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russo-Ukrainian War Analysis

Econometrics final project report

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26 May 2022

Abstract

On the 24th of February, 2022, russia started a **full-scale invasion** of Ukraine. This day marked a new phase of russo-Ukrainan conflict since 2014 and escalated it into a full-scale war. For three months already Ukrainian military forces continue defending the country's sovereignty. Since then, russian forces have suffered an enormous number of casualties: both in personnel and in military equipment.

Introduction

The war has made a significant geopolitical and economic impact on the whole world. Therefore, millions of people now follow the real-time events in Ukraine. Because many authorities have been connected both to Ukraine and to russia economically, multiple sides are quite interested in the war's end. A tool that could gather a statistically significant intel about any possible factors that could help to estimate the amount of time the war conflict will continue or will be useful in the casualties estimation (which is quite a good indicator of country's military durability as well) demonstrate a high value in the eyes of these interested sides right now.

Considering that, to the research's **target audience** belong: Ukrainian Armed forces, Ukrainian Government, European countries, World bank systems etc. Altogether, all mentioned can be summarized into the following: this research might be handy for organizations, which try to analyze or forecast effects of russian invasion.

Therefore, the primary objective of this research is to perform a **detailed analysis of russian casualties** so far, represented in a time-series form and to provide the statistical testing of **two following hypotheses**:

1. Weather (temperature, pressure, cloudiness and wind speed) influence on the russian casualties.

2. Validity of the russo-Ukrainian war breakdown into multiple phases based on the military activities (measured in casualties scale).

Additionaly, there is a task to test the models for **making the predictions**, if any correlation between russian losses and weather conditions would be found. After the experementing, the goal is to find the best model, tune its parameters and discuss why other failed. The results are presented in *Prediction Model Validation* section.

Brief data description

The data consists of several blocks, namely:

1. **russian casualties** split by categories (e.g. soldiers, tanks, helicopters etc.)

2. **Weather conditions** in eight cities that form the frontline region-chain represented on Figure 1, Appendix. Includes temperature, pressure, precipitation etc.

Detailed data description can be found in the appendix, *Data Dictionary* section.

Data collection

russian casualties time-series data is formed via a day-by-day data collection from the official Ukrainian Armed Forces reports in Facebook.

Weather time-series data at each of the selected region is formed via a day-by-day data collection from the *gismeteo.ua* website that stores the archive weather data in every specified region. To compensate for the data amounts needed during the data smoothing process described below, the weather data has been collected for ten days prior to the war as well.

Achieving the Stationarity of the Data

Because the research focuses on time-series analysis, the **Dickey–Fuller test** is firstly applied on the collected data to check its stationarity. Test's null hypothesis states that the data is not stationary and an alternative one rejects it. As a valid measure for the rejection, a p-value indicator was used. Because the russian casualties were collected in a cumulative form, the first difference method has been used to detrend it. After running the test on each category, all variables, except helicopters (p-value equals 0.608), possessed p-values lower than 0.05 that satisfied the condition of rejecting the null hypothesis.

A similar problem arose while working with the weather data. Besides the first difference method, the data smoothing approach has been also conducted onto temperature and wind data for each region separately. Finally, after combining all eight regions' data into temperature, pressure, cloudiness and wind variables (the process is described in details in the *Testing Weather influence* section), the Dickey–Fuller test has been conducted. The results proved that each of the four aforementioned variables is stationary.

Weather Data Smoothing

For the weather hypothesis testing the data smoothing method was decided to be applied onto the *temperature* parameter to remove the fine-grained variation between time steps, preserving the main tendency image.

A moving average requires the specification of a window size (window width). This defines the number of raw observations needed to calculate the moving average value. The moving average implies the process that the window with the specific width slides along the time series to calculate the average values in the new series. To achieve stationarity the window size parameter was set to value 9.

Due to the work with the time-series data, the **Trailing Moving Average** approach that calculates the value at time (t) as **the average** of the raw observations **at and before** the time (t) was followed. The results are represented in the appendix, *Data smoothing* section.

Testing Weather influence

Model Construction

To test the weather significance the following approach was considered.

The idea behind this algorithm is the uncertainty about the place, where russian casualties were collected. So the notion of mean value was needed. It introduces the weight for each 8, according to the proportion of air alarm time to the total time of air alarms in those regions. Moreover, a dummy variable *active_north* was added to exclude the influence of *Kyiv*, *Chernihiv* and *Sumy* regions starting from the April 5th (1 before that date, 0 - otherwise). This has been done due to the russian de-escalation from that territories starting from early April which brings no active fightings onto them. Subsequently, all weather variables were merged into one complete dataset consisting of 4 weighted measurements (*temperature*, *wind*, *pressure*, *cloudiness*). Then the multiple linear regression model was ran for each category as response variables and four weather features as control variables. E.g. one the models was as follows:

$$drones = \underset{(1.337)}{9.9714} - \underset{(0.978)}{0.9345} \cdot temp - \underset{(2.477)}{0.1286} \cdot wind + \underset{(0.028)}{0.0180} \cdot pres - \underset{(0.641)}{2.4613} \cdot cloud, \quad R^2 = 0.177$$

For this particular model almost all regressors were insignificant (using t-statistics), except for cloudiness. But in order to test the joint significance, an F-test was applied. The $H0$ is: weather is statistically insignificant. The reported p-value is 0.00275, so the null hypothesis is rejected at 0.005 significance level.

All in all, most of the models showed mediocre results, but some of them actually contained significant regressors. For instance, there were strong connection between cloudiness and drones:

$$drones = \underset{(1.075)}{9.2152} - \underset{(0.517)}{2.1208} \cdot cloud, \quad R^2 = 0.165$$

Or for the first 2 months the temperature was correlated with boat casualties:

$$boats = \underset{(0.047)}{0.1377} - \underset{(0.063)}{0.1232} \cdot temp, \quad R^2 = 0.042$$

Using common sense, there is a strong belief that cloudiness really affects drones destruction. When it comes to boats, the authors tend to believe that is perfect example of coincidence or correlation without causation. During the first phase russia was concentrating on defeating the capital of Ukraine. However after dramatic loss, russian forces focused on southern and eastern Ukrainian parts. That's why more boats are destroyed nowadays, because the war concentrated near Mariupol, Melitopol and other near-sea territories.

There is one **additional approach** that can possibly be developed in the future research: take all weather conditions for all 8 cities (from Feb 24 till Apr 20), merge together and then run a linear regression with all weather conditions as independent variables and one of $soldiers, tanks,$ and $armveh$ as a regressand. Here are the p-values, associated with F-test for described models.

regressand	p-value
soldiers	0.236
tanks	0.010
armveh	0.049

From such an output it is not enough to conclude that the weather conditions were jointly significant for soldiers, but still for tanks and armored vehicles they are. The same procedure was applied to regions (but now with data collected from Feb 24 till May 22) without northern cities (Kyiv, Chernihiv, Sumy), since solid war concentrated on eastern and southern parts of Ukraine. However, these results do not imply automatically that all the 32 weather variables are jointly significant - 32 variables for 87 observations possibly make the constructed model overdetermined. Thus, this field requires further studies.

Testing Phases Breakdown

Model Construction

The process of discovering war phases had an approach of attempting to find the most proper breakdown **visually** and then to test whether the stated assumptions are statistically proven. To interpret the results easily it was decided to omit several military categories of the russian army and, instead, to focus on testing the aforementioned breakdown on some categories separately that were most commonly used during the escalation.

Therefore, most of the collected categories were ignored in favor of *soldiers*, *tanks*, and *armored vehicles*, as their losses at best demonstrate how intense the escalation proceeds. The more individuals of such categories are destroyed, the more frequently and intensively they are used. Observing the categories above in the *Time-series data visualization* section in the Appendix, the reader can easily find the best-fit breakdown – 16 March, 2022. It is clear that most of the losses occurred during the first days of the invasion. Visually the breakdown corresponds to a spike on March 16.

After the hypothesis claim, there was added a dummy variable *phase_one* which equals 1, if the observation (day) is before March 16 and 0 otherwise. It basically demonstrates the difference in average casualties for each category between two aforementioned time periods. Then, the simple linear regression model was constructed and for each of three aforementioned categories *phase_one* showed significant results.

Model Results

Here are three models that were constructed:

$$soldiers = \underset{(52.803)}{243.5714} + \underset{(119.451)}{456.4286} \cdot phase\_one, \quad R^2 = 0.147.$$

$$tanks = \underset{(1.156)}{13.0143} + \underset{(2.615)}{8.1622} \cdot phase\_one, \quad R^2 = 0.103.$$

$$soldiers = \underset{(6.499)}{27.3571} + \underset{(14.702)}{44.7605} \cdot phase\_one, \quad R^2 = 0.098.$$

The conclusion about the significance was made by using *t-test* for single hypothesis testing. In this case, there were three different models with *phase_one* as explanatory variable. The highest *p-value* among those three categories was 0.003 in *armveh*. Thus, *phase_one* is very significant and the null hypothesis is rejected at 1% confidence level for each of the chosen categories.

Furthermore, in each model the coefficient near *phase_one* was positive, which corresponds to the more intensive fighting during the first twenty days. The slope's values demonstrate the average casualties difference between phases. Interpreting the aforementioned results:

1. During the first war phase the casualties in *soldiers* were higher by 456 on average than those in the second phase.

2. During the first war phase the casualties in *tanks* were higher by 8 on average than those in the second phase.

3. During the first war phase the casualties in *armveh* were higher by 44 on average than those in the second phase.

There are a few guesses why it happened, but to validate them a solid military education/experience is required. One of such theories is that russia underestimated the strength of Ukrainian military forces and had no other option than to de-escalate the invasion to the couple of valuable regions. Moreover, the western sanctions and and an increasing military support of Ukraine has motivated russia to alter its main fighting strategies. Thus, invasion intensivity dropped and so do russian casualties.

Conclusion

Despite the statistical testing of the hypotheses defined before, one of the primary products of this research is an informational basis that has been constructed and can be used for the future studies. Furthermore, all the work done has demonstrated which study directions can be followed further and which will possibly bring no actual results.

Overall, this research has shown that military casualties explanation is a quite complex topic that requires more specific data (casualties distribution at each region) and wider factors analysis (arms supply, the impact of sanctions etc.). Anyway, the study succeeded in detecting some interesting insights in the russo-Ukrainian war that could be taken into account during the deeper analysis.

Making the predictions

It is important to remember that the main focus of this research is not on prediction. This part is rather experimental to share the found insights. Before any assumptions, it was decided to train and test the models using "out-of-sample validation". The target was to predict 6 lags, so the training data was from 24 Feb till 16 May.

ARMA

To do find the military categories which could be predicted, each possible casualty variable was discovered by auto-correlation function (ACF) and partial auto-correlation function (PACF). Also the Dickey-Fuller test was used to test the stionarity. After this stage, the authors focused only on 3 main categories: *soldiers*, *tanks*, *armveh*. The next step was to find the most suitable AR and MA parameters. The best orders were selected according to Akaike Information Criterion (find the model with least AIC) and also Ljung-Box test was applied to test the autocorrelation in residuals. The results are below.

category	AR	MA
soldiers	1	1
tanks	2	0
armveh	0	3

The model results are in the *Prediction Model Validation. ARMA*

It is clear that the model does not do the job. It misses the trends and for *armveh* after the lag 3 all the predictions are equal to the mean difference value (the property of moving average model).

Linear Regression

Firstly, the weather measurements from the northern parts were removed from the dataset. Then, only those independent variables were left, which had the magnitude of correlation with *soldiers*, *tanks* or *armveh* greater than 0.2. After that the mupliple regression model was ran and only variables with p-value less than 0.1 were left. Then training part consisted of endless cycle until only statistically significant explanatory variables were left. The following control variables were found to be important.

regressand	regressors
soldiers	intercpet, kharkiv_temp, melitopol_temp, donetsk_temp, izyum_temp, izyum_wind
tanks	intercept, kherson_pres, donetsk_pres, kharkiv_pres, izyum_pres
armveh	intercept, donetsk_pres

The model results are in the *Prediction Model Validation. Linear Regression*

ARIMAX

Briefly, the idea behind this model is to include exogenous regressors into ARIMA model. The best-fit parameters for ARMA are already found. Significant regregressors are also collected, so the results of validation are below. The mean absolute errors of the models are in the following table.

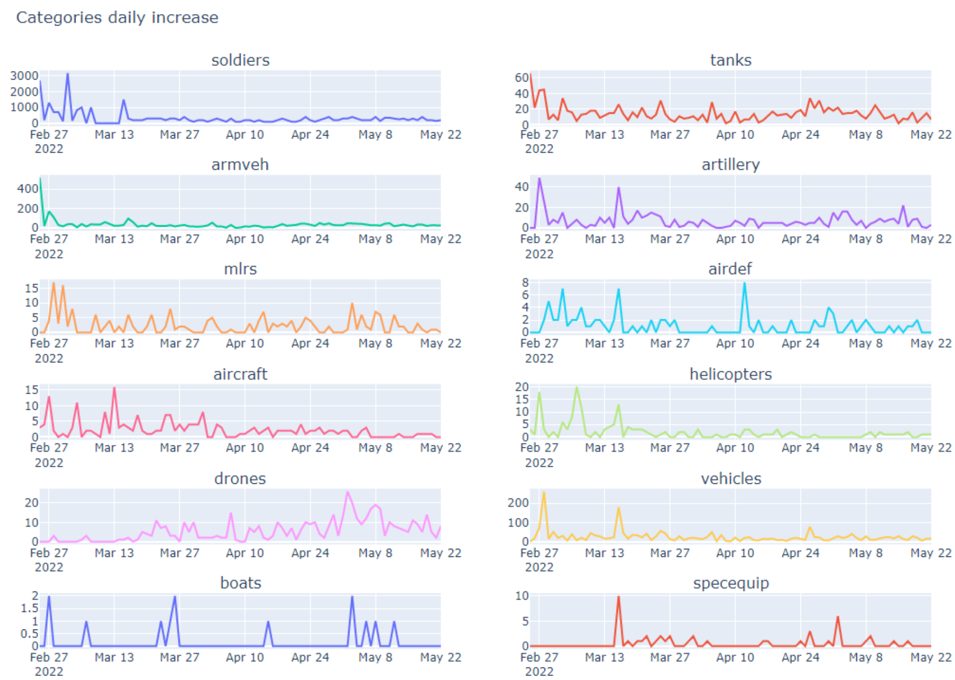
model	soldiers	tanks	armveh
ARMA	764	29	83
Linear Regression	589	31	27
ARIMAX	475	25	139

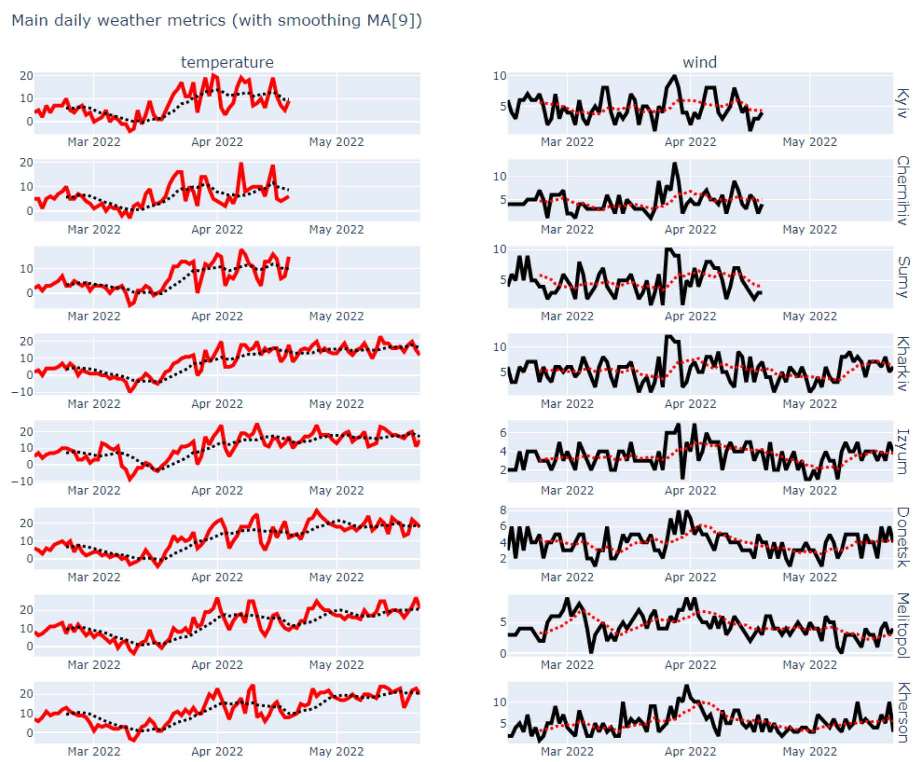
The model results are in the *Prediction Model Validation. ARIMAX*

From all the aforementioned results, a conclusion arises that such process as military casualties prediction is rather not trivial and requires a wider range of data and special knowledge in the related area. However, the provided analysis may be a powerful initial step for further studies.

Descriptive statistics visualization

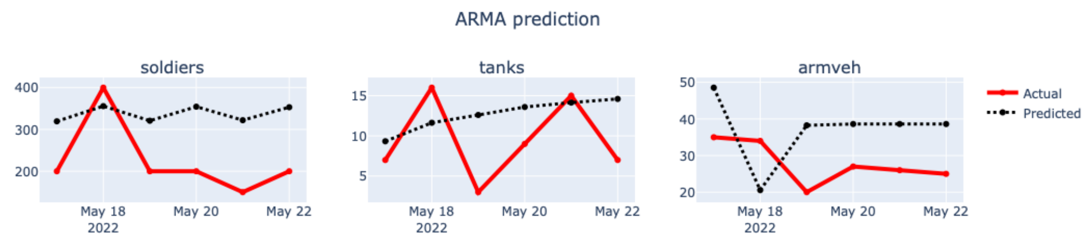
Time-series data visualization



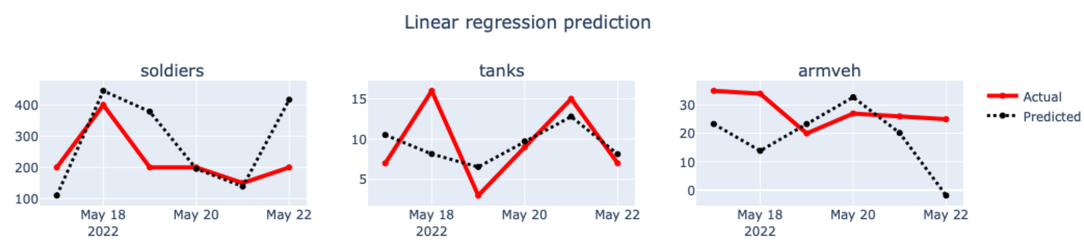


Prediction Model Validation

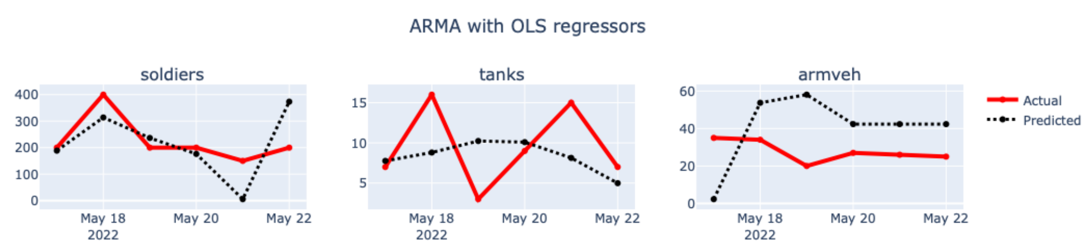
ARMA



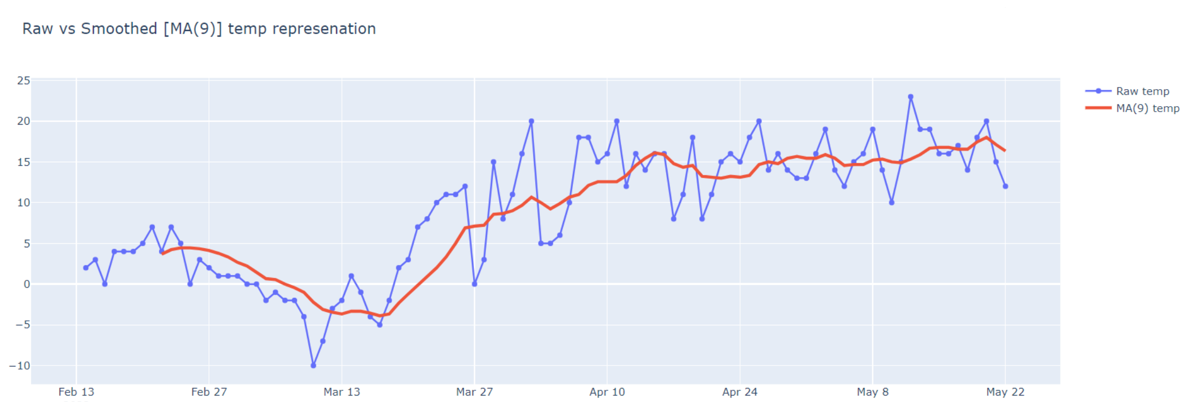
Linear Regression



ARIMAX



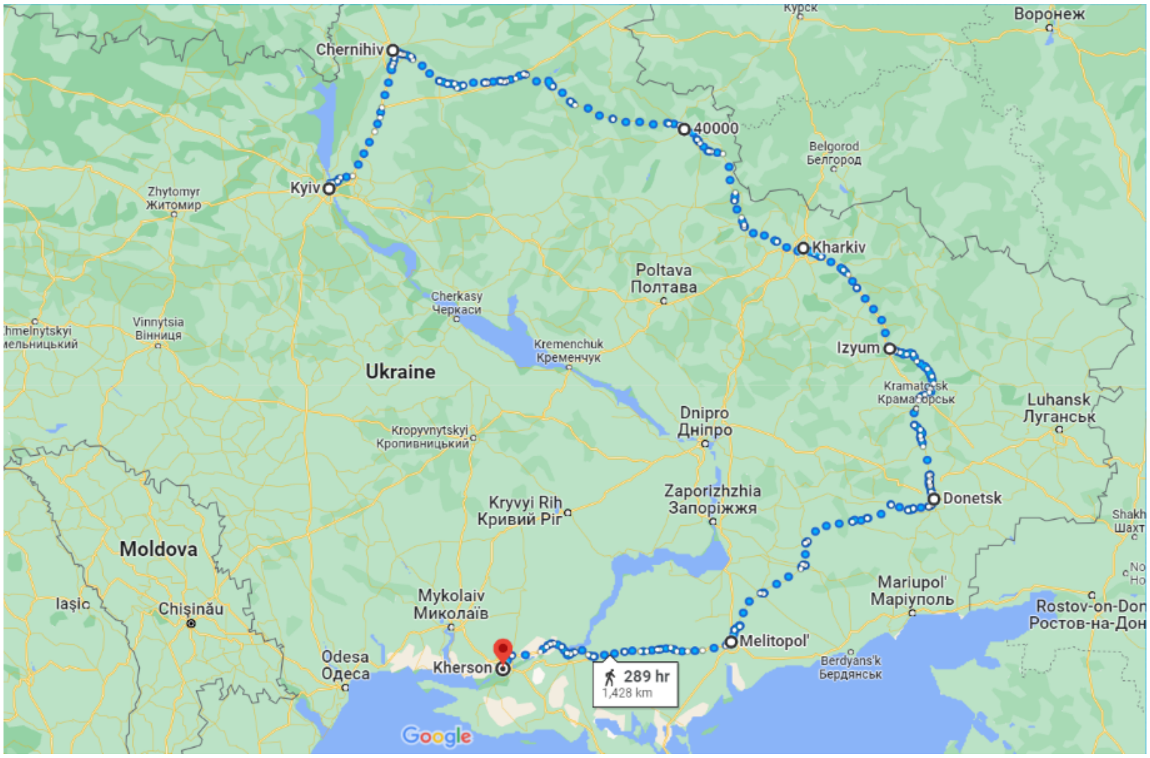
Data smoothing



Data Dictionary

1. **russian casualties** (cumulative):
   (a) *soldiers*, number of lost soldiers;
   (b) *tanks*, number of lost tanks;
   (c) *armveh*, number of lost armored vehicles;
   (d) *artillery*, number of lost artillery systems;
   (e) *mlrs*, number of lost Multiple Launch Rocket System;
   (f) *airdef*, number of lost air defenses;
   (g) *aircraft*, number of lost aircrafts;
   (h) *helicopters*, number of lost helicopters;
   (i) *drones*, number of lost drones;
   (j) *milveh*, number of lost military vehicles;
   (k) *fueltanks*, number of lost fuel tanks;
   (l) *boats*, number of lost boats;
   (m) *specequip*, number of lost special equipment;
   (n) *buksys*, number of lost buk-systems.

2. **Weather conditions**:



(a) The weather data was collected for **8 Ukrainian cities**. The exact list is not random. The primary aim was capturing the regions would at best cover the frontline (see Figure above): *Kyiv*, *Chernihiv*, *Sumy*, *Kharkiv*, *Izyum*, *Donetsk*, *Melitopol*, *Kherson*.

(b) Important: due to the conflict's de-escalation on the teritories in the North of Ukraine since

(c) For each of earlier mentioned cities, the following measurements were collected:

i. *temp*, day-temperature in ºC;

ii. *pres*, pressure in mm of mercury (mm Hg);

iii. *cloud*, cloudiness, measured as integer from 0-min to 3-max;

iv. *wind*, wind velocity in m/s;

References

[1] `https://www.gismeteo.ua`.

[2] `https://www.facebook.com/GeneralStaff.ua`.

[3] `Research Code Source`