

Spatial crime scripting and meso-level analyses of illegal pangolin trade

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Abstract Human-related threats such as poaching and illegal trade remain the dominant risk to pangolin conservation. Using crime science focused on illegal pangolin hunting, we compare expert vs. community member's spatio-temporal knowledge about the different stages of pangolin poaching and trade process at a national scale; explore spatial trajectories between stages; and explore spatial predictors of each stage. We conducted participatory risk mapping in December 2025 and April 2026. Points mapped by participants (n = 2,161) were coded and analyzed alongside open access secondary spatial data using a geographic information system. Participants had over 85% agreement in spatial knowledge about crime-related pangolin behavior. Vector pattern analysis signaled the existence of multi-destination groups rather than individuals, and distance to major cities dominated every crime stage, challenging assumptions about offenses being governed by distinct environmental variables. Integrating community spatial knowledge with crime scripting can inform evidence-based, geographically targeted interventions for endangered species protection.

Keywords conservation criminology, crime scripting, Gabon, journey to crime, participatory mapping, wildlife trafficking

Pangolins (Order: *Pholidota*; Family: *Manidae*) are medium-sized, nocturnal, scaly mammals living in diverse Asian and African habitats¹. Pangolins' defense mechanisms help protect against natural predators but also make them vulnerable to humans who consume pangolin meat as a source of local protein and delicacy in restaurants along with various body parts believed to have properties useful for traditional medicine²⁻⁵. Although pangolin conservation is impacted by climate change, land use and land cover change, and health-

related issues like parasites⁶, human-related threats associated with consumption remain the predominant risk to pangolin conservation⁷. Over a decade ago, pangolins were labeled the “world’s most trafficked mammal⁸” because of the high volume of pangolin seizures reported, which led conservation biologists to believe that trade in whole animals and their parts had reached unsustainable levels.

Unlike some species involved in the illegal wildlife trade (IWT) like elephants and tigers, there are no reliable estimates of the size of pangolin populations due to their nocturnal and elusive nature, particularly for arboreal species. Nor are there easy ways to monitor pangolin poaching, because pangolin carcasses are not left by poachers in the field for authorities to detect⁹. Wildlife crime researchers overwhelmingly use two methods to estimate both the number of pangolins involved in, and economically value, the illegal trade: local wild meat market surveys and individual seizures^{9,10}. These field-intensive and case-based approaches provide information about species involved in trade and source-transit-destination chains, usually on an annual basis¹¹. Importantly, although wild meat market surveys can provide information about pangolin-related crimes, wild meat represents subsistence hunting, underpins food security, and provides economic opportunities for low-income rural households and women^{12–14}. Substantial normative differences exist for wildmeat and IWT based on motivation, scope, scale, and economic context; these differences can restrict the applicability of wild meat data for wildlife crime research^{15–17}. In some instances, limitations and biases associated with market surveys and seizure data are being overcome with advancements in statistics, computer science, and forensics^{18–20}. The United Nations Office on Drugs and Crime (UNODC) identified better geographic targeting and building national-level datasets as precursors to evidence-based interventions for all species of plants and wildlife involved in IWT, including pangolins⁹. More rapid and measurable progress for pangolin conservation, particularly for issues associated with IWT, could be achieved if interventions were informed by stronger scientific evidence and made more strategic⁹. The Conference of Parties (CoP) to the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) adopted Resolution Conf. 17.10, which encouraged range States to implement pangolin conservation at the national level and for States affected by illegal trade risks to review national activities to prevent, detect, and address crimes involving pangolins to ensure they remain effective⁷.

These policy mandates inspired this research, the contributions of which emerge from 1) combining community-based methods and expert knowledge to assess wildlife crime risks (e.g., participatory risk mapping), 2) a national-level geographic perspective (e.g., Republic of Gabon), and 3) applying a novel theoretical framework (e.g., spatially-integrated crime scripting and journey to/from crime). Community-based methods like focus group discussions are not commonly used to capture local knowledge (e.g., perceived risk of wildlife crime) about and assess influence of human behavior like IWT. A 2026 review paper reported such methods comprised only 16% of the entire published literature on pangolins, 75% of which focused on hunting and trade⁶. The review paper reported Nigeria, South Africa, and Cameroon were the dominant study sites for pangolin conservation, globally. Countries with exceptional habitat integrity and intact forested landscapes, like Democratic Republic of Congo, Gabon, and Republic of the Congo were less represented in

the reviewed literature; when they were included it was often in a regional and not national context⁶. “Long-term neglect” of other parts of pangolin range hinders comprehensive understanding about trends, risks, and conservation needs at the intermediate or meso-level scale of analysis between a specific protected area and species range⁶. Today, all 8 species of pangolin are listed on CITES Appendix I, which prohibits international commercial trade. Every pangolin range State is a signatory to CITES and only 3 of the 50+ lack domestic legislation protecting pangolins²¹. Criminology is central to pangolin conservation, however, not only does systematic application of the geography of crime to illegal pangolin trade remain uncommon, the subdiscipline remains overwhelmingly focused on urban crime and a single point in time during crime stage (e.g., the commission of the crime). We set three objectives for this research, with pangolin hunting in Gabon (i.e., poaching, because all pangolin hunting is illegal in the country) as the IWT context of interest.

- 1) Compare and contrast expert vs. community member’s spatio-temporal knowledge about six activities associated with three crime stages of pangolin poaching (i.e., PreActivity, Activity, Post-Activity) in an under-researched geography at a meso (i.e., national) level;
- 2) Explore differences in spatial trajectories between crime stages; and
- 3) Explore spatial predictors of crime stages of pangolin poaching derived from both expert and community members’ spatial knowledge.

Results

Six pangolin-associated activities (e.g., pangolin poaching, exchange, planning for exchange, transportation of pangolins, pangolin product storage, pangolin supplies obtained), were identified during participatory risk mapping activities with community members (n = 104) and subject matter experts (n = 19) in December 2025 and April 2026. A total of 12 paper maps were produced with 2,161 activity points (**Fig. 1**) that were assigned to one of three crime stages (i.e., Pre-Activity, Activity, Post-Activity) using crime script analysis.

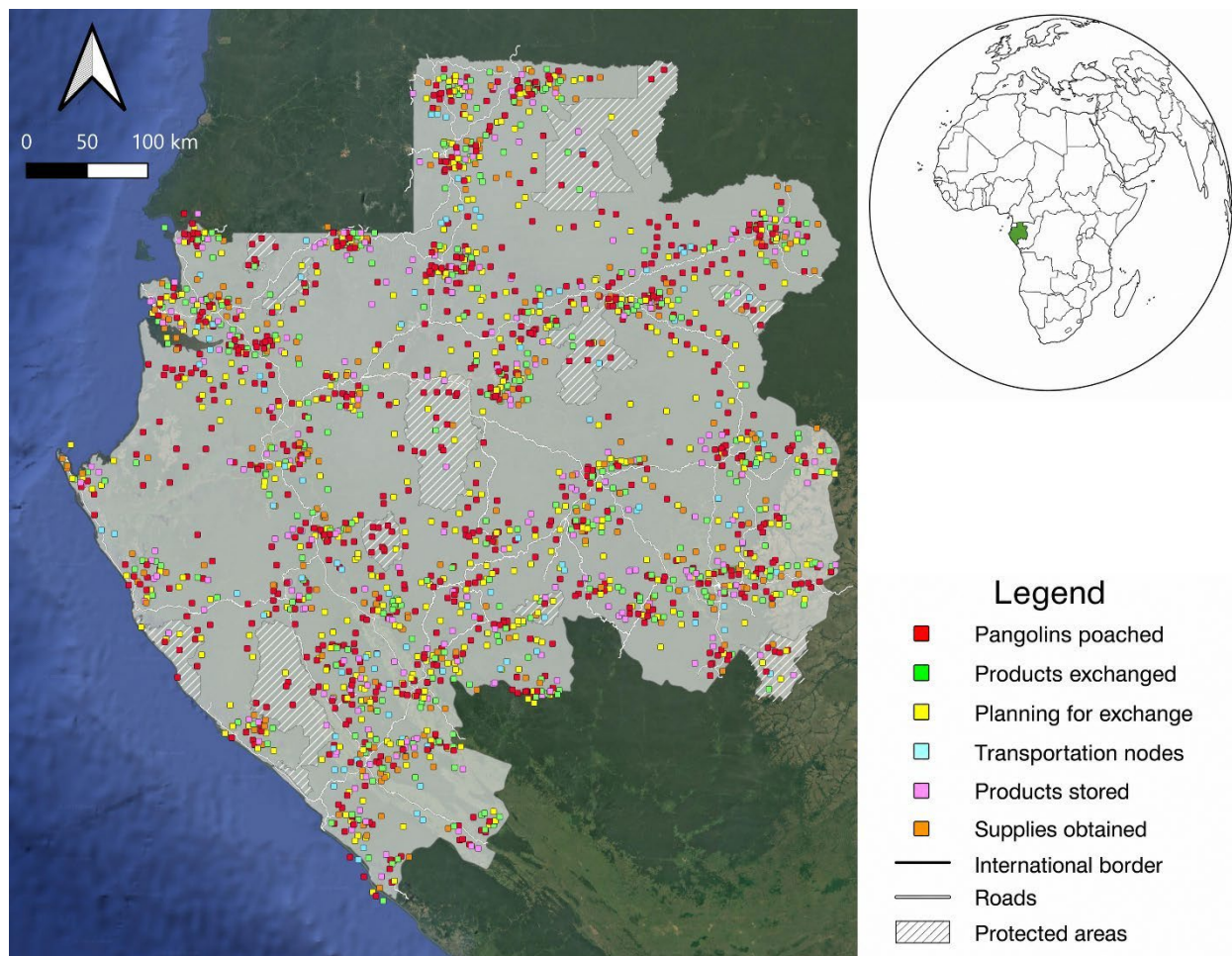


Fig. 1. Raw annotation of six pangolin-associated activities, listed in the legend, that were identified during participatory risk mapping, digitized as points, and color-coded to be visualized alongside roads and national parks. The locations of mapping activities are not marked on the map for human subjects protection, however all mapping participants were provided with a map of the entire country, making the data collection national in scope. To include annotated points that lay offshore as well as to reduce the sudden artificial loss of intensity near the boundary of Gabon²², the country shapefile layer was extended by 15km to create the outline of our region of interest.

Spatio-temporal knowledge comparison between experts and community members. Across all 3 crime stages (i.e., the Pre-Activity, Activity, and Post-Activity stages), experts and community members showed more than 86.59% (268,578.5 km²) agreement in their spatial knowledge based on a comparison of normalized kernel density estimation (KDE) surfaces representing the relative spatial distribution of crime-stage locations reported by each group. This indicated extraordinary high alignment in risk perception. Where knowledge diverged, experts identified larger areas for all 3 stages (**Fig. 2**). Experts identified higher crime intensity [points km⁻²] in 9.95% of our region of interest (ROI) for Stage I/ Pre-Activity, 13.01% for Stage II/Activity, and 3.70% for Stage III/Post-Activity

(Fig. 2). In all crime stages, the areas where community members identified significantly higher crime intensity constituted less than 1%.

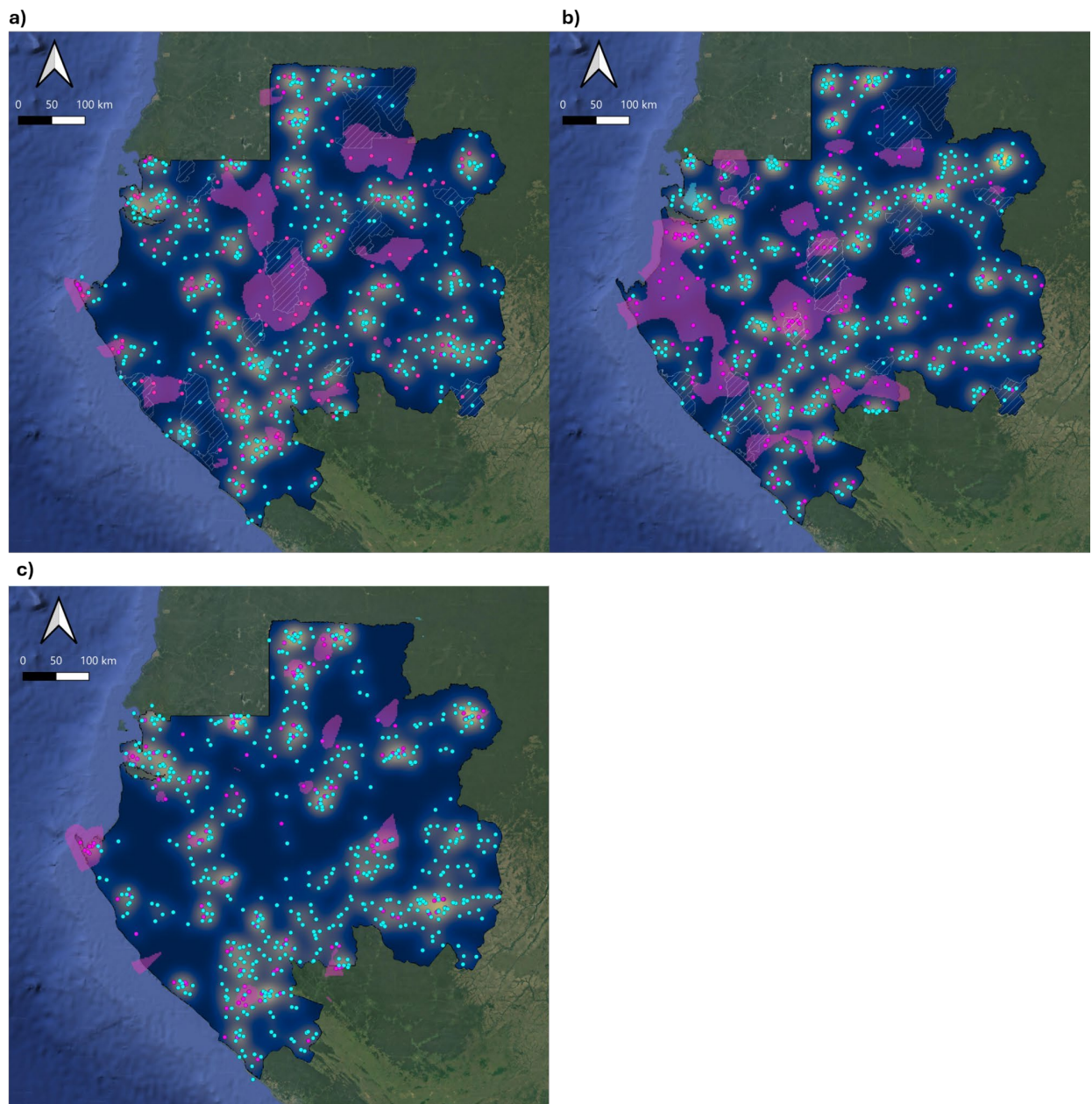


Fig. 2. The spatial distribution of points of where subject matter experts (denoted in magenta) and community members (denoted in blue) annotated locations for different activities associated with pangolin hunting behaviors across three crime stages in Gabon: (a) Stage I/Pre-Activity (b) Stage II/Activity, and (c) Stage III/Post-Activity. Magenta shaded polygons denote areas where the kernel density estimation-based comparison showed significantly higher relative spatial intensity among experts than community members.

Spatial trajectories between crime stages for pangolin hunting. By computing the difference in perceived crime intensity between crime stages and considering adjacent areas of

change, we plotted 84 gradient vectors representing spatial transition between Stage I and II and 111 vectors between Stage II and III. The mean magnitude of vectors in units of change in crime intensity per kilometer [$\text{points km}^{-2} \text{ km}^{-1}$] in both instances was similar: $1.43\text{e-}4$ from Stage I to II and $1.35\text{e-}4$ from Stage II to III. The dominant cardinal direction of vectors differed between stages; westerly journeys were most common between Stage I and II (17.9%, $n = 15$) and easterly journeys were most common between Stage II and III (19.8%, $n = 22$) (**Fig. 3**).

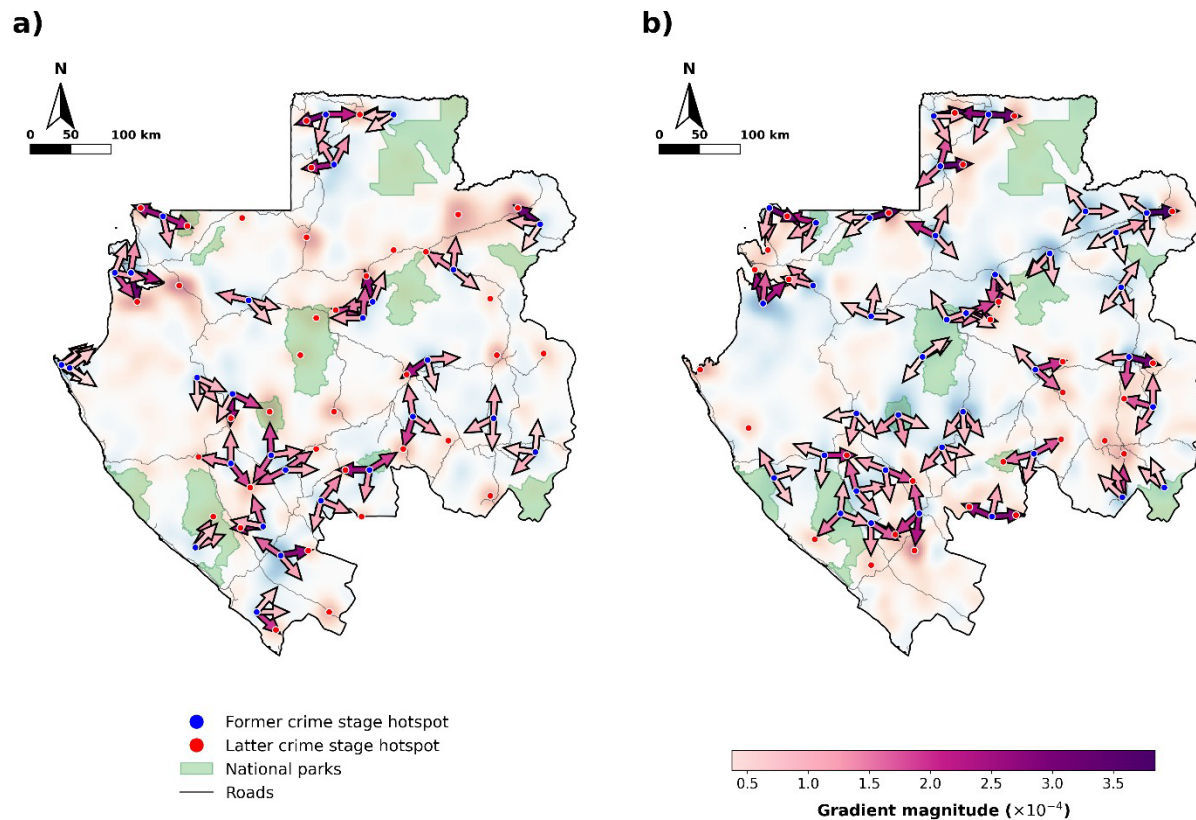


Fig. 3: Arrows depicting vector magnitude and direction between the crime stages, between Stage I and II depicted in panel (a) and Stage II and III depicted in panel (b). Arrows are overlain over a map of the difference in crime intensity between the consecutive crime stages. Vectors originate from hotspots of former crime stages visualized as blue dots and project towards hotspots of later crime stages visualized as red dots to indicate possible directions of transition from one crime stage to the next. Darker vectors depict higher tendency of movement from one crime stage to the next as well as higher differences in intensity and closer proximity between crime stages.

Spatial predictors across the three stages of the pangolin hunting process. We modelled each crime stage using a spatial binomial generalized additive model (GAM). Across the three final spatial binomial GAMs, distance to major Gabon cities had the largest standardized coefficient in magnitude and was negatively associated with participatory-mapped

occurrence at every crime stage (Stage I: $\beta = -1.036$; Stage II: $\beta = -1.067$; Stage III: $\beta = -1.152$) (**Fig. 4**). Thus, grid cells (2km x 2km) closer to major cities were more likely to contain at least one mapped annotation. Cells located one standard deviation closer to major Gabon cities had substantially higher odds of being mapped as crime-occurrence locations: 2.82 times higher for Stage I, 2.91 times higher for Stage II, and 3.16 times higher for Stage III.

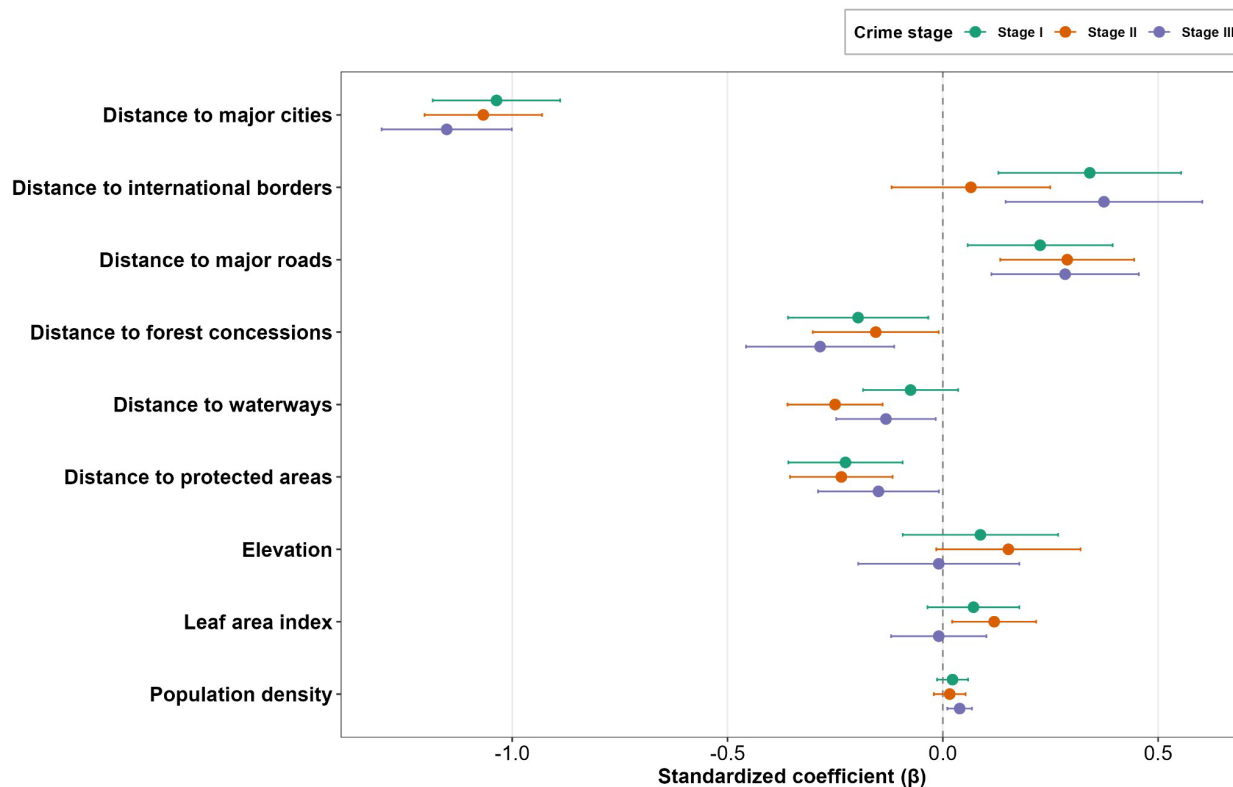


Fig. 4: Standardized coefficients from spatial binomial generalized additive models for the three crime stages. Points show the estimated association between each covariate and the occurrence of at least one participatory-mapped annotation within a grid cell; colours distinguish the crime stages. Horizontal whiskers show 95% confidence intervals, and the dashed vertical line marks zero association. Negative coefficients indicate lower odds of mapped occurrence as the covariate increases, while positive coefficients indicate higher odds.

Discussion

Spatio-temporal knowledge comparison between experts and community members. In conducting a meso-scale analysis of pangolin poaching in Gabon using participatory mapping data and geospatial crime script analysis, this research offers a range of novel empirical and interdisciplinary insights about the relationship between human systems, environmental risks, and biodiversity conservation. The first noteworthy finding from this research emerges from results linked to Objective 1. We know wildlife-related risk and risk perception are inherently spatial because exposure is location dependent and vulnerability

varies across space and time²³. That participating experts and community members had over 85% agreement in spatial knowledge about pangolins represented an extremely high level of alignment. The spatial bounds of human behaviors associated with pangolin poaching were highly legible to participating stakeholders. This alignment in spatiotemporal knowledge and risk perception across groups indicates there existed no practical knowledge gap; consensus has been achieved either deliberately or unintentionally. Although it is beyond the scope of the data to explain why such extraordinarily high alignment existed among participants, the literature notes that when environmental risk is directly experienced, it can reflect both groups having experience with the same risks, resulting in shared understanding²⁴. The implications of spatial knowledge alignment are broad. Practically, the existence of consensus provides a robust, socially validated foundation for targeted, zone-based policy interventions²⁵. High-confidence targeting of conservation interventions can help reduce resource misallocations²⁶. Methodologically, results offer accelerated baseline dataset creation for pangolins in an under-researched geography. Results also offer a ground truthing of pangolin-associated risks at a meso/national level and help justify shifting from knowledge to implementation gaps (e.g., policy execution, conservation incentive structures).

Spatial trajectories between crime stages for pangolin hunting. A second noteworthy finding from this research emerges from Objective 2 results. Beyond helping to overcome locational uncertainty, results have implications for journey to and from crime, as well as group offending, in the context of biodiversity conservation. Our analysis identified 84 vectors associated with the journey *to* crime, or between Stage I and II, and 111 vectors associated with the journey *from* crime, or between Stage II and III. The fact that we identified a larger proportion of vectors associated with journey from crime means the dataset had a higher reporting density for post-offense movements than pre-offense movements. Some scholars term this imbalance splitting²⁷ and note it signals the existence of multi-destination groups, where a single journey to crime vector brings a single offender or group of offenders to a site but they disperse using multiple vectors after the fact²⁸. The spatial dynamics of this type of crime, group crime, are asymmetric by design. After the crime occurs (i.e., Stage 2/Activity in this research), a group intentionally splits up to divide attention, prevent apprehension, and reduce risk; multiple vectors linked with journey from crime can represent intentional efforts to obfuscate trade routes.

We found the same average magnitude in journey to and from crime vectors, signaling the spatial boundaries of the local context; the entire operation was bounded by a localized awareness space and friction of distance. Pangolins and their products (e.g., scales) are frequently moved alongside timber or agricultural goods^{29,30}. Moving these goods requires using existing local roads and transit hubs and the spatial friction of the local terrain limits how far anyone can travel in a single leg of a journey. In practice, our data suggests that the group(s) of co-offenders—the poachers bringing in pangolins and the groups dispersing pangolins and their products—are poaching and trading within the same geographic boundary, indicating that the hub itself can catch both sides of the value chain (i.e., Stage I/Pre-Activity, Stage III/Post-Activity).

Group offending remains an under-researched concept for IWT research, yet IWT rarely involves a lone actor engaging in all activities along the illicit supply chain^{26,31}. IWT relies on structured multi-tiered networks³². Journey to and from crime is often modeled as a unified logistics chain from origin to middleman, compressing multiple vectors into fewer single distinct tracked vectors (i.e., consolidation)^{33,34}. Results suggest that in this research context, the journey from crime involved groups engaging in splitting, likely to mitigate risk of getting caught and/or maximizing the chance of their pangolins or pangolin products advancing to the next destination in the value chain. Group offending can be a tactical partnership³⁵ and criminal network a logistical infrastructure^{36,37}. Group offending refers to specific, localized clusters of individuals who team up to execute an offense; such groups tend to be small, with little hierarchy and limited repetition³⁸. Co-offending is also spatially patterned, as offenders, including co-offenders, tend to select targets near their homes and within their awareness spaces^{39,40}. Criminal networks are systems of interconnected nodes that sustain illicit operations^{41,42} and in IWT they range from loose, opportunistic ties to more organized structures^{36,43}. Criminal networks are enduring and resilient and the network exists independently of the specific individuals operating within it at any given time. Networks are transnational, and local^{43,44}. Based on these well-published definitions, our results signal journey to crime vectors involved localized group offending and journey from crime represented products being handed off to a network. In this way, our results target a blind spot in conservation criminology: transit logistical asymmetry. Most journey to crime research assumes a round trip where an offender leaves home, commits crime, and then returns home³³. Our vector data showed a different behavioral pattern. The local supply chain acted as an asymmetrical gateway where animals were harvested via tight predictable routes and subsequent dispersal triggered larger webs of distributed routing to evade detection.

Spatial predictors across the three stages of the pangolin hunting process. A third noteworthy finding from this research was that distance to major cities was the primary spatial feature key to all stages of pangolin hunting. Spatial drivers usually change as an offense progresses (e.g., poachers choose hunting sites based on animal prevalence/density, cultural norms, presence of neighboring hunters and hunting territory boundaries but transport routes are based on roads)⁴⁵. This finding contrasts with findings that different stages of pangolin crime can be governed by distinct environmental variables like the stage-specific ecological predictors⁴⁶. Currently, Gabon is the most urbanized and one of the least populated nations in Africa⁴⁷ and Africa is urbanizing faster than any region on the planet⁴⁸. Gabon's urbanization rate offers a demographic context for why distance to major cities dominated every stage of the crime script and offers a harbinger. Distance to major cities can serve as a proxy for infrastructure (e.g., access to roads, fuel, equipment, transport networks) in places like Gabon where interior forests exist that are less populated. It is also important to consider Gabon's settlement and transport geography. Since the colonial period, most villages have been relocated along the main roads connecting major urban centers, most of which are relatively small, with the exception of Libreville, Port-Gentil and Franceville. This spatial configuration may also influence the relationship between distance to major cities

and distance to main roads. Although it may be reasonable to assume that early crime stages are dictated by ecological factors³⁰ like forest cover or pangolin abundance, the fact that proximity to major cities was the primary predictor for all crime stages shows that non ecological drivers can override ecological drivers in highly urbanized contexts, as found in a research study in Cameroon on pangolin scale trade⁴⁶. Will these meso-level spatial patterns of wildlife crime transition away from rural, forest-dependent communities and increasingly center on urban logistics, capital and transit hubs as the continent urbanizes? How and with what impacts on sustainability? Future longitudinal research on rural-to-urban migration at national scales would be extremely fruitful in providing answers. Beyond being scalable to the other pangolin range states, the methodological and analytical approach described herein can be adapted to other contexts and help address the gaps in geographic targeting and national-level datasets undermining desired progress toward mitigating socio-ecological harms associated with IWT⁴⁹.

Globally, threats to pangolin conservation and efforts to overcome them will remain dynamic into the future⁵⁰. So too will scientific approaches for identifying trends and drawing inferences about these dynamics be encumbered by states of data deficiency⁵¹. Synthesizing participatory mapping data with spatial crime scripting established a scalable, national-level dataset for an under-represented pangolin range States, jumpstarting the data deficiency to data availability transition. Methods can be adapted and replicated in other pangolin range States or for other species. Beyond contributing methodological advances, this research grounded national-level spatial trajectories in local participatory data, demonstrating how post-activity trade asymmetric splitting can connect localized group offending to broader networks. In practice, high spatio-temporal alignment between experts and local communities provides a socially validated, ground-truthed foundation to inform pangolin conservation by moving from knowledge generation to targeted, zone-based policy execution. Countering illegal pangolin trade demands targeting the asymmetrical post-offense transit nodes where localized poachers hand off products to broader criminal networks. Building scalable national datasets through participatory risk mapping may provide critical entry points for other states seeking to translate local community knowledge into evidence-based, zone-based policies supporting conservation of species impacted by illegal trade, including pangolins⁵².

Methods

Expert vs. community member perceptions of environmental risk

Understanding risk perceptions is important for all forms of environmental management, including conservation crime, because one cannot predict how people will respond to an issue (e.g., conservation crime prevention) without knowing how they perceive it⁴⁹. Risk perception can be mapped, quantified, and qualified and can be compared to identify similarities and differences among groups^{53,54}. Two groups commonly engaged in environmental risk related research are experts (e.g., trained professionals with employment expertise and experience) and laypersons (e.g., members of the general public or indigenous peoples and local communities with traditional knowledge based on lived

experience and expertise). Here, we apply the term community members to refer to laypersons. Extant studies confirm that there can be, but are not always, differences in the way in which risks are perceived between experts and community members^{24,55}. Often, experts perceive risks as being *less* risky than community members; in some instances experts and community members *share* similarities in risk perception. Experts consistently rate risk lower than community members for environmental issues, particularly for species loss and animal/plant suffering⁵³ but also for risks including nuclear waste⁵⁶, chemical toxicity⁵⁷, and climate change^{53,58}. Similarities and differences between experts and community members are consistently reported in policing and crime research, for example Bogaard et al.⁵⁹ detected differences in perceived risk of deception between police and students, and Murray et al.⁶⁰ found similar patterns between groups when they assessed offender dangerousness. Risk is central to crime and conservation. Measuring both expert and community member perceptions of pangolin conservation risks from poaching and trade to determine areas of convergence and divergence is critical for mapping the full scope of a hazard at any spatial scale, optimizing resources, and supporting compliance with policies or programs⁶¹. Importantly, community members in conservation contexts can often include indigenous people and local communities (IPLCs) who live adjacent to protected areas and habitats where pangolins, and other wildlife, live. Globally, indigenous people are disproportionately victims of crime and proportionally a higher number of indigenous people encounter the criminal justice system⁶². Although pangolin hunting is illegal in Gabon, it continues to take place in areas where pangolins persist, often because illegality is contested⁶³ by IPLCs or hunting remains socially licit⁶⁴. This research considered the general history of IPLC victimization and did not presuppose community members (or subject matter experts) were offenders or perpetrators of pangolin crime, but rather a knowledgeable source of unique information about risks to pangolin conservation.

The geography of conservation crime

Journey to and from crime. Journey to crime is a concept examining the spatial decisions an individual or members of a co-offending group make when traveling or traversing space to the location where they commit an offense^{34,65}. Journey from crime is the analog spatial consideration for what happens *after* crime commission. Traditionally, journey to crime is applied to crimes including homicide or burglary, and is measured using geometric data (e.g., kilometers traveled) to denote the start and end point, treats the journey as a vector and uninterrupted line, and assumes the journey ends when the crime is committed³³. Crime geographers have identified consistent mathematical and behavioral patterns that govern how offenders move across a landscape; the concept is not universal but rather varies based on the type of offense (e.g., property crime, violent crime) and the person committing it (e.g., juveniles)^{66,67}. Journey to crime, and often from crime, is useful for predicting offender and victim behavior, profiling serial criminals, and designing crime prevention strategies⁶⁵. By understanding pathways relevant to the crime commission process law enforcement authorities or space managers (e.g., urban planners, protected area rangers) can implement situational crime prevention measures to disrupt the journey³³. Mapping a journey can also support predictive policing, helping authorities to

deploy patrols along specific high risk routes^{34,65}. The concept has not been explicitly applied to conservation, although some of the concept's associated metrics like distance decay have been explored, based on our search of the literature⁶⁸.

Crime scripting. A crime script is a conceptual framework from criminology that breaks down a crime event into a sequential and procedural chain of events, or process. The purpose of a crime script is not just to understand crimes, but to help prevent or disrupt them at any stage in the process. While every crime has a unique context and process, criminologists often use a 4-stage universal crime script for standardized analysis: preparation, pre-activity, activity, and post-activity. Crime scripts have been widely applied beyond traditional crime like urban car theft, including to both wildlife poaching⁶⁹ and pangolin scale trade³⁰, cyberattacks, human trafficking, and terrorist plots. Crime script analysis involves systematically organizing data about the crime of interest– for example, people involved, key places and spaces, or skill development–into the corresponding stage in the sequence of events⁶⁹. Crime scripts are overwhelmingly constructed from police case files or court documents⁷⁰; they are not traditionally, but can be, created directly from spatial data.

Crime scripts can be constructed from data collected via participatory mapping, but this rarely occurs because the latter is typically spatial and perceptual and the former behavioral and sequential and thus script analysis requires specialized geospatial analysis skills^{71,72}. Crime scripting can help transform a two-dimensional journey using crime metrics into a multi-dimensional perspective producing novel insights relevant to theory and practice⁷³. Instead of focusing purely on space, space-time considerations can be considered. Instead of assuming the journey ends where the crime is committed, the vital logistics associated with the journey *away* from the scene can be included. Treating the journey as a series of environmental actions, for example during the preparation and pre-activity stages, may help distinguish if the crime of interest (e.g., poaching, laying snares) involves high preparation and professionalism (e.g., supplies intentionally carried far distances) or high opportunism and amateurism (e.g., supplies picked up accidentally along the way)⁷⁴; the spatial attributes of the pathways and nodes may help reveal patterns and trends of high-risk spaces²⁰. The post-activity stage represents the journey *from* crime; which may or not be different from the journey *to* crime. Describing similarities and differences between the journey to and from crime can help identify the spatial attributes relevant to both. Scripting can extend the spatial footprint of the crime process, indicating that the journey from crime can be structurally wider than the journey to it⁷⁵. Practically, using crime scripting to understand the journey to and from crime can help target specific community development or informant networks, focus ranger patrols on high-density zones near boundaries, or consider deploying sensors at strategic checkpoint locations. Traditional policing often focuses on catching an offender *after* the commission of crime or increasing blanket patrols across an entire protected area. By understanding the spatial attributes of transit routes and geographic boundaries encountered during the crime commission process, planners can introduce more highly-targeted environmental fixes. Prevention emerges from thinking about conservation crime as a predictable logistical chain that can be broken before an offender ever reaches the victim.

Spatial predictors. Spatial variables can act as predictors of cues or constraints that dictate whether or not an offender can successfully transition from one stage of a crime script to another. Spatial predictors may be structural and infrastructural (e.g., road or river density, proximity to national park and national boundaries)^{76–78}, ecological (e.g., habitat and vegetation profile)^{79,80}, or human dynamics (e.g., population density, market accessibility, proximity to resource extraction)^{79,81–83} in nature. Spatial variables may help predict outward vectors from pre-activity to activity to post activity stages in a crime script (e.g., movement into and out of forest). Understanding how spatial predictors influence the journey at each crime stage allows park managers to move away from reactive policing to predictive and situational interventions^{68,72,84}. For example pre-activity stage interventions could focus on access control on specific route intersections (e.g., physical barriers, camera traps, acoustic sensors) to intercept the journey before poaching occurs. Activity stage interventions could focus on targeted guardianship to increase risk of apprehension during the act of poaching. Post-activity interventions could involve setting up more strategic checkpoints with sniffer dogs or monitoring regional highways connecting protected habitats with transit points³⁰.

Study site. In general, national park-level studies are excellent for ecology but tactically isolated for crime prevention. Global studies rely on generalizations about distance and trade yet obscure internal logistics. Conducting research at a national-level provides scientific opportunities to reveal how illegal wildlife trade scales up, aligns with sovereign state power, and provides a blueprint for how pangolins move between protected spaces, rural communities and urban or border exit points. In general, the knowledge base lacks empirical understanding about how illicit goods such as wildlife scale up from the micro to macro scale. This research empirically explored pangolin trade in Gabon at the meso scale. The Republic of Gabon has high ecological integrity, a closed and high-contrast transport network, sufficient internal sourcing, and capacity for global export. Gabon is an upper-middle income Western and Central African country home to 2.53 million people in 2024⁸⁵; Gabon's urban population is 92%, making it one of the most urbanized countries in the world and in 2023, 94% of the population had access to electricity. The nation's economy is driven mainly by oil, wood, and manganese. Gabon is part of the Congo Basin Forest, the 2nd largest primary tropical rainforest in the world. Traversed by the equator and bordered by Equatorial Guinea, Cameroon, and Republic of the Congo, Gabon has 885 km of Atlantic coastline and 267, 667 km² of surface area⁸⁶. The country has maintained low levels of deforestation rates, at around 0.6 percent per year in 2000-2020; this rate is low compared to regional peers, which averaged three times higher during the same period⁸⁷. Gabon has three topographical zones: coastal alluvial plain, inland plateau and low elevation mountain zones. Extensive wetlands sustain forest and coastal ecosystems. The Ogooué River traverses over 800 km of the country before reaching the Atlantic Ocean, crossing habitats for approximately 198 species of mammals, 680 species of birds, 98 species of amphibians, 160 species of reptiles, 184 species of freshwater fish and 10,000 species of plants⁸⁶. Gabon is home to many species of conservation concern, including African forest elephants, sea turtles, great apes, and three of the four African pangolin species⁸⁸. Multiple laws provide protection for pangolins in Gabon, including the Forest Code (Law 016/01), which

established the legal framework for wildlife protection, and Decree No. 0040bis/PR/MEFPECCHF of 2 November 2023 which updated the classification of wild animal species, distinguishing between fully (e.g., giant pangolins) and partially protected species (e.g., white-bellied and black-bellied pangolins). Hunter-gatherer history from the Ogooué region dates to the Early Stone Age, shifting as agriculturalist Bantu tribes immigrated to the area 5,000 years ago⁸⁹. Europeans arrived in 1472, seeking timber, ivory, and slaves; Gabon was part of French Congo and then French Equatorial Africa until achieving reindependence in 1960⁸⁶. Gabon's current national park system was established by Presidential decree in 2002 and the National Parks Agency created in 2007, although the country has a very long history of protected area management⁹⁰. Today, Gabon has 13 national parks, a Presidential reserve, faunal reserve and arboretum, several hunting domains and cultural sites, 2 World Heritage sites, 9 Ramsar Wetlands, and 22 marine protected areas^{91,92}. Gabon's legal framework does not allow displacement of people from protected areas, and provides for community exploitation zones⁹⁰.

Primary data collection

Participatory mapping. This research used participatory crime risk mapping with projective questioning. Participatory mapping (PM) is a data collection method that merges local knowledge with geographic data. The approach involves creating maps based on local knowledge that represents resources and social realities rather than relying on official datasets or satellite imagery⁹³. PM is highly collaborative and typically follows a structured progression from community engagement to data creation^{72,94}. The method is extremely flexible and can accommodate high and low tech mapping tools as well as variation in participants' map literacy⁸⁴; participants with any knowledge origin—local, indigenous, expert⁹⁵— can engage in ground mapping using sticks and stones to draw on direct, paper mapping using markers and transparent overlays, or digital mapping using handheld or open-source digital tools^{93,96}. Advantages of PM include its ability to capture local ecological knowledge that other data collection methods cannot; giving marginalized or indigenous voices a visual data-based voice^{26,94}; and having high accuracy for local use. Drawbacks of the method include its resource intensiveness and requiring significant time and trust-building with participants. Dominant voices can hijack the PM process if subgroups are not properly constructed; and mapping rare resources (e.g., endangered wildlife) or risks (e.g., poaching) can expose participants to exploitation if results are improperly shared^{72,97}. Participatory risk mapping (PRM) is a type of PM that focuses specifically on identifying hazards (i.e., physical threats), vulnerabilities (i.e., elements exposed to hazards) and capacities (i.e., risk-related resources)^{98,99}. PRM can be used to map where crime risks exist, where vulnerabilities are created, and where spaces are ripe for crime-generating activities based on their lived experience in and perceptions of the community^{100,101}. PRM is well suited for projective questioning, where participants are asked to map their risk knowledge onto an object (e.g., map); this technique provides safety and anonymity for participants by shifting the focus of questions from what happened to you to what happens here^{26,102,103}. Projective questioning during PRM extracts highly accurate, localized crime data while keeping participants safe and engaged^{72,104}.

We conducted identical PRM activities with 123 participants in 20 village communities surrounding 6 National Parks and Libreville, in December 2025 and April 2026. The six parks were Akanda, Ivindo, Lopé, Minkébé, Monts de Cristal, and Moukalaba-Doudou National Parks; village names are withheld in compliance with research ethics approval requirements. The PRM script is available in French online¹⁰⁵. Participants were informed of the study's purpose and how their contributions would be used and provided informed consent through voluntary participation in the mapping workshops. The Florida International University Office of Research Integrity reviewed and approved as Exempt the research study for the use of human subjects (IRB-23-0500 IRB, Date: 10/24/23, TOPAZ Reference #: 113333). The research was approved and authorized by Gabon's Centre National de la Recherche Scientifique et Technologique, (AR029/25/MESRSIT/CENAREST/CG/CST/CSAR).

Primary data processing. Rather than using crime scripting to analyze data *principaliter*, we applied the framework to guide data processing in support of downstream spatial analysis. We scanned all paper maps using a roller scanner, saved files in both JPEG and PDF formats, and uploaded files into QGIS for georeferencing. We georeferenced maps using the existing coordinates on each map and four control points. We applied linear transformation and a nearest-neighbor resampling to all points and referenced each map to WGS 1984 global coordinate system. We compiled, reprojected (EPSG 5223), cleaned, and rasterized the data from the two separate sampling periods in ArcGISPro and QGIS 3.40.5Bratislava¹⁰⁶.

Three stages of crime scripting. All points mapped by participants during PM activities were first coded as being associated with one of four, mutually-exclusive universal crime script stages. We then combined preparation and pre-activity points into a single stage to reduce theoretical bloating and academic over-complication and better reflect operational realities on the ground for managers, law enforcement authorities, and community members tasked with reducing risks associated with threats to pangolin conservation¹⁰⁷. Points classified as pre-activity (i.e., Stage I) included locations for planning to exchange pangolins and their products and obtaining supplies for transporting pangolins and their products. Points classified as activity (i.e., Stage II) included locations for pangolin poaching. Points classified as post-activity (i.e., Stage III) included locations for storage of pangolins and their products, locations for exchanging pangolins and their products, and transportation nodes.

The participatory mapping dataset. The final dataset had 2,161 points; 1,086 points from December 2025 mapped by community members and experts and 1,075 from April 2026 mapped by community members. Data about the 6 behaviors of interest across the 3 crime stages from both stakeholder groups and collection dates were pooled for analysis (**Table 1**).

Table 1. The total dataset from participatory risk mapping activities December 2025 and April 2026 with 123 participants in 20 villages living adjacent to 6 National Parks plus experts in Libreville included 2,161 discrete points labeled with 6 behaviors across 3 pangolin-related crime stages.

Crime stage	Behavior of Interest	Points mapped (n)
Stage I (Pre-activity)	Planning for exchange	484
	Supplies obtained	218
Stage II (Activity)	Pangolins poached	763
Stage III (Post-activity)	Products stored	251
	Products exchanged	349
	Transportation nodes	96

527

528 *Secondary data collection*

529 *Spatial layers.* Geopolitical and conservation-related shapefiles containing points, lines, and
530 polygons were obtained via open access sources including Humanitarian Data Exchange²²,
531 World Database on Protected and Conserved Areas¹⁰⁸, and United Nations Office for the
532 Coordination of Humanitarian Affairs. Secondary data was either used to create the
533 basemap used across all objectives or used in objective 3 as a spatial predictor (**Table S1**).

534 *Data analysis*

535 *Objective 1.* The total number of points annotated by each group for the 3 crime stages was
536 Stage I/Pre-activity (n = 702; experts = 205, community members = 497), Stage II/Activity
537 (n = 763; experts = 209, community members = 554), and Stage III/Post-activity (n = 696;
538 expert = 140, community member = 556). Intensity maps of each crime stage for both
539 groups were constructed using Kernel Density Estimation (KDE) with grid cell size of 2km x
540 2km and a 11.98-km bandwidth for both community and experts, executed using the
541 Rstudio library spatstat with the function *density.ppp*¹⁰⁹.

542 We used Gaussian kernels with a common bandwidth of 11.98 km, calculated as the mean
543 of the three stage-specific bandwidths selected using *bw.ppl*¹⁰⁹ and mapped hotspots for the
544 two groups and 3 crime stages. To include annotated points that lay offshore as well as to
545 reduce the sudden artificial loss of intensity near the study-area boundary the Gabon
546 country shapefile layer was extended by 15km. Moreover, Diggle edge correction was
547 applied (diggle = True) to account for edge effects. Because more community members
548 participated in the mapping exercise than experts, the two groups contributed unequal

numbers of mapped locations. This difference in sample size could have inflated the intensity map of community members and erroneously create false positives. It is not the case that community members believed there were higher incidences of crime than experts, but rather the group had a larger sample size. We normalized each group's KDE by its total number of points ($1/n$) using the "weights" argument in the RStudio *density.ppp*(weights =)¹⁰⁹ function. Resulting surfaces represented the relative spatial distribution of crime-stage locations perceived by each group rather than reflecting differences in participation or reporting volume. Weighting each point ensured intensity maps had a volume integral equal to 1, and points normalized to respective sample sizes.

A difference surface was computed as expert KDE minus community member KDE, where positive values indicated relatively greater expert density and negative values indicated relatively greater community member density. To compute the spatial distribution of the regions of significant difference, we constructed a sampling distribution of the difference in intensity between groups at each grid-cell of approximate size of 2 km x 2 km via Monte Carlo simulation ($n = 999$). At each iteration, the group label was randomly shuffled and intensity computed followed by a difference raster. This enabled consideration of the distribution of the difference in intensity at each 2km grid cell had the labeling of groups been inconsequential. The result was null hypothesis distribution. We used a two-sided test of independent statistical significance for each grid cell. Cells with $p < 0.05$ were classified as having significantly higher community member density or significantly higher expert density; all remaining cells were classified as not significant. The resulting stage-specific significance maps were exported as GeoPackage rasters.

Objective 2. We constructed crime intensity maps for each of the 3 crime stages through KDE using the *density.ppp*¹⁰⁹ function. We did not subdivide intensity maps according to stakeholder groups as discussed in Objective 1, nor did we weight data and normalize the KDE surface. We calculated cell-by-cell difference surfaces for Stage II minus Stage I and Stage III minus Stage II. Positive values (red zones in **Fig. S1**) identified areas with higher mapped-location intensity in later stages. Negative values (blue zones in **Fig. S1**) identified areas with higher intensity in the earlier stages. The centroid for each of those regions was located through local minima and local maxima searches and included in analysis if the absolute value of its magnitude was > 1.5 times the SD of the difference raster surface. Centroids which were less than 6km apart (i.e., 3 pixels) were considered a single hotspot point. Both crime intensity difference rasters had a mean of 0, resulting in 37 hotspots for the latter crime stage and 28 for the former crime stage for KDE2 - KDE1 (**Fig. S1, a**) and 29 hotspots for the latter crime stage and 37 for the former crime stage for KDE3 - KDE2 (**Fig. S1, b**). We considered adjacent areas of change to indicate potential spatial transition(s) between crime stages. For example, considering KDE2 - KDE1 (**Fig. S1, a**), adjacent areas of relatively higher Stage I/Pre-activity intensity (i.e., hotspots of Stage I) and relatively higher Stage II/Activity intensity (i.e., hotspots of Stage II) indicated a spatial transition. Transitions between stages were represented with a gradient vector. Based on the journey to crime principle that when presented with different options an offender will choose the path of least resistance/closest path⁶⁶, we considered the three closest hotspots of the next crime stage to every hotspot of a former crime stage as a possible next destination and

constructed a gradient vector between them. We computed the gradient vector value as the change in KDE pixel values between the hotspots of consecutive crime stages and divided it by the distance between them.

Directionality for each gradient was categorized according to the 4 main cardinal and 4 intercardinal directions, however vectors and directionality measures do not represent observed origin-destination trajectories.

Objective 3. We used a set of 9 spatial predictor variables based on the literature and access to high-quality, open access datasets (**Fig. S2**). All spatial covariates were processed to have the same coordinate reference system (WGS 84 / Gabon Transverse Mercator; EPSG:5223), grid-cell size, extent, and grid origin. Continuous covariates, including leaf area index (LAI), elevation, and population density, were resampled to 2km grid cell size using bilinear interpolation. LAI and population rasters did not fully cover the western portion of the buffered analysis extent over the Atlantic Ocean; consecutive NoData cells occurring westward of the first valid data cell in each raster row were assigned a value of zero. This padding was applied only to the westward extension and did not replace missing values elsewhere. We assessed pairwise Spearman rank correlations among candidate covariates. We used $|\rho\rho| \geq 0.70$ as a screening threshold for potentially problematic collinearity¹¹⁰. No pair exceeded this threshold; the largest absolute Spearman correlation was $|\rho\rho| = 0.608$, between distance to major cities and distance to major roads. Therefore, all nine covariates were retained. Because Gabon is so forested and there is an absence of pangolin population density distribution data for the country, we assumed uniform population density across the country for pangolins. This assumption allows us to model the association of the participatory mapped points to the 9 covariates listed without the pangolin population density, as it is assumed to be uniform everywhere.

The participatory annotated point maps were first converted into binary occurrence maps. Each grid-cell was coded to have a value of 1 when it contained at least one participatory-mapped annotation for that stage and zero otherwise. Less than 1% of the grid cell contained more than one participatory-mapped point. The nine covariates were z-score standardized and entered as linear terms into the spatial binomial generalized additive model (GAM). A two-dimensional smooth of grid-cell coordinates accounted for broadscale spatial patterns not captured by the covariates. For cross-validation, our ROI was divided into 80-km spatial blocks which are then grouped into five folds. The blocks kept cells within each block together, reducing the splitting of nearby cells between training and testing; no spatial buffer was applied between folds. The GAM then produces a probability map in which each grid cell is assigned the estimated probability of containing at least one participatory-mapped annotation for the relevant crime stage.

The GAM showed a modest ability to generalize to held-out areas of Gabon: it ranked grid cells containing participatory-mapped annotations above cells without annotations better than would be expected by random spatial ordering. Spatial out-of-fold PR-AUC was 0.0177 for Stage I (prevalence = 0.0090), 0.0274 for Stage II (prevalence = 0.0100), and 0.0174 for Stage III (prevalence = 0.0090), indicating discrimination above random ranking for each stage. Brier scores were close to the prevalence-only baseline, indicating limited probability

calibration. Out-of-fold residuals retained positive spatial autocorrelation (Moran's I = 0.0136, 0.0674, and 0.0189 for Stages I–III, respectively), indicating that some spatial structure remained unexplained. The final model was then fitted to all grid cells to estimate covariate associations.

Code Availability

R and Python codes are publicly available at <https://github.com/eldayitbarek/PangolinSpatialCrimeScripting-Gabon>

Data availability

Participatory mapping data are not openly available due to human subjects protection restrictions. All other data is publicly available as referenced in the main manuscript or supplementary information document.

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950 **Author contributions**

951
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953 investigation, methodology, project administration, writing-original draft; BM investigation,
954 methodology, writing-original draft; CM conceptualization, funding acquisition,
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958 writing-original draft; HM investigation, methodology, writing-original draft; BD
959 conceptualization and writing; MS conceptualization and writing; MG conceptualization,
960 funding acquisition, investigation, methodology, resources, supervision, writing-original
961 draft. All authors read and approved the final version.

963 **Competing interests**

964
965 The authors declare no known competing interests.

Spatial crime scripting and meso-level analyses of illegal pangolin trade

Supplementary Information

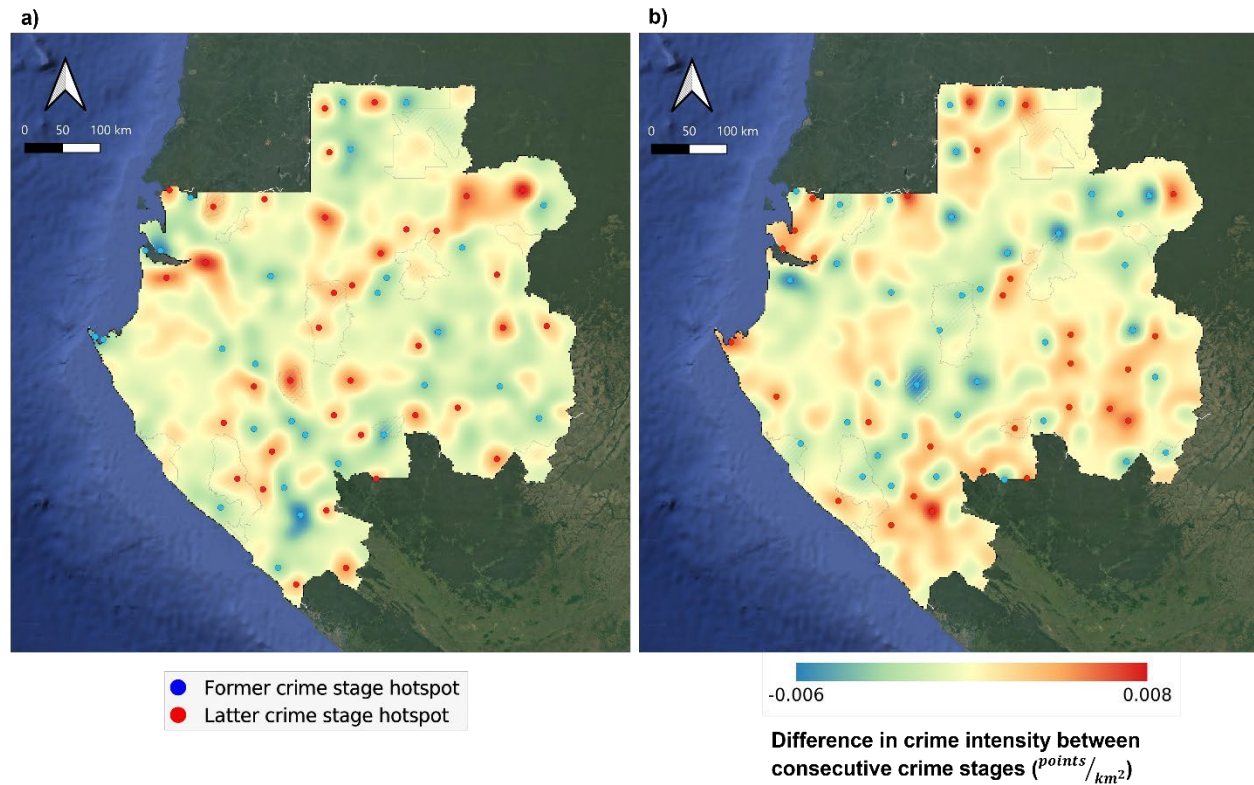


Fig. S1: Based on participatory mapping about pangolin poaching in Gabon, we computed the difference in crime intensity between consecutive crime stages, where positive/increased intensity is depicted in red as a hotspot and negative/decreased intensity is depicted in blue as a coldspot. Differences were calculated by subtracting kernel density estimates of Stage I/Pre-activity from Stage II/Activity (panel a) and Stage II/Activity from Stage III/Post-activity (panel b).

Table S1. Nine spatial variables were included in prediction analysis, based on the extant literature and being publicly available.

Predictor Variable	Source	Motivation and processing (if applicable)
Distance to forest concessions ^{1,2}	ANPN ³	Help understand if access to locations where pangolins (in forest concessions) are more likely to live correlates with poaching behavior

Distance to international borders ⁴	UNOCHA ⁵	Help understand if annotated points are driven by international trade or for local consumption
Distance to major cities ^{1,6}	CBI ⁷	Help understand if distance to human settlement(s) correlates with poaching behavior
Distance to major roads ^{8, 2}	HOSMT ⁹	Help understand if road access correlates with poaching behavior; filtered in trunk roads (i.e., major high-capacity highway), primary, and secondary roads from total roads network; computed raster with 2km spatial resolution whose pixel's value is distance to nearest major road
Distance to protected areas ^{1, 2}	UNEP-WCMC ¹⁰	Help understand if access to locations where pangolins (in protected areas) are more likely to live correlates with poaching behavior; filtered out the marine protected areas out of the analysis as pangolins are terrestrial animals
Distance to waterways ^{1,2}	HOSMT ¹¹	Help understand if waterways as a transportation route correlate with poaching behavior; computed raster layer with pixel value = nearest distance to waterway; hunters use boats on waterways to access and transport pangolin products
Elevation ²	NASA SRTM ¹²	Help understand if topography correlates with poaching behavior; Global 1 arc-second / ~30 m
Leaf Area Index (LAI) ^{2,13}	NASA MODIS ¹⁴	Help understand if density of forest as measured by LAI influences poaching behavior; 4-day, 500 m, Collection 6.1
Population density ^{8,4}	World Pop Population Data 2020 ¹⁵	Help understand if highly populated areas attract or repel poaching behavior; 100 m resolution

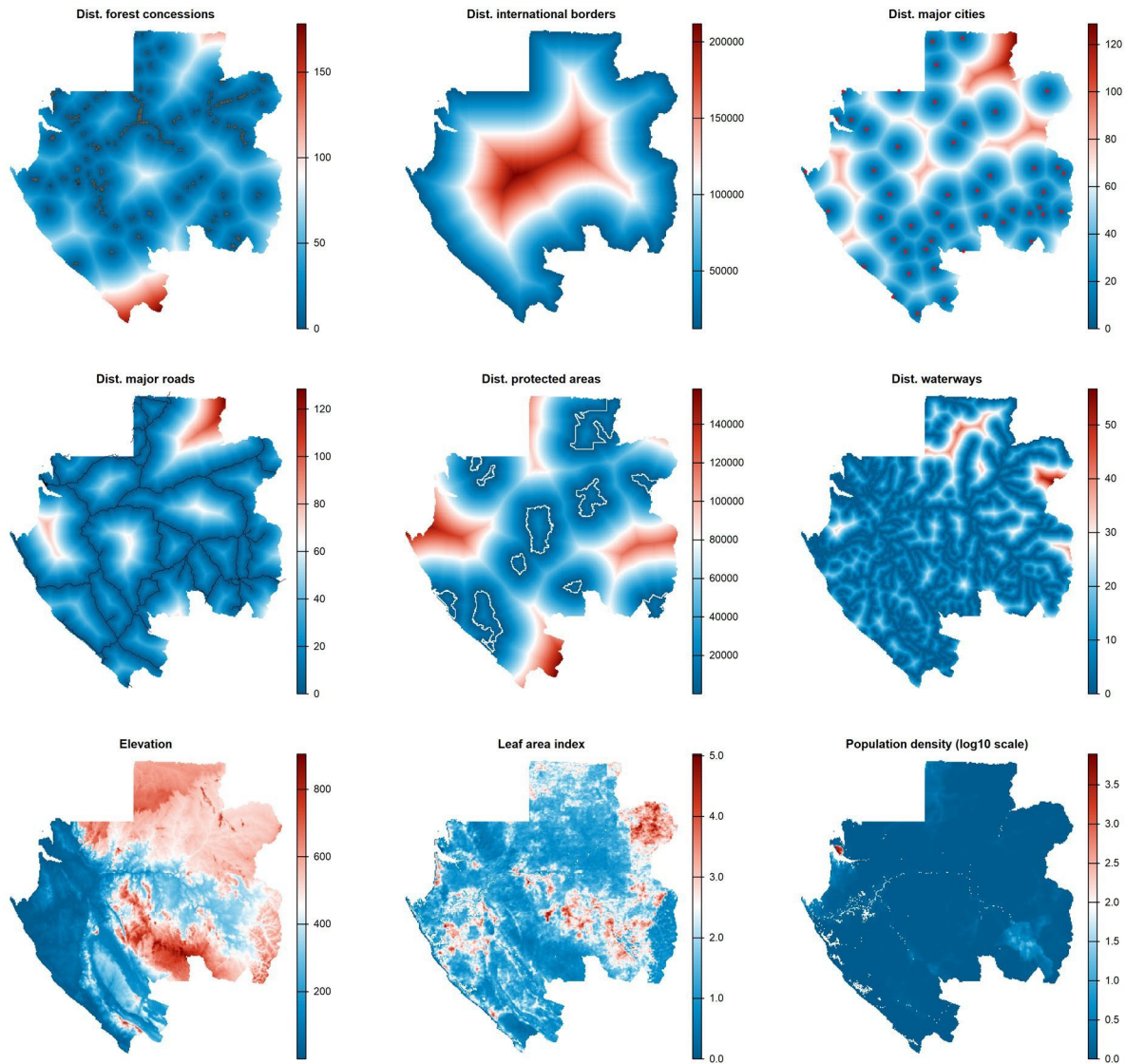


Fig. S2. Individual maps of covariates used to analyze spatial predictors of pangolin poaching across three crime stages. Distance to protected areas is the distance to the boundary of the protected area from inside or outside the boundary. The distance to forest concession is the distance to forest concession boundaries whose polygons can be seen overlain on the ‘Dist. forest concession’ map.

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