Abstract - In this paper, we develop a novel method for forest biomass estimation. Intensity values of ALOS-AVNIR-2 and PRISM images, and texture features of JERS-1 image are used in a multilayer perceptron neural network (MLPNN) that relates them to the forest variable measurements on the ground. A proposed Speckle noise model is also applied for modelling and reducing the speckle noise in the SAR image. Reducing the speckle would improve the discrimination among different land use types, and would make the textual classifiers more efficient in SAR images. Ideally, the filters will reduce the speckle without loss of information. In the process of the forest biomass estimation, the filters should preserve the backscattering coefficient values and edges between the different areas. We investigate both quantitative and qualitative criteria in speckle reduction and texture preservation to evaluate the performance of the proposed filter in the forest biomass estimation. We will also show the biomass estimation accuracy is significantly improved in a MLPNN when the radar and the optical data are used in combination compared to estimating the biomass by using single data only. The RMSE value is decreased when the proposed method is used (RMSE=2.175 ton) compared the classic method (RMSE=5.34 ton).

Index Terms -- Speckle noise, ALOS, AVNIR-2, PRISM, JERS-1, SAR, biomass, forest estimation, neural network.

I. INTRODUCTION

Biomass, in general, includes the above-ground and below-ground living mass, such as trees, shrubs, vines, roots, and the dead mass of fine and coarse litter associated with the soil. Due to the difficulty in collecting field data of below-ground biomass, most previous researches on biomass estimation have been focused on the above-ground biomass (AGB).

Different approaches have been applied for above ground biomass (AGB) estimation, where traditional techniques based on field measurement are the most accurate ways for collecting biomass data.

A sufficient number of field measurements are a prerequisite for developing AGB estimation models and for evaluating its results. However, these approaches are often time consuming, labour intensive, and difficult to implement, especially in remote areas; also, they cannot provide the spatial distribution of biomass in large areas.

The advantages of remotely sensed data, such as in repetitively of data collection, a synoptic view, a digital format that allows fast processing of large quantities of data, and the high correlations between spectral bands and vegetation parameters, make it the primary source for large area AGB estimation, especially in areas of difficult access. Therefore, remote sensing-based AGB estimation has increasingly attracted scientific interest [1], [2], [3], [4], [5], [6], [7]. There are also other papers including [8]-[16] with SAR-based methods in above ground biomass estimation.

One strategy that can be used for AGB estimation is to combine synthetic aperture radar (SAR) image texture with optical images based on the classification analysis. Limitation on the used only optical data is the insensitivity of reflectance to the change in biomass and different stands. The use of the SAR data has the potential to overcome this limitation. But presence of the speckle in SAR data is also a barrier to the exploitation of image texture. Reducing the speckle would improve the discrimination among different land use types, and would make the textual classifiers more efficient in radar images. Ideally, the filters will reduce speckle without loss of information.

Many adaptive filters that preserve the radiometric and texture information have been developed for speckle reduction. Adaptive filters based upon the spatial domain are more widely used than frequency domain filters. The most frequently used adaptive filters include Lee, Frost, Lee-Sigma and Gamma-Map. The Lee filter is based on the multiplicative speckle model, and it can use local statistics to effectively preserve edges and features [17]. The Frost filter is also based on the multiplicative speckle model and the local statistics, and it has similar performance to the Lee filter [18]. The Lee-Sigma filter is a conceptually simple but effective alternative to the Lee filter, and Lee-Sigma is based on the sigma probability of the Gaussian distribution of image noise [17]. Lopes et al. [19] developed the Gamma-Map filter, which is adapted from the Maximum a Posterior (MAP) filter [20]. Lee, Frost and Lee-Sigma filters assume a Gaussian distribution for the speckle noise, whereas Gamma-Map filter assumes a Gamma distribution of speckle [19], [21]. Modified versions of Gamma-Map have also been proposed [22], [23]. Nezry et al. [22] combined the ratio edge detector and the Gamma-Map filter into the refined Gamma-Map algorithm. Baraldi and Parmiggiani [23] proposed a refined Gamma-Map filter with improved geometrical adaptively. Walessa and Datcu combined the edge detection and region growing to segment the SAR image and then applied speckle filtering within each segment under stationary conditions. Dong et al. [24] proposed an algorithm for synthetic aperture radar speckle reduction and edge sharpening. The proposed algorithm was...
functions of an adaptive-mean filter. Achim et al. [25] proposed a novel adaptive de-speckling filter using the introduced heavy-tailed Rayleigh density function and derived a maximum a posterior (MAP) estimator for the radar cross section (RCS). The authors [26] proposed a filter based on the least square method for speckle reduction in SAR images.

In this paper, we develop a novel method for the forest biomass estimation. Both SAR and optical images are used in a multilayer perceptron neural network (MLPNN) that relates them to the forest measurements on the ground. We use a speckle noise model that proposed by the authors in 2008 [26] for reducing the speckle noise in the SAR image. Reducing the speckle would improve the discrimination among different land use types, and would make the textual classifiers more efficient in SAR images. We investigate both quantitative and qualitative criteria in speckle reduction and texture preservation to evaluate the performance of the proposed filter on the forest biomass estimation.

In summary, the objectives of this paper are:

1- The efficiency of the proposed filter by the authors in 2008 [22] in forest biomass estimation and,
2- Improved the accuracy of forest biomass estimation when using both SAR images texture and optical images in a non-linear classifier method (MLPNN).

The proposed speckle filter has been developed by the authors in the Canadian journal of remote sensing in 2008 [26]. In this paper, we first describe the methodology and implementation of this paper for the forest biomass estimation based on the filter in [26] and then we will give the experimental results in the next section.

![Study Area](image)

**North of Iran**

**Study Area**

REZVANSHAHR

37.91(deg)

48.975(deg)

(a)

Fig. 1. (a) Study area of the north of Iran, (b) Plots in the study area indicated with circles.

II. THE STUDY AREA

The study area is located in the northern forests of Iran around the Rezvanshahr city (Fig. 1(a)). The dominant trees of these forests are: Maple, Alder, Conifer, Beech, Hornbeam, Azedarach and Acorn. Remote sensing data also consist of: AVNIR-2 and PRISM images from ALOS and a JERS-1 image. The JERS-1 image has a spatial resolution of approximately 13m and, AVNIR-2 and PRISM images have the spatial resolutions of 10m and 2.5m respectively.

III. METHODOLOGY AND IMPLEMENTATION

The methodology used for the forest inventory is distinct according to the vegetation type. In forest areas, different parameters are measured namely: diameter at breast height (DBH), total and commercial height, crown cover percent, and location of each plots. Total height is the height from the upper branches of a tree to the ground and the commercial height is the height of the main trunk of a tree. The crown cover percent is also percent of the number of trees in a hectare. We measured the total height during the field survey and used it in the allometric equation. In addition, the identification of botanical species is also conducted.

The field work consists of collecting some bio-physical and dendrometric parameters which allowed the biomass estimation of the plots and the physiognomic—structural characterization of the different vegetation types considered. The precise geographic coordinates of each plot are obtained using a high-precision Global Positioning System (GPS), which allows the localization of each plots, in the previously geo-referenced images.

According to Fig. 1(b), the ground data is collected at five plots in the study area. Each plot was a square with size of 50m×50m with 25 subplots with size of 10m×10m approximately. The minimum DBH considered was of 37cm. The plots were mostly covered by two classes: Acorn and Azedarach. The distribution of the classes with numbers of stands where measured in each subplots are shown in Table I. Table I summarizes some of the ground measurements and resulting calculations.

The biomass in table I is modelled based on the direct DBH and the total height measurements performed during the field survey and included afterwards in the general allometric equation (1) [27].

\[
\text{biomass} = 0.044 \times ((DBH)^2 \times \text{height})^{0.9719}
\]

(1)

Where: DBH is in cm, height is in m, and biomass is in kg/tree.

For speckle reduction in the SAR image, our proposed filter published in [26] is applied on the JERS-1 image of the study area and then its result is compared with several of the most widely used adaptive filters including the Kuan, Gamma, Lee and Frost filters.

In order to investigate the performance of the proposed filter, we use some quantitative criteria including speckle smoothing measures and texture preservation to evaluate the performance of the proposed filter.
The ratio of the original intensity image to the filtered image enable us to determine the extent to which the reconstruction filter introduces radiometric distortion so that the reconstruction departs from the expected speckle statistics. The mean and standard deviation (SD) can then be estimated over the ratio images. When the mean value differs significantly from one, it is an indication of radiometric distortion. If the reconstruction follows the original image too closely, the standard deviation would be expected to have a lower value than predicted. It would be larger than predicted if the reconstruction fails to follow genuine RCS variations. This provides a simple test that can be applied to any form of RCS reconstruction filters. Table II, columns 2 and 3, shows the mean and standard deviation values of the ratio images for comparison of the filters.

According to Gagnon and Jouan [28], Equivalent number of Looks (ENL) is often used to estimate the speckle noise level in a SAR image and is equivalent to the number of independent intensity values that are used per pixel.

\[
\text{ENL} = \left( \frac{\text{mean}^2}{\text{variance}} \right)_{\text{UniformArea}}
\]

ENL is used to measure the degree of speckle reduction in this study. The higher the ENL value concludes the stronger the speckle reduction.

Texture preservation is another measure that is important in a SAR image for interpretation and classification. Therefore, the texture preserving capability should play an important role in measuring the performance of a speckle filter. A second-order texture, variance [29], is used to measure the retention of texture information in the original and the filtered images.

The ENL and the second-order texture values of the filtered images are shown in table II columns 4 and 5 respectively. Of the four commonly used filters, Enhanced Frost filter has higher speckle-smoothing capabilities than Kuan, Gamma and Enhanced Lee filters. The ENL value of the proposed filter is 26.78 that is comparable to Enhanced Frost filter. According column 5, Variance Texture Operator (VTO), in table II, the texture preservation of the proposed filter is better than, or comparable to, those of the commonly used speckle filters. We concluded the proposed filter is slightly better than the commonly used filters in terms of preserving details in forestry areas. Furthermore, the proposed filter also affects in smoothing speckles. This improvement in the accuracy of the speckle reduction can be played an important role in the forest biomass estimation.

After reduction the speckle noise, the texture of SAR image must be measured. Of the many describing texture methods, the grey-level co-occurrence matrix (GLCM) is the most common [30], [31], [32] in remote sensing.

Nine texture measures are calculated from the GLCM for a moving window with size of 5x5 pixels that centred in pixel \(i, j\) of the de-speckled JERS-1 image. After the Gram-Schmidt process, just four texture measures: contrast, correlation, maximum probability and standard-deviation are selected as the optimum measures in this area.

The PRISM image is transformed in the universal transverse Mercator (UTM) projection with a WGS84 datum based on the GPS measurements and is used as the base map. Two GPSs measured the coordinates of points along the roads of the study area. To place all data sets in a unified coordinate system, the AVNIR and JERS-1 image are registered to this map. The co-registered and geo-referenced data sets contain PRISM, AVNIR and SAR images are used to extract intensity values and texture measures respectively.

### IV. RESULTS

Intensity value and texture measures from the co-registered and geo-referenced data sets are used in the algorithm to estimate the forest biomass. The data sets are related to the forest biomass through a classification analysis. The correspondence between the data sets and ground plots is made using PCI Geomatica software, where the ground plot GPS locations are superimposed on the data set. For each selected pixel (or point) from data set, a window with size of 5x5 pixels around the point is used and the average intensity values for the PRISM and three channels of the AVNIR images with four texture values of the JERS-1 image are calculated. Thus each selected point contains a vector with eight attributes where the first four elements are the average intensity values and the second four elements are the texture measures values. These vectors of data set construct the feature space. The vectors belong to the pixels of the ground plots and subplots are used as training patterns in the classification process.

The classification analysis is done with an MLPNN. A multi layers neural network is made up of sets of neurons assembled in a logical way and constituting several layers.

### TABLE I

<table>
<thead>
<tr>
<th>Plot</th>
<th># of subplots for Acorn Azedarach</th>
<th>Mean height (cm)</th>
<th>Mean DBH (cm)</th>
<th>Mean Biomass (ton/tree)</th>
<th># of stands for Acorn Azedarach</th>
<th>Total mean biomass (ton) for Acorn Azedarach</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20</td>
<td>28.5</td>
<td>40</td>
<td>1.484</td>
<td>15</td>
<td>26.712</td>
</tr>
<tr>
<td>2</td>
<td>07</td>
<td>34</td>
<td>55</td>
<td>3.275</td>
<td>08</td>
<td>25.960</td>
</tr>
<tr>
<td>3</td>
<td>19</td>
<td>26.5</td>
<td>35</td>
<td>1.066</td>
<td>24</td>
<td>25.584</td>
</tr>
<tr>
<td>4</td>
<td>15</td>
<td>29</td>
<td>45</td>
<td>1.897</td>
<td>14</td>
<td>26.558</td>
</tr>
<tr>
<td>5</td>
<td>04</td>
<td>27.5</td>
<td>38</td>
<td>2.373</td>
<td>06</td>
<td>14.238</td>
</tr>
</tbody>
</table>

### TABLE II

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Ratio image</th>
<th>Filtered image</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S. D</td>
</tr>
<tr>
<td>Proposed algorithm</td>
<td>0.991</td>
<td>0.037</td>
</tr>
<tr>
<td>Kuan</td>
<td>0.968</td>
<td>0.195</td>
</tr>
<tr>
<td>Gamma</td>
<td>0.968</td>
<td>0.195</td>
</tr>
<tr>
<td>Enhanced Lee</td>
<td>0.968</td>
<td>0.195</td>
</tr>
<tr>
<td>Enhanced Frost</td>
<td>0.968</td>
<td>0.195</td>
</tr>
</tbody>
</table>
Three distinct types of layers are present in the MLPNN. The input layer is not itself a processing layer but is simply a set of neurons acting as source nodes which supply input feature vector components to the second layer. Typically, the number of neurons in the input layer is equal to the dimensionality of the input feature vector. Then there is one or more hidden layers, each of these layers comprising a given number of neurons called hidden neurons. Finally, the output layer provides the response of neural network to the pattern vector submitted in the input layer. The number of neurons in this layer corresponds to the number of classes that the neural network should differentiate [33], [34], [35].

The network that is used in this study arrange in layers as following. The number of neurons in the output layer is taken to be equal to the number of classes desired for the classification. Here, the output layer of the network used to categorize the image in five classes should contain five neurons. The input layer contains eight neurons corresponding to the number of attributes in the input vectors. The input vector to the network for pixel $i$ of the data sets is the form $v_{10i} = \{v_{1i}, v_{2i}, ..., v_{10i}\}$. Where the first four elements belong to the intensity values of PRISM and AVNIR images and the second four elements belong to the texture measures of JERS-1 image for a window with size of $5 \times 5$ around pixel $i$ of the geo-referenced data sets. After the determination of the input layer, the number of hidden layers required as well as the number of neurons in these layers still needs to be decided upon. An important result, established by the Russian mathematician Kolmogorov in the 1950s, states that any discriminate function can be derived by a three-layer feed-forward neural network [36]. Increasing the number of hidden layers can then improve the accuracy of the classification, pick up some special requirements of the recognition procedure during the training or enable a practical implementation of the network. However, a network with more than one hidden layer is more prone to be poorly trained than one with only one hidden layer.

Thus, a three-layer neural network with the structure 8-10-5 (eight input neurons, ten hidden neurons and five output neurons) is used to classify the data sets into five classes.

Training the neural network involves tuning all the synaptic weights so that the network learns to recognize given patterns or classes of samples sharing similar properties. The learning stage is critical for effective classification and the success of an approach by neural networks depends mainly on this phase. The learning stage is critical for effective classification and the success of an approach by neural networks depends mainly on this phase.

Increasing the number of hidden layers can then improve the accuracy of the classification, pick up some special requirements of the recognition procedure during the training or enable a practical implementation of the network. However, a network with more than one hidden layer is more prone to be poorly trained than one with only one hidden layer.

After classification, it is needed to determine the degree of classification accuracy. The most commonly used method of representing the degree of accuracy of a classification is to build confusion matrix.

The confusion matrix is usually constructed by a test sample of patterns for each of the five classes. A set of test sample with 105 patterns based on the ground truth collection were randomly selected in the classified image for accuracy assessment. The values 70% and 65% are achieved for overall accuracy and kappa coefficient respectively. One reason for misclassification can be due to poor selection of training areas, so that some training patterns don’t accurately reflect the characteristics of the classes used. Another reason can be due to poor selection of land cover categories, resulting in correct classification of areas from the point of view of the network, but not from that of the user. Thus the classification accuracy can be improved by redefining the training patterns and land cover categories.

In order to show the texture of SAR image and the neural network classifier improve the accuracy of the classification and then forest biomass estimation, we employ the Maximum Likelihood (ML) classifier method using only the intensity values of the PRISM and AVNIR images. The overall classification accuracy of 57% is achieved with ML classifier. The accuracy of 70% with the neural network is significantly better than the accuracy of 57% with ML.

In comparison between the MLPNN and ML classifiers, the advantages of MLPNN that is used in this study are:

(i) It can accept all kind of numerical inputs whether or not these conform to statistical distribution or not.
(ii) It can recognize inputs that are similar to those which have been used to train them.
(iii) Because the network consists of a number of layers of neurons, it is tolerant to noise present in the training patterns.

Thus, we can estimate the forest biomass of the classes in the classified image which has been classified based on the SAR image texture and the MLPNN classifier. We also
evaluate the biomass for two classes based on the allometric equation (1) for the classic method based on the ML classifier and the proposed method. The results are shown in Table III, where the classic method and the proposed method have been applied in the classified image to estimate the biomass for two classes.

<table>
<thead>
<tr>
<th>TABLE III</th>
<th>ESTIMATED BIOMASS FOR THE CLASSIC METHOD AND THE PROPOSED METHOD BY BOTH OPTICAL AND SAR DATA.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>The classic method</td>
</tr>
<tr>
<td></td>
<td>Acorn</td>
</tr>
<tr>
<td>Area (ha)</td>
<td>883.217</td>
</tr>
<tr>
<td>Mean height (m)</td>
<td>34</td>
</tr>
<tr>
<td>Mean DBH (cm)</td>
<td>55</td>
</tr>
<tr>
<td># of tree (ha)</td>
<td>34</td>
</tr>
<tr>
<td>Mean biomass (kg/tree)</td>
<td>3272</td>
</tr>
<tr>
<td>Total biomass (tons/ha)</td>
<td>94918.85</td>
</tr>
</tbody>
</table>

For the accuracy assessment of the proposed method, Table IV shows how well the results agree with the ground measurements results from table I, when the classic method and the proposed method are used for biomass estimation. Table IV shows the estimated biomass when both methods are used. The root mean square error (RMSE) of estimated biomass with both methods is indicated in the table. The RMSE values is decreased when the proposed method is used (RMSE=2.175 ton) compared the classic method (RMSE=5.34 ton).

<table>
<thead>
<tr>
<th>TABLE IV</th>
<th>ACCURACY ASSESSMENT FOR THE CLASSIC METHOD AND THE PROPOSED METHOD USING THE GROUND MEASUREMENTS FROM TABLE I.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>The classic method</td>
</tr>
<tr>
<td></td>
<td>Estimated biomass (ton) for Acorn</td>
</tr>
<tr>
<td>Plot 1</td>
<td>25.712</td>
</tr>
<tr>
<td>Plot 2</td>
<td>25.960</td>
</tr>
<tr>
<td>Plot 3</td>
<td>25.584</td>
</tr>
<tr>
<td>Plot 4</td>
<td>26.558</td>
</tr>
<tr>
<td>Plot 5</td>
<td>14.238</td>
</tr>
<tr>
<td>RMSE</td>
<td>4.71</td>
</tr>
<tr>
<td>Mean RMSE</td>
<td>3.34</td>
</tr>
</tbody>
</table>

From the above paragraphs, the accuracy of the proposed method is better than, or comparable to, the classic method used for biomass estimation. We conclude using both optical image and SAR image texture in a non-linear classifier method, neural network, significantly improve the accuracy of the forest biomass estimation.

V. DISCUSSION

It is often difficult to transfer one model developed in a specific study area to other study areas because of the limitation of the model itself and the nature of remotely sensed data. Foody et al. [5] discussed the problems encountered in model transfer. Many factors, such as uncertainties in the remotely sensed data (image preprocessing and different stages of processing), AGB calculation based on the field measurements, the disparity between remote sensing acquisition date and field data collection, and the size of sample plot compared with the spatial resolution of remotely sensed data, could affect the success of model transferability. Each model has its limitation and optimal scale for implementation. Models developed in one study area may be transferred to (1) across-scene data, which have similar environmental conditions and landscape complexity, to estimate AGB in a large area; and (2) multi-temporal data of the same study area for AGB dynamical analysis if the atmospheric calibration is accurately implemented. The spectral signatures, vegetation indices, and textures are often dependent on the image scale and environmental conditions. Caution must be taken to ensure that there is consistency between the images used in scale, atmospheric and environmental conditions. Calibration and validation of the estimated results may be necessary using reference data when using transferred models.

The data sources used for AGB estimation may include field-measured sample data, remotely sensed data, and ancillary data. A high-quality sample dataset is a prerequisite for developing AGB estimation models as well as for validation or assessment of the estimated results. Direct measurement of AGB in the field is very difficult. In general, AGB is calculated using the allometric equations based on measured DBH and/or height, or from the conversion of forest stocking volume. These methods generate many uncertainties and calibration or validation of the calculated AGB is necessary. Previous research has discussed the uncertainties of using the allometric equations [39], [70], [41] [42] and of conversion from stocking volume [38]. It is important to ensure that the remote sensing data, ancillary data, and sample plots are accurately registered when ancillary data are used for AGB estimation. Understanding and identifying the sources of uncertainties and then devoting efforts to improving them are keys to a successful AGB estimation. More research is needed in the future for reducing the uncertainties from different sources in the AGB estimation procedure. Many remote sensing variables, including spectral signatures, vegetation indices, transformed images, and textures, may become potential variables for AGB estimation. However, not all variables are required because some are weakly related to AGB or they have high correlation with each other. Hence, selection of the most suitable variables is a critical step for developing an AGB estimation model. In general, vegetation indices can partially reduce the impacts on reflectance caused by environmental conditions and shadows, thus improving correlation between AGB and vegetation indices, especially in those sites with complex vegetation stand structures [43]. On the other hand, texture is an important variable for improving AGB estimation performance. One critical step is to identify suitable textures that are strongly related to AGB but are weakly related to each other. However, selection of suitable textures for AGB estimation is still a challenging task because textures vary with the characteristics of the landscape under investigation and images used. Identifying suitable textures involves the determination of appropriate texture measures, moving window sizes, image bands, and so on [3]. Not all texture measures can effectively extract biomass information. Even for the same texture measure, selecting an appropriate window size and image band is crucial. A small window size, such as 3x3, often exaggerates the difference within the moving windows, increasing the noise content on the texture image. On the other hand, too large a window size, such as 11x11 or
larger, cannot effectively extract texture information due to smoothing the textural variation too much. Also, a large window size implies more processing time. In practice, it is still difficult to identify which texture measures, window sizes, and image bands are best suited to a specific research topic and there is a lack of guidelines on how to select an appropriate texture. More research is needed to develop suitable techniques for identification of the most suitable textures for biomass estimation.

In addition to remotely sensed above ground biomass estimation in data, different soil conditions, terrain factors, and climatic conditions may influence AGB estimation because they affect AGB accumulation rates and development of forest stand structures. Incorporation of these ancillary data and remote sensing data may improve AGB estimation performance. Geographical Information System (GIS) techniques can be useful in developing advanced models through the combination of remote sensing and ancillary data.

VI. CONCLUSION

In this paper, we proposed a novel method for forest biomass estimation. One speckle noise model was used for reducing the speckle noise in SAR images. The proposed filter was slightly better than the commonly used filters in terms of preserving details in forestry areas. A combination of spectral responses from optical images and textures from SAR images improved biomass estimation performance comparing pure spectral responses or textures. Intensity values of ALOS–AVNIR-2 and PRISM images and texture features of JERS-1 image were used in a multilayer perceptron neural network (MLPNN) that relates them to the forest variable measurements on the ground. We showed the biomass estimation accuracy was significantly improved when MLPNN was used in comparison to estimating the biomass by using classic method only. The RMSE values were decreased when the proposed method was used (RMSE=2.175 ton) compared the classic method (RMSE=5.34 ton).

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