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SURFACE TEMPERATURE ESTIMATION USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT:

This research presents an alternative method to extrapolation land Surface Temperature (ST) through artificial neural network, using positional variables (UTM coordinates and altitude), temperature and air relative humidity. The study region was the Rio dos Sinos Hydrographic Basin (BHRS), in Rio Grande do Sul state, Brazil. For training the neural network was used a thermal image from NOAA satellite, with pixel size of 1X1 km, with known ST information referring to 12/06/2003. After training many network sets were done and one of them with the best performance and composed by a single intermediate layer (with 4 neurons and logistic sigmoid activation function) was selected. The training network was tested inside the BHRS where were collected 60 points of ST values supported by a portable laser sensor on date 3/18/2008. The average error provided by this model for ST measurement was 2.2ºC and through executed statistical tests was possible to verify that not exist variation between average ST values accepted as true and the values provided by the neural model with a significance level of 5%.

1. INTRODUCTION

Artificial Neural Networks (ANN) are organized and interconnected collections of processing units (neurons or nodes), whose operation is analogue to a neural structure of intelligence organisms (Müller and Fill, 2003). ANN extract its computational power from its solid parallel distribution structure and ability to learn/generalize, allowing the resolution of complex propositions in many knowledge areas (Haykin, 2001).

ANN execution is inspired on human brain (Haykin, 2001) and has been used in many applications with success. In agreement with Galvão et al. (1999), by the reason of its nonlinear structure the ANN can acquire more complex data characteristics, which are not always possible using traditional statistical techniques.

According to Müller and Fill (2003), conventional methods don't have the necessity to know the problem intrinsic theory and also don't need to analyze relations that aren't totally known between involved variables in modeling, so ANNs have a greater advantage over them.

Surface Temperature (ST) is established by a fenologic parameter that is significantly influenced by climate variations and is an indicator of plants hydrous state. Therefore its estimation has a large utility to surveys that need to assure the observation of hydrous culture demand, contributing in a significative way the irrigation programs (Silva, 2007).

Currently a mostly used method to ST estimation is through the use of thermal satellite images. Rivas (2004) recommends the use of NOAAAVHRR (National Oceanic Atmospheric Administration/Advanced Very High Resolution Radiometer) images adapted to split windows equation to estimate ST values. Such modeling connects emissivity variables and atmospherical data. Is a complex method because beyond it processes not simple statistical models, it has the necessity to work with digital images in the emissivity determination process.

So is much important to have methods of ST estimation in a more convenient way as, for example, the combination of temperature, air relative humidity and geographical data position (Veronez et al., 2006).

Some authors realized researches using ANNs with the finality of ST estimation based on climate elements (Yang et al., 1997; Atluri et al., 1999; George, 2001; Veronez et al., 2006; Mao & Shi, 2008), where all of them have found satisfactory results.

Yang (1997) describe the importance to develope a model capable to assist agricultural processes, once that ST estimation in distinct depths is complex due its large number of involved variables. The author have used as ANN input the following variables: daily precipitation, evapotranspiration, air maximun and minimun temperature and days of year, been all these information easy to obtain on meteorological station.

Atluri (1999) has modeled through ANNs the humidity and soil ST with the Levemberg-Marquardt algorithm and after many tests he obtained an accuracy estimation of 98.7% with these variables. The same author describes the importance to establish an efficient system to extrapolate such information, once that these variables are required by distinct geosciences areas.

George (2003) describes the importance of usage ANNs to estimate soil surface temperature using easy access data. Thinking on it Veronez et al. (2006) proposed the ANN usage to model such variable using only positional information (East and North UTM coordinates), altitude and air average temperature. The network was established through a supervised training, where ST information was extracted from NOAA satellite images.

The results found by Veronez et al. (2006) show that is possible to extrapolate ST values on distinct periods from NOAA image processing date using as ANN input a variable that changes with the time. For the specific case of this research the used variable was air average temperature. The ST processing was based on NOAA satellite image with a surface coverage from 6/12/2003. ST values were extrapolated on 10/8/2005 and the model validation was accomplished in a municipality urban area located on Rio dos Sinos Hydrographic Basin (BHRS). The authors collected ST information with a laser thermometer and compared them with values provided by ANN, having an average error less than 2.3ºC.

Although some researches aim to simplify the input data on ST estimation process, is understood that exist another options to be learned using climate data associated with thermal images. So the purpose of this research was propose an ANN aiming to extrapolate values of ST during a period of time taking as modeling variables only altitude, position and air average temperature. For ANN supervised training was used ST information from processing NOAA thermal image with a surface coverage from 6/12/2003. The research was developed on BHRS and its validation was executed inside the Vale do Rio dos Sinos University campus where was collected ST information with a laser thermometer on 3/18/2008.

2. MATERIALS AND METHODS

2.1 Study area

This research was based on Rio dos Sinos Hydrographic Basin located on Rio Grande do Sul state as ilustrated on Figure 1. In this same figure the Vale do Rio dos Sinos University campus located in São Leopoldo city is emphasized because sample points for model validation process were taken from this location.

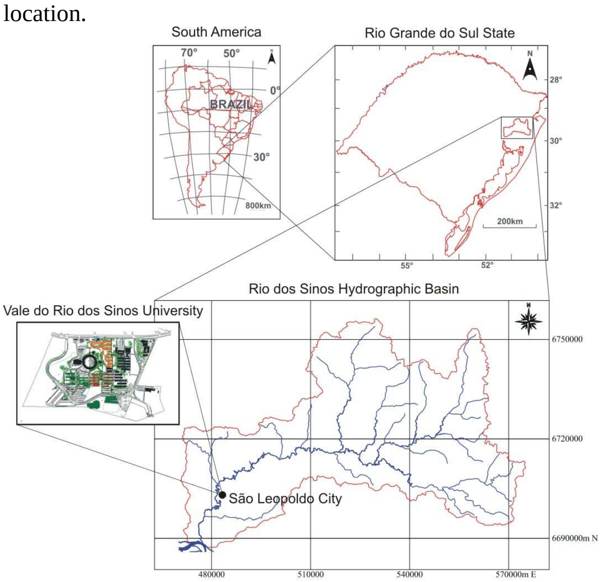

Figure 1. Study area location

2.2 ST obtainment for neural network training

As first stage the NOAA/AVHRR image with a surface coverage from 6/12/2003 and pixel size of 1X1 km was radiometrically and geometrically corrected. The radiometric correction was obtained through radiancebased
procedure developed by NOAA (Kidwell, 1998). So the digital number values (DN) were converted in radiance and after in reflectance for channels 1 (0.58-0.68 lm) and 2 (0.725-1.10 lm) and in brightness temperatures for thermal channels 4 (10.3-11.3 lm) and 5 (11.5-12.5 lm).
The equation that transformed the digital number registered by sensor in radiance – for a given channel j centered in a determinate number of wave v – is given by equation 1:

$$B_{j(v)} = S_{j(v)} \cdot DN + I_{j(v)} \tag{1}$$

where: Bj(v) correspond to radiance (mW/sr m2 cm-1);
Sj(v) correspond to angular coefficient from calibration equation for channel j (mW/m2 sr cm-1);
• DN correspond to digital number from image;
• Ij(v) correspond to linear coefficient from calibration equation for channel j (mW/m2 sr cm-1).

The coefficients from calibration equation have information relative to sensor answer function in a determinate channel. More details about these coefficients can be found on user guide on polar orbit data from NOAA (Kidwell, 1998).
Due the linearity deficiency from AVHRR sensor answer, became necessary to execute radiance corrections obtained by equation 2, in the following way:

$$B_{j(v)corr} = A_j . B_{j(v)} + B_j . B_{j(v)}^{2} + D_j \tag{2}$$

where: Bj(v)corr correspond to corrected radiance (mW/sr m2 cm-1);
• Aj, Bj and Dj correspond to correction coefficients for a determinate channel j, due the linearity deficiency from AVHRR sensor.

The coefficients Aj, Bj and Dj, in the case of NOAA-14 satellite, assume values equal to 0.92378; 0.0003822 and 3.72, respectively, for channel 4 from AVHRR.
For channel 5 these values are equal to 0.96194; 0.0001742 and 2.00, respectively. The radiance conversion from brightness temperature to a given temperature strip (265 to 320K) is given by equation 3:

$$T_{bj} = \frac{1,438833 \cdot v_j}{\ln\left(\frac{1 + 1,1910659 \ \mathrm{x}\ 10^{-5} \cdot v_j^{\,3}}{B_{j(v)corr}}\right)_j} \tag{3}$$

where: Tbj correspond to brightness temperature on channel j;
• Vj correspond to wave number on channel j;
• Bj(v)corr correspond to corrected radiance according to equation 2.

The channels 4 and 5 were used to calculate the surface temperature applying the split-window algorithm approached by Czajkowski et al. (1998). Many split-window algorithms were developed to estimate surface temperature by authors that use information from AVHRR sensor (Dash et al., 2002): AVHRR on NOAA-7 (Preço, 1984), AVHRR on NOAA-9 (Becker and Li, 1990), AVHRR on NOAA-11 (Sobrino et al., 1991), etc. The filter functions for channels 4 and 5 from AVHRR lightly differ from each sensor of NOAA satellite series, been necessary different coefficients to the split-window model. This fact can conduct to a considerable error of surface temperature estimation with approximately 2.3 K (Czajkowski et al., 1998).
An incorrect calibration can generate an error of 0.3 K on surface temperature determination (Cooper and Asrar, 1989) and the variation on surface emissivity (approximately 0.2%) can provide and error of 1 K (Ottle and Vidal-Madjar, 1992). Using the algorithm proposed by Czajkowski et al. (1998) with coefficients from split-window model for NOAA-14/AVHRR satellite, the ST was determined in the following way:

$$T_s = 5,54 + T_4 + 2,08 \cdot (T_4 - T_5) \tag{4}$$

where: ST correspond to surface temperature;
• T4 and T5 correspond to brightness temperature of channels 4 and 5 from AVHRR, both in degrees Kelvin.

Following the NOAA/AVHRR satellite image was georeferenced on UTM projection system (Universal Transverse Mercator) using 15 control points on terrain and rectified with an average quadratic error of approximately 1 pixel. The processing image from study area wasn't polluted by clouds. Figure 2 illustrates the processing image with ST values.

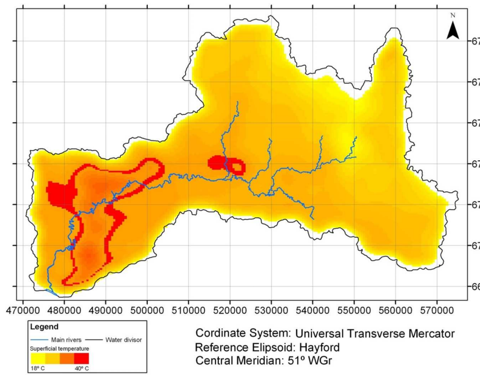

Figure 2. NOAA image processed with ST information from 6/12/2003 on Rio dos Sinos Hydrographic Basin

With the processing and georeferencing image was possible to put over it a digital elevation model obtained from isolines at vertical equidistant of 20m and georeferenced on Torres vertical datum. Next, for each pixel centroid was obtained the following information: east and north UTM coordinates, altitude and ST.

2.3 Proposed neural network structure

The ANN was structured on multilayer perceptron (MLP), whose algorithm principle is based on errorcorrection learning. When a pattern is presented to the network for the first time, it produces a random output. The difference between this output and the intended compose the error, that is calculated by the self algorithm. The backpropagation algorithm makes that the weights from output layer been the first to be adjusted and after the weights from residual layers, correcting them from back to front, with the objective of reduce the error. This process is repeated during the learning until the error become acceptable (Silva et al., 2004).
The neurons utilized in the ANN were set based on the model proposed by Haykin (2001), as show the Figure 3. In the synaptic weights (Wkj) the k index refer to the neuron in question while the j index report to the synapse input signal which weight has relation. The function of the weight is multiply the synapse input signal connected to the neuron. ANNs can also present additional weights, called "bias", that have the role in preventing error generation when all input data are null, because so the matrix of weights don't suffer modifications in the training. Activation function is a function of internal order, been a decision made by self neuron over what do with the resultant value from the sum of pondered inputs. Transference function is a function of output or logic threshold. It controls the activation intensity to obtain the wanted performance from network.

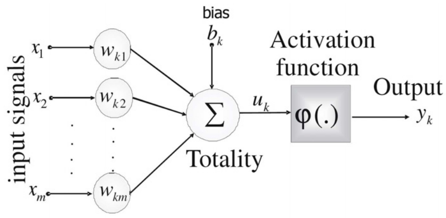

Figure 3. Artificial neuron structure utilized on ANN. Adapted from Haykin (2001)

Mathematically, Figure 3 can be expressed in equations 5, 6 and 7.

$$u_k = \sum_{j=1}^{n} \left(w_{k,j} \cdot x_j \right) \tag{5}$$

$$\upsilon_k = u_k + b_k \tag{6}$$

$$y_k = \varphi(\upsilon_k) \tag{7}$$

where: uk is the output from linear combinator (additive junction);
- wk,j are the synaptic weights;
- Xj are the input variables;
- is the activation potential;
- b it the bias;
- yk is the output signal of k neuron;
- is the activation function.

For the network was used a supervised training through the Levemberg-Maquardt algorithm, which used the Newton method that applies the minimum approximation for error function (Haykin, 2001). In this case, ANN was trained through pairs of input and output presentations, in others words, for each input provided for network exist an expected output that is also provided for the training. The network produces an output answer where it self is compared with the expected output (that was provided). The difference between network answer and expected answer (known), generate a residue (error). This obtained error is used to calculate the necessary adjust for synaptic weights from network, that will be corrected until the network answer coincide with expected output. Such is the minimization error process (Haykin, 2001).
Continue talking about this learning type (Haykin, 2001), the necessary calculations to minimize the error are important and related to utilized algorithm, like on backpropagation, for example, where the consider parameters as interactions number by input pattern are used to get the minimum error value on training (network capability to escape from local minimums).
Equation 8 shows the error function (MSE – Mean Squared Error) that will be minimized on training step:

$$MSE = \frac{\sum_{j=1}^{n} \left(d_j - y_j \right)^2}{n} \tag{8}$$

where:
- dj is the expected output value from ANN;
- yj is the obtained output value;

With the objective to select an ANN that could supply a better performance, were realized many tests, modifying the number of intermediate layers, the number of neurons per layer and the activation function, enable the selection of the best ANN for ST estimation.
The ANN variables from input and output layers were normalized inside the interval [0-1].

2.4 Results analysis

ANN was trained by information extracted from processing NOAA thermal satellite image with a surface coverage from 6/12/2003. Its pixel size of 1X1 Km provided a quantity of 3737 points for the training process. The existing meteorological stations on BHRS enabled the temperature and averages of air relative humidity obtainment from satellite image period.
To test the proposed model were collected in field ST information with a laser thermometer on 3/18/2008. With the assistance of a GPS receiver model Trimble Pocket were obtained the UTM coordinates (SIRGAS) for ST sample points. Temperature and averages of air relative humidity were taken

from a meteorological station located inside the test area. The test was made inside Vale do Rio dos Sinos (UNISINOS) campus situated on São Leopoldo/RS city. The sample points for test were located on places with vegetation, concrete and asphalt paving.
Each collected point had the necessary information to be inserted in the trained neural model (UTM coordinates, altitude, temperature and averages of air relative humidity). The model supplied for each point a ST value that was compared with the value obtained in field by laser thermometer.
The statistical analysis used on research results presentation were based on a comparison between ST values modeled through ANN and ST values considered true by obtainment by a laser thermometer. Were used the statistical t-student test and coefficient of determination (R^2) analysis with linear regression.
Being x the size of certain elements attribute from an A population (ST modeled by ANN);
Being y the size of the same elements attribute from a B population (ST obtained by laser thermometer);
Being x and y ordinarily distributed with unknown variances;
Being the hypothesis: $\mu x = \mu y$ which μx = average of x and μy = average of y.
For testing the hypothesis of averages equality from the two populations was utilized the t test, but for that was necessary to initially test if the two populations presented equal variances using the F test from Fischer:

$$F = \frac{SQD_x}{SQD_y} \tag{09}$$

$$s_x^2 = \frac{SQD_x}{(n_x - 1)} \tag{10}$$

$$s_y^2 = \frac{SQD_y}{(n_y - 1)} \tag{11}$$

$$F_{calculated} = \frac{s_x^2}{s_y^2} \tag{12}$$

where: SQDx and SQDy correspond, respectively, to the sums of square deviations from x and y;
and correspond, respectively, to sample variances from x and y;
nx and ny correspond, respectively, to the number of variables from x and y.

The tested hypothesis (H0) was that the population variance from x is equal to the population variance from y. If Prob > F is less than 5% then H0 is accepted. If Prob > F is bigger than 5% then H0 is refused. If the population variances were statistically equals, then a common variance is calculated ( ):

$$s_c^2 = \frac{(SQD_x + SQD_y)}{[(n_x - 1) + (n_y - 1)]} \tag{13}$$

$$s_c^2 = \frac{[(s_x^2 \cdot (n_x - 1)) + (s_y^2 \cdot (n_y - 1))]}{[(n_x - 1) + (n_y - 1)]} \tag{14}$$

Afterward was tested the H0 for population average equality using the t random variable, defined by:

$$t = \frac{\mu_x - \mu_y}{\sqrt{v \cdot (\mu_x - \mu_y)}} \tag{15}$$

Being:

$$v \cdot (\mu_x - \mu_y) = v(\mu_x) + v(\mu_y) = \frac{s_x^2}{n_x} + \frac{s_y^2}{n_y} \tag{16}$$

where: v correspond to the average variance.

Accepting $s_x^2 = s_y^2 = s_c^2$ there are:

$$v \cdot (\mu_x - \mu_y) = \frac{s_c^2}{n_x} + \frac{s_c^2}{n_y} = s_c^2 \cdot \left(\frac{1}{n_x} + \frac{1}{n_y}\right) \tag{17}$$

$$t = \frac{\mu_x - \mu_y}{\sqrt{s_c^2 \cdot \left(\frac{1}{n_x} + \frac{1}{n_y}\right)}} \tag{18}$$

In degrees of freedom (*n*) = $(n_x + n_y - 2)$ (19)

In case of different variances there are:

$$t = \frac{\mu_x - \mu_y}{\sqrt{\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}}} \tag{20}$$

The degree of freedom is calculated with the following equation:

$$n = \frac{\left(\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}\right)^2}{\frac{\left(\frac{s_x^2}{n_x}\right)^2}{n_x - 1} + \frac{\left(\frac{s_y^2}{n_y}\right)^2}{n_y - 1}} \tag{21}$$

3. RESULTS AND DISCUSSIONS

The ANN that presented the best performance was composed with an input layer (5 variables), an intermediate layer (with 4 neurons) and an output layer (with one neuron), as show on Figure 4. The fact that the selected network, with the best performance, has only one intermediate layer, is in accord with the results found by Kumar et al. (2002) and Zanetti et al. (2008), because these authors have modeled the evapotranspiration and concluded that an ANN with only one intermediate layer was sufficient to represent a nonlinear relation between the climatic elements and the modeled variable.

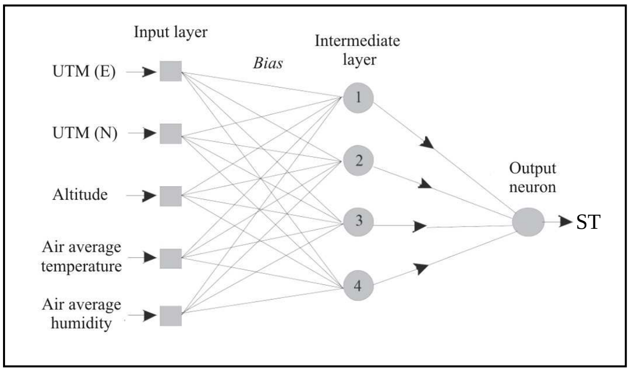

Figure 4. Neural network structure used on ST modeling

The activation function utilized was the logistic sigmoid and the number of training cycles was 600.
On Figure 5 is presented the modeled ST values (maximum of 54 ºC, minimum of 19.1 ºC and average of 39.18 ºC) and the known ones (maximum of 54 ºC, minimum of 25 ºC and average of 37.39 ºC) where is possible to verify a similar behavior between the two curves. In terms of discrepancy between the modules of ST values the model afforded an average value of 2.2 ºC with a standard deviation around 1.4 ºC.
If we analyze the obtainment of ST values through processing thermal images associated with the Split Window algorithm, which its average error is 1.5 ºC (Coll and Caselles, 1997), and if we compare with the results found on this research, is possible to ascertain that the method can be an efficient way to obtain the ST. A great advantage of this method is its capability to generate ST values based only on climatic and positional variables that have easy access.

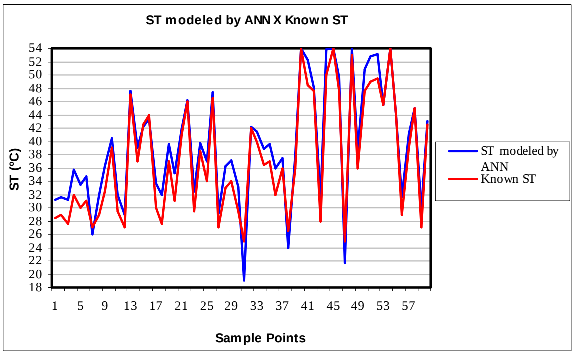

Figure 5. Graph of comparison between ST modeled by ANN and Known ST.

On regression analysis (Figure 6) was verified a strong correlation between modeled and known ST values (R^2 = 0.948) given efficiency evidences of ST extrapolation process on proposed ANN.

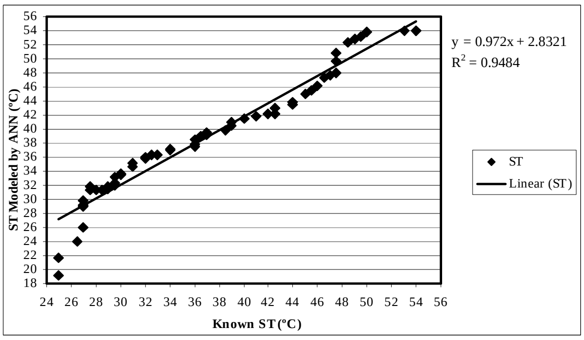

Figure 6. Linear regression between ST values modeled by ANN and Known

Beyond the regression analysis was implemented a test of hypothesis to verify if the proposed model is statistically equal to the one taken as real.
For a significance level of 5%, through the t-student test was evaluated the equality from the two averages (M1 e M2).The tested hypothesis was H0: M1 = M2 e H1: M1 ≠ M2. In this case, if Prob > t was less than 0.05 the hypothesis would be rejected and then M1 would be different from M2. Table 1 shows the results from accomplished statistical test.

Table 1. Statistic indexes between ST values obtained by ANN and taken as real (M1= real values and M2= simulated values)

M	N	Average	Standard deviation	Variance	*t*	Degree of freedom	Prob >(*t*)
1	60	37.39	8.68	Unequal	-1.1276	118.0	0.2618
2	60	39.18	8.66	Equal	-1.1276	118.0	0.2618

For H_0: variances are equals, F′= 1.00
Prob > F′= 0.9898
Level of significance = 5%
H_0: $M_1 = M_2$ H_1: $M_1 \neq M_2$

Analyzing Table 1 and comparing the values of real and modeled temperature with application of t test for independent samples was found that the averages are statistically equals. Therefore the modeling by ANN was capable to calculate ST values that driven to an average value equal to the mean of values measured in field with a level of significance of 5%.

4. CONCLUSIONS

This research proposed a method to extrapolate ST values for the Rio dos Sinos Hydrographic Basin/RS, based on an ANN that was trained in a supervised way through a NOAA thermal satellite image from 6/12/2003, using on it the split window algorithm. The involved variables were positional (UTM coordinates and altitude) and climatic information (temperature and air relative humidity). The model was tested through an experiment realized on 3/18/2008 inside the Vale do Rio dos Sinos University campus. Seeing the average error (2.2 ºC) and the maximum error (5.9 ºC), the conclusion that the ANN is suitable for simulation will depend on the application of itself. If the associated errors for each observation didn't were relevant for practice finalities, then could be concluded that network rightly simulates the temperature values.
New experiments have been realized in direction of better evaluations for ANN efficiency on the process to determinate ST values based on variables of easy obtainment.

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