

Wildlife crime moves in spatial pulses

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Abstract: The geography of crime is often treated as a static backdrop to criminal activity, yet where crime occurs may change as a crime unfolds. We show that wildlife crime has a dynamic geography that expands, contracts, and becomes anchored in persistent places. Combining crime scripting with participatory mapping, we examined pangolin hunting and scale trade across Cameroon and Gabon and found that both forms of wildlife crime moved in spatial pulses rather than progressing steadily through a linear supply chain. Hunting was highly spatially elastic, expanding and contracting markedly across crime stages, whereas trade was comparatively spatially anchored. Despite these differences, persistent hot spots for hunting and trade converged geographically, with persistent hunting hotspots largely nested within persistent trade hotspots. The geography of illicit supply chains is therefore shaped not only by movement between places but also by spatial inertia and stage-specific changes in the spatial footprint of activity. Spatializing crime scripts reveals that geography is not a fixed backdrop to illicit activity but a dimension that changes as crime unfolds and provides a framework for understanding wildlife crime as a dynamic spatial process.

Keywords: conservation criminology, crimes affecting the environment, crime script analysis, illegal wildlife trade, pangolin, participatory mapping

Crimes affecting the environment (CAE), like illegal wildlife trade (IWT), are often grouped alongside other serious crimes, including drug and gun trafficking, because of shared infrastructure, business models, and threats to security (1–4). The United Nations Protocol on Transnational Organized Crime, originally designed to prevent and combat crimes *excluding* CAE, has codified requirements to include scientific evidence in policymaking and law enforcement protocols (5). Proposals for an additional Protocol call for CAE to be *included* and similarly evidenced (4). CAE have features that do not exist for other illicit trades; they are woven directly into legal community livelihoods, dynamic landscapes, biological limits, and changing ecosystems (6, 7). Modern geography of crime models built for urban crimes, and conservation biology-based models focused on species exploitation, have been unable to wholly address and incorporate these unique features (7–9). Analytical blind spots remain about the dynamics of global CAE phenomena (9–11), inhibiting translation of evidence into policymaking and insights for illicit trade writ large. In particular, the extant literature lacks detail about how CAE operate in informal, customary, and unmonitored spaces because top-down data collection about the issue consistently ignores community spaces (12, 13), involves multi-stage procedural activities that transition across spatial scales (2, 14), and can be over reliant on official law enforcement data that easily conflates institutional absence with crime absence (15, 16). These knowledge gaps inspired this research, the

contributions of which emerge from bridging historically disconnected methods: crime scripting, geospatial crime mapping, and participatory research methods, across countries and crime types.

Traditional quantitative spatial data about crime, such as law enforcement seizure records, show where authorities both sought and identified criminal activity (16–19). This offers a measure of enforcement capacity, not necessarily true crime distribution. For many CAE, official data are lacking completely, cannot be shared or scaled beyond a protected area, or restricted to species-specific information peripheral to crime analysis (20–23). When incomplete and/or biased datasets exist, data derived via participatory mapping may be a suitable source of information for understanding or modeling crime, including CAE. Participatory mapping data can be derived via collaborative processes where stakeholders like community members share spatial knowledge and experiences. Such data offer insights that official customs or law enforcement data can miss, including insight about informal spaces and places that authorities often fail to detect or ignore. Participatory mapping data can complement law enforcement data when they are available (18). While engaging with the lived realities of local communities to provide visibility into otherwise hidden and unmonitored spaces associated with CAE is a key benefit of participatory mapping, it is not without biases (24, 25). The method is inherently social and political, and participants may have strategic biases, including overreporting illegal activities committed by outsiders or rival communities while under-reporting local infractions (26). Participants may deliberately map sensitive areas inaccurately to protect local livelihoods or community reputation. Ultimately, mapped points represent perceived risk, localized power dynamics, and community vulnerabilities (27, 28). Replication can help minimize threats to reliability; while replication does not confirm locations where crime happens, it does illustrate where people report it consistently. Participatory mapping data represent community-reported and perceived crime activity, not verified crime events or their magnitude.

Traditional crime mapping identifies static hot spots or seizure points (29) and spatially disaggregated models can provide insights about crime operations (17). Yet CAE are not traditional in that they rarely maintain a consistent spatial pattern from start to finish (30, 31), can exhibit temporal variation, and are constrained by biological limits (7). Using crime scripting to detail the procedural stages of crime commission can organize criminogenic information temporally, improve understanding, and help prevent or disrupt crime at any stage (e.g., preparation, pre-activity, commission, post-activity)(32–35). Spatializing each ordinal temporal stage can demonstrate how and where different locations are used over time, turning static data into temporally elastic maps able to account for the dynamic nature of conservation crime (36). Conducting participatory crime mapping and spatializing crime script analyses at a national scale introduces a community-derived dimension that changes how data are interpreted across scales (36). When spatial data come from local stakeholders and their lived realities, it enables unique bottom-up insights (37, 38). Participatory mapping at a meso level produces data that easily align with the sovereignty of the enforcement jurisdictions, legal authorities, and criminal justice systems.

We examined two CAE – pangolin hunting (39–41) and scale trade (42–44) – in two countries, Cameroon and Gabon. Pangolins embody CAE in their serial depletion and steep value gradients (7). Globally, humans have hunted and traded pangolins for 40,000 years for meat consumption and traditional medicine (41). Today, the Convention on International Trade in Endangered Species of Fauna and Flora (CITES) has banned international commercial trade of the four African pangolin species, yet it continues (43–45). Scales remain the most illegally traded pangolin body part globally (46), although species-specific preferences differ between scale exports versus local meat consumption. A systematic review found illegal hunting and trade were the most documented threats to pangolin conservation in Africa (40), a finding supported by community-based crime scripting in Cameroon (34). We set three

objectives: (1) use participatory methods to spatialize crime stages for pangolin hunting and scale trade; (2) explore activity point hot spot distribution and change within and across crime stages; and (3) examine spatiotemporal development patterns across crime types and countries.

Results

Spatializing universal crime stages using participatory methods. Cluster analysis on the combined participatory mapping dataset including both countries and crime types (**Fig. 1**) generated evidence of clear spatial patterning and geographic concentration within each of the four crime stages (**Table 1**). Because of Gabon-specific study design (see Supplementary Material), while the raw participatory mapping data from Gabon were processed such that the two Gabon crime type datasets share the same points the four crime stage labels did not have identical assignment across both crime types. Hunting post-activity had the largest median cluster size – the measure most robust against spatial outliers – ($M = 14$) and hunting preparation had the smallest ($M = 9$). Median 1 SD spatial area for hunting expanded from 770 km² at preparation to 1,212 km² at pre-activity, contracted sharply to 221 km² at commission, and partially recovered to 578 km² at post-activity. Trade showed a different profile: median area expanded from 253 km² at preparation to 711 km² at pre-activity, remained stable at commission (717 km²), and contracted modestly to 660 km² at post-activity.

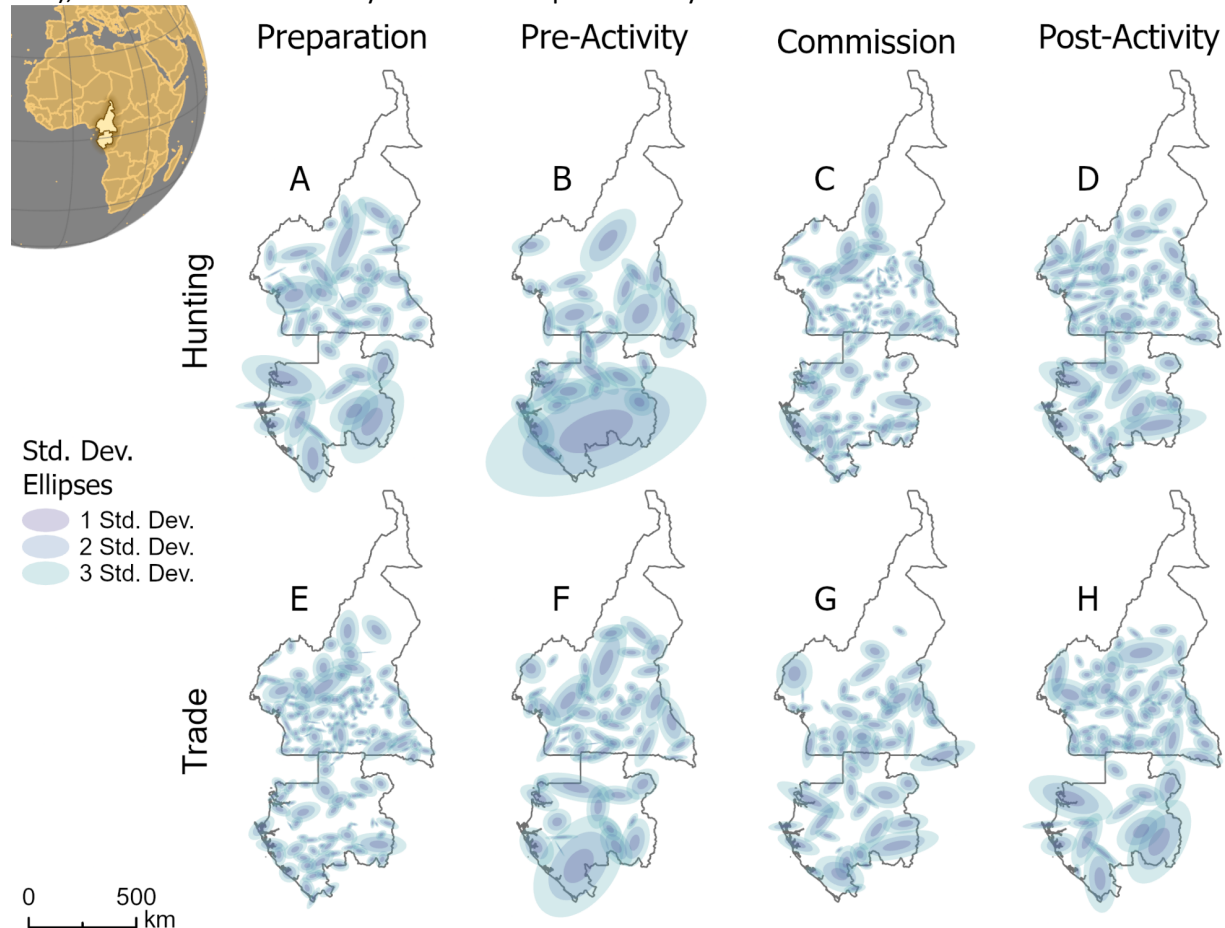


Fig. 1. Standard deviational ellipses (1, 2, and 3 SD) for clusters ($n = 681$) of pangolin hunting (A–D) and scale trade (E–H) activity in Cameroon and Gabon across four crime stages. Hunting showed a non-monotonic pattern in median 1 SD ellipse area: expansion from preparation to pre-activity (A to B),

sharp contraction at commission (C), and partial recovery at post-activity (D). Trade showed a different profile: expansion from preparation to pre-activity (E to F), stability at commission (G), and modest contraction at post-activity (H). Median areas are reported in **Table 1**. Cameroon consistently exhibited a multi-nodal network of ellipses, consistent with denser road networks and multiple international land borders. Gabon exhibited coastal-centric skewing, consistent with vast interior forests bounded by coastal urban centers.

Table 1. Cluster analysis of nationally pooled participatory mapping data focused on pangolin hunting and pangolin scale trade in Cameroon and Gabon. For hunting, contraction patterns (i.e., nodes) emerged at pre-activity to commission by mean ellipse area and median ellipse area; for trade, contraction nodes can be seen at the pre-activity to commission stage by mean ellipse area and commission to post-activity by median ellipse area. Some mean areas are double or triple the median areas, indicating the presence of extreme "mega-clusters" that heavily skewed the average; these clusters were likely influenced by Gabon's heavily forested landscape.

Crime	Stage	Sample Size	Clusters	Cluster Size Histogram	Cluster Points	Noise Points	Signal:Noise Ratio	Mean Cluster Size	Median Cluster Size	Modal Cluster Size	Mean 1st StDev Area Area (km ²)	Mean 2nd StDev Area Area (km ²)	Mean 3rd StDev Area Area (km ²)	Median 1st StDev Area Area (km ²)	Median 2nd StDev Area Area (km ²)	Median 3rd StDev Area Area (km ²)
Hunting	Preparation	692	55		557	135	4.13	10.13	9	5	1,329	5,314	11,957	770	3,081	6,933
	Pre-Activity	750	36		597	153	3.90	16.58	10	9	2,846	11,383	25,612	1,212	4,848	10,908
	Commission	2,478	140		1,814	664	2.73	12.96	10	6	405	1,619	3,642	221	886	1,993
	Post-Activity	1,885	93		1,553	332	4.68	16.70	14	7	754	3,017	6,788	578	2,314	5,206
Trade	Preparation	3,390	166		2,525	865	2.92	15.21	12	5	374	1,496	3,366	253	1,011	2,275
	Pre-Activity	915	59		763	152	5.02	12.93	10	5	1,322	5,288	11,898	711	2,843	6,397
	Commission	948	60		746	202	3.69	12.43	11	6	998	3,991	8,979	717	2,869	6,456
	Post-Activity	1,471	72		1,187	284	4.18	16.49	13	5	1,074	4,297	9,667	660	2,641	5,943

Exploring crime activity distribution and change within and across crime stages. Using optimized hot spot analysis on participatory mapping data for both countries and crime types, we identified that the single largest spatial change in the dataset occurred during the transition from pangolin trade preparation to trade pre-activity, with ~65% of active hot spot area (92,180 km²) transitioning from hot to not significant (**Fig. 2**). Comparing the spatial persistence of hot spots (i.e., hot to hot) over transitions between crime stages (i.e., preparation to pre-activity, pre-activity to commission, commission to post activity) revealed differences in structural longevity. For pangolin trade, hot to hot area transitions were somewhat spatially stable, increasing by only 5.85% (48,933 km² to 51,794 km²) from preparation to pre-activity and pre-activity to commission and then 23.34% (51,794 km² to 63,881 km²) from pre-activity to commission and commission to post activity. In contrast, pangolin hunting hot to hot transitions were more spatially dramatic, increasing 25.16% (33,790 km² to 42,293 km²) from preparation to pre-activity and pre-activity to commission and then 57.99% (42,293 km² to 66,819 km²) from pre-activity to commission and commission to post activity. Emerging hot spots (i.e., not significant to hot) increased 85.66% (42,528 km² to 78,958 km²) during the transition from hunting pre-activity to commission across both countries. In Cameroon, hot spots were more persistent and structured than in Gabon, where hot spots were more ephemeral and unstructured. Changes in net area complement insights about proportional volatility in stage transitions. Net area change (i.e., not significant to hot, hot to not significant) signaled three structural behaviors. First, hunting hot spot net area expanded between the pre-activity and commission stages, moving from 82,399 km² to 126,557 km², meaning that activities supporting the physical harvest of pangolins expanded by 44,158 km² (**Fig. S5**), indicating 53.6% growth in the perceived geography of hunting activity. Second, trade hot spot net area collapsed as trade moved from preparation to pre-activity; total hot spot territory decreased 50.8% from 145,446 km² to 71,506 km² (**Fig. S5**). Spatially, this loss was concentrated in central and eastern Cameroon, while persistent hot spots (i.e., hot to hot) were retained primarily in southern Cameroon and a smaller

number of Gabonese sites (**Fig. S6, D**). Third, net area was essentially unchanged from trade commission to post-activity (-0.5%) (**Fig. S5**), but this masked substantial spatial turnover, with ~27,000 km² lost and ~27,000 km² gained. At this stage, spatial equilibrium was reached; the total spatial footprint did not expand or contract, despite changes in the locations of the hot spot areas.

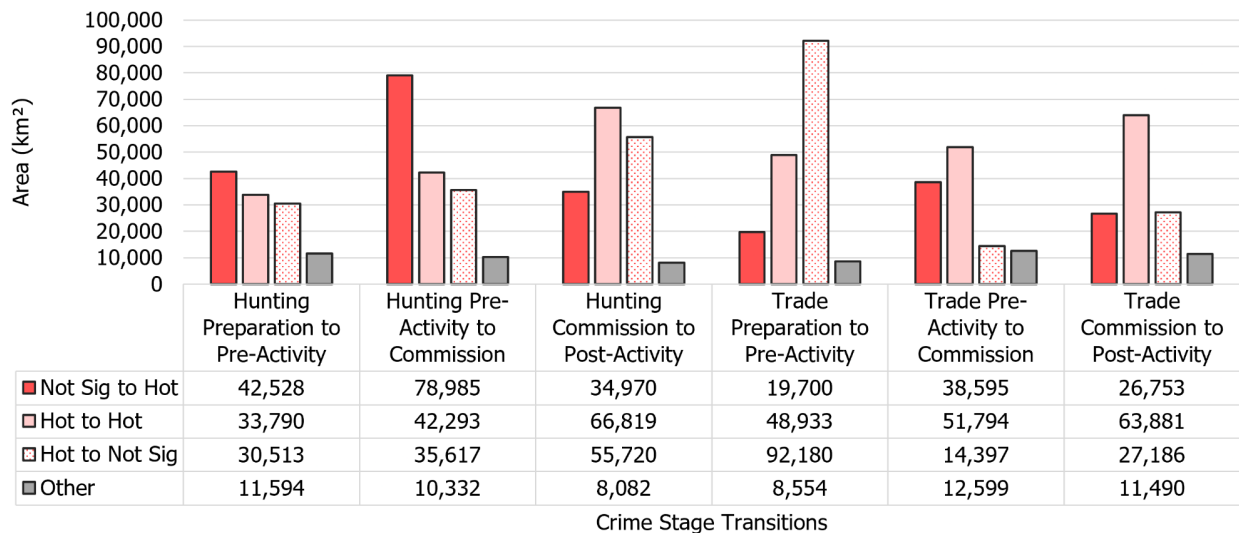


Fig. 2. Area by hot spot comparison class across four crime stages for pangolin hunting and pangolin scale trade in Cameroon and Gabon. Area values reveal the physical expansion or contraction of each crime type by stage across an international landscape. Hunting illustrated a contraction from commission to post-activity by hot spot area and trade illustrated a contraction from preparation to pre-activity by hot spot area. Comparison classes were based on transitions between initial analysis-cell classification of “not sig” (i.e., not significant) and “hot” (i.e., significant at 90% confidence level or above). The overwhelming majority of comparison cells were classified as “not sig to not sig.” Those area counts are not included in the graph because they render the y-axis unreadable. Cells classified as “other” were significant, but inconsistent in directionality (see Supplemental Material for additional information about the “other” class).

Examine spatiotemporal patterns common across time types and countries. The total spatiotemporal footprint of the combined crime types and stages – hunting or trade across all four crime stages in both countries – was 209,450km², or approximately the size of Belarus (207,600 km²) (**Fig. 3, B**). The total intersecting footprint of hunting and trade across all four crime stages in both countries was smaller at 177,431 km² (approximately the size of Uruguay at 176,215 km²). The union of both crime types and their respective crime stages revealed granular high-frequency zones across both countries (**Fig. 3, B**, dark purple/pink clusters). These zones represent persistent places where multiple crime-related activities co-occurred significantly across seven or eight crime stages, comprising 4.5% (33,258 km²) of the two-country analysis area. Even though the footprints were nearly identical at 194,642 km² for hunting (**Fig. 3, A**) and 192,256 km² for trade) (**Fig. 3, C**), the persistence profiles of each crime type showed that trade was more spatially anchored than hunting. Hunting declined steadily across frequency classes whereas trade dropped once and then flattened. Persistence cores were few, small, and concentrated in southern Cameroon (**Fig. 3, B**). The persistent core of hunting sat largely inside the persistent core of trade, but not the other way around. Approximately 47% of trade’s persistent core (16,659 of 35,186 km²) was persistent for hunting (i.e., significance frequency of 4 for individual crime

and 8 for crime union). Thus ~ 18,527 km² was anchored across all four trade stages but not across all four hunting stages. Union analysis results indicated that the two crime types differed in how persistently places are used, not in which places were used; the stage-by-stage use of the same territory differed according to crime type. The footprint exclusive to one crime type was small: ~17,200 km² for hunting and ~14,800 km² for trade; these areas signal places to explore crime-specific mechanisms.

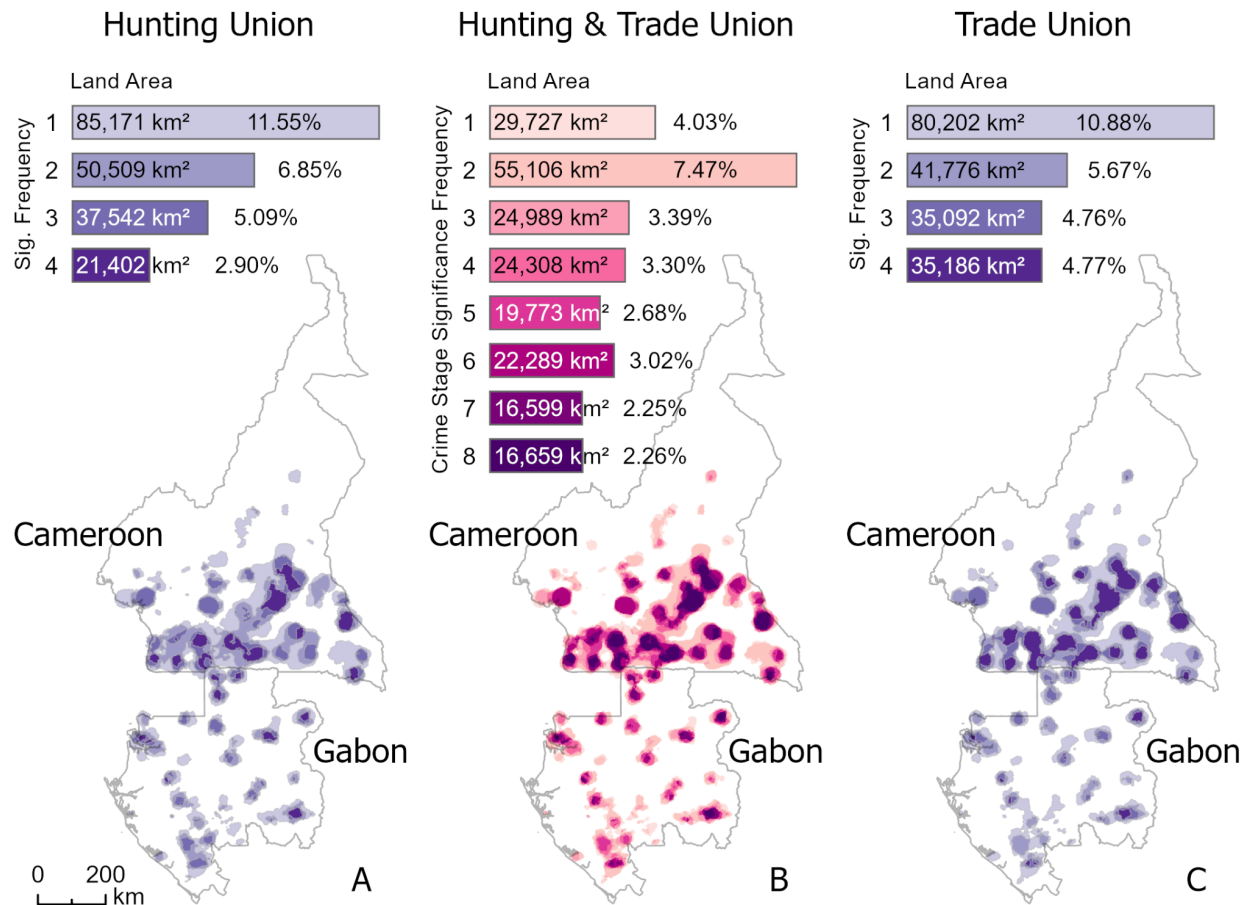


Fig. 3. Cell values show the frequency at which they were consistently classified as significant hot spots at confidence levels $\geq 90\%$ for each stage across the multi-stage crime analyses (four for hunting and four for trade). A frequency count > 2 does not denote both crime types, but rather combinations of stage significance within a single crime (A, C) or across both crimes (B).

Discussion

CAE like IWT operate as dynamic systems that expand, contract, and anchor themselves within natural ecosystems. By bridging environmental criminology, geospatial science and conservation, and using primary spatial data generated through participatory methods, this research provides a novel orientation for how CAE behave in physical space. Methodologically, this research delivers a blueprint for studying the behavior of illegal economies, particularly those operating in regions where official state data are absent, biased, and/or suppressed.

The first noteworthy finding emerges from spatially articulating crime stages across two crime types and two countries. Integrating geography into crime scripting is not new. Conventional script analysis (47)

conceptualizes crime sequentially as a procedural flow of stages characterized by distinctive actions (e.g., $S1 \rightarrow S2 \rightarrow S3 \rightarrow S4$), while spatial analysis is treated as a separate layer of complementary information. This research spatialized the crime script concept, revealing a range of emergent, temporal insights, such as where spatial crime stage collapse can occur in the CAE context (e.g., **Fig. 2**). These emergent characteristics became evident only *after* spatiotemporal articulation. For example, the multi-stage pattern observed for trade suggests that the illegal (pangolin) supply chain does not necessarily follow a linear progression (e.g., funnel), but rather can exhibit distinct phases of spatial concentration and dispersal between origin and destination. A single late contraction (e.g., port of exit) would have indicated trade remained diffuse until export. Trade consolidated at earlier stages, with the number of clusters falling from 166 to 59, and hot spot area declining by roughly half, between preparation and pre-activity. Union analysis results indicated 85.58% of the significant crime activity footprint exhibited multi-stage hot spot overlap across both crimes (**Fig. 3, B**) - stage progression did not require geographic displacement. Results signal how specific landscape spaces acted as crime settings that simultaneously satisfied the requirements for all of the stages of the crime script at once. Spatially articulated crime stages use spatial footprint area (A) = f (Crime Stage S) to demonstrate that the stages of CAE are not merely a sequence of actions but a continuous transformation of geographic space or pattern of life. Because of spatiotemporal articulation, results support the notion that the space of CAE can expand and contract across stages and that nodes can be temporary convergence filters compressing crime activity space rather than acting as fixed environmental features.

Practically, spatial patterns signal where CAE-related intervention opportunities can differ by crime type and stage. For hunting, spatial extent per cluster contracted sharply at commission (median 1 SD area: 1,212 to 221 km²), but the number of clusters rose (36 to 140) (**Table 1**), indicating fragmentation into many small, localized sites rather than convergence on a single chokepoint. Though interdiction at this stage would require coverage of many dispersed locations, preventing crime here is the only point at which the ecological and conservation impacts are mitigated. For trade, the number of clusters fell from 166 at preparation to 59 at pre-activity, and hot spot area declined by roughly half, indicating spatial consolidation into fewer areas, even as the per-cluster footprint widened (median 1 SD area: 253 to 711 km²) (**Table 1**). This transition space can serve as a candidate for concentrated intervention. Median trade footprint then remained stable through commission and contracted modestly at post-activity, with no further consolidation. Rather than designing separate interventions for individual crime stages, stakeholders could prioritize areas of high stage overlap (**Fig. 3, B**), such as the dense hot spots along the Cameroon side of the Cameroon-Gabon border. This location may provide unique opportunities for joint, binational task forces along shared transit corridors. These interpretations would ideally be tested against seizure or patrol data.

Hot spot change analysis results revealed CAE-associated illicit supply chains can demonstrate behavioral pulses governed by spatial inelasticity and inertia rather than moving continuously in a linear fashion toward a single or monocentric hub before dispersing. This living geography matters because it helps justify replacing static supply chain diagrams for CAE with dynamic and system-level frameworks governing how networks expand, contract, and stabilize across international landscapes. The idea of spatial pulses offers a conceptual shift away from static, point-based hot spots and silos toward thinking of CAE as a dynamic system. For example, a CAE with a highly structured repeatable pulse indicates an entrenched network, whereas an erratic and shifting pulse suggests opportunistic and decentralized actors. Phases of spatial pulses follow a logical sequence, so changes in one phase predict changes in the next; by considering the temporal difference between expansion and contraction phases, enforcement agencies and their partners can shift from reactive post-seizure investigations to predictive, intelligence led interdictions.

262
263 Practically, preventing hunting or trade during an expansion/diffusion phase requires massive resources
264 relative to returns. Paradoxically, most CAE funding and effort is directed at the extremes of the pulse
265 because that is where the most significant ecological consequences exist, which are also the spatially
266 expansive diffusion spaces (7, 9), making intervention resource intensive with low immediate returns.
267 For a range of reasons, CAE authorities also continue to work mostly in silos; park authorities operate
268 where a pulse is diffused (e.g., protected areas), and customs operate where the pulse is corridor-bound
269 (e.g., border crossings)(48, 49).
270

271 A third noteworthy point is that this research suggests dissolving disciplinary dichotomies to pursue
272 evidence that informs action. In conservation biology, poaching is often treated as ecologically driven
273 (i.e., constrained by forest cover), while trafficking is treated as market driven (i.e., constrained by
274 infrastructure) (19, 50). CAE are often considered spatially separate and divided into distinct operational
275 zones depending on the decision-making objective (e.g., conservation, law enforcement). Results
276 suggest the existence of spatial anchoring and convergence, showing that in some cases, hunting can be
277 embedded within trade. By demonstrating spatial anchoring, results refute single-discipline studies
278 employing an ecology versus economics dichotomy segregating CAE like IWT into ecological drivers
279 where animals live versus economic drivers where markets sit (7, 51–54). Results expand the crime
280 generator concept in the context of CAE (55, 56), showing that hunting preparation locations are not
281 merely passive crime attractors (i.e., places poachers go) but also function as active commercial crime
282 generators that draw illegal trade infrastructure into natural ecosystems. Replicating research with
283 other species or CAE would help crystallize these relationships, because unlike other species involved in
284 IWT (e.g., rhinoceroses for their horns), pangolin scales in trade are a byproduct of meat from hunting,
285 creating a distinct form of embeddedness.
286

287 This research spatialized two interconnected crime types showing that the geography of CAE does not
288 have to be a fixed backdrop against which a script unfolds, but a dimension that can change with each
289 stage. For pangolin hunting and trade in Cameroon and Gabon, this approach helped identify stage-
290 place relationships and their patterns, signaling where they contract into bottlenecks and where they
291 persist as multi-stage crime generators, offering decision-makers a way to target specific stages and
292 places rather than treating every stage of a script as equally actionable. Findings draw on two countries
293 and two forms of IWT, using data that reflect what communities perceive, experience, and report rather
294 than a documented record of crime events. The stage-level patterns and persistent nodes observed here
295 should be treated as evidence from this case, not as a generalizable law for illegal wildlife trade. The
296 clearest test of the approach's reach is replication: applying spatialized crime scripts to other species
297 and CAE types would show whether stage-level geographic structure is a general feature of CAE supply
298 chains or a property of this system. Proposals to explicitly include CAE in a revised UN Protocol on
299 Transnational Organized Crime call for exactly this kind of evidence (5); spatialized crime scripts,
300 generated from data that communities themselves hold, offer one way to meet that call in places where
301 official records are absent, biased, or suppressed. Even with that open question, treating a crime script
302 as a spatial object that transforms stage by stage, rather than a flowchart with geography added as an
303 afterthought, is a method that extends beyond pangolins, beyond Central Africa, to any CAE where
304 communities hold knowledge that official records do not. Even if official records exist, community-held
305 knowledge adds value for understanding the stage-resolved structure where CAE persist and move.
306
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Supplementary Material

Methods and Materials

Universal crime scripting

Crime scripting is an established tool from crime science, derived from cognitive psychology and situational crime prevention, that breaks down the commission of an offense into a step-by-step sequence, modeling crime as a sequence of decisions, actions, and logistical prerequisites across time (47, 57). Universal crime scripting uses a standardized four-stage procedural (i.e., temporal) model that can be applied across crime types, geographic locations, or actor networks, and has been widely applied in crimes affecting the environment (CAE) such as illegal wildlife trade (34, 58). Although crime scripting can be customized for specific scenarios, the universal crime script categorizes illicit behaviors into four stages: gathering resources (*Preparation*), moving into position (*Pre-Activity*), executing the illegal act (*Commission*), and processing, transporting, or laundering goods (*Post-Activity*). This method enables direct comparative analysis across crime contexts, acts as a foundation for spatial mapping, and provides a structural blueprint for decision-making (34, 35). Delineating the procedural (i.e., temporal) sequence of CAE advances understanding of the crime commission process beyond static event sites like a seizure point or poaching location to an extended behavioral continuum by breaking a crime down into distinct chronological or temporal steps. This chronological categorization enables interventions to target specific behavioral decisions in sequence rather than focusing solely on late-stage or illegal-only acts such as poaching or scale trade. Scripting stages also help uncover offender decision-making logic, procedural dependencies, and logistical requirements across time and space. Community-based crime scripting for pangolin trade in Cameroon underscored the utility of focusing intervention on early and late stages of the crime commission process (34).

Rather than maintaining a rigid or fixed geographic boundary, the spatial characteristics of crime are dynamic in shape, size, and density, and may disregard geographic boundaries (59, 60). Spatializing crime stages transforms static crime maps into dynamic systems that reveal how crimes like CAE expand, contract, and shift across landscapes as they transition from raw natural resource extraction to market consolidation. Spatializing crime stages produces otherwise undetectable signals about the living geography of CAE; for example, the early and late crime stages can be compared for spatial elasticity (i.e., shifting fluidly across landscapes) or inertia (i.e., anchoring to fixed locations such as border crossings). In practice, this insight helps identify areas to avoid implementing low-yield expansion interdictions (60–62). Stationing static checkpoints during high-elasticity expansion stages yields low returns because opportunistic offenders easily adapt and bypass fixed posts (63).

Mapping crime stages exposes multi-stage overlaps and contraction nodes by attaching spatial dimensions such as geographic coordinates, directional ellipses and density hot spots to each chronological step of the script. Participatory mapping generates spatial data that helps replace incomplete or biased official seizure data (16–19) which may conflate an absence of police presence with an absence of crime (16–19) with community-driven spatial knowledge that includes early-stage activities that authorities can miss (36, 64, 65). Practically, this helps enable interventionists like law enforcement agencies to target high-yield, multi-stage convergence zones rather than wasting resources during spatial expansions. It also helps enable conservation authorities to shift from reactive post-seizure operations to predictive intelligence-led interdictions that target spatial contraction bottlenecks. Importantly, a trait of our participatory mapping methodology is that it contributed insights about perceived and reported crime geography, not crime magnitude. This method can help capture

information that is often invisible to enforcement records about where activities occur. This may be viewed as a central strength of the approach, but it also means that what is measured is the footprint of what communities know and are willing to report, which can be shaped by who participated, their relationship(s) to hunting and trade networks, and the risks of disclosure or reputational damage. Results provide evidence of where crime activity is concentrated in community knowledge and experience. Spatial and stage-level patterns should be interpreted accordingly.

Study site and context

Two conservation crimes in two countries. This research considered two conservation crimes (hunting and trade) in two countries (Cameroon and Gabon) for a comparative multi-case study design (66). This design is appropriate when underlying independent variables (e.g., place, time) are not manipulated and participants and crime data (e.g., poaching) cannot be randomly assigned to countries. This analytical approach is associated with higher external (i.e., generalizability) than internal validity (i.e., causality) and is useful for describing real-world contexts and mapping cross-national phenomena (66).

Pangolin scale trade and pangolin hunting (i.e., poaching) are closely related but different forms of conservation crimes. They differ in criminogenic drivers and motivations, commodity processing, actors and networks involved, incompatibility of intervention strategies, market drivers and distribution, and end users (33, 51, 63, 67, 68). We therefore considered the two to be distinct forms of conservation crime to avoid masking these criminogenic variations. Pangolin scale trade deals with a single processed product: the keratin scales, which are removed, dried, and usually aggregated into bulk shipments to Southeast Asia via cargo ships. These scales are durable, have relatively high economic value, and are typically used for traditional medicine (e.g., Traditional Asian Medicine, Traditional African Medicine). The harms associated with pangolin scale trade are overwhelmingly social, although ecological impacts are clear (34). Pangolin hunting involves the whole animal, which is moved live or freshly killed for meat consumption. Pangolin meat is perishable, and trade can be domestic or international. The primary harms associated with pangolin hunting are ecological damage and local pangolin population decline, although cultural impacts are widespread. Pangolin scales are a byproduct of harvesting the meat and were historically discarded as trash (34).

Cameroon and Gabon share many ecological features and conservation-oriented legal frameworks but occupy different positions within IWT networks and conservation governance. Both nations lie within the Congo Basin and are home to White-bellied (*Phataginus tricuspis*), Black-bellied (*Phataginus tetradactyla*), and Giant (*Smutsia gigantea*) pangolins. Each country protects pangolins (i.e., Category A/Law No. 2024/008 in Cameroon, Class A/Law 016/01 in Gabon). Under national wildlife laws, it is illegal to hunt, capture, possess, or commercially trade pangolins or their parts without authorization (69). Drivers of local hunting (e.g., wildmeat demand) remain alongside traditional practices, and both countries recognize opportunities to improve enforcement of conservation laws (70). However, key differences exist: Cameroon is considered a consolidation and transit hub for pangolin scales in the global supply chain, while Gabon is less prominent in global maritime shipping but is a sourcing area for wildlife and wildlife products (3, 42, 70, 71). While Gabon is highly forested with lower overall connectivity and human population density concentrated in urban areas, Cameroon has a higher human population density, greater forest fragmentation, and shares a border with Nigeria, which is known as the world's largest pangolin export hub (3, 72–74). General organized crime penetration is considered high and syndicated in Cameroon versus low and localized in Gabon (3, 75). Finally, Cameroon's conservation governance and enforcement models are best characterized as public-private partnerships

involving strong civil society organizations, whereas Gabon has a strong state-led conservation infrastructure with heavily protected national park networks (69, 73, 76).

Data collection

Participatory mapping. The same core team of field researchers, working alongside local enumerators, implemented participatory mapping procedures that were as equivalent as possible in both countries, including the data collection instrument, basemap scale, community entry, and ethical standards. All fieldwork was conducted in French by native French speakers. Because random sampling or allocation of communities is rarely feasible in rural and remote settings, and can be culturally disruptive, we treated the two countries as a non-equivalent group comparison and held procedures constant to limit measurement differences between them (66, 77, 78). This group-level comparison helps expose and mitigate group-level strategic biases, retains high ecological and external validity, and reduces logistical burdens in challenging terrains (64, 79). Data collection instruments were created based on multiple scoping trips, traditional and conservation authority feedback and review, peer-reviewed literature, insights from team members, and previous crime script research (14, 33, 35, 36, 57). The Gabon data collection instrument was amended to be shorter than the Cameroon instrument based on the feedback of national conservation authorities about minimizing research fatigue among study participants. Sixteen participatory mapping exercises were conducted in Cameroon (July 2024-July 2025), with local community members (n = 190) and subject matter experts (n = 90) producing a total of 44 paper maps. Seven participatory mapping exercises were conducted in Gabon (December 2025-April 2026), with local community members (n = 104) and subject matter experts (n = 19) producing a total of 12 paper maps. All maps were scanned, digitized, cleaned, and audited before being uploaded into a GIS for processing and analysis (80). The Cameroon dataset and data collection instrument are publicly available along with additional dataset description, data collection details, and participant recruitment details (80). While the Gabon dataset cannot be shared or made public because of data sharing agreements, the data collection instrument for Gabon is available online (81). The Florida International University Office of Research Integrity reviewed and approved the research study as Exempt for the use of human subjects (IRB-23-0500 IRB, approved 24 October 2023, TOPAZ Reference #: 113333). In Cameroon, the research was approved and permitted by the Cameroon Ministry of Scientific Research and Innovation (Permit #s 000120, 000121, and 000124). In Gabon, the research was approved and authorized by the Centre National de la Recherche Scientifique et Technologique, (AR029/25/MESRSIT/CENAREST/CG/CST/CSAR).

Shapefiles. Country boundary shapefiles were retrieved from ArcGIS Living Atlas. Both country boundary layers provided a 2025 boundary with total population count (82, 83). Data were accessed in accordance with the Esri Master License Agreement with the University of Maryland, College Park.

Data preparation

Spatializing universal crime stages derived from participatory mapping. For each country, points associated with crime-relevant activities were sorted into subsets for each of the four universal crime stages: preparation, pre-activity, commission, or post-activity. The sorting process was completed twice, once for each crime type, with activity points appearing in a maximum of one crime stage subset per crime. Under this schema, a point could be assigned to both crime-type subsets. All researchers involved in data collection independently reviewed the assignments. In Cameroon, the final hunting dataset contained 3,760 points across 16 crime-relevant activities and the final trade dataset contained 4,679 points across 19 crime-relevant activities. In Gabon, the final hunting and trade datasets both contained 2,045 points across five crime-relevant activities (**Table S1**).

Data analysis and processing

We used ArcGIS Pro geoprocessing tools to achieve all research objectives following a systematic development workflow (**Fig. S1**). In line with our study design, we considered Cameroon and Gabon, as well as hunting and trade, as separate cases for comparison. However, we pooled data from both countries into a single analysis for Objective 1 to test for the emergence of trans-boundary clustering. To achieve Objectives 2 and 3, we kept country-level data independent, and then merged analysis results into a single map for visualization and interpretation (66), enabling the exploration of emergent properties associated with multi-case comparisons at a national scale for Objective 3.

Additional Text

Objective 1. Spatialize crime stages for pangolin hunting and pangolin scale trade. First, to evaluate the null hypothesis of random point distribution of activities in each crime stage subset, we used the *Average Nearest Neighbor geoprocessing tool* to generate the Average Nearest Neighbor ratio, z-score, and p-value for all subsets of pangolin crime activity points in both countries as a pooled dataset (84). Z-score values indicated <0.1% chance the clustering patterns were random for each of the eight crime stages (i.e., 4 hunting, 4 trade) (**Table S2**). We then used the self-adjusting *HDBSCAN algorithm* with the *Density-Based Clustering geoprocessing tool* to examine potential clusters at various levels, selecting for optimal stability, evaluating the mutual reachability distance between points, and constructing clusters based on the probability of cluster membership (**Fig. S2**) (85). This approach was appropriate because machine-learning algorithms are capable of efficiently identifying spatial clusters based on feature distribution and minimum cluster threshold. Results were used as inputs for the *Directional Distribution (Standard Deviation Ellipse [SDE]) geoprocessing tool*. SDE captures three spatial characteristics of a given cluster in the x-y plane: mean center, spread, and directional tendency (86). SDEs were calculated at one, two, and three standard deviations from mean center for all clusters identified by the Density-Based Clustering step, then merged. Results were produced iteratively for all four crime stages for both the hunting and trade crime types. To confirm that we were able to see emergent clusters that did not exist separately and check our work before advancing to our next objective, we explored cluster analysis results separately for Cameroon (**Table S3**) and Gabon (**Table S4**). Although this information was not part of the main analysis, we report it here to document the intermediate step.

Objective 2. Explore activity point hot spot distribution and change within and across crime stages. We evaluated the statistical significance of the distribution of each crime stage activity point subset across each country using the *Optimized Hot Spot Analysis tool* and the Getis-Ord G_i^* statistic. Lacking robust guidance in the extant literature on appropriate parameters, we selected the aggregation cell size empirically, using the *Optimized Hot Spot Analysis tool*. For candidate cell sizes, the larger of the Average Nearest Neighbor distance or Median Nearest Neighbor distance was doubled for each subset (87). A consistent, representative cell size was then chosen using consistently applied judgment to enable uniform analysis and comparison across all crime stages, crime types, and countries. The initial location of the hexagonal grid pair used for hot spot analysis – one each for Cameroon and Gabon, spatially aligned to facilitate merging – was arbitrarily positioned so that all bins intersected with a buffer around the national borders equal to twice the height of a single hex bin. However, arbitrary grid placement is still subject to the zonation effect of the Modifiable Areal Unit Problem (MAUP), wherein analysis results may be dependent on the specific subdivision of the analysis area (88). To mitigate spatial bias due to zonation, a set of 21 total unique analysis grid pairs were produced by applying a set of geometric translations of the original grid pairs while eliminating redundant patterns (**Fig. S3**). The *Optimized Hot*

Spot Analysis tool was run iteratively across each crime stage activity point subset for each of the 21 analysis grid pair positions. Within a given analysis run, hot spot analysis was conducted for each aggregated cell (89). Cells were evaluated as hot (high concentration) or cold (low concentration) for the intensity of clustering with confidence level based on the G_i^* statistic, equivalent to a z-score. Each respective, spatially aligned grid pair was then merged, using the G_i^* -based hot spot classification of greater magnitude in areas of overlap (i.e., along the shared border), to produce a set of 21 merged hot spot analyses spanning both countries for each crime stage. We used the *Union Geoprocessing tool* to calculate the spatial union of the 21 merged results for each crime stage separately, resulting in sets of triangular grids with each cell containing 21 confidence level determinations. Classification counts, proportions, and majority confidence-level classes (not significant; significant at confidence levels $\geq 90\%$) were then calculated for each crime stage union result for both crime types and mapped (**Fig. S4**). Comparing hot spot analysis results helped identify whether statistically significant spatial clustering occurred between successive crime stages. We used the *Hot Spot Analysis Comparison tool* across each pair of 21 respective analysis grid positions in successive crime stages. Comparison results were based on spatial fuzzy kappa, comparing observed similarity with expected similarity for independent results. Similarity was calculated from a decision matrix considering both a distance weight and similarity of the G_i^* -derived hot/cold spot confidence-level categories of coincident cells from the two input layers. Expected similarity was calculated in the same way as similarity, but using random cells instead of neighboring cells for neighborhood comparison. Cells were finally classified by hot/cold/not-significant transitions between the input crime stages based on the calculated fuzzy kappa value (90). Using the *Union geoprocessing tool*, the union was calculated for each set of 21 hot spot change analyses, and counts, proportions, and majority significance level transition classes (not significant to not significant; not significant to hot; hot to hot; hot to not significant; and other, denoting no majority change directionality) were calculated for each crime stage transition.

Objective 3. Examine spatiotemporal patterns common across crime types and countries. To create summary union layers, we used the *Union geoprocessing tool* to calculate the frequency of cell membership in a majority significant confidence level class ($\geq 90\%$) across all four universal crime stages for each crime separately, and for both crimes combined. Across each crime stage, each cell was classified with a binary value of 0 for each crime stage where the majority confidence level was not significant, and 1 for each stage where the majority confidence level was significant (at confidence levels $\geq 90\%$). These values, summed respectively for hunting, trade, and both in combination, yielded a comprehensive overview of crime stage frequency. Although these unions combined results derived from some activity points included in one subset each for both crimes, points represented simultaneous yet distinct crime stage and crime type pairings.

Table SM 1. Participatory mapping in Cameroon and Gabon generated points that were subset into one of four crime stages for each of two crime types (i.e., hunting, trade). Final point counts are not measures of crime frequency or magnitude, but rather lived experience and expertise about crime-related behaviors occurring during a given stage in a particular place.

	Illegal Hunting				Illegal Trade			
	Preparation	Pre-Activity	Commission	Post-Activity	Preparation	Pre-Activity	Commission	Post-Activity
Cameroon	474	266	1,735	1,285	2,163	664	599	1,253
Gabon	218	484	743	600	1,227	251	349	218

Table S2. Average Nearest Neighbor Ratio values, z-scores, and p-values derived from cluster analysis of crime activity points for pangolin hunting and trade in the Cameroon and Gabon pooled datasets across four crime stages. These results informed spatial pattern evaluation.

Crime	Stage	Average Nearest Neighbor Ratio	z-score
Hunting	Preparation	0.556	-22.329*
	Pre-Activity	0.624	-19.708*
	Commission	0.580	-39.975*
	Post-Activity	0.581	-34.820*
Trade	Preparation	0.587	-46.026*
	Pre-Activity	0.514	-28.119*
	Commission	0.512	-28.744*
	Post-Activity	0.571	-31.509*

* $p < 0.001$

Table S3. Output from cluster analysis of participatory mapping data focused on pangolin hunting and scale trade in Cameroon.

Crime	Stage	Sample Size	Clusters	Cluster Size Histogram	Cluster Points	Noise Points	Signal:Noise Ratio	Mean Cluster Size	Median Cluster Size	Modal Cluster Size	Mean 1st StDev Area Area (km ²)	Mean 2nd StDev Area Area (km ²)	Mean 3rd StDev Area Area (km ²)	Median 1st StDev Area Area (km ²)	Median 2nd StDev Area Area (km ²)	Median 3rd StDev Area Area (km ²)
Hunting	Preparation	474	40		401	73	5.49	10.03	9	5	911	3,646	8,203	740	2,961	6,662
	Pre-Activity	266	18		182	84	2.17	10.11	9	5	1,807	7,226	16,259	1,305	5,219	11,742
	Commission	1,735	95		1,298	437	2.97	13.66	11	5	322	1,287	2,897	142	568	1,278
	Post-Activity	1,285	63		1,066	219	4.87	16.92	15	7	604	2,414	5,432	563	2,251	5,065
Trade	Preparation	2,163	108		1,694	469	3.61	15.69	12.5	6	343	1,371	3,086	165	661	1,486
	Pre-Activity	664	43		572	92	6.22	13.30	10	10	917	3,667	8,251	679	2,718	6,115
	Commission	599	36		455	144	3.16	12.64	12	15	834	3,335	7,504	621	2,485	5,590
	Post-Activity	1,253	58		1,034	219	4.72	17.83	14.5	6	710	2,841	6,391	558	2,231	5,020

Table S4. Output from cluster analysis of participatory mapping data focused on pangolin hunting and scale trade in Gabon.

Crime	Stage	Sample Size	Clusters	Cluster Size Histogram	Cluster Points	Noise Points	Signal:Noise Ratio	Mean Cluster Size	Median Cluster Size	Modal Cluster Size	Mean 1st StDev Area Area (km ²)	Mean 2nd StDev Area Area (km ²)	Mean 3rd StDev Area Area (km ²)	Median 1st StDev Area Area (km ²)	Median 2nd StDev Area Area (km ²)	Median 3rd StDev Area Area (km ²)
Hunting	Preparation	218	14		174	44	3.95	12.43	10	5	3,280	13,119	29,517	2,035	8,142	18,319
	Pre-Activity	484	18		418	66	6.33	23.22	11.5	9	3,935	15,739	35,412	1,171	4,684	10,540
	Commission	743	45		518	225	2.30	11.51	10	8	584	2,334	5,253	398	1,592	3,582
	Post-Activity	600	30		490	110	4.45	16.33	14.5	9	1,075	4,299	9,672	704	2,815	6,333
Trade	Preparation	1,227	58		832	395	2.11	14.34	12	14	432	1,728	3,888	349	1,395	3,139
	Pre-Activity	251	16		203	48	4.23	12.69	9	8	2,800	11,201	25,202	1,749	6,995	15,738
	Commission	349	25		292	57	5.12	11.68	11	6	1,166	4,666	10,497	884	3,535	7,954
	Post-Activity	218	14		174	44	3.95	12.43	10	5	3,280	13,119	29,517	2,035	8,142	18,319

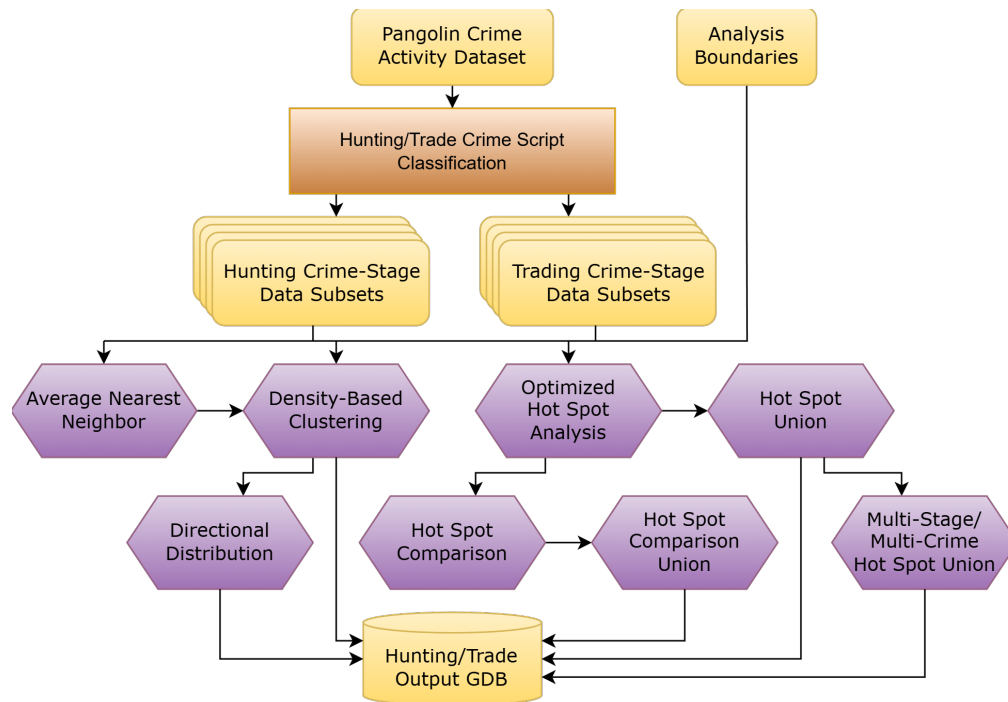


Fig. S1. The ArcGIS Pro development workflow and analysis pipeline used to achieve research objectives. Yellow rectangles denote datasets and subsets, the orange rectangle denotes dataset pre-processing, purple hexagons denote analyses, and the yellow cylinder denotes output as a geodatabase.

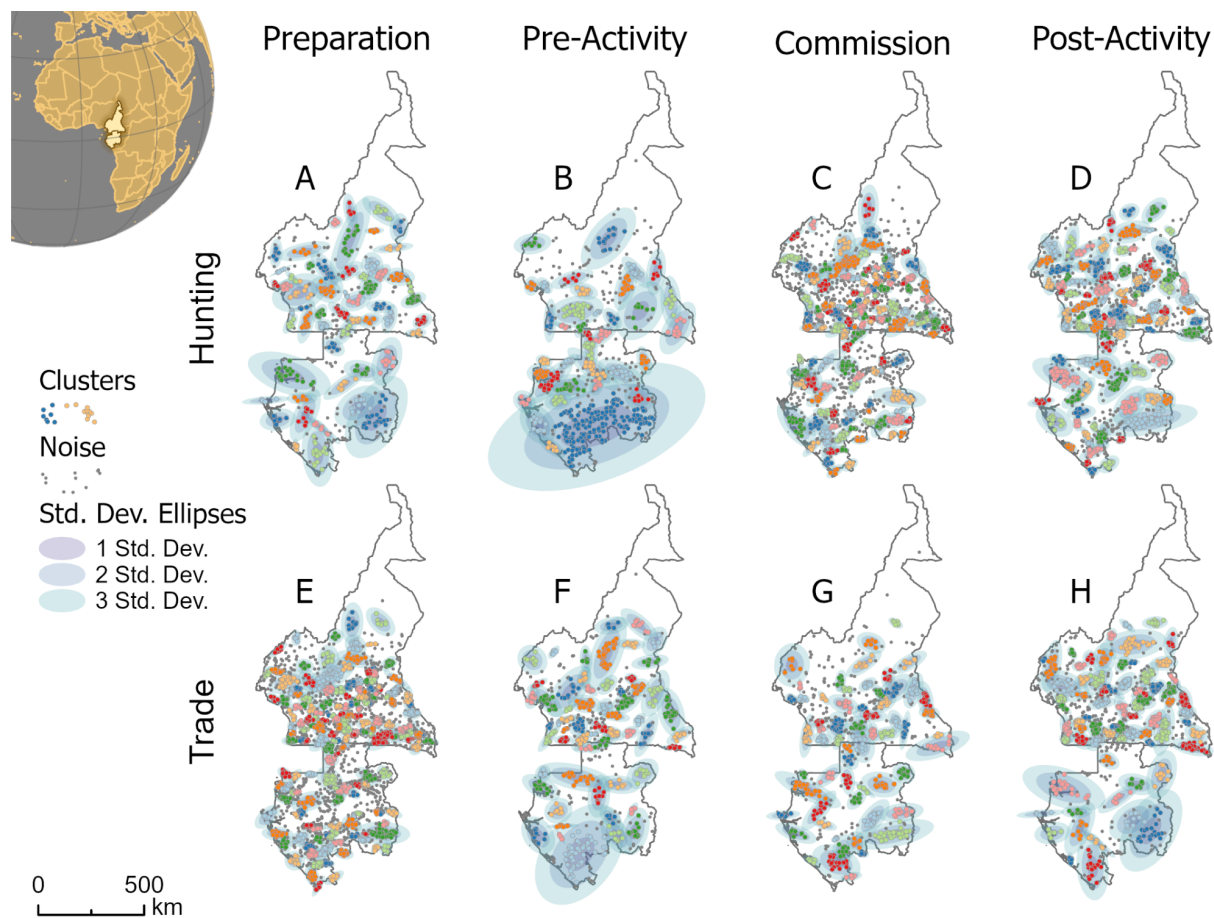


Fig. S2. The HDBSCAN algorithm identified clusters for each crime type and stage. This visualization includes clusters, noise (grey points), and standard deviational ellipses at one, two, and three standard deviations from cluster mean center.

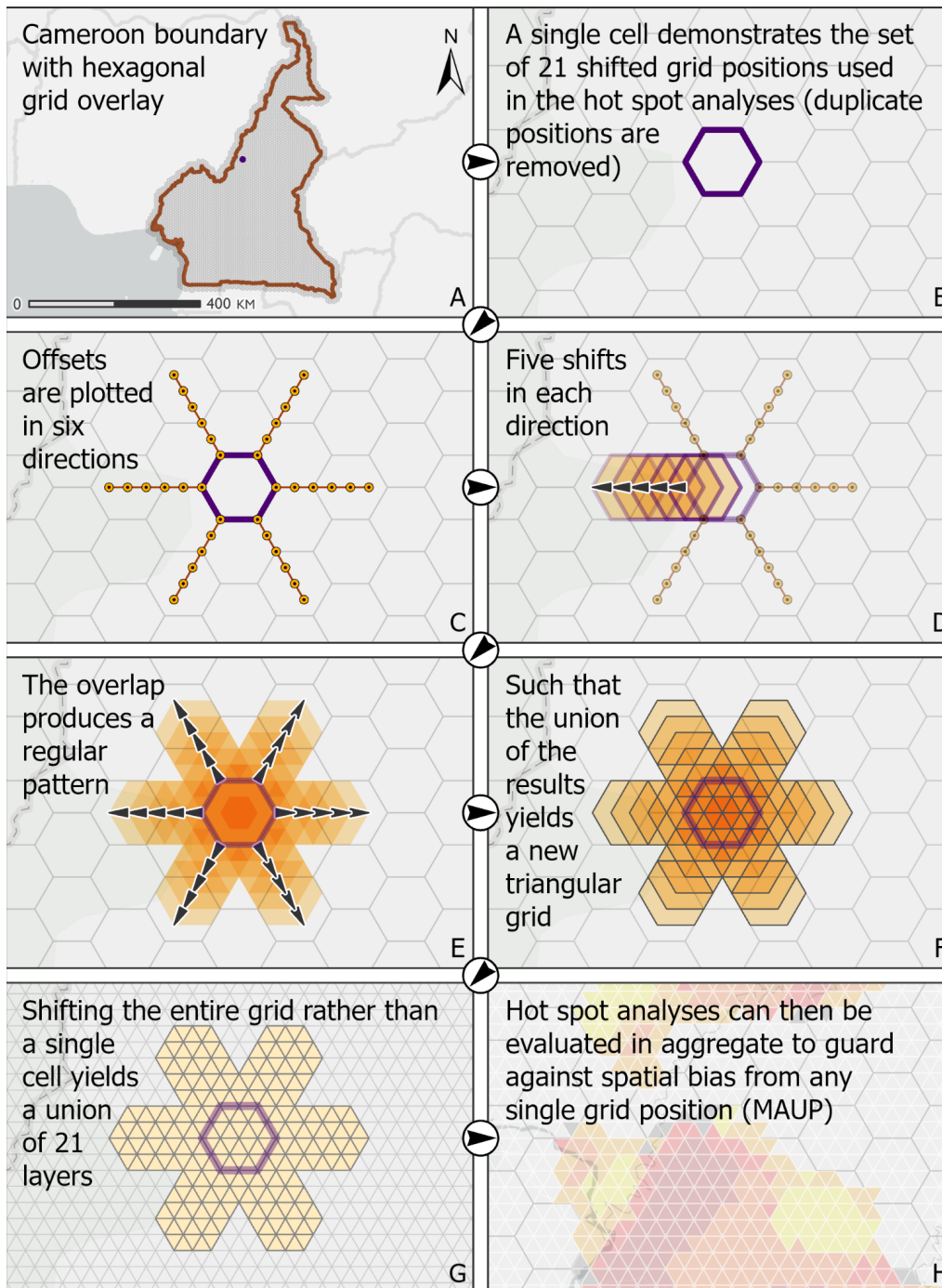


Fig. S3. A set of geometric translations was applied to the initial hot spot analysis grid to help mitigate spatial bias in analyses.

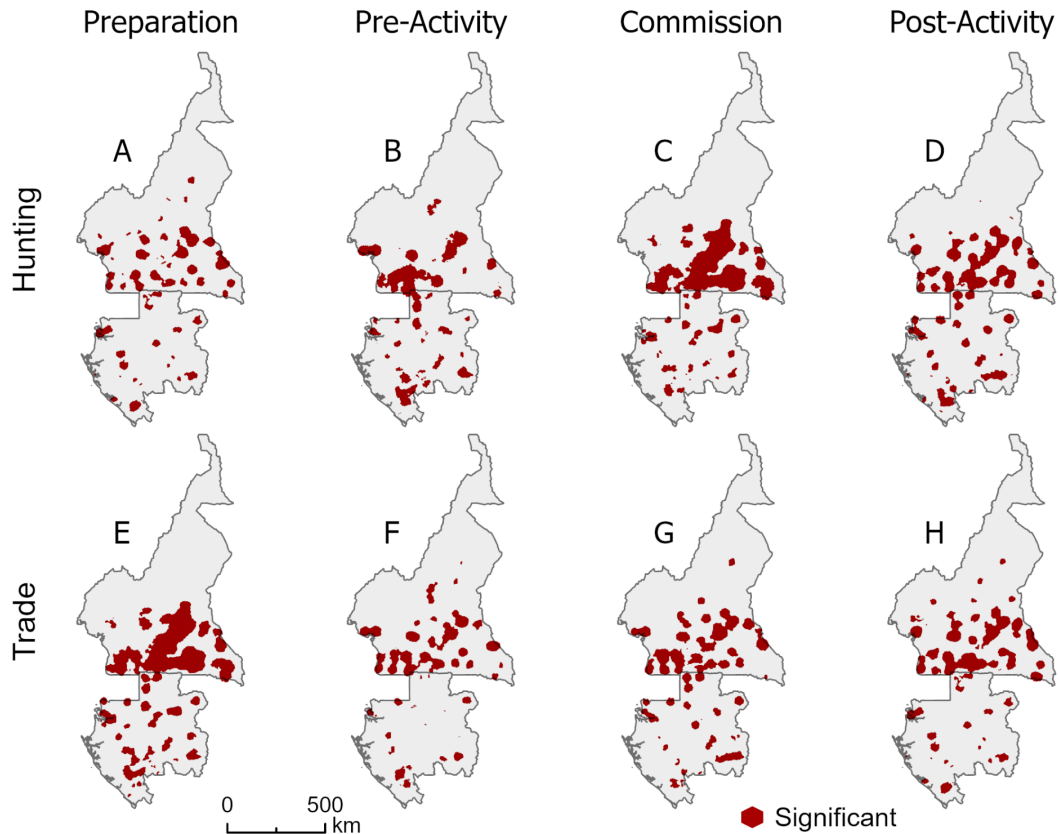


Fig. S4. Outputs of hot spot analysis with a simplified classification scheme of significant (red, cells with majority confidence levels $\geq 90\%$) and not significant (grey cells). Panels E and F show consolidation; trade at preparation has a large contiguous area running across central and eastern Cameroon and scattered patches in Gabon. At pre-activity, most of the large area is gone and what remains is smaller discrete hot spots. These results were used as inputs for multi-stage and multi-crime union geoprocessing analysis.

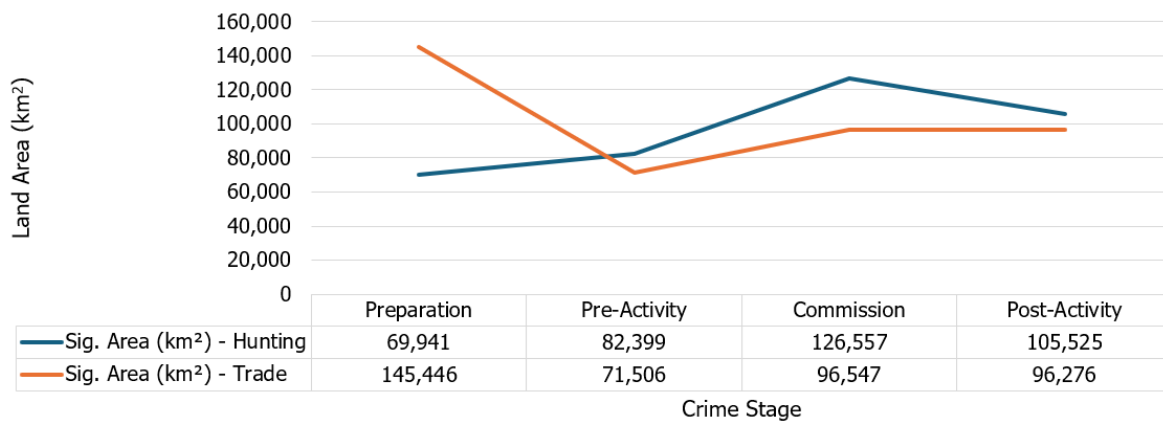


Fig. S5. The total significant land area, or footprint, of four crime stages and two crime types across both Cameroon and Gabon based on a majority significant confidence level class $\geq 90\%$.

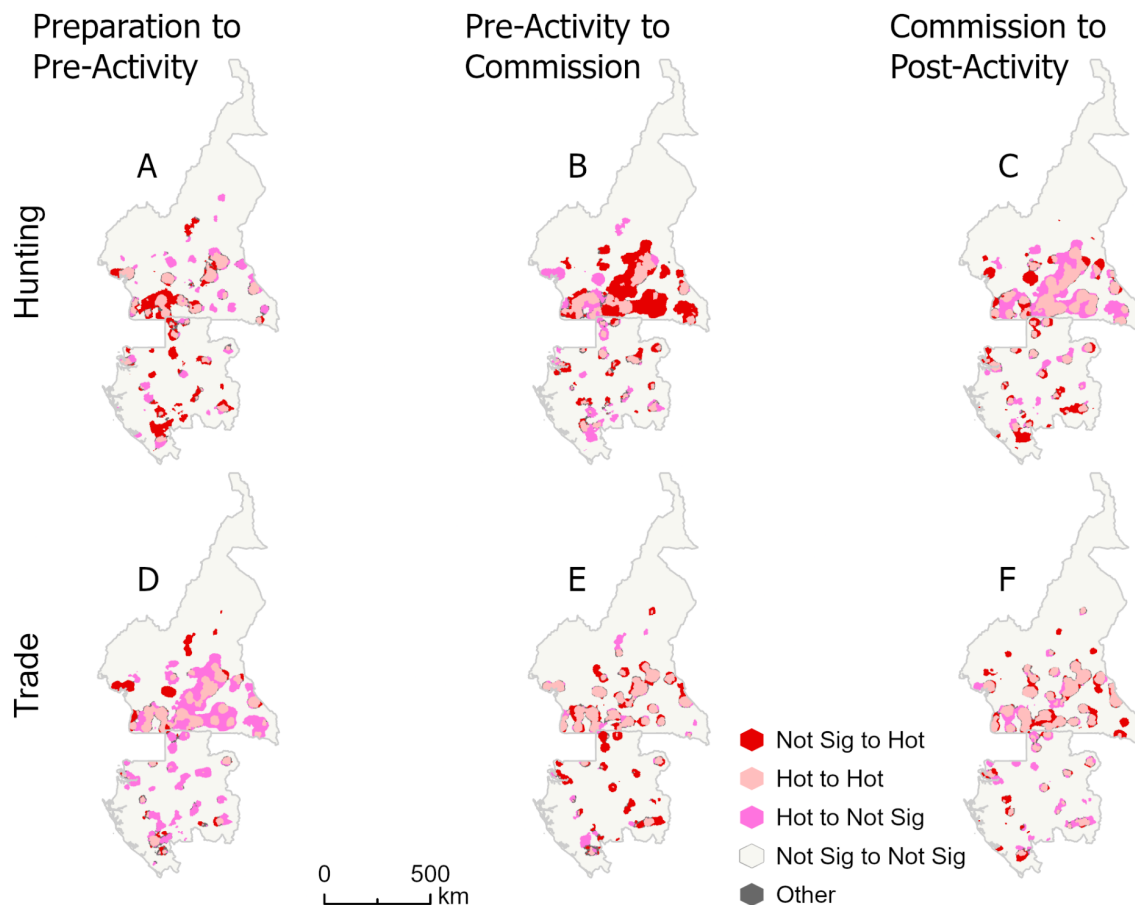


Fig. S6. Union majority hot spot change classifications for pangolin hunting and trade across temporal transitions between crime stages. For each crime type and crime stage transition (i.e., preparation to pre-activity, pre-activity to commission, commission to post-activity), the union of five spot classifications (i.e., not significant to not significant, not significant to hot, hot to hot, hot to not significant, other) was mapped. Trade consolidation is evident (panel E), where hot to hot cells indicate persistence in the central southern region of Cameroon and small patches in Gabon.

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Data, code, and materials availability. Data for Cameroon, data collection instruments for Cameroon
and Gabon, and code is publicly available at Zenodo on the Conservation Criminology & Nature Crime
community page (<https://tinyurl.com/2sbxc6bf>). Data for Gabon is not publicly available due to human
subject protection requirements.

List of Supplementary Materials

Materials and Methods

Supplementary Text

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