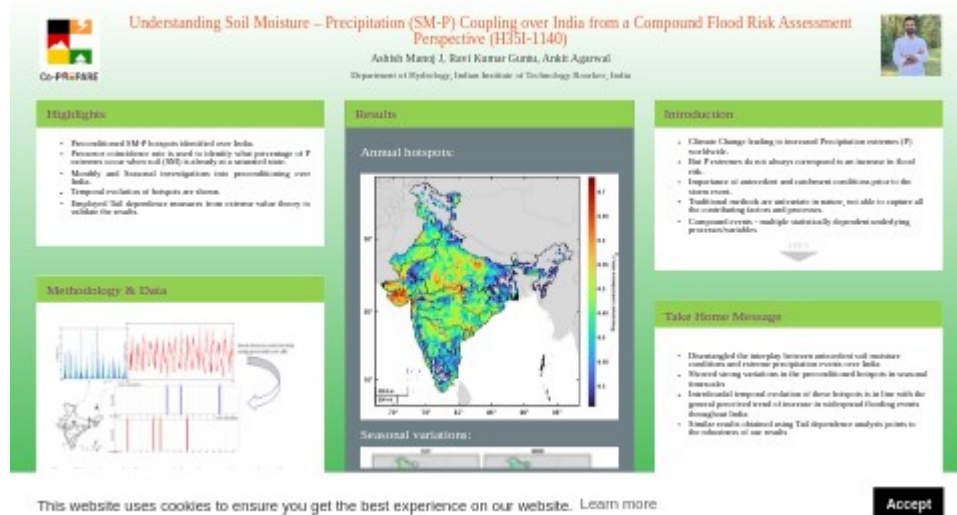
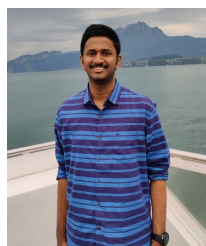


Understanding Soil Moisture – Precipitation (SM-P) Coupling over India from a Compound Flood Risk Assessment Perspective (H35I-1140)



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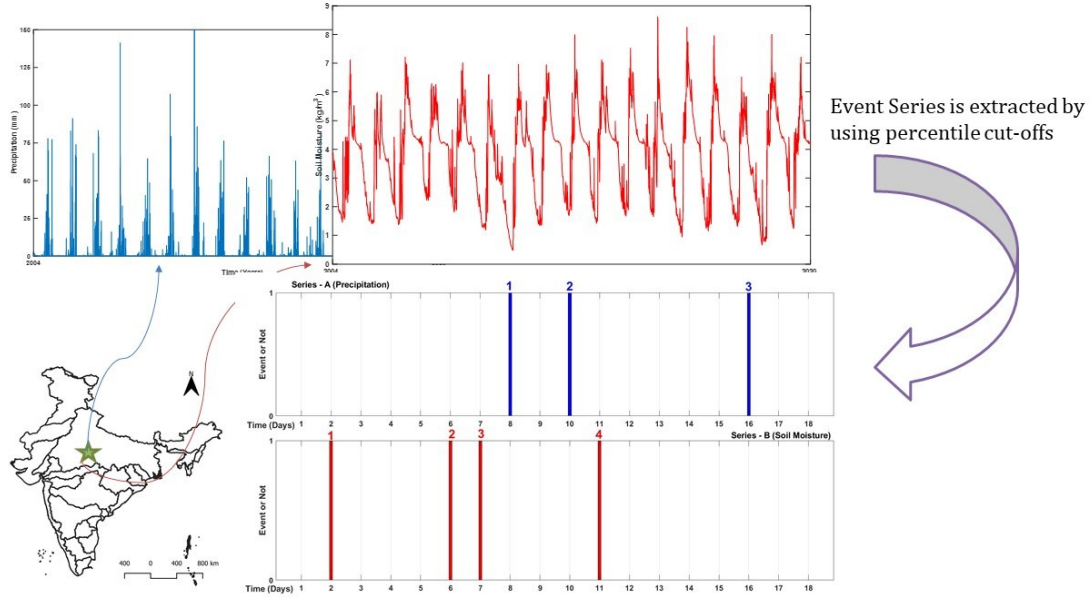
PRESENTED AT:



HIGHLIGHTS

- Preconditioned SM-P hotspots identified over India.
- Precursor coincidence rate is used to identify what percentage of P extremes occur when soil (SM) is already at a saturated state.
- Monthly and Seasonal investigations into preconditioning over India.
- Temporal evolution of hotspots are shown.
- Employed Tail dependence measures from extreme value theory to validate the results.

METHODOLOGY & DATA



Event Coincidence Analysis - event-based approach to evaluate the statistical interdependencies between the phenomena/processes under consideration. (Donges et al., 2016, 2011; Schleussner et al., 2016; Siegmund et al., 2017; Sun et al., 2018)

Precursor coincidence rates are defined as:

$$r_p = \frac{1}{N_A} \sum_{i=1}^{N_A} \mathbf{H} \left(\sum_{j=1}^{N_B} I_{[0, \Delta T]} \left((t_i^A - \tau) - t_j^B \right) \right)$$

The precursor test is, in fact, a retrospective analysis with the condition that P extreme has occurred; the inner summation loop checks whether an SM anomaly was already existing at the site within the prefixed tolerance window, ΔT (taken as 3 days on our case). The lag parameter τ is used to take into account the lagged responses (taken as 0 in our case). Higher values of r_p indicates more fraction of P extremes occurring coincident with SM anomalies and hence higher flood risk. A simple statistical significance test was carried out to ensure that the coincidence reported is not purely random. Statistically insignificant values are masked out using NA for all subsequent plotting and analysis.

Tail dependence is a measure of how similar two variables behave in the tail of their distribution. In the present work, we use the estimator given by Coles et al. (1999)

$$\chi(u) = 2 - \frac{\log P(F_X(x) < u, F_Y(y) < u)}{\log P(F_X(x) < u)}$$

The function $\chi(u)$ can be regarded as a quantile dependent measure of dependence (Coles et al., 1999), where u denotes the percentile limit.. To ensure that the choice of limit has minimal impact on the final results, we employ the method suggested by Timmermans et al., (2019). Hence, we computed $\chi(u)$ averaged over a high quantile interval and then reported the resulting single value for each grid point.

$$\bar{\chi}(u) = \sum_{0.90 < u \leq 0.95} \chi(u)$$

The value of $\bar{\chi}(u)$ can be interpreted as the probabilistic risk that the P extreme conditioned

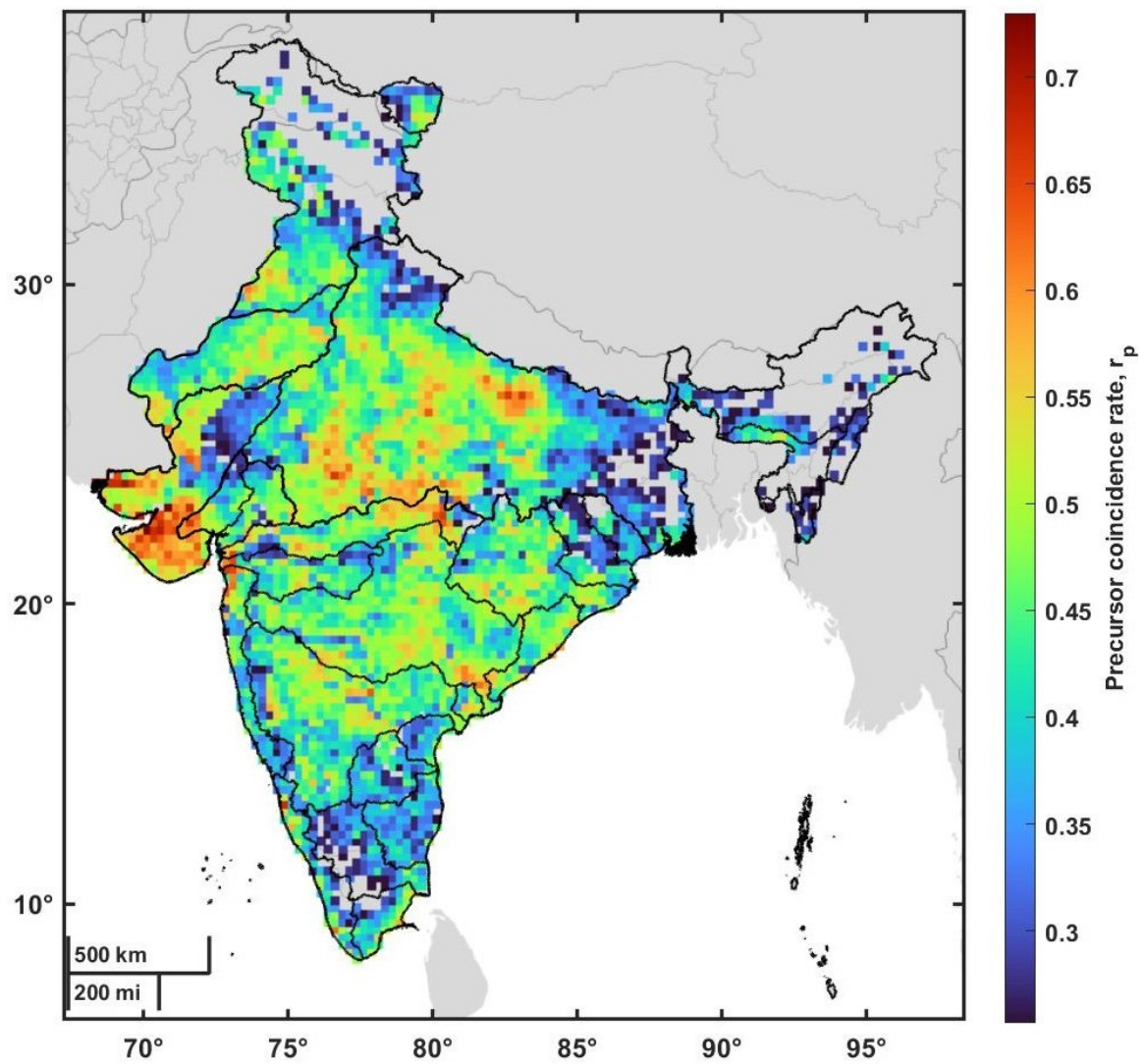
on SM also being extreme.

Datasets

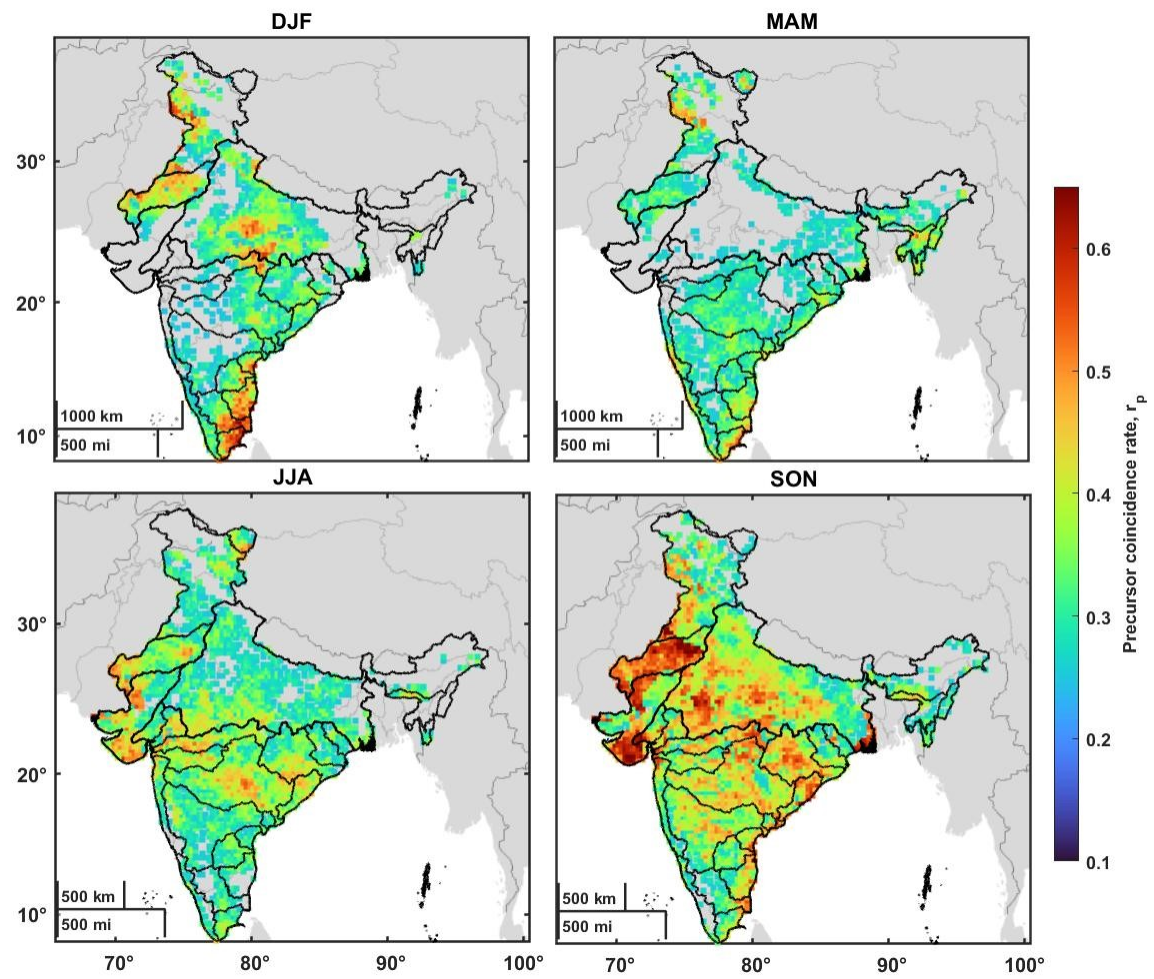
Soil moisture data consisting of daily gridded model outputs from the Global Land Data Assimilation System (GLDAS – 2.2). (Kumar et al., 2006; Li et al., 2019; Rodell et al., 2004). The daily precipitation product used in the current study is the Global Precipitation Mission (GPM) product retrieved using the Integrated Multi-satelliteE Retrievals (IMERGv6) algorithm (Huffman et al., 2020).

RESULTS

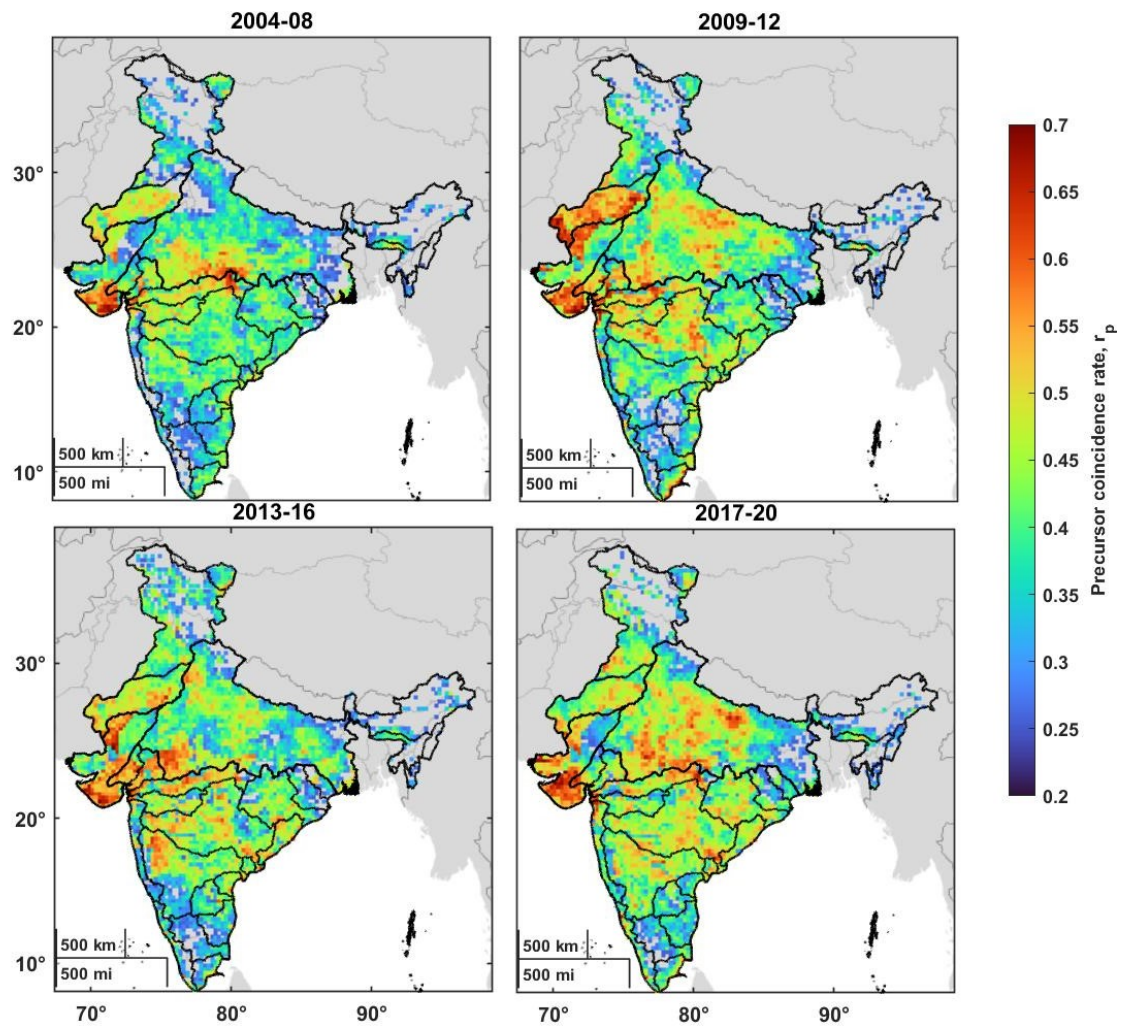
Annual hotspots:



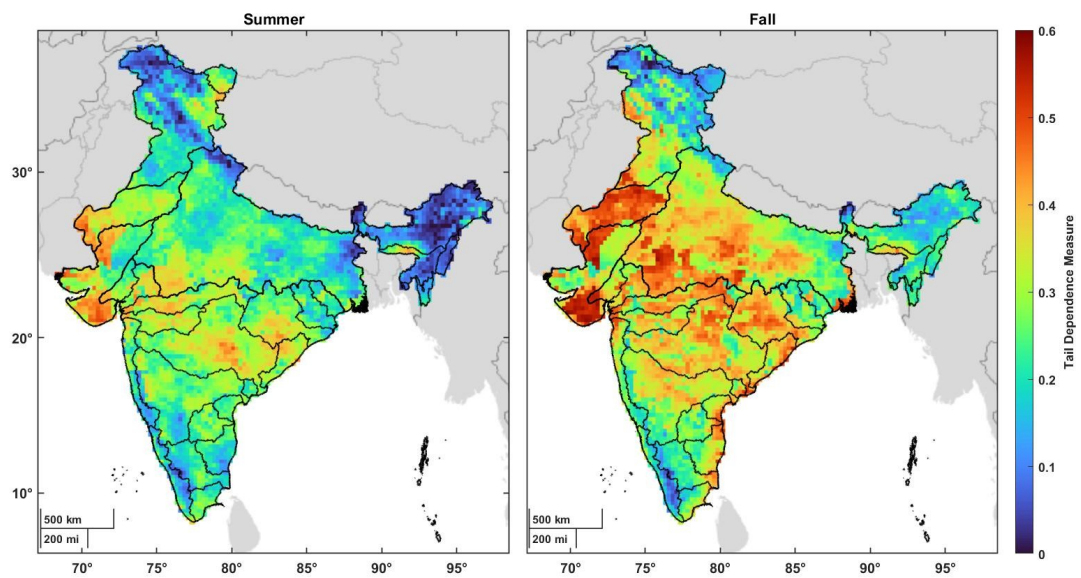
Seasonal variations:



Temporal evolution:



Tail Dependence Analysis



INTRODUCTION

- Climate Change leading to increased Precipitation extremes (P) worldwide.
- But P extremes do not always correspond to an increase in flood risk.
- Importance of antecedent and catchment conditions prior to the storm event.
- Traditional methods are univariate in nature, not able to capture all the contributing factors and processes.
- Compound events - multiple statistically dependent underlying processes/variables
- Preconditioned compound event - underlying weather-driven or climate-driven precondition leads to increased impact
- Soil moisture (SM) plays an important role in modulating flood characteristics.
- In the present work, we identified and quantified preconditioned hotspots of SM-P coupling over India

TAKE HOME MESSAGE

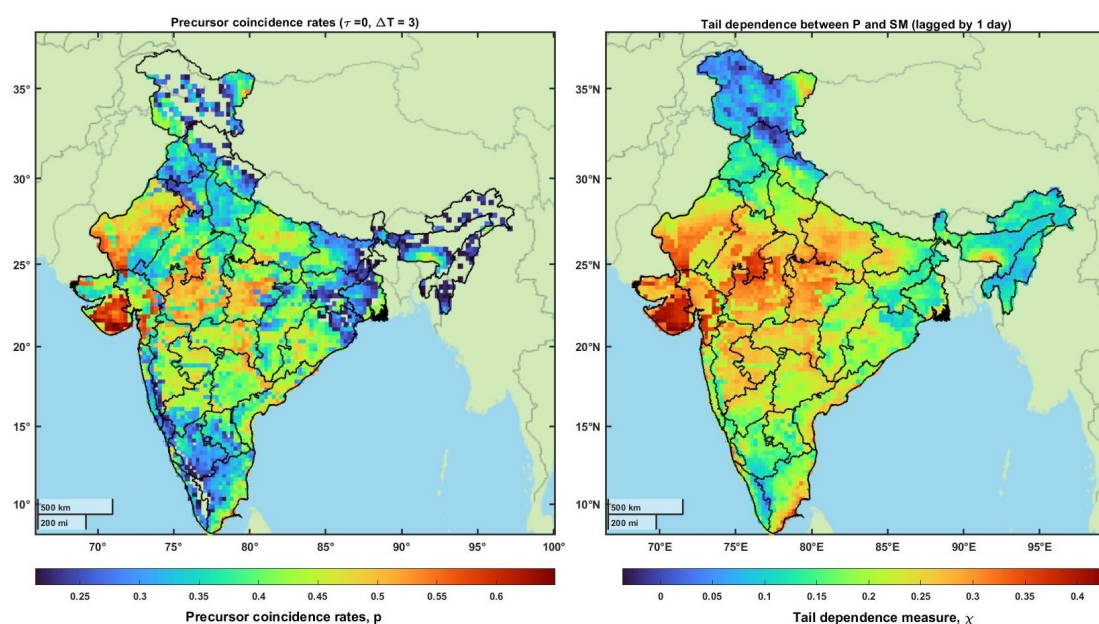
- Disentangled the interplay between antecedent soil moisture conditions and extreme precipitation events over India
- Showed strong variations in the preconditioned hotspots in seasonal timescales
- Interdecadal temporal evolution of these hotspots is in line with the general perceived trend of increase in widespread flooding events throughout India
- Similar results obtained using Tail dependence analysis

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ABSTRACT

Compound event research has gained significant momentum over the past few years. Traditionally risk assessment studies considered either one climatic driver or process at a time. However, it is now being recognised that it is the combination of multiple drivers and their statistical dependencies that lead to aggravated, non-linear impacts. We aim to identify hotspots for SM-P coupling over India from 2004 to 2020 using Event Coincidence Analysis (ECA) and an extremal tail dependence measure. We further characterise how these complex interconnected interactions can lead to more significant flash floods and landslide risk. The analysis is done at different temporal scales to pinpoint a location prone to floods during the year. High precursor coincidence rates ($>60\%$) were obtained for traditional flash flood-prone areas over India, indicating the robustness of the approach. ECA results were compared with the probabilistic extreme value approach, and a similar pattern was observed in both. The increase in hotspots from 2004 to 2020 matches the observed increase in flood-prone districts reported by earlier studies. We also used the trigger coincidence rate to identify areas where soil moisture anomalies can trigger extreme precipitation. The seasonal variations in precursor coincidence rates are observed to be the same as those usually expected due to changing atmospheric circulation patterns. Our results will complement the traditional flood risk assessment studies and have implications for better understanding the dynamic, ever-evolving nature of compound preconditioned flooding events worldwide.



(https://agu.confex.com/data/abstract/agu/fm21/1/8/Paper_827781_abstract_770762_0.jpg)

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