# Identification Of Critical Water Futures In The Indus River Basin

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## 1. Motivation

- The Indus River Basin (IRB) faces significant water scarcity challenges due to climate change, population growth, unregulated water abstraction and unsustainable agricultural practices.
- Integrated Assessment Models (IAMs) can provide comprehensive assessments of these complex interactions.
- Recent study conducted by Dolan et al. (2021) used Global Change Analysis Model (GCAM) to generate a large ensemble of 3,000 plausible future scenarios across multiple dimensions.

## 2. Objectives

- Utilising the IRB as a case study, we develop a methodology that harnesses the power of such large ensembles of databases
  - i. To discover critical water futures as **"Ensemble of Outliers".**
  - ii. Analyse their attributes, including what makes them critical.

## 3. Illustrated Methodology

- We apply Gaussian Mixture Models (GMM) clustering algorithm to irrigation withdrawals for cotton 2100 and highlight candidate Ensemble of Outliers. Then, we calculate the Mahalanobis distance and p-values to identify Ensembles of Outliers.

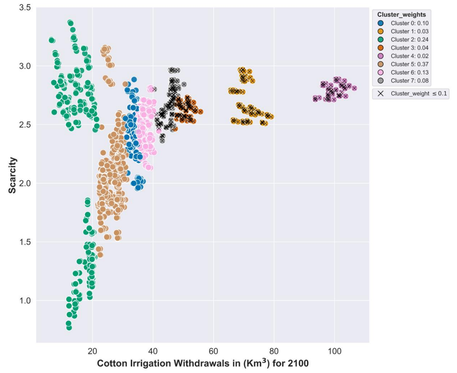



**Fig 1. GMM clustering for Cotton 2100 highlighting candidates of Ensemble of Outliers (black)**

$$D^2 = (\mu_{cl} - \mu)^T * \Sigma^{-1} * (\mu_{cl} - \mu)$$

$D^2$ = squared Mahalanobis distance ,

$\Sigma^{-1}$= inverse covariance matrix,

T = transpose,

$\mu_{cl}$ = mean of the cluster,

$\mu$ = mean of the entire dataset

**Eq 1. Mahalanobis distance**

$$p\_value = P(D^2 > x^2)$$

$P$ = Probability , $x^2$ = chi-square statistic

**Eq 2. p_value**

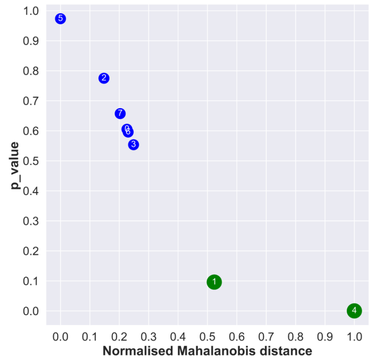



**Fig 2. Ensemble of Outliers for IRB Cotton 2100 (green)**

| Cluster / No. of Scenarios | Characteristics (*SSP-Shared Socioeconomic Pathways*) | | |
|---|---|---|---|
| | **Socioeconomics** | **Agriculture** | **Land Use Scenario** |
| **4/60** | **SSP3** Regional rivalry, Limited cooperation, Income disparities | **SSP1,SSP5** Sustainable practices, High input farming with intensive use of resources | **Universal Carbon Tax** Low carbon technologies |
| **1/90** | | **SSP1, SSP5, SSP2** A combination of sustainable and conventional agriculture practices | - |

**Table 1. Characteristics of Potential Ensembles of Outliers**

## 4. General Validation

- For validation we generate a synthetic dataset of irregular shape with known outliers and implement our methodology to identify Ensembles of Outliers. Here an example of 1500 datapoints with standard deviation 6 and 150 outliers with standard deviation 4 is displayed.

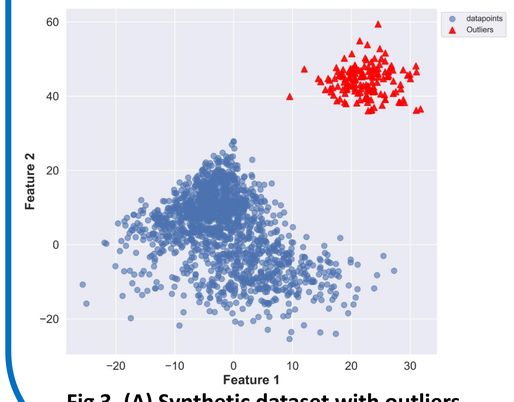
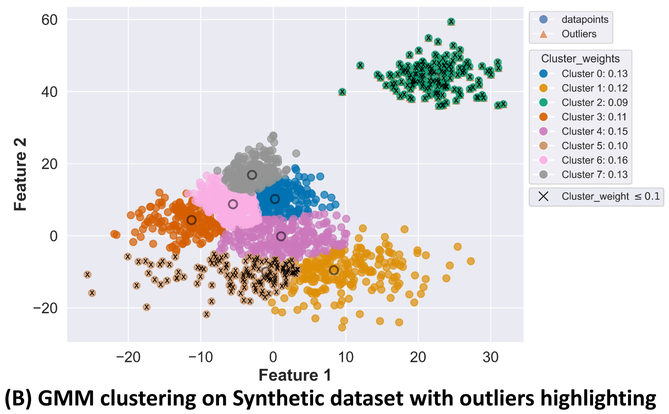
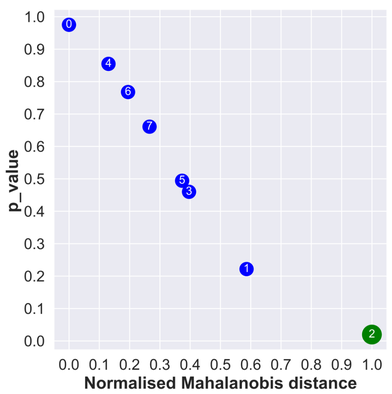



**Fig 3. (A) Synthetic dataset with outliers highlighted (red)**




**(B) GMM clustering on Synthetic dataset with outliers highlighting candidate Ensembles of Outliers (black)**




**(C) Ensembles of Outliers highlighted (green)**

## 5. Future Work

- **Integrate identification and characterisation of ensembles of critical futures.**
  - Method for Ensemble of Outlier detection (this poster).
  - Systematic detection of critical futures across multiple basins / regions / sectors.
  - (Un)supervised classification to characterise these critical futures.
- **Broaden methodology to larger datasets.**
  - Identification of scenarios that are outliers in many basins / sectors at once.
  - Dynamics: when / how do critical futures emerge?

**References**

- Dolan, F., Lamontagne, J., Link, R., Hejazi, M., Reed, P., & Edmonds, J. (2021). Evaluating the economic impact of water scarcity in a changing world. Nat Commun, 12(1), 1915. https://doi.org/10.1038/s41467-021-22194-0
- Calvin, K., Bond-Lamberty, B., Clarke, L., Edmonds, J., Eom, J., Hartin, C., Kim, S., Kyle, P., Link, R., Moss, R., McJeon, H., Patel, P., Smith, S., Waldhoff, S., & Wise, M. (2017). The SSP4: A world of deepening inequality. Global Environmental Change, 42, 284-296. https://doi.org/10.1016/j.gloenvcha.2016.06.010

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