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Winter wheat yield estimation base upon spectral data and ground measurement

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ABSTRACT

In Iran, Yield forecasting is important for determining import–export policies, government aid for farmers, and allocation of subsidies for regional agricultural programs. Crop models have been used for monitoring crop growth and predicting yield. This research was curried in the lands under cultivation of dry-land Wheat in Malayer region in order to create an experimental regression model between the amount of yield or product and vegetation index. Measuring the coordinates of 150 points of the wheat sample with maximum amount of accuracy by GPS when the dry-land wheat of the region was ripen completely. The layers of gLAI and NDVI were crossed together in the context of ILWIS software in order to extract the amounts of NDVI corresponding with gLAI. The approach of determining LAI by establishing a relationship between NDVI and LAI is widely used due to its simplicity and ease of computation. In this case study a single date images, as demonstrated in this study, still provides good information to predict middle of season yield as long as it is within time when there is maximum vegetation between panicle initiation and heading stage. This research showed that NDVI has a good correlation with LAI and there is a good correlation between NDVI and yield but using NDVI as end-of- season yield estimator gives unsatisfactory results because of the problems of choosing the best time of the image to use, vegetation indices calculated from images taken at panicle initiation and heading stages have high correlation with yield too. Although simulation error was increased due to sLAI was used instead of gLAI (n = 30 & n = 120) is 0.36 and 0.55 %, respectively, but this amount equals less than one percent. Moreover, it is evident that there would not be errors when calculating in the farming planning in the region.

Keywords: RS, GIS, yield forecasting, spectral data

INTRODUCTION

Estimating crop yield before the harvest is one of the greatest concerns in agriculture, since variation in crop yield from year to year impacts international trade, food supply, and market prices. Early estimating of crop yield on the global and regional scale offers useful information to policy planner. Appropriate recognition of crop productivity is essential for sound land use planning and economic policy [1, 7]. At the field –scale, crop yield information helps the farmer to make quick decisions for upcoming situations, such as the choice of alternative crop and whether to abandon a crop at an early stage of growth. More recently, assessment of crop productivity at the within-field level has become an important issue in precision farming.

Yield forecasting, or determining yield in advance of harvest, has been used in many parts of the world to assess national food security and provide early food shortage warning. Early assessment of yield can help in strategic planning and decision-making. It is especially useful in countries where the economy depends on crop harvest [1, 5]. In Iran, it is important for determining import–export policies, government aid for farmers, and allocation of subsidies for regional agricultural programs. Crop models have been used for monitoring crop growth and predicting yield. However, their use in large areas has been limited because the required inputs are generally available only at field scale. Remote sensing provides observations over large areas at regular intervals, and saving time make it useful in order to crop modeling. Numerous studies have been conducted on its use in assessing crop growth and yield at regional and national levels. Remote sensing in crop modeling refers to quantification of a plant community attribute obtained with instruments that are not in contact with the plants. This often involves the measurement of electromagnetic radiation in specific wavelengths reflected or emitted by the plants [12].

The role of satellite data as part of a crop yield estimation system is a natural alternative because of the ability of satellites to provide relatively economical, consistent and repeated coverage over large areas. These characteristics of satellites allow collecting data useful for timely estimation of crop conditions throughout an entire growing season covering either important agricultural production regions or remote regions where accurate information is normally unavailable. Even though we have little control over the impacts of weather on crops, with remote sensing technology we have the ability to monitor and assess the impact that weather has on crops. This information is critical to reducing economic risk. The sooner this information is available, the lower the economic risk translating into greater efficiency and increased return on investments.

Kastens, J.H et al [10], essay entitled “Assessment of durum wheat yield using visible and near-infrared reflectance spectra of canopies”. This study researched that the empirical models for the estimation of grain yield generally stronger and more robust assessment of grain yield than previously assayed spectral indices. For the best model, correlation coefficients between genotype means of predicted and measured yield within each of the five environments ranged from 0.53 to 0.76. They concluded that, although the models did not provide an accurate quantification of grain yield, they could still be used to rank genotypes for breeding purposes. The most reliable ranking of genotypes was attained using measurements made at milk-grain stage on medium to high productivity environments.

S. Bazgeer’s [3], article entitled “Pre-harvest wheat yield prediction using agromet-spectral-trend-yield models for Hoshiarpur and Rupnagar district of Punjab”, it was found that Agro met-Spectral-Trend-Yield model could explain % 96(SEOE = 87 kg/ha) and 91% (SEOE = 146 kg/ha) of wheat yield variations for Hoshiarpur and Rupnagar districts, respectively.

The study by M. Moriondo, et. al [15], essay entitled “The A simple model of regional wheat yield based on NDVI data”. Proposed methodology that was applied in two Italian provinces where wheat is widely grown (Grosseto and Foggia). In both cases, attention as first devoted to the production of multi-year NDVI data sets descriptive of wheat conditions. Next, the current methodology was applied to estimate wheat yield. The results obtained showed the high accuracy of the method in estimating wheat yield at the provincial level. Correlation coefficients equal to 0.77–0.73 were obtained between measured and simulated crop yield, with corresponding root mean square errors (RSME) 0.47 and 0.44Mg/ha for Grosseto and Foggia, respectively.

Ren, J., et al. [18] studied about “Regional yield estimation for winter wheat with MODIS-NDVI data in Shandong, China”. The results showed that the relative errors of the predicted yield using MODIS-NDVI were between 4.62% and 5.40% and that whole RMSE was 214.16 kg ha^{-1} lower than the RMSE (233.35 kg ha^{-1}) of agro-climate models in this study region. A good predicted yield data of winter wheat could be got about 40 days ahead of harvest time, i.e. at the booting-heading stage of winter wheat. The method suggested in this paper was good for predicting regional winter wheat production and yield estimation.

Fariba Esfandiary et al [8], in an article entitled “Wheat Yield Prediction through Agro Meteorological” found predicted the yield two months in advance before harvesting time which was coincide with commencement of reproductive stage of wheat (5th of June). It revealed that in the final statistical models, 83% of wheat yield variability was accounted for variation in above agro meteorological indices.

The aim of this study is estimation wheat yield base upon remotely sensed data and field study.

MATERIALS AND METHODS

Malayer Township is located between 34° to 34°, 40', 13"Latitude and 48°, 23', 55" Longitude to 49°, 8', and 51" of Greenwich Meridian.

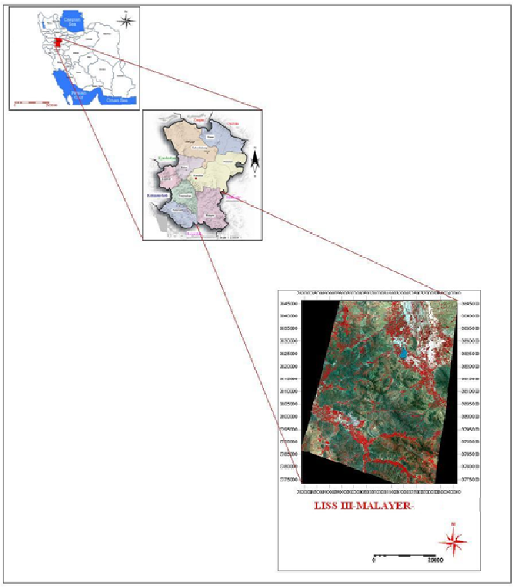

Fig1. Position of study area

Methodology

This research was curried in the lands under cultivation of dry-land Wheat in Malayer region in order to create an experimental regression model between the amount of yield or product and vegetation index. The main use of model simulation in evaluating lands is the (estimation crop) prediction of the amount of product or yield. Principally, the main idea behind making these kinds of models is based on this principle that there is a relationship or correlation between vegetation indices and estimation crop and we can estimate the amount of yield production by establishing this kind of correlation. As far as it is concerned with the analysis of yield amount (y), the following formula is used:

$$Y = f\,(X_1, X_2, X_3 \ldots)$$

In this formula, Xs are an indicative of independent variable, which are the vegetation indices in our research. Basically, vegetation indices are mathematical conversions which have been designed for spectral assessment of plants in multi-spectral satellite observations. These indices are mostly used in places where the spectral satellite data have been placed in the confine of red and near infrared bands. These vegetation indices based on having the property of red light, absorption by pigments inside the chlorophyll of plants, act in such a way that they experience minimum reflection in red band and maximum reflection in infrared waves.

Field operation (work):

1. The coordinates (x,y) of 250 points in farm lands and some others from other main products were obtained by GPS.
2. The point coordinates of dry-land wheat of the region under study was obtained. In this procedure, these 150 points (x,y) were obtained by GPS when the dry-land wheat had the maximum chlorophyll and leaf area.
3. The points (wheat plants) were transferred to laboratory, where the leaf area index was measured by leaf area meter. These measures were called Ground Measured LAI[1], or it is better to say “gLAI”.
4. Measuring the coordinates of 150 points of the wheat sample with maximum amount of accuracy by GPS when the dry-land wheat of the region was ripen completely. These measures were called Ground Measured Yield, or it is

[1] *-Leaf Area Index*

better to say "gYield". Now, by considering the coordinates of gLAI available in GPS, a vector map (point map) was created in GIS environment.

Leaf Area Index (LAI) is an important structural property of a plant canopy. It is a bio-physical variable influencing land surface processes such as photosynthesis, transpiration, and energy balance. LAI is a required input for various agricultural models. LAI is defined as the projected area of leaves per unit of ground area. The amount of leaves in the canopy is a factor in determining the amount of light intercepted by the canopy, which in turn controls photosynthetic rates. Leaves contain pores, called stomata, through which carbon dioxide and water pass between the plant and the atmosphere. So the leaf area also sets limits on transpiration and photosynthesis. For different vegetation types LAI can vary from less than 1 for deserts to over 6-8 for rain forests. There are a variety of methods for measuring LAI. The most straightforward, usually used in herbaceous or grassy canopies, is to simply define an area on the ground, clip off all the leaves, and measure their area. Dividing the total area of all the leaves by the ground area gives LAI.

Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index, the NDVI was also proposed by Rouse et al. It is expressed as the difference between the NIR and red (RED) bands normalized by their sum:

$$NDVI=(R_{Nir.} - R_{Vis}) / (R_{Nir} + R_{Vis})$$

Now, by considering the coordinates of gLAI available in GPS, a vector map (point map) was created in GIS environment. Then, by taking the above equation into account, NDVI variable was calculated by making use of red bands (R) and infrared bands (NIR). The layers of gLAI and NDVI were crossed together in the context of ILWIS software in order to extract the amounts of NDVI corresponding with gLAI. Then, the extracted amounts were transferred to SPSS software to elicit the information necessary for our analysis. To derive remotely-sensed LAI, the following empirically derived logarithmic regression model was developed:

$$sLAI= f\,(NDVI) \qquad \text{(Eq.1)}$$

As it was mentioned before, the data used for the development of this model were also obtained in growth season in 2009 out of 150 data points (120 points for models and 30 points for pilot study). The NDVI was used because it seems that it correlates well with canopy and has been demonstrated to give satisfactory LAI estimates [17]. The approach of determining LAI by establishing a relationship between NDVI and LAI is widely used due to its simplicity and ease of computation [7].

RESULTS AND DISCUSSION

According to the table acquired by the results of statistical operation in SPSS software, the amount of determination coefficient (R^2) between the variables gYield and gLAI was 0.928 and P = 0.000 in regression model. The number of observations in this regression was 120 points which led to logarithmic regression equivalence as it follows:

$$Y= yield= 0691*Ln\,(LAI) +1.312 \qquad \text{(Eq.2)}$$
$$Y = Mgha^{-1} \quad , \quad R^2= 0.928$$

Table 1 Coefficients (gyield & gLAI)

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
LN(gLAI)	0.691	0.018	0.964	39.116	0.000
(Constant)	1.312	0.008		174.563	0.000

In addition, as table 1 indicates, there is a significant correlation between these variables (P= 0.000). In other words, the more the gLAI, the more the gYield. With regard to the importance of NDVI as it was mentioned above, the amount of the determination of coefficient between two variables including NDVI and gLAI was calculated with respect to the tables acquired from regression model in SPSS software (R^2= 0.869).

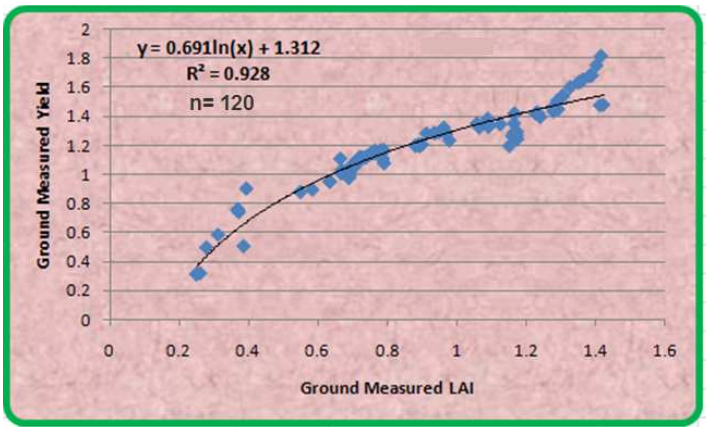

Fig.2 Result of the regression between two variable gLAI & g Yield

Table 2 : Result of the regression between two variable gLAI & NDVI

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.932	0.869	0.868	.112

The independent variable is NDVI.

Table 3: ANOVA (NDVI & gLAI)

	Sum of Squares	df	Mean Square	F	Sig.
Regression	9.729	1	9.729	781.689	0.000
Residual	1.469	119	0.012		
Total	11.197	120			

Table 4: Correlation (NDVI & gLAI)

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
$LN_{(NDVI)}$	1.035	0.037	0.932	27.959	0.000
(Constant)	2.050	0.042		49.025	0.000

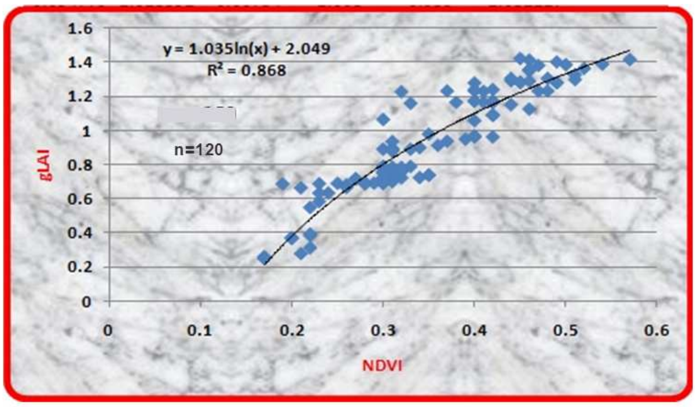

Fig. 3 Regression between gLAI & NDVI

Therefore, we can say that the following empirically derived algorithmic regression model can be developed to derive remotely sensed LAI.

$$sLAI = 1.035 \times Ln_{(NDVI)} + 2.05 \quad Eq.3$$

As it is explained in the table 4, there is a significant relationship between these variables at the level of 0.999(P = 0.000). Also, as it is clear from the related graph between the variables, an increase in the amount of NDVI leads to an increase in the LAI amount.

Generally, the NDVI was used for some studies as it correlates well with foliage density and has been demonstrated to give satisfactory LAI estimates. According to Colombo et. al [4], the approach of determining LAI by establishing a relationship between NDVI and LAI is widely used due to its simplicity and ease of composition.

As it is evident from table 5 with regard to the obtained results of establishing a correlation matrix between LAI and NDVI, we can draw this conclusion that there is a significant correlation between NDVI and gLAI variables (r = 0.861; p= 0.000). On the other hand, there is also a significant relationship between NDVI and gLAI.

Table 5: Correlations between SAVI.07, NDVI.07, gLAI.07, n = 120

		NDVI.07
NDVI.07	Pearson Correlation	1
	Sig. (2-tailed)	
gLAI.07	Pearson Correlation	0.861**
	Sig. (2-tailed)	0.000

Therefore, by taking the results of this study into account, we can express that, in order to estimate and obtain the amount of LAI to derived satellite images.

After calculating sLAI, which was obtained by establishing a gLAI regression with the NDVI, a correlation matrix was created in order to see whether there is any significant relationship between two variables including, sLAI $_{(NDVI)}$, and g LAI, and to determine the amount of correlation among them as you can observe the results from the table6. According to table 6, the correlation coefficient between sLAI $_{(NDVI)}$ with gLAI were r = 0.912, which can be an indicative of this point that there is a significant relationship between sLAI $_{(NDVI)}$ and gLAI at the level of (P=0.000).

Table 6 : Correlation between, sLAI ($_{NDVI}$)., gLAI

		sLAI$_{(ndvi)}$
sLAI$_{(ndvi)}$	Pearson Correlation	1
	Sig. (2-tailed)	
gLAI	Pearson Correlation	0.912**

Then, a Pearson correlation coefficient was established between the present variable after estimating the yield by the resulted indices from the equations 2, 3, the ground yield measured by the present researcher, and the measured amounts, which have been recorded in the reports of Bushel Measurement in the Agricultural office for the year 2008-2009(table 7).

Table 7 Correlation between syield$_{(SAVI)}$, syield ($_{NDVI}$), gyield, Rep.yield, s.Yield $_{(gLAI)}$

	s.yeild$_{(ndvi)}$	**g.yield**	**Rep.yield**	**s.yeild$_{(glai)}$**
s.yeild$_{(ndvi)}$ Pearson Correlation Sig. (2-tailed)	1 0.000			
g.yield Pearson Correlation Sig. (2-tailed)	0.916** 0.000	1		
Rep.yield Pearson Correlation Sig. (2-tailed)	0.839** 0.000	0.948** 0.000	1	
s.yeild$_{(glai)}$ Pearson Correlation Sig. (2-tailed)	0.927** 0.000	0.963** 0.000	0.886** 0.000	1

As it is clear from table 7, the result obtained indicate that there is a high significant correlation at P=0.000 level between s.Yeild $_{(NDVI)}$, s.Yeild $_{(gLAI)}$ with g.Yield. Regarding these results, another important point which is worth mentioning here is that there is very little difference between the amount of correlation coefficient of s.Yeild $_{(NDVI)}$ and s.Yeild $_{(gLAI)}$, which can be easily ignored. Therefore, based on the available data in table 7, we can come to this conclusion that the estimated yield from sLAI $_{(NDVI)}$.

In addition, results comprising the use of Eq. (2,3) with (2008-2009) data set (n=120) indicated a satisfactory match between sLAI $_{(NDVI)}$ and gLAI.

As it was already mentioned in methodology, 20% of the selected points (n=30) were implemented accidentally for the purpose of validating the equations. Then, as we can see the results in table 8, a Pearson correlation was established between two variables including $SLAI_{(NDVI)}$ and gLAI. The results indicated that there is a significant relationship between NDVI and gLAI with correlation coefficient of r = 0.888 (P = 0.000).

Table 8 Correlation between, $sLAI_{(ndvi)}$. & gLAI.. (n = 30)

		$sLAI_{(ndvi)}$
$sLAI_{(ndvi)}$	Pearson Correlation	1
	Sig. (2-tailed)	0.000
gLAI.	Pearson Correlation	0.888**
	Sig. (2-tailed)	0.000

Another Pearson correlation was established among the variables after calculating the yield by establishing a regression model from sLAI $_{(NDVI)}$, and gLAI variables, and calculating it from regression model of Eq.2. With regard to the obtained results, as it is has been indicated in table 9, we can conclude that there is a significant relationship between s.Yeild $_{(NDVI)}$ and s.Yeild $_{(gLAI)}$ index with the measured yield at the level of P= 0.000 and this index has more correlation coefficient than that of other variables with gYield variable.

Table 9: Correlation between $s.Yeild_{(gLAI)}$, g.Yield, $s.Yeild_{(savi)}$, $s.Yeild_{(ndvi)}$. Rep.Yield n=30

		$s.yeild_{(gLAI)}$	g.yield	$s.yeild_{(ndvi)}$	Rep.yield.
s.Yeild $_{(gLAI)}$	Pearson Correlation	1	0.990**	0.887**	0.955**
	Sig. (2-tailed)		0.000	0.000	0.000
g.Yield.	Pearson Correlation	0.990**	1	0.870**	0.972**
	Sig. (2-tailed)	0.000		0.000	0.000
$s.Yeild_{(NDVI)}$	Pearson Correlation	0.887**	0.870**	1	0.815**
	Sig. (2-tailed)	0.000	0.000		0.000
Rep.Yield	Pearson Correlation	0.955**	0.972**	0.815**	1
	Sig. (2-tailed)	0.000	0.000	0.000	

***Correlation is significant at the 0.01 level (2-tailed).*

In simulating crop growth with a process-based model, comparison between the model output and the measurement is an important activity to test the model accuracy and locate room for further improvements. The comparison is often based on correlation between the calculated and measured values, and regression of measured on calculated values. When Kiniry et al[11] compared measured and simulated yields of maize for 10 yr from 1983 to 1992 at nine locations in the USA, measured yields were plotted against simulated ones, the correlation coefficient was calculated, and regression lines were fitted. This has been common practice in the comparison between calculated and measured values [5,19]. In this approach, the correlation is a criterion of the predictive accuracy of the model along with the requirements for the regression line (i.e., the intercept is not significantly different from zero and the slope is not significantly different from unity). Statistical testing of these requirements for the regression line has been established.

Table. 10 Measured and simulated wheat grain yield in study area

Year		measured($Mgha^{-1}$)	$Sim_1(Mgha^{-1})$	$Sim_2(Mgha^{-1})$	SE_1 (%)	SE_2 (%)
2009 (n=120)	Mean	1.11	1.204	1.265	1.11	1.65
	RMSE	-	0.15	0.18	-	-
	MSD	-	0.02	0.03	-	-
	SDSD	-	0.001	0. 001	-	-
2009 (n=30)	Mean	1.02	1.130	1.140	1.02	1.38
	RMSE	-	0.14	0.19	-	-
	MSD	-	0.02	0.03	-	-
	SDSD	-	0.001	0.001	-	-

RMSE between sLAI $_{(ndvi)}$ & gLAI = 0.32

The production rate of dry land wheat per unit area in the study area was obtained in three ways:
A) Ground direct measurement by the researcher

B) Using the product Model and gLAI.
C) Using the product Model and sLAI. (Of course, all calculations for both parts was done (n = 120 & n = 30).

It shows that these two are well-matched and the amount of the RMSE was two times 0.21 which is range presented by the Global Terrestrial Observation System (GTOS) and Global Climate Observation System (GCOS). This amount is acceptable for the threshold performance from -1 to +1 and for the optimum performance is from -0.5 to + 0.5 [14]. Validation results showed that the product model was satisfactorily evaluated with accuracy. So for the validation of the product model, the measured product and product model were compared. The results are displayed in Table 10. Validation is taken here to mean checking if the model's outputs are sufficiently close to the observed data and if the model works with totally independent datasets: that is, it accurately predicts yield (Boote et al., 1996). Validation is an essential process for models that are applied, with predictions used to replace costly field measurements [14].

CONCLUSION

The results of the measurements and calculations showed that the estimation accuracy of yield model is acceptable and can be used for estimating dry land wheat in the study area. The rate of RMSE model under estimation was equal to 0.15 $Mgha^{-1}$ (n=120) and 0.19 $Mgha^{-1}$ (n=30), which indicates good accuracy for farming year in the study area and indicates that the model with both variables of sLAI & gLAI are accurate enough to estimate products. As shown in the above table, by replacing gLAI by sLAI in (Eq.3) the rate of simulation error reached from 1.11 percent to 1.65 and from 1.02 to 1.38 percent at n=120 & n=30, respectively. It also shows that when sLAI was Used instead to gLAI (at n=120) the rate of simulation error did not change significantly (from 1.11 to 1.65 percent) and there was about 0.36 difference at n=30 i.e., from 1.02 to 1.38 percent. Besides the, mean simulation error increased about 0.36 at n=30 and 0.55 at n=120.

To measure the overall deviation of the yield model, the MSD for the study area was calculated. The MSD value (n=120) was higher when the model used sLAI (0.02 vs. 0.03) and was the same for n=30. When using the two different types of LAI input resulted in similar values for SDSD. Finally, this study shows that the LAI-based yield model can be used for estimating wheat dry-land in Malayer region. The model can estimate wheat crop with a mean simulation error of less than 1% using gLAI or sLAI.

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