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LONG-TERM FORECASTING OF INFLUENZA-LIKE ILLNESSES IN RUSSIA

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Abstract: This paper compares the feasible methods for the long-term forecasting of the incidence rates of influenza-like illnesses (ILI) and acute respiratory infections (ARI), which is important for strategic management. A literature survey shows that the most appropriate techniques for long-term ILI & ARI morbidity projections are the following well-known statistical methods: simple averaging of observations, point-to-point linear estimates, Serfling-type regression models, autoregressive models such as autoregressive integrated moving average (ARIMA) models, and generalized exponential smoothing using the Holt-Winters approach. Using these methods and official data on the total number of ILI & ARI cases per week in 2000–2012 in Moscow, St. Petersburg, Novosibirsk, Yekaterinburg, Nizhny Novgorod and Yakutsk, we developed one-year projections and evaluated their accuracy. Different methods yielded the best results, depending on the time series. Generally, it is preferable to use the Serfling model. The Serfling model forecasts almost matched the point-to-point linear estimates. In certain cases, ARIMA outperformed the Serfling model. Simple averaging can ensure a fairly good prediction when the ILI & ARI time series do not exhibit a trend. The results of exponential smoothing were poorer than those of other techniques.

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1. Introduction

The challenge of forecasting morbidity rates has been a research focus for more than a century. Recently, the number of publications about this subject has grown due to the development of biosurveillance information systems and the accumulation of large volumes of data that are available for analysis. These studies are mainly focused on short-term (up to a few weeks) predictions and the detection of disease outbreaks. Their results are used in real-time management. However, only a handful of papers [70, 17, 35] tackle the subject of long-term (for months into the future) morbidity forecasting, partly because such forecasts cannot be made with high reliability. Long-term projections, however, are very important for strategic control: they are necessary for estimating future production volumes of drugs and vaccines, planning medical staff deployment and allocating emergency department resources. For instance, the lead time for delivering medical supplies to pharmacies can run up to six months. Predictions that are two or more months ahead of time are the most useful to health services [51] and provide sufficient time for implementing a preventive response.

The objective of our study was to develop long-term projections for the morbidity of influenza-like illnesses (ILI) and acute respiratory infections (ARI) in Russian cities. These temperate latitudes show a strong seasonal pattern. ILI & ARI are the most common infectious diseases affecting humankind [40]. Despite a variety of mitigation measures, the incidence of ILI & ARI has not decreased. This paper compares the feasible methods for a year-long forecast of the ILI & ARI incidence in a city under the Russian-type influenza surveillance system.

The circulation of the influenza virus in Russia is monitored by 59 regional base laboratories (RBLs) [41]. RBLs provide data to the Research Institute of Influenza and the Ivanovsky Research Institute of Virology, which are involved in the World Health Organization Global Influenza Surveillance and Response System. RBLs submit the weekly number of ILI & ARI cases. We used these data, which were collected from 2000–2012 in six cities that were geographically distant from one another and had different population sizes.

Numerous morbidity and mortality forecasting methodologies have been proposed. Surveying these methods was an important part of our study. Therefore, we shall briefly review the existing techniques, choose the ones suitable for long-term ILI & ARI projections and evaluate their accuracy. We cannot cover the entire range of methodological approaches in a single paper, but we tried to mention the most commonly used techniques.

2. Morbidity Forecasting Methods

For convenience, we divided the morbidity prediction techniques into several categories: statistical methods, machine learning-based and case-based methods, filtering-based methods, and mathematical modeling of infectious diseases. These categories are very tentative and overlap partly.

2.1. Statistical Methods

The simplest long-term forecasting method is averaging past observations for a certain calendar period (a week or a month of a year). This technique has been used for many years by epidemiologists to estimate baseline influenza-associated morbidity and mortality [4, 13]. This technique not only ignores correlations between sequential observations but also presupposes the absence of any discernible trends.

If a trend is present, it can be captured by a slight adjustment, using point-to-point linear estimates [61]. Thus, straight lines are fitted to observations during appointed periods, for instance, for each of the 52 calendar weeks. All lines have a common slope but result in different means and projections. This method is applicable if there is no significant difference in the slope of the regression lines. A similar approach can also be used with other regression functions.

Conventional regression analysis is perhaps the most popular morbidity prediction tool. Two groups should be noted among the variety of regression models [11]: non-adaptive models, where parameter values are estimated from all available data, and adaptive models, where the values are computed within a sliding window of recent observations.

Non-adaptive models usually use a cyclical regression function because morbidity commonly has a consistent seasonal pattern [70, 4, 47, 65, 66, 2, 54, 26],

$$\hat{y}_t = \sum_{j=0}^{\nu} \alpha_j t^j + \sum_{j=1}^{\kappa} (\beta_{2j-1} \sin\theta_j + \beta_{2j} \cos\theta_j), \qquad (1)$$

which was first proposed by R. E. Serfling [61]. Here, $\hat{y}_t$ denotes the morbidity approximation for the period t; α_j and β_j are the parameters; the polynomial degree of ν is usually equal to one; and θ_j is a linear function of t that can be chosen using spectral analysis [36, 70]. The most used function is $\theta_j = 2\pi jt/T$, where T is the number of periods per season, for instance, 12 months or 52 weeks. There are rarely more than two harmonics (κ).

When daily morbidity data are available, the Serfling model is expanded to account for day-of-week effects [11, 9]. The Serfling model was not developed for multivariate regression. When time series for several predictors are available (weather and similar factors), a Poisson regression model is applied [4, 73, 75, 80]. This model is similar to the Serfling model but requires a logarithmic transformation of the values. These types of non-adaptive models assume that seasonal patterns do not vary from year to year. When they do, more complex hierarchical models can be applied [9].

In contrast, the adaptive models allow for simpler regression functions — for instance, polynomial functions [78, 23]. The size of the sliding window depends on the time-series properties and can dynamically change during the year. Such algorithms are usually applied to daily data; thus, indicator functions denoting day-of-week effects are added to the polynomials [11, 10, 8]. Adaptive regressions are appropriate only for short-term forecasting, whereas non-adaptive modeling is more suited to long-term projections.

After non-adaptive regression, autoregressive models are the second most popular option [17, 4, 2, 20, 18, 1, 56, 44, 55, 68, 69, 50, 74, 28]. This type of model is commonly used in the Box-Jenkins methodology [7] and allows the use of the data correlation structure. A general form of the seasonal autoregressive integrated moving average (ARIMA) model with order $(p, d, q)(P, D, Q)_T$ is given by

$$\left(1 - \sum_{j=1}^{p} \phi_j L^j\right)\left(1 - \sum_{j=1}^{P} \Phi_j L^{Tj}\right)(1-L)^d (1-L^T)^D y_t = \mu + \left(1 - \sum_{j=1}^{q} \theta_j L^j\right)\left(1 - \sum_{j=1}^{Q} \Theta_j L^{Tj}\right)\varepsilon_t. \quad (2)$$

Here, μ, ϕ_j, Φ_j, θ_j, and Θ_j are the parameters; ε_t is the residual (white noise) at time t; T is the number of periods per season; and L is the lag operator, defined as $Ly_t = y_{t-1}$. Differencing $(1 - L)y_t = y_t - y_{t-1}$ is needed to obtain a stationary series.

ARIMA, which has been used at the Centers for Disease Control and Prevention (US, Atlanta) since the 1980s [20], is suitable both for short-term and long-term forecasts. However, ARIMA requires a large number of observations and certain assumptions about the time series. Hence, alternative autoregressive approaches are also used [50, 74, 28]. For instance, integer autoregressive models yield good results for a short morbidity series [50].

2.2. Machine Learning-Based and Case-Based Methods

Dynamic Bayesian networks constitute another modeling technique that can incorporate data autocorrelation effects [74, 45, 60, 77, 64]. Bayesian networks represent probabilistic dependencies between variables via a graph. After learning, this tool provides an estimate of the probability of a particular event for the observed variables values. This currently burgeoning methodology is mostly applied to morbidity forecasting in the simple form of hidden Markov models (HMM). Thus, HMMs with two states (endemic and epidemic) are used to detect disease outbreaks [45, 77]. Such models require extensive computing resources; thus, the predictions are based on recent observations and calculated for the short term.

A remarkable machine learning-based tool is the artificial neural network (ANN). The ANN is represented by a directed graph, whose nodes resemble biological neurons. The nodes receive input signals, which can activate an output signal. The learning process is intended for estimating the weights of the node interconnections. The weights determine the strength of the input signals. Although different ANN architectures and learning paradigms [5, 43] can be used for disease forecasting, this method is presently better suited to short-term projections because recognizing complex long-term patterns with ANNs would require too much training data.

Case-based reasoning is a family of methods whose application is not limited to prediction. These methods are based on a search for solutions among the already known ones. When applied to morbidity forecasting, this technique is called the method of analogues [76, 59]. Using this method, the historical sections $y_\tau, y_{\tau-1}, \dots, y_{\tau-k}$ that most closely match the present observations $y_t, y_{t-1}, \dots, y_{t-k}$ are extracted from the time series. Different metrics — for instance, minimizing the distance $\sum_{j=0}^{k} (y_{t-j} - y_{\tau-j})^2$ — can be used for this selection. The forecast for the time $(t+h)$ is computed as the weighted mean of n sections: $\hat{y}_{t+h} = \sum_{j=1}^{n} w_j y_{\tau_j+h}$. The weights w_j are assigned according to the distance value. The method of analogues was designed for short-term predictions. Its use for long-term forecasting would require huge data sets as well as a more complex metric that would allow for, at least, information aging effects.

2.3. Filtering-Based Methods

A morbidity time series can be considered to be a stochastic process consisting of a useful signal and high-frequency noise. The signal reflects the epidemic situation. Removing noise allows for adjustments of the projections and can be performed during the initial data processing. For example, wavelet decomposition is used to denoise biosurveillance data [35, 74, 63]. Furthermore, there are forecasting methods that are directly based on filtering.

For instance, exponential smoothing is a filtering technique that is well-known in finance and economics. Exponential smoothing is a variant of the weighted moving average [49]. The smoothed value of incidence (level) at time t can be obtained as $l_t = \alpha y_t + (1-\alpha)l_{t-1}$, where α is the smoothing coefficient ($0 < \alpha < 1$). Then, the forecast is the most recent level estimate: $\hat{y}_{t+h} = l_t$.

Simple exponential smoothing is inapplicable to time series containing trends or seasonality. Generalized models [15, 16, 32] are used in these cases. In particular, morbidity can be expressed using the following additive Holt-Winters method:

$$\begin{aligned} l_t &= \alpha(y_t - s_{t-T}) + (1-\alpha)(l_{t-1} + r_{t-1}), \\ r_t &= \gamma(l_t - l_{t-1}) + (1-\gamma)r_{t-1}, \\ s_t &= \delta(y_t - l_t) + (1-\delta)s_{t-T}, \\ \hat{y}_{t+h} &= l_t + hr_t + s_{t-T+h}, \end{aligned} \tag{3}$$

where r_t describes the trend; s_t is a seasonal factor; and γ and δ are their respective smoothing coefficients. Although generalized exponential smoothing is suitable for both short-term and long-term morbidity prediction, it is an uncommon approach in such studies [11, 26].

The class of exponential smoothing models overlaps but does not coincide with ARIMA models [16, 39]. All of these models have equivalent state space representations [39]. In a generalized form, any epidemic process in a state space can be specified by the following system of difference equations [36]:

$$\begin{aligned} \mathbf{x}_t &= \mathbf{A}\mathbf{x}_{t-1} + \mathbf{w}_t, \\ \mathbf{y}_t &= \mathbf{H}\mathbf{x}_t + \mathbf{D}\mathbf{f}_t + \mathbf{v}_t, \end{aligned} \tag{4}$$

Here, $\mathbf{x}_t$ is an unobserved state vector at time t; $\mathbf{y}_t$ denotes a vector of the observed variables; $\mathbf{f}_t$ is the vector of exogenous factors; and $\mathbf{w}_t$ and $\mathbf{v}_t$ are vectors for the white noise. Then, the predictions can be obtained using the methods of control theory, in particular, Kalman filtering [10, 62]. The matrices of the parameters $\mathbf{A}$, $\mathbf{H}$, $\mathbf{D}$ determine the model of the morbidity process and are selected depending on the problem — long-term or short-term forecasting.

2.4. Mathematical Modeling of Infectious Diseases

All of the above-mentioned methods are based on historical data patterns and do not account for the aspects of the infection transmission process. The infection spreading features are modeled explicitly using the so-called "biological approach"[51]. We treat models of this type as mathematical models of infectious diseases (MIDs). Numerous MIDs have been developed; their review would require a separate paper. We shall go over only the notable classes of MIDs.

Conventional compartmental MIDs represent epidemic process dynamics through a system of differential equations. The most known among them include the famous SIR model, proposed by W. O. Kermack and A. G. McKendrick, and its modifications [64, 21, 29, 6]. These models divide the population into compartments, such as susceptible (S), infected (I), and recovered individuals (R). The system of equations defines variations in the size of the selected compartments. There are stochastic variants of the SIR model [34, 22, 31]; some models use the Markov chain framework [64, 25]. Spatial SIR-based models have been developed [3]; gravity-like models are applied for similar purposes [46, 57].

Presently, the most actively progressing MIDs are the simulation models that express the behavior of each individual in a population. Simulation MIDs evolved from simple cellular automata [67] to network models that acknowledge the irregularity of contacts between individuals [58]. This concept was further developed in discrete-event population-based MIDs [53, 14], which structure individuals' contacts based on social groups. A similar approach is used in promising agent-based (individual-based) models [64, 24, 52], where the behaviors of individuals are decentralized and specified for particular agents.

MIDs are efficient for both short-term and long-term forecasting. However, MIDs cannot be applied in our study. ILI & ARI data consist of diverse disease cases, whereas MIDs rely on the transmission mechanisms of a single infection.

2.5. Mixed Techniques

The reviewed methods are used both in the pure form and in various modified and hybrid forms. For instance, the Serfling model parameters can be estimated not only with least squares but also with robust weighting [4]. Wavelet decomposition is utilized along with autoregressive models [35, 63]. Kalman filtering is applied to the state-space representation of the SIR model [62].

Decomposition is a widespread technique that is used to forecast time series that exhibit consistent seasonality. This use is an attempt to separate the low-frequency seasonal component of a time series from the high-frequency random component and the long-term trend [38]. Decomposition allows a representation of these components through different types of models. For example, the seasonal component can be extracted by regression analysis [44] or by averaging data points (which correspond to each other within a seasonal period) of the original [1, 56, 55] or smoothed series [48]. ARIMA can model time series after removing the seasonal component [56, 44]. Decomposition is better suited to short-term projections because in long-term forecasts, the high-frequency component is virtually unpredictable.

Thus, long-term predictions of the ILI & ARI morbidity can be obtained using statistical methods, filtering-based methods, and their modifications. ANNs can also be applied for long-term forecasting when lengthy historical data are available.

In this study, we examined non-modified methods. We compared the forecasting accuracy for the following: simple averaging of observations, point-to-point linear estimates, Serfling-type regression models, Box-Jenkins ARIMA models, and the Holt-Winters method. Modeling incidence as a dynamical system in a state-space framework requires a separate study; thus, we have reserved such modeling for future work. All of the following computations were performed in R statistical analysis software version 3.0.0 [71].

3. ILI & ARI Data

We evaluated the one-year projection accuracy using the selected methods for six Russian cities (Table 1). These cities have different population sizes and are geographically distant from one another; thus, the morbidity time series in the cities exhibit slightly different patterns. We suppose that these data represent the overall ILI & ARI situation in Russia. The analysis and forecast were performed using the ILI & ARI weekly incidence data supplied by the Research Institute of Influenza [41]. The data comprised the total ILI & ARI visitor volume to outpatient clinics, hospitals and health centers in a city. To obtain comparable results for different cities, we measured the morbidity using the weekly incidence rate per 100000 of the city's population [4]. Thus, six time series for the city ILI & ARI incidence rates from 2000–2012 were analyzed.

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[1]The column features the results of a simple linear regression for the time series of the weekly ILI & ARI incidence rate per 100000 persons. The intercept is set to the mean value of the incidence rate in 2000–2012, and t denotes the index number for the week. The slope

City	Population [72]	Coordinates	Incidence rate[1]
Moscow	11503501	55°45'N 37°37'E	$518 - 0.15t$
St. Petersburg	4879566	59°57'N 30°18'E	$472 + 0.32t$
Novosibirsk	1473754	55°01'N 82°56'E	$512 - 0.01t$
Yekaterinburg	1349772	56°50'N 60°35'E	$392 + 0.19t$
Nizhny Novgorod	1250619	56°20'N 44°00'E	$597 + 0.11t$
Yakutsk	269601	62°02'N 129°44'E	$520 + 0.25t$

Table 1: Cities where morbidity forecasting was performed

Figure 1 represents one of the incidence time series and shows the outlier values in the first days of January of each year, which arise from the protracted official holidays. We adjusted all of the data and replaced the January outlier values with interpolations from the adjacent points. The incidence in some cities tended to increase (Table 1), while all time series showed a clear seasonal pattern. Spectral analysis confirmed the seasonality with a one-year period.

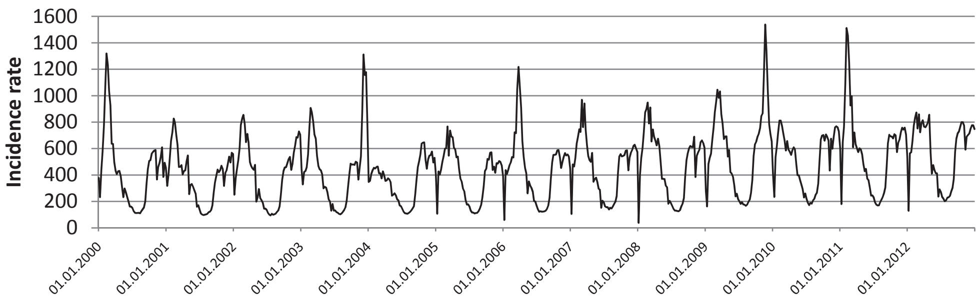

Figure 1: Weekly ILI & ARI incidence rates per 100000 persons in St. Petersburg

The morbidity data were collected by calendar weeks, and the number of weeks in a year varied: 52 or 53. To synchronize the measures of different years and to ensure recurrence of the seasonal pattern with the period of 52 weeks, we divided every calendar year into 52 intervals of 7 days each, starting from January 1. Then, we estimated the incidence rate y'_k for each of the intervals. Given that the incidence rate per calendar week k was y_k, we assumed that the incidence rate per day of this week was equal to $\psi_\tau = y_k/7$. The number of ILI & ARI cases recorded during a week is certainly irregular, but we cannot

[1] coefficient indicates the existence of a linear trend.

evaluate that number more accurately now. Using daily incidence data, ψ_τ, we calculated $y'_k = \sum_{j=1}^{7} \psi_{7(k-1)+j}$ for $k = 1 \dots 52$. The incidence data for the year's last days, ψ_{365} and ψ_{366}, were discarded. This adjustment for each year not only fixes the seasonal period to 52 weeks but also smoothes the time series, reducing the high-frequency fluctuations of the observations. The adjusted data used in the subsequent analysis are available from the authors upon request.

Detecting morbidity predictors has fundamental importance for accurate forecasting. The most frequently proposed covariates are related to weather [17, 80, 18, 69]: air temperature, relative humidity, precipitation, and air pressure. According to a previous study [33], there is a correlation in St. Petersburg between the ILI & ARI incidence and air temperature fluctuations, with a three-day lag. We computed the Pearson correlation coefficient for the incidence rates and the air temperature. Its average value for all of the cities was -0.65. Unfortunately, weather dependencies cannot be used in long-term morbidity projections because this would require long-term weather forecasts.

Seasonality factors are much more important for our study. There are different explanations for the seasonal cycles of infectious diseases: migration of the pathogen across the equator, host-behavior changes, and environmental changes [27]. For example, an annual light/dark cycle influence on human resistance to infections is possible. One study [37] even claims variability in the activity of the viruses themselves. There is no consensus about the causes of ILI & ARI seasonality. Therefore, we based our projections solely on historical data patterns. We assumed that the incidence rate time series are additive; thus, all of the models we used have an additive trend, an additive seasonal component and an additive remainder component.

Importantly, the ILI & ARI data consist of various cocirculating infections cases, including influenza. The influenza activity is estimated by the selective laboratory diagnosis [41]. Generally, almost no influenza viruses are isolated, but during an epidemic period, influenza's share in the ILI & ARI incidence data increases to 10 % and higher. Major outbreaks substantially change the shape of the incidence curves; influenza burden estimation is a notable problem [42, 19]. Official ILI & ARI epidemic thresholds in Russia are based on the averaging of weekly baseline observations [13]. We detected significant threshold crossings (for 10 % or more) in 2000–2012. There were only four such crossings; the timespan between them varied from two to six years, and there was no discernible periodicity. Therefore, we currently believe that there is no way to predict the next major influenza epidemic.

In most studies, epidemic morbidity is excluded from the analysis [54]. We used the entire ILI & ARI incidence series because it is impossible to separate the influenza morbidity with certainty. Furthermore, we do not want to undervalue the projected incidence rates because seasonal epidemics recur almost every year. Surely, long-term forecasts under such circumstances are rather presumptuous, but even rough estimates of future morbidity are useful.

4. Results

We evaluated the accuracy of the predictions using 2000–2010 as the model fitting period and the 2011 data to compare forecasts with actual observations. Then, we used 2000–2011 as the fitting period and 2012 as the forecasting period. In 2011, a major influenza outbreak occurred, whereas in 2012, there was moderate morbidity. Thus, the 2011 and 2012 ILI & ARI data differ, and the accuracy of the forecasting methods can vary significantly.

We measured the models' goodness of fit by computing the root mean squared error (RMSE) during the fitting period. The number of parameters in the Serfling and ARIMA models was selected based on the minimal value of the Akaike information criterion (AIC) [12]. The AIC was estimated as $\mathrm{AIC} = n \ln(\mathrm{MSE}) + 2k$, where n is the number of observations during the fitting period, MSE is the mean squared error value, and k is the number of model parameters. We compared the accuracy of the projections using the RMSE value for the forecasting period. Additionally, the mean absolute percentage error (MAPE) was calculated for the forecasting period.

We used the Shapiro-Wilk test to check for the normality of the residuals, the Goldfeld-Quandt to determine the heterosedasticity, and the Ljung-Box test to determine the independence of the residuals. When testing the hypotheses, differences with a p-value less than 0.05 were considered statistically significant.

As an example, Table 2 features the detailed St. Petersburg results. Table 3 represents evaluations of the forecast accuracy for all of the six cities.

The quality of predictions obtained through simple averaging was unexpectedly high. This method can be successfully applied in cities without a morbidity trend, such as Moscow. However, generally, long-term trends should certainly be factored in somehow.

The point-to-point linear estimates avoided the main shortcoming of simple averaging and produced reliably good results. In most cases, this forecasting algorithm was not optimal, but it yielded results that were no worse than the average.

The Serfling model (Eq. (1)) was used with a linear trend ($\nu = 1$) and phases of $\theta_j = 2\pi jt/52$, where t denotes the index number for the week. The

	Goodness of fit (2000–2010)		Forecast accuracy (2011)	
	RMSE	AIC	RMSE	MAPE
Averaging	126.6	5642.6	209.3	22.9 %
Point-to-point linear estimates	117.3	5557.3	165.0	12.3 %
Serfling model	119.2	5497.6	166.6	12.1 %
ARIMA $(1,1,1)(0,1,1)_{52}$	59.9	4690.1	166.8	13.8 %
Automatic ARIMA	51.2	4519.9	161.1	11.7 %
Holt-Winters method	68.8	4846.2	175.9	16.4 %
	Goodness of fit (2000–2011)		Forecast accuracy (2012)	
	RMSE	AIC	RMSE	MAPE
Averaging	134.3	6219.7	137.0	23.5 %
Point-to-point linear estimates	121.1	6092.1	67.6	8.5 %
Serfling model	123.0	6033.8	75.2	9.8 %
ARIMA $(1,1,1)(0,1,1)_{52}$	61.0	5138.1	131.0	22.7 %
Automatic ARIMA	53.3	4978.5	79.1	9.6 %
Holt-Winters method	96.9	5714.1	163.6	14.8 %

Table 2: Comparison of the ILI & ARI forecasting methods in St. Petersburg

number of harmonic terms κ was individually set for each time series. Mainly, six harmonic terms were required for minimizing the AIC. In almost every city, the residuals of the Serfling model for the fitting period were homoscedastic, but their distribution was not normal. Moreover, the residuals were significantly correlated. Hence, Serfling model residuals should be modeled separately to improve forecasts.

All projections based on the Serfling model nearly coincided with the point-to-point linear estimates. We tested the hypothesis about the equality of their forecasting errors. Paired two-sample t-tests showed no differences between these prediction techniques. The average accuracy of the linear estimates was slightly greater than that of the Serfling models, but this was an insignificant difference.

We selected the ARIMA models (Eq. (2)) in two ways. First, we identified a model by visually analyzing the autocorrelation function estimates (ACF) and partial autocorrelation function estimates (PACF). Second, we used an automatic procedure, developed by R. J. Hyndman [39] and implemented in the "forecast"package (version 4.04) for R [30].

The ILI & ARI incidence rate time series are not stationary; thus, differencing is necessary[2] ($d = 1$). The models with ($D = 1$) and without ($D = 0$) seasonal differencing were examined. Applying seasonal differencing is preferable

[2]ILI & ARI incidence rate time series after seasonal differencing ($d = 0$, $D = 1$) are still non-stationary.

	Averaging	Point-to-point linear estimates	Serfling model	ARIMA $(1,1,1)\times(0,1,1)_{52}$	Automatic ARIMA	Holt-Winters method
				2011		
Moscow	130.6	140.0	138.3	166.0	134.7	149.2
St. Petersburg	209.3	165.0	166.6	166.8	161.1	175.9
Novosibirsk	242.2	244.7	245.4	258.5	272.2	298.3
Yekaterinburg	201.6	186.4	185.0	152.9	157.6	164.8
Nizhny Novgorod	168.7	153.3	153.2	203.3	119.8	171.4
Yakutsk	192.0	173.9	177.3	183.9	253.4	145.6
				2012		
Moscow	52.5	67.4	68.5	108.3	70.6	128.6
St. Petersburg	137.0	67.6	75.2	131.0	79.1	163.6
Novosibirsk	89.7	90.6	94.9	78.0	91.4	260.7
Yekaterinburg	143.7	103.9	106.4	85.9	86.5	159.7
Nizhny Novgorod	103.5	104.0	108.9	111.7	115.7	196.2
Yakutsk	242.0	202.3	211.0	199.0	204.2	253.3

Table 3: Prediction accuracy: root mean squared error computed for the forecasting period

because it prevents the seasonal pattern from dissipating. After differencing, the ACF tapered sinusoidally, while the PACF oscillated and decayed exponentially. Thus, we selected $p = q = 1$ [7]. The ACF only had a negative spike for the seasonal period; the PACF decayed exponentially across the seasonal lags. Therefore, we set $P = 0$ and $Q = 1$ [38].

Hyndman's stepwise procedure for ARIMA model selection does not always converge to an optimal model, as measured by the AIC. Thus, we searched for the best model using two iterations. We ran an automatic ARIMA algorithm with limitations on the number of parameters: first $p \leq 2$ and $q \leq 2$, and then $p \leq 5$ and $q \leq 5$[3]. In most cases, the former iteration yielded a more accurate model, both in terms of the AIC and the forecast.

The ARIMA results were mixed. Depending on the time series, the accuracy of the ARIMA-based projections was better or poorer than the average. For certain cities, the best results were yielded by ARIMA $(1,1,1)(0,1,1)_{52}$ (Novosibirsk, Yekaterinburg, Yakutsk); for others, the automatic forecasting procedure (Moscow, St. Petersburg, Nizhny Novgorod) was best. In many cases, ARIMA provided the best predictions, but for some other occasions, it produced less accurate results than the point-to-point linear estimates. Almost all ARIMA residuals for the fitting periods were homoscedastic and independent. Their distribution was not normal, although the shape of the histograms was close to

[3]In all cases, the maximum permissible value of P and of Q was two.

the normal probability density function.

The additive Holt-Winters method (Eq. (3)) was used for exponential smoothing. Parameter values were selected by applying the built-in R optimizer ("HoltWinters"function). For all time series, the value of the coefficient γ was zero, and the values of α and δ ranged from 0.9 to 1. The results of smoothing substantially depended on the choice of the starting values of l_0, r_0, and s_0. We tried initializations based on the first and the last observations during the fitting period, as described [16, 48]. The initialization by recent observations yielded markedly better results. Nonetheless, in all but one case, smoothing produced a much poorer forecast than the other methods.

5. Discussion

The analysis of the ILI & ARI incidence rate time series showed a fairly common phenomenon: under conditions of essential uncertainty, long-term forecasting with simple methods can produce results as good as those produced by sophisticated statistical techniques. When an incidence time series exhibits a consistent seasonal pattern and does not have a trend, there is no reason to use forecasting methods that are more complex than averaging.

Given a long-term linear trend, it is possible to apply point-to-point linear estimates. Nevertheless, we prefer the more conventional Serfling model, which can be modified to incorporate different types of trends. The Serfling model has long been a well-known tool for morbidity predictions that are always as accurate as point-to-point linear estimates. The Serfling model can be recommended as a basic incidence forecasting approach that almost always produces medium-precision projections.

The Serfling model residuals are correlated; thus, this forecasting method can be improved. For instance, modeling of the residuals with ARIMA [56, 44] is quite a good technique. This modeling ensures better quality in short-term predictions but does not give considerable advantages in long-term predictions because the residuals do not reveal any periodicity. The Serfling model can be regarded as a decomposition variant that allows for the isolation of a trend and a seasonal component of the time series.

In most cases, the ARIMA models are comparable to the Serfling models in terms of long-term forecasting accuracy, and the former models do not have any significant benefits over the latter models. Nonetheless, the ARIMA models are less reliable and can perform poorly in some situations. However, if an initially stable morbidity pattern starts to change for the most recent years of observations — for example, if a trend arises — ARIMA can successfully model the future dynamics of the time series.

Similar to ARIMA, exponential smoothing is a technique developed for short-term predictions. In our study, the Holt-Winters method produced low-precision projections, perhaps due to the large random variation in ILI & ARI incidence data [15], although it is generally better suited than ARIMA to non-stationary time series [16, 39]. Possibly, the exponential smoothing results can be improved with a more careful selection of the starting values.

Unfortunately, a single ILI & ARI morbidity forecasting method that would be optimal for any time series does not appear to exist. The results suggest that the Serfling model should be used by default. The ARIMA models, used both in conjunction with the Serfling method and separately, allow for improved predictions in many cases. However, their application requires an additional analysis and is not always warranted.

The accuracy of the incidence projections is conditional not so much on the method as on the features of the time series, namely, the year and the city. The average RMSE value of the Serfling model during the forecasting period was 144 disease cases, with a MAPE of 14.5 %. Automatic ARIMA modeling yielded an average RMSE value of 145 disease cases, with a MAPE of 14.6 %. The precision of long-term predictions leaves much to be desired, but we were able to estimate the ILI & ARI morbidity in 2013. Figure 2 features the incidence rate forecast for St. Petersburg as an example.

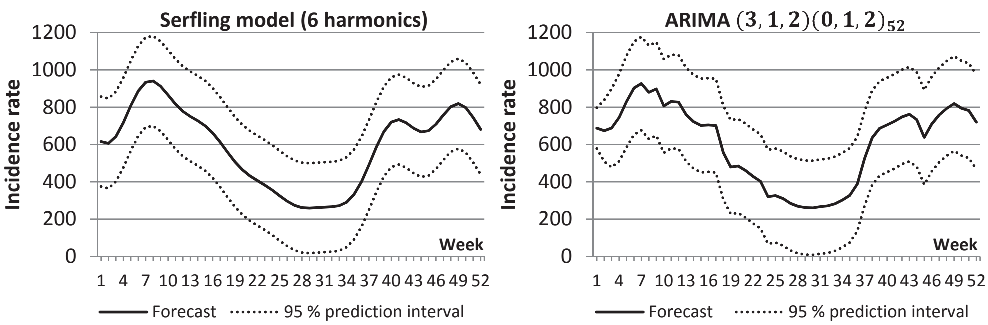

Figure 2: Forecast of the weekly ILI & ARI incidence rates per 100000 persons in St. Petersburg, 2013

The diversity of the geographical settings and population sizes of the examined cities leads us to believe that the findings are sufficiently representative to be applicable to any other city in Russia, as well as in other countries with a similar influenza surveillance system — for instance, the former Soviet republics.

We analyzed the ILI & ARI cases for patients of all ages. The ILI & ARI incidence time series of separate age groups are analogous; thus, the same prediction methods can be applied to all ages. Moreover, it is possible to perform long-term forecasting of visitor flow for individual health centers (or emergency departments) in the same way. This prediction can be used to estimate the centers' workload and revenue and to prevent overcrowding [17, 28].

The proposed forecasting techniques are maintenance-free and can be used in an automatic mode, even by personnel without special training. Because disease surveillance is automated, it would make sense to integrate morbidity prediction and analysis procedures into information surveillance systems.

We are aware of all of the imperfections of long-term ILI & ARI projections; it is hardly possible to achieve accurate predictions with considerable random variation in the data and irregular influenza outbreaks. However, we still believe that the results of this study have important practical implications.

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