

ASI Seminar · 22 August 2026

Understanding El Niño

Probability, Severity & Economic Impact · 2026–27 Outlook

Nishanth Veerapaneni · Catastrophe & Climate Liability Modelling



OPEN-SOURCE DATA · 10,000-EVENT MONTE CARLO

www.actuariesindia.org

Agenda

Eleven sections in sixty minutes

01 Introduction

Why El Niño matters globally and to India

02 El Niño Fundamentals

Mechanism, ENSO indices, severity scale

03 Historical Record

1950–2024 timeline and notable events

04 Drivers of Severity

Features that predict occurrence and intensity

05 Project Methodology

Architecture, datasets, statistical approach

06 2026–27 Outlook

Probability estimates and return periods

07 Supply Chain Impact

WIOT propagation and marine trade routes

08 India-Specific Deep Dive

Monsoon, IOD, kharif, sectoral effects

09 Indian Insurance Industry

Strategic implications for insurers

10 Conclusion

Key takeaways and forward observations

11 Disclaimer

Modelling caveats and legal disclaimers

COMPANION

Streamlit dashboard with interactive country-pair risk playground

SECTION 01

Introduction

Why El Niño matters — for the world, and especially for India



Why El Niño concerns the world

One climate cycle that shifts weather, food prices and insurance losses globally

\$45B

Direct economic loss

1997–98 event — strongest measured until 2015–16

\$100B+

Estimated total impact

2015–16 — agriculture, fires, drought, humanitarian

60+

Nations hit at once

Simultaneous losses break diversification assumptions

10 / 10

Hottest years on record

All in the last decade; the two warmest (2023–24) coincided with El Niño

ESTIMATED GLOBAL LOSS BY EVENT (US\$ BN, DIRECT + INDIRECT)



El Niño is the single largest year-to-year driver of natural climate variability — and a material underwriting risk factor.

Figures are tangible direct/indirect losses (World Bank 2016; Swiss Re sigma 2/2016; NOAA NCEI; FAO 2016). Macro-econometric studies (Callahan & Mankin, Science 2023) put multi-year global income losses far higher — \$2.1tn for 1997–98 and \$3.0tn for 2015–16. www.actuariesindia.org

Why El Niño concerns India most

A convergence of agricultural dependence and climatic exposure

THE EXPOSURE GAP — SHARE OF INDIA'S ECONOMY vs
WORKFORCE

Agriculture → GDP



Agriculture → Employment



Population agri-dependent



Agriculture is a sixth of output but nearly half of all employment — a monsoon shock lands on household balance sheets long before it lands on GDP.

15–25%

kharif output loss from just a 10–15% rainfall deficit

–18%

Average kharif loss in Strong events: 2002, 2009, 2014–15

₹1.5 L Cr

Approximate annual agricultural loss in a major event

3–5 yrs

Groundwater recovery — back-to-back events compound

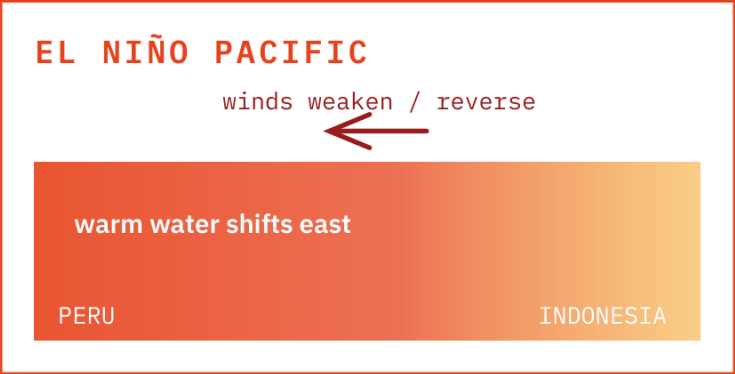
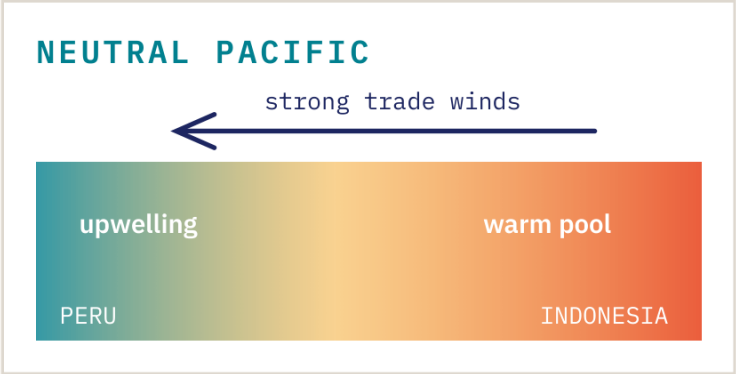
SECTION 02

El Niño Fundamentals

Physical mechanism, ENSO measurement, severity classification

What is El Niño?

Periodic warming of the equatorial Pacific that reorganises global weather



- 1**

Neutral conditions

Trade winds push warm water west; cold upwelling off Peru
- 2**

Winds weaken

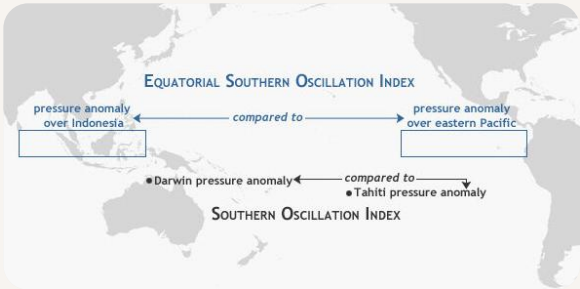
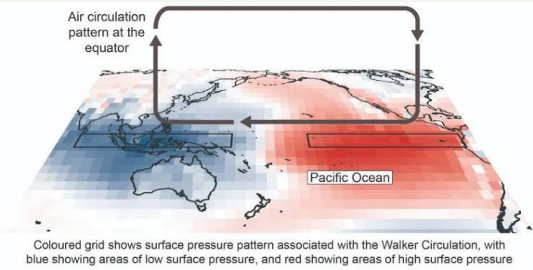
Warm water sloshes east; convective rainfall follows it
- 3**

Jet streams shift

Walker circulation reorganises; Indian monsoon weakens
- 4**

Global cascade

Asian drought, American floods, suppressed Atlantic hurricanes



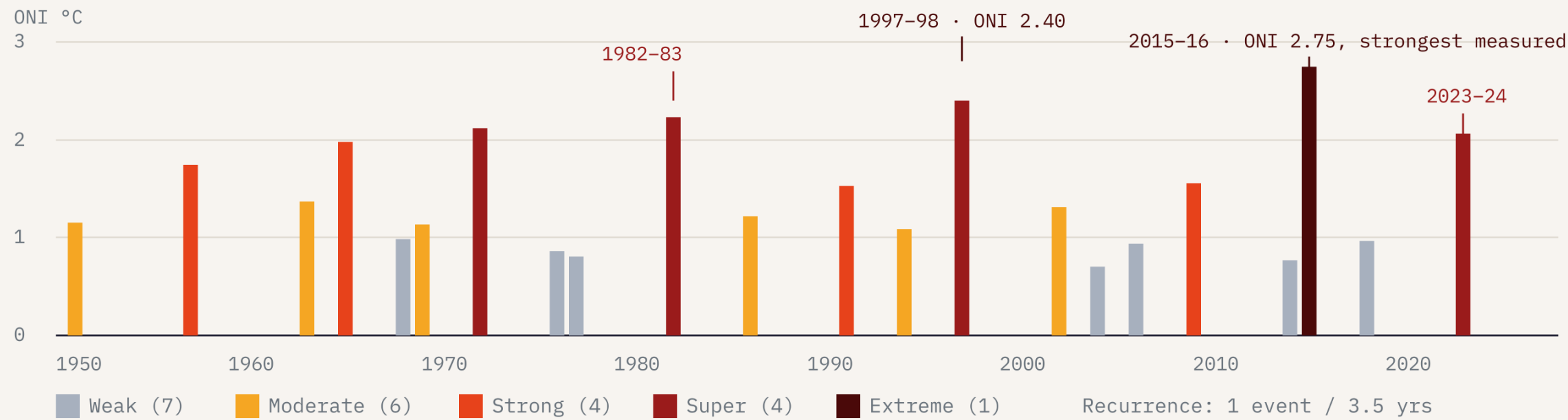
AT A GLANCE	
Frequency	Every 2–7 years
Duration	9–24 months
Peak season	Dec–Feb
Primary metric	ONI
Threshold	$\geq +0.5^{\circ}\text{C}$, 5+ months
Opposite phase	La Niña
Key region	Niño 3.4 5°N–5°S, 170–120°W

Sources: NOAA CPC; IPCC AR6 WGI Ch.8; Cai et al. (2014) Nature Climate Change.

Seventy-five years of El Niño

Peak ONI in each of the 22 El Niño years since 1950

$$ONI = SST_{Niño\ 3.4} - SST_{normal}$$



Source: NOAA CPC ONI, 1950-2026 – peak ONI per El Niño year computed directly from the series.



Five severity categories

Classification follows NOAA peak three-month ONI thresholds



Bar height shows relative economic impact per event, not frequency: Weak and Moderate events dominate the count, Super and Extreme dominate the loss.

Source: NOAA peak three-month ONI; project historical catalogue (22 events, 1950–2024).

What drives El Niño and its severity?

51 engineered features, ranked by relative model contribution

OCCURRENCE

P(onset within 6 months)

Lagged ONI (1–12m)



MEI v2 leading indicator



ONI momentum (3m, 6m)



SOI 3-month MA



Recharge oscillator state



Seasonality (sin/cos)



Spring-barrier flag



SEVERITY

P(class | El Niño)

Peak ONI, trailing 6/12m



Intensification rate



Niño 4 vs Niño 3 anomaly



Duration above +0.5



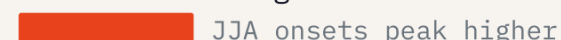
MEI at onset



Niño 1+2 SST anomaly



Onset-month timing



The DMI (Indian Ocean Dipole) feature was added in the latest revision — it carries little weight for global occurrence but is decisive for the Indian monsoon response (slide 29).

Sources: Wolter & Timlin (2011); McPhaden (2015); Saji & Yamagata (1999, 2003).

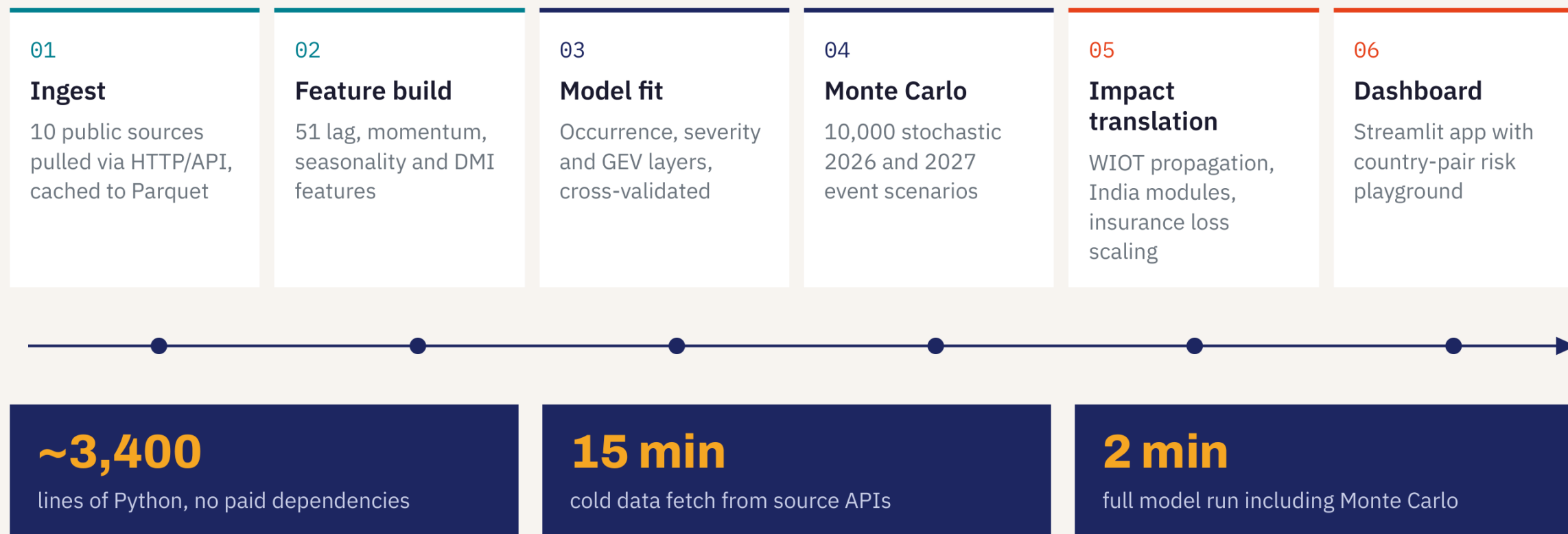
SECTION 03

Project Methodology

Architecture, datasets, libraries and statistical approach

End-to-end project pipeline

Six stages, fully reproducible from open-source data



All stages reproducible end-to-end; intermediate artefacts cached as Parquet.

Ten open-source datasets

Climate, economic, supply-chain and Indian monsoon — all freely accessible

NOAA CPC

ONI

Oceanic Niño Index, monthly 1950+. Primary ENSO metric.

NOAA PSL

MEI v2

Multivariate ENSO Index — SST, wind, pressure, OLR.

NOAA CPC

SOI

Southern Oscillation Index — Tahiti–Darwin pressure.

NOAA CPC

Niño SST indices

Sub-region anomalies: Niño 1+2, 3, 3.4 and 4.

IMD / IITM PUNE

AIMSR

All-India summer monsoon rainfall, JJAS 1871+, % of LPA.

NOAA PSL

DMI

Indian Ocean Dipole, monthly 1870+. Monsoon modulator.

WORLD BANK

Macro indicators

GDP, agriculture, trade, inflation — 15 countries.

FAO FAOSTAT

Food prices & crops

Monthly Food Price Index and annual crop yields.

WIOD 2016

World input-output

44 countries × 56 industries, 2014 vintage.

MIN. OF AGRI
(INDIA)

PMFBY statistics

Premium, claims and sum insured by state and season.

Sources: NOAA CPC; NOAA PSL; IMD/IITM Pune; World Bank Open Data; FAO FAOSTAT; WIOD 2016; Ministry of Agriculture (India).

Technology stack

Every component open-source, reproducible and maintainable by an actuarial team

NUMERICAL CORE

numpy
pandas
scipy
pyarrow

STATISTICS

statsmodels
scipy.stats
– genextreme

MACHINE LEARNING

scikit-learn
lightgbm
shap

DATA ACCESS

requests
tqdm
openpyxl

VISUALIZATION

plotly
matplotlib
seaborn

DASHBOARD

streamlit

Interactive country-
pair risk playground

Estimated reproduction time: 15 minutes data fetch + 2 minutes full model run.

Three-layer statistical model

Occurrence × severity × extreme value, fused in a Monte Carlo engine

LAYER 1

01

Occurrence

METHOD

Logistic regression with isotonic calibration

OUTPUT

P(El Niño onset within 6 months)

VALIDATION

CV-AUC 0.91

LAYER 2

02

Severity

METHOD

Multinomial logistic regression, El Niño months only

OUTPUT

P(Weak | Moderate | Strong | Super | Extreme)

VALIDATION

50/50 empirical blend

LAYER 3

03

Extreme value

METHOD

Generalized Extreme Value, block maxima

OUTPUT

Return level for any T-year period

VALIDATION

Bootstrap CIs

FUSION

All three layers feed the 10,000-event Monte Carlo engine that produces the probabilistic 2026–27 outlook.

Disclosure: CV-AUC is largely persistence-driven, not pure forecast skill.



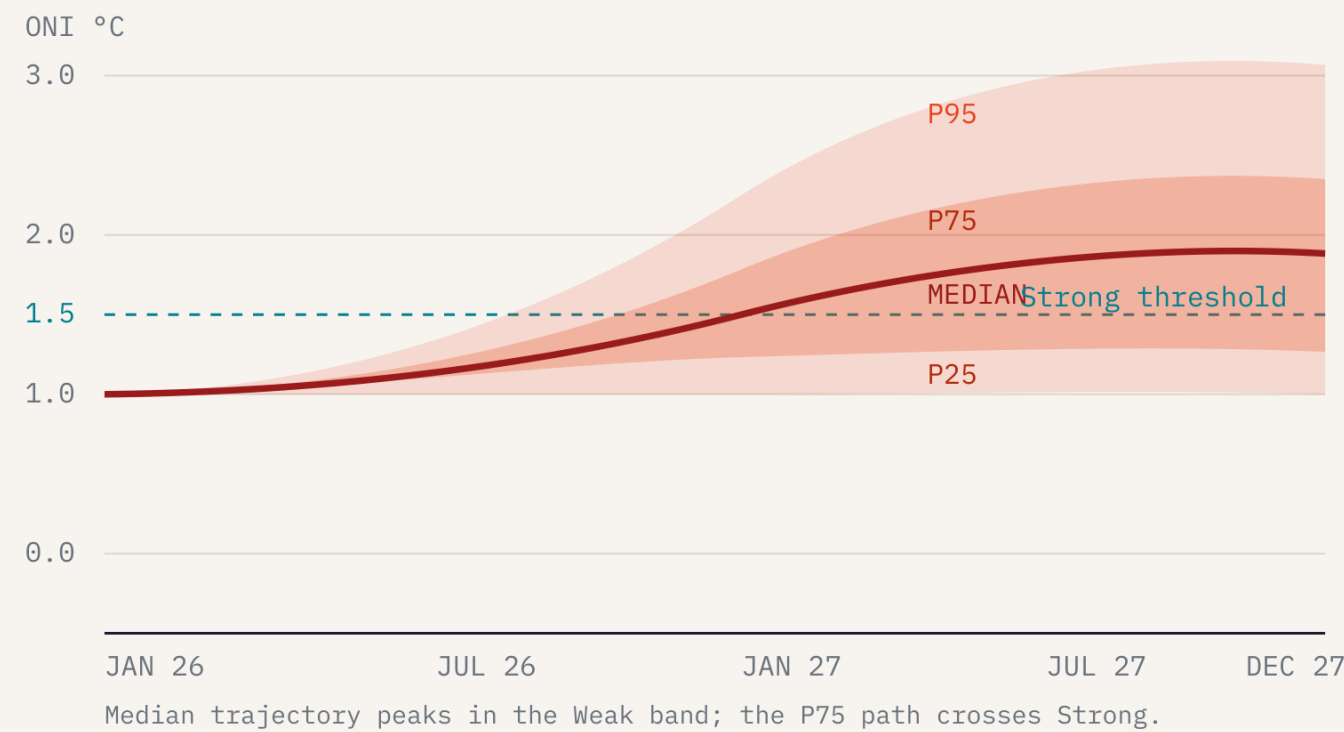
Monte Carlo simulation engine

10,000 event scenarios → probabilistic 2026–27 ONI trajectories

DRAW SEQUENCE – PER SIMULATION

1	P(El Niño)	Bernoulli(p)
2	Severity class	Multinomial
3	Peak ONI	Trunc. Normal
4	Duration	Poisson(λ)
5	Onset month	Empirical
6	GDP impact	Normal(μ , σ)
7	FFPI change	Normal(μ , σ)
8	Disaster flags	Cond. binary

SIMULATED ONI TRAJECTORY FAN, JAN 2026 → DEC 2027



SECTION 04

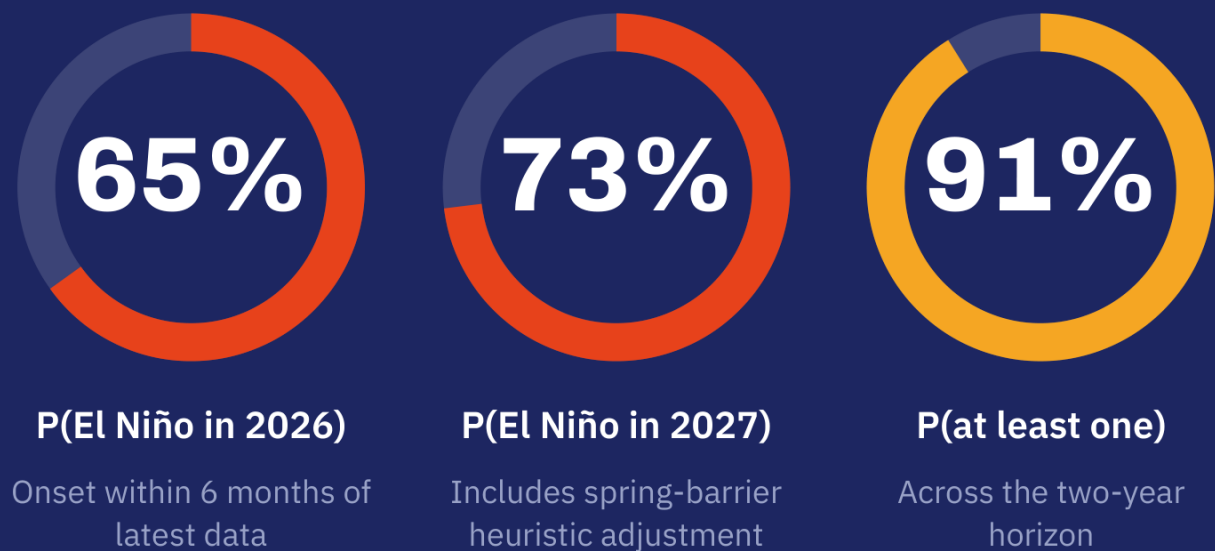
2026–27 Outlook

Probability estimates, severity distribution and return periods

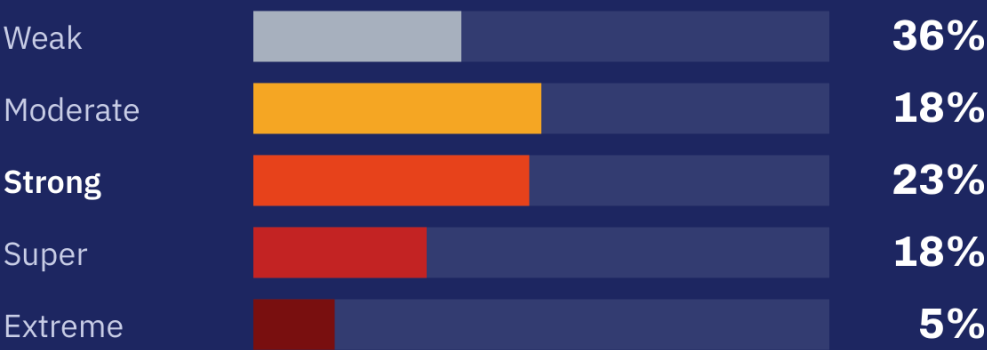


2026–27 probability outlook

Headline numbers from the integrated model



SEVERITY DISTRIBUTION, CONDITIONAL ON OCCURRENCE



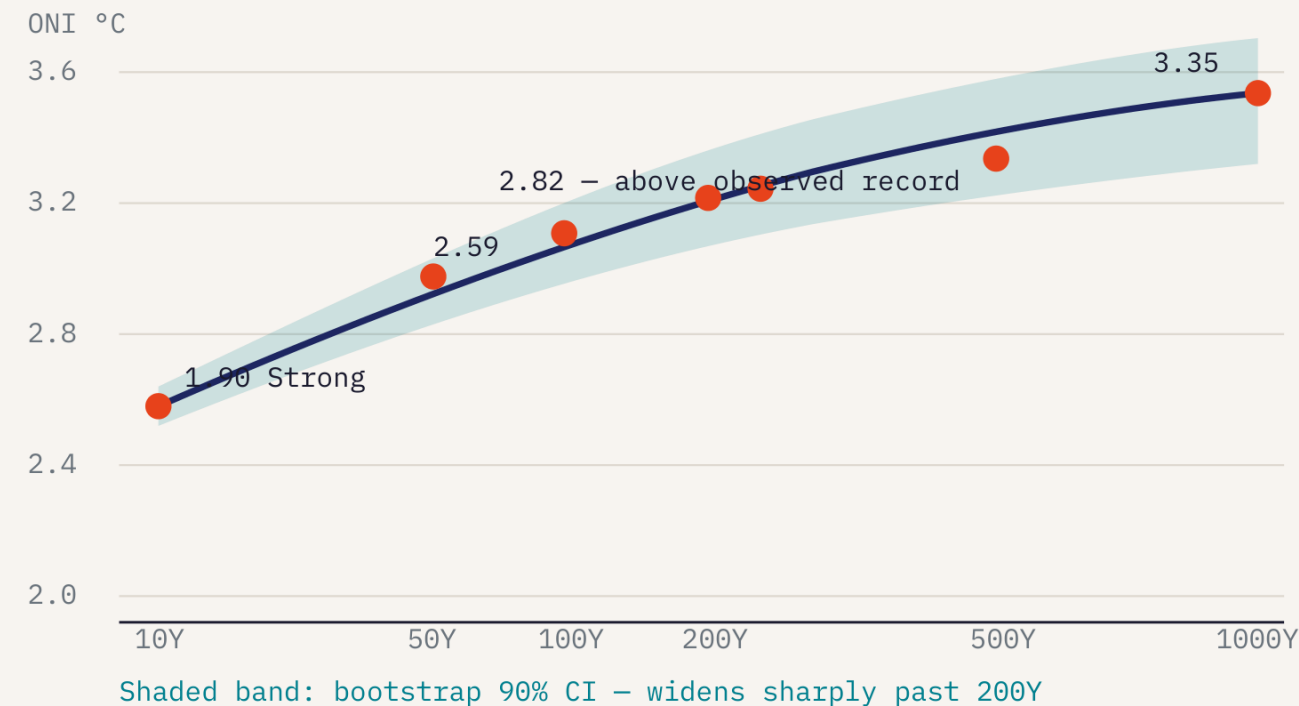
45% of events since 1950 were **Strong or higher** – 10 of the 22 events in the record

Method: occurrence model (CV-AUC 0.91), March 2026 vintage. Severity mix is the observed 1950–2024 frequency (8/4/5/4/1 of 22 events).



Return periods and return levels

GEV-fitted peak ONI with bootstrap confidence bands



RETURN LEVEL TABLE

RP	ANNUAL EP	ONI	SEVERITY
10Y	10.0%	1.90	Strong
50Y	2.0%	2.59	Extreme
100Y	1.0%	2.82	Extreme
200Y	0.5%	3.01	Extreme
250Y	0.4%	3.06	Extreme
500Y	0.2%	3.22	Extreme
1000Y	0.1%	3.35	Extreme

The 100-year level (2.82) sits just above the observed record of 2.75 (2015–16). Levels past 200Y rest on GEV extrapolation from 75 years of data – treat as order-of-magnitude.

Method: GEV maximum likelihood; bootstrap confidence intervals.

SECTION 05

Supply Chain Impact

WIOT-based propagation, marine trade routes and global production network effects

Geographic impact tiers

Three lenses — where the loss is felt, where it is paid, and where it propagates

TIER 1

FINANCIAL EXPOSURE

Where the losses are underwritten

Mature insurance and reinsurance markets absorb correlated claims from every other tier simultaneously.

UNITED STATES

EU

UK

JAPAN

SWITZERLAND

~70%

of global insured CAT capacity

TIER 2

PHYSICAL VULNERABILITY

Where the physical damage lands

Rain-fed agriculture, low insurance penetration, high share of employment in exposed sectors.

INDIA

INDONESIA

AUSTRALIA

PHILIPPINES

PERU

ETHIOPIA

VIETNAM

THAILAND

< 15%

of agricultural losses insured

TIER 3

PROPAGATION

Where the shock arrives second-hand

Food-import-dependent and input-dependent economies hit through prices and throughput, not weather.

BANGLADESH

SRI LANKA

NEPAL

GULF STATES

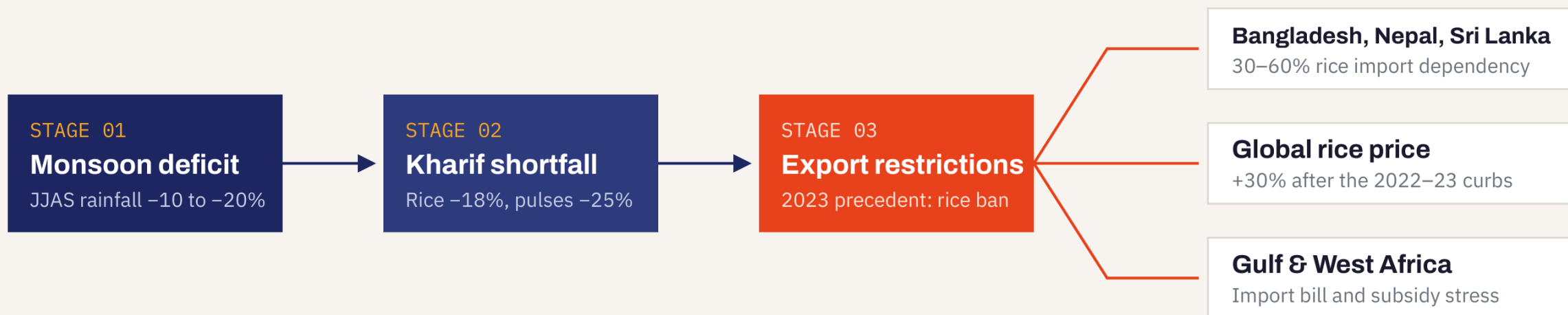
WEST AFRICA

30–60%

rice import dependency

India agricultural exports — the global cascade

A Strong event triggers food security stress across high-dependency importers



INDIA'S GLOBAL POSITION

#1 rice exporter (~40% of world trade) • #2 wheat producer • #1 milk, pulses and spices producer

China and Taiwan technology chain

Yangtze flooding and Taiwan typhoons reach the global electronics economy

CHINA MANUFACTURING & ELECTRONICS

01 Yangtze basin flooding

Disrupts the Yangtze Delta cluster — ~25% of China's GDP

02 Pearl River basin floods

Guangzhou and Shenzhen electronics assembly

03 North China drought

Power generation stress — hydro plus coal cooling water

04 Summer heat waves

Industrial load shedding; output caps in peak months

**5–
15%**

estimated manufacturing output loss under Super or Extreme severity

TAIWAN SEMICONDUCTORS

01 Enhanced super-typhoon risk

Direct-hit exposure to Hsinchu and Tainan fab clusters

02 Water and grid stress

Ultrapure water rationing throttles wafer throughput

03 2021 drought precedent

Fabs trucked in water; showed the vulnerability is live

04 Concentration risk

~60% of the world's advanced logic wafers on one island

**4–8
wks**

worst-case fab disruption under Extreme severity — contingent BI exposure



Marine trade route disruption

Five ENSO-sensitive corridors — four negative, one positive

CORRIDOR 01

Panama Canal

Drought lowers Lake Gatun → draft limits → transit slots auctioned or cut.

–36%

transits, Oct 2023 – Jan 2024

CORRIDOR 02

Mekong & Yangtze

Inland barge draft collapses in drought; rice and manufacturing inputs stranded.

\$0.33T

annual inland cargo exposed

CORRIDOR 03

Trans-Pacific

Eastern Pacific storm enhancement forces weather routing detours.

+1–2 d

added voyage time per sailing

CORRIDOR 04

Arabian Sea & Bay of Bengal

Intensified Cat 4–5 cyclones put Indian coastal ports and cargo at risk.

12 ports

major Indian ports in the path

CORRIDOR 05 • POSITIVE

North Atlantic

Wind shear suppresses hurricane formation — the overlooked upside for insurers.

–30/50%

Atlantic hurricane activity

UNDERWRITING GAP

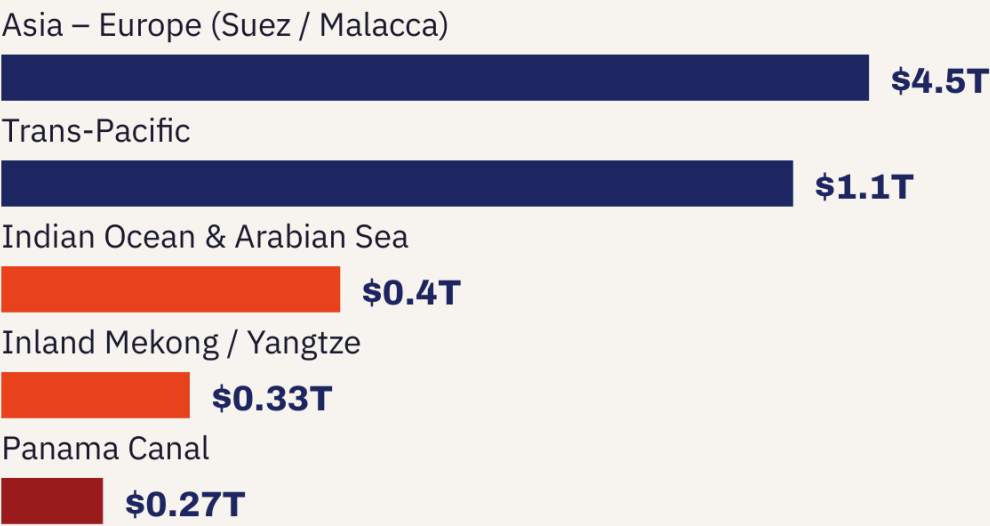
Traditional CAT models cover property and crops, not throughput. Route restriction losses land in business interruption and contingent BI — where they are only partially priced.



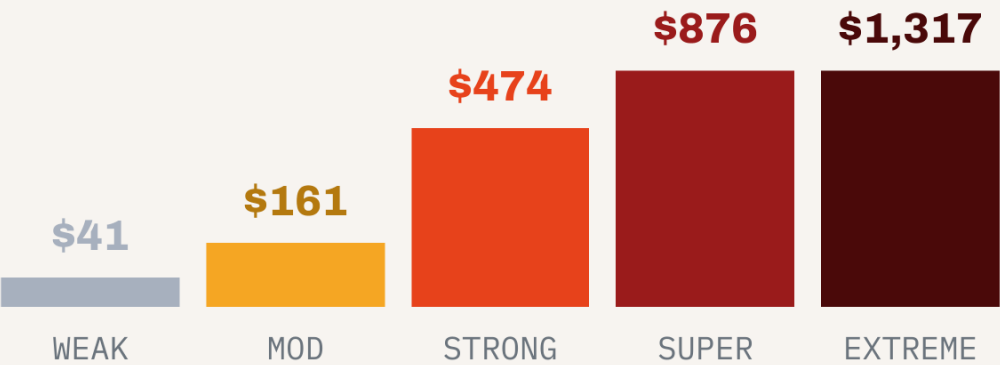
Aggregate marine trade at risk

~\$7.45 trillion of annual cargo moves through ENSO-sensitive corridors

ANNUAL CARGO VALUE BY CORRIDOR (US\$ TRILLION)



ESTIMATED DISRUPTION VALUE BY SEVERITY (US\$ BN, NET)



Figures are net of the Atlantic hurricane suppression benefit.
Marine cargo, hull, P&I and contingent BI all activate together in Strong+ years.

~1/3 of global goods trade by value
Reroute via the Cape of Good Hope adds 10–14 days transit and 15–20% fuel cost per voyage.

Method: project marine_routes module – annual cargo values weighted by severity impact, calibrated to observed 2023–24 disruption.

SECTION 06

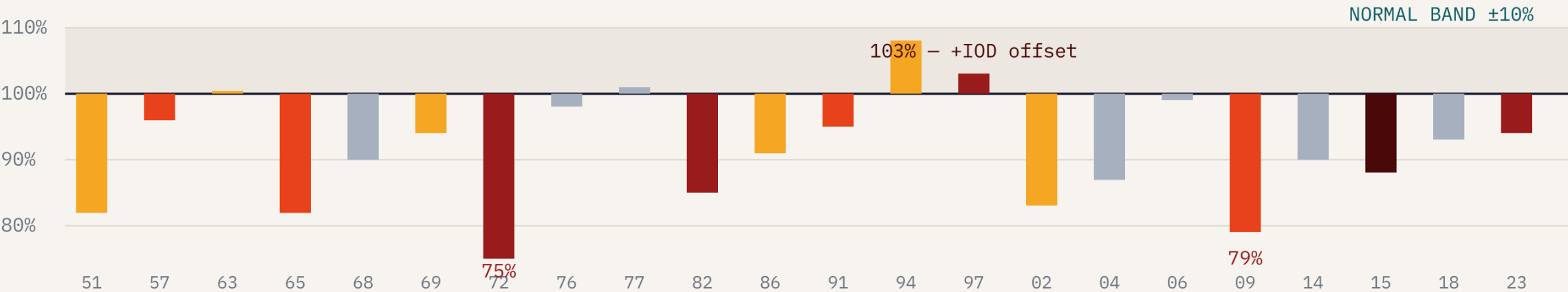
India Deep Dive

IMD monsoon record, IOD modulation, kharif crops, sectoral and disaster impact



All-India summer monsoon in El Niño years

JJAS rainfall as % of long period average — every El Niño year since 1950

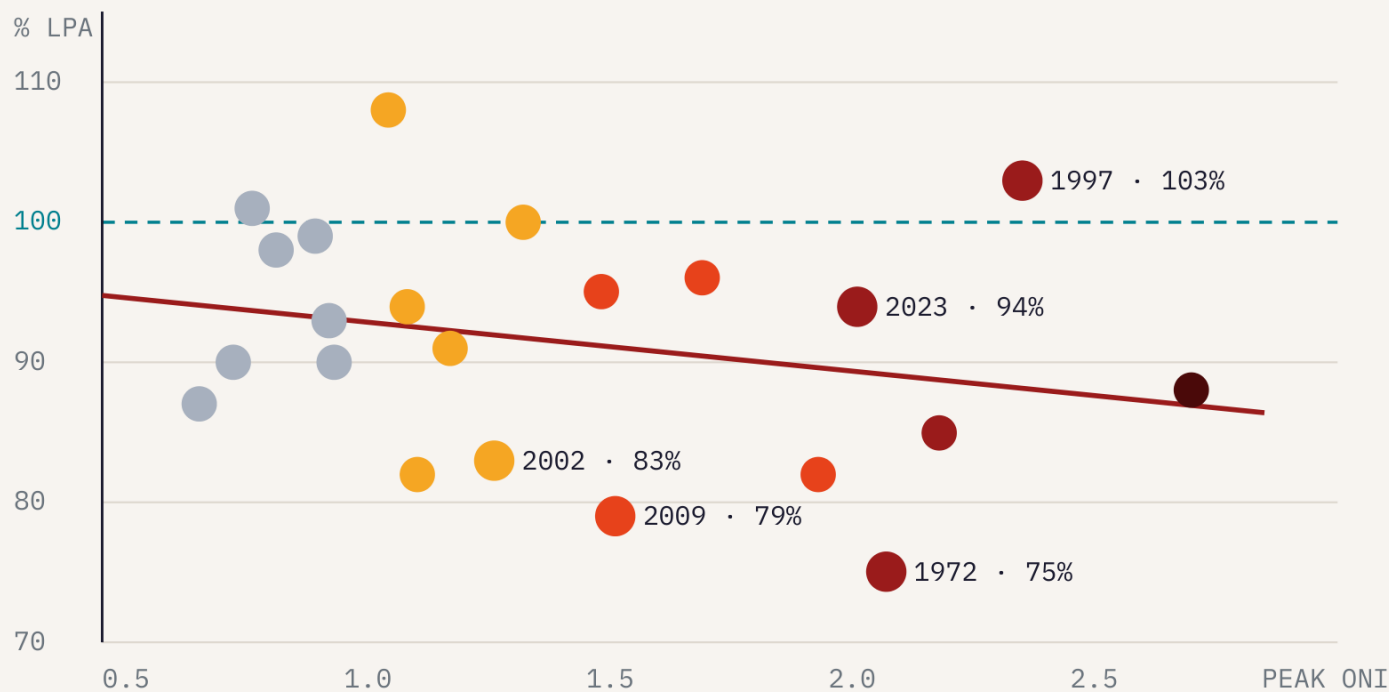


IMD LONG RANGE FORECAST 2026 • OFFICIAL

Below Normal at **92% of LPA ±5%** (13 Apr 2026), revised to **90% ±4%** in the May second-stage forecast — IMD attributes this to El Niño developing in the second half of the season

Monsoon performance vs El Niño intensity

Empirical relationship across 22 El Niño years, 1951–2023



-0.25

Correlation between peak ONI and monsoon % of LPA — real, but far from deterministic

-3 / -25%

Typical monsoon deficit range in Strong or higher events

THE EXCEPTIONS

1997 (ONI 2.40) and 1994 delivered near-normal rainfall despite significant Pacific warming — a positive Indian Ocean Dipole offset the ENSO signal.

- Weak
- Moderate
- Strong
- Super
- Extreme



Indian Ocean Dipole — the critical modulator

Why some El Niño years still deliver a normal monsoon

WHAT IT IS

The sea-surface temperature gradient between the western and eastern tropical Indian Ocean, measured as the Dipole Mode Index (DMI).

POSITIVE IOD

Warm west, cool east

Enhances monsoon convection and offsets El Niño drought.
1997–98: ONI 2.40 with a 103% monsoon.

NEGATIVE IOD

Cool west, warm east

Suppresses the monsoon and amplifies the El Niño deficit.
1965 and 2004 are the reference years.

IN OUR MODEL

DMI enters as a model feature; the joint state should be re-

checked against IMD and BoM bulletins each April to September.
Sources: Saji & Yamagata (1999, 2003); NOAA PSL DMI; Ashok et al. (2001) GRL.

JOINT-STATE MONSOON ANOMALY (% DEVIATION FROM LPA)

	NEGATIVE IOD	NEUTRAL IOD	POSITIVE IOD
EL NIÑO	-18 worst case	-10 central case	-3 offset case
ENSO NEUTRAL	-6	0	+4
LA NIÑA	-2	+5	+9 best case

A 15-point spread separates the best and worst El Niño outcomes for Indian rainfall — pricing on the ENSO state alone discards half the information.
www.actuariesindia.org



Kharif — the heart of India's exposure

JJAS rainfall delivers 80% of the annual total; kharif is three-quarters of foodgrain output

₹26.3_{Lcr}

Total kharif gross value added, FY24 estimate

75%

Of total foodgrain volume comes from kharif

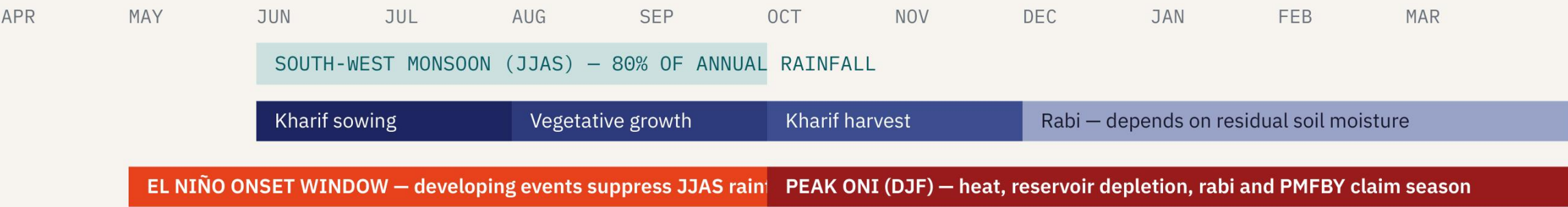
105_{Mt}

Rice produced annually, ~60% of it kharif

60%

Of kharif acreage is rainfed — no irrigation buffer

THE KHARIF CALENDAR — AND WHERE AN EL NIÑO BITES

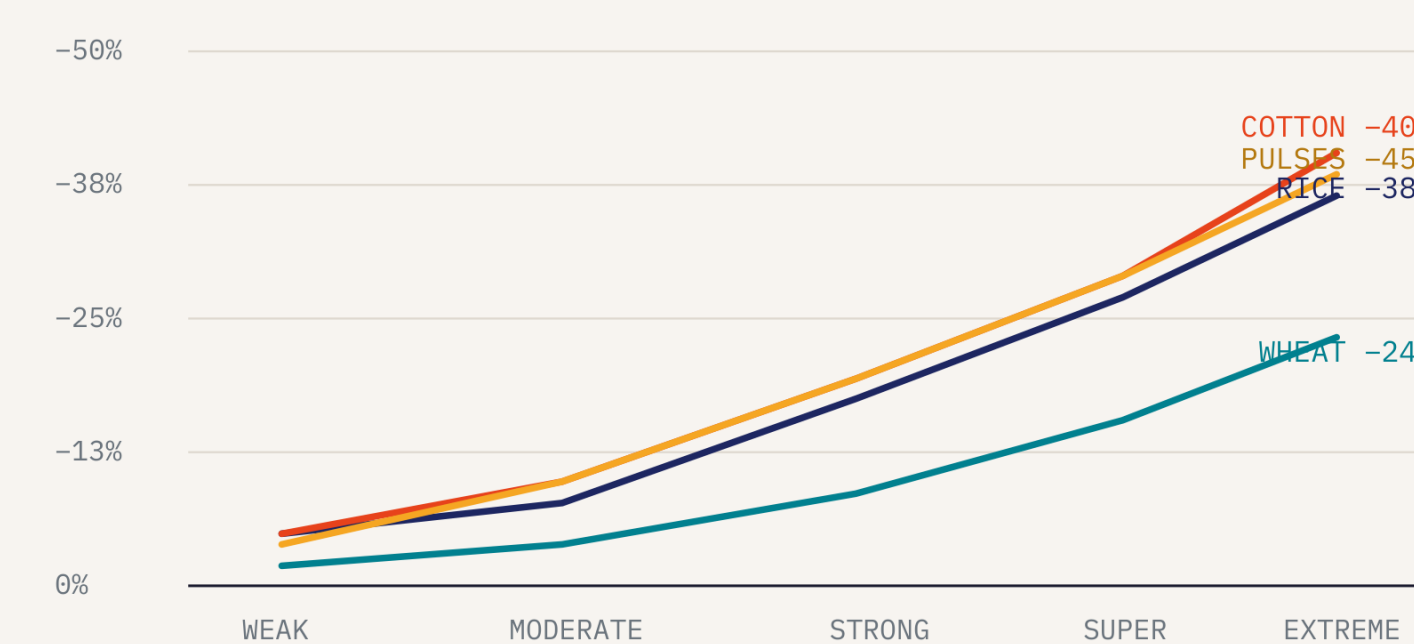


Monsoon failure → kharif shortfall → food inflation → rural distress → PMFBY claims — a twelve-month transmission, not a single event.



Crop production shock by severity

Output loss grows non-linearly — and unevenly across crops



Pulses is the most exposed crop; wheat resists until groundwater is exhausted.

ESCALATION PATTERN

WEAK	Localised north-west deficits; no national signal
MODERATE	Kharif -8 to -12%; regional procurement stress
STRONG	Pan-India deficit; export curbs; food inflation +6-8pp
SUPER	Reservoir crisis; kharif -28%; rabi carry-over damage
EXTREME	1877-type failure; humanitarian response required

~27 Mt

Rice volume lost in a Strong event — larger than the annual output of most exporting nations.

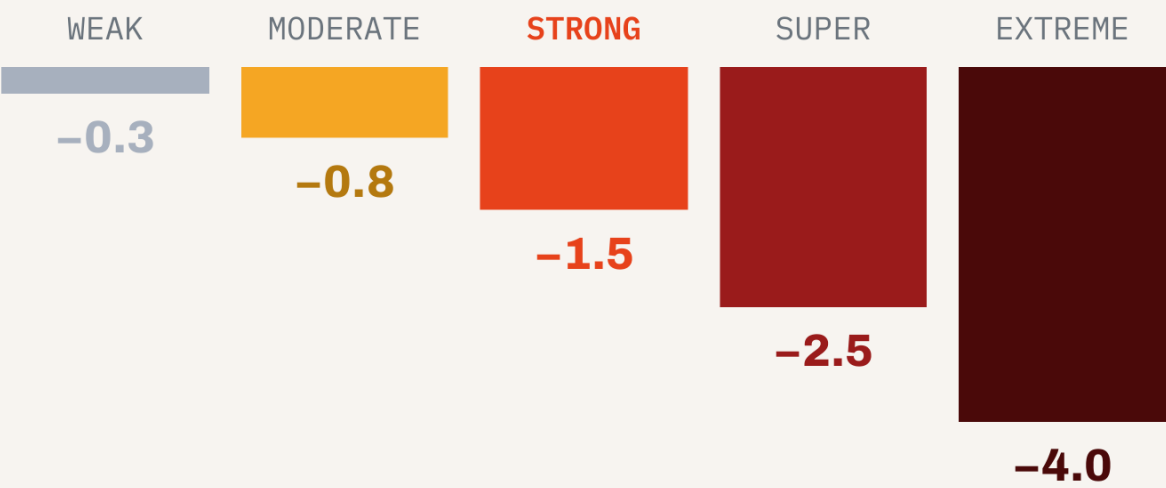
Sources: NCAER; Ministry of Agriculture; IMD rainfall-yield regressions.



GDP impact by severity

Moderate events are manageable; Super and Extreme events are macro shocks

ESTIMATED GDP IMPACT (% OF ANNUAL GDP)



SECTORAL TRANSMISSION

Agriculture	Direct kharif crop failure
Food inflation	+3 to +15pp depending on severity
Manufacturing	Indirect, via input cost pass-through
Power sector	Hydro shortfall and cooling water stress
Fiscal	Subsidy and relief expenditure spike
Trade	Export bans on rice and wheat; FX impact
Rural consumption	MGNREGA, DBT and remittances buffer partially

The step from Strong to Super raises the macro cost about 1.7× — the tail, not the mode, drives capital requirements.

Sources: NCAER; RBI; NITI Aayog.



Secondary disaster matrix

Drought is primary, but hazards manifest together – and correlated

	DROUGHT	HEAT WAVE	FLOOD	CYCLONES	KHARIF LOSS	INFLATION
WEAK	NW patchy	Mild pre-monsoon	—	Bay slight ↑	–5%	+1–2pp
MODERATE	NW –10 to –15%	Elevated May	—	Arabian Sea ↑	–10%	+3–5pp
STRONG	Pan-India –20%	Record May temps	SE India ↑	Cat 4+ risk	–18%	+6–8pp
SUPER	Severe failure	Heat emergency	SE flooding	Multiple Cat 4–5	–28%	+10–15pp
EXTREME	Near-total failure	46 °C+ in the IGP	Coastal extreme	Cat 5 events	–38%	+15–20pp

A Strong year compresses drought, heat, flood and cyclone activity into twelve months. Standard CAT pricing treats these perils as independent.

SECTION 07

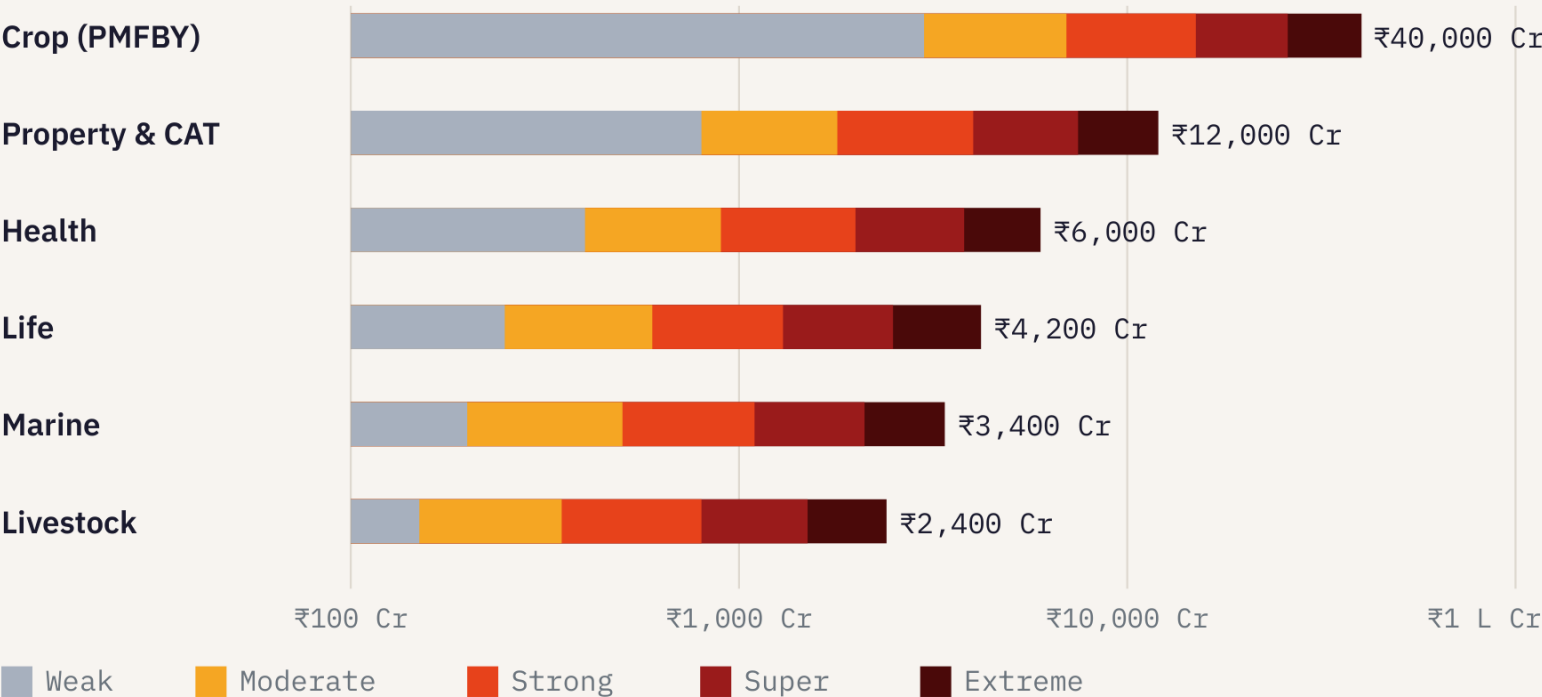
Insurance Implications

PMFBY, lines of business, state concentration and strategic response



Correlated loss across every line

Estimated additional claims by line and severity — ₹ crore, log scale



₹40k Cr

Crop claims in an Extreme year — the single largest direct exposure

6 of 6

Lines activate simultaneously — diversification credit is overstated in ENSO years

A log axis is required because the spread from Weak to Extreme is nearly two orders of magnitude. Tail years are a different business, not a worse one.

Calibrated to PMFBY 2018-19 actuals; cross-line ratios from IRDAI annual reports.



PMFBY and its ENSO sensitivity

India's flagship crop scheme — loss ratio tracks the ENSO phase

₹3 L Cr+

Sum insured, FY24

~5.5 Cr

Farmers insured

77%

Eight-year average loss ratio

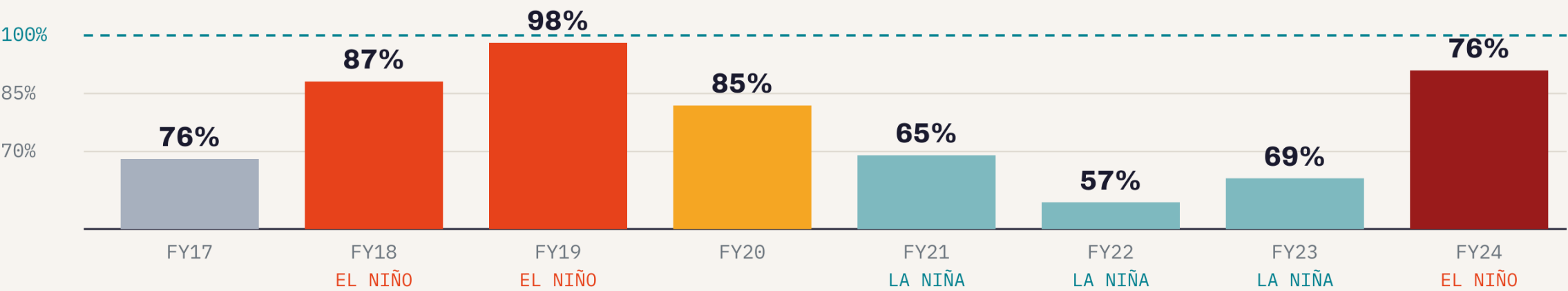
> 90%

Expected LR in a Strong+ year

70–80%

Government share of premium

PMFBY LOSS RATIO BY YEAR, WITH PREVAILING ENSO PHASE



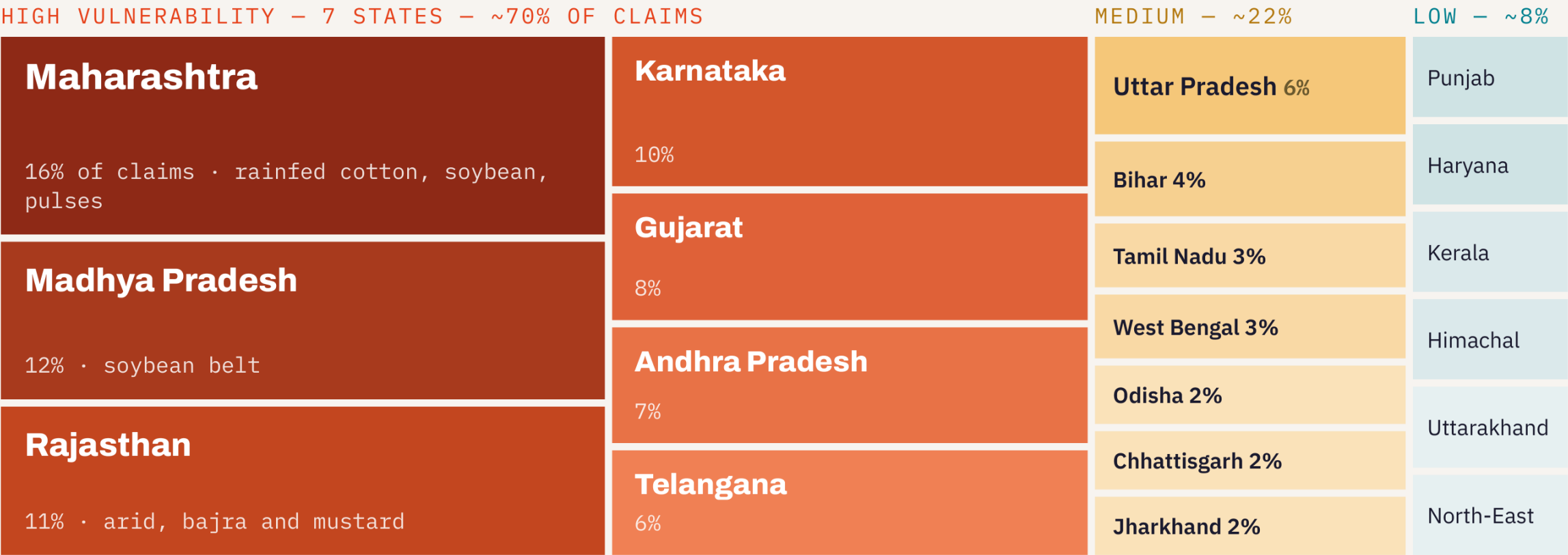
THE PATTERN

El Niño years cluster at the top of the range (FY19 98%, FY18 87%, FY20 85%), though FY24 came in at 76%; La Niña years sit lowest (FY22 57%, FY21 65%). A Strong+ 2026–27 implies ₹10,000–20,000 Cr of claims above normal.



State-wise vulnerability and claim share

Area = share of expected PMFBY claims in a Strong+ year



70% of expected Strong+ claims sit in seven states. Differential state pricing is the most direct lever available to insurers — and it is largely unused.

Impact by line of business

Crop is the largest direct exposure; the correlation across lines is the systemic risk

Crop

PMFBY — LARGEST EXPOSURE

~₹26,000 Cr portfolio premium

Strong or Super event drives claims ratios past 200% in affected states

Concentrated in monsoon-fed states

Government subsidy buffers insurer net loss

Property & CAT

FLOODS AND CYCLONES

Tamil Nadu and Andhra coastal flooding rises during El Niño

Arabian Sea cyclone intensification hits Gujarat and Maharashtra

Retrocession capacity tightens after a global Super event

Grid failure exposure in deficit zones

Health & Life

EXCESS MORTALITY

Heat wave excess mortality concentrated in the Indo-Gangetic Plain

Vector-borne disease surge after the event

Higher hospitalisation cost through pre-monsoon heat

Outdoor-worker group life shows measurable El Niño beta

Livestock & Marine

DROUGHT AND TRADE

Livestock mortality from fodder scarcity

Marine cargo exposed to route shifts and port closures

Aquaculture in Andhra and Tamil Nadu hit by SST anomalies

Agriculture-adjacent SME credit exposed indirectly

Strategic opportunities for insurers

Products, partnerships and risk transfer — all buildable with existing data

01

ENSO-indexed parametric cover

Trigger payouts on ONI peak or a rainfall index — fast settlement, low fraud, well suited to smallholders.

02

Reinsurance diversification

Pre-arrange capacity for correlated years rather than competing for retro capacity after a global event hardens it.

03

Crop portfolio rebalancing

Reweight PMFBY exposure toward irrigated states and price the residual rain-dependent risk at El Niño frequency.

04

Heat-wave mortality products

Group covers for outdoor labour on parametric heat-day triggers, paired with employer wellness programmes.

05

Climate risk bonds

Sovereign or insurer-sponsored cat bonds transfer tail risk to global capital markets at favourable spreads.

06

Dynamic pricing on ENSO beta

A multi-year forecast horizon supports differential pricing between El Niño, neutral and La Niña years.

Every item above is implementable with open data and existing IRDAI product frameworks.

SECTION 08

Conclusion & Disclaimers

Key takeaways and methodological caveats

Key takeaways

What we know, what we estimate, and what we recommend

KNOWN

91%

El Niño is highly likely in 2026–27

Our model and the major international ensembles converge on a 91% probability of at least one event, with roughly a 45% chance of Strong or higher.

ESTIMATED

45%

Severity distribution skews high

Conditional on occurrence, about 45% of the probability mass sits in Strong or above. Indian agriculture should plan for an 5–38% kharif loss range.

UNCERTAIN

200Y+

Extrapolation past the record

With 75 years of data, 500-year and 1000-year return levels carry wide confidence intervals. Paleoclimate proxies would tighten them materially.

RECOMMENDED

ENSO

Treat it as a portfolio risk factor

Standard diversification assumptions fail in Super and Extreme years. Build the ENSO state into stress testing, capital planning and product design.

This is a methodology walkthrough, not a production model. A commercial ENSO or catastrophe model is built by specialist teams over many years, each component — ocean dynamics, downscaling, vulnerability, exposure — its own research programme. What is offered here is the shape of the problem and a reproducible path through it. The objective is not to forecast the event, but to be priced and capitalised across the full range of outcomes.

Disclaimer and limitations

Read before applying any model output to a commercial decision

01

Methodology demonstration, not a production model

All probability and severity numbers are model outputs from historical statistical relationships.

Model vintage: March 2026, when observed ONI stood at +0.13. Observed ONI has since risen to +0.51 (April) and **+0.98 (May 2026)** — an event is already developing, so the 2026 probability shown here is conservative and should be read as the position at model cut-off, not as a current forecast.

02

Probability labelling shorthand

'P(El Niño in 2026)' means onset within six months of the latest data. P(2027) applies the spring-barrier heuristic $p \times 1.05 + 0.05$ to P(2026).

03

Historical record limitations

ONI covers roughly 75 years. Return periods beyond 200Y rely on GEV extrapolation; paleoclimate proxies are not yet incorporated.

04

Climate change non-stationarity

The models assume stationary ENSO dynamics. Evidence suggests extreme event frequency is rising, so estimates may understate tail risk.

05

Insurance ranges are illustrative

Loss estimates are calibrated to

06

Open-source data limitations

WIOT is a 2014 vintage (pre-

07

Marine and monsoon calibration

AISMR uses an embedded

08

No investment or trading advice

Nothing in this presentation

Thank you

Questions & discussion

Open-source datasets — every figure reproducible

10,000-event Monte Carlo catalogue

GEV return periods with bootstrap intervals

Streamlit dashboard with the country-pair risk playground

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