When Method Isn’t Enough: Framing, Relevance, and Computational Evidence in Borderland Research

During my fellowship with XCEPT, it became clear that technical rigor and methodological innovation, while crucial, benefit significantly from clear policy framing. My computational spatial model of border dynamics, featuring detailed indices and interactive maps, provided nuanced insights into complex interactions between trade potential and conflict exposure. However, translating these rich analytical outputs into direct policy action highlighted an important complementarity: robust computational methods gain greater policy relevance when anchored explicitly to specific institutional questions—such as, "Should resources prioritize trade infrastructure in high-conflict-risk districts?" Rather than suggesting a limitation in the computational approach itself, this realization emphasizes that clarity in policy questions can further enhance the utility of technical methods. Computational outputs, such as indices or maps analysis, thus become most impactful when integrated within institutional decision-making frameworks that clearly define the intended actions or priorities they aim to inform. evidence shows that without interpretive labor to contextualize them, such tools remain too abstract for practical use​[[1]](#footnote-0) In my case, I presented maps of borderland risk and potential, yet policy colleagues responded with polite confusion. What *exactly should we do with this?*

I came to realize that this supplementary note is not just an add-on to the “real” research; it is a methodological intervention in its own right. Its purpose is to examine how data-driven evidence becomes *legible* and *actionable* within institutional settings. Legibility here means making complex realities understandable in the simplified terms that bureaucracies and policy processes can work with. Actionability means framing insights in ways that directly inform planning or choices. Achieving these is not automatic; it requires translating technical findings into the language of needs, risks, and trade-offs that policy actors recognize. This note, therefore, documents a reflexive process of interpretation that was missing from the initial model deployment. By reflecting on how the evidence was received (and sometimes ignored), I aim to show that making complexity legible is a deliberate process.

**What I Did: The Study in Plain English**

The heart of the project was a spatial model examining how trade and conflict intersect along the Kenya–Uganda border. In plain terms, I was trying to map out where economic opportunities and security risks overlap in this region, and why. Building on the foundational work of Eberhard-Ruiz,who applied a Market Potential approach to measure armed conflict exposure at the border-post level.[[2]](#footnote-1) I developed an index-based model that could score different border districts on various relevant factors. The model’s key components included:

* **Market Potential Index (MPI)** – a composite measure of an area’s trade potential based on how many people it can reach, how well-connected it is by roads, and how far it is from major markets. For example, a town with large nearby populations, good highway access, and short travel times to a trade hub would score high on MPI. This index essentially asked: *if you invested in economic infrastructure here, how much market activity could it generate?* It combined demographic data, transportation network metrics, and distance calculations to quantify that potential.
* **Conflict Exposure Index (CI)** – a measure of an area’s security risk, based on its proximity to conflict events and the intensity of violence. I used geocoded conflict incident data to calculate how often and how close a given location has come to violent events in recent years. The idea was to capture the likelihood that trade or communities in that district could be disrupted by conflict. If a district bordered a zone of recurrent clashes or rebel activity, it received a higher CI, signaling greater risk.
* **Relational Layer** – a qualitative overlay capturing social and cultural relationships that transcend the border. This layer accounted for factors like shared ethnicity, language, and kinship ties between communities on either side of the Kenya–Uganda boundary. The premise was that these *informal trust networks* can heavily influence trade and cooperation. For instance, if people in District A (Kenya) share a language or family ties with those in District B (Uganda), they might preferentially trade with each other and support one another during unrest, even if formal infrastructure is lacking. This layer attempted to make such relational dynamics legible by mapping ethnic/linguistic groups and historical kinship links across the border.

Using these components, I scored and mapped border districts to see patterns of economic potential versus conflict risk. The findings revealed clear patterns. For example, the bustling border towns of Busia and Malaba ranked very high on the Market Potential Index – not surprising, given that they sit on East Africa’s busiest trade corridor (with tens of thousands of people crossing daily for commerce)​[[3]](#footnote-2). However, they also showed relatively high Conflict Exposure. While this region is not an active warzone, the risk factors were non-negligible: there have been cross-border security incidents and criminal violence, and any major conflict in Uganda or Kenya could quickly impact these hubs due to their strategic importance. This combination – high trade potential coupled with notable conflict risk – makes it difficult to prioritize interventions. Should policy-makers invest heavily in trade infrastructure at these crossings to capitalize on economic opportunity? Or does the conflict risk advise caution, perhaps diversifying trade routes to safer areas? The model by itself could not answer that, but it clearly flagged a dilemma: Busia and Malaba are *high-reward, high-risk* zones.

In contrast, some peripheral districts like Kaabong and Amudat (in the far northeast of Uganda) showed the opposite profile. They scored low on MPI – these areas are remote, sparsely populated, with poor road connectivity, so they don’t promise large market returns in the short term. They also, according to the Conflict Exposure Index, had low recent exposure to conflict events (indeed, after years of instability in the Karamoja region, these particular districts have been relatively calm in recent times). In other words, they emerged as *stable but overlooked* zones. Low risk and low visibility. From a policy standpoint, such areas rarely get attention precisely because they aren’t “squeaky wheels” – no crises erupting, but also not obvious economic engines. Yet one could argue that their stability is an opportunity: targeted investments here might be less likely to be derailed by violence, and could slowly build up these regions’ connectivity. The model highlighted that Kaabong and Amudat were essentially blank spots on the usual policy map: peaceful, but largely ignored in development planning. This raises the question of whether policy should proactively support these quiet areas, rather than only focusing on the high-potential but high-risk corridor.

Another important insight was how much the relational factors appeared to shape cross-border interactions. The overlay of ethnic and linguistic networks showed that trade routes did not strictly follow the most paved roads or shortest paths – they often followed the paths of trust. For example, certain secondary border crossings, while smaller in infrastructure, were heavily used by local traders because the communities on either side belonged to the same ethnolinguistic group. In the southern part of the border, many Samia people live on both the Kenya and Uganda side, and they tend to trade within their kin network. In the north, Pokot communities span the border of Kenya’s West Pokot County and Uganda’s Amudat District, maintaining close ties​[[4]](#footnote-3). The data suggested that even when conflict made some areas dangerous, traders would reroute goods through areas where they had relatives or shared culture, counting on those relationships for protection and reliability. In essence, kinship and language ties created alternative geographies of commerce that sometimes superseded formal routes. This finding reinforced a key point: relational and cultural context matters, even in ostensibly “technical” problems of trade and security. The fact that these softer variables influenced outcomes was exactly why I included the relational layer. It made clear that what might appear as *irrational routing* in a purely economic model was quite rational once you consider trust and social capital.

Despite these findings, I found myself at a loss when it came to the question of *“What should be done?”* The analysis yielded insights – e.g., certain places are high priority but risky, others are stable but neglected, and that social networks play a big role. However, without a pre-defined policy objective, I struggled to translate those insights into recommendations. Should we fortify high-potential hubs against conflict? Launch development projects in the stable periphery? Support cross-border cultural exchanges? Each of these would depend on the priorities of stakeholders (economic growth vs. risk mitigation vs. equity in regional development).

The project was not co-constructed with policymakers from the outset. Instead, the model was built independently to explore the data and uncover patterns that might be relevant to policy. This exploratory approach generated several key insights. The analysis revealed distinct patterns in the data. For example, the model highlighted zones with simultaneously high levels of opportunity and high risk, and identified areas that were relatively stable but seemed to be neglected by existing policies. It also brought attention to the importance of relational networks (social or institutional relationships) in structuring these patterns.

However, because the research had not been guided by a jointly defined policy question, the model’s results offered several possible directions without answering the fundamental “what should we do?” question. The findings pointed to multiple potential pathways for action, but it was unclear which path to pursue. This was a crucial lesson: in isolation, data and models can highlight problems and patterns, but deciding on a course of action requires clarity about values, goals, and priorities from the outset. The robust model, in the absence of that clarity, could not by itself resolve the “what do we do?” question. That question remains an open conversation with policymaker.

## **Why Co-Construction Matters: Methodological Positioning**

This research project sits squarely within the domain of computational social science (CSS), which bridges the quantitative and qualitative traditions of social inquiry. In this *interpretive, integrative* strand of CSS we emphasize understanding meaning and context as much as pattern detection.n this interpretive, integrative strand of computational social science (CSS), we emphasize understanding meaning and context as much as detecting patterns data science—and by extension CSS—thrives when it fosters a "happy marriage" between quantitative rigor and qualitative insight, offering a methodological path distinct from purely statistical or purely interpretive traditions[[5]](#footnote-4). Rather than treating computation as purely objective, our work remains reflexive about how coding choices and model assumptions shape findings. In short, we take an integrative view in which computational models are informed by rich social theory and qualitative insight, and vice versa.

A key lesson from this research project is that *co-defining* questions with policy-makers would have strengthened the project’s relevance and impact. Co-creating research agendas is now widely championed in both practice and guidance. UKRI, for example, highlights that co-production can (and should) happen at all stages, explicitly including “identifying research questions” together with stakeholders​. Involving users and decision-makers early helps ensure the project addresses real needs and diverse forms of expertise are integrated into the work​[[6]](#footnote-5) This also tends to improve uptake: by directly involving policy actors, researchers gain insider insights on timing and framing, and stakeholders gain ownership of findings[[7]](#footnote-6). For this research, if we had co-designed the questions from the outset, we likely would have produced outputs better aligned to specific decision timelines and local priorities (rather than only proving technical feasibility). In short, co-construction is not just a buzzword: it is increasingly seen as an ethical best practice that makes research *actionable*[[8]](#footnote-7)

## **The Value of Computational Approaches for Policy: Reflexive, Collaborative**

Despite the need for better co-design, computational methods still offer unique value in policy contexts. By bringing large data sets and formal models to bear, CSS can *map* the complexity of social systems in ways that traditional methods cannot. For example, agent-based models and network analyses can represent heterogeneous actors and the web of relationships among them. These tools reveal how local interactions produce global patterns – illustrating feedback loops, tipping points, and emergent behaviors beyond the reach of simple linear models[[9]](#footnote-8) In practical terms, computational models have helped simulate issues from land-use and epidemic spread to economic shocks They make relational dynamics visible: a node’s position in a social network determines its influence, and network structure governs how quickly information or contagion spreads and how resilient the system is to shocks​. Such insights can feed into “decision intelligence” frameworks by clarifying which actors are strategic and what interventions might cascade through the system. Importantly, CSS also allows systematic scenario analysis: for instance, hybrid ABM‐network models have been used to test different policy interventions (like technology subsidies) and show how adoption outcomes depend sensitively on social structure. In sum, computational social science adds value by extending the policy toolkit – providing data-driven maps of complexity, surfacing relational dependencies, and structuring decision frameworks in a way that is richer than purely narrative or linear approaches

In borderland conflict and fragility studies, the future computational research should be more reflexive and deeply collaborative. Reflexivity means critically examining assumptions (about data, about model design, about our own biases) and being transparent about the limits of our methods. Collaboration means forging genuine partnerships with policy and community institutions. For example, the “embedded researcher” model is one promising approach: researchers based within policy organizations can bridge academic and practice cultures, building capacity for evidence use​. Studies show that embedding researchers – even part-time – tends to *enhance* an organization’s research capacity and development of a learning culture​[[10]](#footnote-9)

**Conclusion**

In short, the supplement is an exercise in delving into the gap between computational analysis and policy practice – a guide for understanding how evidence gains meaning within institutions. Rather than an afterthought, it is an essential part of ensuring that robust analysis does not *stall* at the level of academic output but moves into the realm of usable knowledge. Looking ahead, future computational policy projects should prioritize two-way engagement. Policymakers should define or co-define the policy problems from the beginning, and computational scientists should then design analytical frameworks and models accordingly. By aligning research questions with policy goals from the outset, this collaborative, question-driven approach can ensure that data analysis more effectively informs decision-making and leads to actionable guidance.

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2. [Eberhard-Ruiz, “The Impact of Armed Conflict Shocks on Local Cross-Border Trade.”](https://www.zotero.org/google-docs/?C1CgD7) [↑](#footnote-ref-1)
3. Hugh Lamarque and Hannah Brown, ‘Key Considerations: Cross-Border Dynamics Between Uganda and Kenya in the Context of the Outbreak of Ebola, 2022’ (Institute of Development Studies, 14 December 2022),<https://doi.org/10.19088/SSHAP.2022.043>. [↑](#footnote-ref-2)
4. Andrew Malinga, ‘Regional Pastoral Livelihoods Resilience Project (RPLRP) and Pastoralism and Stability in the Sahel and Horn of Africa (RPLRP/PASSHA)’, *IGAD, CROSS BORDER CONFLICT ATLAS REPORT*, 2017. [↑](#footnote-ref-3)
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6. ‘Co-Production in Research’, n.d.,<https://www.ukri.org/manage-your-award/good-research-resource-hub/research-co-production/>. [↑](#footnote-ref-5)
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10. Dylan Kneale et al., ‘The Implementation of Embedded Researchers in Policy, Public Services, and Commercial Settings: A Systematic Evidence and Gap Map’, *Implementation Science Communications* 5, no. 1 (16 April 2024): 41,<https://doi.org/10.1186/s43058-024-00570-3>. [↑](#footnote-ref-9)