Expert interview : Ratul Debnath, Geoscientist & Innovative Geospatial Risk Modeler

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Staff Reporter : Ratul Debnath is a geoscientist and GIS pipeline integrity analyst who has developed a suite of innovative geospatial models for flood hazard prediction, landslide early warning, infrastructure corridor monitoring, and pipeline risk assessment. Holding an MS in Geographic Information Systems from Sam Houston State University and a Master of Urban and Regional Planning from Alabama A&M University, he has published seven peer-reviewed studies attracting over 131 citations. His models span deep learning, multi-sensor fusion, convolutional neural networks, and weighted spatial overlay analytics, each designed not merely as research outputs but as deployable decision-support systems. A certified FAA Part 107 Remote Pilot, Debnath currently serves as GIS Pipeline Integrity Technician at Centric Infrastructure Group, Texas, where he participates in federally regulated pipeline safety programs. His work is oriented toward a single conviction: that the most consequential advance in infrastructure and environmental safety is not more data, it is better models to translate that data into action.

1. **You have developed multiple innovative models across different hazard domains. What drives that range?**

Debnath : Every infrastructure safety problem is ultimately a spatial prediction problem, where will a flood overtop? Which pipeline segment will fail first? Where is terrain unstable enough to threaten a corridor? The sensor technologies to answer those questions exist. LiDAR, SAR, hyperspectral cameras, multispectral satellites — they generate enormous volumes of data. What does not yet exist, at operational scale, is a standardized set of models to convert those datasets into precise, actionable risk maps. That is what I have been building, one domain at a time, with a consistent methodology: fuse the best available inputs, validate against independent ground truth, and design the output to be compatible with the regulatory or operational framework the end user already works within.

2. **Walk us through your deep learning flood hazard model. What makes it innovative?**

Debnath: Most flood models rely on either hydraulic simulation or coarse satellite-derived inundation mapping. My 2026 model takes a different approach: it fuses LiDAR-derived digital elevation models with Sentinel-2 multispectral imagery through a deep learning architecture trained across approximately 1.25 million raster cells. By combining micro-topographic terrain features, slope, curvature, flow accumulation, with spectral land-cover signatures that influence infiltration and runoff behavior, the model learns spatial patterns that neither data source captures alone. It achieved an AUC-ROC of 0.94 and an AUC-PR of 0.63 on validation data, representing a substantial improvement over single-source approaches. Critically, the output is a continuous flood vulnerability probability surface at a resolution fine enough to distinguish block-level terrain conditions, exactly the scale at which planning and mitigation decisions are made.

3. **Your multi-sensor landslide early warning model has 46 citations. What is novel about its design?**

Debnath: Most landslide detection models optimize for technical accuracy, a high AUC or low miss rate, and stop there. My 2023 model addresses a different problem: early warning systems fail not only because of technical errors but because practitioners do not trust or act on the outputs. I designed my SAR-LiDAR-Sentinel-2 fusion model to produce auditable, graded evidence products alongside the change maps themselves. The Multi-Sensor Change Evidence Score fuses standardized change indicators from all three sensors into a single interpretable metric, and I validated it not only against terrain data but against a structured survey of 162 operational professionals, disaster managers, GIS analysts, engineers, planners, measuring their decision confidence and trust in the alerts. Three-sensor agreement zones produced mean confidence ratings of 4.34 versus 3.61 for single-sensor zones. That gap in practitioner trust is what determines whether a warning triggers evacuation or gets ignored. My model is designed to close it.

"The most consequential advance in infrastructure safety is not more data, it is better models to translate that data into action."

4. **How does your infrastructure corridor remote sensing model work?**

Debnath: Conventional infrastructure inspection relies on field surveys and visual assessments that cannot cover large geographic areas cost-effectively and often detect damage only after it has already progressed. My 2022 model applies spectral anomaly detection across multispectral, thermal infrared, and SAR imagery to identify degradation signatures along infrastructure corridors without physical inspection. Tested across 480 corridor segments confirms that remotely sensed spectral patterns carry statistically significant predictive information about the physical condition of infrastructure materials. Specific band combinations in the shortwave infrared and thermal ranges showed the strongest correlations with known degradation indicators, giving operators a targeted screening tool for prioritizing which segments warrant follow-up inspection.

Innovative Model Portfolio

Deep Learning Flood Model

Fuses LiDAR DEM + Sentinel-2 multispectral across 1.25M raster cells. AUC-ROC 0.94. Micro-topographic flood vulnerability mapping at planning scale.

Multi-Sensor Landslide EWS

SAR + LiDAR + Sentinel-2 fusion via MSCES score. Validated with 162 practitioners. 3-sensor agreement confidence M=4.34 vs single-sensor M=3.61.

Corridor Integrity RS Model

Spectral anomaly detection across multispectral, thermal & SAR imagery. 480 corridor segments analyzed. $R^2=0.62$. SWIR-thermal bands most predictive.

GIS Pipeline Risk Framework

Weighted overlay + Getis-Ord Gi* hotspot analysis. Pipeline attributes fused with soil, flood, and terrain hazard layers. DIMP/TIMP regulatory-compatible output.

UAV Hyperspectral-Thermal Fusion

210 spatial zones. Fused Red Edge, SWIR, and thermal anomaly indices for 3-class environmental risk classification. Outperforms single-sensor use.

CNN Nitrogen Prediction

Convolutional neural network on UAV-derived Red Edge and NIR imagery. Predicts switchgrass canopy nitrogen levels as a substitute for destructive tissue sampling.

Walkability Equity Model

ArcGIS Network Analyst-based spatial accessibility equity model. Identified underserved populations and quantified walkable service area gaps across Huntsville, Alabama.

5. **Your UAV-based models cover both agricultural and environmental hazard applications. How do they connect?**

Debnath: The underlying methodology is the same: fuse multiple sensor modalities at the zone level, extract indices that are physically meaningful for the target variable, and validate the fused classifier against independent ground truth. In my UAV hyperspectral-thermal study, I deployed co-registered hyperspectral and thermal infrared sensors across 210 spatial zones and derived red-edge chlorophyll indices, shortwave infrared water content indices, and thermal land surface temperature differentials. Fusing these into per-zone composite signatures and classifying each zone as soil moisture-stressed, erosion-susceptible, or flood-vulnerable, the multi-sensor approach consistently outperformed either sensor alone. In my CNN nitrogen prediction model for switchgrass, I applied the same spatial preprocessing logic, ArcGIS Pro for plot delineation and zonal statistics extraction, then deep learning on the spectral inputs, to achieve nitrogen concentration predictions accurate enough to replace destructive tissue chemistry sampling. Both models demonstrate that UAV-based multi-sensor fusion is a general framework, not a domain-specific technique.

"My pipeline GIS framework does not just model risk, it speaks the regulatory language that operators and federal inspectors already use. That is what makes it deployable."

6. **What makes your pipeline GIS risk framework different from existing risk assessment tools?**

Debnath: Existing pipeline risk tools tend to be either purely attribute-based, scoring a segment based on its material age and pressure without spatial context, or purely environmental, mapping hazard exposure without connecting it to asset-level attributes. My framework integrates both layers explicitly. Pipeline attributes including material type, installation age, diameter, and operating pressure are joined spatially to environmental hazard layers covering soil corrosivity classification, high consequence area proximity, FEMA flood zone designations, and LiDAR-derived terrain instability indicators. Weighted overlay analysis assigns a composite risk score to each pipeline segment, and Getis-Ord Gi* hotspot detection identifies spatial clusters of elevated risk across the network. The output is a spatially explicit, tiered risk map. Crucially, the parameter structure maps directly to the threat categories defined under PHMSA's Distribution Integrity Management Program and Transmission Integrity Management Program frameworks, so the outputs are not an add-on, they are compliance-ready. That is what makes the model deployable rather than merely publishable.

7. **What comes next: what models are you building toward December 2026 and beyond?**

Debnath: Two collaborative projects are already in development. Beginning November 2026, in collaboration with NASA-funded remote sensing researchers at Sam Houston State University, I will be integrating UAV-derived hyperspectral and thermal data with GIS-based spatial modeling to assess soil moisture variability and environmental stress indicators across Texas agricultural landscapes, extending my UAV fusion model to a NASA FARMGO-aligned application context. Beginning December 2026, in collaboration with energy sector GIS professionals at XTO Energy, I will be developing and field-testing a GIS-based environmental sensitivity and terrain risk overlay for active Permian Basin pipeline corridors, incorporating LiDAR elevation data, soil classification layers, and real-time inspection records. Both projects extend existing model architectures into new operational environments. The goal in each case is the same: models that do not sit in a journal but run in a system that someone depends on to make a safety decision.

8. **What global problems can your models actually solve?**

Debnath: Three problems. Flooding affects 1.8 billion people globally, my deep learning model fuses LiDAR and Sentinel-2 imagery, achieves an AUC-ROC of 0.94, and produces neighborhood-level flood vulnerability maps deployable anywhere in the world. Landslides kill 4,000 people annually in regions where early warning systems barely exist, my SAR-LiDAR-Sentinel-2 fusion model detects slope instability before failure, validated with 162 professionals and proven to raise decision confidence from 3.61 to 4.34. And millions of kilometers of aging pipeline infrastructure across West Africa, South America, and Central Asia operate with no systematic risk monitoring, my GIS pipeline risk framework delivers a deployable, regulatory-compatible scoring system adaptable to any national context. The satellite data already exists everywhere. The models to turn it into decisions did not. Now they do.

Closing Remark

Mr. Ratul Debnath is a geoscientist and GIS pipeline integrity analyst based in The Woodlands, Texas. His seven peer-reviewed publications have accumulated, across flood hazard modeling, landslide early warning, infrastructure corridor assessment, and pipeline risk frameworks built on globally accessible satellite data. He holds an MS in GIS from Sam Houston State University, serves as GIS Pipeline Integrity Technician at Centric Infrastructure Group, and is a certified FAA Part 107 Remote Pilot. Reach him at ratuldebnathgis@gmail.com