Cloud-Robust SAR–Optical Flood Segmentation via Evidential Multi-Branch Fusion

A concise summary of the model, dataset, and test results.

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1. Model

1.1 Backbone and decoder (shared across all four trails)

- **Backbone**: TerraMind v1 base, pretrained, **frozen**. Joint ViT — S1 and S2 tokens attend to each other inside the encoder. `merge_method=mean` pools per-modality tokens.
- **Neck**: `SelectIndices [2,5,8,11]` → `ReshapeTokensToImage` → `LearnedInterpolateToPyramidal`.
- **Decoder**: U-Net decoder, channels `[512, 256, 128, 64]`, **unfrozen**.
- **Head**: 1×1 Conv with 2 output channels, dropout 0.1.

1.2 Multi-branch training (input-mask slim)

For every batch, the task slices the multi-modal input dict into three configurations and runs a **full backbone + neck + decoder forward** for each:

`M : { S1, S2 } → { fused: {S1, S2},  s: {S1},  o: {S2} }`

Each forward produces `(B, 2, H, W)` logits. The training loss is the weighted sum of per-branch losses,

$$L = w_f\, L_f + w_s\, L_s + w_o\, L_o, \qquad w_f = 2, w_s = w_o = 1.$$

Three forwards per training step. Validation/test default to a single fused forward; adaptive test combines the three outputs (§1.4).

1.3 EDL head reinterpretation

The decoder's `(B, 2, H, W)` output is treated as **Dirichlet evidence**, not class logits. Per pixel, per branch:

$$\begin{aligned} e_k &= \mathrm{softplus}(\mathrm{logit}_k),\ k \in \{0,1\} && \text{evidence} \\ \alpha_k &= e_k + 1 && \text{Dirichlet concentration} \\ S &= \alpha_0 + \alpha_1 && \text{Dirichlet strength} \\ \bar{P}_k &= \alpha_k / S && \text{expected class prob.} \\ u &= K/S = 2/S && \text{vacuity } (1 = \text{total ignorance}) \end{aligned}$$

Per-branch loss (digamma variant) over valid pixels (`y ≠ −1`):

$$
\begin{aligned}
A_{\text{pix}} &= \sum_k y_k^{\text{oh}} \left[\psi(S) - \psi(\alpha_k) \right] && \text{data term} \\
\tilde{\alpha}_k &= (\alpha_k - 1)\,(1 - y_k^{\text{oh}}) + 1 && \text{wrong-class evidence} \\
\text{KL} &= \text{KL}\left[\text{Dir}(\tilde{\alpha}) \,\|\, \text{Dir}(1,1) \right] && \text{closed form} \\
\lambda(t) &= \min\big(1, (t+1)/T\big),\ T = 10 && \text{anneal coef} \\
L_{\text{branch}} &= \text{mean}_{\text{valid}} \left[A_{\text{pix}} + \lambda(t)\, \text{KL}_{\text{pix}} \right]
\end{aligned}
$$

The KL term pulls *wrong-class* evidence toward 1 while leaving correct-class evidence free, so the model learns to emit **flat α (high vacuity)** on hard pixels and **peaked α (low vacuity)** on easy ones. Annealing prevents the prior from dominating before the data term has fit.

Hard predictions are unchanged from the cross-entropy baseline: $\text{argmax}(\alpha) \equiv \text{argmax}(\alpha/S)$.

1.4 Adaptive mixer at test time

Three forwards produce three Dirichlet outputs $\alpha_b, b \in \{f, s, o\}$. Define per-branch **purity** confidence under the law of total variance (LoTV) of the Dirichlet–Categorical model:

$$
\begin{aligned}
c_b &= 1 - \big(\text{aleatoric}_b + \text{epistemic}_b \big) \\
&= \sum_k \bar{P}_{b,k}^2 \in [0.5, 1] \quad \text{(binary)}
\end{aligned}
$$

Aleatoric and epistemic are S-dependent individually but their **sum is S-independent** — c_b depends only on $\bar{P}_b$. The three-way mix:

$$
\hat{y}(h,w) = \frac{c_f\, \bar{P}_f + c_s\, \bar{P}_s + c_o\, \bar{P}_o}{c_f + c_s + c_o + \varepsilon}
$$

No external detector. No cloud-specific labels. The same forward stack used in training produces both the prediction and its weight in the mix.

1.5 Trails compared

Code	Architecture	Test path	Cloud signal source
`baseline`	Single fused forward, vanilla seg task	one fused forward, argmax(P_f)	none
`m1_fused`	Multi-branch CE, `mode_fused`	one fused forward, argmax(P_f)	none
`m1_adaptive`	Multi-branch CE + s2cloudless U-Net gate	`ŷ = (1 − p_o)·P_s + p_o·P_f`	external supervised gate
`m2_lotv`	**Multi-branch EDL, three-way LoTV mix**	**`ŷ = Σ c_b·P̄_b / Σ c_b`**	**own Dirichlet vacuity**

`m1_fused` is the within-method ablation — same model as `m1_adaptive`, just no gate at test time. It isolates "the gate decides when to fall back" from "the multi-branch training objective made the fused branch better."

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2. Dataset

Sen1Floods11, hand-labeled subset.

Split	N chips	Source	Hand-labels	Role
train	252	10 countries	yes	training
valid	89	same	yes	val/mIoU monitor
test	90	same	yes	IID evaluation
bolivia	15	held-out	yes	**geographic OOD**

Train countries: Ghana, India, Mekong, Nigeria, Pakistan, Paraguay, Somalia, Spain, Sri-Lanka, USA. Bolivia is never seen during training.

Modalities per chip (224 × 224, native): - S2L2A: 12 spectral bands + SCL band (Sen2Cor scene classification, used only for cloud-fraction stratification — *not* a training label). - S1GRD: 2 bands (VV, VH). - LabelHand: `{0, 1, −1}` (background, flood, ignore). - S1OtsuLabelHand: per-event SAR-Otsu water proxy, used only as a **reference** in the SAR cross-check (Bonafilia et al. 2020).

Cloud cover (s2cloudless prob > 0.3, fraction over valid pixels).

Split	N	mean	median	max
train	252	0.253	0.059	1.000
valid	89	0.245	0.096	1.000
test	90	0.214	0.037	1.000
bolivia	15	0.206	0.177	0.592

The IID test split has a long clear-sky tail (median 3.7 % cloud); Bolivia has the highest median (17.7 %) and no near-clear or near-fully-cloudy chips — the regime where adaptive routing matters most.

Cloud-fraction stratification (used for per-stratum evaluation):

Bin	Range	test (n)	bolivia (n)
clear	< 5 %	46	3
low	5–25 %	21	4
medium	25–50 %	10	3
high	50–75 %	3	1
heavy	**≥ 75 %**	**10**	**4**

The four Bolivia heavy-cloud tiles are the cell where the cloud-recovery question lives.

Flood prevalence: train 9.4 %, test 13.5 %, bolivia 17.0 % — Bolivia is flood-enriched, which suppresses the macro-IoU floor and makes per-tile deltas interpretable.

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3. Test results and metrics

Two splits — IID test (90 tiles) and held-out Bolivia (15 tiles). All four trails evaluated through three orthogonal axes: per-stratum metrics (hand-label reference), SAR cross-check (S1Otsu reference), and uncertainty calibration. EDL ckpt at `T = 10`, val/mIoU = 0.8992.

3.1 Headline — Bolivia heavy-cloud bin (4 tiles)

Metric	base-line	m1_fused	m1_adaptive	**m2_lotv (EDL)**
IoU_Flood vs hand-label	0.0000	0.0000	0.2225	**0.5016**
mIoU vs hand-label	0.4518	0.4518	0.5717	**0.7203**
κ vs SAR (under-cloud region)	0.000	0.000	0.469	**0.603**
IoU vs SAR (under-cloud region)	0.000	0.000	0.393	**0.498**

Naive joint fusion (baseline, m1_fused) **collapses to zero flood IoU** under heavy cloud — the joint encoder does not back off from S2 on its own. The s2cloudless-supervised gate (m1_adaptive) recovers part of the signal. The EDL three-way LoTV mix (m2_lotv) recovers ~50 % flood IoU from the same architectural budget, **without any external detector or cloud-specific labels**, and the same ranking holds against an independent SAR reference.

3.2 Per-stratum mIoU (hand-label reference)

Split	bin	baseline	m1_fused	m1_adaptive	**m2_lotv**
test	clear	0.8598	0.8472	0.8209	0.8438
test	low	0.9135	0.9097	0.8974	0.9142
test	medium	0.8954	0.8938	0.8760	0.8937
test	high	0.9888	0.9934	0.9842	0.9882
test	heavy	0.7087	0.7112	0.7195	**0.7335**
test	*all*	0.8850	0.8786	0.8617	0.8793
bolivia	clear	0.7691	0.8346	0.8472	**0.8491**
bolivia	low	0.8290	0.8431	0.8041	**0.8792**
bolivia	medium	0.8578	0.8519	0.8174	**0.8938**
bolivia	high	0.7840	0.8043	0.7705	**0.8433**
bolivia	heavy	0.4518	0.4518	0.5717	**0.7203**
bolivia	*all*	0.7852	0.7952	0.7864	**0.8613**

LoTV wins every bin on Bolivia and never costs more than 0.04 mIoU on IID test. The s2cloudless gate (m1_adaptive) hurts on the IID `_all_` row (−0.023 vs baseline) because it over-fires on partially-cloudy clear scenes and recruits the weaker S1-only branch where it isn't needed.

3.3 IoU_Flood per stratum (Bolivia)

bin	baseline	m1_fused	m1_adaptive	**m2_lotv**
clear	0.5496	0.6758	0.6997	**0.7038**
low	0.7534	0.7744	0.7156	**0.8279**
medium	0.7605	0.7500	0.6908	**0.8217**
high	0.7486	0.7734	0.7298	**0.8233**
heavy	0.0000	0.0000	0.2225	**0.5016**
all	0.6370	0.6535	0.6380	**0.7676**

LoTV improves Bolivia overall IoU_Flood by **+0.131** vs baseline (0.637 ⟶ 0.768).

3.4 SAR cross-check (independent reference)

Per-event SAR Otsu (Bonafilia et al. 2020) used as a label-free reference under cloud cover. Same model ranking as §3.2/3.3 across both regions:

Region	metric	baseline	m1_fused	m1_adaptive	**m2_lotv**
labelled (Bolivia)	κ vs hand	0.395	0.412	0.471	**0.558**
labelled (Bolivia)	IoU vs hand	0.357	0.378	0.418	**0.500**
under-cloud (Bolivia, *all*)	κ vs SAR	0.147	0.204	0.331	**0.424**
under-cloud (Bolivia heavy)	κ vs SAR	0.000	0.000	0.469	**0.603**

The verdict is reproduced against a reference that does not depend on the hand-labels at all.

3.5 Uncertainty signals as pixel-level error detectors (AUROC)

Signal	test (`_all_`)	bolivia (`_all_`)	bolivia heavy
m1_adaptive / p_cloud	0.539	0.613	0.602
m2_lotv / 1−c_f	**0.952**	**0.907**	**0.857**
m2_lotv / 1−c_s	0.814	0.832	0.900
m2_lotv / 1−c_o	0.886	0.815	0.423
m2_lotv / aleatoric_f	0.952	0.907	0.874
m2_lotv / epistemic_f	0.952	0.906	0.874

LoTV's fused-branch purity `1 − c_f` is the **strongest single error detector**: AUROC 0.95 on IID, 0.91 on Bolivia, ≥ 0.78 in every per-stratum cell. The s2cloudless gate `p_cloud` is **not a useful error detector for the fused output** — chance-level on IID, anti-correlated under heavy IID cloud — because the gate's job is to flag bad S2, not to flag where the mix is still wrong.

EDL pre-pilot (`T = 10`, the LoTV ckpt directly):

split	branch	accuracy	ECE	u_mean	AUROC(u → err)
test	fused	0.973	0.022	0.094	**0.908**
test	S1	0.946	0.016	0.117	0.862
test	S2	0.969	0.024	0.097	0.902
bolivia	fused	0.956	0.041	0.158	**0.920**
bolivia	S1	0.899	0.035	0.200	0.925
bolivia	S2	0.822	0.089	0.224	0.920

Vacuity is non-degenerate (`u_mean ∈ [0.09, 0.22]` everywhere — neither saturated at 0 nor at 1), so the LoTV mix's per-branch confidences are trustworthy inputs without further training.

3.6 Known LoTV failure mode (transparency)

On clear in-dist tiles where S1 is **wrong but confident** — typically urban radar shadow over built-up areas — the mix amplifies the S1 error rather than damping it. Documented case: `Pakistan_70625` (clear urban scene), where baseline correctly identifies just the river (mIoU 0.184 above LoTV) but LoTV hallucinates flood pixels in the city. This failure mode does not fire on Bolivia (rural / sparsely-built scenes) and does not fire on cloudy in-dist tiles. Worth flagging when deploying on urban floods.

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4. Take-aways

1. **Q1 — does naive joint fusion automatically back off from S2 under cloud?** No. Bolivia heavy bin: baseline IoU_Flood 0.000, κ vs SAR 0.000. The encoder does not learn to ignore the cloud-degraded optical channel on its own.
2. **Q2 — can a *label-free* training method make it back off?** Yes. LoTV (EDL three-way mix) lifts Bolivia heavy IoU_Flood to 0.502 and κ to 0.603, with overall Bolivia IoU_Flood +0.131 vs baseline. IID performance is unchanged. The s2cloudless-supervised gate also helps, but less, and at a measurable IID cost.
3. **LoTV self-flags its own residual mistakes.** AUROC of `1 − c_f` against pixel error: 0.95 IID, 0.91 OOD. The gate's `p_cloud` does not carry this information.
4. **Cross-axis consistency.** Hand-label per-stratum metrics, SAR Otsu cross-check, and uncertainty calibration give the same ranking `baseline ≤ m1_fused ≤ m1_adaptive < m2_lotv`. The verdict is not an artefact of how the hand-labels were drawn.

S8 — Per-tile inference samples

Every available `fig4_inputs_conf` panel (Sentinel-2 RGB · Sentinel-1 VH · spatial classification result with per-tile mIoU/F1) is embedded below, grouped by split ⟶ cloud-fraction stratum ⟶ tile. On Bolivia, each tile is shown twice back-to-back — first the **baseline** prediction, then the **m2_lotv (EDL three-way LoTV mix)** prediction — so the same scene can be compared directly across the two models. The IID test split shows **baseline** only because per-tile renders for `m2_lotv` on that split were not produced; the curated 20-tile subset (heavy + top-disagreement, all four models) lives under `S8_qualitative/viz_test_subset/`. Images here are 1400px-wide JPEG re-renders of the source PNGs in `output/figure/final/`, generated solely to keep the bundled PDF compact.

S8.1 IID test split — baseline (90 tiles)

Clear (<5% cloud) — 46 tiles

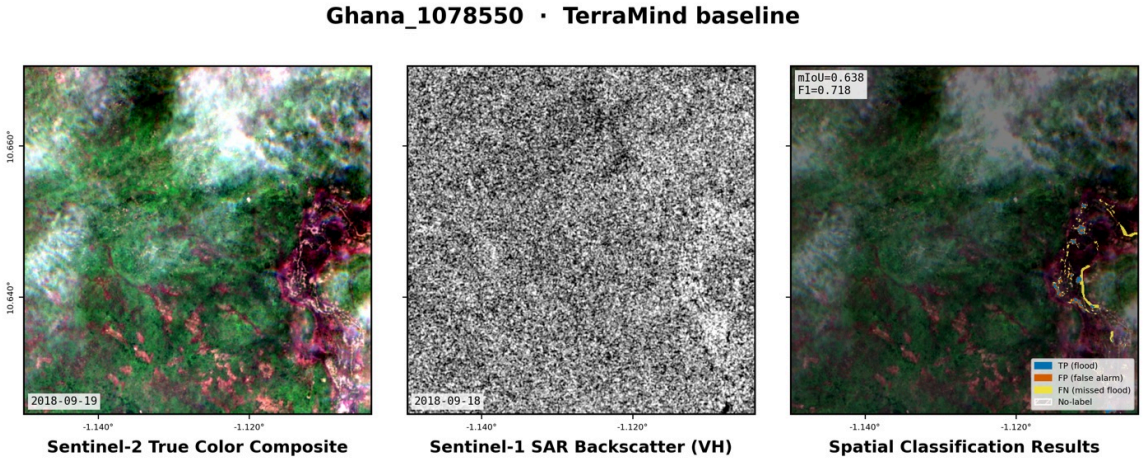

Figure 1: Ghana_1078550 · TerraMind baseline · cloud 0.06%

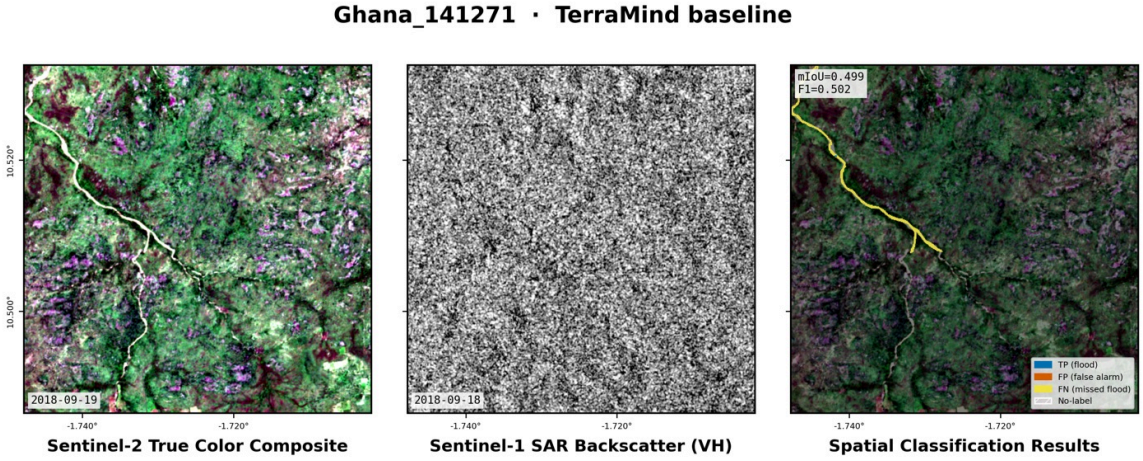

Figure 2: Ghana_141271 · TerraMind baseline · cloud 0.00%

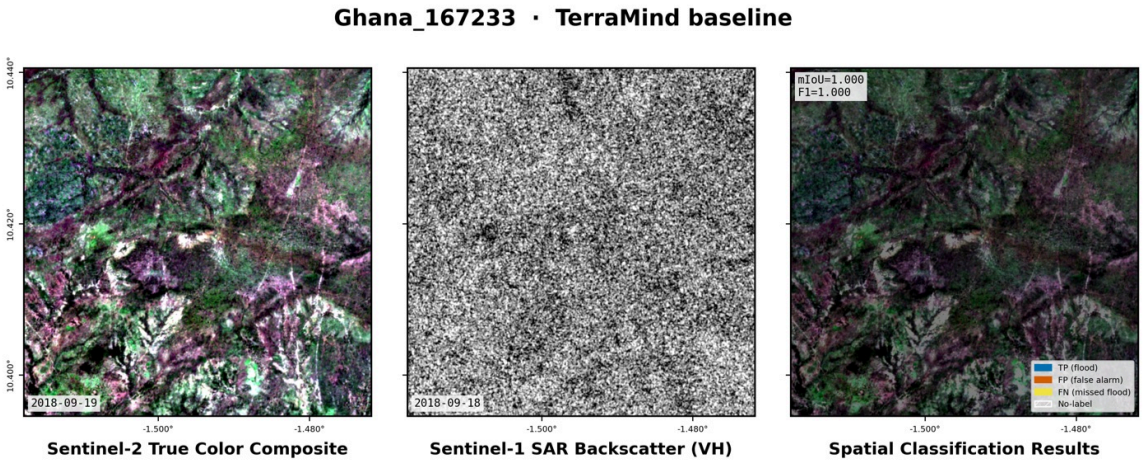

Figure 3: Ghana_167233 · TerraMind baseline · cloud 0.00%

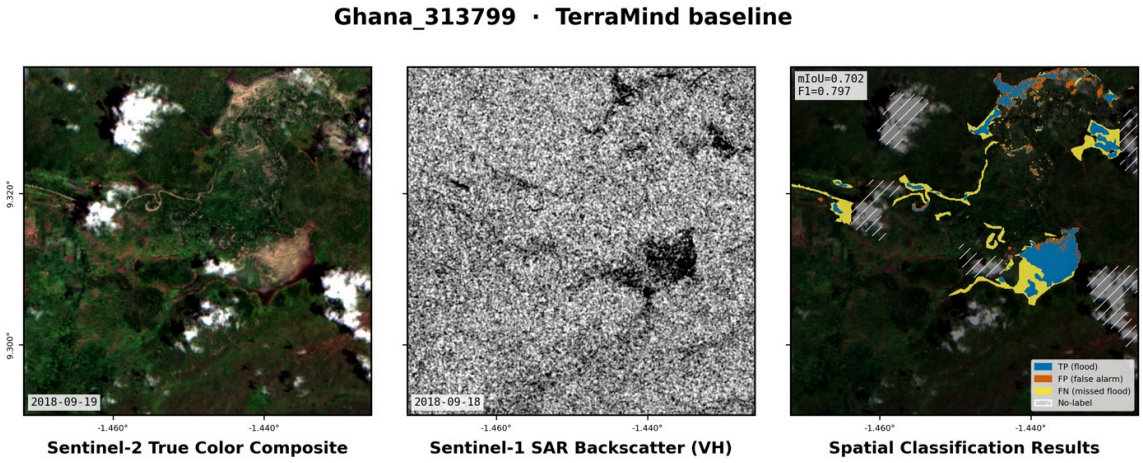

Figure 4: Ghana_313799 · TerraMind baseline · cloud 0.51%

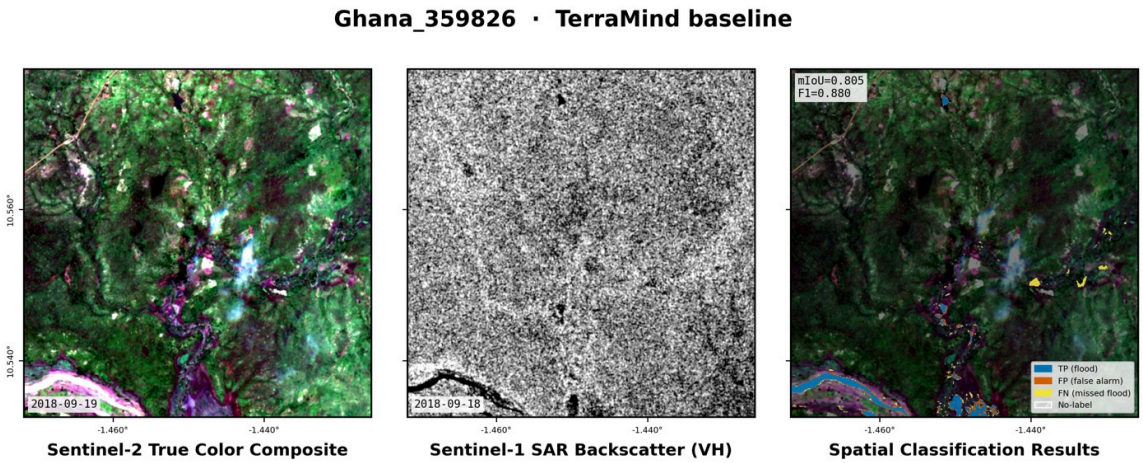

Figure 5: Ghana_359826 · TerraMind baseline · cloud 0.08%

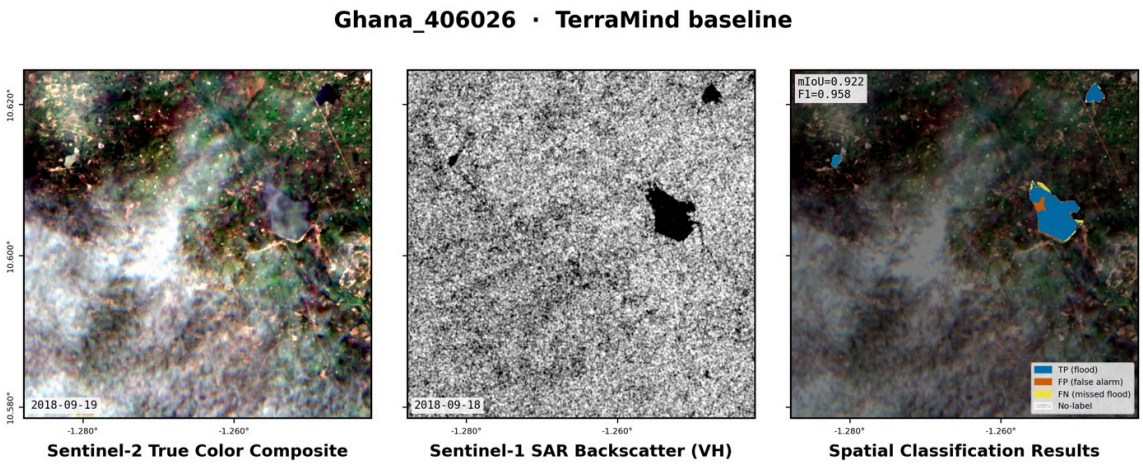

Figure 6: Ghana_406026 · TerraMind baseline · cloud 0.03%

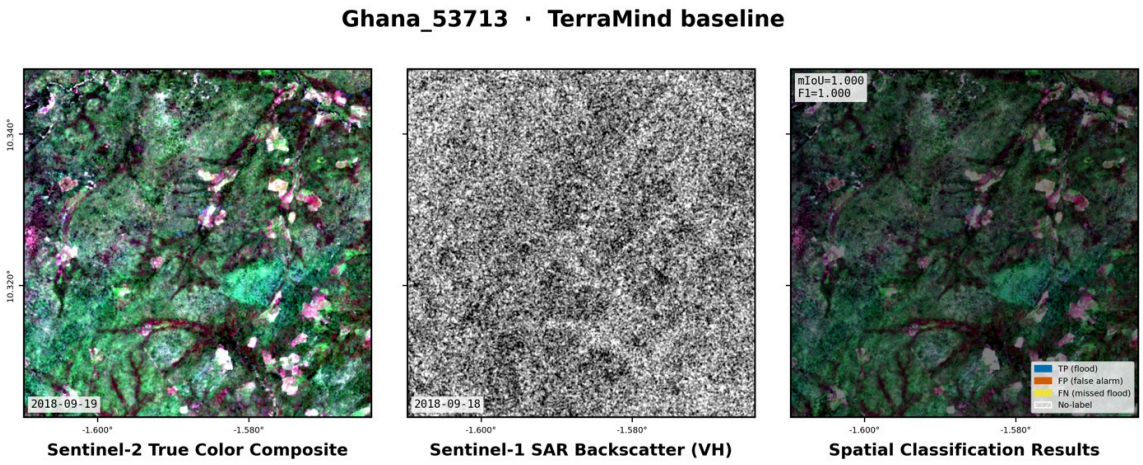

Figure 7: Ghana_53713 · TerraMind baseline · cloud 0.00%

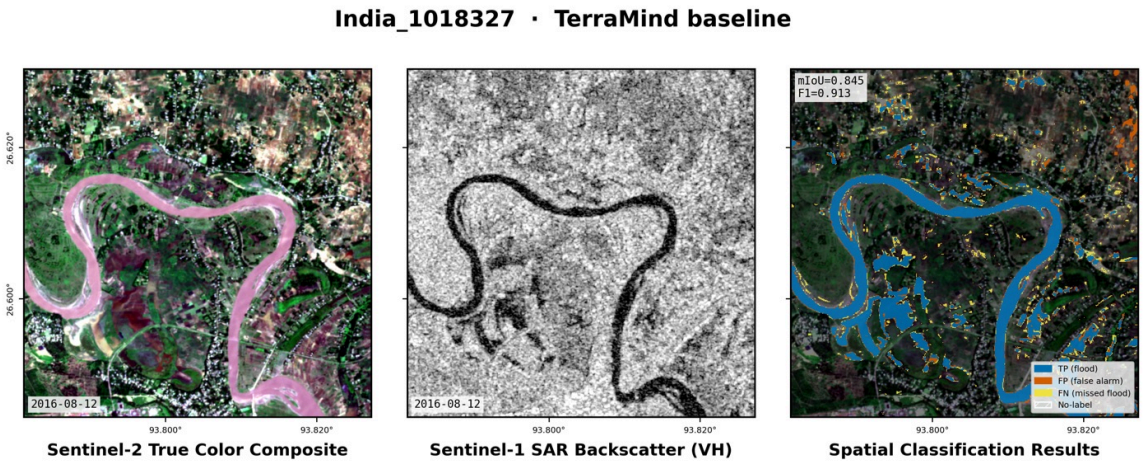

Figure 8: India_1018327 · TerraMind baseline · cloud 2.72%

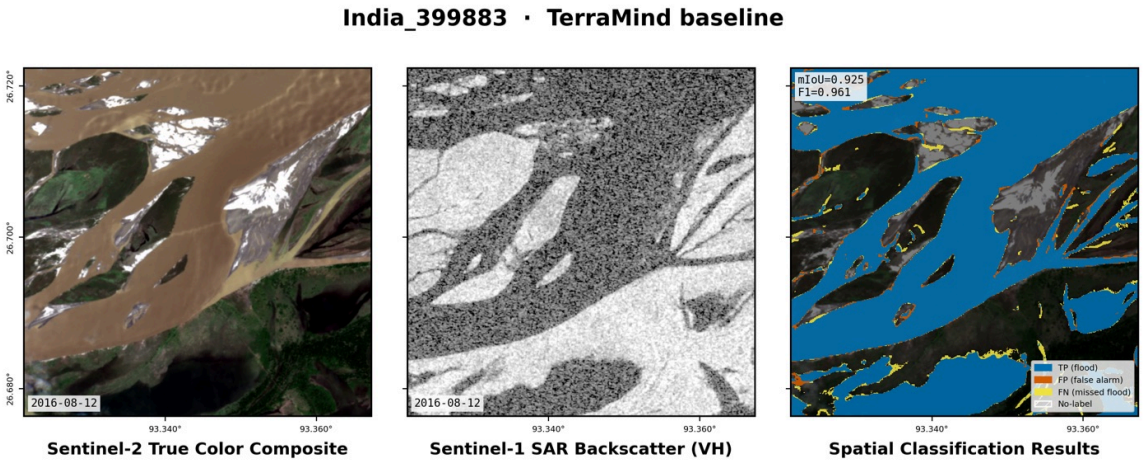

Figure 9: India_399883 · TerraMind baseline · cloud 2.30%

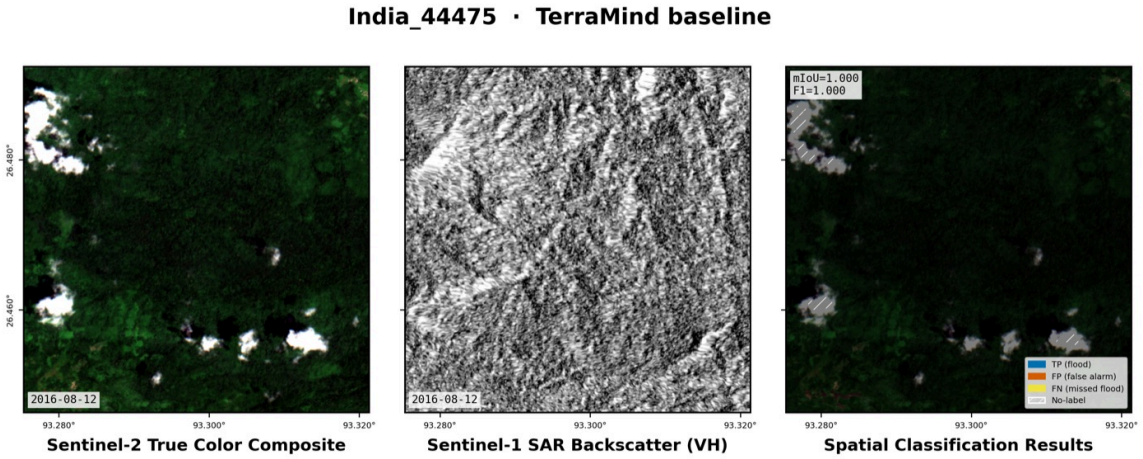

Figure 10: India_44475 · TerraMind baseline · cloud 0.87%

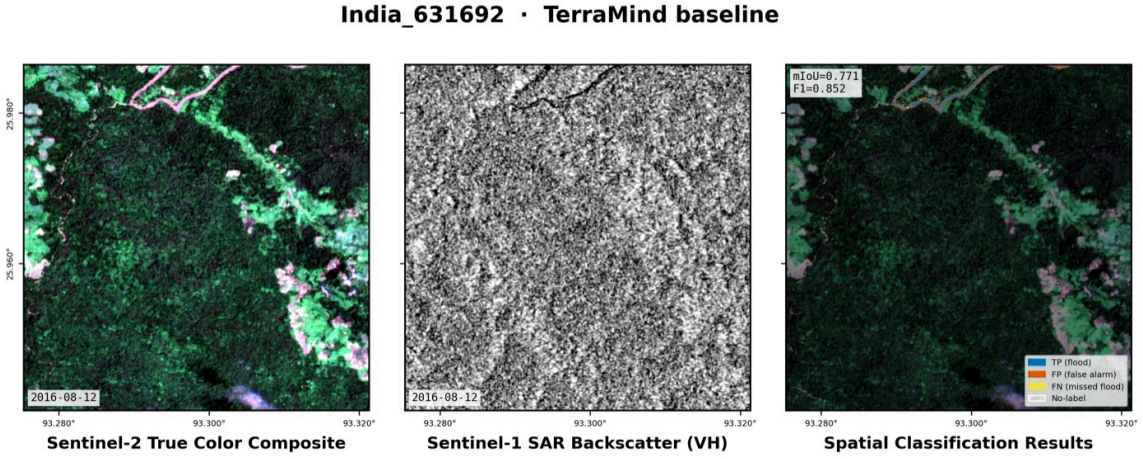

Figure 11: India_631692 · TerraMind baseline · cloud 0.07%

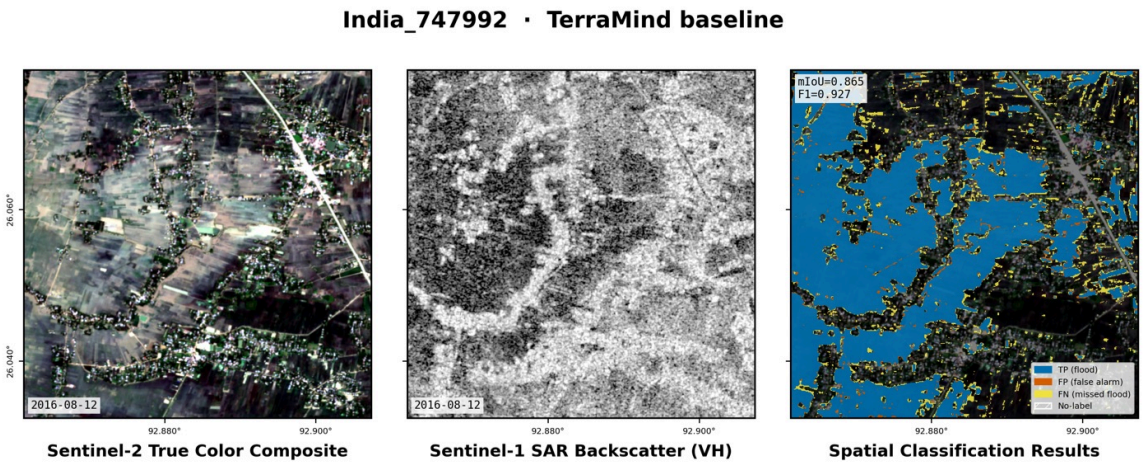

Figure 12: India_747992 · TerraMind baseline · cloud 4.59%

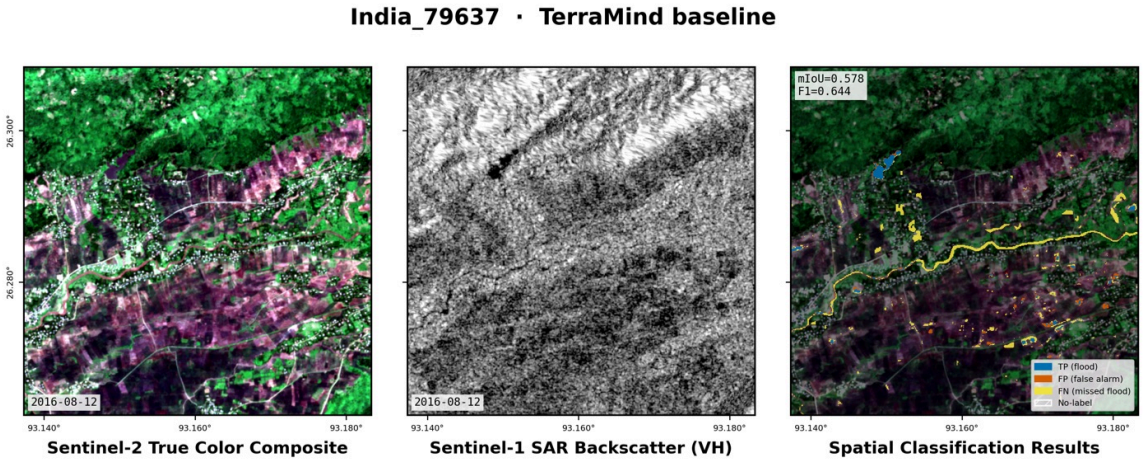

Figure 13: India_79637 · TerraMind baseline · cloud 0.69%

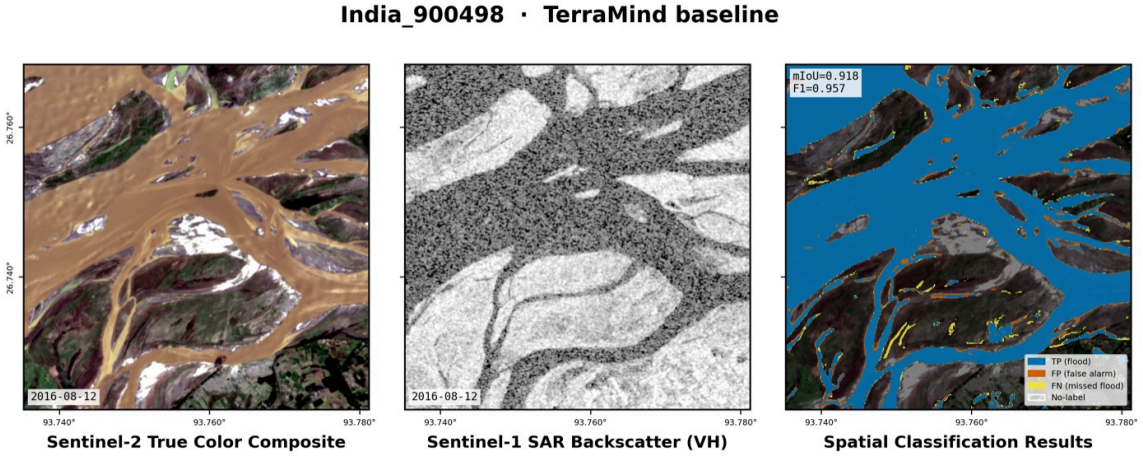

Figure 14: India_900498 · TerraMind baseline · cloud 1.18%

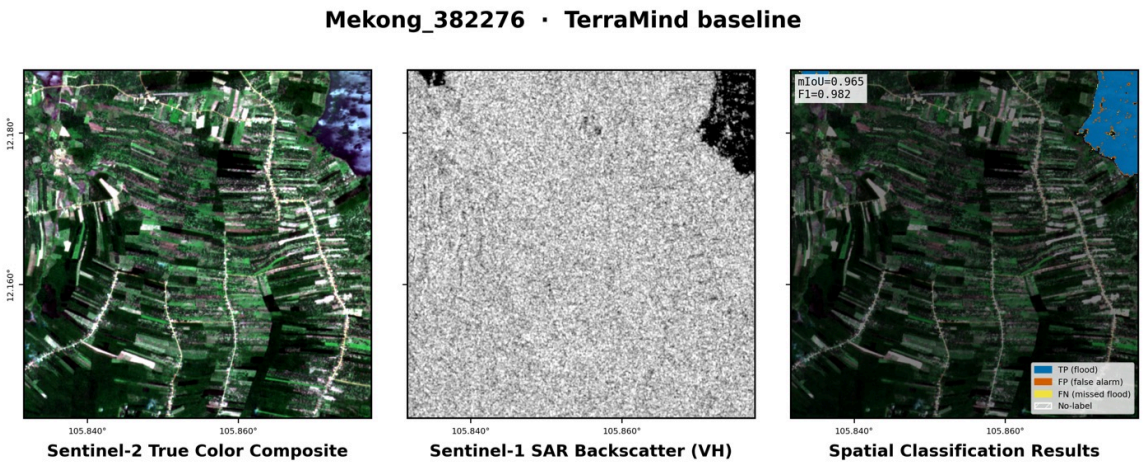

Figure 15: Mekong_382276 · TerraMind baseline · cloud 0.44%

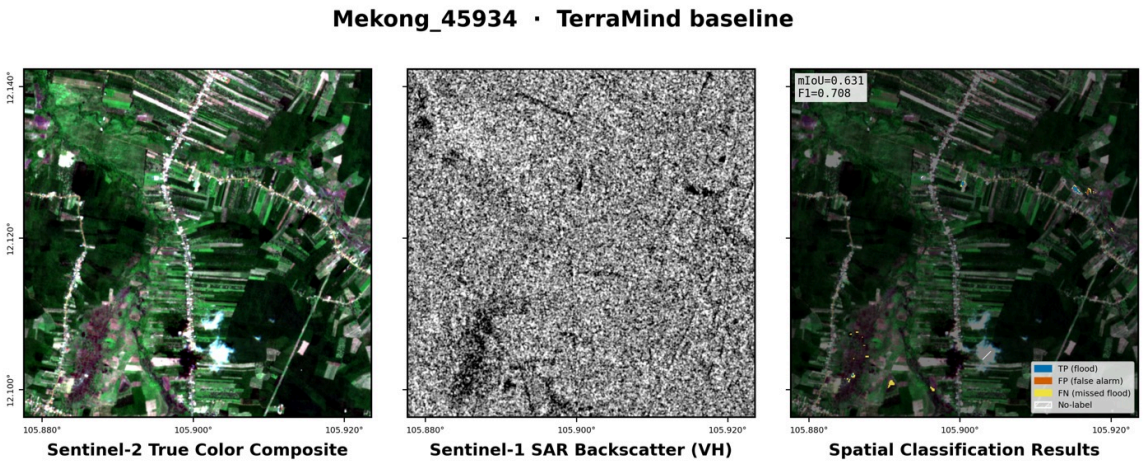

Figure 16: Mekong_45934 · TerraMind baseline · cloud 0.27%

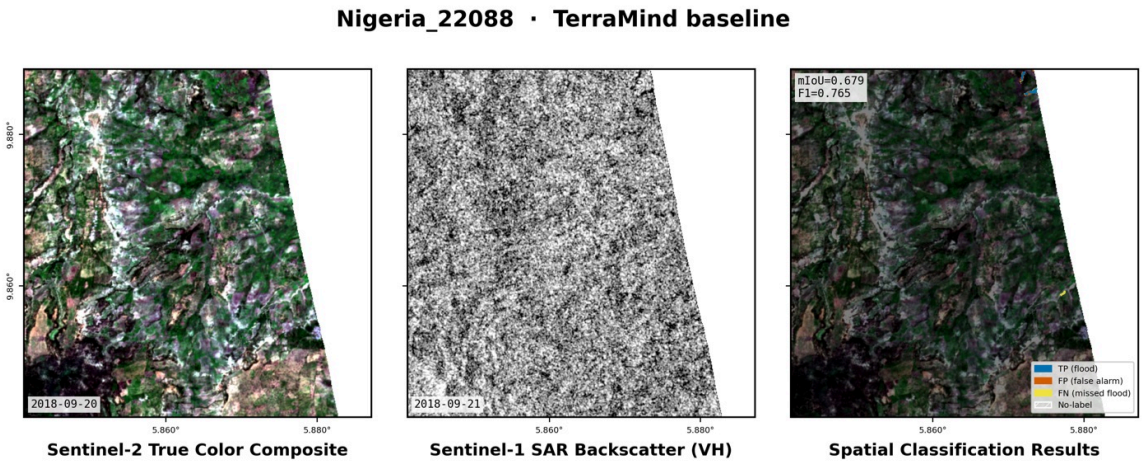

Figure 17: Nigeria_22088 · TerraMind baseline · cloud 0.41%

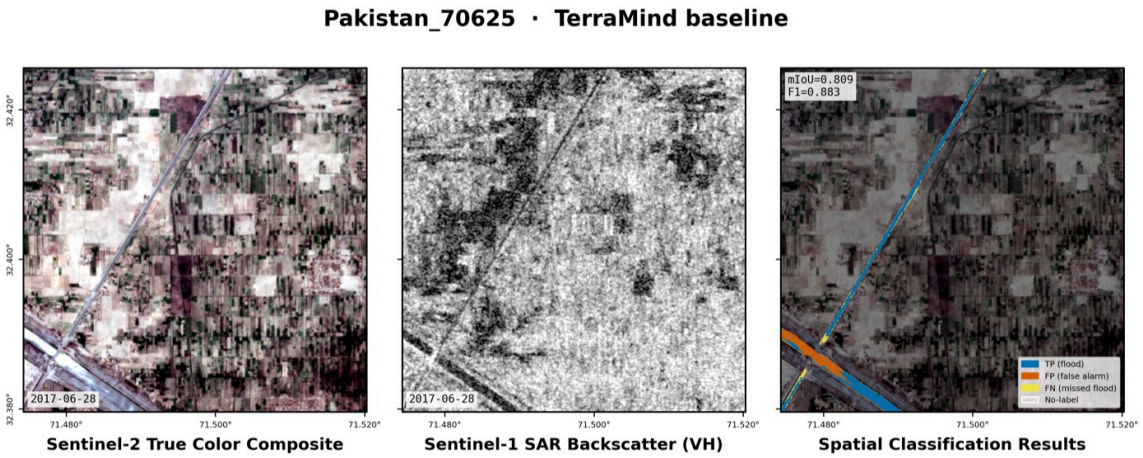

Figure 18: Pakistan_70625 · TerraMind baseline · cloud 0.69%

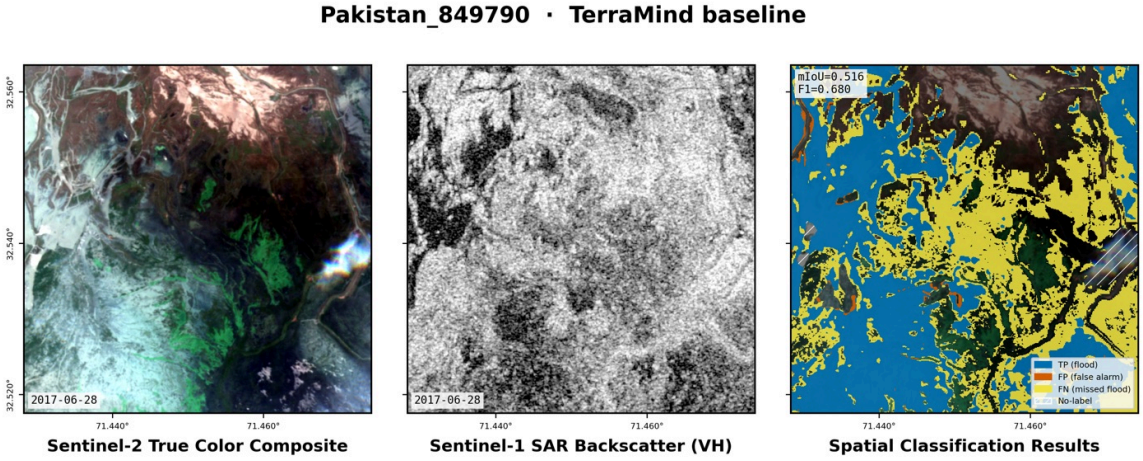

Figure 19: Pakistan_849790 · TerraMind baseline · cloud 1.19%

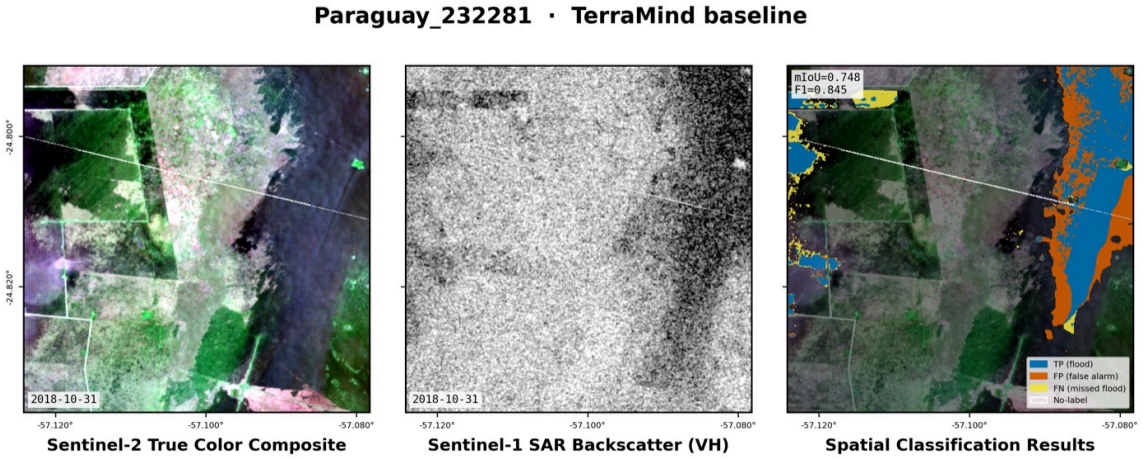

Figure 20: Paraguay_232281 · TerraMind baseline · cloud 1.19%

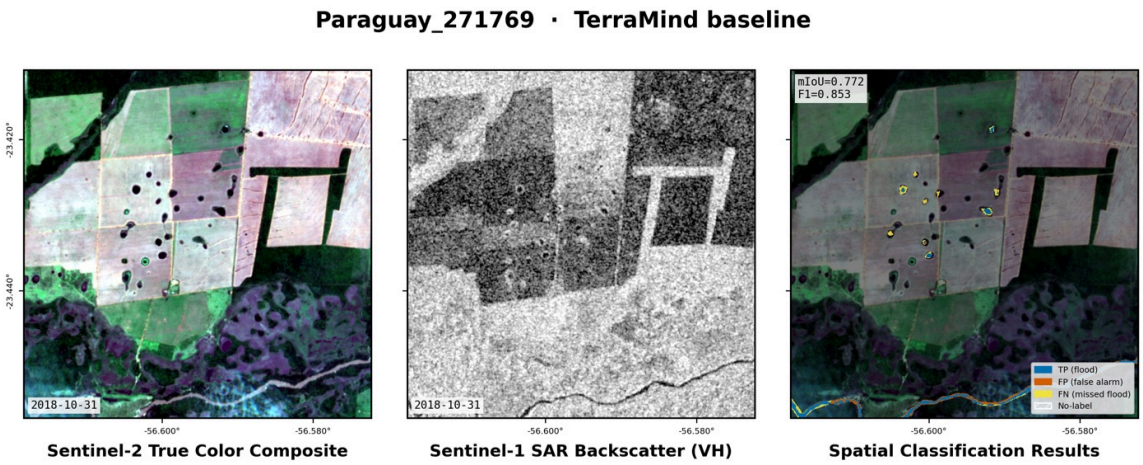

Figure 21: Paraguay_271769 · TerraMind baseline · cloud 0.10%

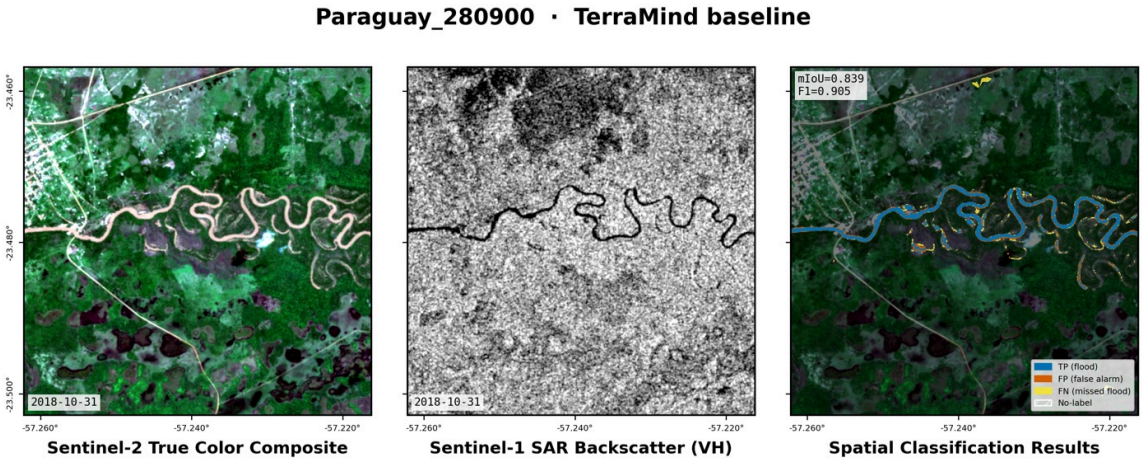

Figure 22: Paraguay_280900 · TerraMind baseline · cloud 0.43%

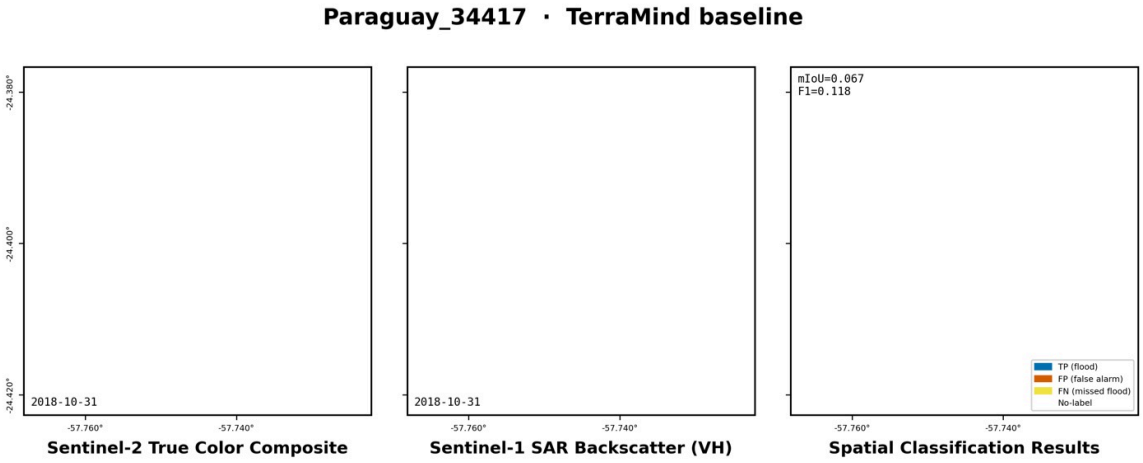

Figure 23: Paraguay_34417 · TerraMind baseline · cloud 1.09%

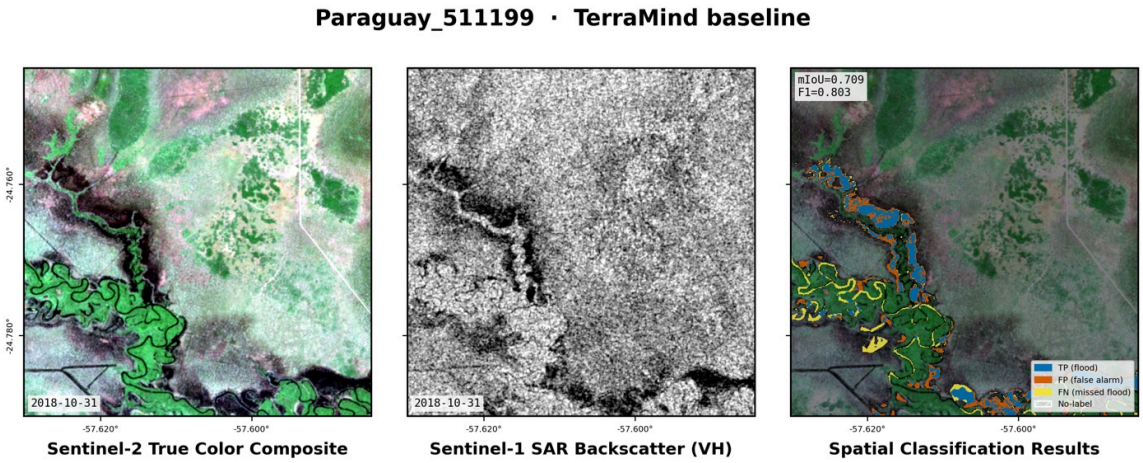

Figure 24: Paraguay_511199 · TerraMind baseline · cloud 2.67%

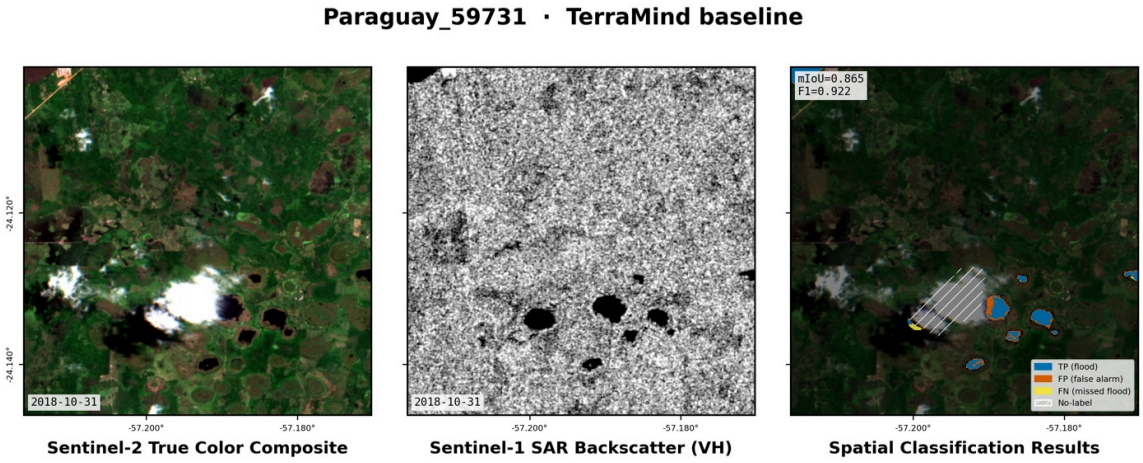

Figure 25: Paraguay_59731 · TerraMind baseline · cloud 2.82%

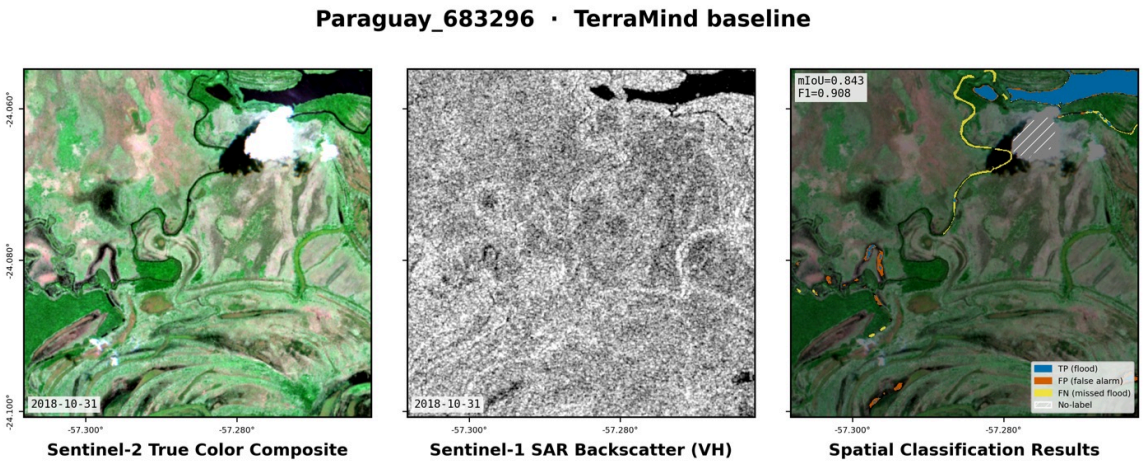

Figure 26: Paraguay_683296 · TerraMind baseline · cloud 3.09%

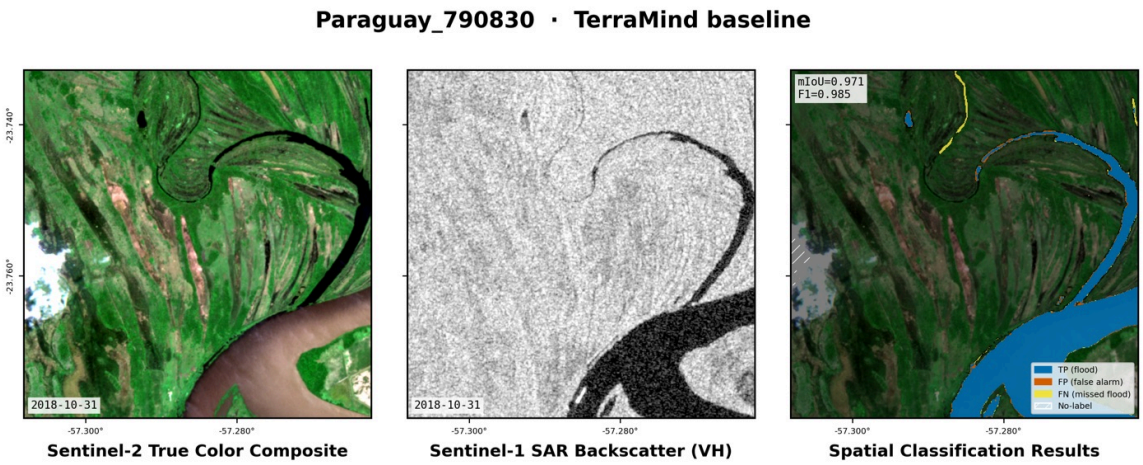

Figure 27: Paraguay_790830 · TerraMind baseline · cloud 1.59%

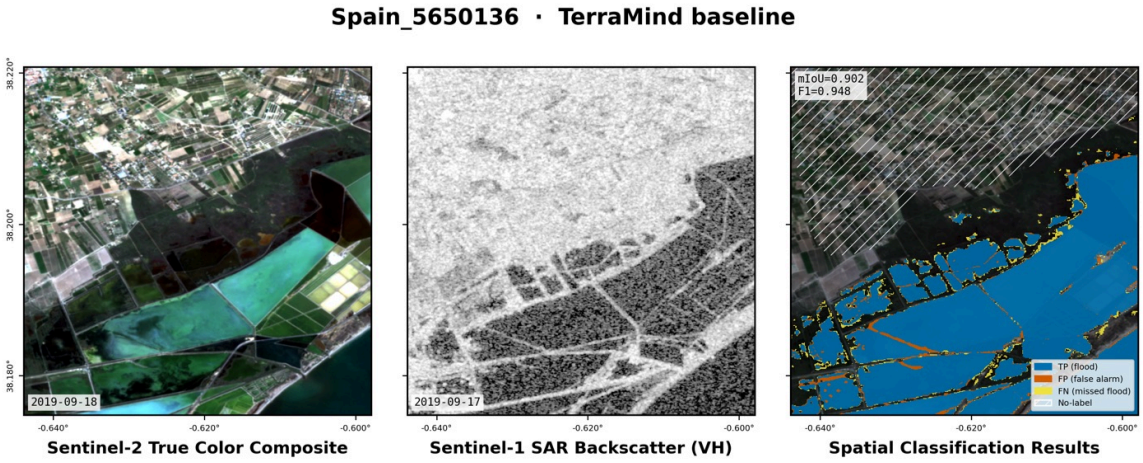

Figure 28: Spain_5650136 · TerraMind baseline · cloud 2.59%

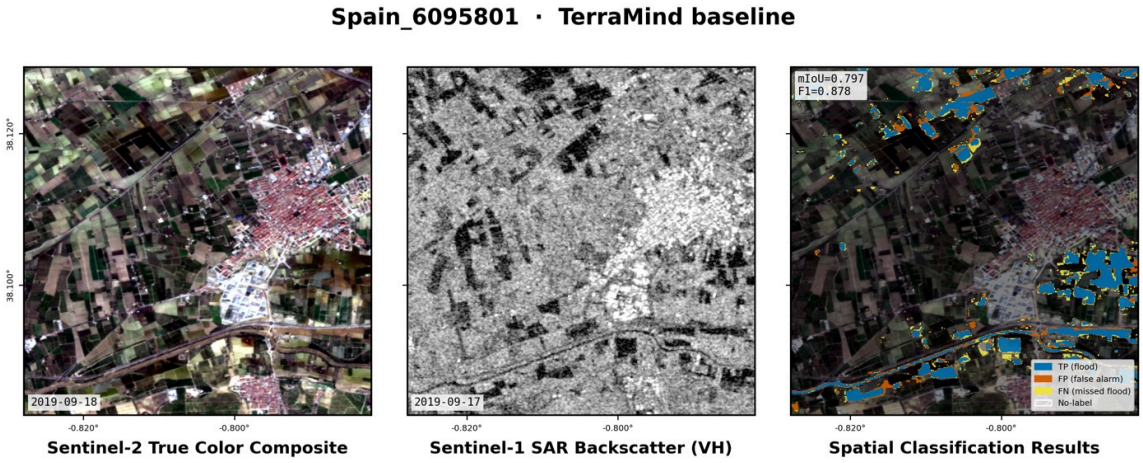

Figure 29: Spain_6095801 · TerraMind baseline · cloud 0.36%

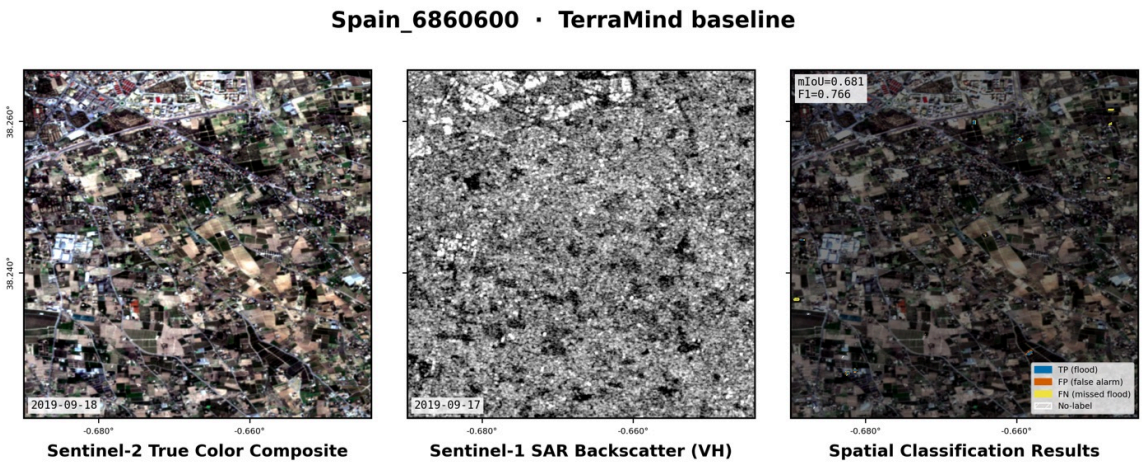

Figure 30: Spain_6860600 · TerraMind baseline · cloud 0.13%

Figure 31: Spain_7558720 · TerraMind baseline · cloud 0.12%

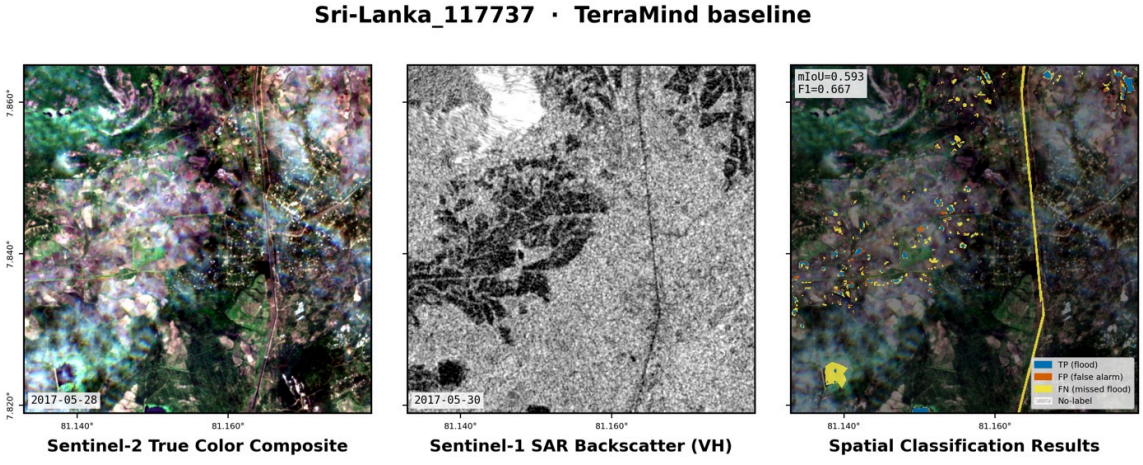

Figure 32: Sri-Lanka_117737 · TerraMind baseline · cloud 0.53%

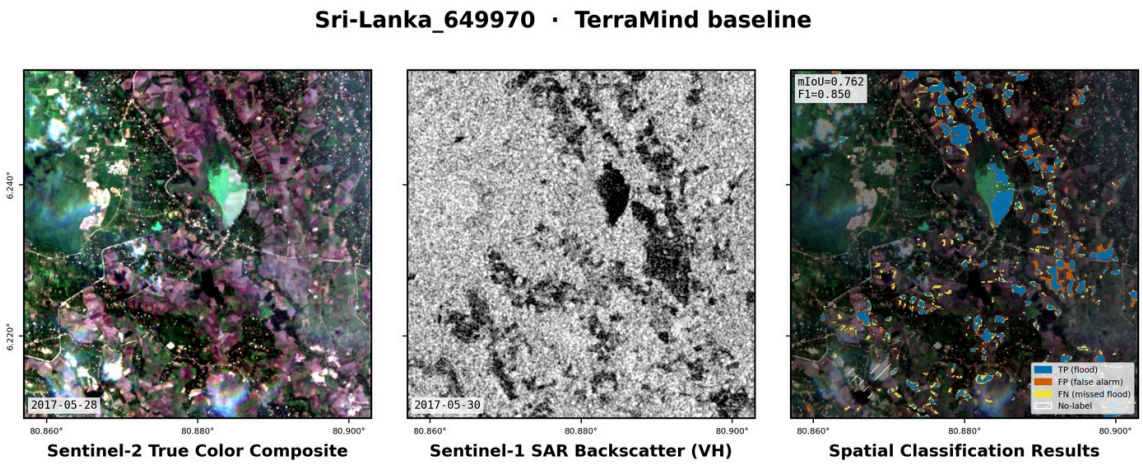

Figure 33: Sri-Lanka_649970 · TerraMind baseline · cloud 2.46%

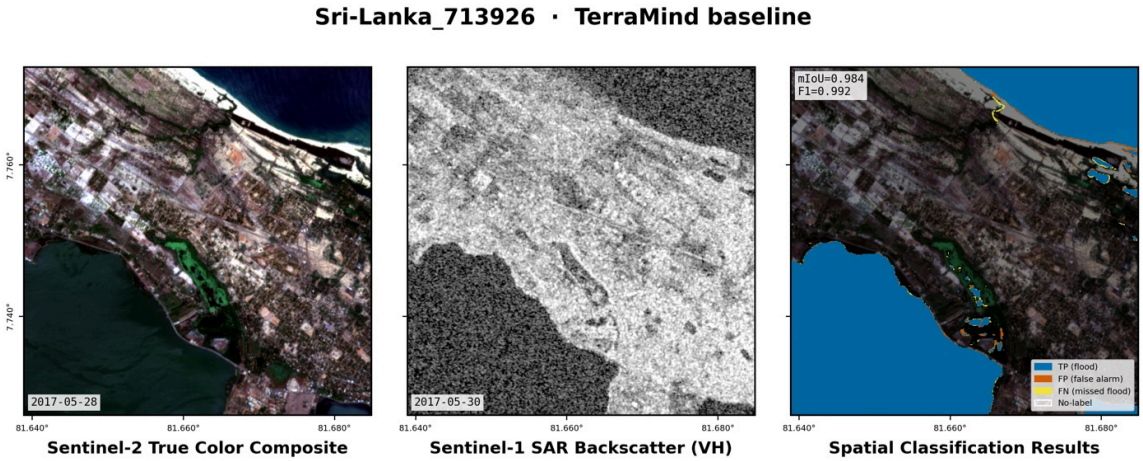

Figure 34: Sri-Lanka_713926 · TerraMind baseline · cloud 0.50%

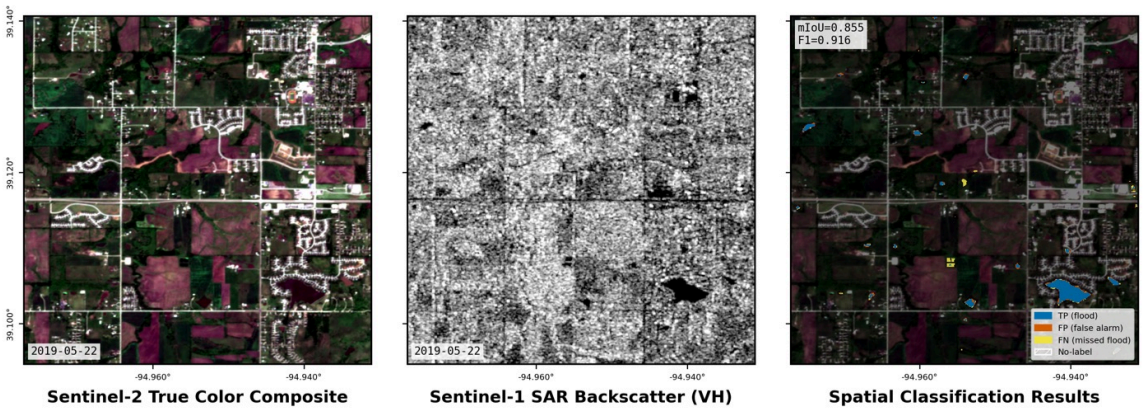

Figure 35: USA_1049586 · TerraMind baseline · cloud 0.38%

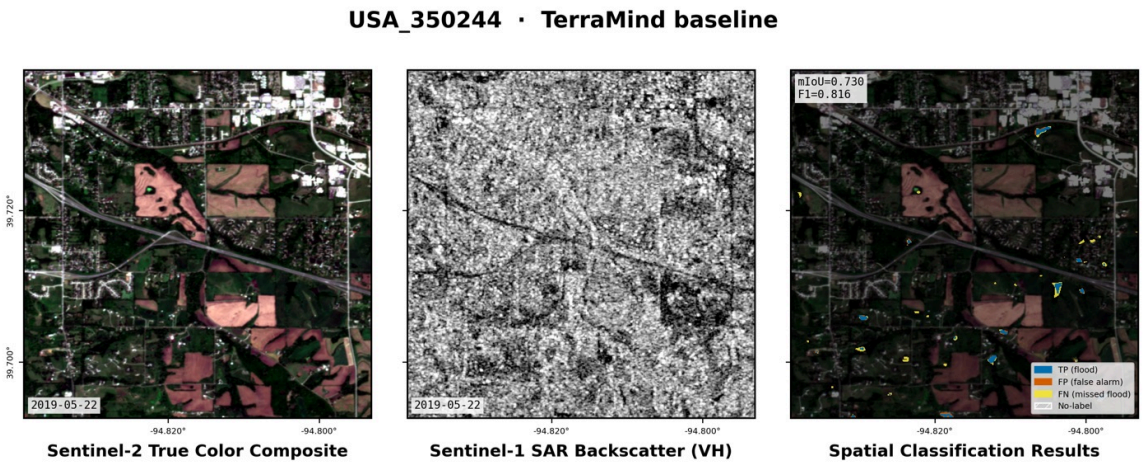

Figure 36: USA_350244 · TerraMind baseline · cloud 0.30%

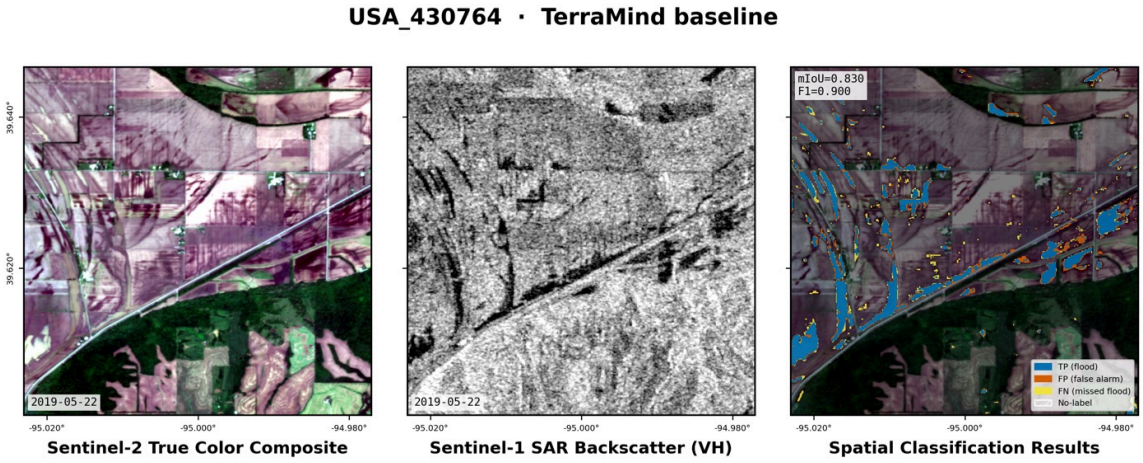

Figure 37: USA_430764 · TerraMind baseline · cloud 1.64%

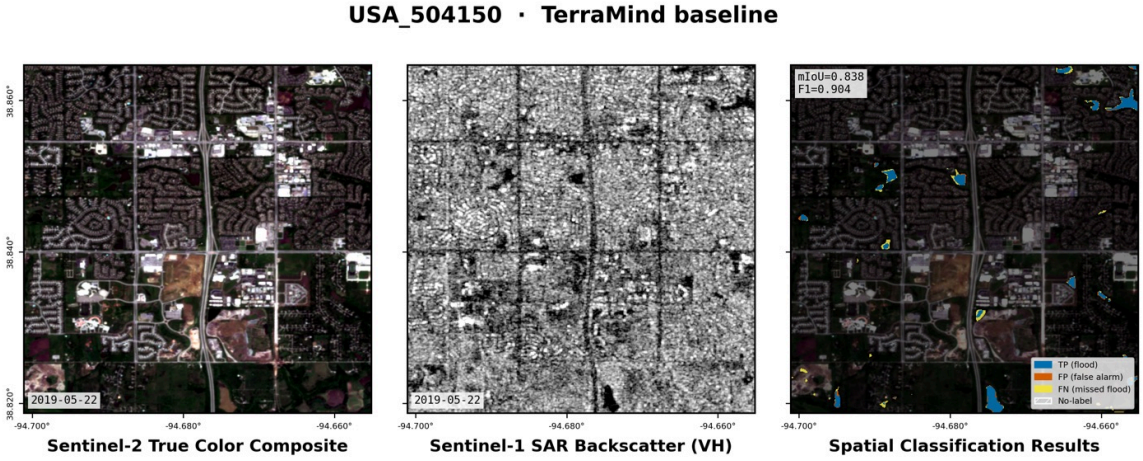

Figure 38: USA_504150 · TerraMind baseline · cloud 0.72%

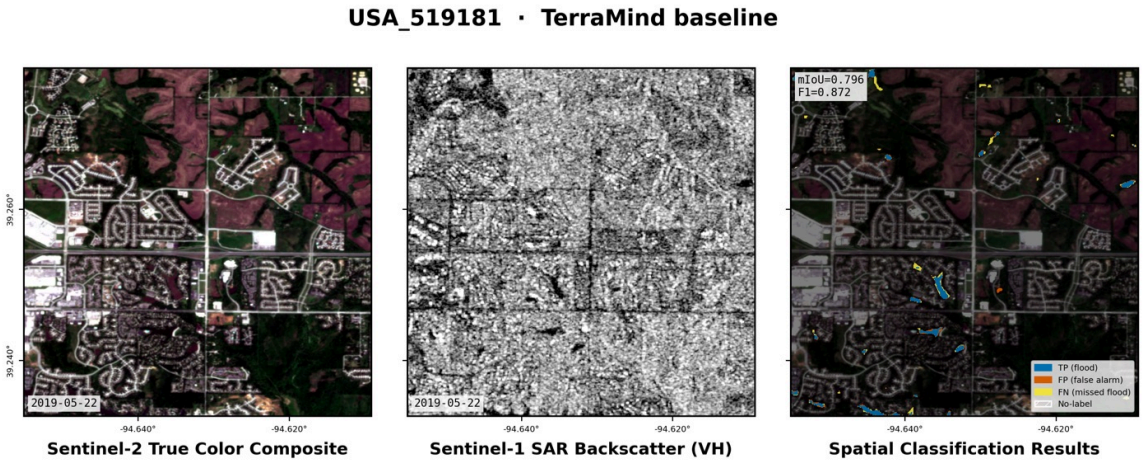

Figure 39: USA_519181 · TerraMind baseline · cloud 1.83%

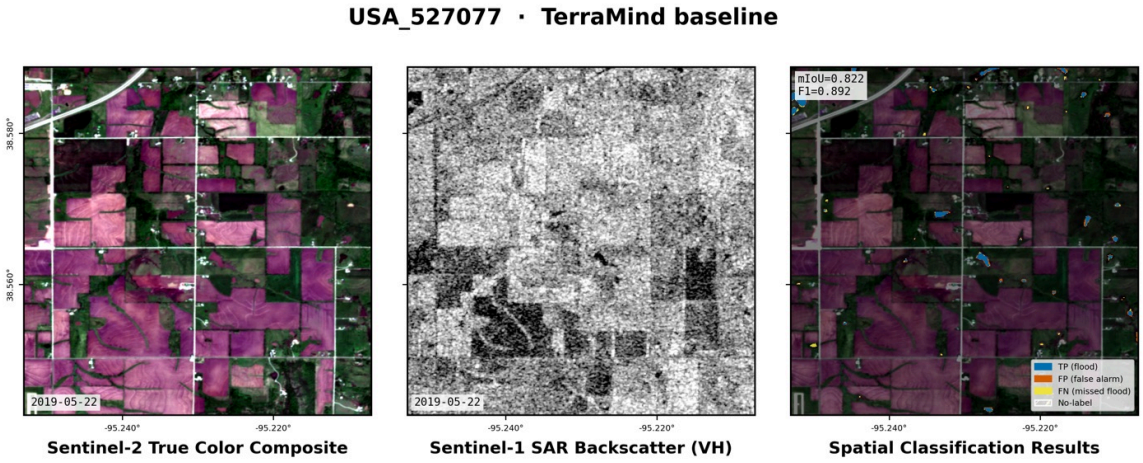

Figure 40: USA_527077 · TerraMind baseline · cloud 0.28%

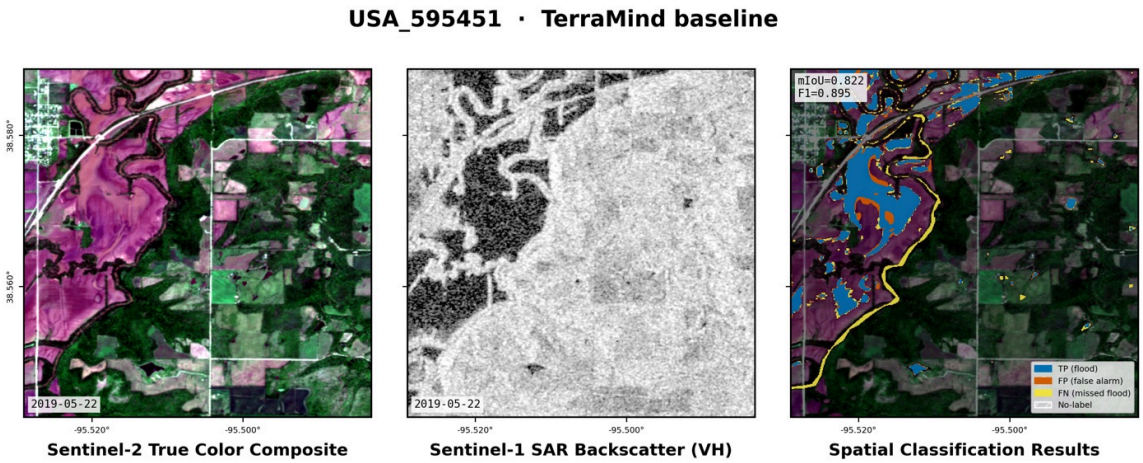

Figure 41: USA_595451 · TerraMind baseline · cloud 3.14%

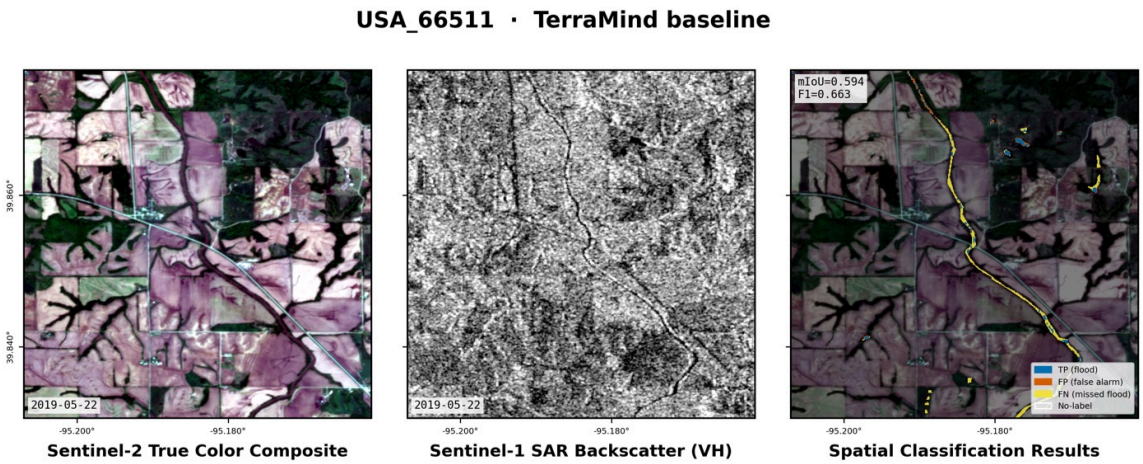

Figure 42: USA_66511 · TerraMind baseline · cloud 0.08%

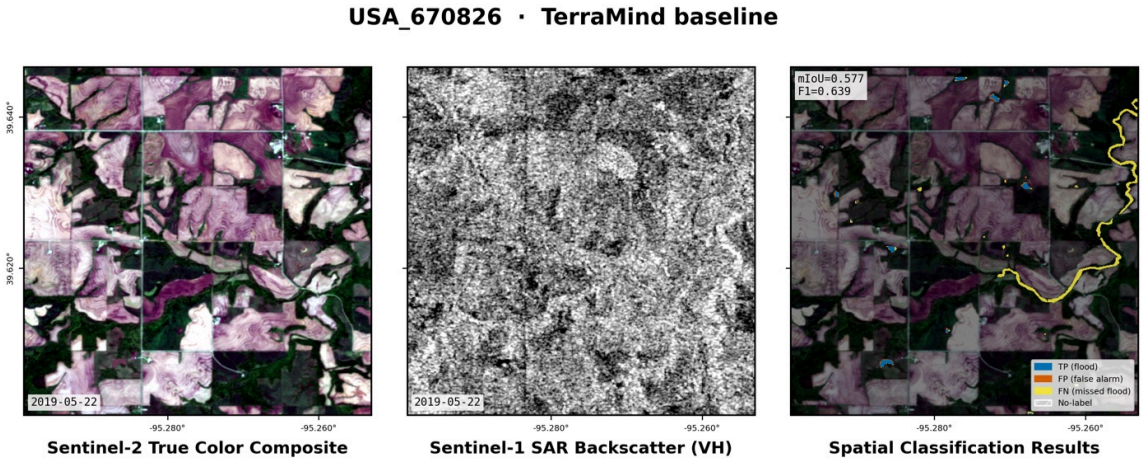

Figure 43: USA_670826 · TerraMind baseline · cloud 0.10%

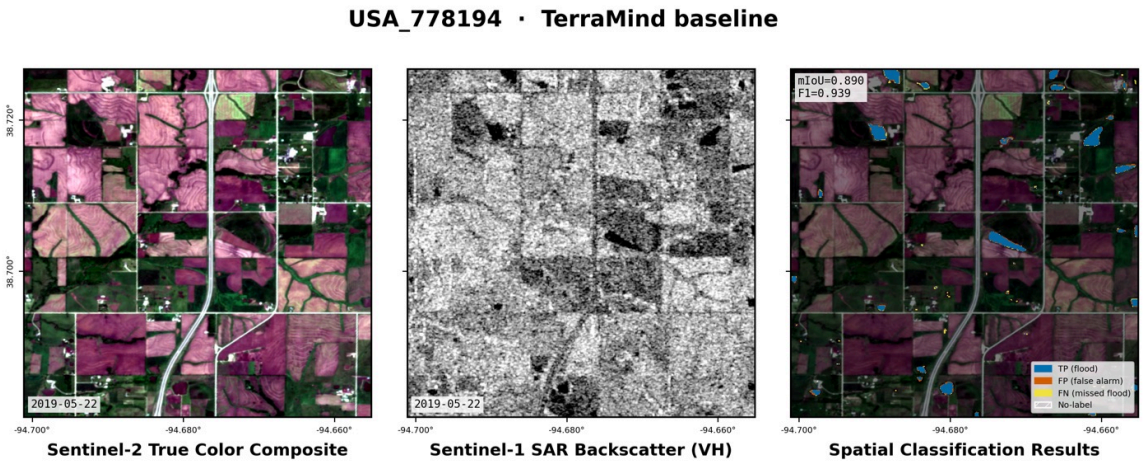

Figure 44: USA_778194 · TerraMind baseline · cloud 0.44%

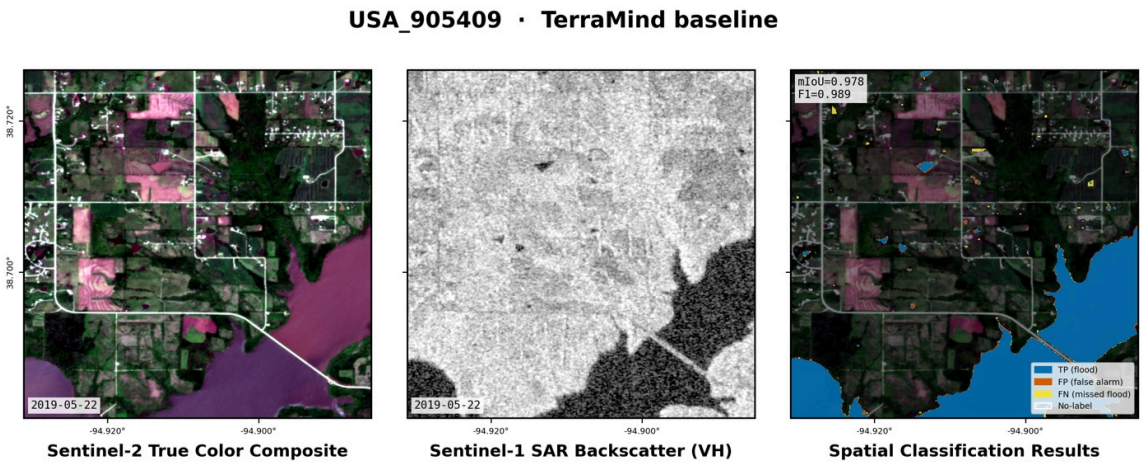

Figure 45: USA_905409 · TerraMind baseline · cloud 0.89%

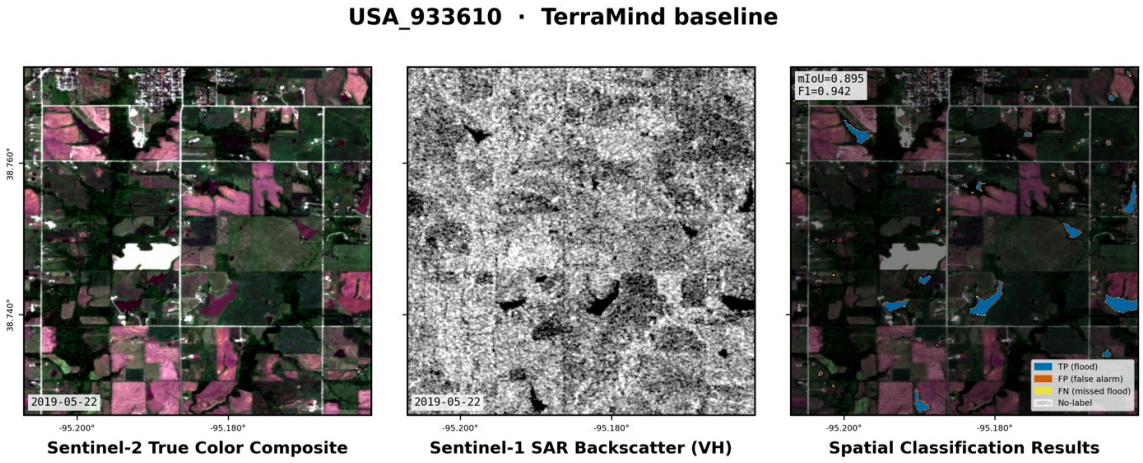

Figure 46: USA_933610 · TerraMind baseline · cloud 0.62%

Low (5–25%) — 21 tiles

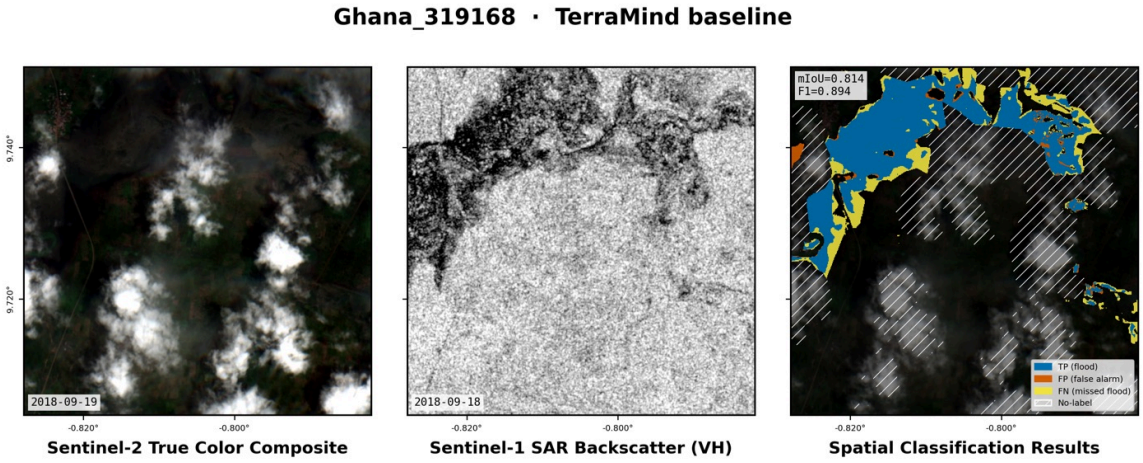

Figure 47: Ghana_319168 · TerraMind baseline · cloud 7.94%

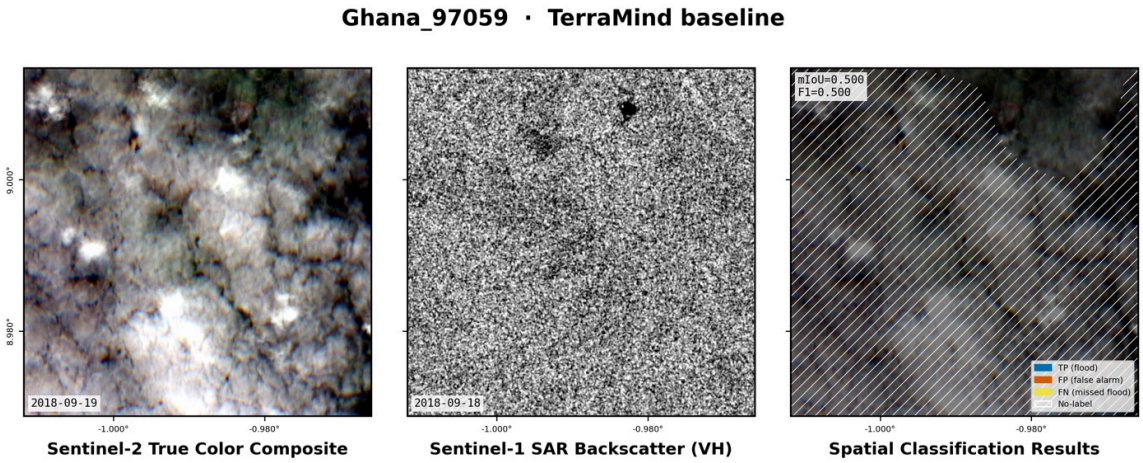

Figure 48: Ghana_97059 · TerraMind baseline · cloud 17.04%

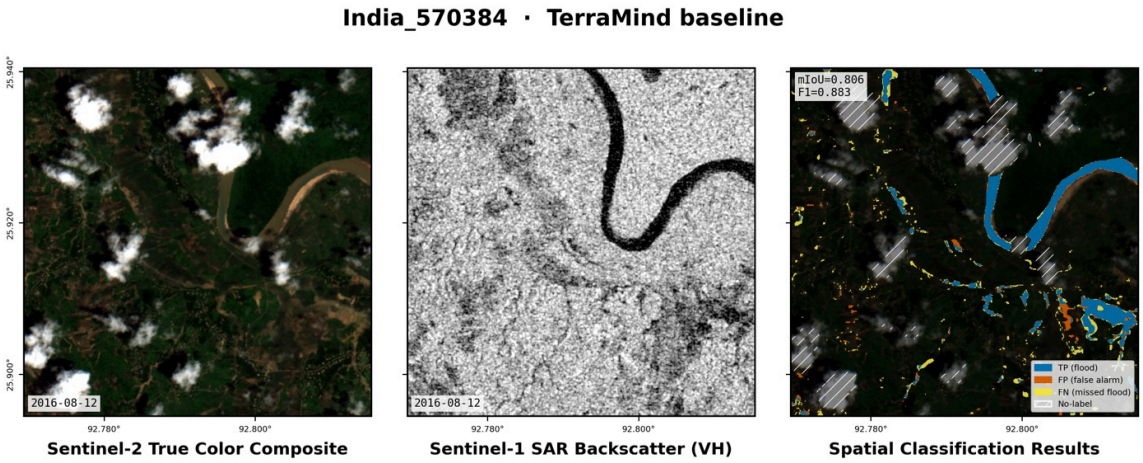

Figure 49: India_570384 · TerraMind baseline · cloud 6.02%

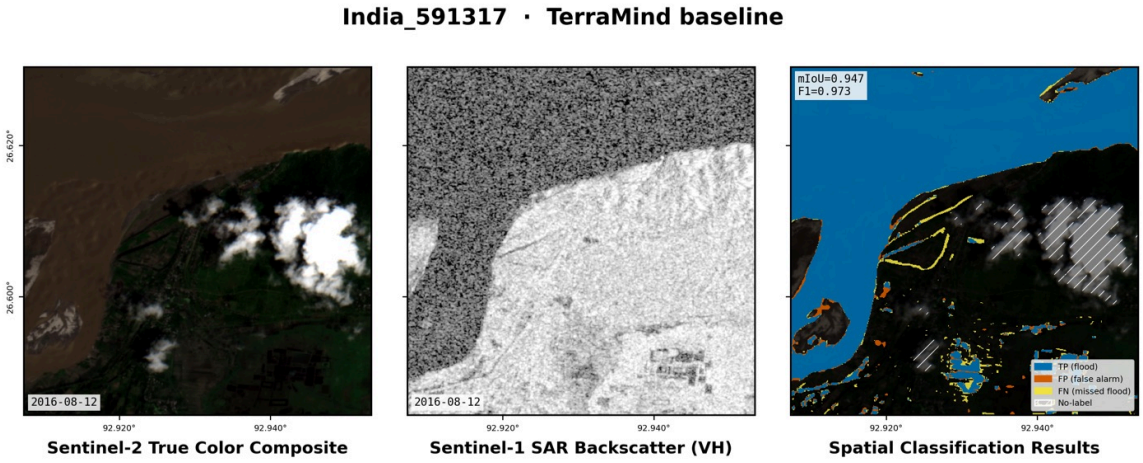

Figure 50: India_591317 · TerraMind baseline · cloud 5.52%

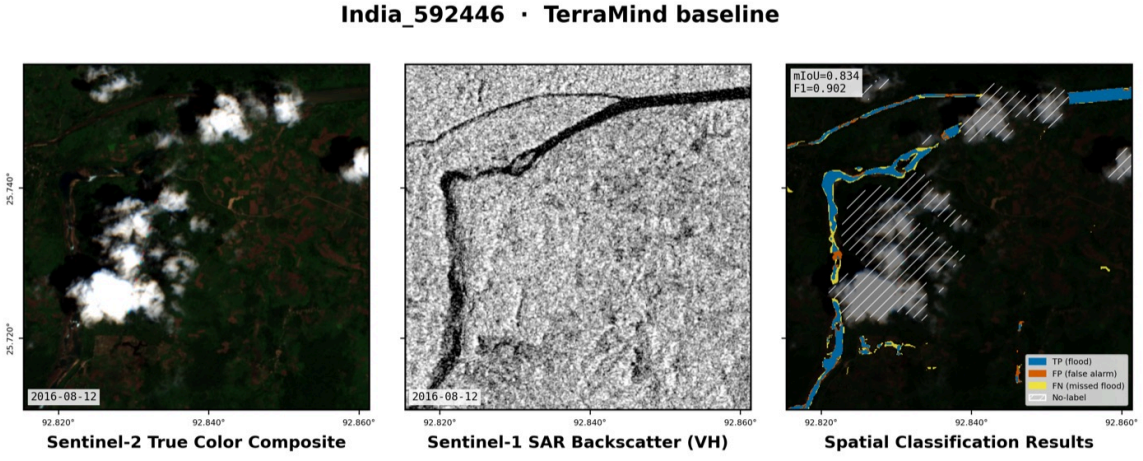

Figure 51: India_592446 · TerraMind baseline · cloud 7.94%

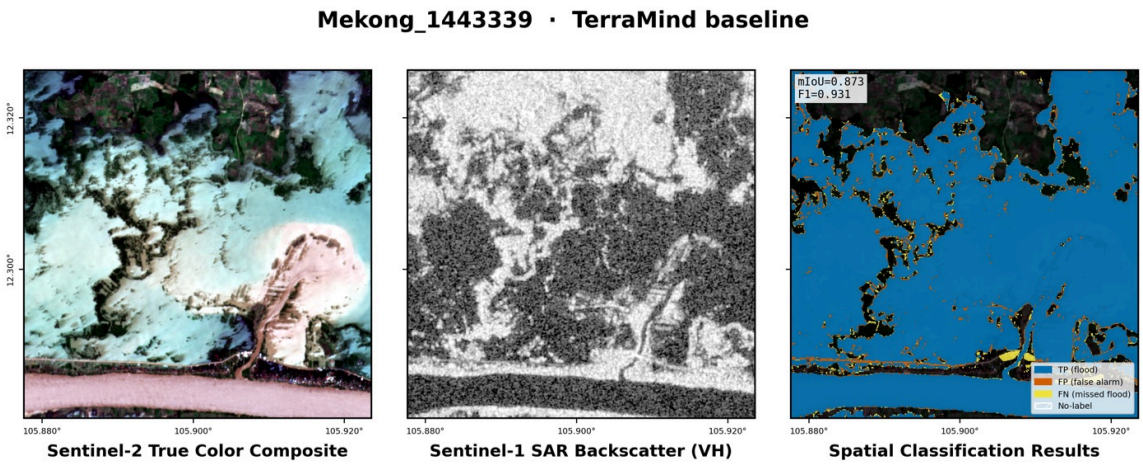

Figure 52: Mekong_1443339 · TerraMind baseline · cloud 7.08%

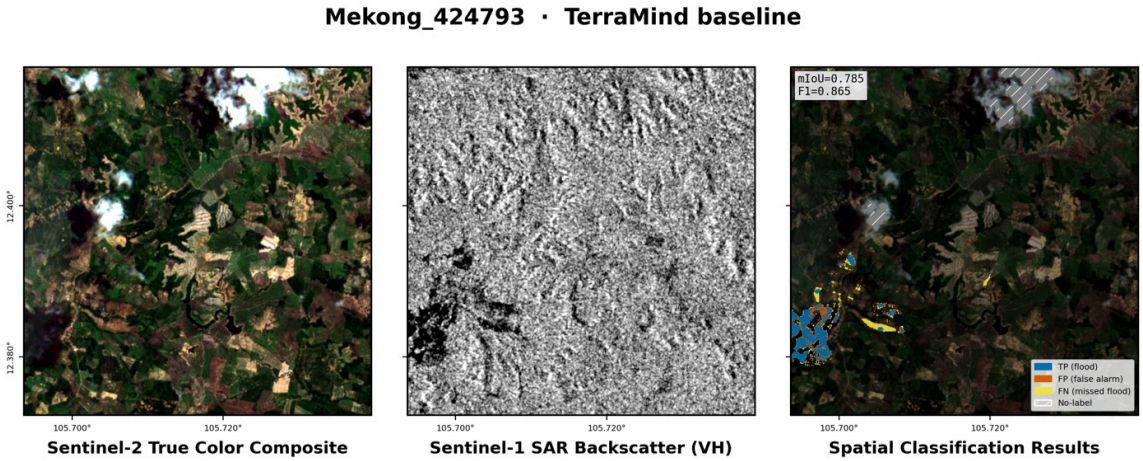

Figure 53: Mekong_424793 · TerraMind baseline · cloud 6.37%

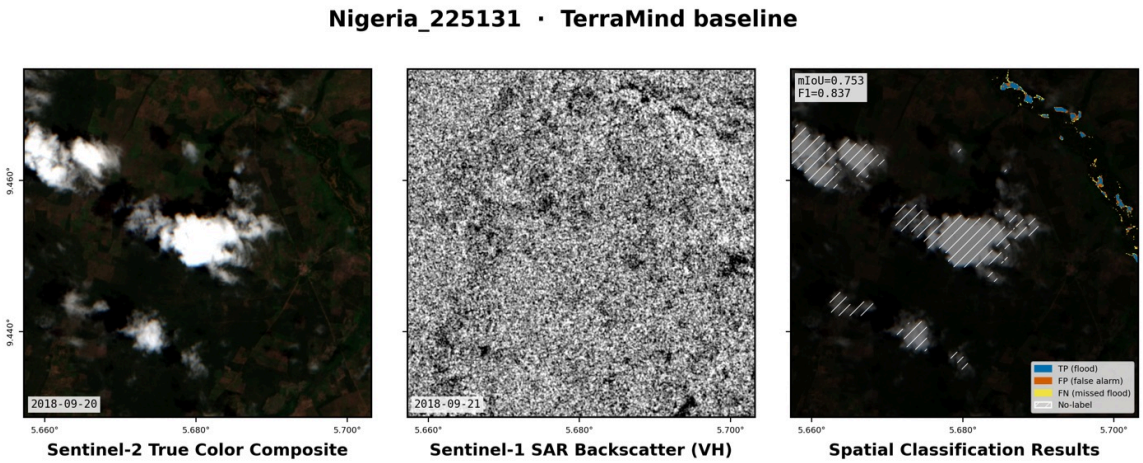

Figure 54: Nigeria_225131 · TerraMind baseline · cloud 7.64%

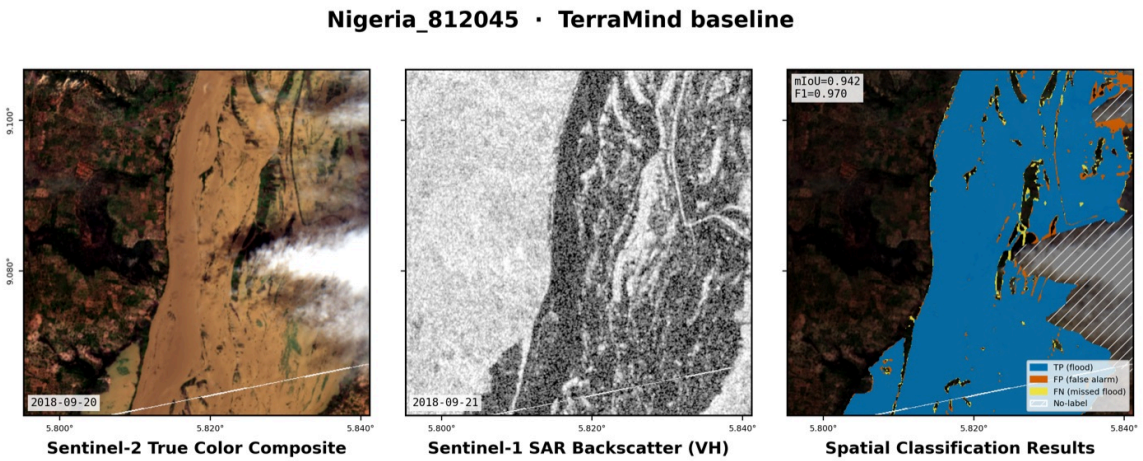

Figure 55: Nigeria_812045 · TerraMind baseline · cloud 10.59%

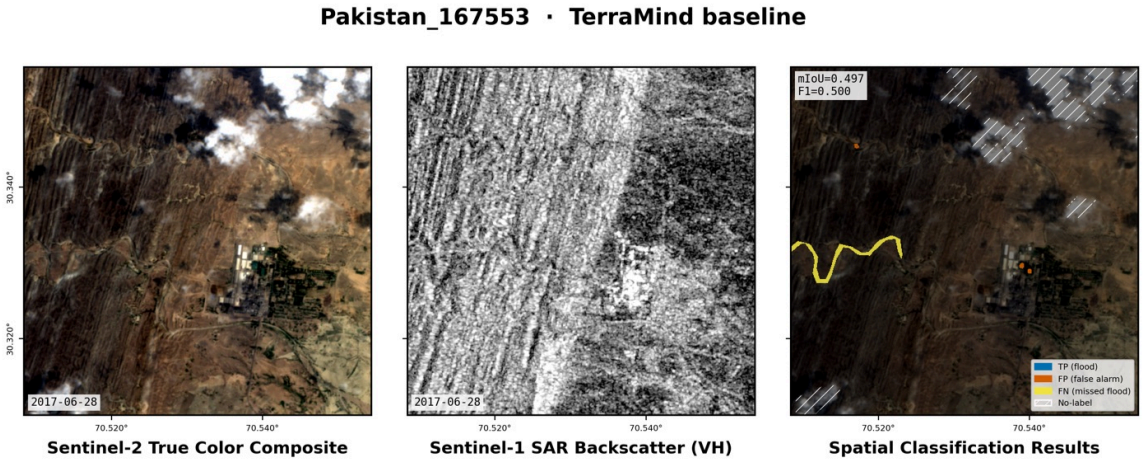

Figure 56: Pakistan_167553 · TerraMind baseline · cloud 11.20%

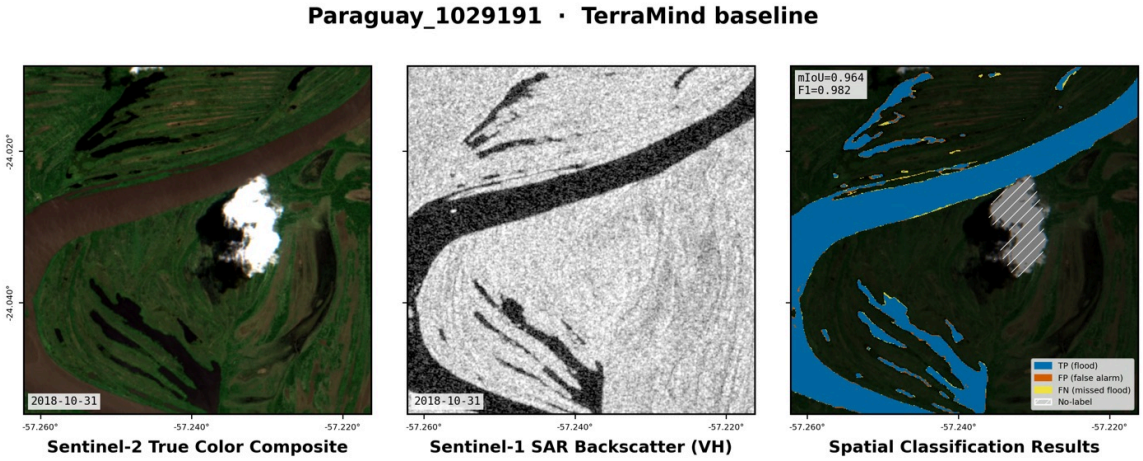

Figure 57: Paraguay_1029191 · TerraMind baseline · cloud 11.51%

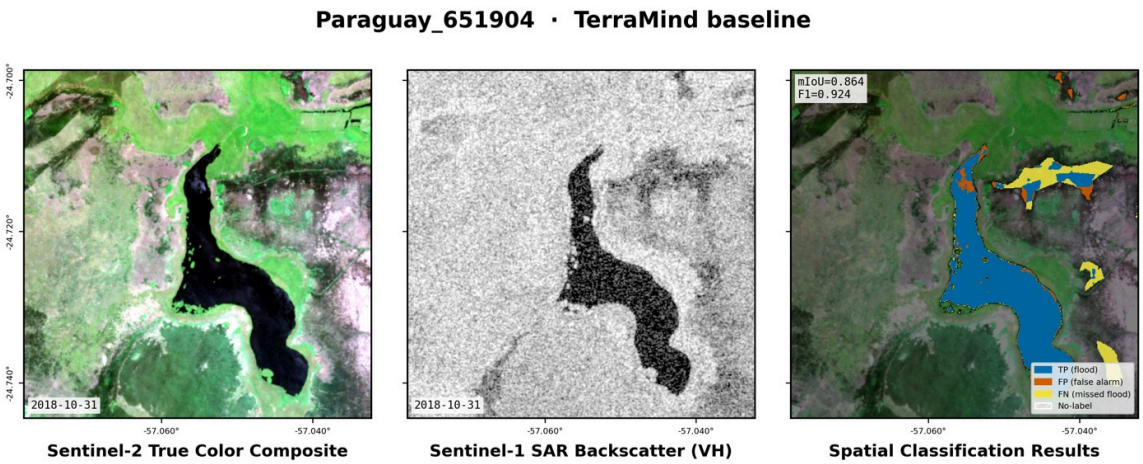

Figure 58: Paraguay_651904 · TerraMind baseline · cloud 7.67%

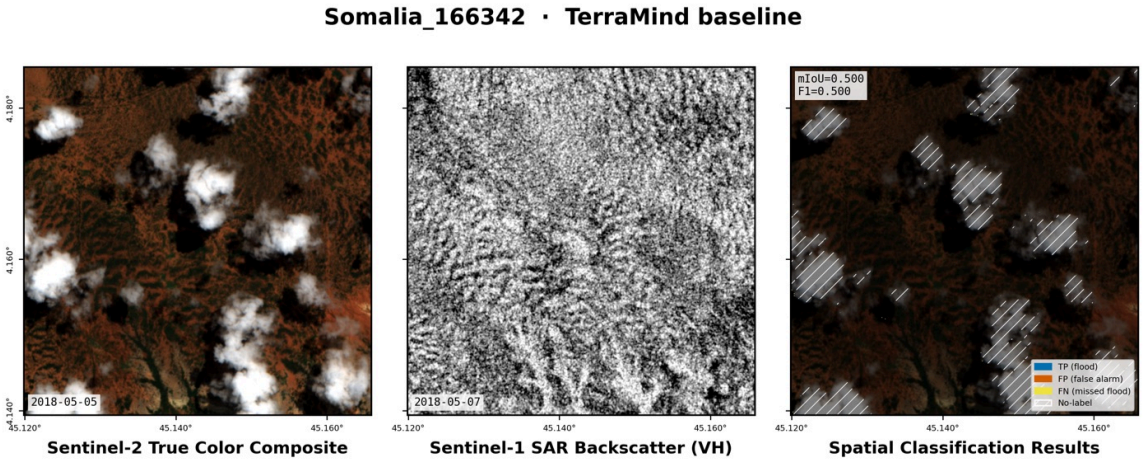

Figure 59: Somalia_166342 · TerraMind baseline · cloud 19.40%

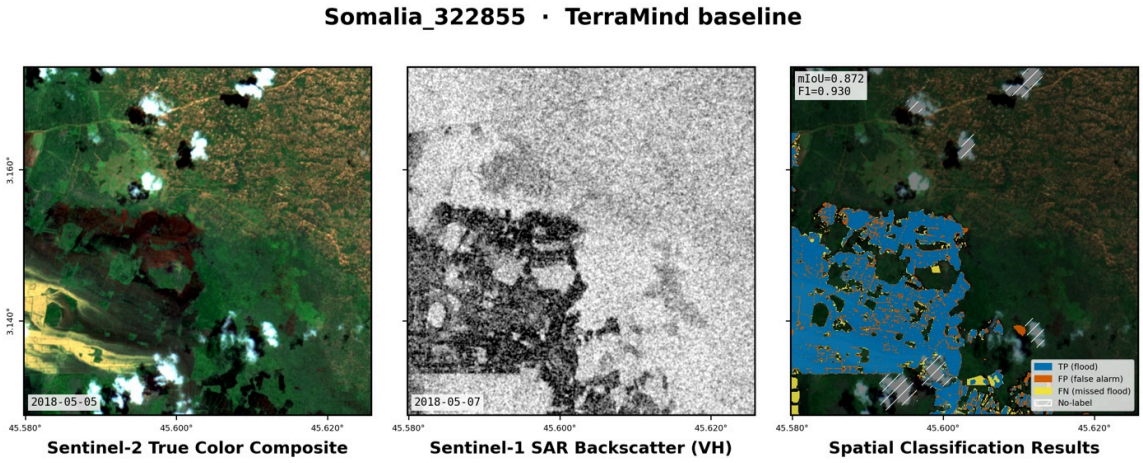

Figure 60: Somalia_322855 · TerraMind baseline · cloud 5.92%

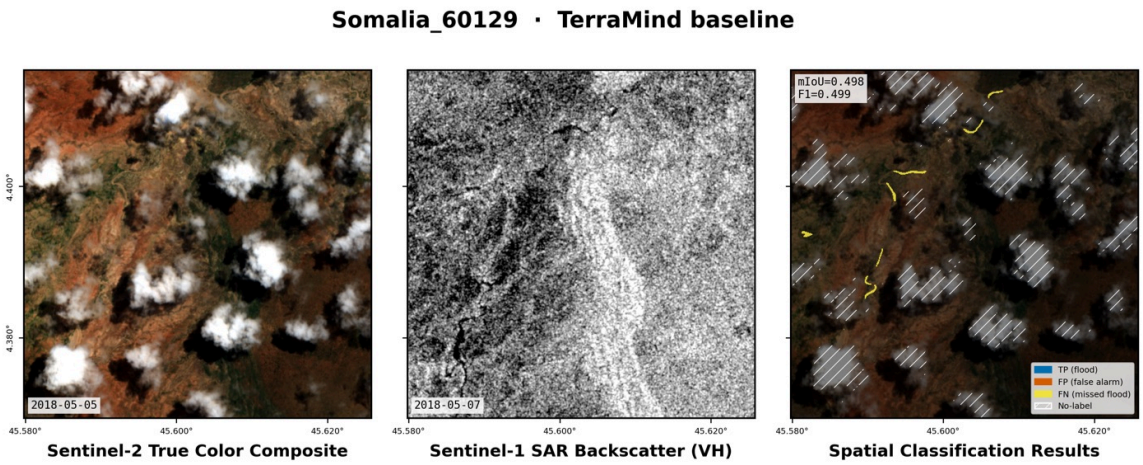

Figure 61: Somalia_60129 · TerraMind baseline · cloud 16.89%

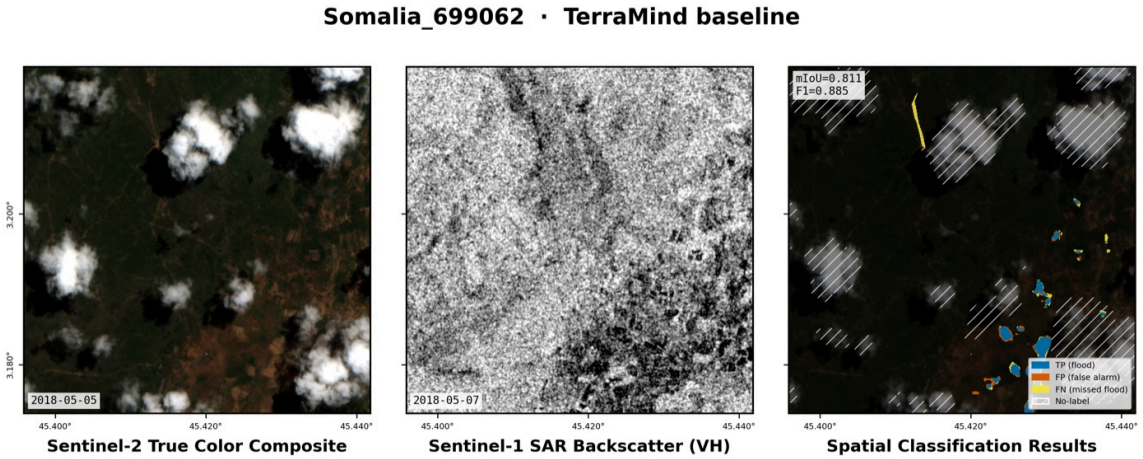

Figure 62: Somalia_699062 · TerraMind baseline · cloud 24.64%

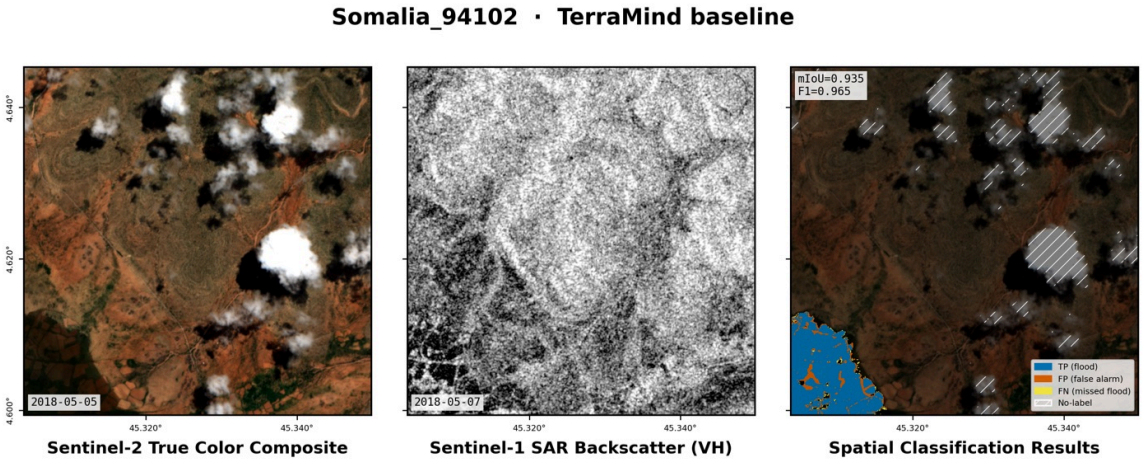

Figure 63: Somalia_94102 · TerraMind baseline · cloud 12.44%

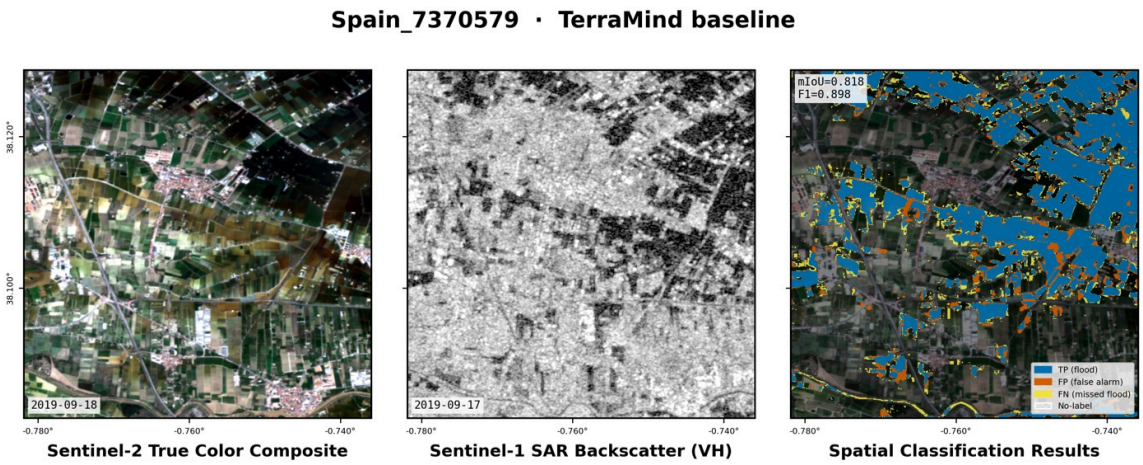

Figure 64: Spain_7370579 · TerraMind baseline · cloud 7.51%

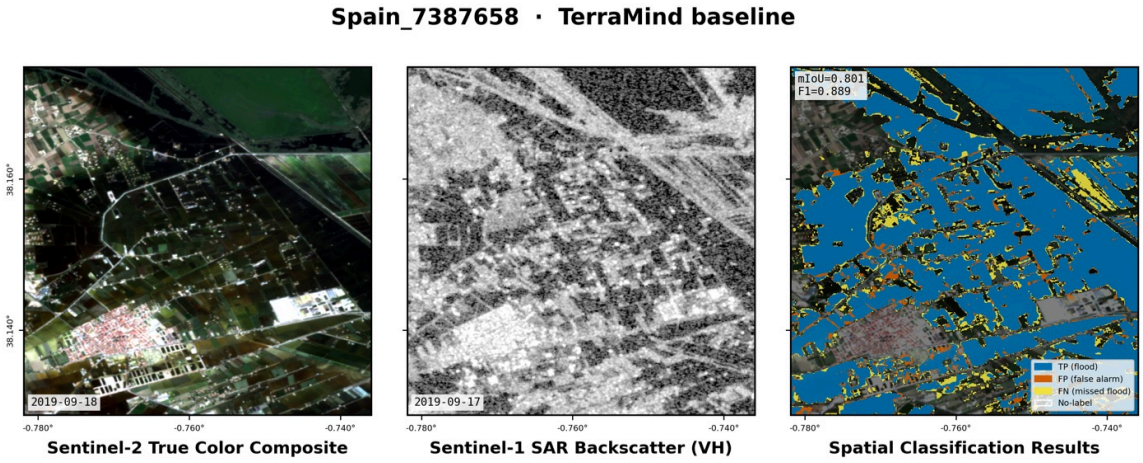

Figure 65: Spain_7387658 · TerraMind baseline · cloud 22.51%

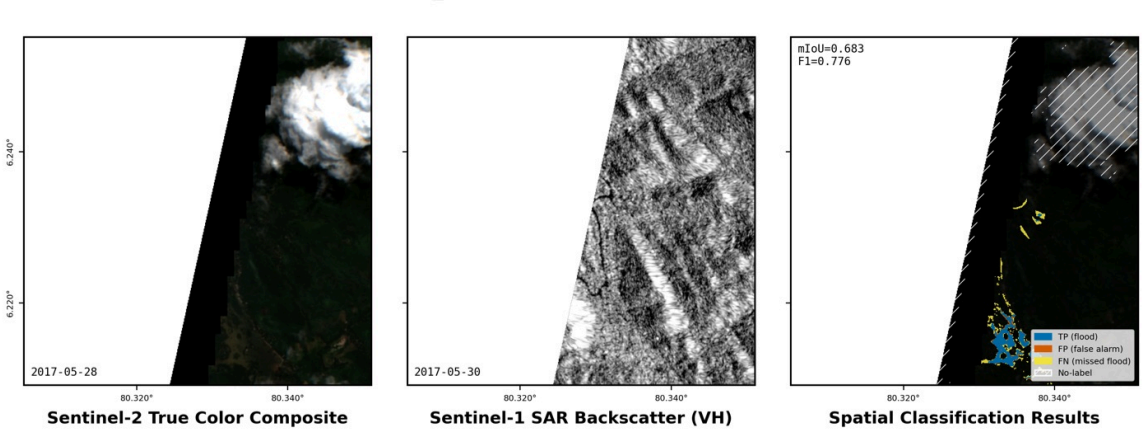

Figure 66: Sri-Lanka_450918 · TerraMind baseline · cloud 12.44%

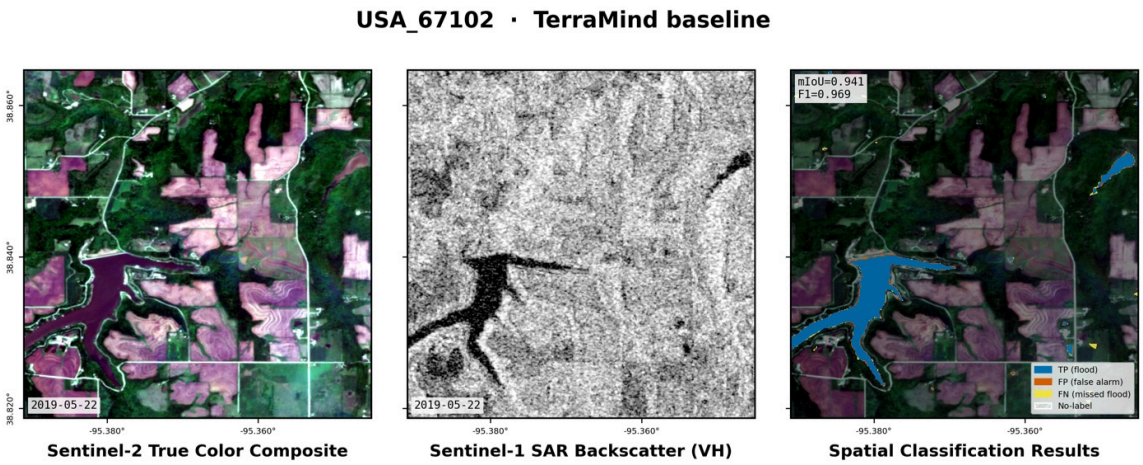

Figure 67: USA_67102 · TerraMind baseline · cloud 16.73%

Medium (25–50%) — 10 tiles

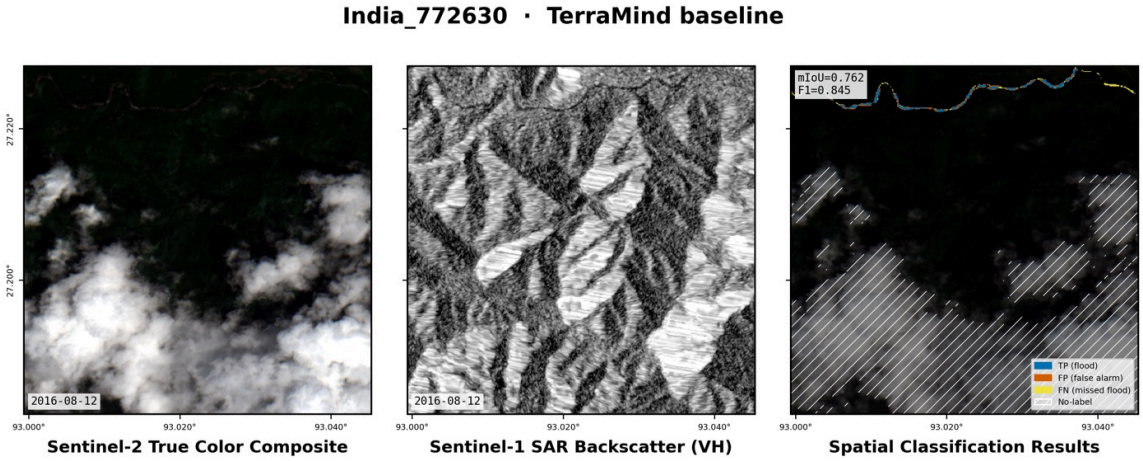

Figure 68: India_772630 · TerraMind baseline · cloud 44.72%

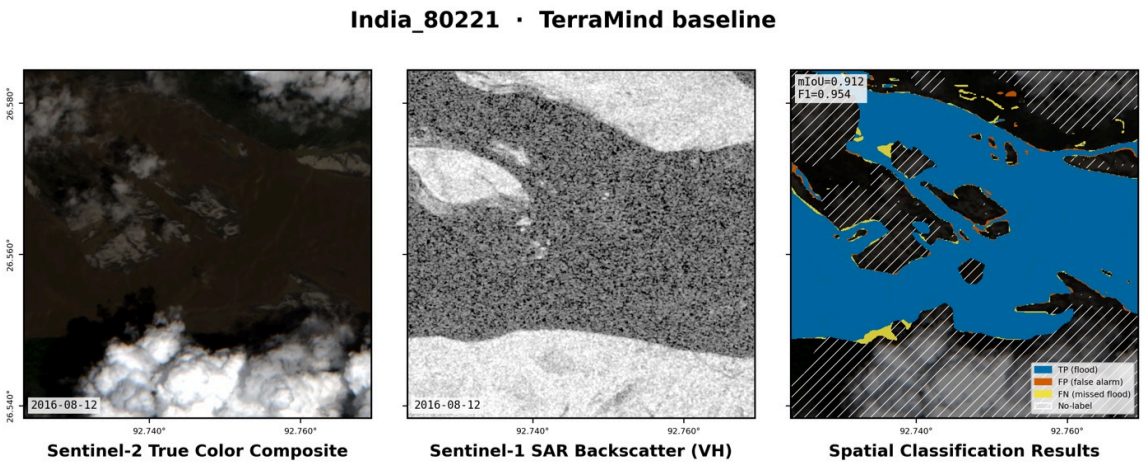

Figure 69: India_80221 · TerraMind baseline · cloud 28.09%

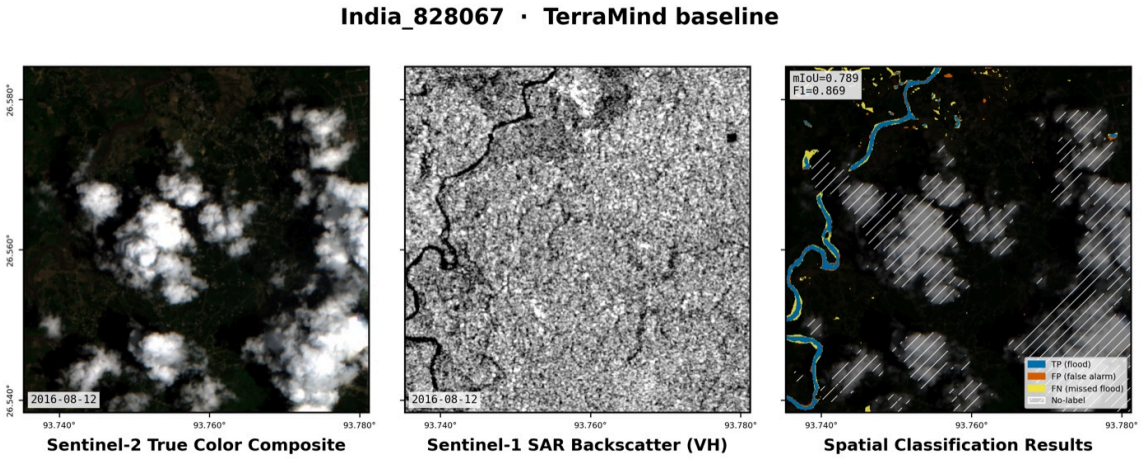

Figure 70: India_828067 · TerraMind baseline · cloud 33.05%

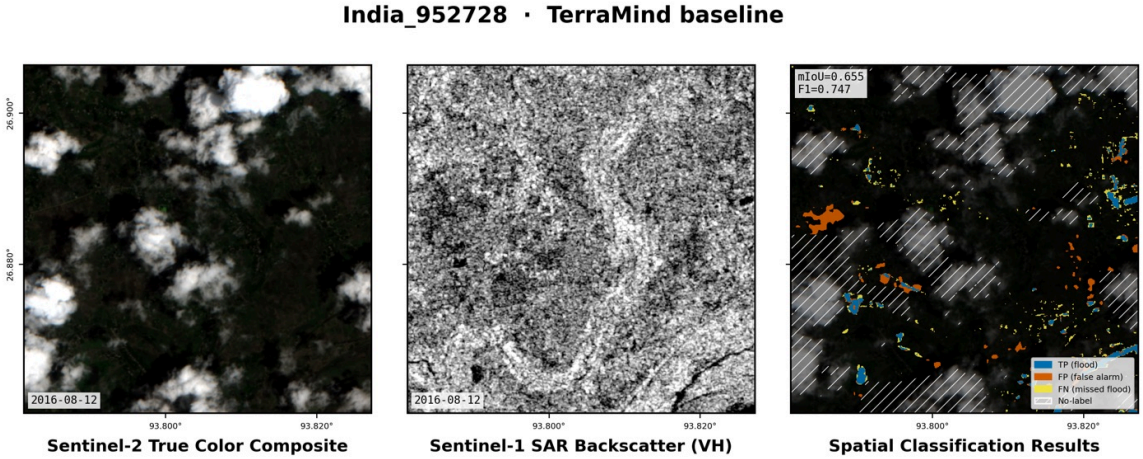

Figure 71: India_952728 · TerraMind baseline · cloud 34.51%

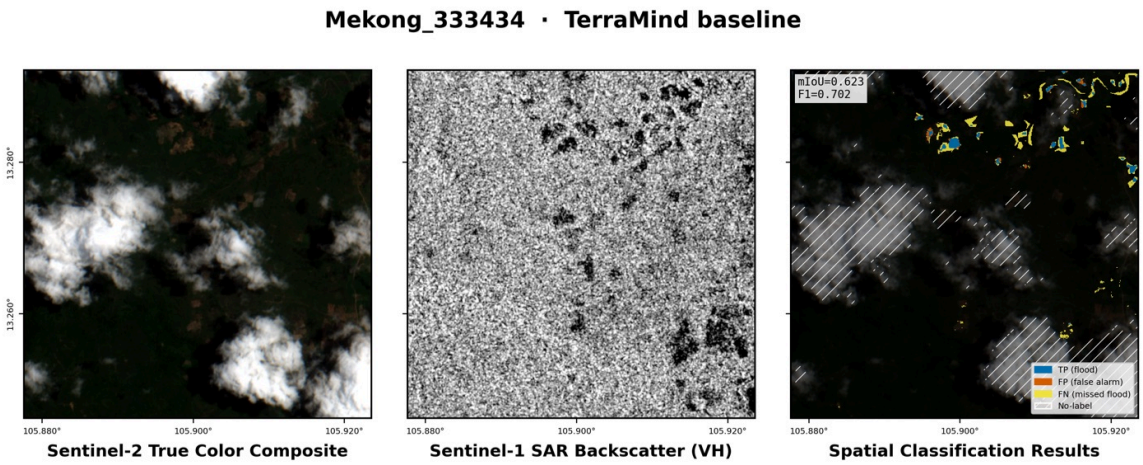

Figure 72: Mekong_333434 · TerraMind baseline · cloud 25.51%

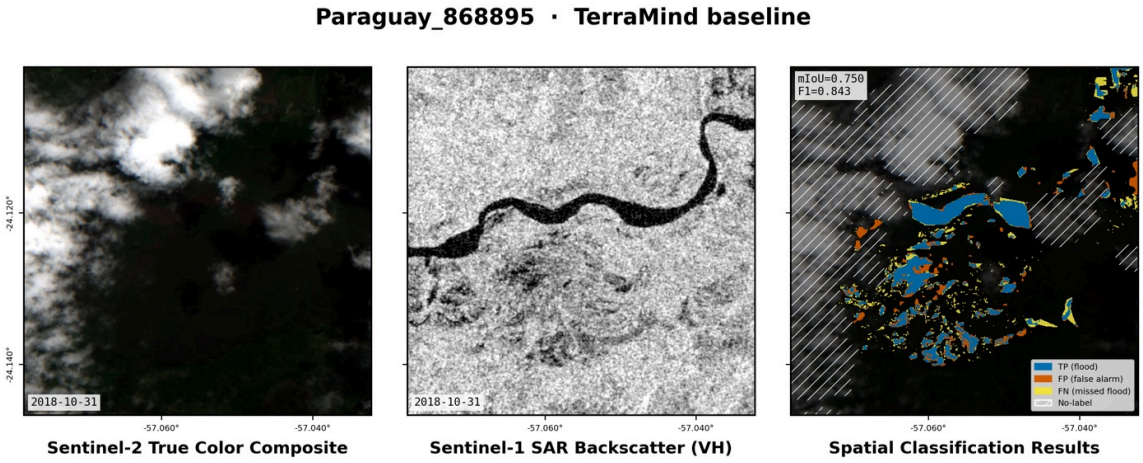

Figure 73: Paraguay_868895 · TerraMind baseline · cloud 43.42%

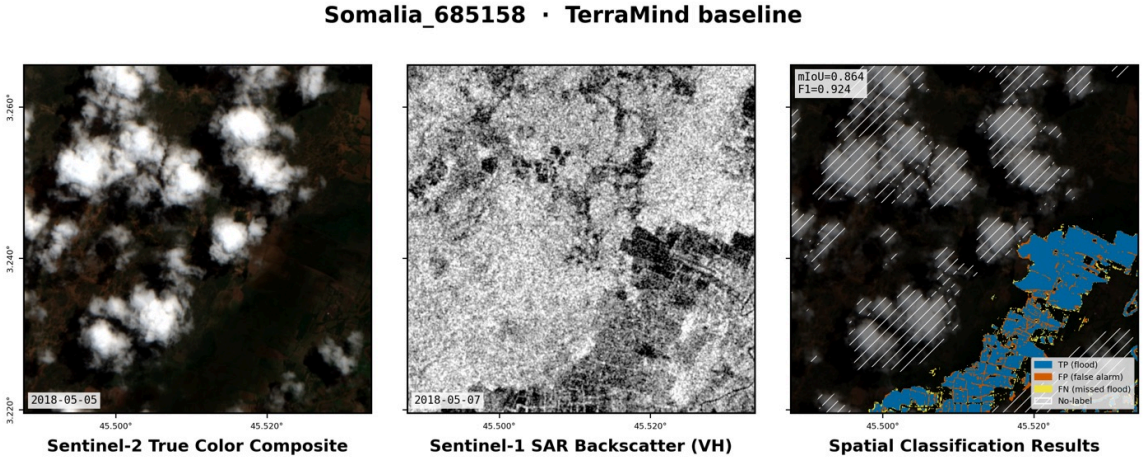

Figure 74: Somalia_685158 · TerraMind baseline · cloud 35.31%

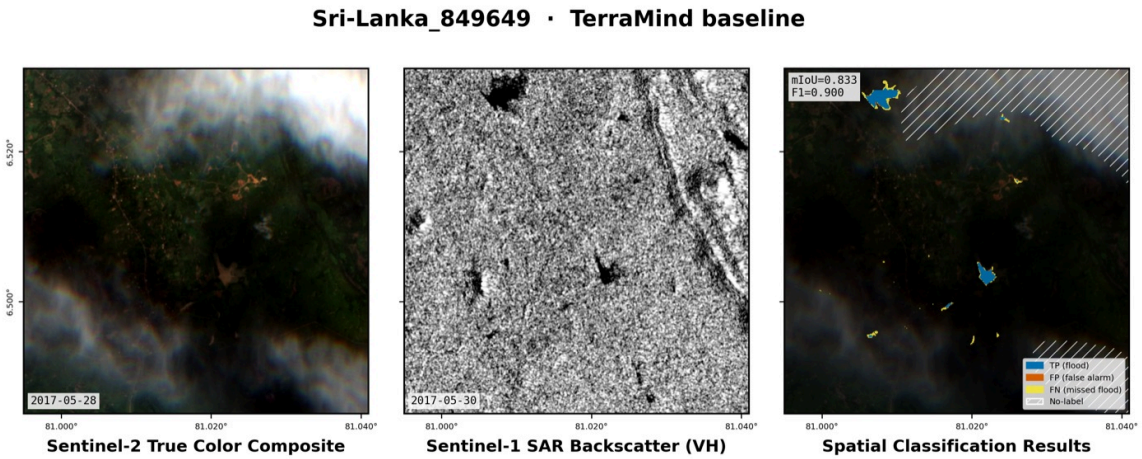

Figure 75: Sri-Lanka_849649 · TerraMind baseline · cloud 46.58%

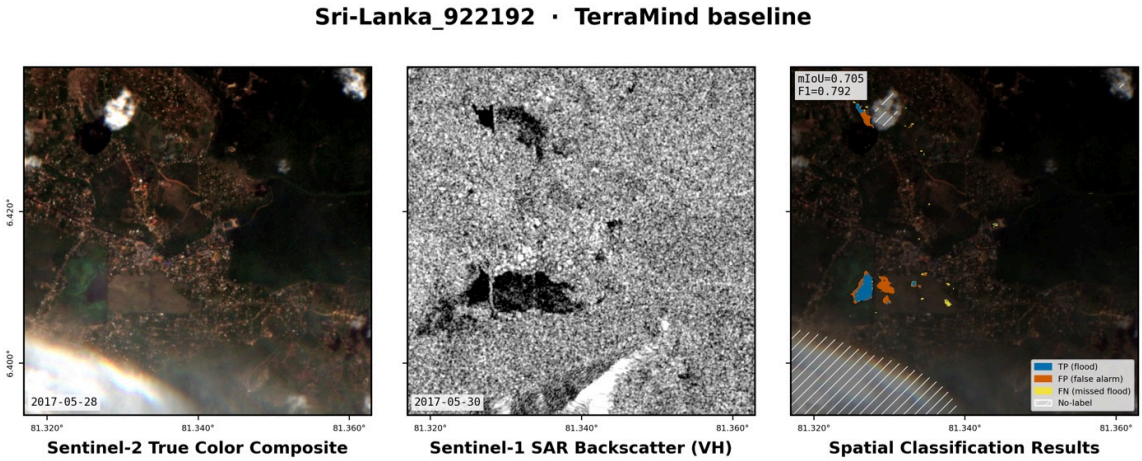

Figure 76: Sri-Lanka_922192 · TerraMind baseline · cloud 47.55%

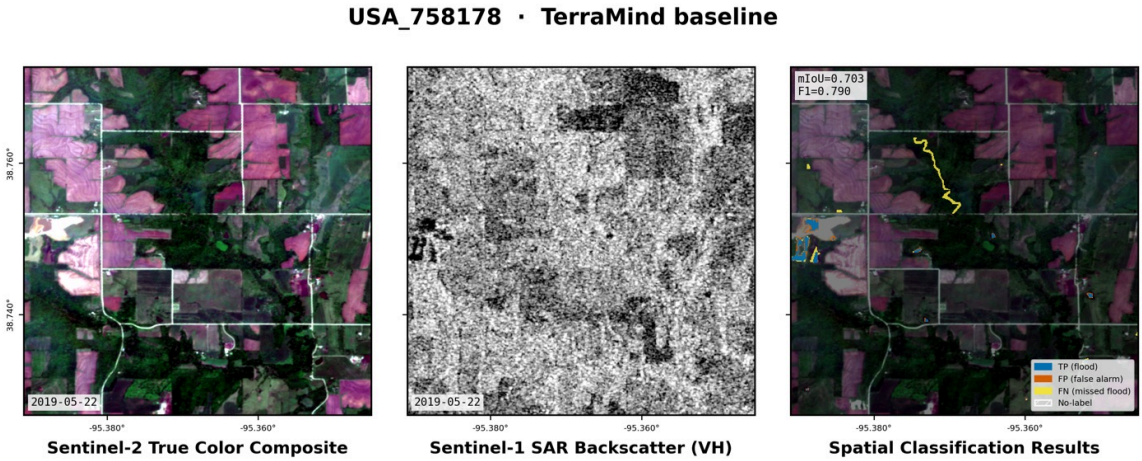

Figure 77: USA_758178 · TerraMind baseline · cloud 47.35%

High (50–75%) — 3 tiles

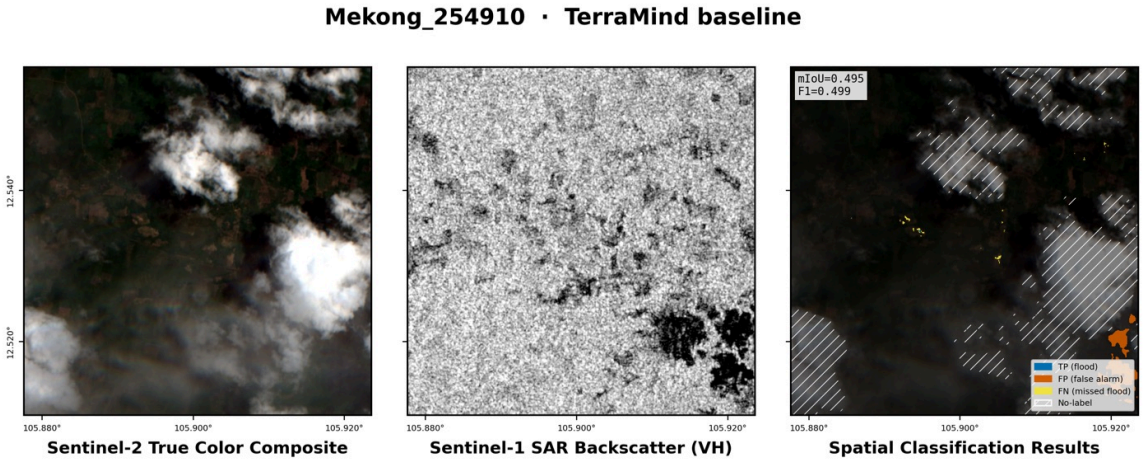

Figure 78: Mekong_254910 · TerraMind baseline · cloud 71.84%

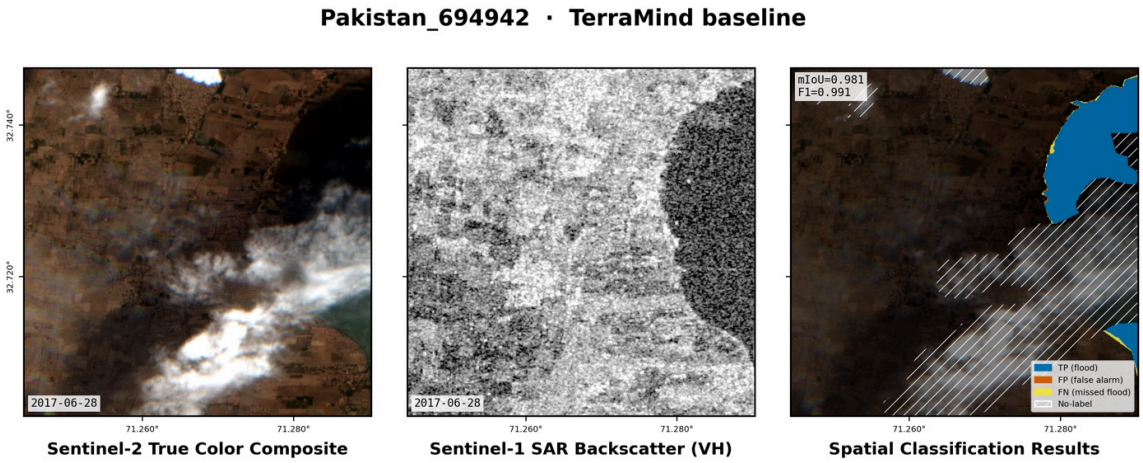

Figure 79: Pakistan_694942 · TerraMind baseline · cloud 51.05%

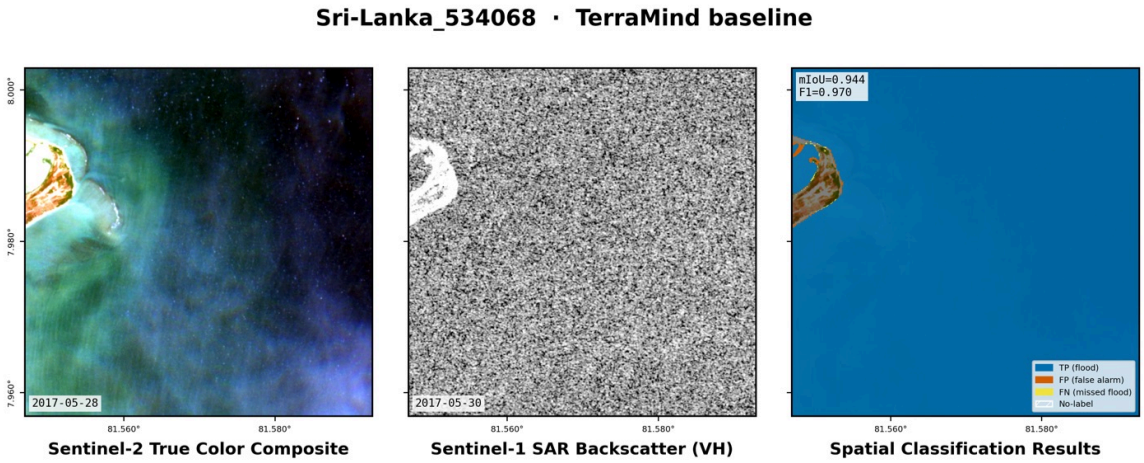

Figure 80: Sri-Lanka_534068 · TerraMind baseline · cloud 62.47%

Heavy (≥75%) — 10 tiles

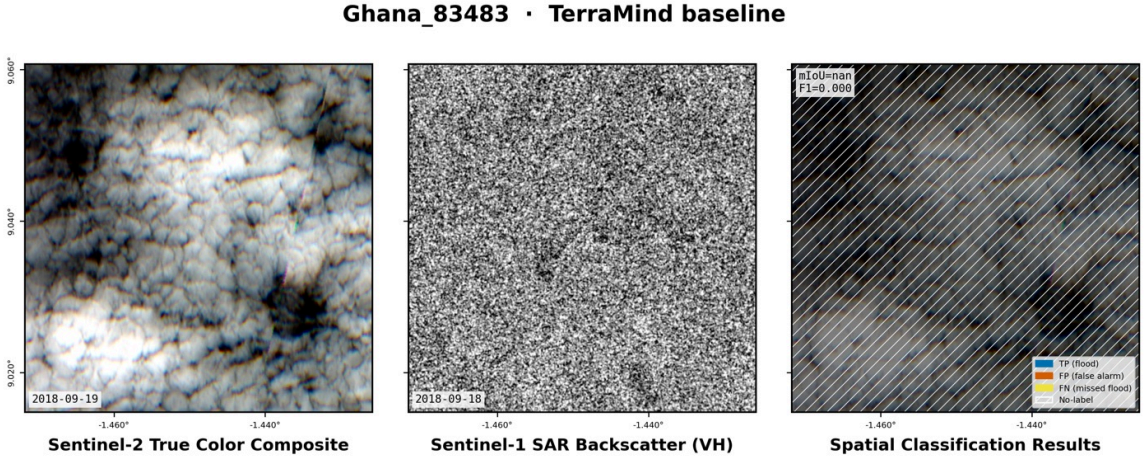

Figure 81: Ghana_83483 · TerraMind baseline · cloud 83.11%

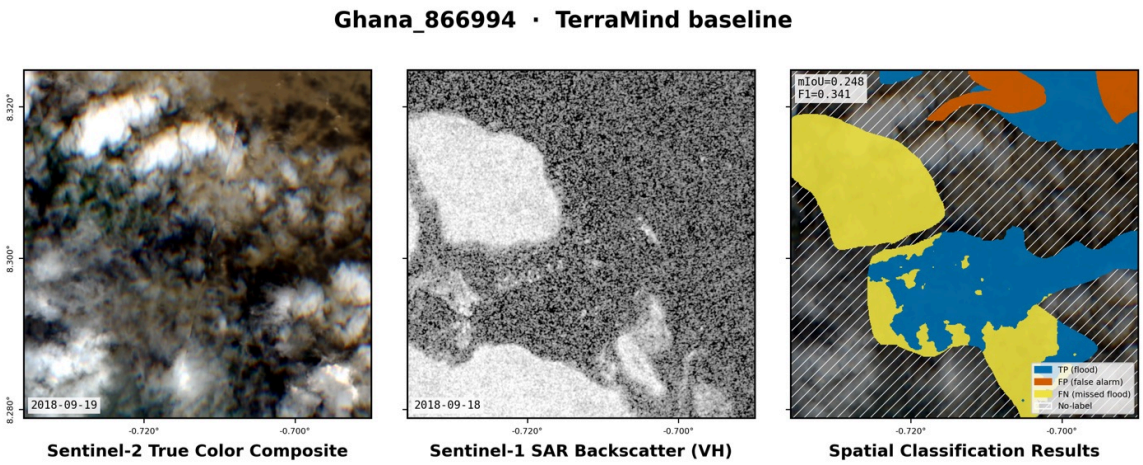

Figure 82: Ghana_866994 · TerraMind baseline · cloud 77.82%

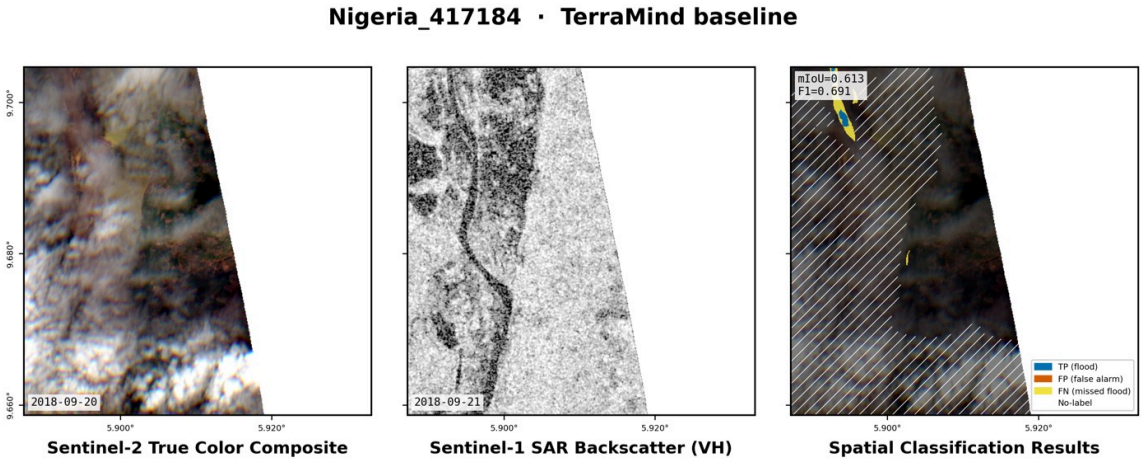

Figure 83: Nigeria_417184 · TerraMind baseline · cloud 90.46%

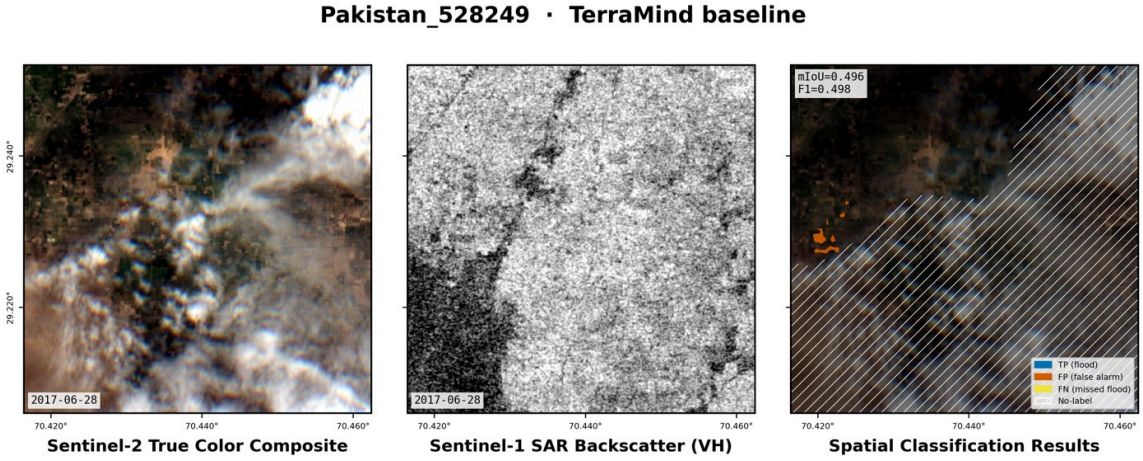

Figure 84: Pakistan_528249 · TerraMind baseline · cloud 82.24%

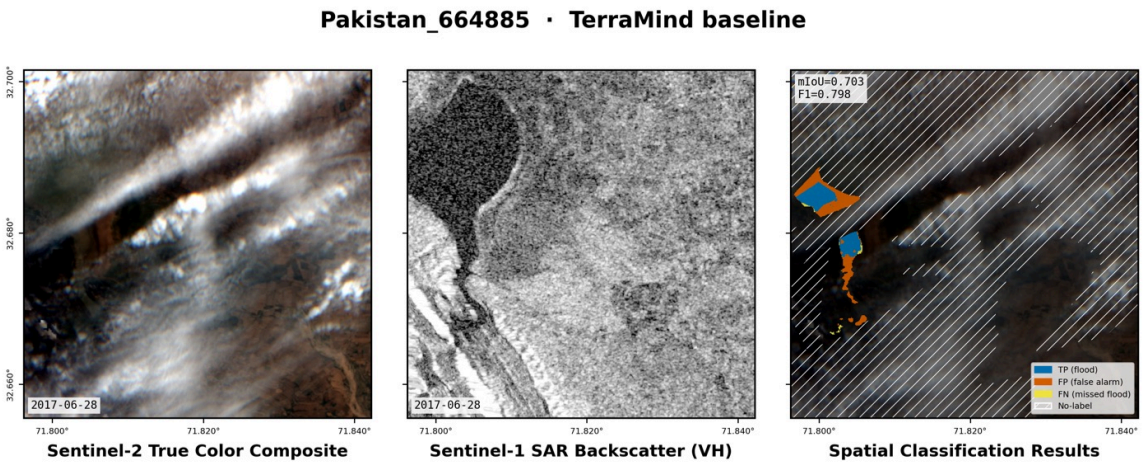

Figure 85: Pakistan_664885 · TerraMind baseline · cloud 83.77%

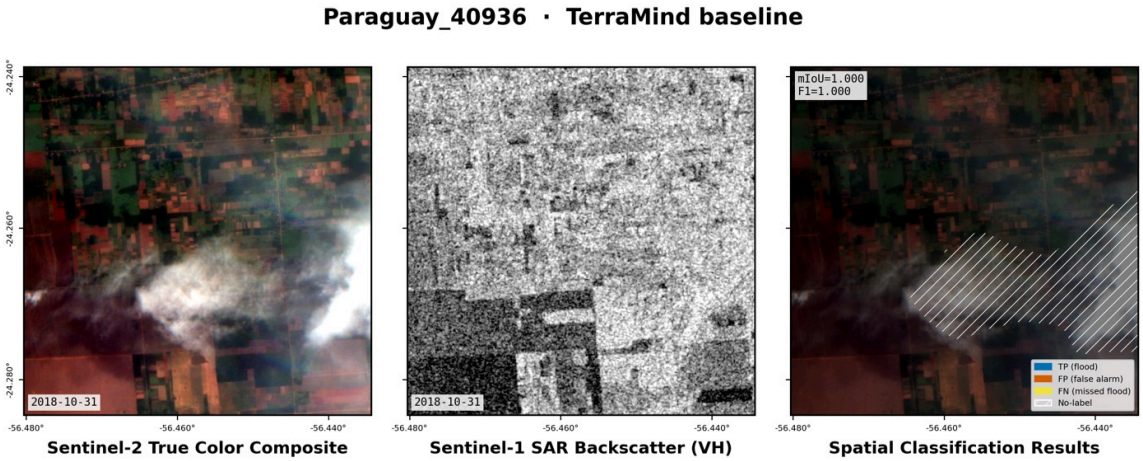

Figure 86: Paraguay_40936 · TerraMind baseline · cloud 100.00%

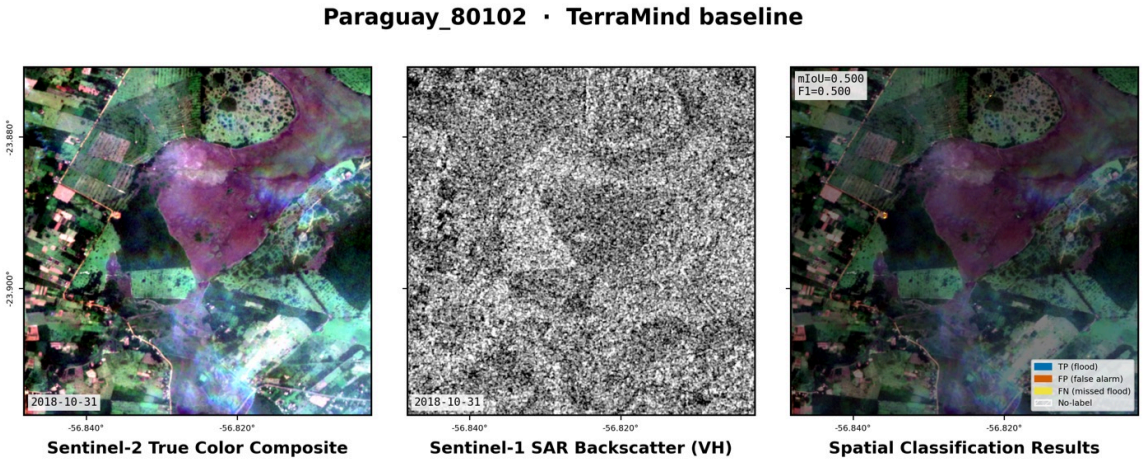

Figure 87: Paraguay_80102 · TerraMind baseline · cloud 97.04%

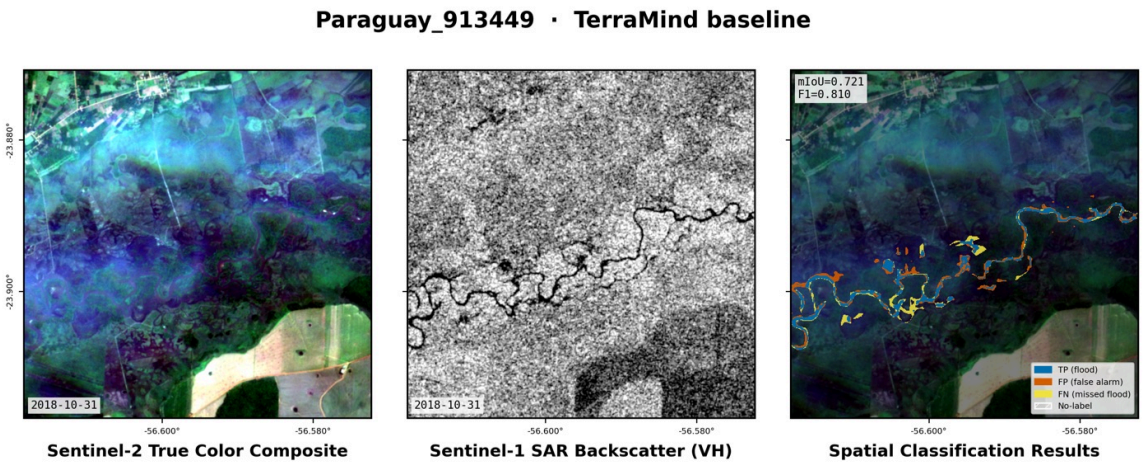

Figure 88: Paraguay_913449 · TerraMind baseline · cloud 100.00%

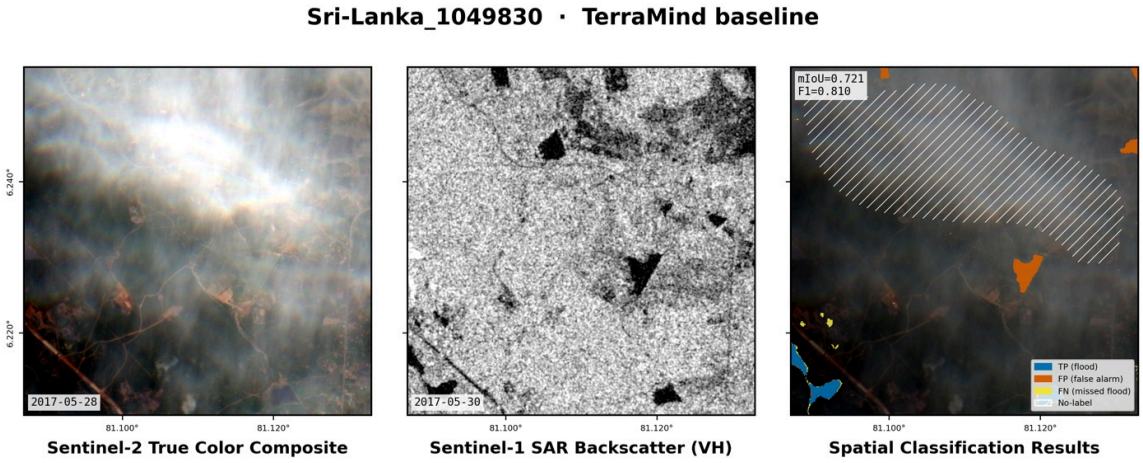

Figure 89: Sri-Lanka_1049830 · TerraMind baseline · cloud 100.00%

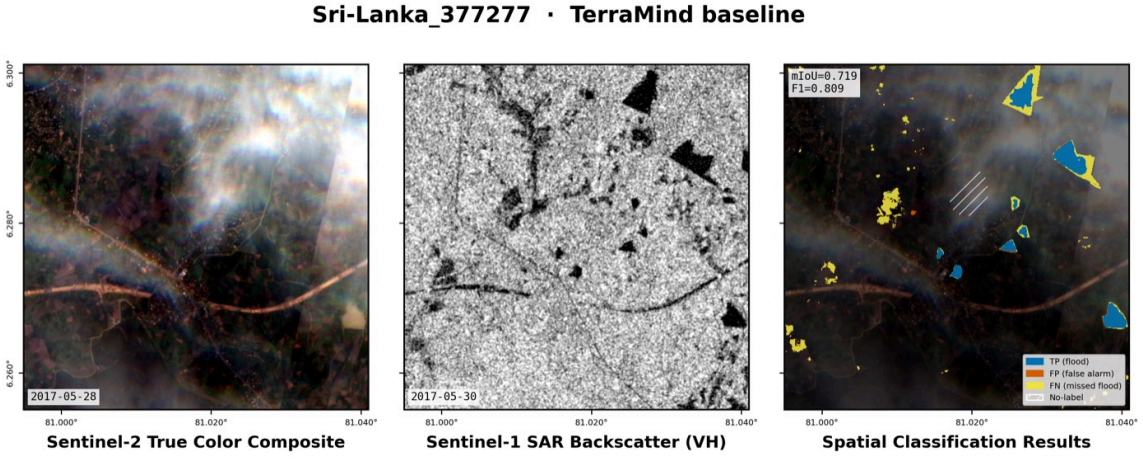

Figure 90: Sri-Lanka_377277 · TerraMind baseline · cloud 100.00%

S8.2 Bolivia held-out split — baseline vs. m2_lotv (15 tiles, paired)

Clear (<5% cloud) — 3 tiles

Bolivia_195474 · cloud 1.40%

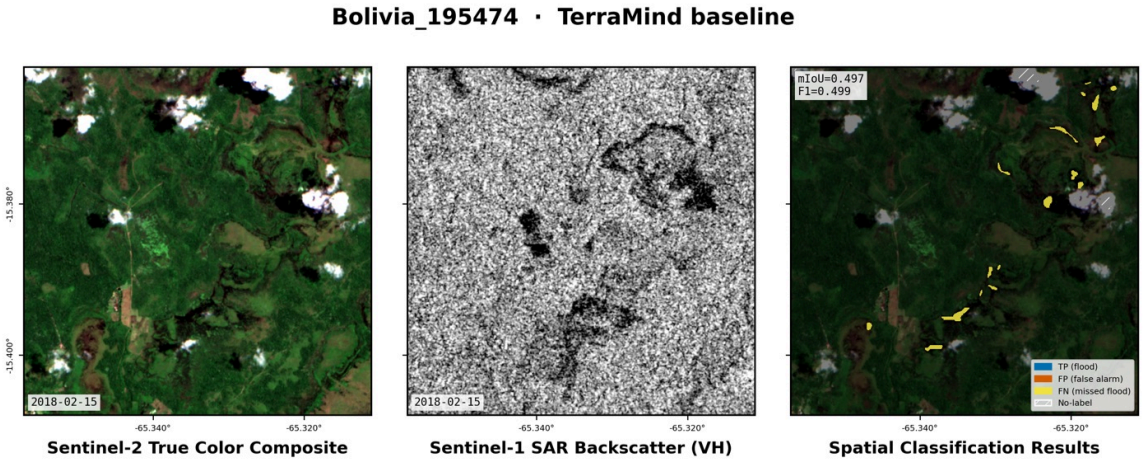

Figure 91: Bolivia_195474 · TerraMind baseline

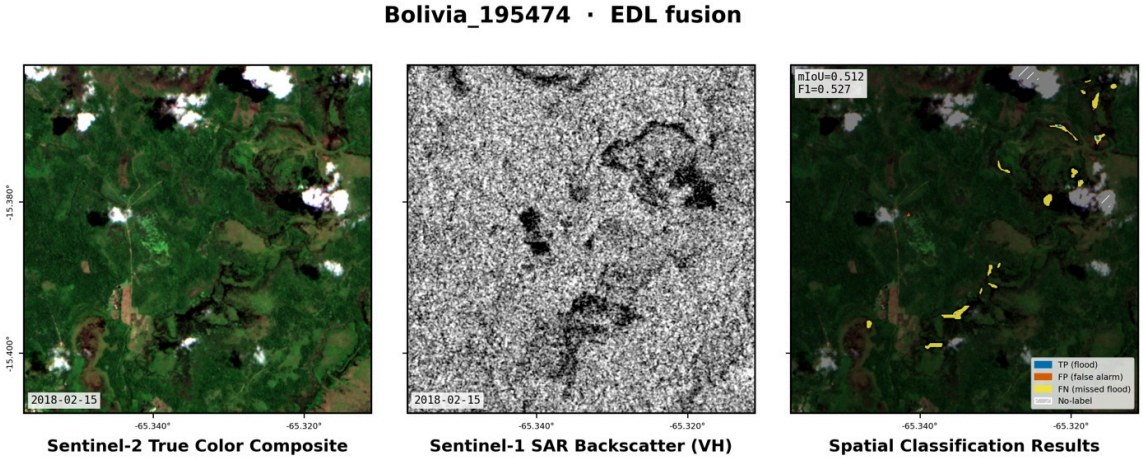

Figure 92: Bolivia_195474 · m2_lotv (EDL LoTV)

Bolivia_23014 · cloud 2.95%

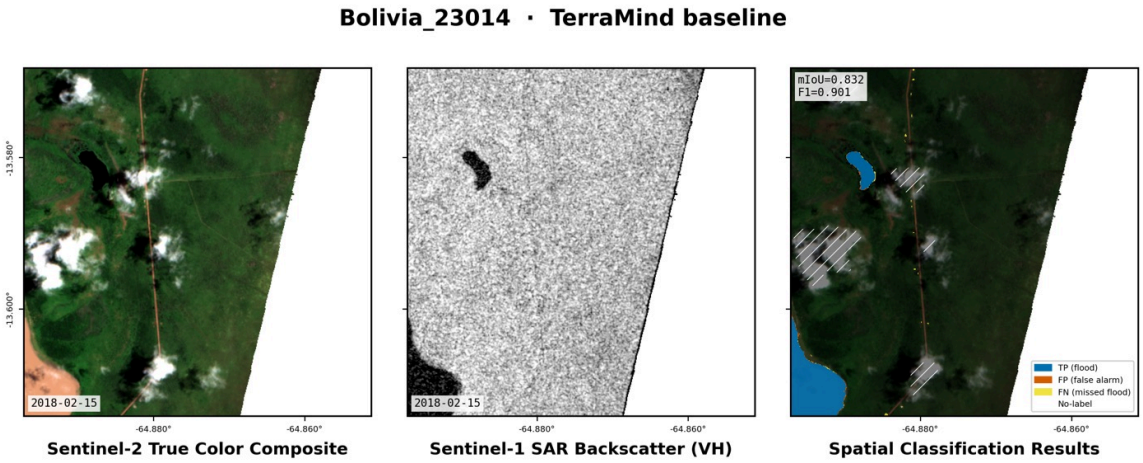

Figure 93: Bolivia_23014 · TerraMind baseline

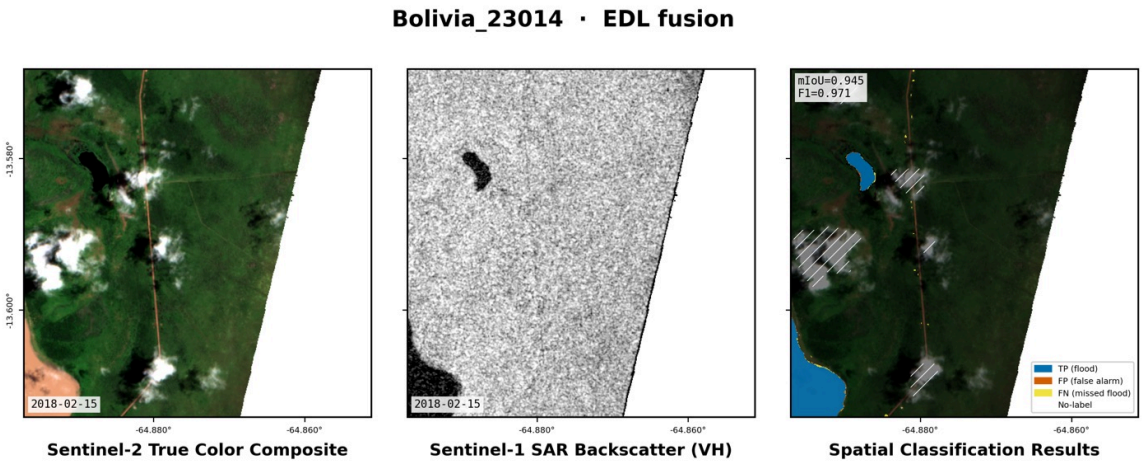

Figure 94: Bolivia_23014 · m2_lotv (EDL LoTV)

Bolivia_360519 · cloud 0.87%

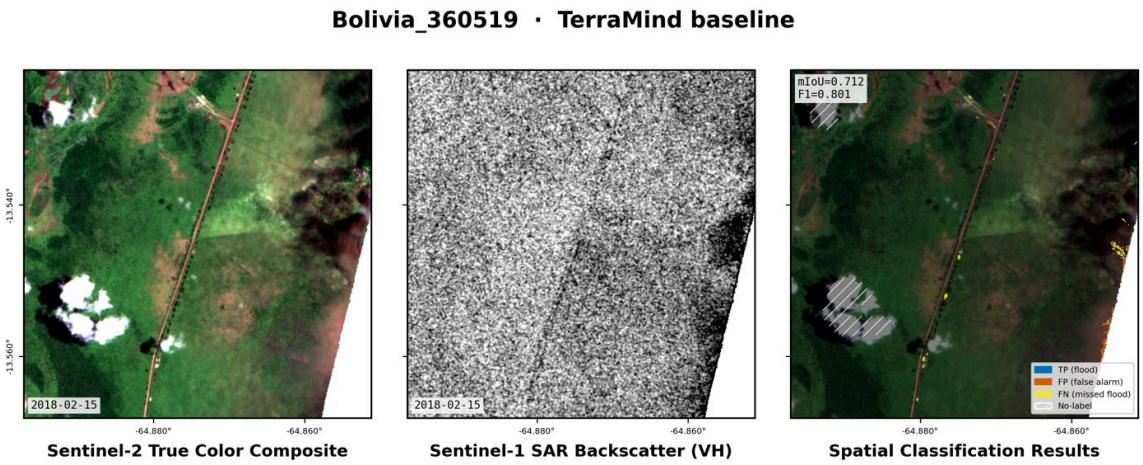

Figure 95: Bolivia_360519 · TerraMind baseline

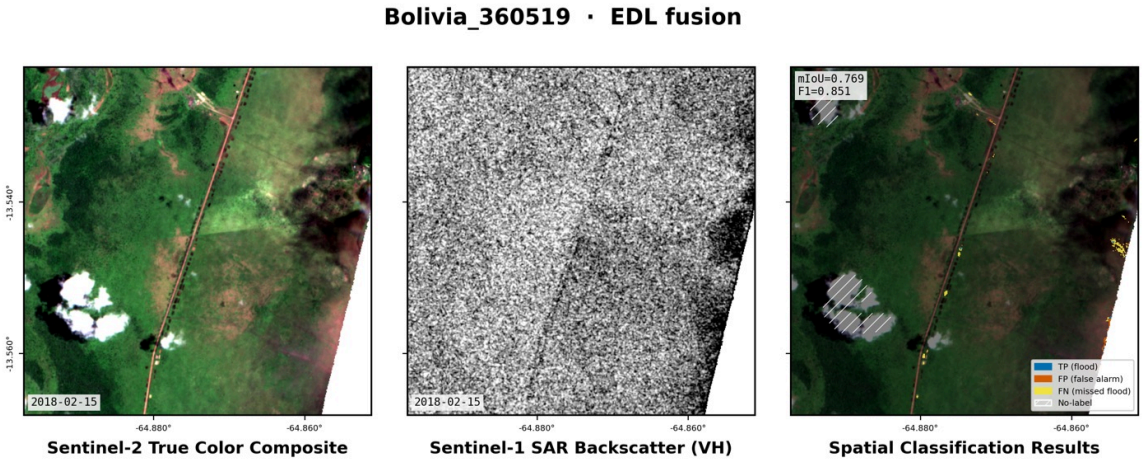

Figure 96: Bolivia_360519 · m2_lotv (EDL LoTV)

Low (5–25%) — 4 tiles

Bolivia_129334 · cloud 20.78%

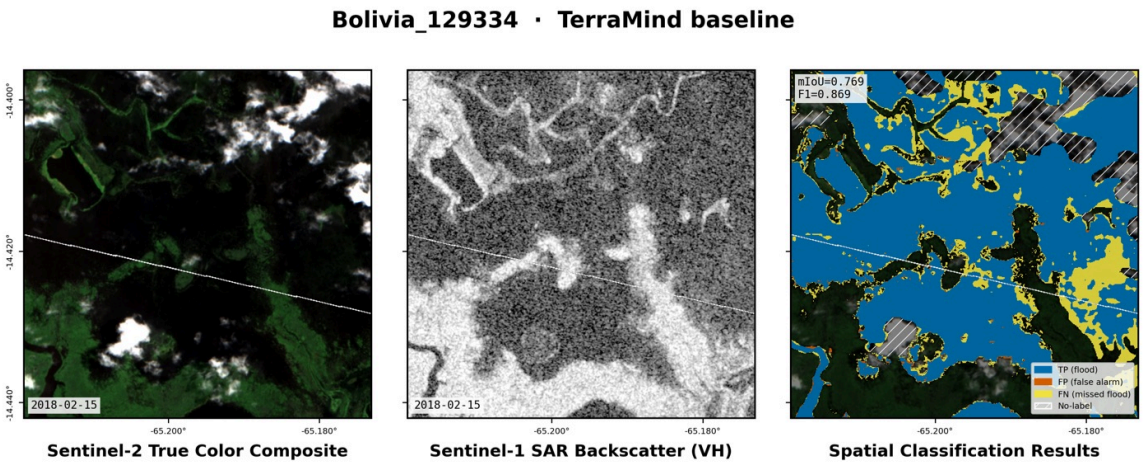

Figure 97: Bolivia_129334 · TerraMind baseline

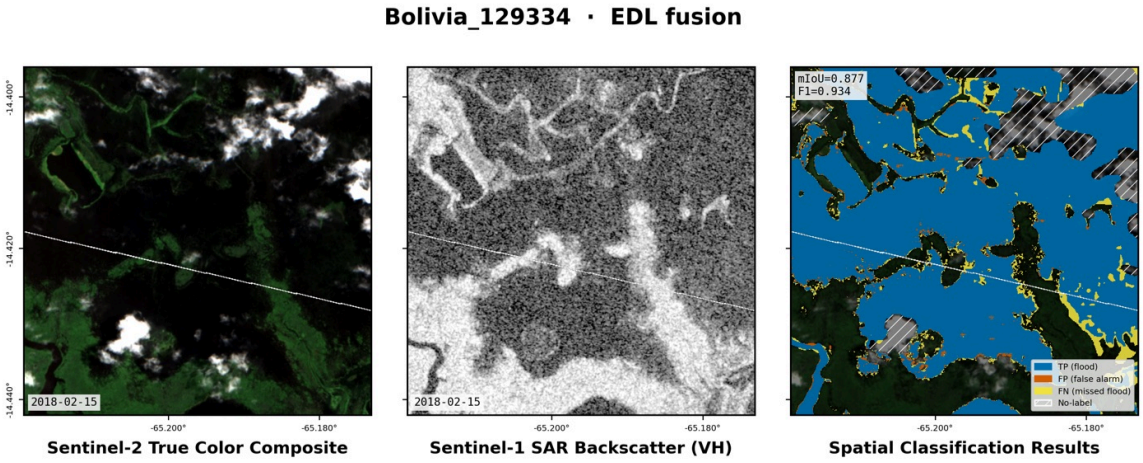

Figure 98: Bolivia_129334 · m2_lotv (EDL LoTV)

Bolivia_242570 · cloud 19.80%

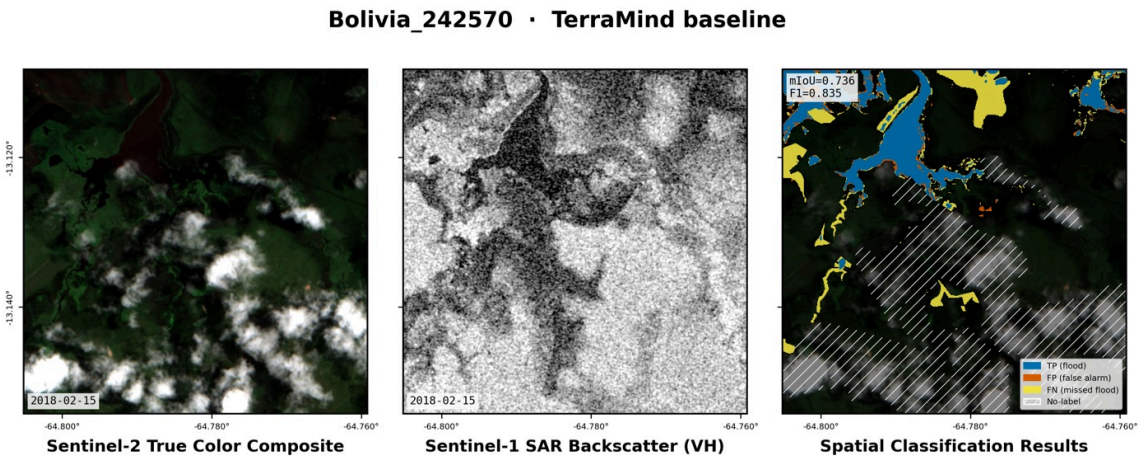

Figure 99: Bolivia_242570 · TerraMind baseline

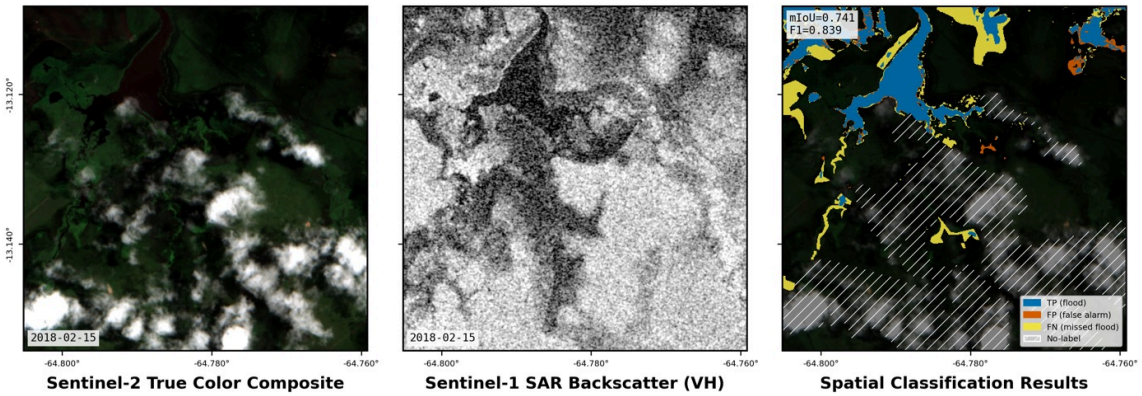

Figure 100: Bolivia_242570 · m2_lotv (EDL LoTV)

Bolivia_290290 · cloud 12.96%

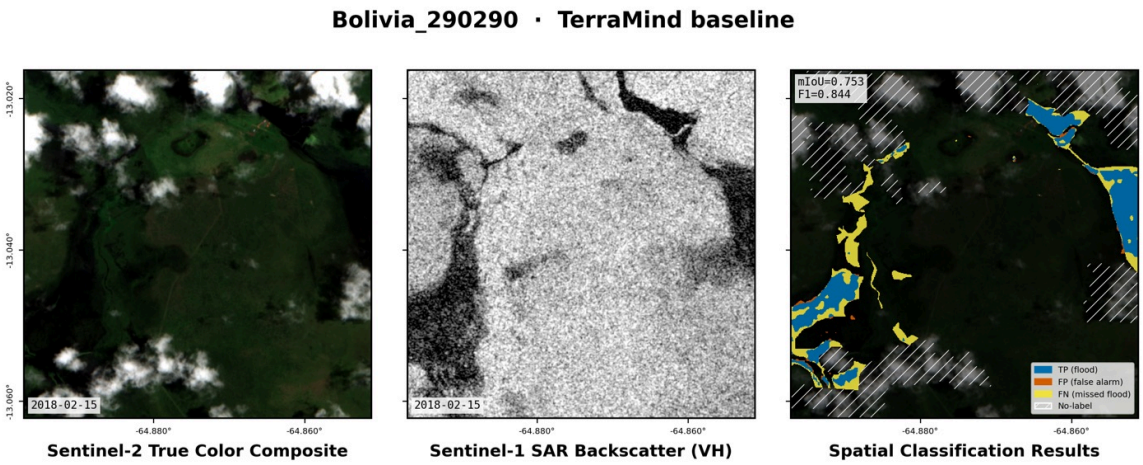

Figure 101: Bolivia_290290 · TerraMind baseline

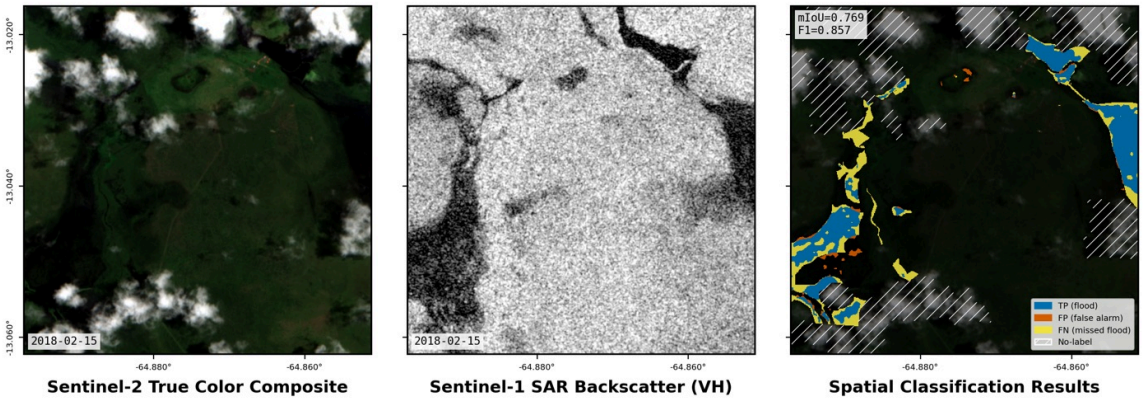

Figure 102: Bolivia_290290 · m2_lotv (EDL LoTV)

Bolivia_294583 · cloud 24.38%

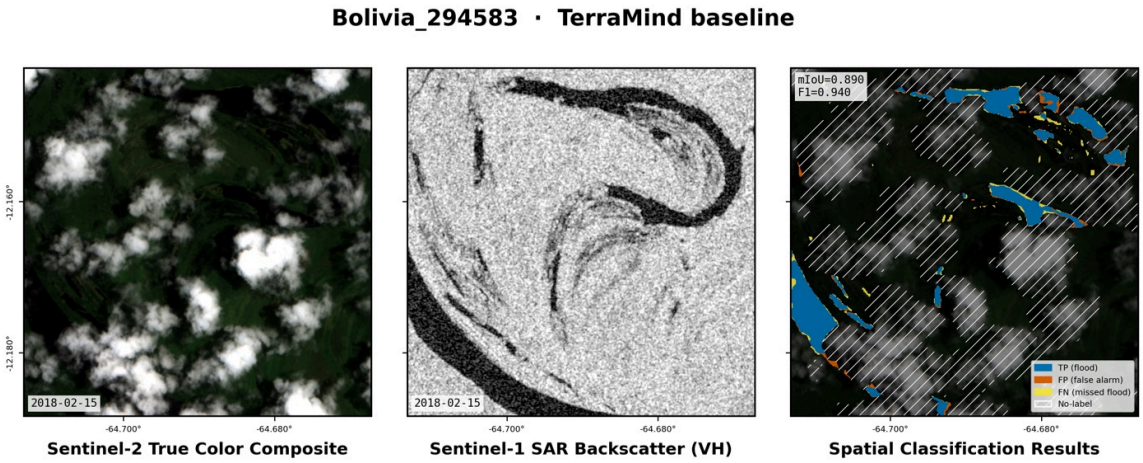

Figure 103: Bolivia_294583 · TerraMind baseline

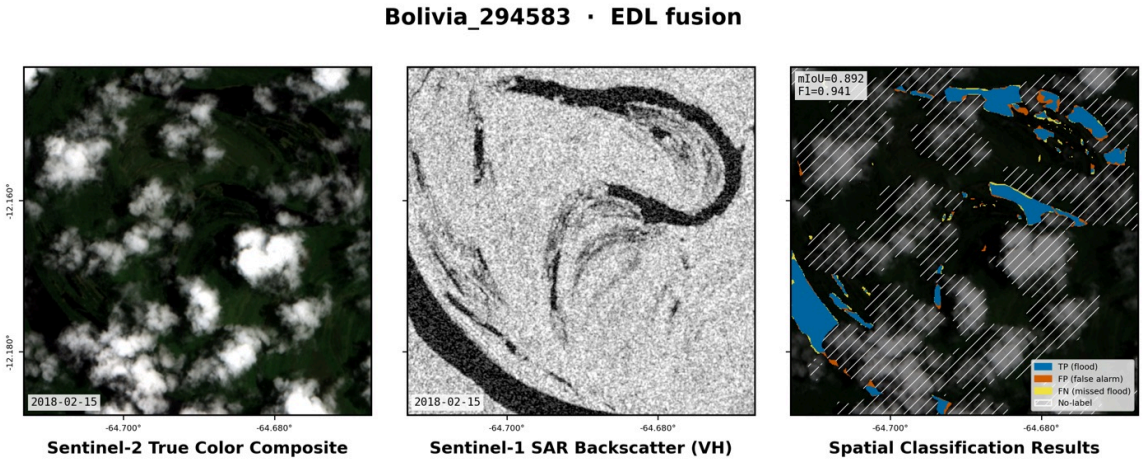

Figure 104: Bolivia_294583 · m2_lotv (EDL LoTV)

Medium (25–50%) — 3 tiles

Bolivia_233925 · cloud 41.11%

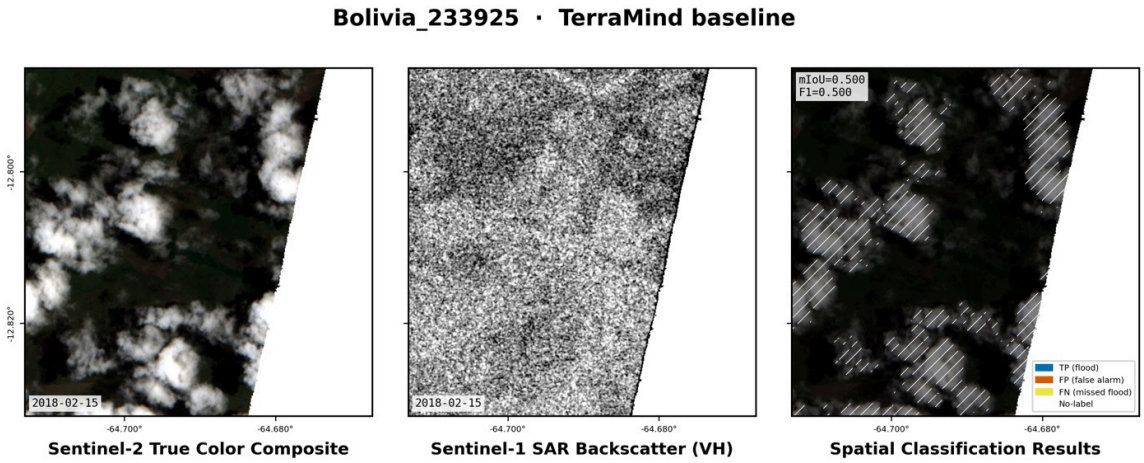

Figure 105: Bolivia_233925 · TerraMind baseline

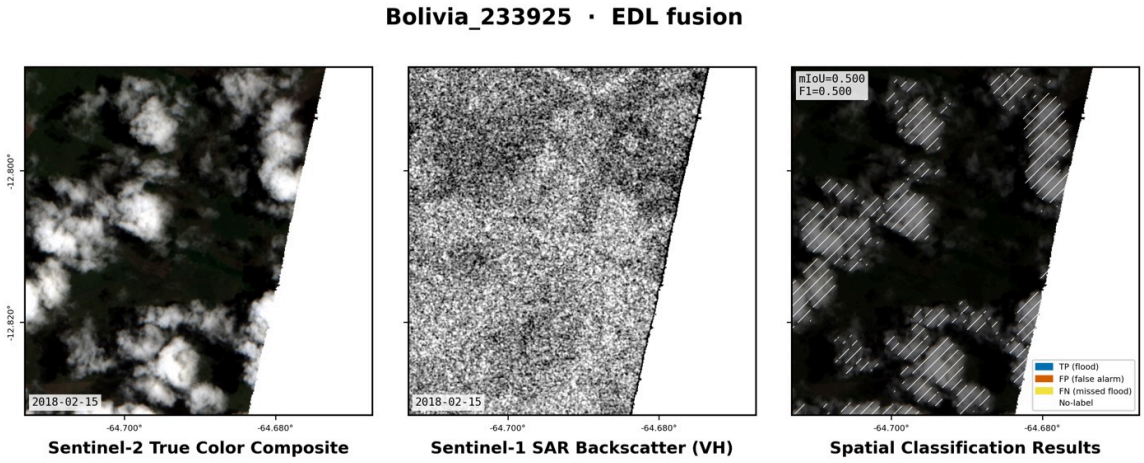

Figure 106: Bolivia_233925 · m2_lotv (EDL LoTV)

Bolivia_314919 · cloud 37.43%

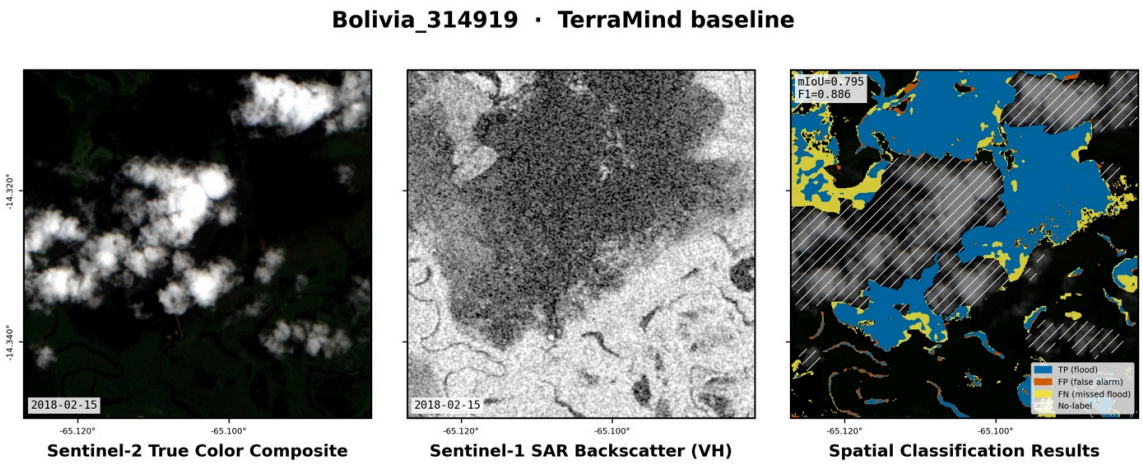

Figure 107: Bolivia_314919 · TerraMind baseline

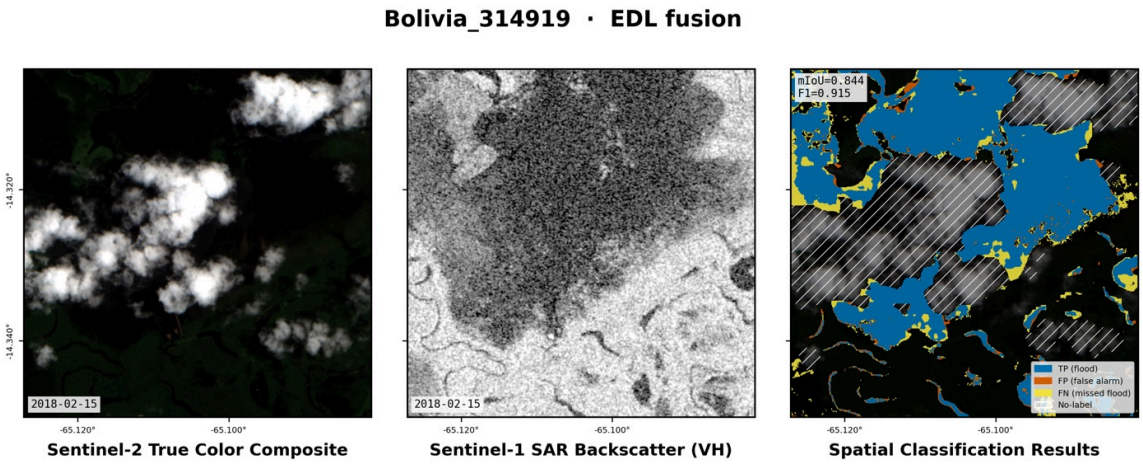

Figure 108: Bolivia_314919 · m2_lotv (EDL LoTV)

Bolivia_76104 · cloud 37.28%

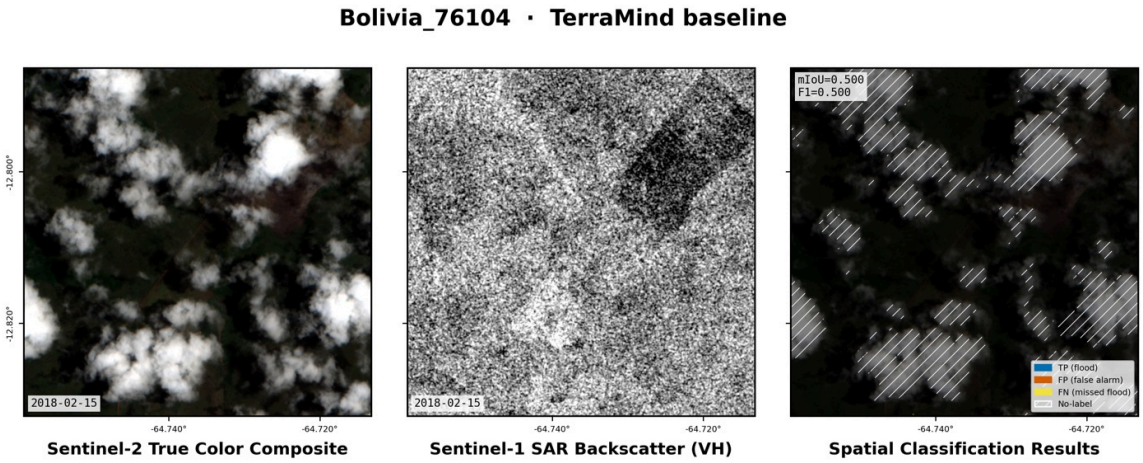

Figure 109: Bolivia_76104 · TerraMind baseline

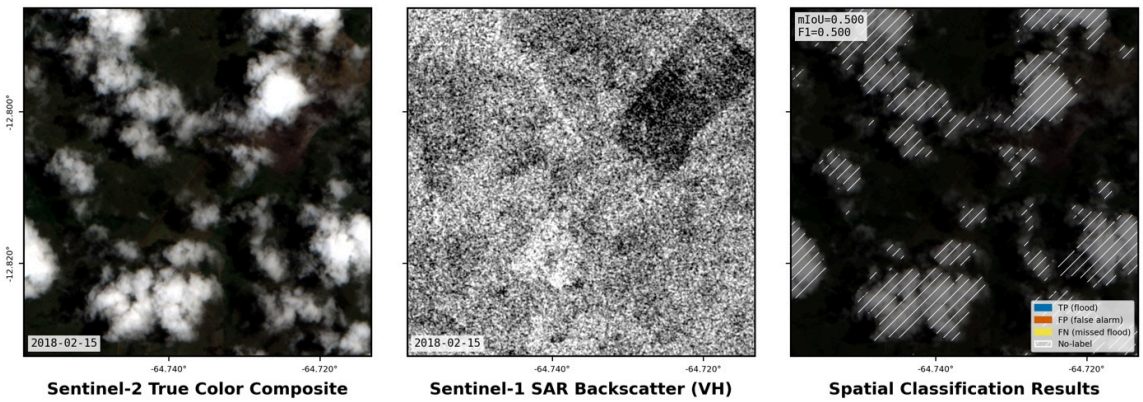

Figure 110: Bolivia_76104 · m2_lotv (EDL LoTV)

High (50–75%) — 1 tile

Bolivia_432776 · cloud 52.30%

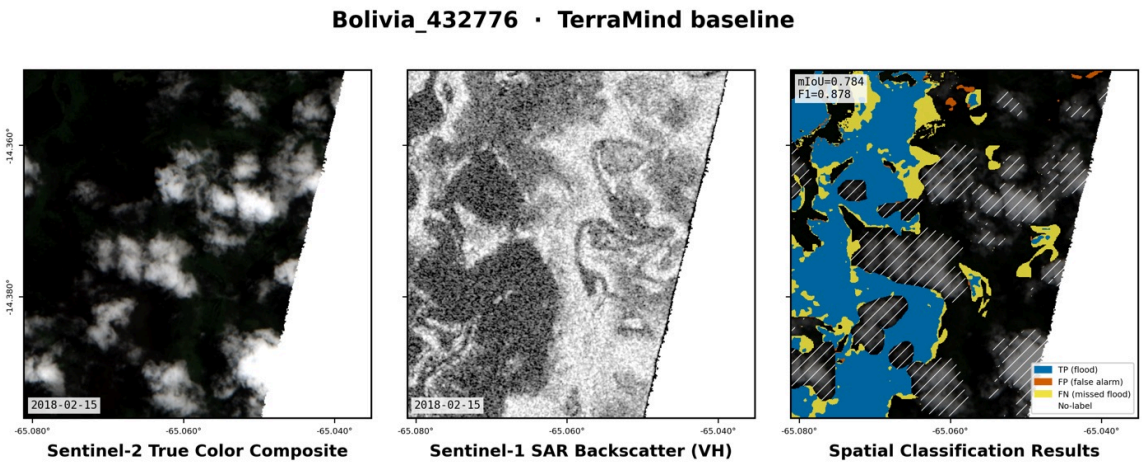

Figure 111: Bolivia_432776 · TerraMind baseline

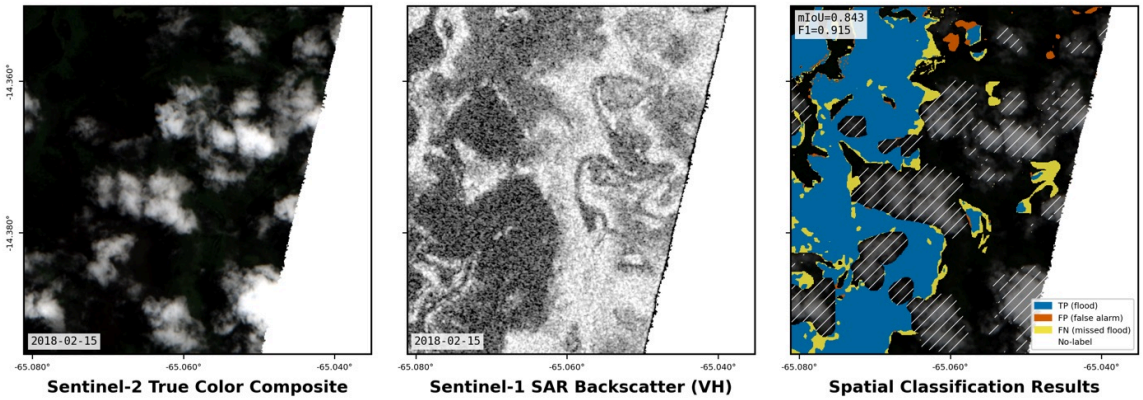

Figure 112: Bolivia_432776 · m2_lotv (EDL LoTV)

Heavy (≥75%) — 4 tiles

Bolivia_103757 · cloud 100.00%

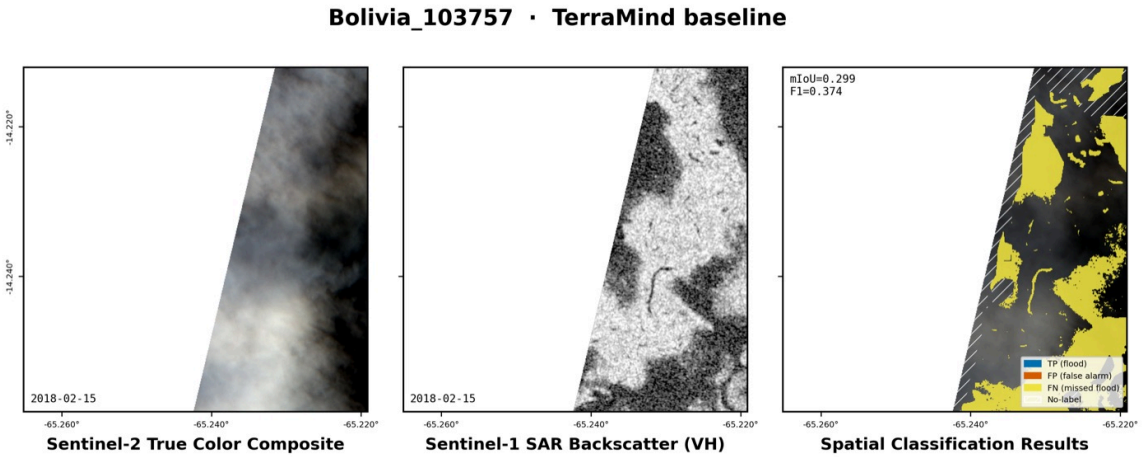

Figure 113: Bolivia_103757 · TerraMind baseline

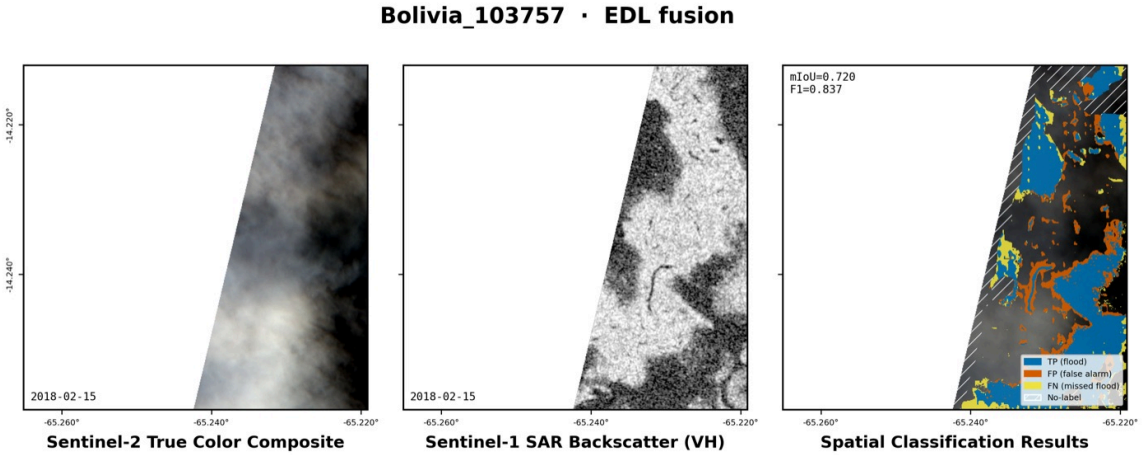

Figure 114: Bolivia_103757 · m2_lotv (EDL LoTV)

Bolivia_312675 · cloud 99.98%

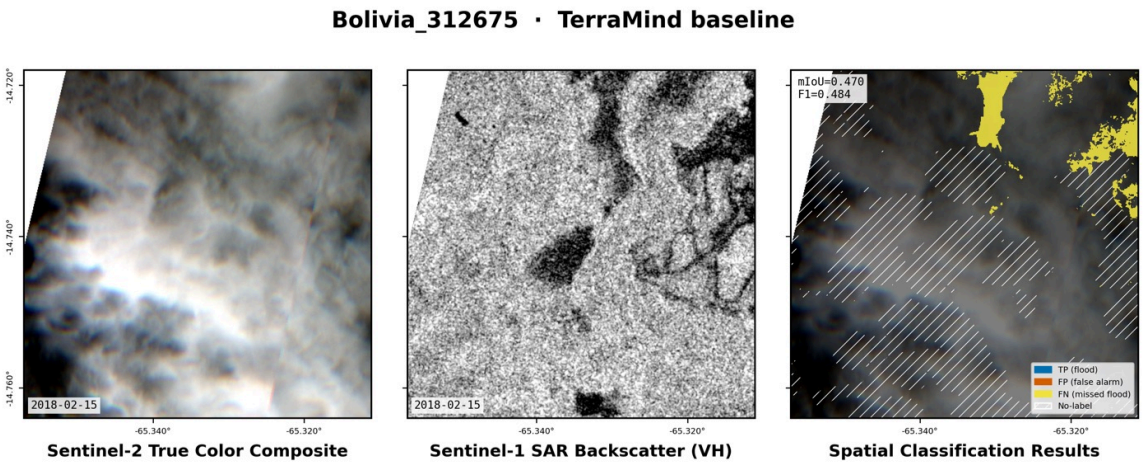

Figure 115: Bolivia_312675 · TerraMind baseline

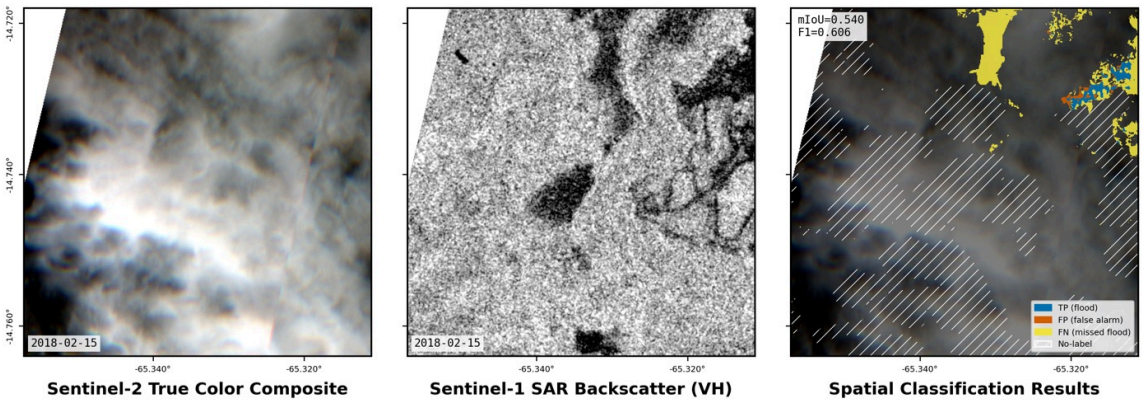

Figure 116: Bolivia_312675 · m2_lotv (EDL LoTV)

Bolivia_379434 · cloud 98.59%

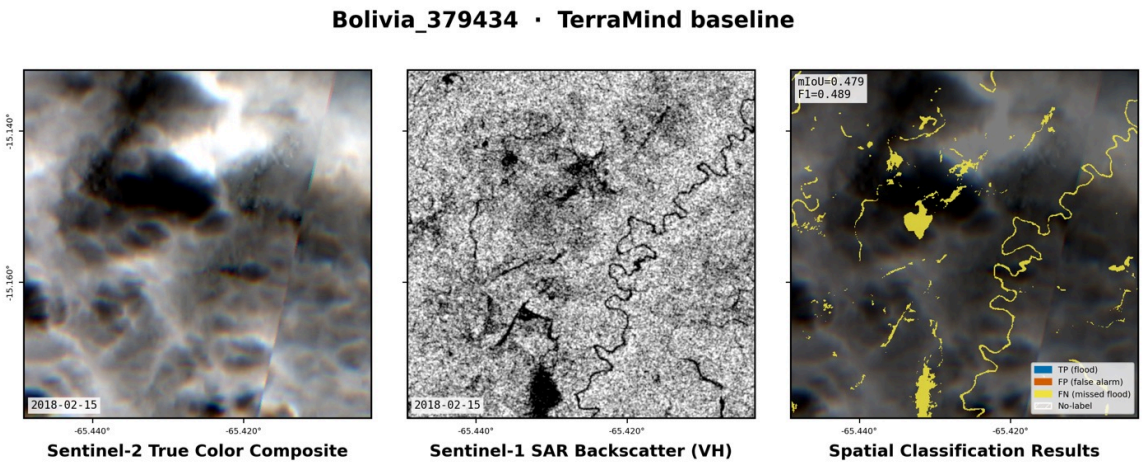

Figure 117: Bolivia_379434 · TerraMind baseline

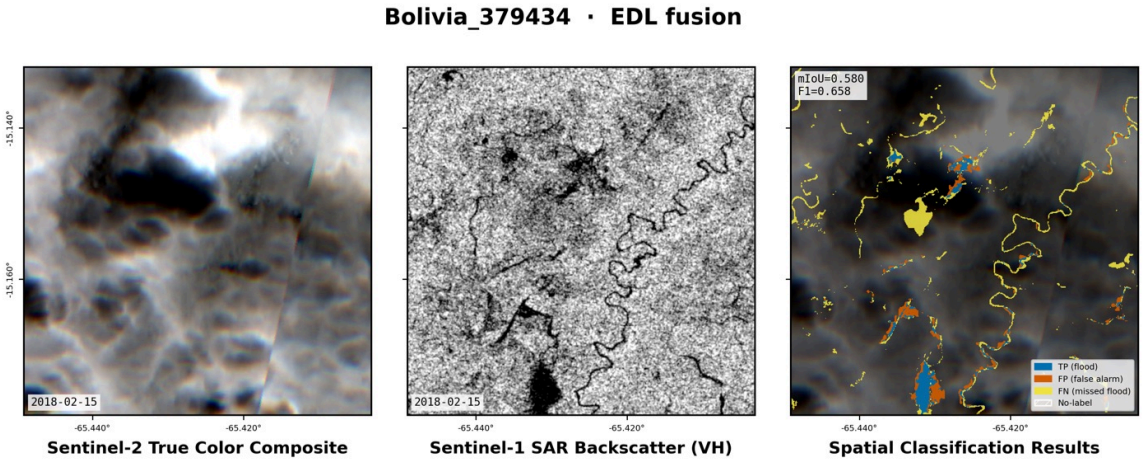

Figure 118: Bolivia_379434 · m2_lotv (EDL LoTV)

Bolivia_60373 · cloud 100.00%

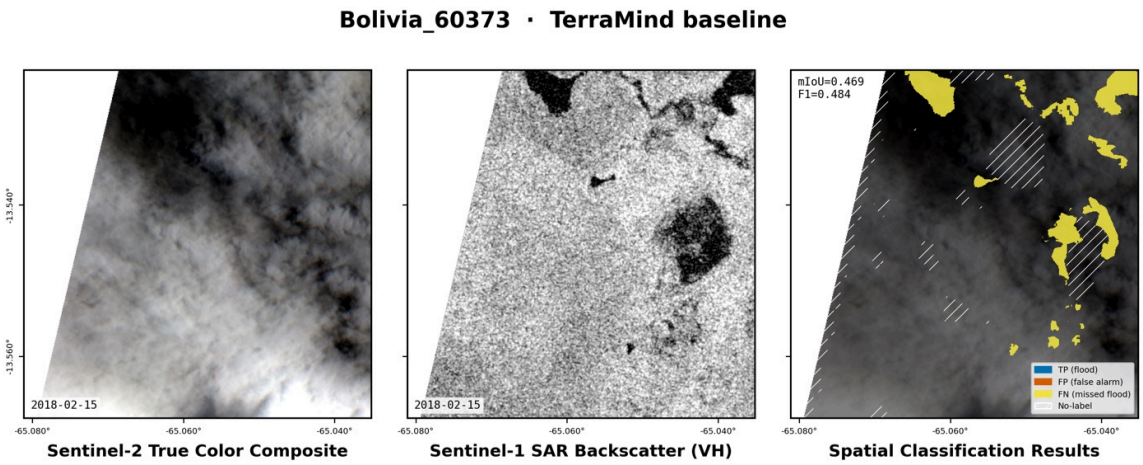

Figure 119: Bolivia_60373 · TerraMind baseline

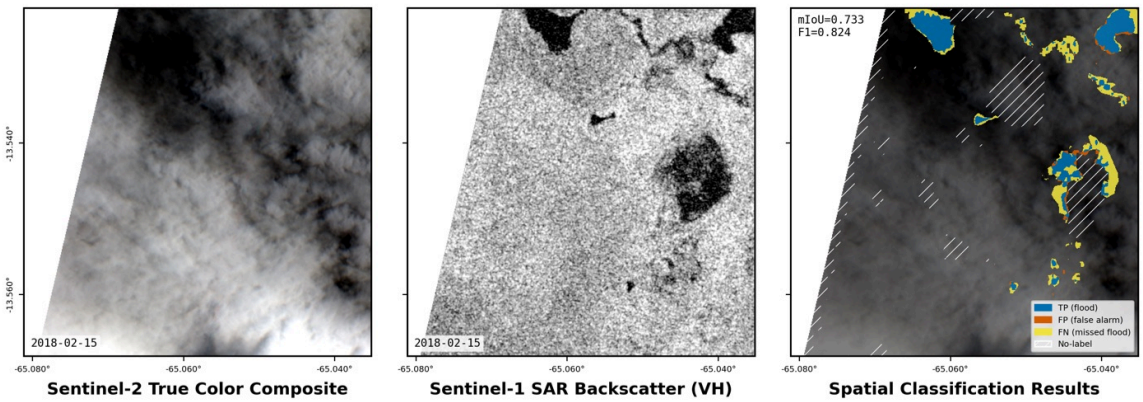

Figure 120: Bolivia_60373 · m2_lotv (EDL LoTV)