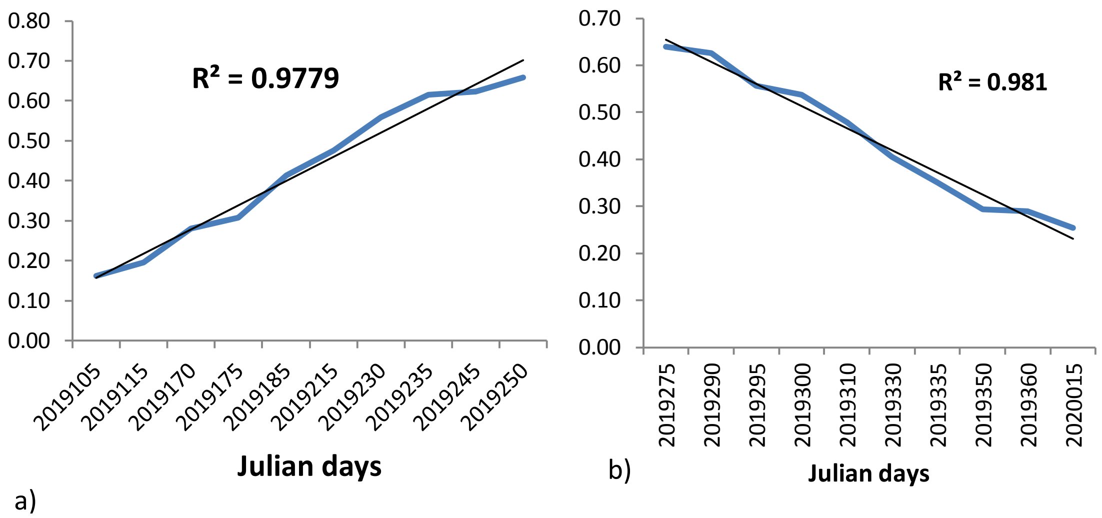

Figure 6. Best linear model fit to the curves of maximum NDVI values within the period of April to December 2019: a) upward, b) downward

To graph maximum NDVI values within the period of field sampling and the percentage of brownness color class and the weight of seedfall of Glasswort simultaneously, the data were normalized by range to rescale the data to allow the comparison of corresponding normalized values (“Normalization”, 2020) (Figure 7). As can be seen in Figure 7, there is a strong positive correlation between normalized value of seedfall and normalized value of brownness within the period of filed sampling period.

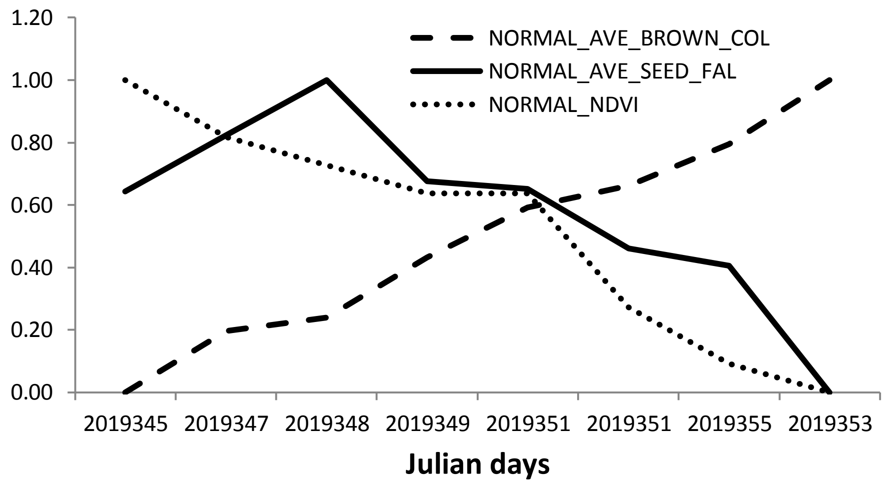

Figure 7. Normalized by range values of maximum NDVI, percentage of brownness color class and the weight of seedfall of Glasswort

The regression summary of NDVI as an independent variable and seedfall percentage as dependent variable has been shown in Table 1. The regression is significant at p value of 0.01 percent. As can be seen in Table 1, NDVI and seedfall are negatively correlated with R^2 of 0.83 which is considered as a strong correlation. The same strong significant negative correlation with the p value of 0.01 is seen between NDVI as an independent variable and brownness color percentage of the plant as dependent variable with R^2 of 0.83 which is also considered as a strong correlation (Table 2).

Table 1. Regression summary output between NDVI (as an independent variable) and seedfall percentage

ANOVA	df	SS	MS	F	Significance F
Regression	1	1205.77	1205.77	19.40	0.01
Residual	4	248.59	62.15		
Total	5	1454.36			
Multiple R	0.91	R Square	0.83	Standard Error	7.88
	Coefficients	Standard Error	t Stat	P-value	
Intercept	-5573.48	1275.07	-4.37	0.01	
NDVI	12325.14	2798.18	4.40	0.01	

Table 2. Regression summary output between NDVI (as an independent variable) and brownness color percentage.

ANOVA	df	SS	MS	F	Significance F
Regression	1.00	165.64	165.64	19.60	**0.01**
Residual	5.00	42.25	8.45		
Total	6.00	207.89			
Multiple R	**0.89**	R Square	**0.80**	Standard Error	2.91
	Coefficients	Standard Error	t Stat	P-value	
Intercept	1972.87	428.44	4.60	**0.01**	
NDVI	-4155.11	938.53	-4.43	**0.01**	

Based on statistically positive and significant correlation of brownness color percentage of Glasswort and the percentage of its seedfall appropriate harvesting time can be set for *Salicornia* herbacea plantation. This correlation needs to be tested for a longer period, in different climatic condition and for other *Salicornia* species such as *Salicornia europea,*·and *Salicornia bigelovii* that grow elsewhere and have been cultivated in the area. However, the results of this research documented the strong correlation between an observable *Salicornia herbacea* brownness color percentage and its seedfall. When the brownness color class of the Glasswort filed exceeds 50 percentages, the seeds have reached to their highest maturity and are ready to be harvested. This strong but negative correlation is seen between maximum NDVI values and Glasswort seedfall that support the findings of the correlation of the filed data. Our findings therefore can help filed workers to have an observable phenomenon of the plant to decide when to start harvesting Glasswort in the study area that is independent from the date of harvesting which can change year by year due to weather and environmental condition fluctuation.

This study confirms the findings of Tuszynska *et al.*, (2018) as they stated that stand-alone NDVI coefficient are not suitable for the determination of the approximate date of harvest. Since the crops drying up before harvest, the NDVI value decrease but there is no noticeable difference in NDVI values before and after harvest.

Although using NDVI changes as a suitable standalone harvesting indicator is difficult and practically inaccessible for field workers, observed strong negative correlation of NDVI value and Glasswort seedfall and its positive correlation with brownness class percentage of the plant between 50 to 70 percent, give us a scientific support to base brownness color percentage of Glasswort as an indicator of the percentage of its seedfall and thus define the harvesting time based on its color class percentage.

It is therefore advised to harvest *Salicornia herbacea* when the field brownness reaches to 50 percent. At this color stage, the seed loss due to late harvesting is minimized. This recommendation might not be applicable for other types of *Salicornia* and in other climatic condition or management practices. It is therefore suggested to test the finding of this research for other types of *Salicornia* species and in other areas and other management practices.

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