

Modeling Ukraine Military Events

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Data Background

- Data is recorded by ACLED (Armed Conflict Location and Event Data), backed by United Nations
 - Slightly deviates from given data set, emphasizes all events across entire country with any political relation
 - County-equivalent (raion) analysis rather than state-equivalent (oblast) level
- Pertinent data includes date, time, location, description, casualties, and actors involved within the event, though additional information is available
- 21 days were missing from the provided data set
 - Reason for missing data was not recorded
 - Assumption of zero conflict was made to ensure the best possible model
- Data spans from 1/1/2020 - 10/23/2024



What is Being Modeled?

Daily Dominant Location of Events

Events analyzed:

- Armed clash
- Air/drone strike
- Shelling/artillery/missile attack
- Disrupted weapons use

Daily Fatality Severity

Separated into bins:

- 0
- 1-100
- 101-200
- 201-300
- 301+



Main Features of the Data

We found an uneven geographic distribution of events

- Donetsk 417 (23.7%)
- Pokrovskiy 365 (20.8%)
- Bakhmutskiy 335 (19.1%)
- Kalmiuskiy 125 (7.1%)
- Alchevskiy 125 (7.1%)
- Polohivskiy 116 (6.6%)
- All other regions combined for about 15.6%



Fatality data skews towards low-severity days

- 699 days recording 0 fatalities,
- 552 days between 1 and 100,
- 306 days between 101 and 200,
- 105 days between 201 and 300, and
- 75 days exceeding 301 fatalities.

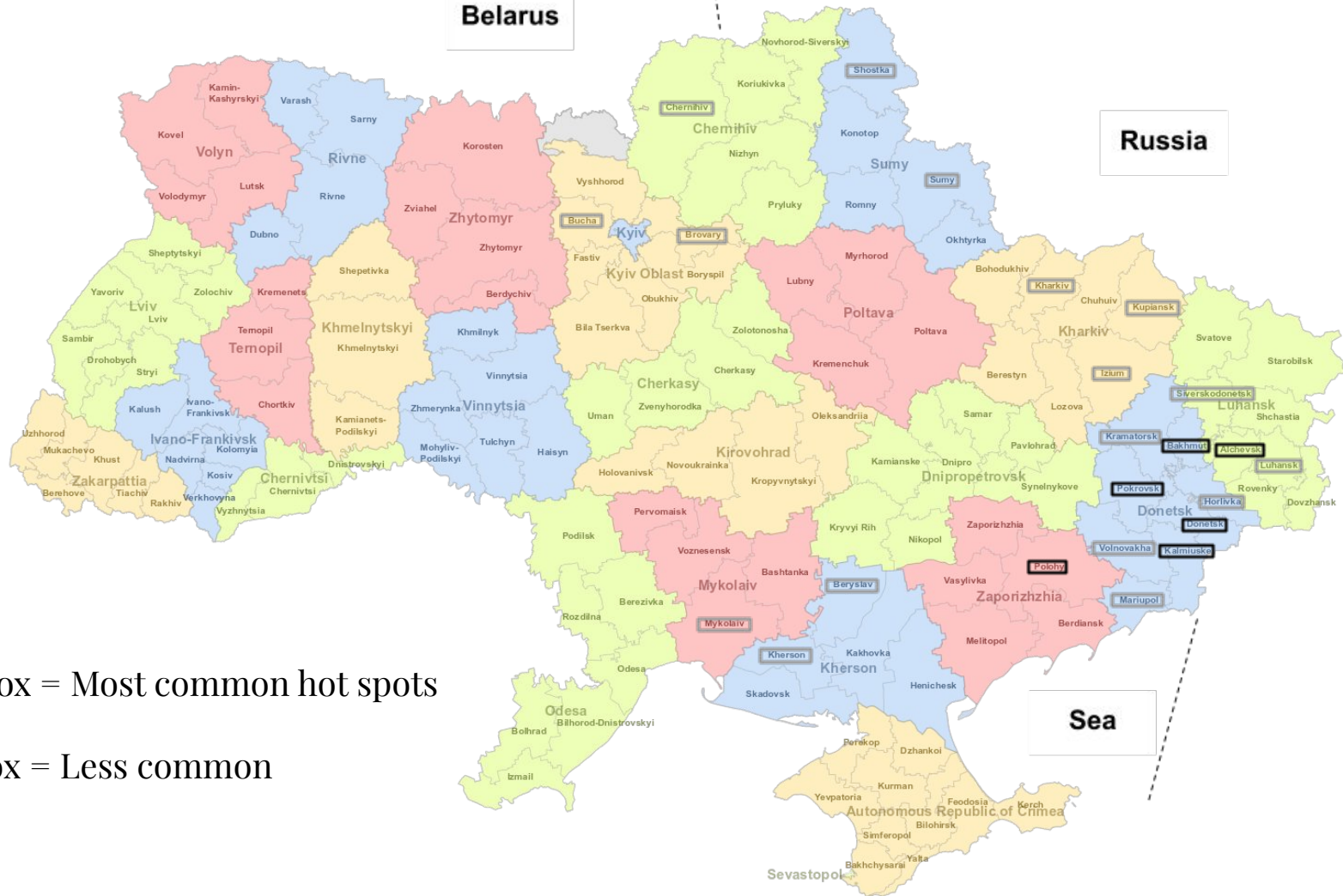
Belarus

Russia

Sea

Black Box = Most common hot spots

Gray Box = Less common



Boundaries of regions from Ministry for Communities and Territories Development of Ukraine

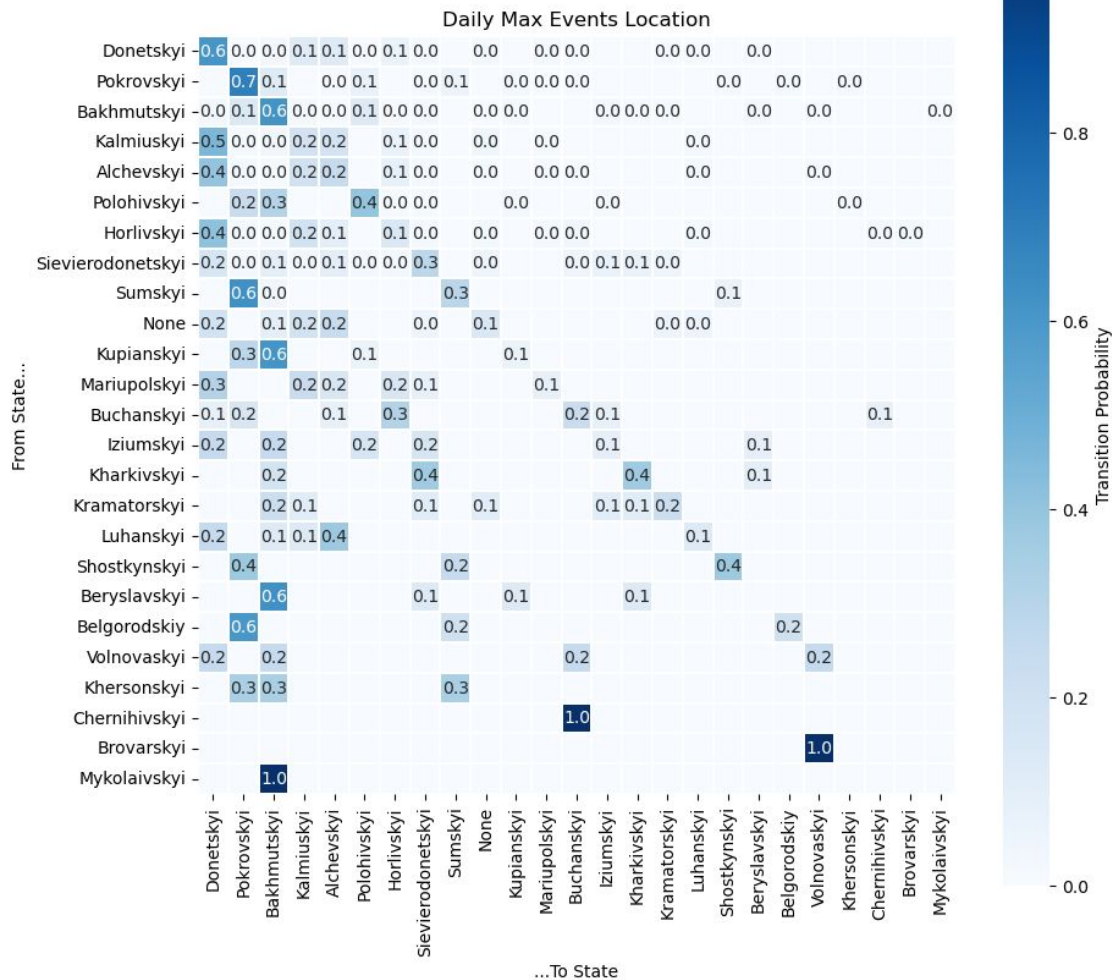
Daily Location of Most Events Markov Chain

Event hotspots include:

- Donetskyi
- Bakhtmutskyi
- Pokrovskyi
- Polohivskyi
- Kalmiuskyi
- Alchevskyi

Two noticeable cycles:

- Pokrovskyi + Bakhtmutskyi + Polohivskyi
(2022 - Pres)
- Donetskyi + Kalmiuskyi + Alchevskyi
(2020 - 2022)





Russia

Sea

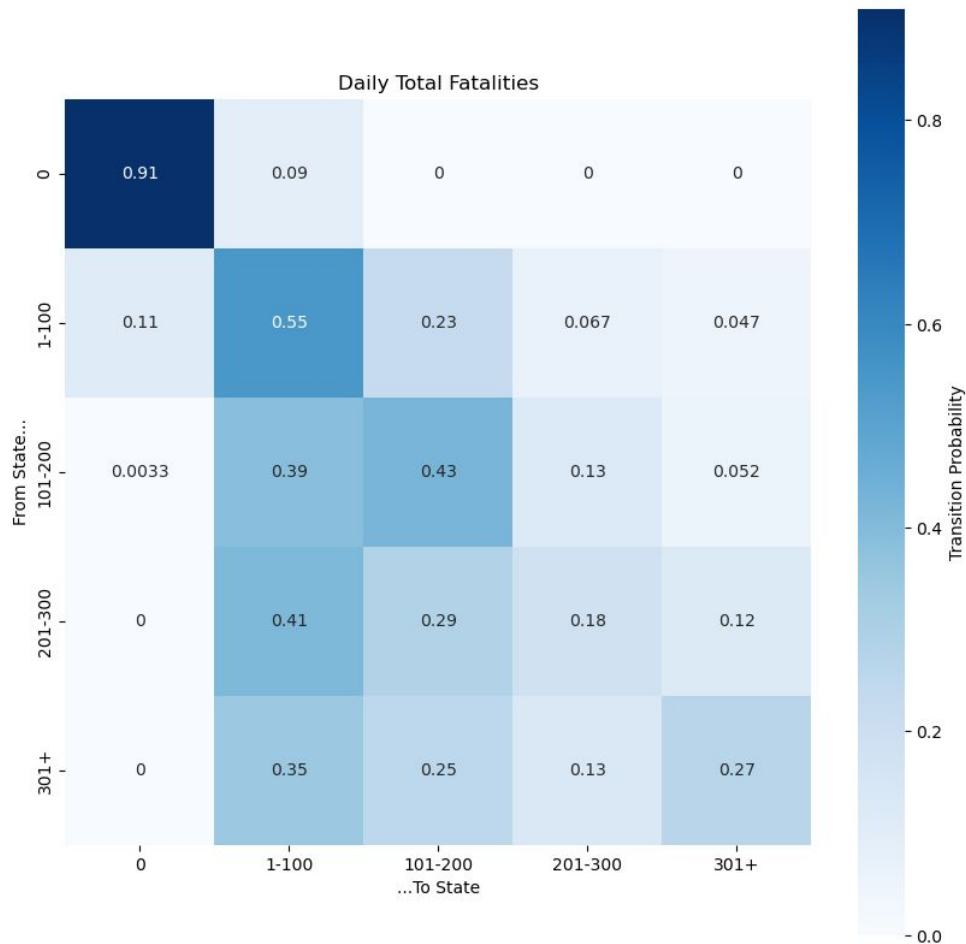
Daily Location of Most Events by year

- Pre 2022 Invasion mostly in Donetskyyi, Kalmiuskyi, and Alchevskyi which forms cycle in Markov Chain
- Post Invasion mostly in Pokrovskyi, Bakhmutskyi, and Polohivskyi which also has cycle
- But this year-to-year progression not truly modeled

admin2	2020	2021	2022	2023	2024
Donetskyi	234.0	159.0	24.0	0.0	0.0
Pokrovskyi	0.0	2.0	13.0	119.0	231.0
Bakhmutskyi	8.0	8.0	164.0	146.0	9.0
Kalmiuskyi	38.0	80.0	7.0	0.0	0.0
Alchevskyi	38.0	68.0	19.0	0.0	0.0
Polohivskyi	0.0	0.0	19.0	87.0	10.0

Daily Total Fatalities Markov Chain

- No single-day jumps from 0 fatalities to 301+ fatalities
 - Increase in fatalities happens gradually, no sudden spikes
- No single-day jumps from 301+ fatalities to 0 fatalities
 - Decrease in fatalities happens at a quicker rate than the increase
- Daily total fatalities is heavily right skewed



Daily Total Fatalities by Year

- Pre 2022 Invasion mostly at zero fatalities
- Post invasion is much higher
- Markov Chain partially models this (stays at zero, or stays higher) but can jump back and forth

fatality_level	2020	2021	2022	2023	2024
0	321.0	330.0	45.0	3.0	0.0
1-100	26.0	34.0	194.0	221.0	77.0
101-200	0.0	0.0	81.0	107.0	118.0
201-300	0.0	0.0	26.0	22.0	57.0
301+	0.0	0.0	18.0	12.0	45.0

Generating New Sequences with Markov Chains

- Used trained Markov chain models to simulate plausible future daily sequences
 - 1000 days of simulated location states
 - Mariupolskyi → Alchevskyi → Donetskyy → Donetskyy → Kalmiuskyi → Alchevskyi → Donetskyy → ...
 - 1000 days of simulated fatality levels
 - 201-300 → 1-100 → 101-200 → 1-100 → 1-100 → 301+ → 1-100 → 201-300 → ...

Outcome of Markov Chain Compared to Train

Table 1: Training vs Simulated Fatality Frequencies

Fatalities	Train	Sim
0	0.402418	0.404
1–100	0.317789	0.311
101–200	0.176166	0.186
201–300	0.060449	0.063
301+	0.043178	0.036

Good for Modeling Fatality
Good for Modeling Location

Table 2: Training vs Simulated Location Frequencies

Location	Train	Sim
Donetskyi	0.237201	0.241
Pokrovskyi	0.207622	0.211
Bakhmutskyi	0.190557	0.211
Kalmiuskyi	0.071104	0.062
Alchevskyi	0.071104	0.070
Polohivskyi	0.065984	0.061
Horlivskyi	0.035836	0.043
Sievierodonetskyi	0.024460	0.017
Sumskyi	0.018203	0.012
None	0.011945	0.008
Kupianskyi	0.010239	0.012
Mariupolskyi	0.007395	0.011
Buchanskyi	0.007395	0.005
Iziumskyi	0.006826	0.001
Kharkivskyi	0.006257	0.004
Kramatorskyi	0.005119	0.005
Luhanskyi	0.004551	0.003
Shostkynskyi	0.004551	0.005
Beryslavskyi	0.004551	0.005
Belgorodskiy	0.002844	–
Volnovaskyi	0.002275	0.006
Khersonskyi	0.001706	0.003
Chernihivskyi	0.001138	0.002
Brovarskyi	0.000569	0.002
Mykolaivskyi	0.000569	–

Why is this happening?

- Single order Markov Chains are limited
 - Not able to predict the longer sequences that may have led to other minority locations
 - Certain locations were not predicted
- All fatality classes were predicted
 - Less classes with more even distribution (compared to location) led to every class being predicted
- Still cannot fully model year-to-year progressions completely
 - Real war looks different before and after 2022 invasion, but simulations will go between those pre and post invasion cycles

Conclusion

- Fatalities rise and fall gradually, with conflict concentrated in recurring hotspot cycles
- Simulations effectively modeled short-term changes in fatalities and geographic spread
- Future work:
 - Higher order Markov models
 - Incorporate more data such as geographic proximity or event characteristics
 - Handle year-to-year changes