Spatial Refinement of MODIS Land Surface Temperature from 1,000 m to 90 m Using Machine Learning

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Abstract

The spatiotemporal trade-off associated with satellite-derived datasets necessitates the downscaling of Land Surface Temperature (LST) to understand temperature dynamics and related phenomena at a finer level. This study employs a Support Vector Regression (SVR) model to enhance the spatial resolution of Moderate Resolution Imaging Spectroradiometer (MODIS) LST from a coarse resolution of 1 kilometer to a finer scale of 90 meters over an approximately 2,500 km^2 area in Haryana, India. The model was trained on datasets from three distinct dates representing three different months (March, April, and May) to refine the MODIS LST and assess its predictive capability. The results demonstrated the model's strong downscaling efficacy with high Coefficient of Determination (R^2) and low Root Mean Square Error (RMSE) values, indicating the feasibility of learning cross-scale relationships.

Keywords: Spatiotemporal trade-off, downscaling, land surface temperature, support vector regression, MODIS, Landsat, spatial resolution.

1. Introduction

High-resolution LST is frequently required to analyze temperature dynamics across different land surface types. However, trade-offs between spatial and temporal resolutions across different satellite sensors present inadequacy for comprehensive mapping of LST over large areas. For instance, the Landsat 8 Thermal Infrared Sensor (TIRS) provides a spatial resolution of 100 m (resampled to 30 m) but has a 16-day revisit interval (temporal resolution), while the MODIS provides images daily but at a coarser spatial resolution of 1 km. This presents challenges in understanding LST dynamics at greater spatial detail and frequency. Thus, integrating multi-source remote sensing data to address and resolve this trade-off has become an important area of research in fine-resolution LST retrieval and its applications.

Traditionally, researchers have employed statistical downscaling, or "thermal sharpening," techniques to enhance the spatial resolution of LST data. These approaches exploit the relationships between LST and a single contributing factor. A foundational method, DisTrad, established an inverse linear relationship between LST and the Normalized Difference Vegetation Index (NDVI) to downscale thermal data (Kustas et al., 2003). Based on this principle, the Thermal Sharpening (TsHARP) algorithm was developed that used Fractional Vegetation Cover (FVC) as the basis for regression, physically augmenting the thermal representativeness of the land surface (Agam et al., 2007). Further studies were conducted to refine LST by drawing correlations between LST and various land use/land cover (LULC) types in heterogeneous environments (Essa et al., 2012). More advanced algorithms like the Spatio-Temporal Adaptive Data Fusion Algorithm for Temperature Mapping (SADFAT) were later proposed, that considered temporal changes in LST and land surface variability (Weng, Fu & Gao, 2014). Incorporating multiple ancillary variables generally yields better downscaling efficiency than the models relying on a single variable. Accordingly, this study uses an extensive set of ten important LST-influencing variables to downscale MODIS LST to 90 meters using an SVR model.

While a single variable such as NDVI is a powerful predictor, it often fails to fully explain LST variations in areas with diverse physical and environmental characteristics. This advanced the domain of traditional statistical methods towards multi-variable models to improve downscaling accuracy. Several studies demonstrated that combining NDVI with a Digital Elevation Model (DEM) significantly improved results by accounting for the topography-driven cooling effect

(Hutengs & Vohland, 2016). For urban settings, studies successfully utilized relevant built-up indices alongside the popular vegetation indices to better account for the surface's unique spatial characteristics that exhibit distinct thermal properties (Deng & Wu, 2013). Inclusion of ancillary data led to the development of more comprehensive models that utilized a wide array of physical variables. For example, studies have successfully implemented algorithms using a subset of predictors including NDVI, Enhanced Vegetation Index (EVI), DEM, albedo, surface emissivity, slope, and sky-view factor to achieve downscaling robustness (Zakšek & Oštir, 2012).

The consensus in the literature indicates that incorporating multiple, physically relevant downscaling variables generally yields more accurate results than single-variable approaches. Hence, this study is built on the work done previously by using a comprehensive set of LST-influencing factors, including spectral bands, various vegetation indices, and topographic data from a Digital Elevation Model (DEM). The objective of this study is to downscale MODIS LST from its native 1 km resolution to 90 m using SVR, an effective non-linear machine learning approach in an agriculture-dominated region of Northwestern India across three acquisitions representing three months.

2. Study Area

The study area (**Fig. 1**) covers an almost square patch of approximately 2,500 km^2 in Haryana, India with a geographical extent of 75°49′ to 76°18′ East and 28°53′ to 29°19′ North. The area is a mixed agricultural mosaic, primarily constituting irrigated cropland, fallow fields, and interspersed water bodies. The elevation above mean sea level of the region ranges from 189–382 m with a mean elevation of 217 m. Characterized by an arid to semi-arid climate, the region receives its predominant rainfall between July and September. Based on the Indian Meteorological Department (IMD) data, the summer air temperatures typically vary from a minimum of 25–28 °C to a maximum of 37–45 °C, sporadically soaring up to 50 °C. This study focuses on the March to May period, which spans the crucial transition from the late-Rabi (winter crop) season to the pre-monsoon phase. This temporal span was intentionally chosen as it exhibits dynamic climatic conditions with steeply rising temperatures, heterogeneous irrigation patterns, and vegetation senescence that produce strong and measurable spatial gradients in LST.

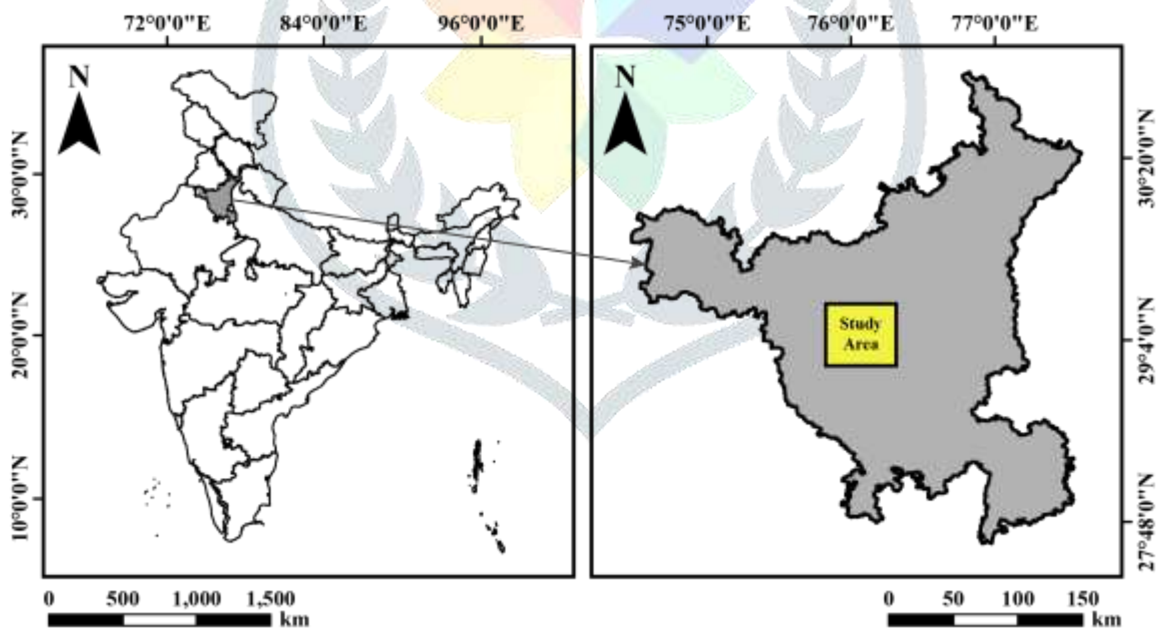

Figure 1 Location of the study area in Haryana, India.

3. Data and Methodology

The study employed a multi-source data integration to enhance spatial resolution of MODIS LST data retrieved over three different dates (**Table 1**) representing three different months (March, April, and May). The independent factors in this study that included surface reflectance, vegetation indices, and DEM were derived from multiple satellite sensors. Surface reflectance bands (Red, Green, Blue, Near Infrared (NIR), Shortwave Infrared 1 (SWIR1), and Shortwave Infrared 2 (SWIR2)) at 500-meter spatial resolution were retrieved from the MODIS sensor (product MOD09GA) onboard NASA's Terra satellite. The vegetation indices NDVI, Normalized Difference Water Index (NDWI), and Normalized Difference Built-up Index (NDBI) (**Equations 3.1–3.3**) were derived from the respective surface reflectance bands. The DEM data at 30 m was retrieved from the collection NASA/NASADEM_HGT/001 and eventually clipped to the area of interest. Landsat 8 LST data at 90 m was processed using the Mono Window algorithm to account for the target variable. All the independent variables were resampled to 90 m using bilinear interpolation for spatial compatibility with the target variable. MODIS and Landsat 8 data were selected from the exact dates across the three months for validation of the downscaling from the trained model.

$$NDVI = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{3.1}$$

$$NDWI = \frac{\mathrm{Green} - \mathrm{NIR}}{\mathrm{Green} + \mathrm{NIR}} \tag{3.2}$$

$$NDBI = \frac{\mathrm{SWIR1} - \mathrm{NIR}}{\mathrm{SWIR1} + \mathrm{NIR}} \tag{3.3}$$

Table 1 Acquisition dates and product IDs.

Month	Landsat 8 TIRS		MODIS	
	Date	Landsat Scene ID	Date	MOD09GA ID
March	2015.03.23	LANDSAT/LC08/C02/T1_L2/LC08_147040_20150323	2015.03.23	MODIS/061/MOD09GA/2015_03_23
April	2015.04.24	LANDSAT/LC08/C02/T1_L2/LC08_147040_20150424	2015.04.24	MODIS/061/MOD09GA/2015_04_24
May	2015.05.26	LANDSAT/LC08/C02/T1_L2/LC08_147040_20150526	2015.05.26	MODIS/061/MOD09GA/2015_05_26

The downscaling methodology (**Fig. 2**) used SVR with a Radial Basis Function (RBF) kernel to derive fine-resolution LST. SVR is a powerful machine learning technique derived from the foundational concepts of Support Vector Machines (SVM) developed by Vladimir Vapnik and his colleagues (Cortes & Vapnik, 1995). While SVMs are used for classification, SVR is adapted for regression tasks, making it ideal for predicting continuous values like temperature. The model was trained on 70% of the data and tested on the remaining 30% to assess the model performance on new unseen data for assessing the downscaling efficacy of the trained model. The following metrics (**Equations 3.4–3.6**) were used to evaluate the downscaling performance of the trained model on the 30% of the test data. The trained model was eventually applied to the complete region of interest to generate the downscaled spatial LST maps (**Fig. 5**). A summary of the datasets used in this study has been presented in **Table 2**.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|LST_{a,i} - LST_{p,i}\right| \tag{3.4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(LST_{a,i} - LST_{p,i}\right)^2} \tag{3.5}$$

Here, $LST_{a,i}$ and $LST_{p,i}$ are actual and predicted LST values for i-th pixel, respectively, and n is the number of pixels.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(LST_{a,i} - LST_{p,i}\right)^2}{\sum_{i=1}^{n}\left(LST_{a,i} - \overline{LST_a}\right)^2} \tag{3.6}$$

Here, $\overline{LST_a}$ is the mean around the actual LST values, and n is the number of pixels.

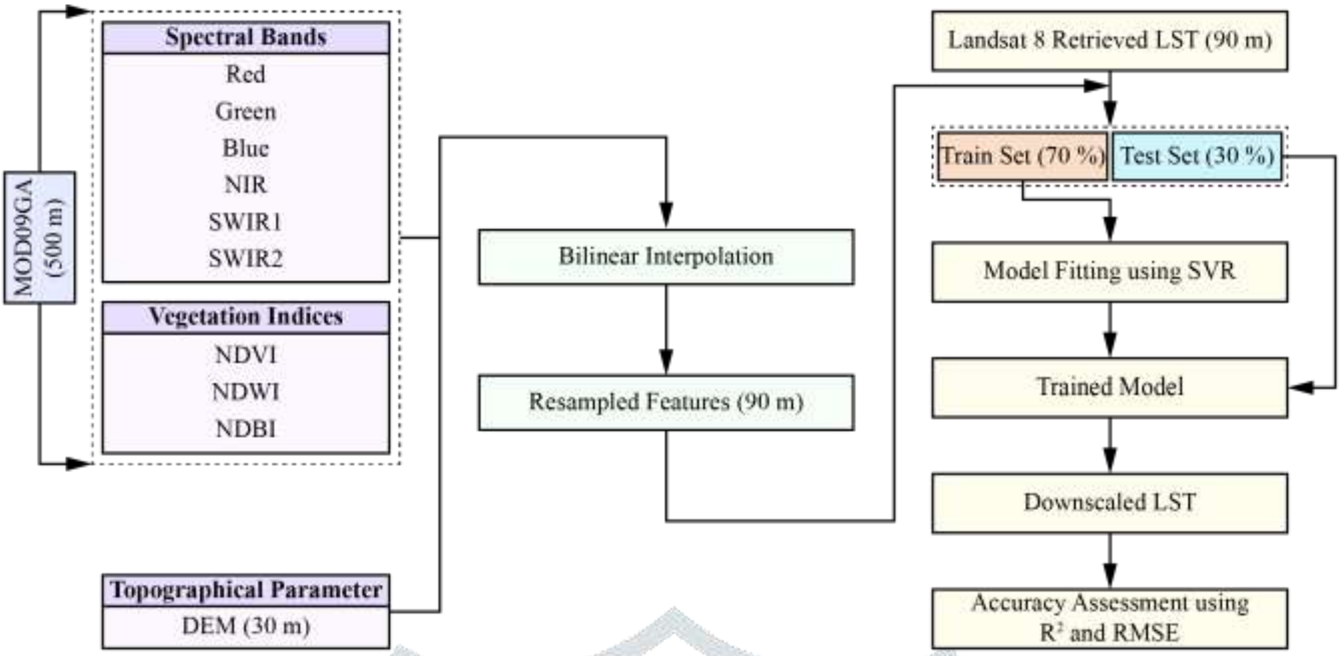

Figure 2 Proposed LST downscaling methodology.

Table 2 Summary of the datasets used in this study.

Dataset	Source	Spatial Resolution	Temporal Resolution	Swath
Land Surface Temperature	MODIS (Terra)	1 km	Daily	2,330 km
	TIRS (Landsat 8)	100 m (resampled to 30 m)	16 days	185 km
Surface Reflectance	MODIS (Terra)	500 m	Daily	2,330 km
Elevation	NASADEM HGT (SRTM-derived DEM)	1 arc-second (~30 m)	N/A	N/A

4. Results and Discussion

The downscaling statistics and performance metrics for the actual and predicted LST on three acquisitions in 2015: March 23, April 24, and May 26, respectively are presented in **Table 3**. In March, the actual LST ranged from 25.70 °C to 40.49 °C with a standard deviation of 4.83, while the predicted LST ranged from 25.93 °C to 40.12 °C with a lower standard deviation of 3.67. The model achieved a Mean Absolute Error (MAE) of 0.76, an RMSE of 1.08, and a Coefficient of Determination (R^2) of 0.76, indicating strong accuracy by explaining 76% of the variance. In April, the actual LST varied from 28.76 °C to 50.07 °C with a standard deviation of 3.88, compared to predicted values ranging from 30.21 to 48.22, and a standard deviation of 2.63. An R^2 of 0.74 was observed in this month indicating slight inefficiency in prediction. The model's performance declined in May with an MAE of 1.15 and RMSE of 1.54 with a 71% variability in prediction. Additionally, the model slightly underpredicts maximum LST across all the months and exhibits lower standard deviations in predictions, indicating the model's weak extrapolation of the actual temperature variances. Overall, the model demonstrated fair predictive accuracy across all dates.

Table 3 Downscaling statistics and performance metrics on the test data.

		Min (°C)	Max (°C)	Standard Deviation (°C)	MAE (°C)	RMSE (°C)	R^2
March (2015.03.23)	Actual LST	25.70	40.49	4.83	0.76	1.08	0.76
	Predicted LST	25.93	40.12	3.67			
April (2015.04.24)	Actual LST	28.76	50.07	3.88	0.85	1.20	0.74
	Predicted LST	30.21	48.22	2.63			
May (2015.05.26)	Actual LST	32.78	51.30	8.91	1.15	1.54	0.71
	Predicted LST	34.49	50.83	6.87			

The test scatterplots (**Fig. 3**) across all the months largely indicate clusters around the 1:1 ideal line, indicating a strong positive correlation and showing that the model successfully captures the overall temperature trends. The spread of the predictions indicates the presence of errors, with the magnitude of these errors varying across the different dates.

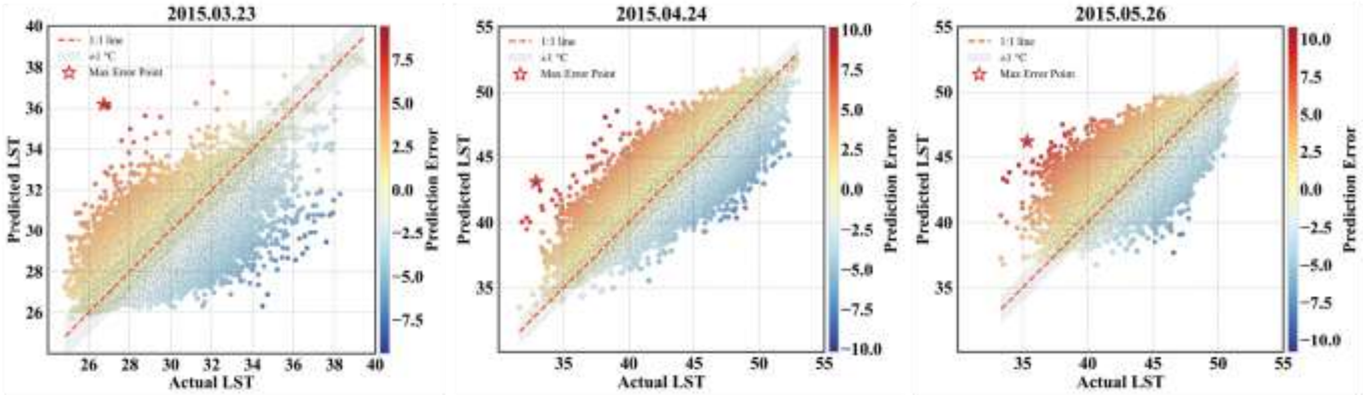

Figure 3 Scatterplots of the predicted refined LST and actual LST on the test data across all acquisitions.

Across all the months, the residuals are symmetrically distributed around the zero mean (**Fig. 4**). The classic bell-shaped distributions indicate that the model has no significant systematic bias. However, the standard deviation of the errors increases progressively from 1.08 in March to 1.53 in May, showing that the model's predictions became less precise and the magnitude of errors grew larger as the season advanced.

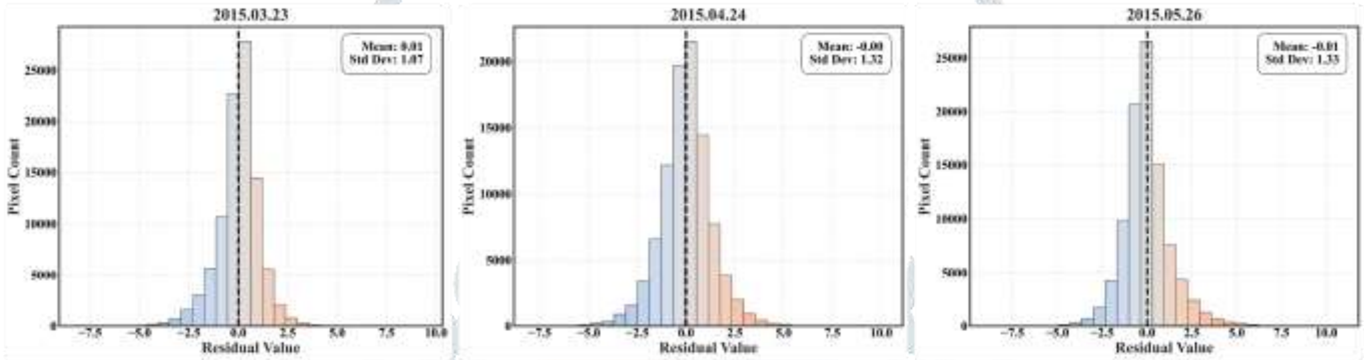

Figure 4 Residual plots of the predicted refined LST on the test data across all acquisitions.

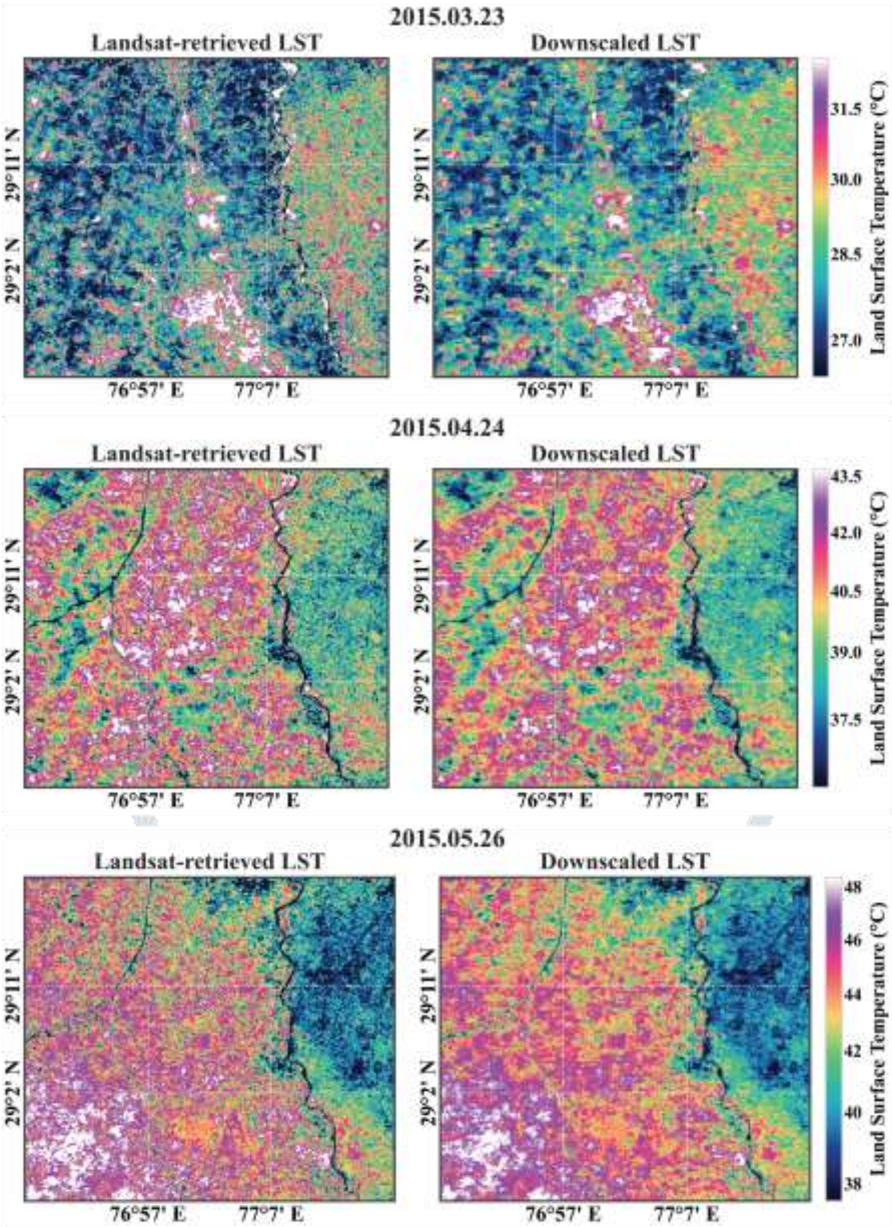

Figure 5 Spatial downscaled LST maps of the entire region of interest across all acquisitions.

5. Conclusion

The study highlights the efficacy of SVR in downscaling MODIS coarse LST and underscores the importance of multiple variables and non-linear regression techniques in enhancing predictive accuracy.

The approach demonstrated here can be extended to other regions with varying surface characteristics to validate and refine the model. Additionally, integrating other downscaling variables and advanced machine learning techniques could further improve the accuracy and reliability of LST predictions, making this model a valuable tool for applications in climate monitoring, urban planning, and environmental management.

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