Deep Learning Based Convective Boundary Layer Determination for Aerosol and Wind Profiles observed by Wind Lidar

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Introduction

1. To investigate the possibility to predict **convective boundary layer** from aerosol backscatter profile.
2. A deep-learning model is used to build a **non-supervised** package to identify the CBLH from aerosol and wind products measured by coherent Doppler lidar (CDL).
3. The modified **Stacked Hourglass Network** used in this study is a conv-deconv architecture typically applied to **human pose** estimation.
4. The ground truth of CBLH is determined from the **vertical-velocity variance**.
5. **Normalized backscatters (NBS)** and **Radical wind speeds (*W_r*)** are individually selected to train the model.
6. The **minimum required data size** for the training is examined. The differences between ground truth and predicted CBLH are presented.

Coherent Doppler Lidar

- Coherent Doppler lidar (CDL, WindPrint S-4000)
- This CDL is jointly developed by Ocean Univ. of China and Leice Transient Technology Co., Ltd.
- Operated in 5-beam DBS model in Taichung City in Central Taiwan in 2018.

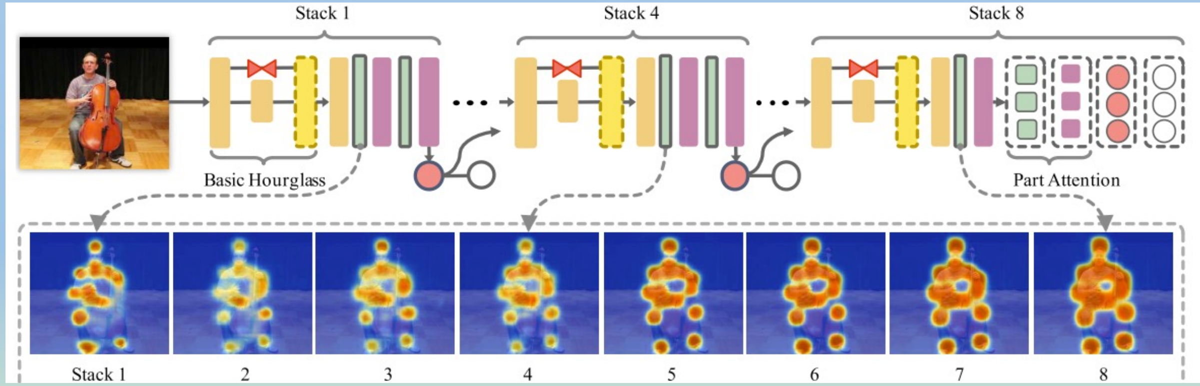
Model	Doppler Wind Lidar
Detection range	40m – 4000m (up to 6 km)
Data update	Up to 0.25s (fastest)
Range resolution	15m/30m/60m (configurable)
Wind speed accuracy	0.1 m/s
Wind speed range	0 – 70 m/s
Wind direction accuracy	0.1°
Power supply	AC 220V/50Hz or DC 12V/24V
Power consumption	200W
	500W when cooling at 40 °C
Operating temperature	-30 °C to +50 °C
Operating humidity	0 – 100%
Housing classification	IP65
LASER Safety Compliance	1M IEC/EN 60825-1 (eyes safety)
Size	600×600×800mm

Vertical-Velocity Variance

- The vertical-velocity variance σ_w^2 from the CDL is used to determine the CBL depth.
- A threshold of σ_w^2 =0.035 is found suitable for our location and was validated with co-launched radiosondes.

Stacked Hourglass Network

- Stacked hourglass network is a state-of-the-art architecture for human pose estimation.
- Image features are learned by convolutional and pooling layers at multi-resolutions to capture the joints of human body.
- A stacked hourglass network contains eight hourglass modules. The first hourglass module produces early predictions, and subsequent modules further improve the predictions.
- The vertical profile of lidar data is formatted as a 2D image and sliced into 15-minute segments. Each segment has 184 lidar samples periodically collected from south, east, west, north, and zenith.
- The values of radical wind speed and NBS (denoted as SNR in raw data) are encoded as 184x192 RGB image. The NBS is individually encoded as gray-scale images.



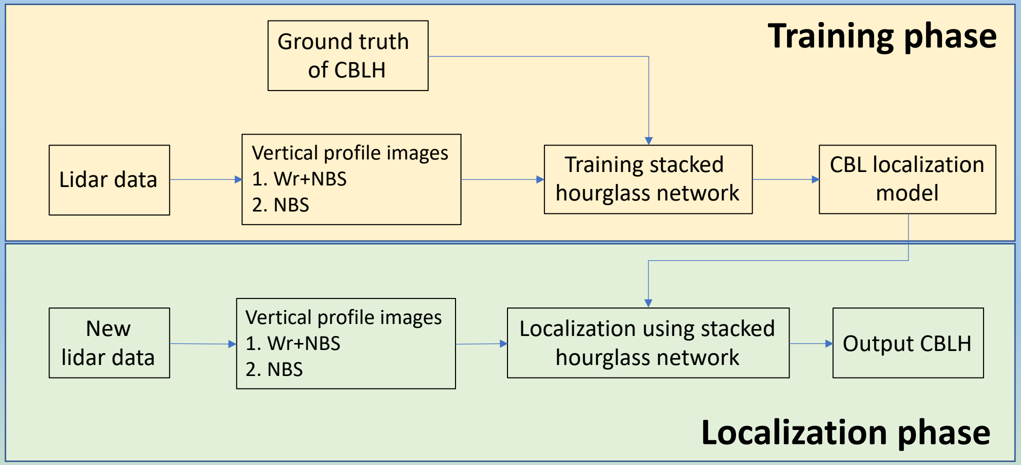
Chu, X et al. (2017). Multi-context attention for human pose estimation. doi:10.1109/CVPR.2017.601

Results

Data Set

- One year of CDL data is collected and 30,000 segment images are generated accordingly.
- Segment images and the ground truths from 36 days, 72 days, 120 days, and 230 days randomly selected from the whole data set are used to train the model.
- Vertical measurements are excluded from training data.
- Data measured during 2018/12/30-2019/1/15 (**excluded from the training period**) are chosen to examine the CBLH predicted by stacked hourglass network.

The flow chart of the training and localization process



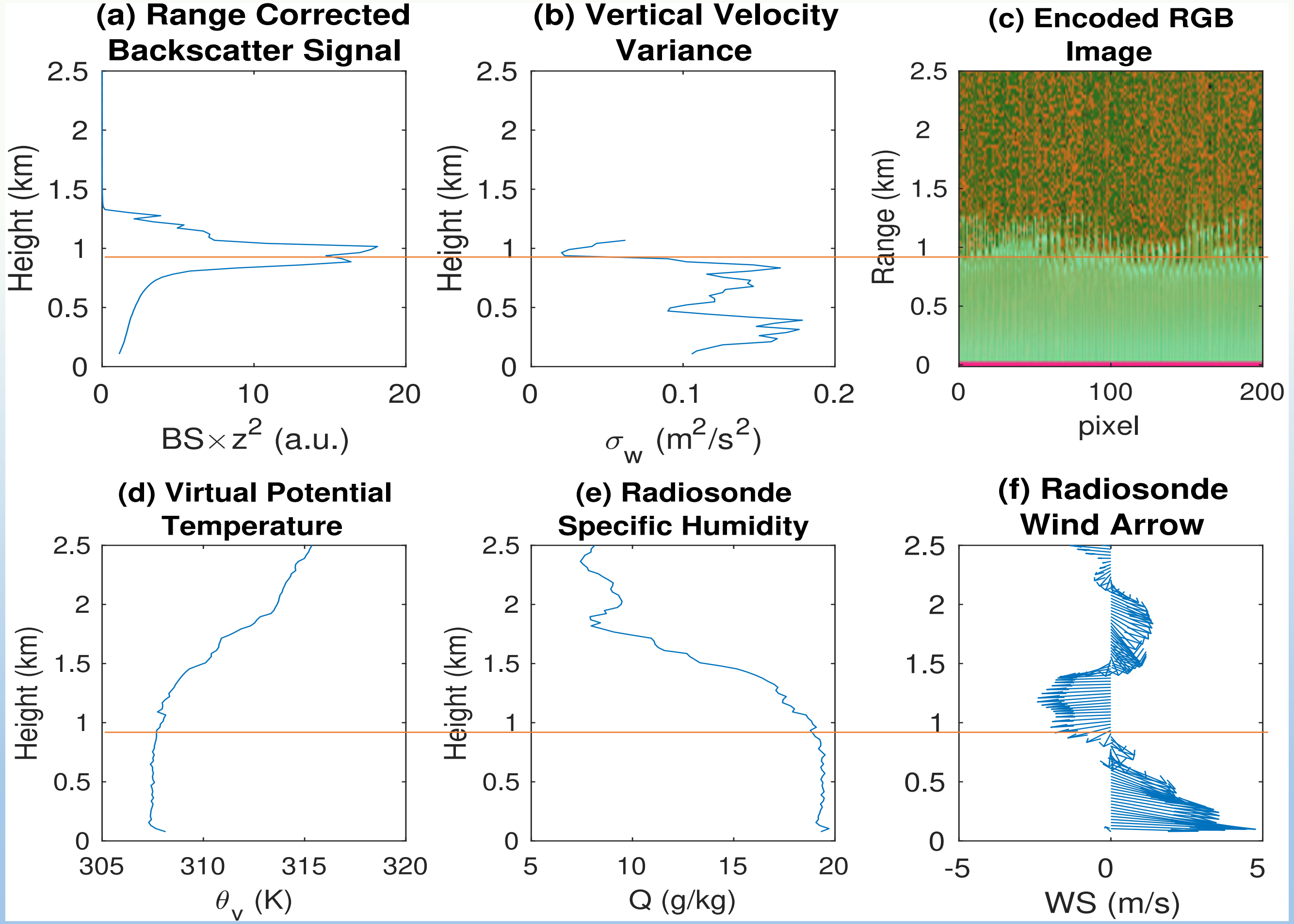


Figure 1:

- (a) Range corrected lidar backscatter and (b) vertical-velocity variance observed on 2018/7/15 15:00-15:10 (local time).
- (c) the image encoded from 15-minute segment (radical wind speed + normalized backscatter or only normalized backscatter).
- (d)-(f) Virtual potential temperature, specific humidity, wind arrow measured by co-launched radiosonde. The CBLH determined by vertical velocity variance is 904 m (red line).

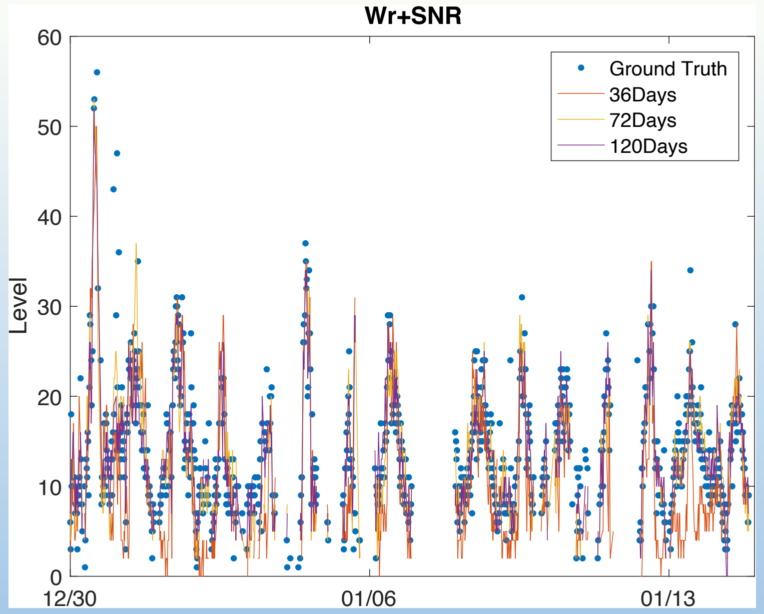


Figure 2:

- The time series (2018/12/30-2019/1/15) of CBLH predicted by stacked hourglass network using 36 days, 72 days, 120 days, and 230 days measurements as the training base.
- The predicted CBLH generally well agrees with the ground truth.

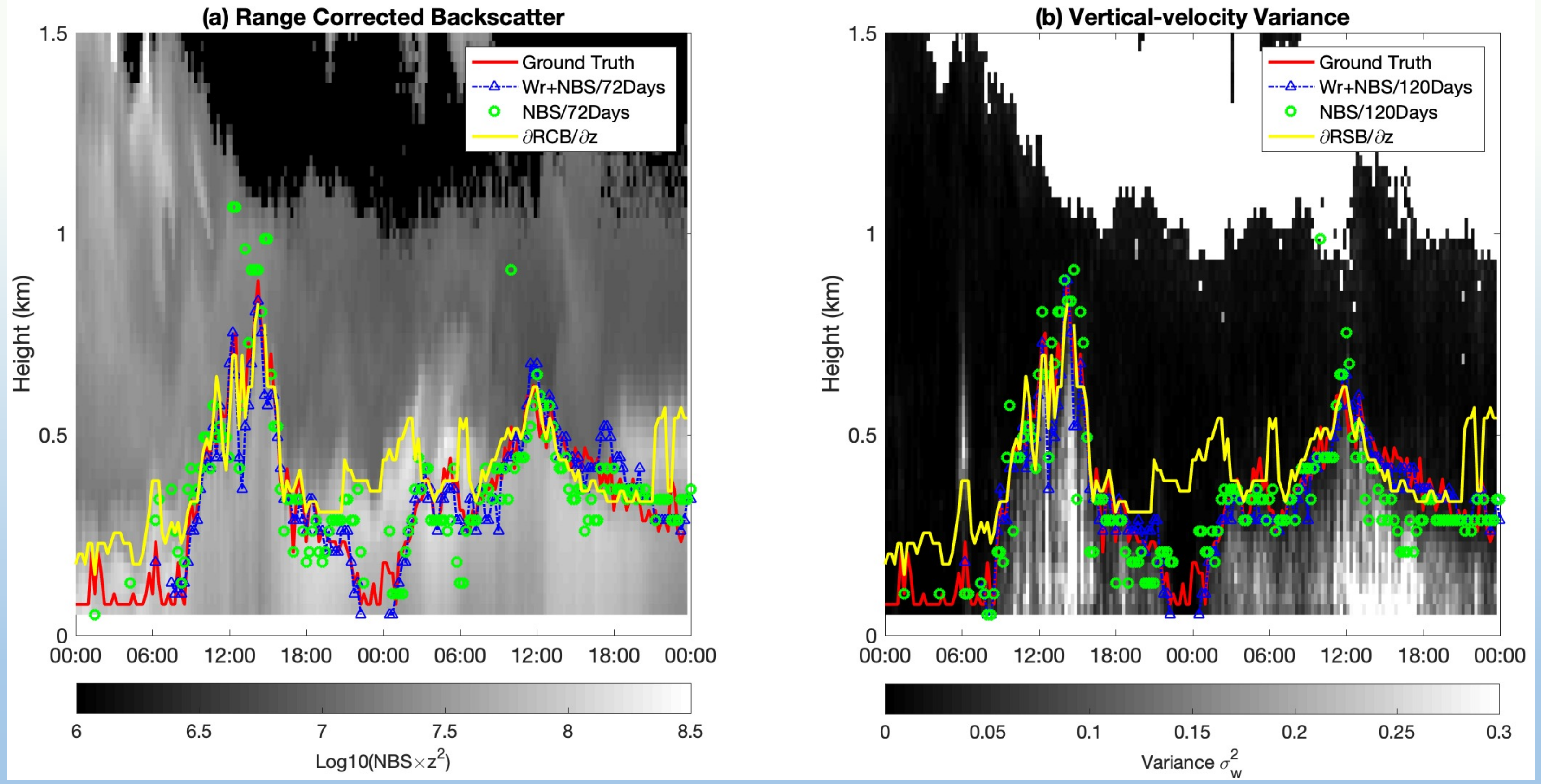
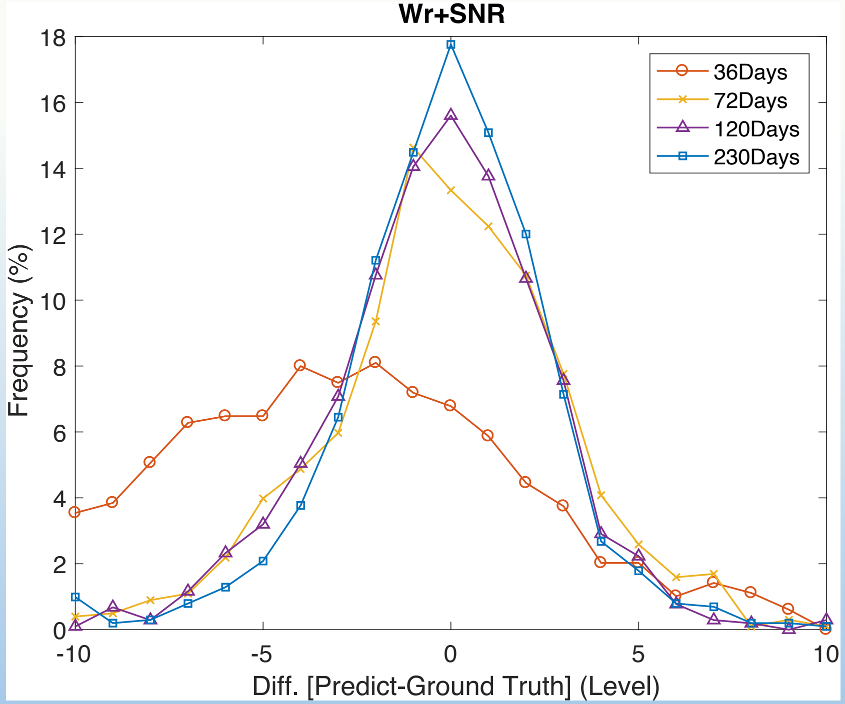
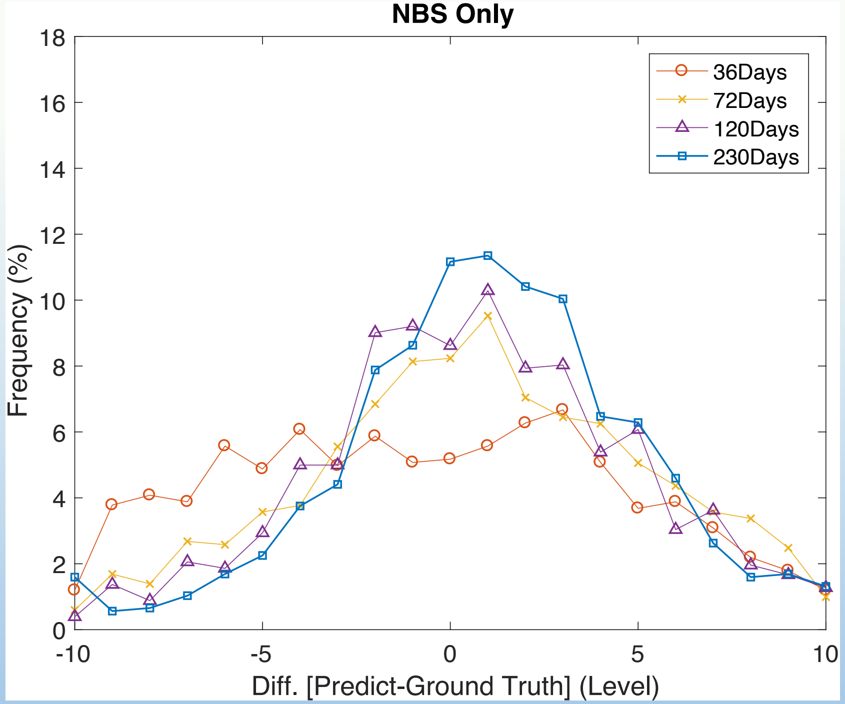


Figure 3:

- Time-height variation of (a) the Range corrected backscatter signal and (b) the vertical-velocity variance measured during 1/12-1/13, 2019. The CBLH predicted from the training bases of 72 days and 120 days Wr (blue △) and NBS (green ○) are composed in (a) and (b).
- Aerosol Layer determined by gradient method (∂RCB/∂z, yellow line) is shown for comparison, where RCB is the range corrected signal in logarithm scale.

Frequency Histogram of the Difference (1 level ≈ 26 m)





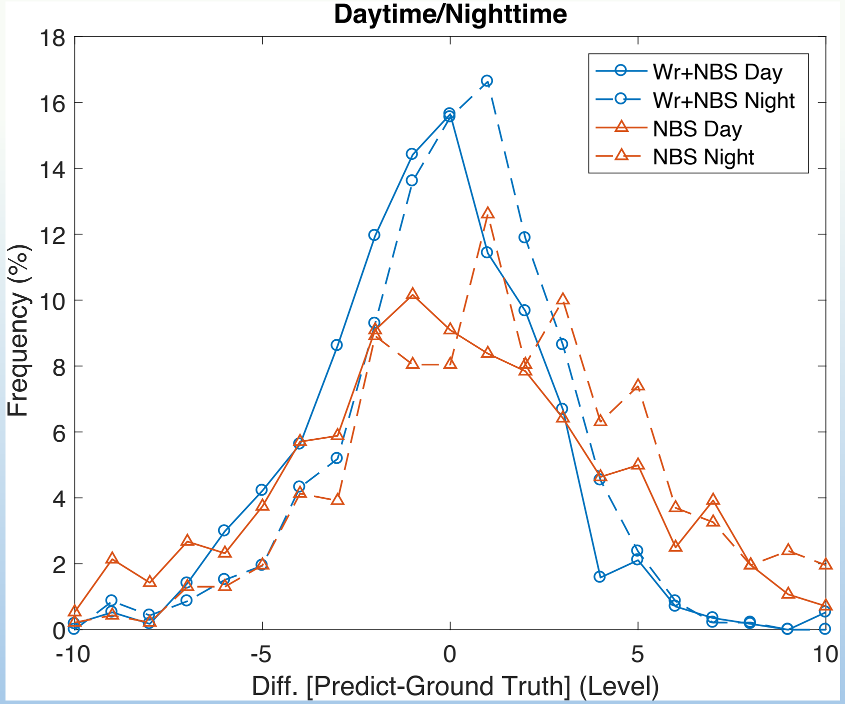


Figure 4:

- The frequency histogram of the difference between ground truths and CBLH predicted using 36, 72, 120, and 230 days Wr+NBS as training data.
- About 47% of predicted daytime CBLH are underestimated and 41% are overestimated.

Figure 5:

- Same figure 4 but using NBS as training data.
- 46% of predicted daytime CBLH are underestimated
- 44% are overestimated

Figure 6:

- Same figure 5 but separate to daytime and nighttime. Training set of 120 days.
- The differences between daytime and nighttime is not significant.
- Both Wr+NBS and NBS tend to 1 level (26m) overestimated in the nighttime and 1 level underestimated in the daytime.
- About 45% of predicted night-time CBLH are underestimated and 59% are overestimated.
- about 32% of predicted nighttime CBLH are under-estimated and 59% are overestimated.

Summary

- The mean value of CBLH during the testing period (2018/12/30 - 2019/1/15) are 433m and 255m for the daytime and the nighttime, respectively.
- The deep-learning based method can efficiently find the feature of CBLH from CDL products with MAE about 60~120m without any prior assumption.
- A number of 72 days measurement is required obtained stable prediction.
- Our results also indicate that it is possible to derive CBLH from backscatter profiles measured by Mie lidars.

Mean Absolute Error (MAE)

	Size of Data for Training			
MAE	36 Days	72 Days	120 Days	230 Days
Wr+NBS	136 m	75 m	65 m	56 m
NBS	147 m	122 m	104 m	89 m
Day /Wr+NBS	140 m	77 m	67 m	54 m
Night/Wr+NBS	140 m	72 m	61 m	57 m
Day /NBS	132 m	126	101 m	91 m
Night/NBS	150 m	116	99 m	85 m

Acknowledgements

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