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THE MONTHLY MAGAZINE ON POSITIONING, NAVIGATION AND BEYOND

AI ≠Black Box
Autonomous and Predictive GIS
Decision fatigue Agentic AI Explainable AI
Geospatial AI Probabilistic Cognitive Engines
Data-to-Insight Lag Cloud-Native Geo-GPTs
Live Maps GeoFMs Predictive Modelling
Explainable AI

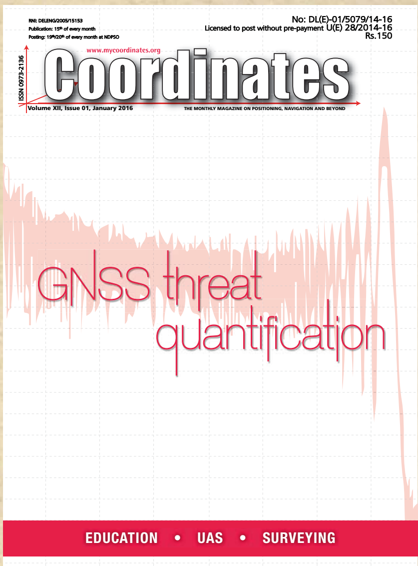
The Mantra for Geospatial AI: Trust, but Verify!

Decision fatigue
Cognitive Earth
AI Model Cards
Dimensionality Reduction
Geo-SAM Spatial Knowledge Graph Spatial data to spatial wisdom
IndiaAI Mission Vision-Foundation Models
Predictive Modelling Data hyper-abundance
The Trust Gap Synthetic Data Loops The EU AI Act
Planetary Geo AI System Synthetic Data Loops
AI Model Cards Space Geo AI System BharatGen
Seamless access to a Geospatial Cloud Archive
Indigenous AI technology Stack
India as Global South's Geo-AI Sovereign
Discrete Global Grid Systems

Accurate 3D point clouds with UAS-LIDAR and UAS-RGB photogrammetry without GCPs?

In Coordinates

10 years before...



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GNSS threat quantification in the United Kingdom in 2015

Dr Chaz Dixon
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Mark Greaves
Ordnance Survey's Lead Consultant for Geodesy, UK

Dr Paul Cruddace
Business Change and Innovation team, Operations Group, Ordnance Survey, UK

This paper introduces a summary of the GEMNet system, and presents two sets of results. Firstly, characteristics of interferers observed operationally along with the impact that they caused on two types of operational GNSS receivers. Secondly the results are presented from laboratory tests where jamming "signatures" were played back to two type of GNSS receivers at substantially higher power.

Evolving GNSS threats – just the tip of an iceberg?

Guy Buesnel
Market Segment Manager- Robust Position, Navigation and Timing
Spirent Communications plc, UK

There is no shortage of incentives for GNSS fraud. Further possibilities could be to avoid GPS based road tolling systems and to outsmart location-based payment authentication services – what if one could withdraw money from an ATM while having a GPS alibi claiming that you were elsewhere when the transaction took place? A recent development has been the use of smart phone tracking as a source of forensic evidence: the police will take a suspect's smart phone to search its movement tracking record. If that record could be falsi¿ed, then again it would provide a powerful false alibi.

Development of collision avoidance system for unmanned aerial vehicles

Harshit Kumar and Rahul Karkara
Scientist/Engineer, ISRO Satellite Center, ISRO, Bangalore

This paper is focused about finding an optimal solution for the collision avoidance of UAV in a busy airspace with both stationary and moving obstacles present in it, using Indian Navigation and Remote Sensing satellites. To achieve this, different algorithms were explored.

The education for cadastral surveying

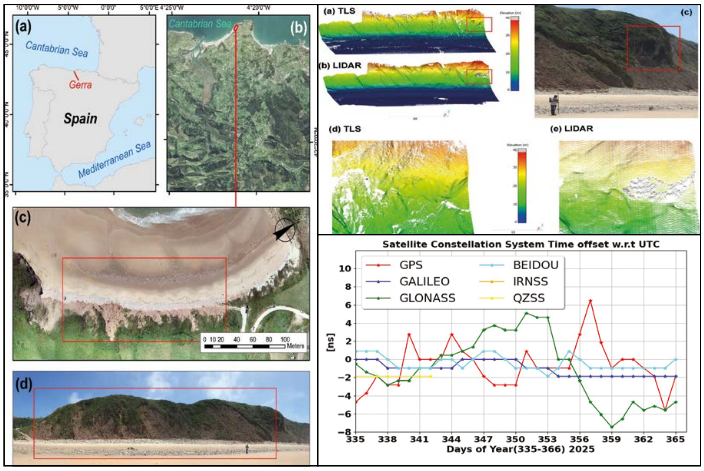
Kazuaki Fujii
Japan Federation of Land and House Investigators' Associations, Hyogo, Japan

The unique system of Japanese land administration has been maintained basically unchanged over 100 years due to modern history of Japan and the concept of possession with the will to occupy a land lot, a different concept from that of the Western nations. Because of the extremely complicated land administration that has been practiced according to local and others customs not specified in relevant laws, there are some experts who even insist that any reforms would not virtually change anything.

Roles of geomatic engineers after great earthquake

Sundar Devkota, Dinesh Kumar Bhandari, Rabin Prajapati and Punya Prasad Oli
Himalayan Collage of Geomatic Engineering and Land resources Management, Kathmandu, Nepal

The monitoring after earthquakes was carried out in the past for scientific studies. Presently high resolution maps and data are used for infrastructure development; meet the spatial data needs of municipalities and quality control of survey data. It is also required to plan new cities by land pooling process including earthquake damage areas. Therefore it is urgent to evaluate the existing control points.



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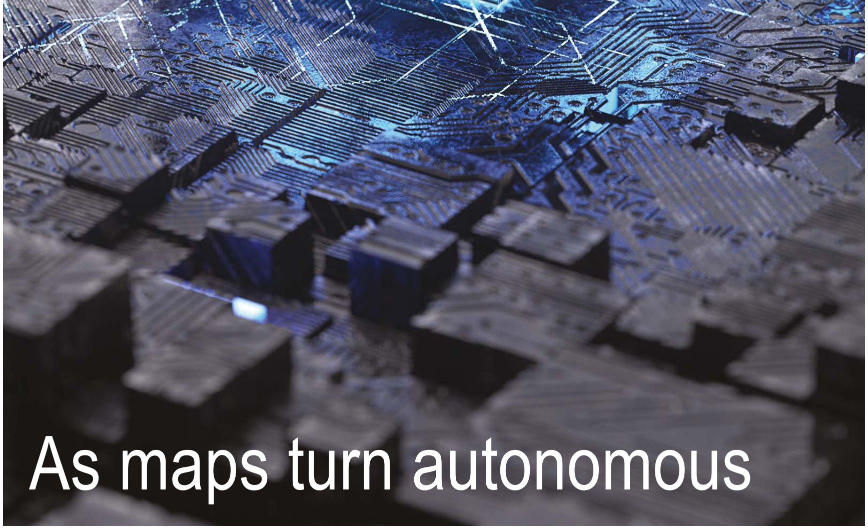

As maps turn autonomous

Geospatial technology is no longer confined to maps, layers, and overlays.

It is rapidly evolving into a living, reasoning system,

That observes, predicts, and decides.

As AI converges Earth observation, GIS, positioning, and analytics,

This delivers unprecedented scale, speed, and insight

While also introducing opacity, bias, and decision fatigue.

In an interview with *Coordinates* magazine,

Dr. Mukund Kadursrinivas Rao reminds us

That as geospatial systems shift

From mapping the world to reasoning about it,

Trust can no longer be assumed,

It must be verified.

Bal Krishna, Editor
bal@mycoordinates.org

"The mantra for Geospatial AI must be only *Trust, but verify*"

says Dr. Mukund Kadursrinivas Rao in an interview with Coordinates magazine, as geospatial systems transition from mapping the world to autonomously reasoning about it.

Dr. Mukund Kadursrinivas Rao
is an internationally recognized leader in space and geospatial technologies, with deep multidisciplinary expertise spanning technology, applications and policies in Earth Observation (EO) and Geographic Information Systems (GIS). With over four decades of experience across government, industry, academia, and consultancy, he has played a pivotal role in advancing the geospatial and space sectors. Having provided leadership to many national and international fora, his work effectively bridges scientific innovation, policy formulation and strategy development. He has voiced and articulated many forward thoughts, particularly in the real-world deployment of geospatial technologies to support societal development, informed governance and knowledge systems.
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What has AI fundamentally changed in how geospatial data is processed, analysed, and interpreted today?

Geospatial technology (or GIS or Geomatics) emerged from research in late 1960s in digital concepts (though in analogue form they have been existed as knowledge systems for much longer). As a result, there is a strong knowledge foundation for GIS. Over the decades, tt has triggered considerable advances in Geospatial education and research, business and societal development activities. On other hand AI, in its present "intelligence" form is emerging into mainstream society in recent years (though in its "earlier Avatars" can be traced through Digitalisation of data and coding, pattern recognition Software/Applications that do a specific job, and Expert Systems solutions that anybody could use). In a way, Geomatics through computerisation - and Geospatial data and AI, have been "fusing" together into a single stream. Now we are in a situation where AI seems to be "encompassing" all technology streams of digital activity, including Geospatial technology and applications. Geospatial activities are seemingly subsumed into "AI" – through spatial data content, locational knowledge and timeline-spatial records – as embedded pillars of "intelligence" of human reasoning.

In the yesteryears Geomatics or Geospatial project workflows, humans acted as the primary "intelli-translators" - manually digitizing maps or digitally analysing features from imagery; defining rigid, rule-based "integration" (as models) to understand spatial relationships; and then provide limited but different, perspective of various natural, social and economic phenomenon.

Today, AI (specifically GeoAI) has flipped that earlier human dynamics - we are moving away from manually/semi-automated **Descriptive GIS** (what is where?) towards fully **Autonomous and Predictive GIS** (why is it happening and what will happen next?). This is a also a major shift from the late 1990s fixed-model **Deterministic GIS** (static layers, manual queries, fixed algorithms) to **Probabilistic Cognitive Engines** with automated reasoning and predictive insights. AI is rapidly transforming Geospatial methods and processes from the earliest Display of Maps through Layer Overlays to a Query system to an Information System to a Decision Support System to a Reasoning system and now into an autonomous **Geospatial AI** *that Detects, Assesses,* and *Decides autonomously*.

In this AI advancement, there are two underpinnings of GIS fundamentals that are powering AI: first, the digital spatial data; and second, the

> AI is rapidly transforming Geospatial methods and processes from the earliest Display of Maps through Layer Overlays to a Query system to an Information System to a Decision Support System to a Reasoning system and now into an autonomous Geospatial AI *that Detects, Assesses*, and *Decides autonomously.*

location (xyz). Together, these two have provided the root to the advanced concepts (or data concepts) of "intelligence" which AI is taking great advantage of. Over the past five decades or so, the availability of digital spatial data with location in a data-bin has revolutionised "intelligence activity" in a significant manner. So, today just any data is characterised by location – be it images, maps, financial records, addresses, landuse, infrastructure, weather, flights, census data, social development, economic spatialisation – anything and everything that is digital on this Earth is now having a location tag – and that makes every bit of data on this Earth amenable to location analytics – brining newer and newer meaning and understanding of Earth and every human activity.

Traditional "silos" (Shapefiles, isolated Rasters) have undergone drastic changes and adapted to scale. The AI era relies on **Cloud-Native** and spherical tessellation into **Discrete Global Grid Systems (DGGS)** to normalize disparate sensors and spatial datasets. Thus, satellite pixels, IoT sensor readings, VGI, tabulated data, text reports and any bit of data on this Earth are hashed to a common index on spatial location. A "flood" tweet and a "soil moisture" vector layer and a "Radar image" now share a common mathematical key (of location), enabling real-time fusion of petabyte-scale datasets on a spatial frame. This brings tremendous advantage to AI models as the model not only undertakes location analytics but streams only relevant byte-ranges without downloading full files or tiles or yesteryears.

AI is now about **"Live Maps"** (unlike earlier time-static maps or displays) - fusing historical, current and streaming satellite/drone images and geospatial layers (elevation, land use etc) with dynamic data streams (live traffic, hourly weather sensors data, and instant device GPS pings). AI acts as the realtime "dual glue" – one, "fixing" and "holding" the location (in xyz domain) of any data AND two, automatically reconciling different data formats and temporal scales and data volumes to provide real-time **LIVE MAPS** fusion and data spatialising.

There are now Foundation Models bespoke for every object (e.g., "find cars"; "what is that object" or "hotspots temperature"). AI now uses **Geospatial Foundation Models (GeoFMs)** pre-trained on Earth Science/Geodesy and DGGS as **Vision Transformers (ViT)** and **Masked Autoencoders** that reconstruct the Earth from sparse data, gaining a latent understanding of terrain, cities, rivers, clouds, rain, atmosphere, climate and even outer Space. **Geo-SAM (Segment Anything Model)** tools instantly convert unstructured pixels (Raster) into topological vectors (Polygons), automating the analysis/digitizing tasks in minutes.

Earlier, Overlay was the foundation of a GIS but now Multi-Modal Logic provides more deeper and truer insights by correlating orthogonal datasets (Optical + Radar + Text + Video + Voice+…) to discover hidden and unknown relationships and insights. Virtually, the world is now modelled in Geospatial AI as a nested graph, not a map - though it is ultimately visualised by humans as Maps in a **Spatial Knowledge Graph (SKGs)** or **Graph Neural Networks (GNNs)**.

The final mile of delivery is **Agentic AI (Agentic GIS)** – GIS Apps and GIS Dashboards and GIS Portals are getting obsolete now. Instead of just displaying an analysed heatmap or a GUI menu or a fixed-Portal, the AI system uses Large Language Models (LLMs) to reason, fuse voluminous data, use pre-trained "intelligence" logic, eliminate improbabilities and provide a more deeper and new insight and action-sets as to why "that heat pattern" or "road alignment" is the best option with human reasoning and logic. The future is also of **Semantic Alerting** based on behavioural anomalies – predicting and alerting about events and phenomenon in advance.

Any human being now can "own" the Agentic AI and through a set of Generative Language Interface or Conversation AI, run LLMs of millions of parameters OR re-train the Agentic AI with advanced prompts and obtain the best of INSIGHTS – a ready solution for action. In fact, the Agentic AI can also embed testing and validation of results to score the "best" from a range of possibilities.

Agentic GIS will make hitherto complex GIS operations and command into a geo-conversation…just talk/question/ask/choose and obtain results or outcomes - in ready form for action!!!

Which areas of geomatics – remote sensing, GIS, photogrammetry, positioning and navigation, are being most transformed by AI right now, and why?

The wide range of Geospatial technology are feeling the "AI effect" and the transformation isn't uniform. The impact is based on data streaming to automating tedious tasks to enabling entirely new ways of perceiving the physical world.

Images - from Satellites or Drones or by humans, are the "Scale" Leader and are transforming because we have so much more and more pixels than human eyes can perceive or an Analyst can ever process. The Geo Foundational Models are **Vision-Foundation Models** that understand Earth's surface, satellite images, Drone captures, Device-camera images etc, not just on Earth but also Earth's interiors, atmosphere and even outer space. These models are already pre-trained on massive global datasets, allowing them to detect, from any IMAGE, floods, fires, crop health, under-canopy activities, vehicles, aircrafts, troop movements, storms and any human and natural activity with minimal additional processing, training and human intervention. The advancement is so intense that **IMAGE** processing is moving from computers, ground servers to the satellites themselves OR to the user's hand-held devices – Edge Processing. The processing can be anywhere for GeoFM data that is everywhere (if Data Centres move to Space then compute would happen there)!!!

High-resolution image analysis and Photogrammetry is shifting from measuring geometry to synthesizing reality and provide the **Fidelity to AI GeoFM**. Traditional photogrammetry relied on matching millions of "feature points" to create meshes. New AI techniques like Gaussian Splatting and Neural Radiance Fields or Auto Cleaning allow for the creation of photorealistic 3D environments from a handful of images. This is revolutionizing "Digital Twins" for cities or creating "real" infrastructure management remote and safe.

Positioning and Navigation is providing the **Resilience of Location** to AI models - ensuring location-*certainty and precision*. The problem of **Multipath Mitigation** in "urban canyons" (tall buildings) or even within Building-GIS, is fused into AI models that look at past data records and predict and cancel out these reflected signals in real-time from a fast and real-time back-and-forth switch between orbiting GPS satellites and Ground PNT systems, allowing for sub-cm accuracy even in dense city centers or within buildings. Similarly, **Dead Reckoning** when GNSS signals are lost (e.g., in tunnels or due to jamming) is way gone as AI models interpret data from IMU sensors (accelerometers/gyros) or streaming time-signals much more accurately than traditional calculus-based filters, "bridging" the gap until the signal returns.

Finally, GIS is enabled as the supreme **"Decision" Agentic Partner.** Natural Language Mapping has broken the GUI barrier and **Geo-GPTs** have come to stay. So now, what is relevant is: *"Identify all residential buildings within 500m of this proposed metro line and calculate the potential land acquisition costs and property tax loss."* Agentic GIS is making **Predictive Simulation** a reality **– Agentic GIS** is no longer just a "map" – in fact, it is now a LIVE model of the world!!

> Globally, we are undeniably in an era of data hyper-abundance, while in India it is not yet so. The "data gap" in GIS has shifted from a lack of information to a lack of "meaningful processing" bandwidth – something of a "Data-to-Insight Lag."

Are we moving from traditional map-making towards real-time spatial intelligence? How central is AI to this shift?

Yes, *the* shift is absolute. We are moving away from **cartography** (a static picture of the past) towards **spatial intelligence** (a real-time nervous system for the planet).

Traditional map-making is retrospective or "What Was" but AI is making it a current or future perspective or "what is" or "what can be". GIS is now to be only LIVE – moving away from **Traditional Mapping of** Collect data → Process in office → Validate → Publish map which used to take months to weeks; now **Spatial Intelligence GeoFMs** start from the IoT/ Satellite stream → Edge AI Processing → Autonomous Fusion → Agentic GIS → Options → Actions – all in few minutes.

Without AI, the sheer volume of real-time spatial data would be a humongous "madness on human analysts". AI performs three critical roles - **Pattern Recognition** from the "LIVE" spatial GeoFM (that could be billions of pings from GPS, thousands of images from cameras, and live streams from various sensors and voluminous historical past data) applying a primary filter, identifying only the meaningful data and changes and ignoring the millions of "un-needed" data points; **Predictive Modelling** which is the real-time intelligence of analysing the present, looking at past and more so about anticipating the future event to occur; and **Agentic Automation** for autonomously monitoring spatial feeds and trigger alert actions.

Are we dealing with a scenario of abundance of geospatial data than we can meaningfully use? Does AI help or complicate this situation?

Globally, we are undeniably in an era of **data hyper-abundance,** while in India it is not yet so (discussed in later sections). The "data gap" in GIS has shifted from a lack of information to a lack of "meaningful processing" bandwidth – something of a **"Data-to-Insight Lag."** While we can capture the entire Earth in high resolution every day, the majority of that data remains "dark" - stored in servers but never actually looked at or used for bettering human lives. AI is the primary force attempting to solve this, but its role is a double-edged sword: it both clears the backlog into meaningful data but creates a new layer of complexity by adding fresh data insights.

Without AI, the abundance of Geospatial data could be just "noise" but AI helps by acting as an automated triaging system

In my view, at the core level – two important soft-skills are fundamental – thinking and imagining, both of which are basic and critical skills/capabilities for the AI era – where a professional must be able to 'think' across any subject and find "model prompts" and 'imagine' wide-ranging scenarios to buttress the "model prompts"

of **Dimensionality Reduction**, to compress massive "data cubes" (layers of time, space, and spectrum) into compact summaries for an Agent; **Feature Extraction at Scale**, from a Foundation Model and **Exception-Based Mapping**, detecting when something *changes*—a new road appearing, a lake drying up, or a ship entering a restricted zone and so on.

But at the same time, I must also underscore that AI must not be treated as a "Black-Box" and requires sound principles and processes for the GeoFMS and Predictive models. Else there can be three complications - **The Trust Gap (Explainability)** because the Deep Learning model is hidden in millions of neural weights making it difficult for legal or justification for high-stake activities; **Synthetic Data Loops** because AI generates more spatial data (e.g., auto-completed maps), there is a risk of "model collapse" where future Agents are trained on data produced by past AI Agents, potentially amplifying small errors into massive "geographical hallucinations"; and **Infrastructure Tax** because managing the AI that manages the GeoFM requires its own massive infrastructure and calls for huge "data plumbing" efforts to ensure the AI pipelines don't break and keep learning and running.

So while it looks that we have solved the "data" problems or "analysis" problems, but we might be creating a **"decision fatigue"** problem. AI can generate thousands of "insights" per unit time and humans can get overwhelmed by the sheer number of insights, alerts and predictions. Further, AI may also tend to tilt towards and be biased on what Decision is being looked for and may provide a complacency bias.

In fact, at present in my experience, it is prudent to say the quality of your Agentic GIS is a function of the quality/depth/intensity of your Generative prompts – varying prompts on same Foundation Models give different outcomes and pose a huge Trust Gap! So a word of caution…it is the Generative prompts (Human Intelligence – so critical!) that are key for an Agentic GIS to be successfully meaningful – else the old GIGO!

So, is it a net Positive? That is what the world is saying and one can hope - the ability to monitor the planet and human activities in near-real-time allows us to respond to climate change, urban growth, reach logistics, undertake profitable business, and manage disasters in ways that were physically impossible even ten years ago. Involuntarily, we may be building a **Planetary Geo AI System** and maybe even a **Space Geo AI System** of Moon and all planets, galaxies put together!

I also wonder – earlier in 1970s we used to envisage a "GIS for Bengaluru" and later "Natural Resources Information System" and later "National GIS" and later Google Earth or Sentinel and so on…so our ability has been in expanding the data horizon (from a city to the state to the nation to the Earth)…today AI is pushing that horizon limit – both in depth of data and widening the spread to every inch of Earth, Moon planets, space…the Planetary Geo AI system!! But the AI data has been and even now is just one aspect…the ability to put to use all that AI outcomes to bettering human life, our knowledge, society, business, harmony, peace, environment, climate, managing strife…and working for a bettering life on Earth…we need to work more intensely and need many examples to establish that Human-AI interface enterprise!

How is AI reshaping professional roles in geomatics? What new skills should surveyors, GIS professionals, and geospatial analysts prioritise?

We are seeing a shift from technical production (making the map) to strategic curation (validating the intelligence). Traditional surveying is moving away from hours of field-based manual point survey to rapid Drone Survey and Field Data Streamers and Satellite constellation Images - becoming more realistic, legal sound and also advisory in nature. Surveyors and Analysts are now the ultimate authority of accuracy, verifying that Geo AI outputs meet rigorous legal and engineering standards, maintaining the cross-consistency in the GeoFM.

Geo AI Professionals are no more "Digitizers" but are "Agent Orchestrators" managing AI Agents that monitor data feeds and trigger analyses automatically. One has to be not only a "software user" but also a "system architect" and also a "logic expert" and have sectoral knowledge. Analysts must act as the bridge between raw AI predictions and real-world policy, interpreting complex patterns for non-technical decision-makers.

To stay competitive in the AI "value chain" would require knowledge of AI Literacy; GeoAI models; Prompt Engineering in GIS; Python/R for Automation; libraries like GeoPandas, TensorFlow, and PyTorch; Data Curation & Ethics; Spatial Reasoning & Logic; Data Storytelling; Critical Thinking & Validation; Explainable AI; Ambiguity Management; Legality of AI; Creative Problem Solving etc and many other knowledge integration.

The above knowledge has to be 'twinned" with knowledge of Geodesy, Geography, Spatial Science, Mapping and GIS concepts. So what we need is a twin-skill of AI+Geospatial in one person – something hard to find, at least in India. We must work on this to build a cadre of AI+Geospatial experts in coming years.

In my view, at the core level – two important soft-skills are fundamental – thinking and imagining, both of which are basic and critical skills/capabilities for the AI era – where a professional must be able to think across any subject and find "model prompts" and imagine wide-ranging scenarios to buttress the "model prompts". In my view, it is these that can make the prompts, LLMs and Agentic GIS so solid, robust, reliable and successful. Any person that can have these two core skills and gain above mentioned AI knowledge – I think they will make the best future Geo AI professionals!!!

In AI-generated spatial insights, how do we ensure trust, accuracy, and accountability in geospatial decision-making?

The mantra for Geospatial AI must be only **"Trust, but Verify."** As we shift toward automated decision-making (say, where AI might trigger flood alerts or approve land-use permits or advance security actions etc), AI "magic box" must be a highly audited pipeline. There are four important structural pillars - **Explainable AI (XAI) & Semantic Clarity** to explain what and which data (pixels or spatial features or text data) influenced the AI model's decision; **Semantic Layering** as a "Guardrail" that ensures the AI isn't just matching patterns, but is following human-like logic (e.g., "A building would not exist in the middle of a permanent water body" – verify such outcomes!) and **AI Model Cards**, which are like a nutrition label, or Metadata documenting its Geo FM data, Training data, known biases, math, reasoning and logic and recommended use cases.

As synthetic imagery or information (AI-generated) becomes harder to distinguish from reality, the Open Geospatial Consortium (OGC) initiative to prioritize IPT (Integrity, Provenance, and Trust) is commendable - where the concept is that every data point carries a digital "passport" that records its source (which satellite/drone), what AI models touched it, and what edits were made and by whom. For high-stake decisions, audit trails are often stored on immutable ledgers to prove that spatial evidence hasn't been tampered with in Blockchain Verifiable Logs.

Ultimately, accountability remains a human dependency and global standards that mandate professional oversight are getting defined. **Exception-Based Reviews** by AI flags "low-confidence" areas where it is unsure, and a human expert (like a licensed surveyor or a Troop Analyst or an Environment Officer) performs a manual audit of only those specific cases. AI based **Ground-Truthing Apps** which are Real-time field apps (like **Fulcrum** or **ArcGIS Field Maps**) allow community groups or field crews to verify AI predictions on-site, feeding "ground truth" back into the model to correct errors instantly.

It is obvious that legal accountability in Geospatial AI is called for. **The EU AI Act** calls for mandatory third-party audits and risk assessments. **Algorithmic Impact Assessments (AIA)** being defined by many nations now require an AIA before deploying AI for public-facing decisions. The India AI Mission is also working details in these lines.

Quite a lot needs to be done in building the trust!

From an Indian perspective, what opportunities does AI-driven geomatics open up, and what structural challenges still need to be addressed?

India has made many attempts in past for nation-wide Geospatial data and applications; it must now develop a National "testbed" for AI-driven Geomatics.

The **National Geospatial Policy 2022** claims to democratize data access and allow Indian startups to build "Bharat-tested" models that can be exported globally. A classic surge in private Map enterprise in India have become successful with private investments. Private EO satellites have been announced. AI is purported to analyze fragmented land holdings (typical of Indian farms) to provide hyper-local crop insurance and yield predictions in a business environment by some industries in India. Under the National Geospatial Mission, high-resolution (5-10cm) 3D "Digital Twins" for urban cities are aiming to be built and unique **Operation Dronagiri** project are on ground. With the **IndiaAI Mission**, India is envisaging indigenous foundation models like **BharatGen** for real-time monitoring of carbon sequestration and climate adaptation, helping India meet its ESG goals.

Recently, in her budget speech, Union Finance Minister Nirmala Sitharaman announced Bharat Vistar, a new AI-driven initiative for India's agriculture sector. Elaborating further, she described Bharat Vistar - the Virtually Integrated System to access Agricultural Resources -as a multilingual AI platform that will integrate India's agri-stack portals with the Indian Council of Agricultural Research (ICAR) package of agricultural practices, powered by AI systems.

However, in my view, real-time AI spatial intelligence in the Indian context is still staring at the scattered and many

> In next few decades, Geospatial AI will have transitioned from multiple Agentic GIS into the autonomous central nervous system of a hyper-connected Planet Earth or a "Cognitive Earth"

long-standing "potholes" of many years and also the wide gaps of deep-seated structural and organisational turfs in India. National alignment and mission approach has been earlier elusive – Geospatial AI will need this alignment to be a successful Indian homegrown initiative – else foreign AI technology and Geo FM data will power Indian Geospatial AI!

Despite the visible optimism of recent years, I still see some long-standing "bottlenecks" remain in the Indian Geospatial ecosystem:

- **The Data Availability "Hurdle" –** which has been a bane in India from 1990s – through NSDI, NNRMS, Bhuvan, NRDMS, National GIS, State-GIS etc. We still face a DATA drought! However, while recent policies have liberalized the business intent for GIS data, the **Data-to-Insight Lag** persists in various ways – especially in form of **Patchy Data** of both historical and current character. Geo AI models require clean, consistent historical and most current data to learn and improve pattern models and robust Agents. In many parts of India, land records are still being digitized, and historical satellite imagery for specific regions are unavailable or difficult or expensive to procure. **EO Image Continuity** from Indian satellites is even now a major problem - most users have to depend on foreign EO data sources – public-domain or commercial – which becomes a bottle-neck and also speaks on national capability! **Seamless access to a Geospatial Cloud Archive** of national level geospatial data is still not available – even a basic Spatial Foundation Dataset is yet to be adopted nationally – users create their own foundations and their own datasets which brings in immense non-standards and "silos". Dronagiri project aims to create localised datasets – but will it be fitting into one National Geo FM is still un-demonstrated. Bhuvan has lots of GIS data and EO content – but access and ingest to Geo FM Models poses great difficulties. Statewide and Nation-wide compilations of standard GIS datasets are hitherto still unavailable. So, with this patchiness in data and multitude, localised data models – the base of a Geo Foundational Model and Agentic GIS across large regions within the country poses a great challenge. However, the spot-light can be on localised Geo FMs and LLMs for small project – just akin to and replicating the large number of GIS Project of yesteryears!! *To me, this is not the way to go – a massive effort at overcoming this Data "hurdle" is called for!*

- **Spatial Heterogeneity:** India's diverse geography (from desert to tropical rain-fed farms to coastal to glacier regions and so on) means a LLM trained in Rajasthan won't work in Karnataka and even in another corner of Rajasthan itself. This "Domain Shift" requires massive amounts of local "Ground Truth" and "pre-training" knowledge for a robust LLM. This can be a challenging task as it labor-intensive and time/resource intensive to collect and organsie. The model and LLM intensity has to be very high to cater to the wide ranging spatial heterogeneity of India's natural, social, economic and security problems. Indian capability in AI Models and LLMs seem more oriented towards "million logics" at local scales (akin to earlier distributed architecture) – though I personally feel that is not the way to go now. We may have tens of thousands of these LLMS in operation in the country at lcalised spread. Like the "kirana stores", the localised LLMs may appear best way to go locally – but managing the thousands of sectoral and localised LLMs (with millions of parameters within them) may not only be inelegant but we may never build a AI Model at scale for the nation and its business ecosystem. Such localised GeoFM and LLMs may also not be most relevant for the large variation of our states, natural resources, social fabric, economic inequity, security perspectives and will, once again in my view, turn out to be a paradox of "part but not the whole" and be a humungous management challenge! However, if we can build a market-place of these thousands of Agentic GIS, maybe the business system may thrive to some degree – not just from domestic and localised market but may also be, at some level, exportable as customised AI models to many other "smaller" nations/regions of the world. Architecturing all of this will be a real innovation!

- **Indigenous AI technology Stack** – dependency outside of India for AI technology stack, GIS Engines, Highres satellite images, advanced Drones, Cloud Systems etc is also a hurdle that needs to be overcome. Until and unless India can create its own AI Technology Stack, the ability of Indian users to use and benefit from AI will always be dependent on outside resources – which is like "repeating" the same music again of the past!

I remember that in 1990s, the debate for building a GIS system was to go "bottoms-up" – build district systems and stitch them into state and national systems, as against "top-down" – building from nation expanding down to villages; India went the "bottoms-up" and demonstrated quite many district/city systems but never could organise a full National or Global system!! Google went "top-down" bit by bit and is now covering the whole Earth! In recent, MapMyIndia is another example that has gone top-down and has covered whole nation. Similarly, in mid 1990s, same debate happened for GIS Engines – indigenous GIS software efforts across the country BUT dependency on more robust foreign COTS GIS Engines fuelled many GIS projects – we lost the GIS Engine software capability!

In fact, when I use some of the AI tools – like Google Earth Engine, ArcGIS AI, Planetary Computer, Navi, Sagemaker EO, Carto, TorchGeo – I am amazed at the diversity of data models and capability of large instruction LLMs that distinguish in image analysis, climate analysis, Sustainability models, ML pipelines etc at scale, and in Conversation Mode, makes open data and custom data registries and geo-spatial processing and modelling so rich, easy and versatile. The world of Geospatial is certainly undergoing so much of advancements in the AI domain.

We must have an India AI Technology Stack that powers the Geospatial AI!!

- **The AI Skill Gap:** There is a massive need for professionals who understand *both* Geospatial and AI and deep learning, as explained earlier. Most Indian GIS professionals are trained in traditional software (ArcGIS/QGIS) but lack the **MLOps** and AI skills needed to deploy AI agents. Conversely, AI engineers often lack the "Spatial Reasoning" and GIS knowledge to understand map projections, coordinate systems, Laws of Geography, Terrain slopes, Landslides, urban taxation etc leading to geographically "hallucinated" results and dearth in Agentic GIS that are technically sound and robust and geographically adaptive. Just the traditional Geomatics skillset which emphasises on mapping and GIS is less of a requirement and relevance today in the Geospatial AI market. Our education and training systems must orient towards twinning "Geospatial+AI" skillset in the country.

The AI Skill Gap must get bridged on a campaign mode – either by creating a new cadre Geospatial AI over time and/or by spotting and encouraging and empowering such existing Geospatial AI individuals within our system immediately.

- **Security vs. Innovation** which is an important case for India. As GeoAI becomes central to national defense and security infrastructure, at the same time central to development needs, the paradigm of constant tension between "Open Data" and "National Security" should get bridged and eliminated. Even Security would require the innovations of Geospatial AI – so an open and inclusive secure working model is called for. The **Digital Personal Data Protection (DPDP) Act** must add a layer of complexity to geospatial data that includes personal information (like land ownership), requiring organisations/companies to build "Privacy-by-Design" into their AI models.

Looking ahead, do you see geomatics becoming an invisible but critical infrastructure for society, and what role will AI play in shaping that future?

That has always the goal even earlier – make EO and GIS embedded in society and governance – make it a part of governance workflow. It should also develop as a commercial enterprise (subscriptions – just look at how many people subscribe to ChatGPT, Gemini, Clause.AI, GEE, ArcGIS AI, CoPilot etc). So we should hope for that and work towards creating an invisible, ubiquitous fabric that *governs* the nation and world around us. Geospatial data will always be a critical data element in the AI business - society will only notice when Geospatial content fails. AI can be the catalyst that makes this paradigm shift for Geospatial technology both as a possibility and also invisibility. Concepts like Ambient Navigation; Predictive Cities; Massive Digital-Twins and Context-aware services (for insurance, tax, penalties, damage etc) and many many others – all as Agentic GIS will dictate the economy of national development and many business enterprise. I have no doubt on that – but the main issue I grapple is whether it will be built an Indian AI Technology Stack or on a foreign and global commercial AI stack!!!

Geospatial technology is moving from the "back office" of mapping to the "front line" AI for effective actions. The value is shifting from **spatial data** to **spatial wisdom**. Government agencies still have overlapping jurisdictions, and "Security" is still used, at times, as an excuse to block data. The mission mode is missing – so we make slow progress. **Frigidity in Bureaucratic Inertia** must not remain – not just at organisational levels but also at deep-down local levels. Local municipal and panchayat bodies still don't know how to use the high-res Geospatial data that the Geospatial Policy has technically "freed". So how will they develop/manage the millions of localised Agentic GIS and develop the Million Parametric Models across the country?

However, I do see very positive developments and improvements over the past. At this stage, I see the net progress is in **Policy Liberalization** - removal of prior security clearances and permission for Indian entities to generate Geospatial data and applications; **Private Pivot** - companies announcing to launching private EO constellations and MapMyIndia's nation-wide GIS maps and services; and **Infrastructure Integration** – emergency of shared geospatial backbone for digital transparency in development and government programmes, like PM Gati Shakti, MGNREGS, Pragati, Bengaluru Challenge 2026, Karnataka-GIS and many others. These are considerable steps ahead – we need to see the outcomes of these and many other initiatives that will set another action-roll ahead to Agentic GIS! The India AI Mission must align, integrate and mission-ise in the coming years.

India spent 200 odd years to make its first topographic maps and in last 50 years trying and trying to build the large-area GIS data content/applications. In 2026, it is essential to imagine and build the spatial intelligence using AI as a Unified Geospatial Interface – speeding Geo FM, private satellite EO images, private sector real-time and Live AI Maps of India, thousands of localised LLMs and Agentic GIS and the Business Ecosystem for a National Geospatial AI.

At a more global level, in next few decades, Geospatial AI will have transitioned from multiple Agentic GIS into the autonomous central nervous system of a hyper-connected Planet Earth or a **"Cognitive Earth,"** a state where a planetary-scale digital twin to monitor environmental shifts but pre-emptively negotiate global resource flows, stabilizes climate micro-systems through automated interventions, and manages "Human Development " of scale. I am also pretty confident that AI will pervade into Planetary Science and Outer Space Eco-system that will be foundation for Moon, Mars, planets, outer space human endeavour – much needed!!

In such an era, India can emerge as the **Global South's Geo-AI Sovereign** an contribute to an **Outer Space.AI**, leveraging its Geospatial AI foundation to leapfrog ahead.

(The thoughts and articulations are shaped from years of professional experience, complemented by curated generative intelligence, to present forwardlooking perspectives of Geospatial AI.)

GNSS Constellation Specific Monthly Analysis Summary: December 2025

The analysis performed in this report is solely his work and own opinion. State Program: U.S.A (G); EU (E); China (C) "Only MEO- SECM satellites"; Russia (R); Japan (J); India (I)

Narayan Dhital
Actively involved to support international collaboration in GNSS-related activities. He has regularly supported and contributed to different workshops of the International Committee on GNSS (ICG), and the United Nations Office for Outer Space Affairs (UNOOSA). As a professional employee, the author is working as GNSS expert at the Galileo Control Center, DLR GfR mbH, Germany.

Introduction

This article continues the monthly performance analysis of the GNSS constellation. Readers are encouraged to refer to previous issues for foundational discussions and earlier results. In addition, there is a short update on the India's regional navigation systems in the performance remarks section.

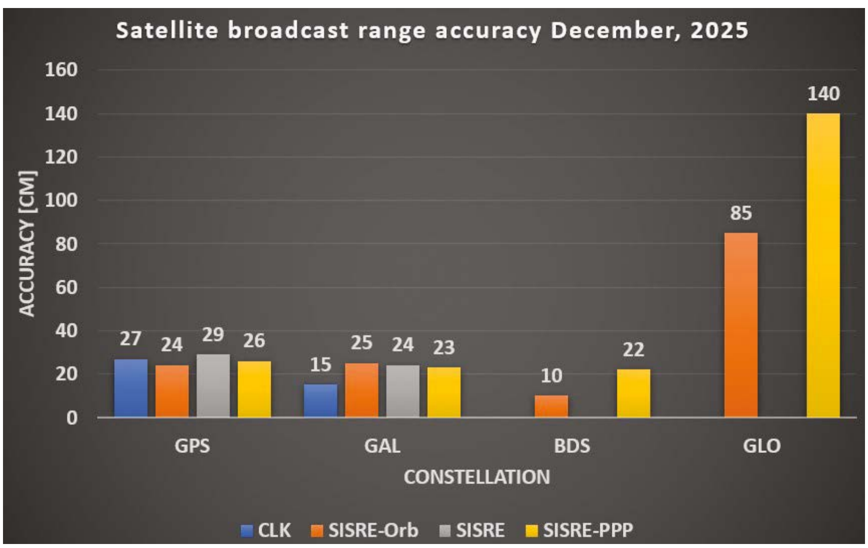
Analyzed Parameters for December 2025

(**Dhital et. al, 2024**) provides a brief overview of the necessity and applicability of monitoring the satellite clock and orbit parameters.

a. Satellite Broadcast Accuracy, measured in terms of **Signal-In-Space Range Error (SISRE)** (**Montenbruck et. al, 2010**).
b. **SISRE-Orbit** (only orbit impact on the range error), SISRE (both orbit and clock impact), and **SISRE-PPP** (as seen by the users of carrier phase signals, where the ambiguities absorb the unmodelled biases related to satellite clock and orbit estimations. Satellite specific clock bias is removed) (**Hauschlid et.al, 2020**)
c. **Clock Discontinuity**: The jump in the satellite clock offset between two consecutive batches of data uploads from the ground mission segment. It is indicative of the quality of the satellite atomic clock and associated clock model.
d. **URA**: User Range Accuracy as an indicator of the confidence on the accuracy of satellite ephemeris. It is mostly used in the integrity computation of RAIM.
e. **GNSS-UTC offset**: It shows stability of the timekeeping of each constellation w.r.t the UTC

Note:- for India's IRNSS there are no precise satellite clocks and orbits as they broadcast only 1 frequency which does not allow the dual frequency combination required in precise clock and orbit estimation; as such, only URA and Clock Discontinuity is analyzed.

(a), (b) Satellite Clock and Orbit Accuracy (monthly RMS values)



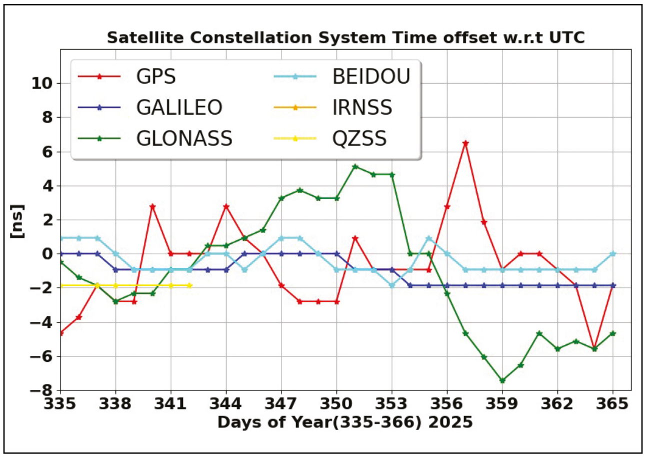
(c) Satellite Clock Jump per Mission Segment Upload

Const	Mean [ns]	Max [ns]	95_ Percentile [ns]	99_ Percentile [ns]	Remark (Best and Worst 95 %)
IRNSS	277.8	1086074.94	5.1	42.81	Best I06 (1.49 ns) Worst I10 (13.11 ns) Big jumps for each satellite in multiple days. I11 will be analyzed in next month's issue.
GPS	4.02	49039.04	0.72	2.24	Best G11 (0.38 ns) Worst G03 (3.18 ns). G27 showed one large discontinuity around 11 December.
GAL	0.09	3.74	0.19	0.46	Best E07(0.16 ns) Worst E19 (0.37 ns). All satellites provide stable clocks for the month.

(d) User Range Accuracy (Number of Occurrences in Broadcast Data 01-31 December)

IRNSS-SAT	2 [m]	2.8 [m]	4.0 [m]	5.7 [m]	8 [m]	8192 [m]	9999.9	Remark Other URA values (frequency)
I02	2987	13	2	-	3	-	-	-
I06	2957	46	-	-	1	-	1	-
I09	1758	9	4	-	2	-	-	-
I10	644	2	1	-	1	1	-	-

(e) GNSS-UTC Offset



Monthly Performance Remarks:

1. Satellite Clock and Orbit Accuracy:
   - The performance of Bediou is a degraded by a small margin (2 cm)
   - IRNS broadcast messages in PRN 11 have been detected in last few months. A detail analysis, together with the recent degradation and gradual failure in IRNS, will be provided in next issue.
2. The UTC Prediction (GNSS-UTC):
   - IRNS has no BRDC-UTC values in the BRDC messages. A separate analysis will be provided in the next issue regarding the recent degradation and gradual failure in IRNS.

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Is it possible to generate accurate 3D point clouds with UAS-LIDAR and UAS-RGB photogrammetry without GCPs?

A case study on a beach and rocky cliff

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Abstract

Context Recently, Unoccupied Aerial Systems (UAS) with photographic or Light Detection and Ranging (LIDAR) sensors have incorporated onboard survey-grade Global Navigation Satellite Systems that allow the direct geo-referencing of the resulting datasets without Ground Control Points either in Real-Time (RTK) or Post-Processing Kinematic (PPK) modes. These approaches can be useful in hard-to-reach or hazardous areas. However, the resulting 3D models have not been widely tested, as previous studies tend to evaluate only a few points and conclude that systematic errors can be found.

Objectives We test the absolute positional accuracy of point clouds produced using UAS with direct-geo-referencing systems.

Methods We test the accuracy and characteristics of point clouds produced using a UAS-LIDAR (with PPK) and a UAS-RGB (Structure-from-Motion or SfM photogrammetry with RTK and PPK) in a challenging environment: a coastline with a composite beach and cliff. The resulting models of each processing were tested using as a benchmark a point cloud surveyed simultaneously by a Terrestrial Laser Scanner.

Results The UAS-LIDAR produced the most accurate point cloud, with homogeneous cover and no noise. The systematic bias previously observed in the UAS-RGB RTK approaches are minimized using oblique images. The accuracy observed across the different surveyed landforms varied significantly.

Conclusions The UAS-LIDAR and UAS-RGB with PPK produced unbiased point clouds, being the latter the most cost-effective method. For the other direct geo-referencing systems/approaches, the acquisition of GCP or the co-registration of the resulting point cloud is still necessary.

Introduction

In the last two decades, one of the most relevant advances in geosciences is the development of high-resolution landscape models of small to medium-sized areas, acquired using different platforms (and sensors) combined with geomatic techniques (Tarolli 2014). Unoccupied Aerial Systems (UAS) allow the acquisition of high-resolution topographic data at relatively low cost compared to conventional aerial and topographic surveys (Colomina and Molina 2014). Two techniques are mainly used to produce these high-resolution 3D datasets: Structure-from-Motion photogrammetry (SfM) and Light Detection and Ranging (LIDAR). SfM photogrammetry comprises a set of techniques and algorithms that allow the production of 3D information of the real world using a set of 2D conventional photographs (Snavely et al. 2006). SfM photogrammetry is a widely used approach in the field of remote sensing and geo-sciences because of several reasons (Eltner and Sofia 2020): spatial accuracy, temporal frequency, relatively low-cost, quick, and easy to use workflows.

One of the most important procedures of the SfM photogrammetric workflow is the scaling and geo-referencing of the models, especially useful for measure, characterize, and estimate the magnitude of earth-surface changes (Tarolli 2014; Tamminga et al. 2015; Darmawan et al. 2018). LIDAR or Terrestrial Laser Scanner derived (TLS) point clouds are metric and there is no need to scale the derived models to perform direct measurements, however, for point clouds comparison, a co-registration is mandatory. The coregistration is the geometric alignment of the relative reference systems of point clouds and may be carried out using a point-based approach (e.g. targets: Telling et al. 2017) or the Iterative Closest Point (ICP; Besl and McKay 1992) algorithm. If the final reference frame is an absolute coordinate system, then the co-registration may be also a geo-referencing procedure. Therefore, geo-referencing is a crucial step for many geomatic applications and landscape change analyses, either using SfM photogrammetry or LIDAR. Classical geo-referencing approaches are based on the use of a set of surveyed points (relative and absolute), the so-called Ground Control Points (GCPs). These GCPs are used to estimate the parameters that allow the transformation between the two coordinate systems which are then applied to the whole dataset. This procedure is known as indirect geo-referencing as the dataset is acquired without accurate known real world coordinates and the final absolute positional accuracy of the georeferenced model relies, significantly, on the GCP network accuracy, commonly surveyed using survey-grade Global Navigation Satellite System (GNSS) devices. However, the GCP acquisition is an expensive and time-consuming task and somewhat risky, especially on unstable areas such as coastal cliffs where recent studies suggest a stratified distribution of GCPs to improve the accuracy of the models (Taddia et al. 2019; Gómez-Gutiérrez and Goncalves 2020).

In the direct geo-referencing approach, the final model is solely georeferenced based on the accuracy of the survey system (sensor/platform), which is known before processing the dataset (Schwarz et al. 1993; Cramer et al. 2001). The location and orientation of the sensor is obtained by means of dual-frequency multi-constellation Global Navigation Satellite Systems (GNSS) receivers and Inertial Measurement Units (IMU) integrated within the UAS. These dual-frequency GNSS receivers should register phase observations and may work either receiving real-time corrections (i.e. working in Real Time Kinematic or RTK) or recording data (in a Receiver Independent Exchange format, i.e. RINEX) to be post processed later using data simultaneously registered by a base station (i.e. working in Post Processing Kinematic or PPK). Recently, commercial UASs have incorporated these dual-frequency GNSS receivers on board at relatively low-cost (Taddia et al. 2019). In SfM photogrammetry there are mixed geo-referencing strategies available (between the direct and indirect geo-referencing: Benassi et al. 2017) such as the Integrated Sensor Orientation (ISO: Heipke et al. 2001). In ISO, low-accurate known coordinates registered by built-in single frequency GNSSs are used besides GCPs to accelerate SfM photogrammetric workflow.

Recent studies assess the quality of point clouds produced with direct geo-referencing approaches using SfM photogrammetric techniques, and of the derived cartographic products such as Digital Elevation Models or DEM, Digital Surface Models or DSM and orthophotographs (Mian et al. 2016; Carbonneau and Dietrich 2017; Forlani et al. 2018; Taddia et al. 2019; Przybilla et al. 2020; Teppati Losè et al. 2020; Štroner et al. 2021a, b; Liu et al. 2022; Taddia et al. 2020a, b). These works concluded that the use of direct geo-referencing with a set of nadiral images acquired with non-calibrated cameras (the classical acquisition strategy) results in a systematic vertical offset due to the wrong estimation of the focal length during the camera self-calibration stage (Forlani et al. 2018). The consequence is a continuous and systematic offset in the altitude of the resulting cartographic products regarding the actual altitude. Štroner et al. (2021b) demonstrated the linear dependency between error in Z-coordinate and focal length uncertainty. The most popular approach to solve this problem reported in the literature is the use of additional oblique photographs combined with the nadiral ones (e.g. Štroner et al. 2021a, b). Moreover, manufactures of UASs with integrated RTK-PPK capabilities have introduced more solutions to this issue. For example, DJI added a final path to the traditional flight plan for the Phantom 4 RTK model at the end of 2019. This modification, known as the altitude optimization option, is enabled by default and command the UAS to acquire a set of oblique images in the operation area to optimize the elevation accuracy. However, neither the manufacturer nor, to the best of our knowledge, any other scientific publication has quantified and published the influence of this parameter in the final accuracy of the resulting cartographic products. Additionally, most of the study cases described in the literature are based on the test of a few points (in the best of the cases hundreds e.g. Liu et al. 2022) or simulations (James and Robson 2014; James et al. 2017a, b), but a spatially intensive analysis of errors is crucial for researchers interested on the estimation of morphological changes, particularly in areas of complex topography or inaccessible, where the deployment of GCPs is very difficult or impossible, such as coastal cliffs, volcanos, gullies, glaciers, etc. (Nesbit et al. 2022; Elias et al. 2024). Liu et al. (2022) reported the necessity of deploying as many Check Points (CPs) as possible to understand the spatial distribution of errors while Nesbit et al. (2022) are, to the best of our knowledge, the only ones that tested the model against a benchmark Terrestrial

Laser Scanner (TLS) dataset. The simultaneous acquisition of a benchmark model by means of a TLS, would provide a dense dataset to test the effect of different landform characteristics on the accuracy of the SfM derived models. This accuracy depends basically on sensor characteristics and calibration, flight plan and image network, SfM algorithm, and surface characteristics. In the monitoring of coastal cliffs by means of UAS-based SfM photogrammetry, the wide range of incidence angles could help to minimize the systematic vertical offset observed in former studies that did not use GCPs. At the same time, complex rough surfaces and steep slopes are prone to larger errors due to subsampling.

Nowadays, LIDAR systems mounted on UASs are becoming more affordable (Torresan et al. 2018; Dreier et al. 2021; Pereira et al. 2021; Štroner et al. 2021a, b) but the accuracy of such systems has been rarely tested (Cramer et al. 2018; Dreier et al. 2021; Jóżków et al. 2016; Pereira et al. 2021; Štroner et al. 2021a, b). UASs equipped with LIDAR systems and survey-grade GNSS-IMU will not need GCPs, will not be affected by the classical non-linear errors (James and Robson 2014) common in SfM photogrammetry or other systematic errors common in SfM photogrammetry without GCPs (Forlani et al. 2018). Testing a LIDAR dataset by means of GCPs needs the use of geometrical figures, like hexagons, and the estimation of centroids (Baltsavias 1999), the intersection of planes (Goulden and Hopkinson 2010) or control planes (Schenk 2001; Ahokas et al. 2003; Hodgson and Bresnahan 2004). However, the continuous and dense nature of LIDAR data is well suited for a comparison overcoming the classical point-based approach commonly used in photogrammetry (Jóźków et al. 2016). Therefore, the cloud-to-cloud comparison will be beneficial to understand the spatial distribution of errors and the role of surface characteristics. The source of errors from LIDAR datasets are commonly related to the laser scanning system (range and scanning angle), the GNSS-IMU component, and the post-processing approaches (Schenk 2001; Ahokas et al. 2003; Hodgson and Bresnahan 2004). Hodgson and Bresnahan (2004) explained that the main source of positional errors in LIDAR datasets are associated with the built-in GNSS system of the aircraft, and the IMU that determines the pointing direction of the survey. In the specific context of UAS-LIDAR systems, the accuracy of the resulting point clouds depends, mainly, on the accuracy of the trajectory estimation which is based on the positional, navigation and orientation systems (i.e. GNSS and IMU) (Baltsavias 1999; Dreier et al. 2021). Previous empirical studies using datasets acquired by LIDAR systems on board of piloted aircrafts have shown that error is, also, a function of flying height, terrain characteristics and land cover (Hodgson and Bresnahan 2004). In this sense, UAS plat-forms allow low-altitude surveys to be carried out, increasing sampling density, which is especially advantageous in complex topography (Dreier et al. 2021). However, tests on datasets acquired by UAS-LIDAR platforms are very scarce in the literature (Jóźków et al. 2016; Dreier et al. 2021).

The geo-referencing without GCPs is a promising approach in the acquisition and processing of high-resolution 3D models either using SfM photogram-metry (Eltner and Sofia 2020) or LIDAR (Dreier et al. 2021), particularly in inaccessible or dangerous areas such as active volcanos, flooded sites, coastal cliffs or glaciers (Elias et al. 2024). The specific case of coastal cliffs is of particular interest for the scientific community as these places are very sensitive to perturbations associated to climate change (e.g., sea level rise), urbanization, and highly dynamics and complex forms (Del Río and Gracia 2009). Coastal cliffs represent a relevant portion of the coasts worldwide (Emery and Kuhn 1982; Trenhaile 1987) and an important part of the population lives or moves through these places.

The objective of this study is to analyse the characteristics and positional accuracy of point clouds obtained from UAS with direct geo-referencing. That is, without using GCPs and without performing any prior co-registration procedure. Specifically, we will test one UAS-LIDAR system with geo-referencing through a PPK approach (the mdLIDAR 1000 by microdrones) and one UAS-photogrammetric system (i.e. with a RGB sensor: UAS-RGB) with geo-referencing through RTK and PPK approaches (the Phantom 4 RTK by DJI). The results produced by these technologies are compared with a 3D benchmark model surveyed simultaneously by means of a TLS and by the traditional approach based on GCPs (and check points). In the case of the UAS-LIDAR system, we designed and used a flight plan based on parallel strips as this is the common strategy for data acquisition. For the UAS-RGB, we also used a flight plan based on parallel strips with the camera close to the nadir position with the aim of evaluating whether the altitude optimization parameter reduces the systematic error in the Z coordinate previously described in the literature (e.g., Stroner et al. 2021). Finally, we discuss advantages and limitations of each approach and the implications of our findings for geomorphic change detection using these survey techniques.

Study area

The study was carried out at Gerra beach and cliff (i.e., cliffed coast fronted by a beach with a length of 300 m, from which 200 m were surveyed, Fig. 1), located in a NE-faced small cove in the Cantabria coast, N of Spain (Fig. 1a and b). The climate is temperate oceanic with an average annual rainfall of 1,100 mm distributed along the year and a mean annual temperature of 15° C. The Gerra beach is the easter part of the San Vicente Merón beaches system and may be classified as a composite beach with an unprotected cliff of Eocene sandstones, marls, limestones, and conglomerates to the east and Triassic clays, gypsum and salts to the west. The study area shows four morphological units modelled by different geomorphological processes (Fig. 1c and d). The first two units belong to the composite beach system:

the sandy foreshore with a very low slope gradient and the backshore with a relatively higher slope gradient and coarser sediments (cobbles and boulders) supplied by the erosion of the cliff. The third morphological unit is the face of the cliff that joins the beach and the top of the cliff and inland (fourth morphological unit), where we observe “rasas”, i.e. ancient abrasion platform. The top of the cliff has an average altitude of 40 m ASL.

The tidal range is about 4 m so the area is considered a mesotidal environment (de Sanjosé Blasco et al. 2020). The sandy foreshore is modelled by the wave action and nearshore currents. Large storms control backshore dynamics which is continuously supplied of sediments from the cliff due to small rockfalls and landslides. These slope processes on the cliff range in magnitude from 1 to 1000 m3 and are controlled by lithology and structure (folded layers and contact between lithologies) (de Sanjosé Blasco et al. 2020). The recent work by de Sanjosé-Blasco et al. (2020) analysed the dynamics of the area for the period from 1956 to 2020 using several geomatic techniques (classical photogrammetry, SfM-UAS photogrammetry, and TLS) and observed an increase in the cliff retreat rates in the last years, leading to more frequent large magnitude slope processes and unstable cliffs.

Material and methods

This section describes the instruments, techniques and methods used to perform the analyses. The first four sections describe the acquisition of data by means of the TLS (Fig. 2a), the GNSS, the UAS-LIDAR (Fig. 2b), and the UAS-RGB (Fig. 2b). The last section details the estimation of distances from every dataset to the benchmark point cloud. All the data was collected simultaneously during low tide. In the analyses, only the overlapping area between all techniques and the stable part of the beach was considered (defined by the red rectangle in Fig. 1); that is, the area affected by the low tide action was not considered.

Terrestrial laser scanner

The benchmark model of the study area was obtained using a TLS Leica Scanstation C10 device (Fig. 2a and Table 1). Four stations were planned to minimize the occlusions and cover the surveyed area (Fig. 3a). The registration of the 4 point clouds was carried out by means of nine circular targets model HDS

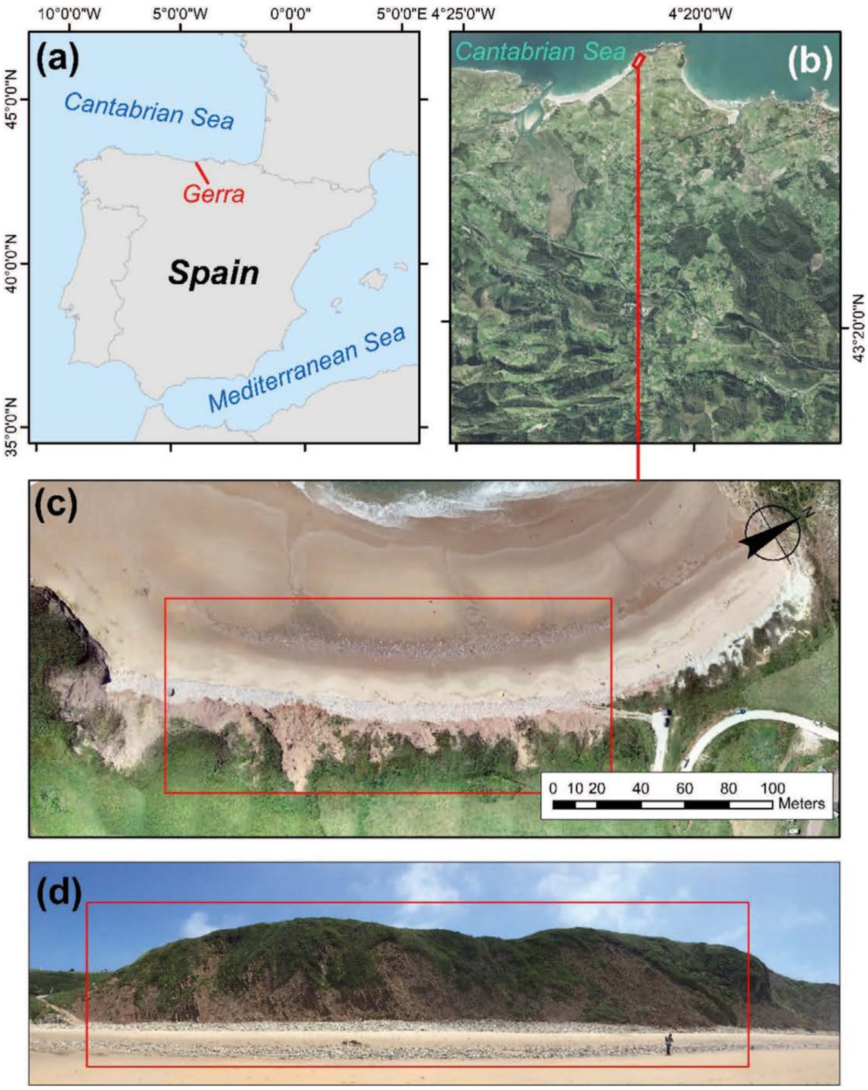

Fig. 1 Spatial contextualisation of the study area located in the Iberian Peninsula (a) and the Cantabria region (b). c Aerial orthophotograph of the study area and d a panoramic view of the shoreline. The red rectangles define the surveyed area

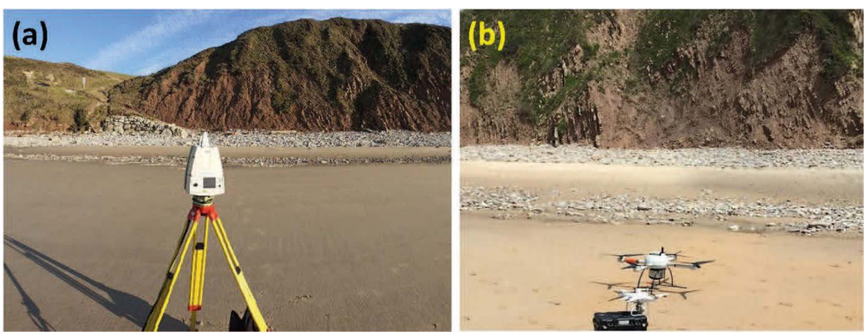

Fig. 2 a TLS Leica Scanstation C10, and b the DJI Phantom 4 RTK (at the front) and the mdLIDAR 1000 system (at the back)

Table 1 Characteristics of the platforms and sensors used

System	mdLIDAR 1000	Phantom 4 RTK	TLS Scanstation C10
Sensor	(a) LIDAR SICK LD-MRS4, field of view 60-85°, point acquisition rate 19,500 pts·s^{-1}, (b) RGB Ladybug 2448 × 2048	RGB 1'' CMOS, 20 Mp, 5472 × 3648 and f = 8.8 mm	LIDAR Pulsed; range 300 m; point acquisition rate 50,000 pts·s^{-1}; field-of-view 360° horizontal/270° vertical; Accuracy of single measurement, 6 mm of position and 4 mm or distance and target acquisition 2 mm
GNSS	Multi-frequency multi-system Trimble APX-15v3	Multi-frequency multi-system high-precision RTK	*External GNSS, Leica 1200. Multi-frequency multi-system high-precision RTK
GNSS processing mode	PPK	RTK and PPK	RTK
Approximate maximum flight time (min)	15	30	–
System weight (g)	6000	1391	13,000

*Note that the TLS does not include a GNSS receiver, but the targets used to register the TLS-point clouds were surveyed with the specified GNSS device

from Leica (with a diameter of 15.24 cm), initially in a relative coordinate system. These targets may be oriented to be registered by any location of the TLS. Additionally, the targets may be set horizontally to survey the geometrical centre of the target in an absolute reference system using a GNSS receiver. From every TLS station, every target is surveyed individually with an accuracy of 2 mm according to TLS manufacturer's specifications. Figure 3 shows the location of the targets and the stations of the TLS instrument. The registered point cloud is then georeferenced using the absolute coordinates of the targets previously surveyed by the GNSS rover in RTK mode (receiving real-time corrections from the OWN station, see the Sect. "Global navigation satellite systems"). The geo-referencing error of this point cloud was 0.8 cm.

Global navigation satellite systems

Three GNSS stations were used for the post-processing of the UAS trajectories. The first was an own station stablished temporarily within the study area (named "OWN" ahead, with an average baseline of 0.14 km, Table 2). The second and third are permanent GNSS stations that belong to the regional Cantabrian continuously operating reference stations (CORS) network. Specifically, Rionansa (RNAN) and Torrelavega (TRLV) stations, located at 13 and 25 km from the study area, respectively. The range of distances (from 0.14 to 25 km) allows to explore the role of the baseline in the final accuracy obtained. The coordinates of the OWN station were calculated by using static records longer than 1 h and simultaneous data registered at 1 s temporal resolution at RNAN and TRLV. Additionally, the OWN station was used to send corrections in real-time to a mobile receiver (Fig. 1b) operating in the study area to survey the GCPs, the CPs and to georeference the TLS model (surveying the targets). A total of 25 points were surveyed as GCPs (or CPs, see Sect. "UAS-RGB and SfM photogrammetry (RTK, PPK and GCP-based)") and 9 as TLS targets (Table 3). These GCPs were distributed in the safe area as the top of the cliff is inaccessible for safety reasons.

UAS LIDAR

The mdLIDAR 1000 system by microdrones is a UAS-based LIDAR system (Sick; Fig. 2b) integrated with a camera (to colour the LIDAR-derived point cloud) and a survey grade GNSS (Applanix APX-15 GNSS/IMU) receiver for direct geo-referencing. The LIDAR system has a field of view of 60° or 85°, with 3 returns and an acquisition rate, for both field of views, of 19,500 pts·s^{-1}. The mdLIDAR 1000 has a minimum and maximum flight altitude of 30 m and 50 m, respectively.

The GNSS/IMU system records sensor location and orientation to be postprocessed, i.e., works in PPK mode. The system has 336 channels including GPS (L1 C/A, L2C, L2E, L5), GLONASS (L1 C/A, L2 C/A, L3 CDMA), BeiDou (B1 and B2), Galileo (E1, E5A, E5B, E5Altboc), QZSS (L1 C/A, L1S, L1C, L2C, L5, LEX), SBAS (L1 C/A, L5) and MSS L-band (Trimble RTX, OmniSTAR). The IMU is a Micro Electro Mechanical System-based inertial sensor with a data rate of 200 Hz. The PPK was car-ried out using the POSPac UAS (v. 8.4) (Applanix-TRIMBLE 2022) software and using as input the trajectory file of the UAS (GNSS location and IMU data), the RINEX files of the GNSS permanent stations (Table 2) and the offset parameters between the LIDAR and the GNSS-IMU systems (boresight angles, mounting angles and lever arms). The bore-sight angles, mounting angles and lever arms values are provided directly by the manufacturer in a calibration report specific to each LIDAR-GNSS-IMU unit. The corrected trajectory of the UAS is then used to compute the location of LIDAR 3D points in the mdLIDAR processing software (v. 1.3.0) (MICRODRONES 2022).

Two flights with flight lines parallel to the shoreline were designed to cover the study area (Fig. 3c) and minimize occlusions. The first one at 30 m of altitude above the top of the cliff to monitor, particularly, the upper part of the cliff, but also the rest of the study area with a field of view of 60°. The second one at 50 m of altitude above the beach to monitor the face of the cliff and the beach with a field of view of 85° (Fig. 3c). Both flights were designed using the mdcockpit app running in a tablet (Samsung S5 with android operative system) and the same app was used at field to monitor data acquisition and UAS telemetry. The whole data acquisition was carried out autonomously according to the predefined flight plan. Flights 1 and 2 had a total duration of 5′24″ and 4′57″ respectively, both flights were carried out at a speed of 3 $m \cdot s^{-1}$. During each flight, the UAS automatically performs two manoeuvres, at the beginning and at the end, necessary for calibrating the IMU. According to the manufacturer the integrated system has an absolute vertical and horizontal accuracy of ± 6 cm. The potential misalignment between the two UAS-LIDAR flights was analysed by selecting the overlap area and calculating the distances between the two point clouds in this area. The calculation of the distance between point clouds was based on the Multiscale Model-to-Model Cloud Comparison algorithm (M3C2: Lague et al. 2013. See Sect. "Analysis of the resulting point clouds"). No misalignment was observed between the flights in the overlap zone, so the two flights were merged without any co-registration procedure. The UAS trajectories were processed using the three GNSS stations independently, and the best solution was selected for subsequent analyses (M3C2 distances to the benchmark TLS model).

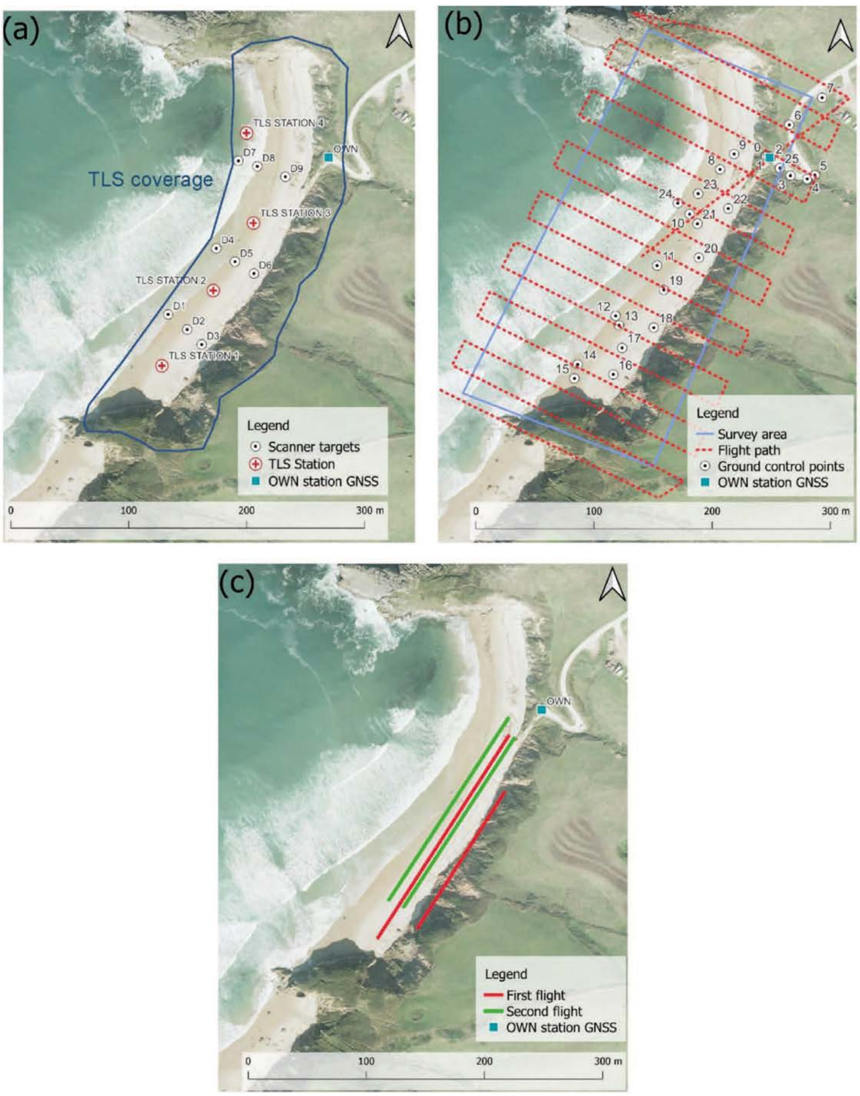

Fig. 3 a Scheme of TLS stations, target locations and GNSS OWN base station within the study area, b pre-programmed flight path for the DJI Phantom 4 RTK and c pre-programmed flight path for the mdLIDAR 1000. Note that despite the area surveyed with each technique differs, a clip was made to the overlapping zone, which is denoted by the red rectangle in Fig. 1b and c

UAS-RGB and SfM photogrammetry (RTK, PPK and GCP-based)

The DJI Phantom 4 RTK is a multi-rotor with a multi-frequency GNSS system and a built-in 1″ RGB CMOS sensor with 20 Mpx on board (Fig. 2b and Table 1). The GNSS system receives and records GPS L1/L2, GLONASS L1/L2, BeiDou B1/B2 and Galileo E1/E5. The RGB sensor has a lens with a field of view of 84° and a focal length of 8.8 mm (35 mm for-mat equivalent: 24 mm).

Three datasets were produced by means of the UAS-RGB and the SfM photogrammetry. The first one was fed by images acquired receiving RTK corrections via NTRIP (Networked Transport of RTCM via Internet Protocol) from a 4G internet connection to the regional (Cantabrian) GNSS service of real-time corrections (network solution NTRIP protocol in format RTCM3.1, MAC3). This dataset will be named ahead UAS-RGB RTK. The second dataset was produced using the same images of the dataset one but post-processed using a PPK approach by means of the REDcatch-REDtoolbox software (REDcatch 2022) that performs the position correction of the UAS at every photo acquisition using the permanent stations data recorded simultaneously. This information is recorded in the EXIF file of the images and used in the photogrammetric processing to constrain camera location and position uncertainty. This dataset will be named UAS-RGB RTK images+PPK and consists of a PPK approach using the same images of the RTK approach. The third approach used the same flight plan of the former two datasets (Fig. 3b) to acquire images just recording data without real-

Table 2 GNSS stations used in this study

Station code	RNAN	TRLV	OWN
Site	Rionansa	Torrelavega	Gerra beach
Coordinates	43°17′45.77079″N 4°24′42.22383″W	43°21′20.14144″N 4°3′20.06642″W	43°24′5.50721″N 4°21′14.00684″W
Ellipsoidal height (m)	587.1617	79.8146	66.6692
Receiver and antenna	Leica GR50 and Leica AR20	Leica GR50 and Leica AR20	Leica 1200 and Leica ATX1230 GG
Average baseline (km)	12.53	24.75	0.14
Average PDOP	1.2	1.2	1.53

PDOP = Position (3D) Dilution of Precision, the values represent the average during the static recording of the three base stations, two permanent (RNAN and TRLV) and one temporary

Table 3 Standard deviation (STD) of Terrestrial Laser Scanner (TLS) targets and Ground Control Points (GCPs) for photogrammetry

	TLS targets	GCPs for photogrammetry
Number of points (n)	9	25
STD X (m)	0.004	0.005
STD Y (m)	0.005	0.005
STD Z (m)	0.012	0.012

Table 4 Parameters and configuration of the photogrammetric software Pix4D mapper Pro used to produce the models

Parameter	Value
Image scale for key points	Full
Matching image pairs	Aerial grid
Calibration method	Standard
Keypoint extraction	Automatic
Internal parameters optimization	All
External parameters optimization	All
Rematch	Automatic
Image scale for densification of the point cloud	1
Point density	High
Minimum number of matches	3
Classifying the point cloud	enabled
Limit camera depth automatically	No

time corrections to carry out a PPK approach later (UAS-RGB PPK). The comparison between datasets will allow to analyse the effect of postprocessing type and changes in image acquisition conditions (such as lighting) on the final accuracy of the results.

The flights were planned at an altitude of 80 masl, resulting in an average GSD of 2.19 cm and following the track shown in Fig. 3b. The front and side overlap were set to 80% and flight speed was the maximum allowed for this configuration (6.3 $m \cdot s^{-1}$). The flight time was approximately 11 min. The camera was close to nadir with a deviation of 4° from nadir.

The images obtained by every workflow, the RTK, the RTK + PPK and the PPK, were used as input in the photogrammetric software, in this case Pix4D-mapper Pro (v.4.5.6) (PIX4D-SA 2022). A total of 282 images were acquired during each flight with a resolution of 5,472·3,648 pixels. The points recorded by the rover GNSS device were marked in all the images and used to estimate the Root Mean Square Error (RMSE) in models with a varying number of CPs and GCPs. The 25 surveyed points were used as CPs in the models without GCPs (i.e., GCP = 0) but additionally, we explored the role of an increasing number of GCPs in the final accuracy of the resulting models. To do this, we used one GCP to support the model and the rest as CPs. The procedure was repeated using every point as GCP and the rest as CPs and the average RMSE was calculated. Then, the procedure was repeated using 2, 3,.., 25 GCPs, and calculating the average RMSE. For example, for 3 GCPs all possible combinations of 3 GCP were used and the remaining 22 points were used as CPs to calculate the average RMSE.

For models without GCPs, the influence of the altitude optimization was explored. This option was introduced at the end of 2019 by DJI manufactures to minimize the wrong absolute altitude estimation in surveys without GCPs. A set of oblique images, in addition to the nadiral ones, are collected if this option is set. We processed the datasets with and without this set of oblique images and compared the accuracy of the resulting models. The photogrammetric processing within the Pix4Dmapper Pro software was carried out with the configuration shown in Table 4.

Analysis of the resulting point clouds

The resulting point clouds were characterized and analysed in terms of point density and coverage. Volumetric point density was calculated using a sphere with radius 0.62 m, which results in a volume of 1 m^3. Additionally, the algorithm M3C2 (Lague et al. 2013) was used to estimate the distance between the benchmark point cloud acquired by the TLS and the SfM (RTK or PPK) or LIDAR-derived point clouds (ahead D_{M3C2}) (Fig. 4). The M3C2 algorithm is a change detection method for point clouds that calculates 3D distances and uncertainties. First, the algorithm estimates local surface normal (*N*) by fitting a plane to points in cloud 1 within a neighbourhood defined by a parameter named normal scale (*D*). The *N* determines the direction in which changes will be measured. Then, a cylinder, with radius *d* (projection scale) and height *h* is projected from point cloud 1 to point cloud 2 along the *N* vector. Finally, the average positions of points within the cylinder in each cloud are calculated, and the distance between these positions along the *N* is the D_{M3C2}. The suitable values for *D* and *d* were empirically evaluated, and those that resulted in *N* values that best represented the landforms in the study area were used. The resulting D_{M3C2} shows the absolute agreement of the analysed point cloud regarding the benchmark model due to all the components of error. In this analysis, the two compared point clouds were acquired simultaneously so we did not use the uncertainty estimation of D_{M3C2} and every calculated value is considered as error. The statistical analysis of the D_{M3C2} variability, using the standard deviation of the D_{M3C2}, for instance, may also provide insight into the range of errors (Nesbit et al. 2022). This analysis was carried out for two datasets acquired by the UAS-RGB RTK (the RTK NTRIP and the most accurate PPK) and the one acquired by the UAS-LIDAR (the PPK dataset with the OWN and RNAN GNSS stations). The preparation of the point clouds and the estimation of the D_{M3C2} was carried out in CloudCompare software (v. 2.12.0) (GPL-Software 2022).

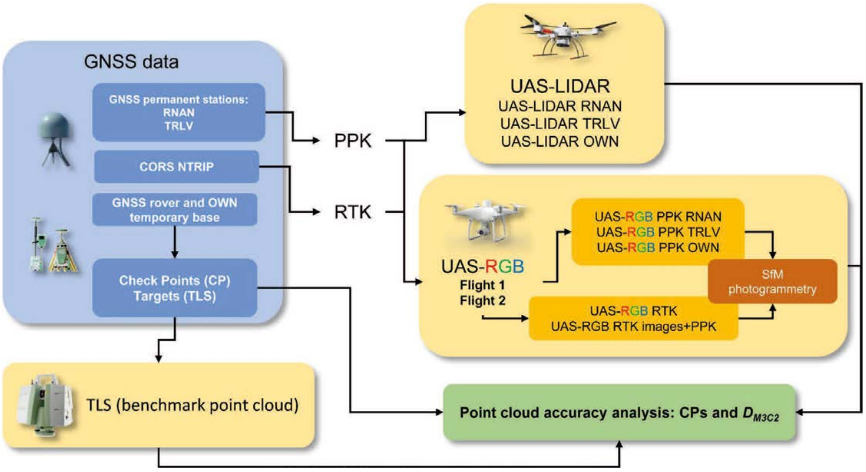

Fig. 4 Workflow diagram with datasets and instruments used. GNSS Global Navigation Satellite System, CORS NTRIP Continuously Operating Reference Station Networked Transport of RTCM via Internet Protocol, TLS Terrestrial Laser Scanner, PPK Post-Processing Kinematic, RTK Real Time Kinematic, SfM Structure-from-Motion, DM3C2 Multiscale Model-to-Model Cloud Comparison Distance

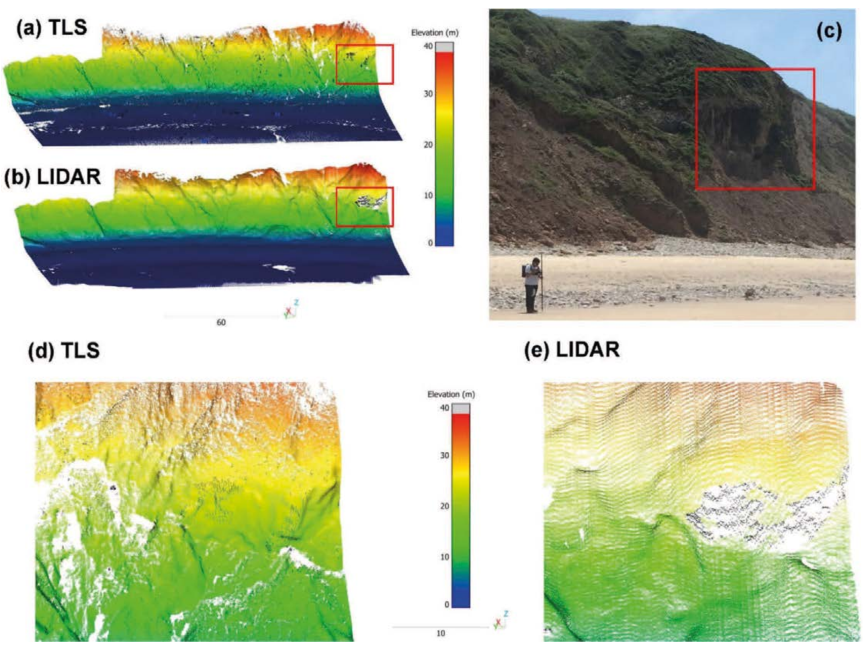

Fig. 5 The resulting point clouds produced by a the TLS instrument and b the UAS-LIDAR system showing the elevation, c view from the beach of the area highlighted by the red rectangle showed in a and b. Detail of the d TLS and e UAS-LIDAR point clouds in the red rectangle. The red rectangle in the figures demarcates an overhanging part of the cliff with shadows and vegetation

Results

TLS point cloud

The benchmark TLS-derived point cloud showed a total of 23.4 million of points, with an average point density of 41,156 pts·m^{-3} (Fig. 5). The TLS coverage was homogeneous, except for small, highly intricate areas in the western part of the cliff (right of the Fig. 5a). The TLS model benefited from the ground perspective, getting points in a shaded and overhanging part of the cliff partially covered by vegetation (Fig. 5d). Table 5 shows the registration and the geo-referencing RMSEs for the TLS dataset. The registration based on targets showed errors lower than 0.006 m while the geo-referencing, based on the coordinates of the targets surveyed by the GNSS in RTK mode, increased errors from 0.005 to 0.007 m and 0.002 to 0.009 m for the planimetric and altimetric components, respectively.

UAS-LIDAR point cloud

The UAS-LIDAR-derived point cloud showed a point density of 27,293 pts·m^{-3}. The resulting LIDAR-derived point cloud has a large coverage (Fig. 5b), being the only aerial technique tested here that captured points in specific overhanging parts of the cliff (Fig. 5e). It was estimated, during post-processing in the Pospac software, a 3D RMSE of

Table 5 Root Mean Square Errors (RMSE) obtained for the registration of the 4 TLS-derived point clouds and the georeferencing of the resulting point cloud

	X	Y	Z	Planimetric	Altimetric
Registration RMSE (m)	0.004	0.006	0.002	0.005	0.002
Georeferencing RMSE (m)	0.009	0.006	0.009	0.007	0.009

0.035 m for the RNAN solution. The PPK processing using different permanent stations produced slight differences in the RMSEs, indicating that, as expected, GNSS stations with baselines < 25 km result in highly accurate point clouds. Three-dimensional RMSEs of 0.037 m and 0.039 m were estimated for TRLV and OWN solutions. From this point on and in subsequent analyses, for the LIDAR data, those obtained using the permanent RNAN station and the temporary OWN station will be used.

UAS-RGB point clouds

The point clouds produced using the UAS-RGB and the SfM photogrammetry technique showed point densities that varied from 964 to 1,163 pts·m^{-3} (Fig. 6). The images used to produce the point clouds in the RTK and the PPK modes were acquired during different flights, consequently, point density for both datasets were slightly different. The point clouds produced with the same images but with different processing methods (RTK vs RTK images + PPK) showed significant differences regarding the presence of data gaps. In fact, the point clouds generated with PPK and RTK images + PPK processing were very similar despite being produced using images acquired in different flights (Fig. 6b and c), indicating that certain processing factors have a decisive influence on the existence of data gaps in the final point cloud. The SfM-derived point clouds showed gaps in the overhanging area and at some vegetated sites over the face and top of the cliff (Fig. 6).

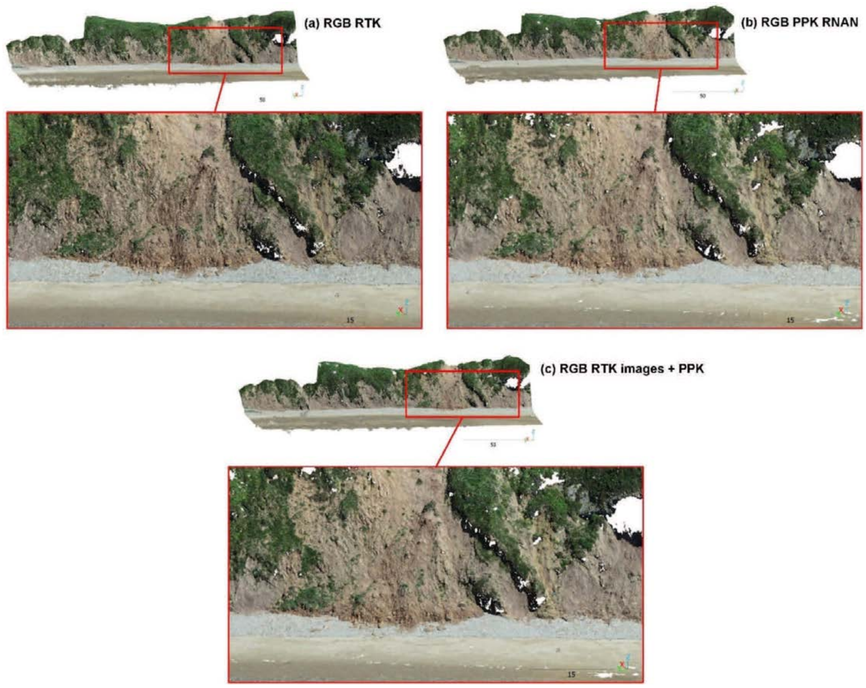

Fig. 6 Point clouds obtained using SfM photogrammetry with images acquired by the UAS-RGB working in a RTK mode, b PPK mode (post-processed with permanent station RNAN) and with different images than the previous RTK flight (same flight plan executed immediately after), and c RTK images but applying a PPK, meaning the same images as in a but adding a post-processing (i.e. RTK images + PPK)

According to the RMSE (Fig. 7), the PPK workflow, independently of the GNSS permanent station used, resulted in more accurate models than the RTK approach. The models obtained in PPK with the RNAN GNSS station were the most accurate in the absence of GCPs (Fig. 7). Our OWN GNSS station did not resulted in the most accurate models despite being the closest one, with an average baseline of 0.14 km. The OWN station also showed the larger Position Dilution of Precision (PDOP = 1.53) compared to RNAN or TRLV (PDOP = 1.20).

Figure 7 shows that the addition of GCPs slightly increased the accuracy of the UAS-RGB resulting models. The RTK approach was particularly benefited by the inclusion of up to 3 GCPs. From 3 GCPs upwards, improvements in the accuracy of the resulting models were negligible. In the PPK approach the influence of adding GCPs was very slight. We did not observe any significant enhancement of adding GCPs to the PPK RNAN dataset (Fig. 8).

The altitude optimization option in the UAS-RGB datasets played a crucial role to reduce the errors in the final models, particularly in the absolute altitude estimation (Fig. 8). The models produced using the oblique photographs acquired due to the altitude optimization option (in PPK or RTK) resulted in more accurate estimations of the camera focal length than those produced using only the nadiral photographs (Table 6). The RTK approach was the most benefited of enabling the altitude optimization option (Table 6). In the RTK approach, the Z coordinate RMSE improved from 0.37 m to 0.12 m when the oblique photographs were used. The X and Y RMSEs of the PPK datasets were also reduced with the use of the oblique photographs. Specifically, the RMSE for the X coordinate decreased from 0.06

to 0.04 m, while the Y-RMSE lessened from 0.09 to 0.04 m.

Assessment of point clouds based on M3C2 distance to benchmark model

The aim of this work is to test datasets produced without GCPs so, henceforth, only the most accurate dataset of every approach

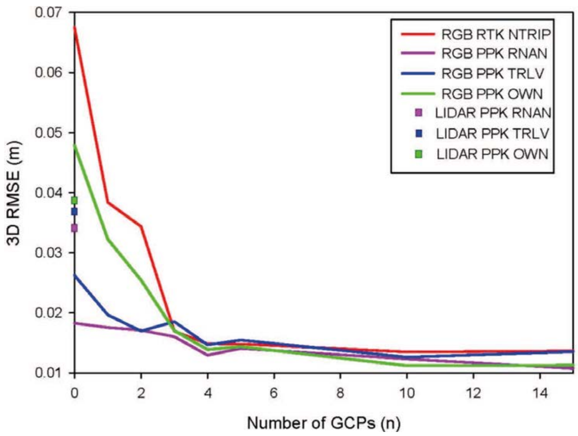

Fig. 7 Three-dimensional Root Mean Square Errors (RMSE) with different number of Ground Control Points (GCPs), i.e. including direct georeferencing approaches (GCP = 0). The lines represent the RMSE of the data collected with the UAS-RGB using different approaches (RTK or PPK) and permanent GNSS stations (OWN, RNAN Rionansa and TRLV Tor-relavega). Note that LIDAR RMSEs are calculated during the postprocessing by the PosPac software and represented as squares

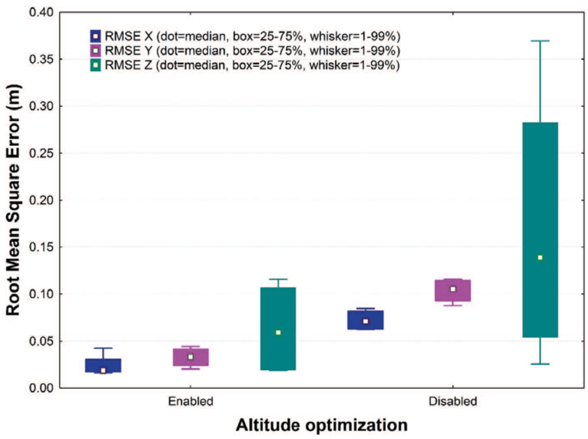

Fig. 8 Root Mean Square Error (RMSE) for SfM-derived datasets acquired by the UAS-RGB and processed without GCPs and enabling/disabling the altitude optimization option

Table 6 Uncertainties in the focal length estimation for datasets that enabled/disabled altitude optimization. STD Standard Deviation, RNAN Rionansa
STD Standard Deviation, RNAN Rionansa

	Altitude optimization	Estimated focal length (mm)	STD in pixels	STD in millimetres
RTK NTRIP	Enabled	8.663	0.127	0.000
	Disabled	8.634	6.202	0.015
PPK (RNAN Station)	Enabled	8.665	0.086	0.000
	Disabled	8.658	2.852	0.007

and technique will be used in the upcoming analysis: the UAS-LIDAR RNAN (permanent station), the UAS-LIDAR PPK OWN (temporary station), the UAS-RGB RTK NTRIP, the UAS-RGB PPK RNAN and the UAS-RGB RTK images processed with PPK. In the case of the SfM-derived datasets, they were acquired setting the altitude optimization option. Furthermore, the LIDAR and photogrammetric systems have such different characteristics (e.g. flight altitude, overlap, etc.) that comparing them would not be fair. However, we can extract valuable information by comparing the RTK and PPK approaches in the case of photogrammetry or the analysis of the accuracies for each landform.

The point clouds produced without GCPs showed average $D_{M3C2} < 0.1$ m, indicating a high degree of agreement with the benchmark model (Table 7). In fact, PPK approaches (LIDAR or SfM) showed average $D_{M3C2} \leq 0.02$ m. This accuracy of the data-sets produced by means of the PPK approach is also shown by the average absolute D_{M3C2} (or $|D_{M3C2}|$) that supress the negative component of the distances. The UAS-LIDAR technique processed with the RNAN station produced the most accurate point cloud according to the $|D_{M3C2}|$ and the standard deviation of the D_{M3C2} that provides insight into the range of errors (Table 7). The UAS-RGB PPK RNAN showed a similar $|D_{M3C2}|$, but a much larger standard deviation of the D_{M3C2} (Table 7). At the same time, the standard deviation of the D_{M3C2} shows a notably larger disagreement of the UAS-RGB RTK NTRIP model with the benchmark model.

The maps of D_{M3C2} show significant differences between techniques and approaches (Fig. 9 and Fig. 10). LIDAR point clouds processed using the RNAN permanent station solution revealed significantly lower D_{M3C2} values compared to those processed with the OWN temporary station (Fig. 9). The differences were particularly noticeable on the cliff face and the backshore. The LIDAR data exhibited minimal noise, with only a few noisy points observed in the foreshore. The photogrammetric point clouds showed noise in the front of the foreshore with the noise decreasing inland (Fig. 10). The post-processed photogrammetric clouds presented significantly lower errors compared to the RTK point cloud. The noise and instrumental errors for every point cloud are reflected in the length of the 5–95% interval in Fig. 11, while the distance from the median to the $D_{M3C2} = 0$ shows the bias of the dataset (systematic error), related to the geo-referencing approach (also in Fig. 11). The datasets post-processed with the RNAN station solution did not exhibit systematic errors (UAS-LIDAR and UAS-RGB PPK; Fig. 11) indicating that these datasets can be used without any prior co-registration procedure to be compared to other cartographic products. The UAS-RGB RTK showed a negative bias while the UAS-LIDAR post-processed with the OWN temporary station solution presented a positive bias

Table 7 Statistics of M3C2 distances (DM3C2) and the M3C2 absolute distances, |DM3C2|, for the UAS-LIDAR (processed with the OWN and RNAN stations), the UAS-RGB RTK NTRIP and the UAS-RGB PPK RNAN

	Average D_{M3C2} (m)	Std. Dev. D_{M3C2} (m)	$\left\| D_{M3C2} \right\|$ (m)
UAS-LIDAR PPK OWN	0.02	0.17	0.12
UAS-LIDAR PPK RNAN	0.00	0.10	0.07
UAS-RGB RTK NTRIP	0.09	0.41	0.14
UAS-RGB PPK RNAN	0.02	0.26	0.06

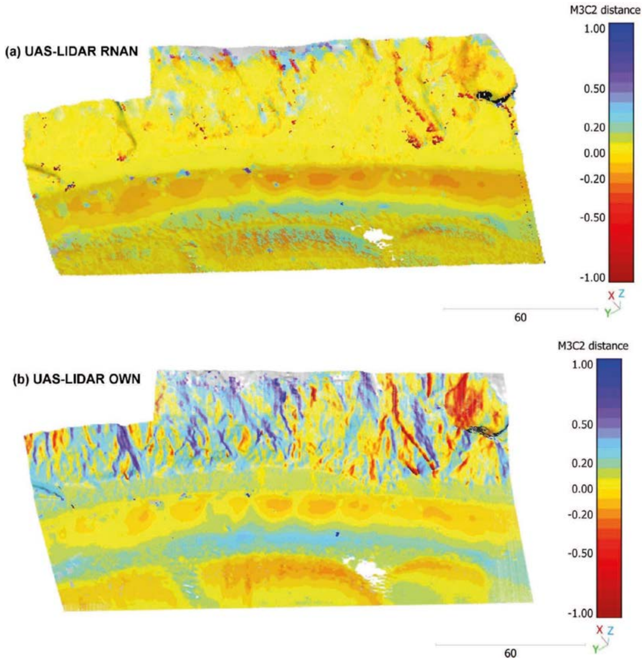

Fig. 9 Map of M3C2 distances (meters) to the benchmark TLS point cloud for the point clouds produced using the UAS-LIDAR postprocessed with the a RNAN permanent station and b the OWN temporary station

in the backshore, the face, and the top of the cliff. The analysis of D_{M3C2} disaggregated by landform and technique provided insight about the achievable accuracy of the geo-referencing without GCPs approach in these environments under similar flight and instruments conditions. If we focus on the datasets post-processed with the RNAN permanent station that do not show systematic errors, we can observe that the 5–95% interval width is substantially larger for the foreshore and top of the cliff landforms compare to the backshore and the face of the cliff.

Discussion

The laser-based techniques resulted in dense point clouds with homogeneous coverage, specifically the UAS-LIDAR system acquired points in vegetated overhanging parts of the cliff (Fig.

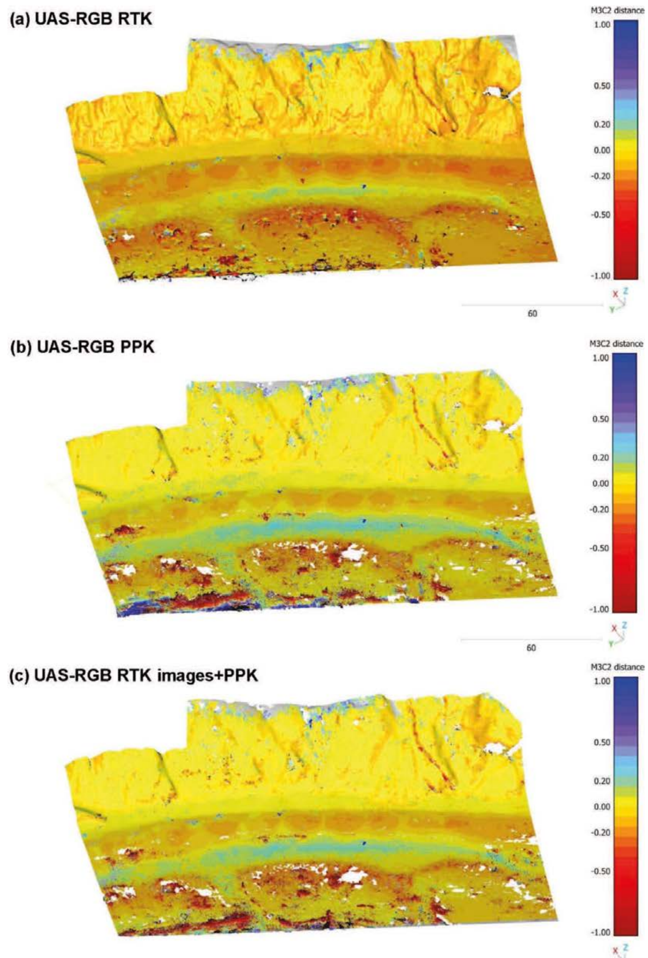

Fig. 10 Map of M3C2 distances to the benchmark TLS point cloud for the point clouds produced using the a the UAS-RGB in RTK mode receiving NTRIP cor-rections, b the UAS-RGB in PPK mode corrected with RNAN GNSS permanent station and c the UAS-RGB with RTK images processed by a PPK procedure with RNAN GNSS permanent station. The grey dots show areas where the TLS did not get points, so the distance was not calculated. Distance units are shown in meters

5). Table 8 shows a qualitative assessment of the characteristics of each point cloud along with the processing time required for each phase of its production and cost of the equipment. The SfM-derived point clouds showed data gaps in an overhanging part in the face of the cliff, some vegetated spots, and some parts of the foreshore beach. We found differences in the distribution of data gaps in the point clouds produced with the same images but different processing methods (e.g., RTK vs RTK images + PPK). However, the pattern of data gaps was similar for point clouds generated with the PPK and the RTK images + PPK approaches despite using different images in each procedure (acquired with the same flight plan). The RTK approach minimizes data gaps compared to the PPK and the RTK images+PPK approaches (Fig. 6), which would indicate that by exhibiting lower accuracy in the positioning of each camera, it would provide more freedom to the photogrammetric processing. The reduction in the positional accuracy of the images may influence: (a) the overlap between images that may be seemingly greater with more information

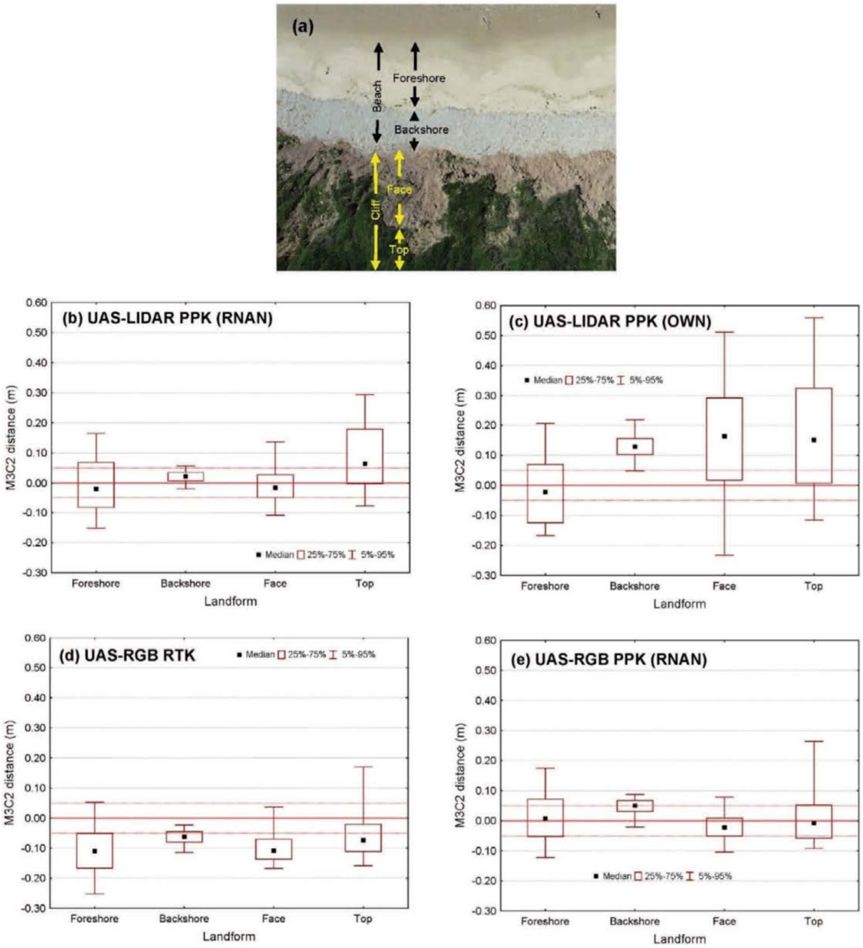

Fig. 11 a Delimitation of the landform units over an aerial view of the study area. The M3C2 distances grouped by land-form for the UAS-LIDAR processed with the RNAN perma-nent station b and the OWN temporary station (c), the UAS-RGB in RTK (d), and UAS-RGB in PPK processed with RNAN permanent station (e). For b, c, d and e a continuous red line is drawn for the 0 distances and dashed red lines are used to define the ± 0.05 m interval

Table 8 Qualitative assessment of the point clouds produced by every system and the time required in every stage of the work

System	TLS	UAS-LIDAR		UAS-RGB		
Georeferencing	-	PPK perma-nent station	PPK tempo-rary station	RTK	PPK	RTK images + PPK
Point cloud coverage	++++	++++	++++	+++	+++	+++
Accuracy	++++	+++	+++	++	++++	++++
Systematic error	–	No	Yes	Yes	No	No
Noise	++++	+	+	+++	+++	+++
Planification time	++++	+	+	++	+	++
Acquisition time	++++	+	+	+	+	+
Postprocessing time	++	+	+	+++	++++	++++
Cost	+++	+++	+++	+		

+ = low, ++ = medium, +++ = high and ++++ = very high

available for the 3D reconstruction, (b) the number of matches or correspondences between visual features in the images leading to a greater number of detected key points and, (c) the uncertainty in the estimation of the position of each point in the cloud which will be larger, resulting in more redundant or erroneous points, contributing to a higher apparent density in the point cloud. This finding is an interesting element to explore in future research as the point cloud generated with RTK processing could be used to fill data gaps in a point cloud generated with PPK processing that according to our results shows a higher accuracy.

Data gaps in overhanging parts are typical in UAS-derived point clouds using SfM photogrammetry and nadir acquisition angles (Jaud et al. 2019). Jaud et al. (2019) suggested the use of higher tilting angles to reduce data gaps in these vertical or over-hanging parts of the cliff and Gómez-Gutiérrez and Gonçalves (2020) directly acquired UAS off-nadir images to model almost vertical coastal cliffs. To deal with these data gaps, in projects interested in the dynamics of the coastline (considering the beach and the top of the cliff) alternatives may be the combination of aerial and terrestrial techniques (Ismail et al. 2022) or the use of varying tilting angles (Jaud et al. 2019). Vegetated surfaces are one of the biggest limitations for SfM-derived 3D models (Westoby et al. 2012; Gomez-Gutierrez et al. 2014). Our study shows a good performance of the UAS-LIDAR (Fig. 5) to overcome the limitations of coastal cliffs (overhanging areas and image poor texture in vegetated or sandy surfaces). The decrease in prices of UAS-LIDAR systems in the last years is positioning this technology as an important alternative to photogrammetry (Pereira et al. 2021; Štroner et al. 2021a, b), particularly for vegetated (or partially vegetated) and complex surfaces like the Gerra study area. Data gaps and noise observed in the foreshore beach for SfM photogrammetry (Fig. 10) are considered a consequence of images' texture in this place while the data gap observed in the foreshore beach for the UAS-LIDAR dataset correspond to a thin water pool (Fig. 9). The presence of noise and vegetation gaps in the photogrammetric point clouds results in a wide range of the D_{M3C2} as can be observed in Fig. 11c and d for the foreshore and the top of the cliff. Note that the range of D_{M3C2} is independent of the geo-referencing systematic error, being the latter represented by an offset between the median D_{M3C2} and 0 in

Fig. 11. For example, the UAS-LIDAR OWN in the backshore shows high precision with a short range of D_{M3C2} but, at the same time, an offset for the median D_{M3C2} that should be handled with a co-registration procedure if the user is interested on the comparison with other cartographic products.

The geo-referencing methods without GCPs based on the PPK approach outperformed the RTK approach in terms of accuracy, with the resulting RTK accuracy observed being similar to the few previous experiences (Hugenholtz et al. 2016; Eker et al. 2021;). The out performance of PPK over RTK approach has to do with several factors: (i) the availability of precise ephemeris data of satellites for the post-processing, providing a more accurate solution (Zhang et al. 2019), (ii) the absence of latency for the application of corrections (Puente et al. 2013) and (iii) the limitation of communication and linkage problems between the rover and the corrections' provider. Despite these advantages, the PPK resulting accuracy is unknown beforehand, relying on the continuous record of data by a nearby GNSS base station. The selection of the GNSS base station is crucial in the case of UAS-LIDAR with the permanent stations providing a solution that resulted in a point cloud free from systematic errors, in contrast to the temporary station that exhibited this error. This finding is particularly relevant for the monitoring of remote and hard-to-reach areas (Elias et al. 2024), where permanent stations are typically not available, making it necessary to use a temporary base station. In our case, the temporary OWN station was located on a concrete path that provides access to the beach, i.e. on a stable surface not exposed to the effects of tides, and potential rockfalls or landslides. In terms of coverage, the ideal location for this station would be the top of the cliff, although this area is not without risks and the philosophy of this work was to carry out the monitoring of inaccessible or dangerous landforms at the minimum risk. Regarding the influence of the baseline length for the PPK approaches, we did not find any significant difference for the two permanent stations with baselines < 25 km and PDOP < 2.5 (Puente et al. 2013), neither the SfM photogrammetry nor the UAS-LIDAR, similarly to the findings of the previous works by Dreier et al. (2021) or Eker et al. (2021).

The errors estimated during the processing of the trajectory of the UAS-LIDAR dataset (3D RMSE of 3.5 cm for RNAN station), and the calculated D_{M3C2} and $|D_{M3C2}|$ (Table 7) agreed in magnitude with previous studies (Gallay et al. 2016; Glennie et al. 2016; Salach et al. 2018) and with manufacturer's specifications (6 cm). These figures add insight to the scarce literature about the accuracy of UAS-LIDAR instruments (Mayr et al. 2020). Focusing exclusively on positional accuracy, the analysis showed that the UAS-LIDAR RNAN produced the best point cloud, followed by the UAS-RGB PPK RNAN, which exhibited a similar $|D_{M3C2}|$ but a larger standard deviation of the D_{M3C2}, due to a greater presence of noise in the point cloud. The point clouds obtained from the post-processing with RNAN data were the only ones that did not exhibit systematic errors, indicating that they could be compared with other cartographic products without the need of any prior co-registration procedure. However, in all other cases, including data acquisition using RTK, this co-registration would be necessary prior to comparison. Some recent studies have managed to increase the positional accuracy of data generated with UAS-LIDAR (from cm to mm) through hybrid geo-referencing supported by photogrammetric data acquired simultaneously (Haala et al. 2022). However, these strategies still require the presence of GCPs or control planes.

The differences observed in the D_{M3C2} for the various landforms are substantial and allow us to tune future topographic change analyses using spatially distributed thresholds (Lague et al. 2013; James et al. 2017a, b; Mayr et al. 2020; Winiwarter et al. 2021; Zahs et al. 2022). In both the UAS-LIDAR RNAN and UAS-RGB PPK RNAN data, we have observed that in the backshore and cliff face, the threshold for distinguishing topographic change from noise can be reduced compared to the foreshore and the top of the cliff. In the case of the LIDAR, the beach may feature small water ponds, while at the top of the cliff, the presence of vegetation also affects the positional accuracy of LIDAR data, as has been observed with airborne sensors (Mayr et al. 2020). In the case of UAS-RGB PPK RNAN, the previous mentioned factors related to poor image texture (vegetation, sand, and water) are the underlying causes of these differences.

The systematic bias in the absolute altitude found in the recent literature for SfM-models produced using geo-referencing approaches without GCPs (e.g. Liu et al. 2022; Taddia et al. 2020a, b) is completely removed in the PPK (Fig. 11e) and substantially reduced in the RTK approach using the oblique photographs acquired by enabling the altitude optimization option within the DJI GS RTK app (Fig. 8). However, if the final purpose of these models is the estimation of topographic changes, the reduced bias may still produce significant over or under-estimations in the case of the RTK approach (Fig. 11c). In this case, we found that the use of three GCPs (similarly to Liu et al. 2022) (Fig. 8) or a previous co-registration of the models would be necessary to produce the most accurate estimations. Recent studies have shown an interesting alternative to traditional co-registration strategies (i.e. the use of the Iterative Closest Point algorithm in stable areas), based on the simultaneous processing of multi-temporal images (Feurer and Vinatier 2018; Blanch et al. 2021), but, to our knowledge, this approach has not been tested yet on RTK or PPK datasets.

The Table 8 shows a qualitative assessment of the point clouds generated by the instruments and techniques used, which can be useful for researchers looking to select the appropriate technique for a specific task. In summary, the TLS offers dense point cloud coverage and accuracy but requires long planning, acquisition and postprocessing time and comes at a high cost. The UAS-LIDAR provides high point cloud coverage and precision with short planning and post-processing times. The selection of the GNSS base station for postprocessing the UAS-LIDAR data must be done with care. In our case, the permanent station RNAN produced an accurate point cloud free from systematic errors. However, the point cloud post-processed with the temporary OWN station exhibited systematic error, making it necessary to co-register this data before comparing it with any other spatial data. The UAS-RGB system in RTK shows moderate accuracy, with noise and systematic errors present. Finally, the UAS-RGB with PPK approaches were the most cost-effective with high accuracy and without systematic errors, however, there are likely to be gaps in densely vegetated areas as well as noise in areas with poor image texture.

Conclusions

We produced point clouds of the coastline by means of two UAS with different sensors (the UAS-LIDAR and the UAS-RGB) without the need of GCPs and compared the results with a benchmark model surveyed with a TLS device. This benchmark model produced a very accurate point cloud with the highest coverage but required long planning, acquisition and postprocessing time and comes at high cost.

The UAS-LIDAR, that only works in PPK, produced a point cloud without noise, with a homogeneous coverage, with low planning and postprocessing time. For this platform-sensor we have observed that the selection of the station used to correct the UAS trajectory is crucial. The use of a nearby permanent station resulted in a point cloud free of systematic error, whereas the use of a temporary station located in the study area produced a point cloud with some degree of systematic bias. According to our results the UAS-LIDAR processed with the RNAN permanent station produced the most accurate point cloud.

The UAS-RGB performing in RTK resulted in point clouds with systematic errors in the foreshore, the face and top of the cliff. This bias was substantially reduced using the oblique images acquired by enabling the altitude optimization option and completely removed in the PPK approach. Both photogrammetric pipelines (RTK and PPK) showed other limitations: data gaps in vegetated areas, noise in the foreshore and long postprocessing times.

Hence, the UAS-RGB with PPK was the most cost-effective method however the advantages of the UAS-LIDAR (accuracy, low noise, homogeneous and dense coverage) along with the decrease in the prices of UAS-LIDAR systems make it an interesting alternative.

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Authors contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by AGG, JJB and MSF. The first draft of the manuscript was written by AGG and all authors commented on previous versions of the manuscript. Reviews were carried out by AGG and MSF. All authors read and approved the final manuscript.

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare no competing interests.

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Vexcel UltraCam Osprey powers Espoo's 3D city model

Vexcel Imaging highlights the City of Espoo, Finland, and its continued success in building one of Europe's most advanced open 3D city models, powered by high-resolution nadir and oblique imagery captured with Vexcel's UltraCam Osprey systems.

Espoo needed a highly accurate, photorealistic 3D model that would integrate smoothly into existing GIS workflows, serve both experts and citizens, and remain maintainable at consistent quality for years. To meet this, the city worked with service providers who, since 2017, captured imagery using UltraCam Osprey sensors. This high-resolution nadir and oblique imagery has been essential for detailed roof geometry, building analysis, and photorealistic texturing. *vexcel-imaging.com*

Hawaii Department of Transportation creates safer roads

Bentley Systems, Incorporated has announced its Blyncsy solution is being used by the Hawaii Department of Transportation (Hawaii DOT) in the Eyes on the Road program—an initiative driven by the Hawaii DOT in partnership with The University of Hawaii to enhance roadway safety statewide

The Eyes on the Road project provides 1,000 free high-resolution dash cameras to Hawaii residents to install in their vehicles, to improve roadway conditions and keep the roads safe. The cameras record video automatically as residents drive normally each day. The collected crowd-sourced imagery captures road safety issues such as guardrail damage, vegetation encroachment, debris on the road or along the shoulder, and other roadway hazards. The footage is uploaded to the cloud through a cellular connection and then automatically analyzed using machine learning algorithms and advanced AI analytics from Bentley's Blyncsy, anonymously. *bentley.com*

GNSS and PNT security deployed at World Economic Forum

Dimetor is providing its NAVSentry airspace situational awareness system to the World Economic Forum annual meeting, in support of the Austrian Armed Forces. The meeting is taking place this week in Davos, Switzerland, close to the Austrian border. NAVSentry is an AI-powered platform for detecting GNSS disruptions in real time, combining different technology layers and securing position, navigation and timing (PNT) data across autonomous and crewed systems from multiple data sources.

The system is providing insights into the integrity of GNSS signals to strengthen the Austrian Armed Forces' ability to monitor, secure and protect the airspace against threats, including including jamming and spoofing attempts targeting the airspace and critical PNT infrastructure. The enhanced situational awareness strengthens the ability to detect anomalies, assess potential threats, and coordinate protective measures across both the physical and cyber domains. *www.dimetor.com*

Upgraded AI for GPS-denied drone operations

Safe Pro Group has announced the deployment of upgraded artificial intelligence algorithms to its patented Safe Pro Object Threat Detection technology. The enhanced capabilities enable rapid battlefield image analysis, including 2D and 3D modeling and explosive threat detection from virtually any drone video feed, and were developed following real world exercises in Ukraine based on end user feedback. *safeprogroup.com*

Advance NTN integration and interoperability

The Mobile Satellite Services Association (MSSA) has released its Reference Architecture document, offering strategic recommendations to accelerate the development, deployment, and global integration of open and interoperable Non-Terrestrial Network (NTN) solutions.As satellite communications advance, NTN systems are increasingly vital to extending connectivity to remote and underserved regions, while complementing terrestrial networks. MSSA's Reference Architecture emphasizes the importance of system-level design to ensure consistent device performance and seamless user experiences.

Developed by the MSSA Technical Committee's Reference Architecture Work Group, the document addresses key challenges and outlines best practices across the entire service delivery chain, from satellite constellations and ground infrastructure to mobile devices, to meet growing demands for high-speed, reliable, and secure connectivity. *www.mss-association.org*

Anello launches Aerial INS

Anello Photonics has launched the Anello Aerial inertial navigation system (INS), a compact, high-performance inertial navigation system built around the company's Silicon Photonics Optical Gyroscope technology and integrated with multi-band GNSS receivers. The Anello Aerial INS is built for demanding aerial platforms, including BVLOS UAS, maritime/shipborne VTOL UAS, ISR/special-mission aircraft, heavy-lift and cargo drones, and other autonomous aerial vehicles. *www.anellophotonics.com*

Space Force ends Resilient GPS program

The U.S. Space Force has ended an exploratory effort to add smaller, lower-cost navigation satellites to bolster the GPS, shelving a program that had been identified as a priority. The effort, known as Resilient GPS, or R-GPS, began in 2024 and funded three industry teams to develop designs and early prototypes for alternative navigation satellites. The Space Force confirmed it does not plan to move forward with deployments or on-orbit demonstrations.

In September 2024, the Space Force selected Astranis, L3Harris Technologies and Sierra Space to develop concepts for smaller, more cost-effective navigation satellites based on commercial designs. *spacenews.com*

SpaceX launches next-generation Italian COSMO-SkyMed satellite

The third satellite part of the COSMO-SkyMed Second Generation (CSG) constellation, owned by the Italian Space Agency and the Italian Ministry of Defense, built by Thales Alenia Space, a joint venture between Thales (67%) and Leonardo (33%) and operated in orbit by Telespazio, a joint venture between Leonardo (67%) and Thales (33%), has successfully been launched from Vandenberg Space Force Base in California (USA), aboard a SpaceX Falcon 9 rocket.

COSMO-SkyMed is a dual-use Earth observation constellation owned by the Italian Space Agency (ASI) and the Italian Ministry of Defense. Regarding the development of the constellation, the Italian industry plays a leading role with Leonardo and the joint ventures Thales Alenia Space, Telespazio and e-GEOS, plus with a significant number of small and medium-sized enterprises. This third Second Generation satellite, built by Thales Alenia Space like the other satellites in the constellation, will guarantee the operational continuity of radar (SAR, Synthetic-Aperture Radar) services, further enhancing the already high performance of the system in terms of image quality and area coverage. *www.thalesgroup.com*

Chinese state and private rockets fail on same day

Chinese space companies experienced two rocket launch failures in a single day. The incidents occurred as the country accelerates its "space rise" ambitions, with some quarters even referring to the day as a "black Saturday."The state-owned space enterprise China Aerospace Science and Technology Corporation (CASC) announced via social media on the 17th that "a Long March 3B carrier rocket was launched from the Xichang Satellite Launch Center in Sichuan Province at 00:55 on the same day to deploy a satellite, but the mission failed." The rocket's first and second stages flew normally, but an anomaly occurred in the third stage. "The specific cause is under further analysis and investigation," it added.

This marks the first failure of the Long March 3B carrier rocket since April 2020. Since its debut in 1996, the Long March 3B has been launched over 115 times, with approximately five failures. *www.chosun.com*

Japan's H3 rocket fails to deploy geolocation satellite

Japan's space agency said its H3 rocket carrying a navigation satellite failed to put the payload into a planned orbit, a setback for the country's new flagship rocket and its space launch program. The Japan Aerospace Exploration Agency said the H3 rocket carrying the Michibiki 5 satellite took off from the Tanegashima Space Center on a southwestern Japanese island as part of Japan's plans to have a more precise location positioning system of its own.

The rocket's second-stage engine burn unexpectedly had a premature cutoff and a subsequent separation of the satellite from the rocket could not be confirmed, Masashi Okada, a JAXA executive and launch director, told a news conference. Whether the satellite was released into space or where it ended up is unknown, and that JAXA is investigating the data to determine the cause and other details, Okada said. *apnews.com*

MICE-1 successfully launched

The Transporter-15 mission by SpaceX successfully launched aboard a Falcon 9 rocket from Vandenberg Space Force Base in California. As part of the mission, MICE-1 (Maritime Identification and Communications system was successfully deployed into orbit. MICE-1 is the first Greek nanosatellite specifically designed for maritime and IoT communication applications. It aims to bring Greek shipping—and critical operational infrastructures in disaster scenarios—closer to the capabilities of space. *prismael.com*

Wingcopter drones to be deployed for aerial surveying in Japan

Wingcopter's authorized partner in Japan, ITOCHU Corporation, has signed a Memorandum of Understanding (MOU) to collaborate on the practical use of Wingcopter's long-range drones in aerial surveying together with PASCO Corporation and YellowScan Japan Co., Ltd. The companies initially plan to use the Wingcopter 198 in disaster management where drone-based surveying is playing an increasingly important role. Carrying out these tasks is way easier and less risky with fixed-wing drones such as the Wingcopter 198 than with traditional human or aircraft-based methods, especially as about 70 percent of Japan's land consists of mountainous and hilly terrain, with steep slopes and short, fast-flowing rivers. Conventional multicopter drones, on the other hand, would not be suitable for such tasks as they are limited in range and coverage compared to the Wingcopter 198. *wingcopter.com*

Enhancing precision and safety in BVLOS drone deliveries

Trimble has announced that Volatus Aerospace Inc. has integrated the Trimble PX-1 RTX™ solution into its commercial delivery drone service to achieve accurate and robust positioning and heading. This provides Volatus' clients with a turnkey solution for highly-accurate aerial data acquisition and fully-remote drone operations in real-world missions, including beyond visual line of sight (BVLOS). Volatus must meet strict guidelines addressing airspace entry and exit, altitude and speed, and communication and remote identification when taking off from and landing at the Edmonton International Airport in Alberta, Canada. The flight corridor approved by Transport Canada and Nav Canada requires them to land and takeoff with precision, while staying at 50-feet altitude when crossing airplane arrival routes. Trimble PX-1 RTX's precise positioning capabilities address crucial accuracy challenges for takeoff and landing, while supporting an exact flight altitude and positioning within the flight corridor. *www.trimble.com*

PointX and StellaX to smart lawn mowing

MOVA has integrated CHCNAV PointX integrated satellite ground service and the StellaX high precision positioning chip into its NAVAX 5000 AWD intelligent robotic lawn mower, unveiled at CES 2026. The integrated positioning solution is designed to support centimeter level accuracy for wire-free mowing, without requiring users to install a local RTK base station or subscribe to cellular data plans.Wire-free robotic mowers are accelerating adoption of virtual boundaries and automated coverage. *https://navigation.chcnav.com*

Expanding global access to reliable positioning and geospatial services

Hexagon has joined the Multilateral Memorandum of Understanding (MMoU) on Strengthening the Global Geodesy Supply Chain. The MMOU is a shared recognition by the United Nations Global Geodetic Centre of Excellence (UN-GGCE) alongside member state government departments and agencies, private sector companies, organisations, associations, and academic institutions, that action is required to make the foundations of positioning, navigation, and timing services robust.

Accurate positioning underpins countless day-to-day. GNSS reliability is essential for keeping projects on schedule, infrastructure safe and operations productive. *hexagon.com*

Genesys launches ADAS maps for India

Genesys has developed India's first large-scale high-definition maps engineered specifically for vehicles enabled with advanced driver assistance systems (ADAS). The HD maps include ADAS-critical features such as lane geometry, road markings, barriers, signage, medians, elevation and curvature profiles, and localization objects like poles and gantries — all processed to achieve centimeter-grade precision.

To achieve the centimeter-level accuracy required for ADAS Level 2 functionality, Genesys relies on the Survey of India's Continuously Operating Reference Stations (CORS) network. Real-time GNSS correction signals along major corridors dramatically strengthen field operations, allowing survey teams to capture lane-level and asset-level detail that meets global automotive standards. This work builds on the existing memorandum of understanding between Genesys and Survey of India, enabling collaboration on digital twin projects, national mapping programs, and high-accuracy geospatial missions.

Quantum navigation system successfully tested at sea

A quantum technology-based navigation system has completed a successful trial at sea, which has shown its potential to operate where other networks are unavailable. The HARLEQUIN system was tested on board the Galatea, a buoy and lighthouse maintenance vessel, and was shown to be capable of functioning in real-world conditions, outside the laboratory. It combines conventional elements of navigation systems with a cold-atom quantum accelerometer. At the heart of this quantum technology is a gMOT (grating magneto-optical trap) cold-atom source, developed over more than a decade through collaboration between Strathclyde and CPI TMD. The sea trials, led by CPI TMD, were carried out in partnership with the University of Strathclyde, Covesion and Trinity House. *www.strath.ac.uk*

High-integrity GNSS with NVIDIA DRIVE AGX

Swift Navigation is collaborating with NVIDIA to enable a more scalable, cost-effective approach to autonomous driving by integrating the NVIDIA DRIVE AGX platform with Swift's globally referenced, centimeter-accurate GNSS positioning. The integration is delivered through the new Starling SAL Plugin for NVIDIA DriveWorks. NVIDIA DRIVE AGX platform is the industry-standard, end-to-end platform for software-defined vehicles, scaling from assisted to fully autonomous operation. *www.swiftnav.com*

Xsens IMUs achieve sub-5 cm heave accuracy

Xsens has announced a major capability upgrade for its industrial-grade Xsens Sirius and Xsens Avior inertial measurement units (IMUs). The new Heave feature delivers centimeter-level vertical displacement measurement, enabling real-time stabilization and wave compensation in a wide range of marine applications. *www.xsens.com*

etherWhere and AsiaRF display new GNSS modules

etherWhere has partnered with AsiaRF to offer two new GNSS modules based on its EW6181, a module that offers low power consumption with fast acquisition time. AsiaRF is offering two module designs (10.1 × 9.7 × 2.3 mm and 18 × 18 × 6.2 mm). The modules are targeted for wireless solutions, including Wi-Fi 7 access points, body-worn cameras, and asset tracking solutions. *www.etherwhere.com*

Positioning Australia expands capabilities with Ginan V4

Geoscience Australia announced the release of Ginan V4, the latest version of its home-grown, open-source toolkit for precise point positioning. Developed under the Positioning Australia program, it delivers world-class GNSS capabilities to innovators, researchers, and industry professionals—now with a brand-new graphical user interface (GUI) that makes data processing faster, easier, and more accessible than ever before.Its headline feature of Ginan V4 is its intuitive GUI, designed to lower the barrier to entry for users across sectors. *www.ga.gov.au*

TrustPoint reaches key milestone in GPS-independent commercial PNT

TrustPoint has successfully transmitted its first Low Earth Orbit Navigation System (LEONS) time-transfer and tracking signals from a compact TrustPoint ground node

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https://dgi.wbresearch.com

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25 - 27 March 2026
Munich, Germany
www.munich-satellite-navigation-summit.org

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www.geoconnectasia.com

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13 – 16, April 2026
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www.forumuav.com

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https://gistam.scitevents.org

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Cape Town, South Africa
https://fig2026.org

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14 - 19 June 2026
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https://iccgis.cartography-gis.com

to spacecraft in orbit. This milestone marks a critical step toward achieving GPS independence, accelerating the advancement of it's next-generation commercial navigation infrastructure, and strengthening the company's ability to deliver resilient, precise, and globally available positioning and timing when it matters most. *www.trustpointgps.com*

ArkEdge Space signs agreements to develop LEO PNT constellation

ArkEdge Space Inc., a significant step toward building a globally trusted, resilient PNT ecosystem. Under its Low-Earth Orbit (LEO) PNT satellite constellation concept, it has signed separate Letters of Intent with TrustPoint Inc. (USA), the Royal Institute of Navigation (UK), and FrontierSI (Australia). These agreements reflect a shared commitment to advancing resilient space-based PNT capabilities for civil, commercial, and security-focused users worldwide. It aims to support informed policy development, help strengthen national PNT resilience strategies, and explore how space-based PNT can enhance the reliability of critical infrastructure and operational assurance in an increasingly contested environment. *arkedgespace.com*

Syslogic launches cm-accurate expansion board

Syslogic has introduced a GNSS expansion board for its rugged embedded computers. The board provides centimeter-level positioning, opening up new applications across industries. It's all-band GNSS board is powered by the u-blox X20 receiver, supporting all major GNSS constellations and frequencies, including L1, L2, L5, L6, and L-band. This enables the use of the upcoming Galileo High Accuracy Service (HAS). HAS supplements standard Galileo Open Service positioning with correction data transmitted directly over the E6/L6 band. The result is centimeter-level positioning via GNSS signals without the need for traditional RTK base stations, costly reference networks, or 5G connectivity. *www.syslogic.com*