인공지능을 활용한 기상/기후 예측

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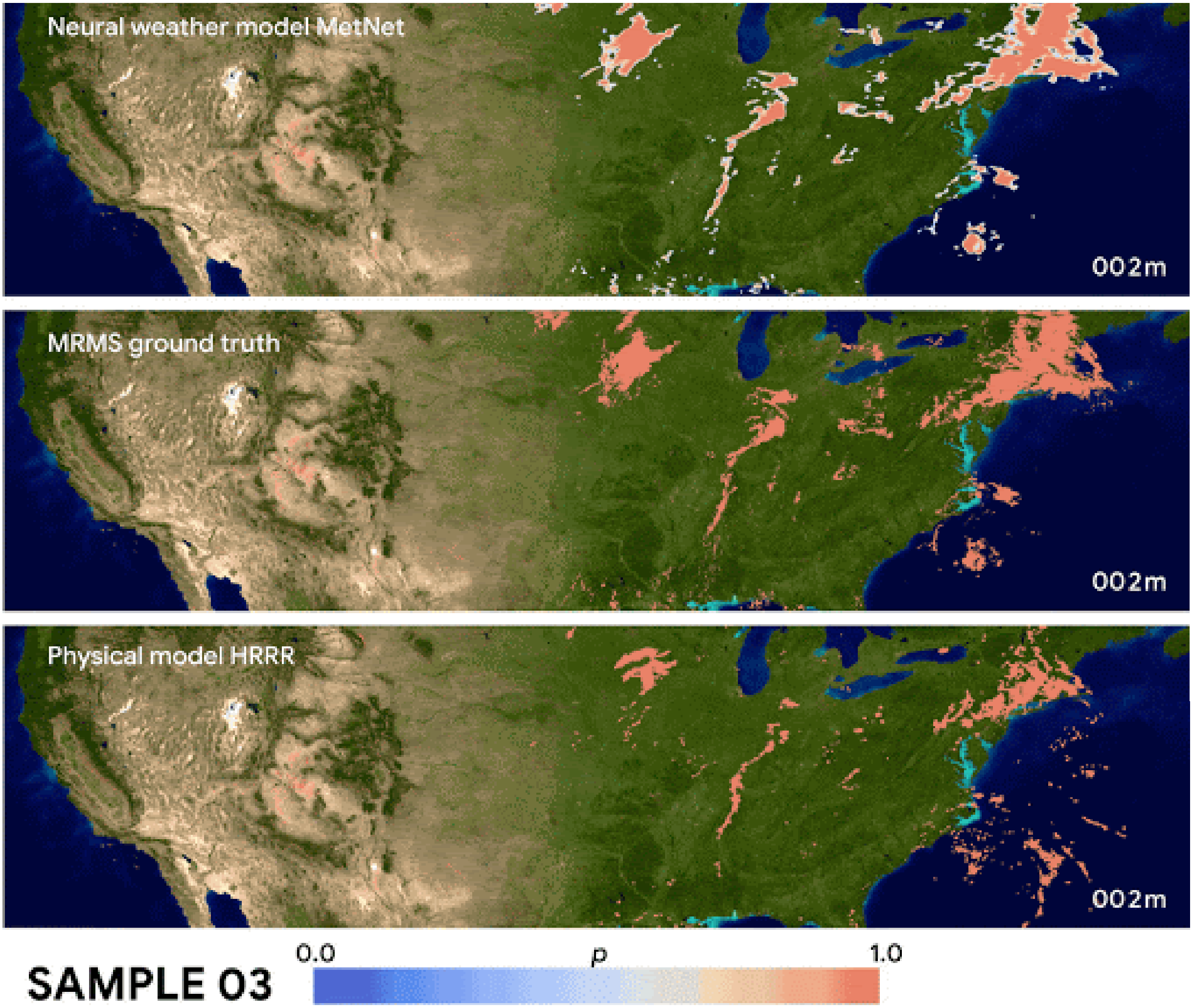
May 11, 2021

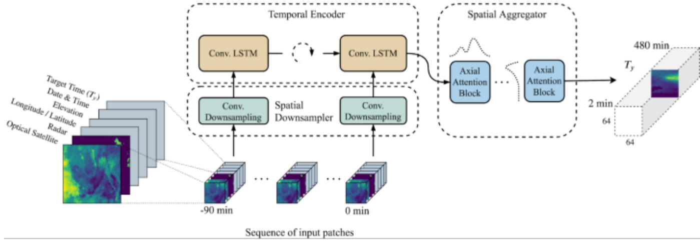
Intelligent Remote sensing and geospatial Information Science (IRIS) Lab

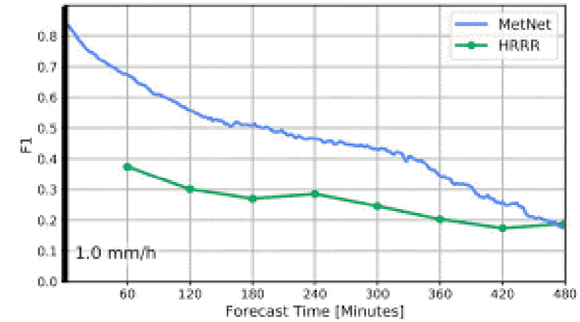
IRIS LAB
iris.unist.ac.kr

인공지능 (Artificial Intelligence)

Google AI (https://ai.googleblog.com)



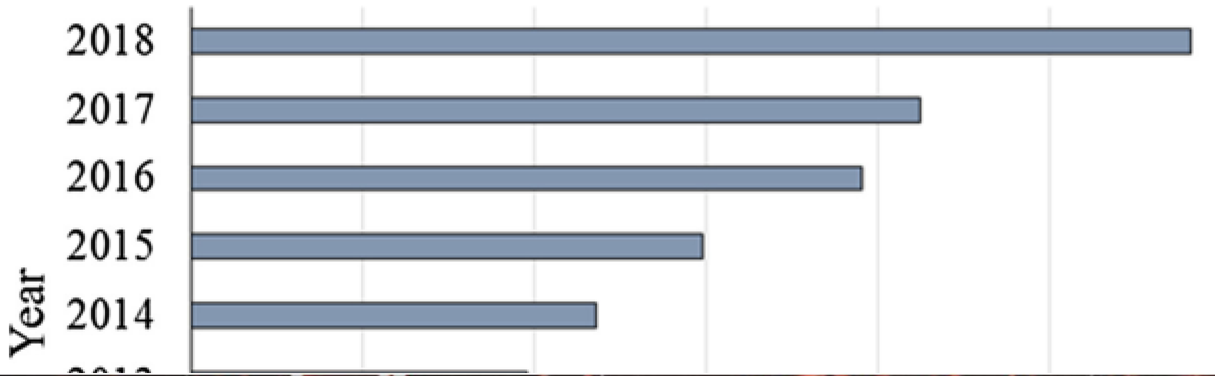


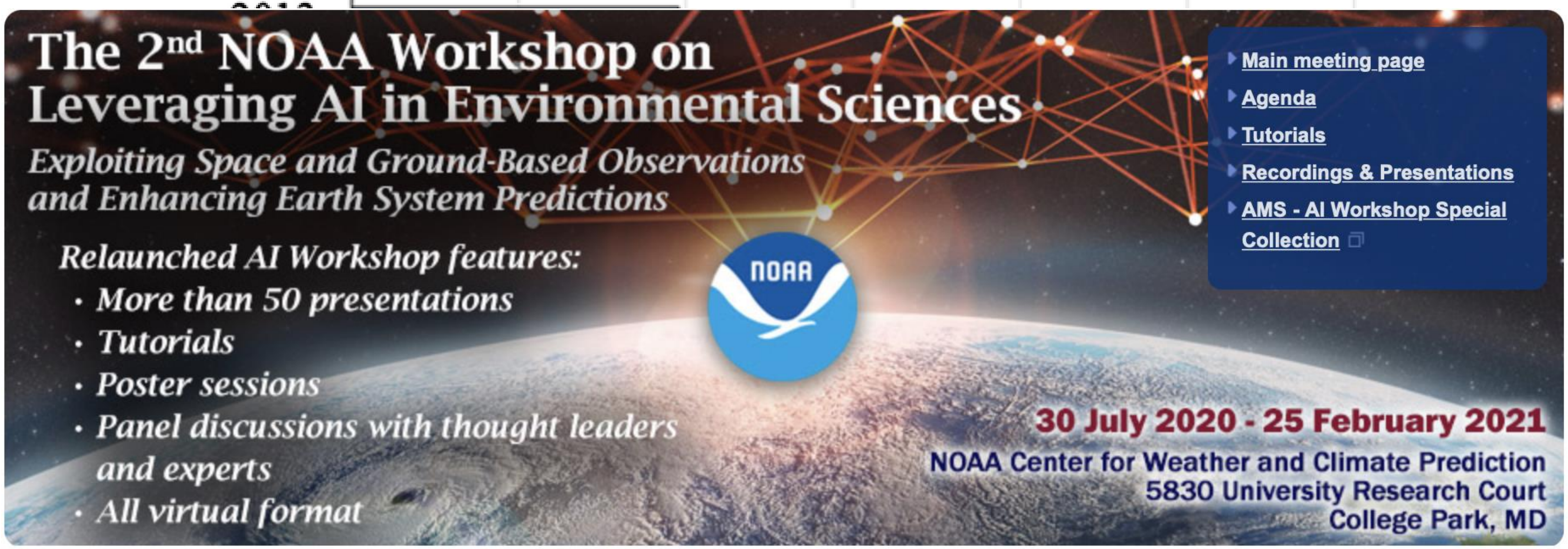


인공지능을 활용한 기상/기후 연구

기상기후분야의 AI 활용 트렌드

Ardabili et al., 2019





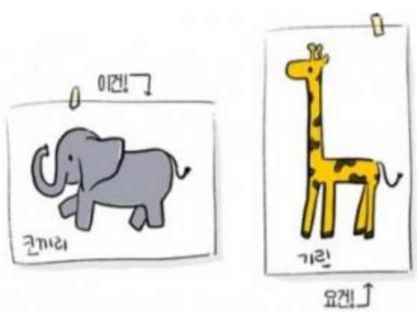
Ardabili, S., Mosavi, A., Dehghani, M., & Várkonyi-Kóczy, A. R. (2019, September). Deep learning and machine learning in hydrological processes climate change and earth systems a systematic review. In *International Conference on Global Research and Education* (pp. 52-62). Springer, Cham.

인공지능 종류 : 학습방법에 따른

인공지능 종류

인공지능
Artificial Intelligence

- **지도학습** Supervised Learning
- **비지도학습** Unsupervised Learning
- **자기지도학습** Self-supervised Learning
- **강화학습** Reinforcement Learning



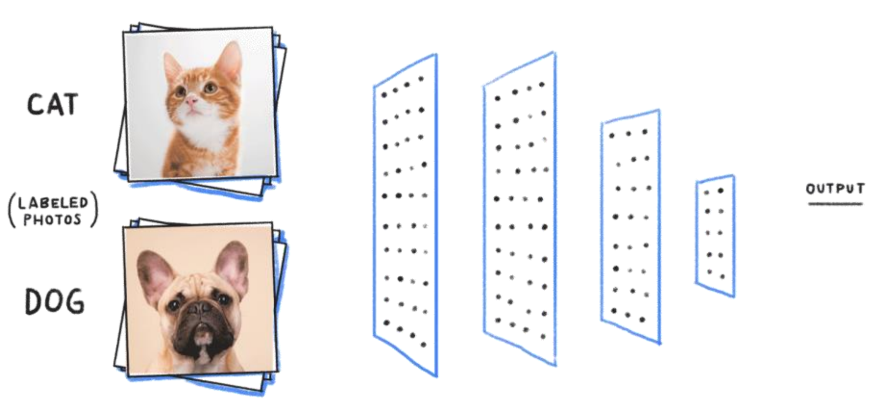
https://www.mobiinside.co.kr/2020/03/12/ai-perceptron/
https://today.duke.edu/2020/06/artificial-intelligence-makes-blurry-faces-look-more-60-times-sharper

인공지능 종류

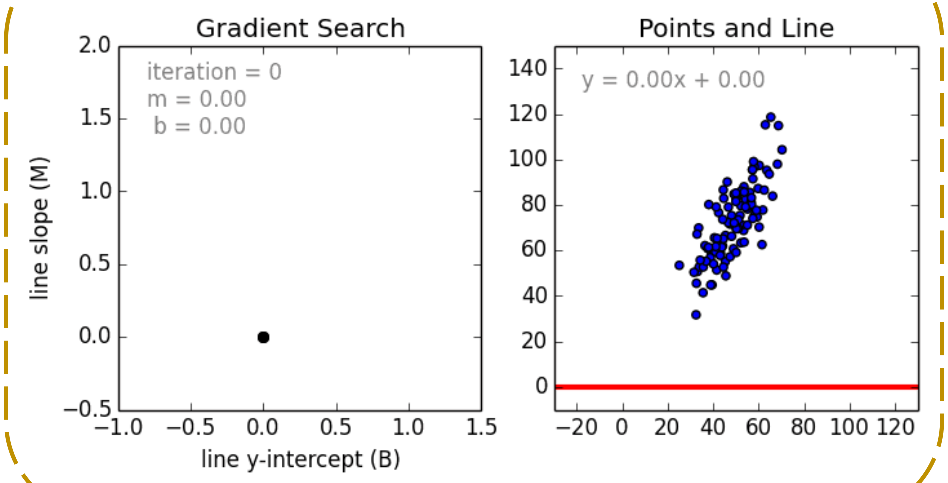
Supervised Learning (지도 학습)

- 데이터에 대한 **명시적 정답인 레이블이 주어진 상태에서 학습**시키는 방법
- **분류 (Classification)** 및 **회귀 (Regression)**에 주로 활용됨
- 대표적인 알고리즘: Logistic Regression, Random Forest, Support Vector Machine 등

Classification



Regression

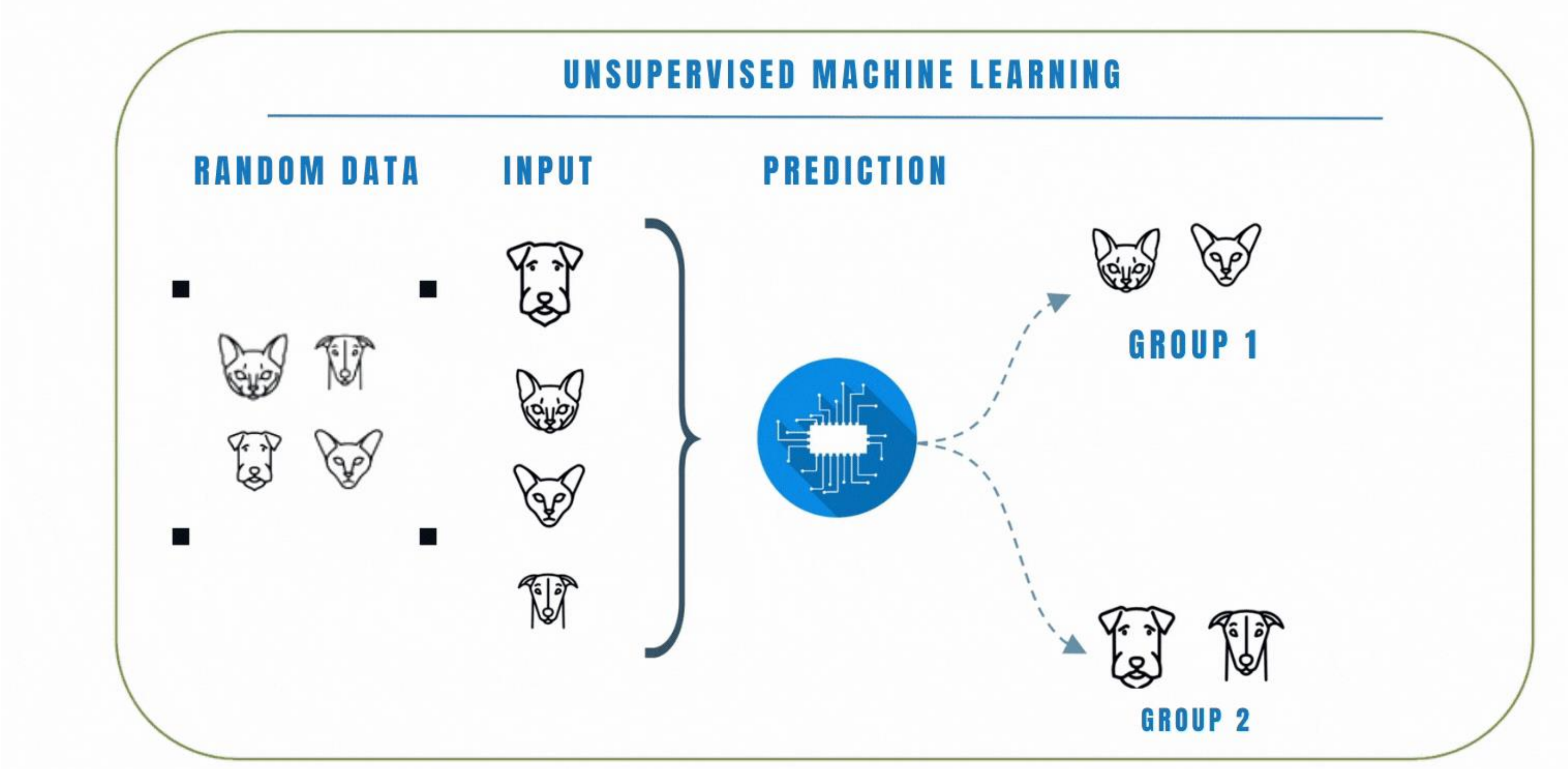


이미지 출처: https://quantumcomputingtech.blogspot.com/2019/02/machine-learning-animated-gif.html

인공지능 종류

Unsupervised Learning (비지도 학습)

- 데이터에 대한 **레이블이 주어지지 않은 상태에서 학습**시키는 방법
- **데이터의 구성** 또는 **특징을 밝히는 목적**으로 활용됨
- 대표적인 알고리즘: Self-Organizing Map, Hierarchical Clustering, Density Estimation 등

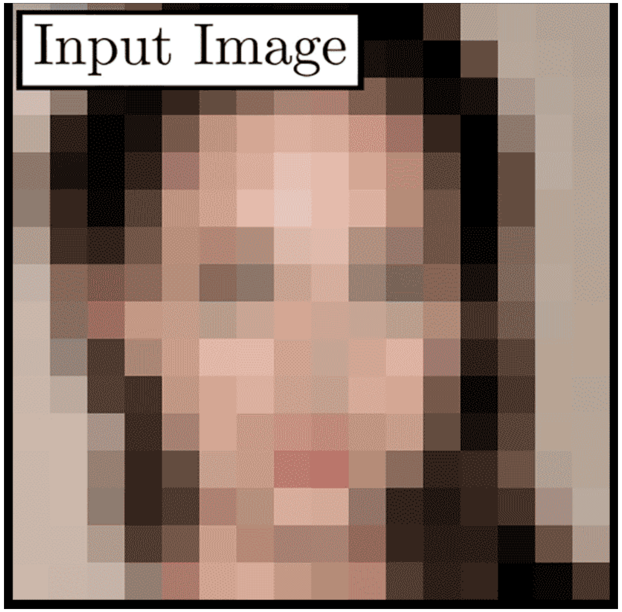


이미지 출처: https://btechmag.com/machine-learning/machine-learning-techniques-every-aspiring-data-scientist-should-know/

인공지능 종류

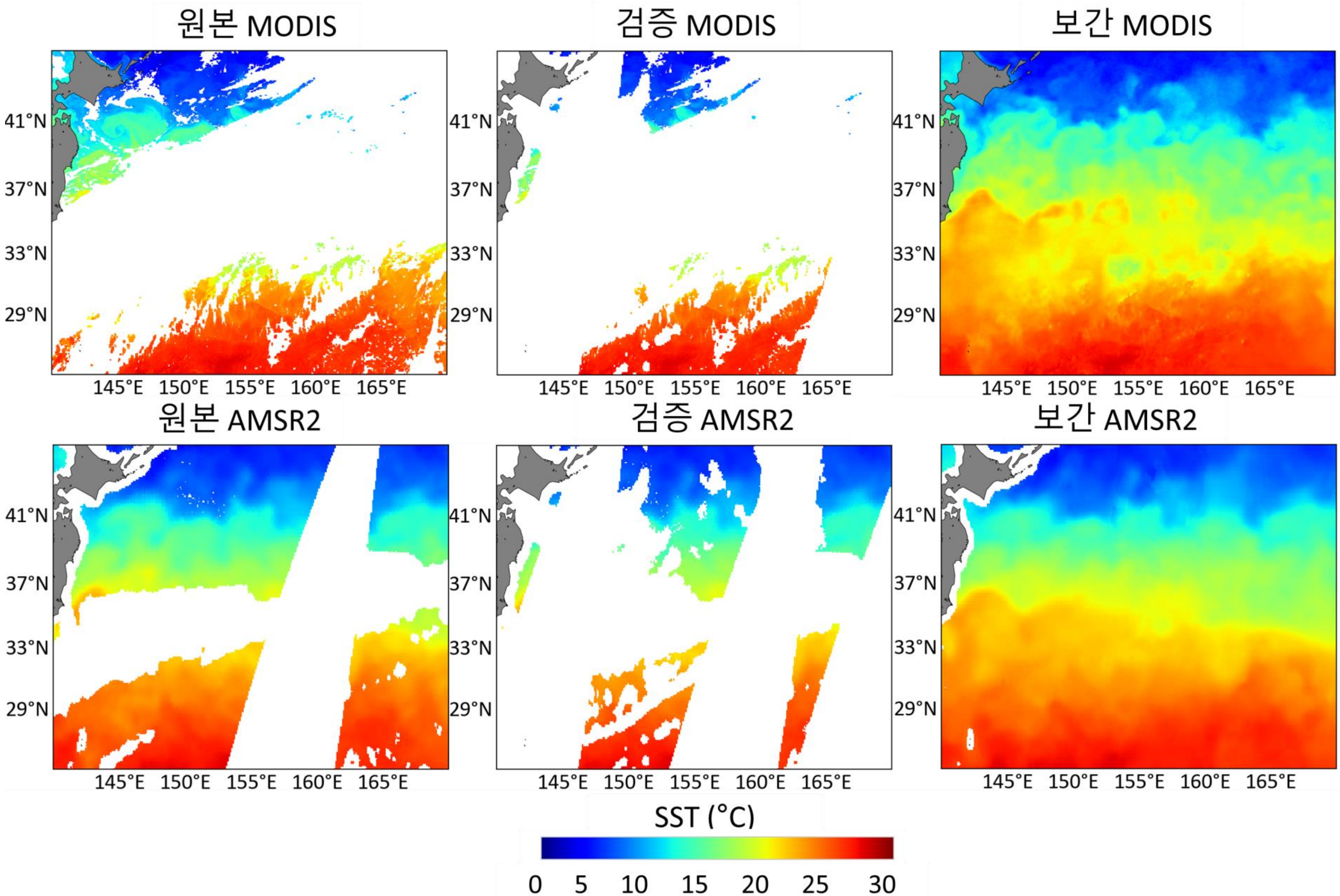
Self-supervised Learning (자기지도 학습)

- 지도학습과 달리, **다량의 레이블이 없는 원데이터로부터 데이터 부분들의 관계를 통해 레이블을 자동으로 생성하여 지도학습에 이용**
- 데이터의 부분 데이터나 손상된 부분으로부터 생성 및 재건
- 대표적인 알고리즘: Autoencoder, Self-supervised GAN 등



이미지 출처: https://subscription.packtpub.com/book/big_data_and_business_intelligence

인공지능 종류 | Self-supervised Learning (자기지도 학습)

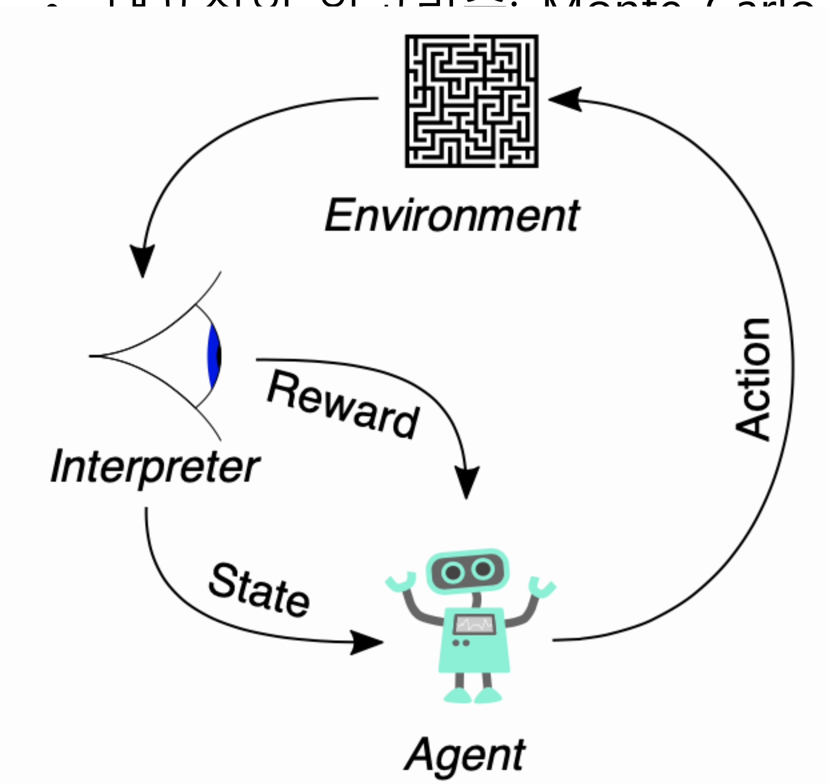


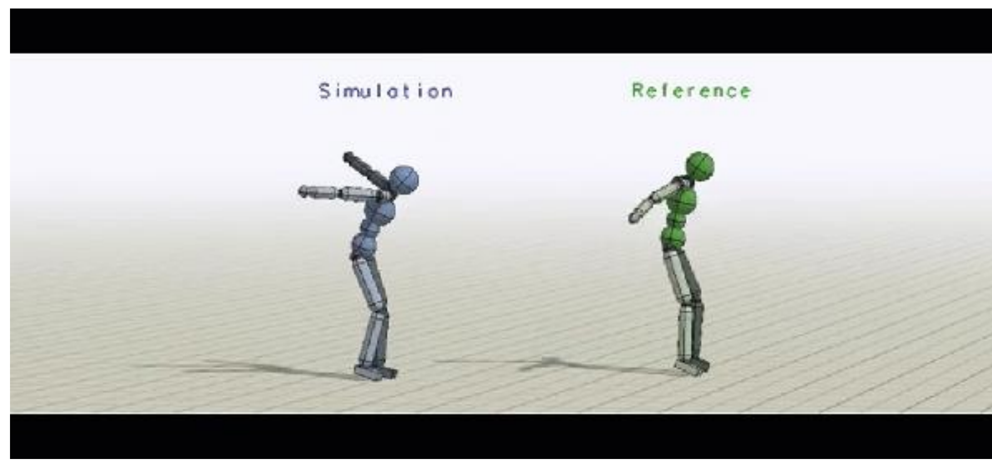
인공지능 종류

이미지 출처: https://riptutorial.com/machine-learning/example/32668/reinforcement-learning

Reinforcement Learning (강화 학습)

- 많은 시뮬레이션을 통해, **현재의 선택으로 미래의 보상이 최대가 되도록 학습**시키는 방법
- **의사결정을 위한 최적의 액션 선택을 목적**으로 활용됨
- 대표적인 알고리즘: Monte Carlo Methods, Q-Learning, Markov Decision Process





출처
bair.berkeley.edu/blog/2018/04/10/virtual-stuntman/
towardsdatascience.com/getting-started-with-reinforcement-q-learning-77499b1766b6

인공지능 알고리즘 훈련

인공지능 훈련 방법 (Hyperparameter Tuning Process)

Original Dataset

- **학습에 사용될 훈련자료**와 **최종 성능 평가를 위한 독립된 테스트 자료** 구분

Training Set | Test Set

- 훈련 자료에서 **최종 모델 선정을 위한 validation 자료** 구분

Training Set | Validation Set | Test Set

Training, tuning, and

Ma

Offline Model vs. Real-time Learning Model

Predictive Model

테스트 자료를 통한 최종 성능 평가

인공지능을 활용한 기상/기후 예측

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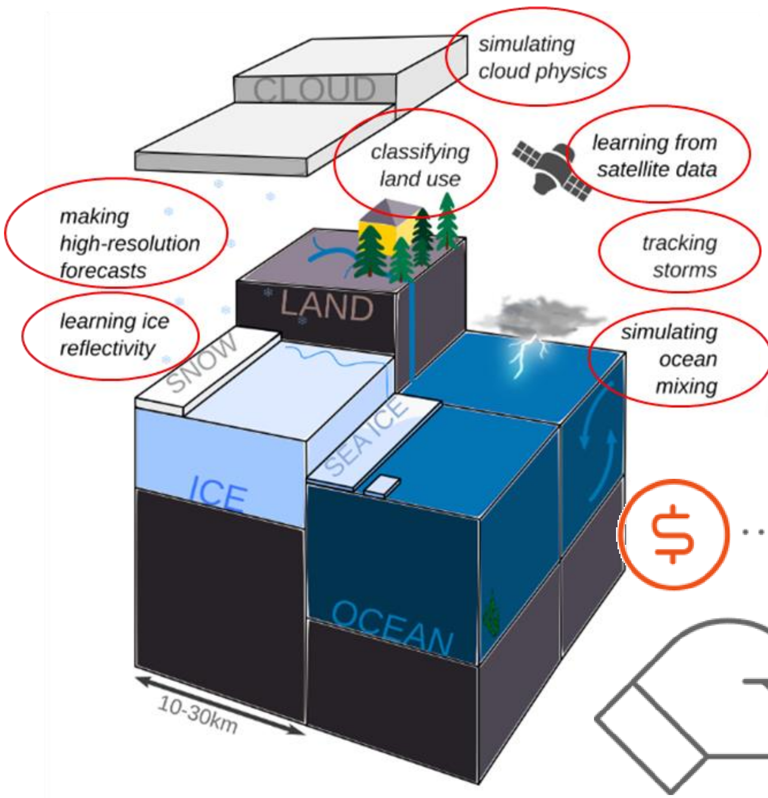
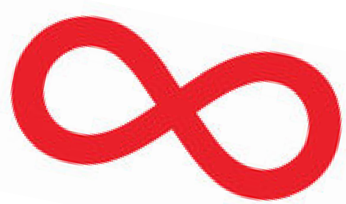


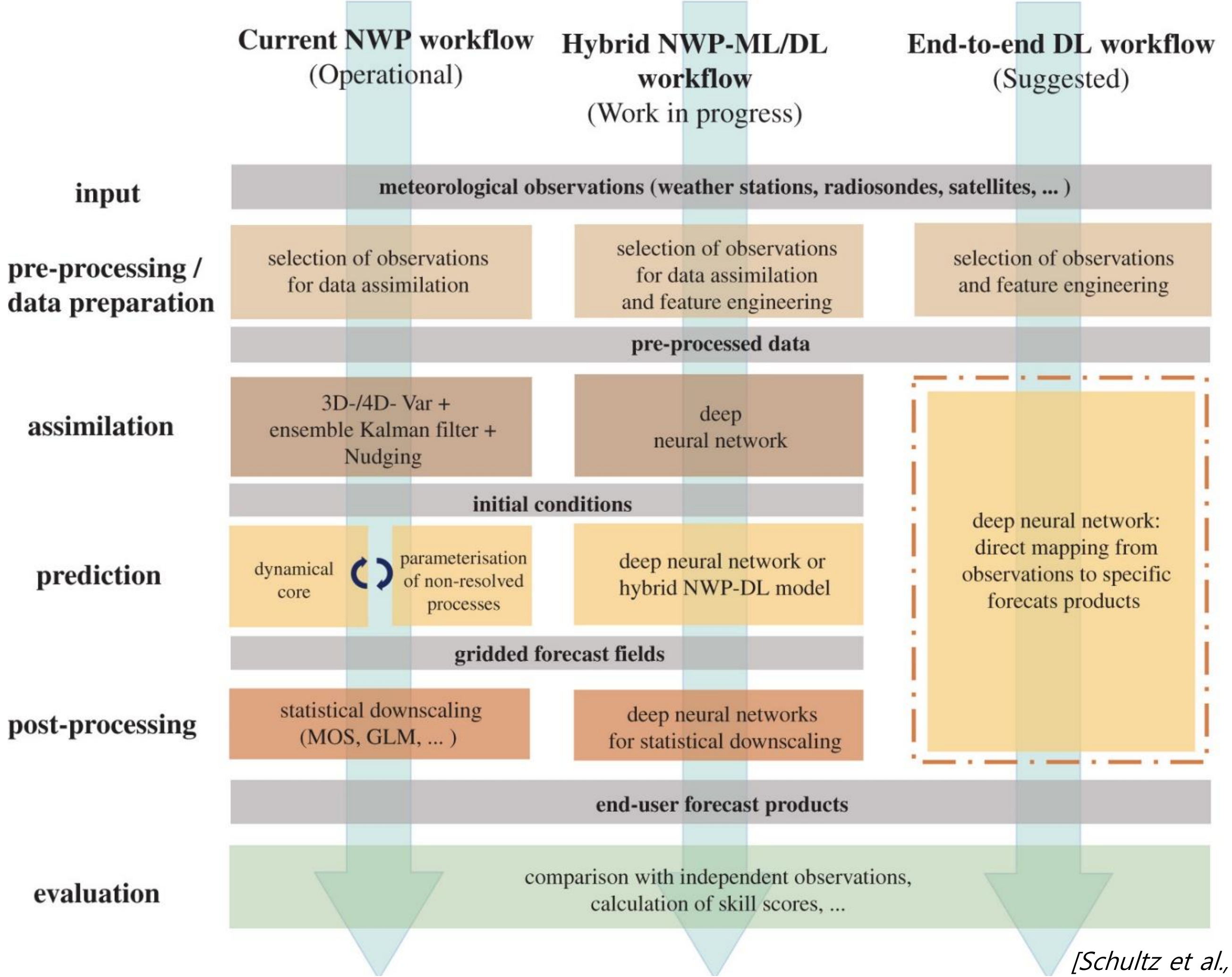


- 상대적으로 빠른 학습(모델링) 장점으로 최근 기상기후분야에 적극 이용되기 시작함

Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., ... & Bengio, Y. (2019). Tackling climate change with machine learning. arXiv preprint arXiv:1906.05433.

인공지능을 활용한 기상/기후 예측

인공지능을 활용한 기상/기후 예측 방법



[Schultz et al., 2021]

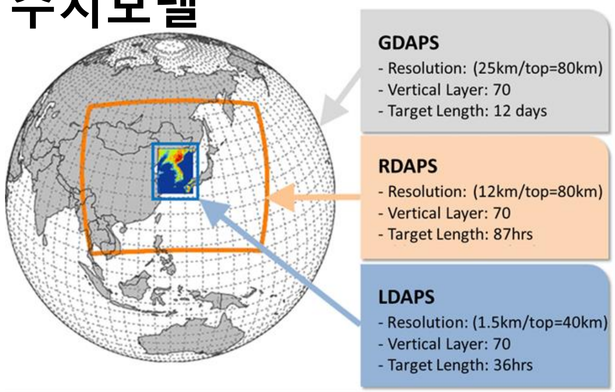
Schultz, M. G., Betancourt, C., Gong, B., Kleinert, F., Langguth, M., Leufen, L. H., ... & Stadtler, S. (2021). Can deep learning beat numerical weather prediction?. *Philosophical Transactions of the Royal Society A, 379*(2194), 20200097.

인공지능을 활용한 기상/기후 예측

기상예측 정확도 향상을 위한 수치예보모델 후처리 보정

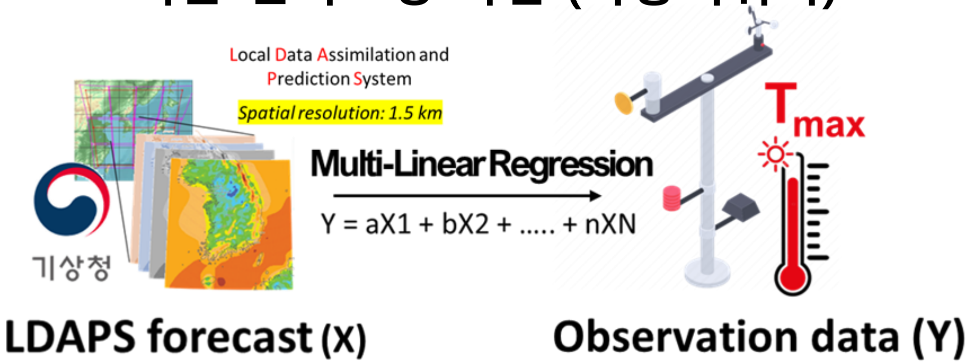
- 수치모델의 예측 산출물에 존재하는 **계통적 오차를 통계적으로 보정**하는 방법

수치모델

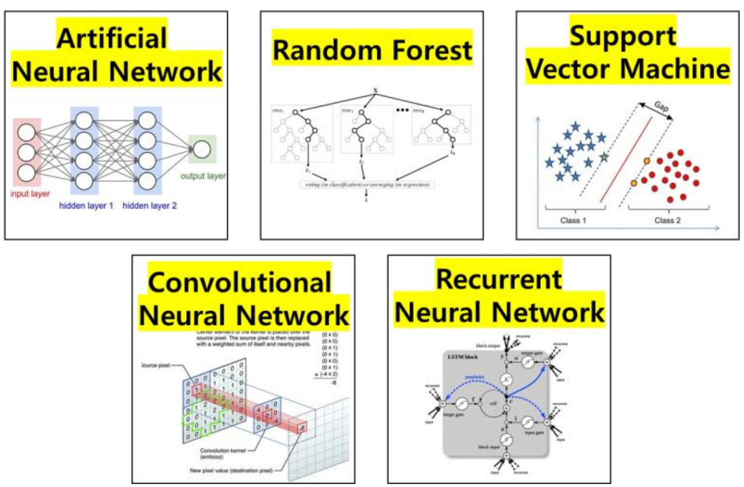


[Source: *https://data.kma.go.kr*]

기존 편의보정 기법 (다중회귀식)



- **제시되는 인공지능 기법**



- **장점**: 후처리 보정을 통해 수치모델의 **예측 자료 정확도를 효과적으로 높일 수 있음**

- **단점**: 후처리 보정은 계통적 오차만을 보정할 수 있기 때문에, **수치모델에 존재하는 무작위 오차 (random error)를 개선하기 힘듦**

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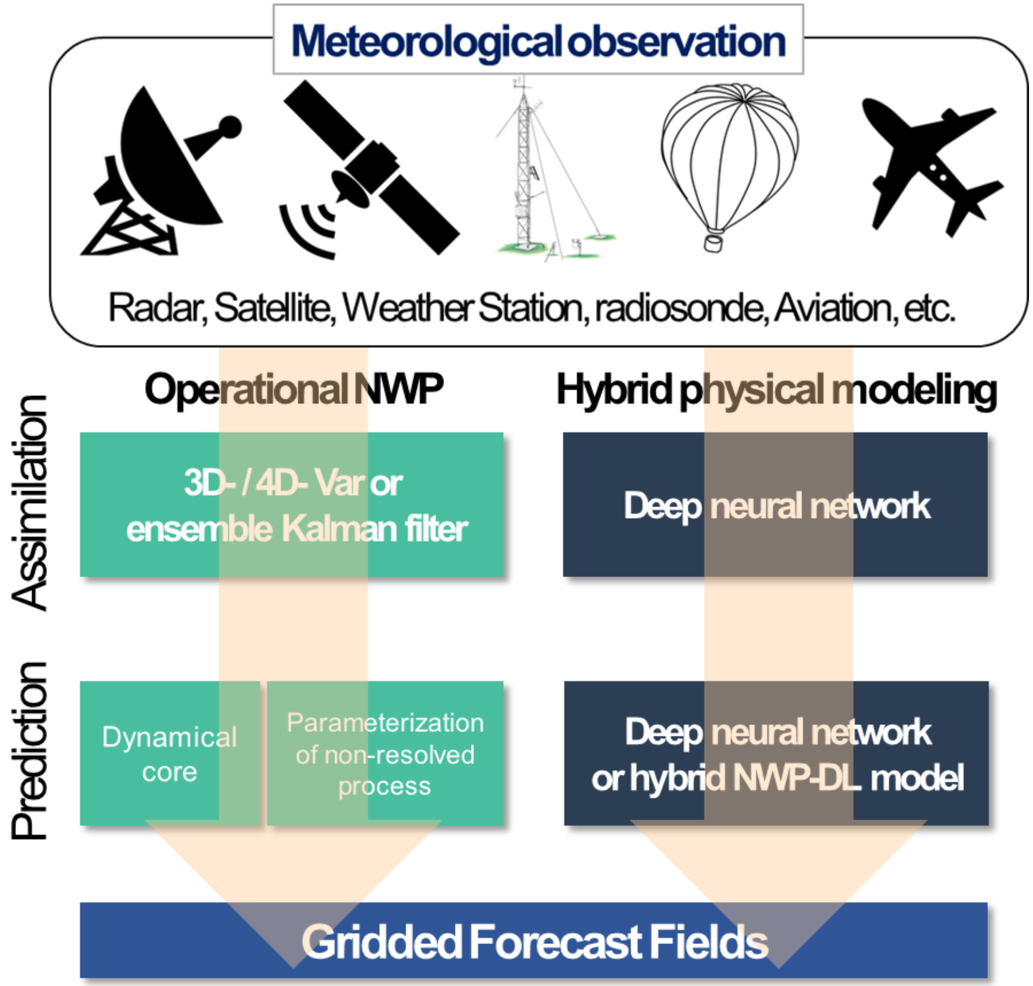
수치모델과 인공지능 기법 결합 (Hybrid physical modeling)

- 수치 모델의 Data assimilation 과정을 딥러닝으로 대체하는 방법



- **장점**: Data assimilation 정확도를 높임으로써 예측 자료 정확도를 높일 수 있음
- **단점**: 예기치 않은 불안정성이 나타날 수 있으며, 수치모델과 인공지능 코드를 하나의 인터페이스에서 구현하기 복잡함

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데이터기반 인공지능을 활용한 기상/기후 예측 (Data-driven modeling)

- 초기장(관측자료)을 기반으로 딥러닝을 활용하여 기상/기후 예측하는 방식


JAMES | Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE
10.1029/2020MS002203

Key Points:
- Benchmarks with strong baselines are a key ingredient for rapid progress on a problem
- Here, we define a benchmark for data-driven global, medium-range weather prediction
- The data are processed for convenient use in machine learning models, and a quickstart guide is provided

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S. Rasp,
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Citation:
Rasp, S., Dueben, P. D., Scher, S., Weyn, J. A., Mouatadid, S., & Thuerey, N. (2020). WeatherBench: A benchmark data set for data-driven weather forecasting. *Journal of Advances in Modeling Earth Systems*, *12*, e2020MS002203. https://doi.org/10.1029/2020MS002203

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Accepted 14 AUG 2020
Accepted article online 19 AUG 2020

WeatherBench: A Benchmark Data Set for Data-Driven Weather Forecasting

Stephan Rasp[1], Peter D. Dueben[2], Sebastian Scher[3], Jonathan A. Weyn[4], Soukayna Mouatadid[5], and Nils Thuerey[1]

[1]Department of Informatics, Technical University of Munich, Munich, Germany, [2]European Centre for Medium-range Weather Forecasts, Reading, UK, [3]Department of Meteorology and Bolin Centre for Climate Research, Stockholm University, Stockholm, Sweden, [4]Department of Atmospheric Sciences, University of Washington, Seattle, WA, USA, [5]Department of Computer Science, University of Toronto, Toronto, Ontario, Canada

Abstract Data-driven approaches, most prominently deep learning, have become powerful tools for prediction in many domains. A natural question to ask is whether data-driven methods could also be used to predict global weather patterns days in advance. First studies show promise but the lack of a common data set and evaluation metrics make intercomparison between studies difficult. Here we present a benchmark data set for data-driven medium-range weather forecasting (specifically 3–5 days), a topic of high scientific interest for atmospheric and computer scientists alike. We provide data derived from the ERA5 archive that has been processed to facilitate the use in machine learning models. We propose simple and clear evaluation metrics which will enable a direct comparison between different methods. Further, we provide baseline scores from simple linear regression techniques, deep learning models, as well as purely physical forecasting models. The data set is publicly available at https://github.com/pangeo-data/WeatherBench and the companion code is reproducible with tutorials for getting started. We hope that this data set will accelerate research in data-driven weather forecasting.

Plain Language Summary WeatherBench provides a new benchmark to test data-driven approaches to weather forecasting. Traditional weather models are based on the discretized equations governing the atmosphere. They perform very well for many tasks but are still found lacking for some others. Data-driven approaches, such as deep learning, directly learn from the best available observations and could potentially produce better forecasts. In this paper, we define a benchmark task—predicting pressure and temperature across the globe 3 and 5 days ahead—which will hopefully lead to progress in data-driven weather prediction and foster collaboration across disciplines.

1. Introduction

Deep learning, a branch of machine learning based on multilayered artificial neural networks, has proven to be a powerful tool for a wide range of tasks, most notably image recognition and natural language processing (LeCun et al., 2015). More recently, deep learning has also been used in many fields of natural science. Much of the success of deep learning is based on the ability of neural networks to recognize patterns in high-dimensional spaces. A natural question to ask then is whether deep learning can also be used to predict future weather patterns.

Currently, weather (and climate) predictions are based on purely physical computer models, in which the governing equations, or our best approximation thereof, of the atmosphere and ocean are solved on a discrete numerical grid (Bauer et al., 2015). Overall, this approach has been very successful. However, today's numerical weather prediction (NWP) models still have shortcoming for many important applications, for example, forecasting mesoscale convective systems over Africa (Vogel et al., 2018). Furthermore, huge amounts of computing power are required, especially for creating probabilistic forecasts which are usually limited to 50 ensemble members or less. For these reasons and the growing popularity of machine learning (ML) there has been a growing interest to improve and speed up NWP with data-driven approaches.

ML can be applied to weather prediction in many different ways. Two long-standing applications of ML are postprocessing—the correction of statistical biases in the output of physical models—and statistical

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RASP ET AL. 1 of 17

[Rasp et al., 2020]

Table 1
List of Variables Contained in the Benchmark Data Set

Long name (예단변수)	Short name	Description
Geopotential	z	Proportional to the height of a pressure level
Temperature	t	Temperature
Specific_humidity	q	Mixing ratio of water vapor
Relative_humidity	r	Humidity relative to saturation
u_component_of_wind	u	Wind in x/longitude-direction
v_component_of_wind	v	Wind in y/latitude direction
Vorticity	vo	Relative horizontal vorticity
Potential_vorticity	pv	Potential vorticity
2m_temperature	t2 m	Temperature at 2 m height above surface
10m_u_component_of_wind	u10	Wind in x/longitude-direction at 10 m height
10m_v_component_of_wind	v10	Wind in y/latitude-direction at 10 m height
total_cloud_cover	tcc	Fractional cloud cover
total_precipitation	tp	Hourly precipitation
toa_incident_solar_radiation	tisr	Accumulated hourly incident solar radiation
Constants		*File containing time-invariant fields*
land_binary_mask	lsm	Land-sea binary mask
soil_type	slt	Soil-type categories
orography	orography	Height of surface
latitude	lat2d	2-D field with latitude at every grid point
longitude	lon2d	2-D field with longitude at every grid point

✓ 과거 날씨 데이터를 학습한 AI 모델이 높은 계산 비용을 필요로 하는 물리모델을 능가할 수 있을지에 초점

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데이터기반 인공지능을 활용한 기상/기후 예측 (Data-driven modeling)

- 제시되는 딥러닝 모델 디자인

[Rasp et al., 2020]

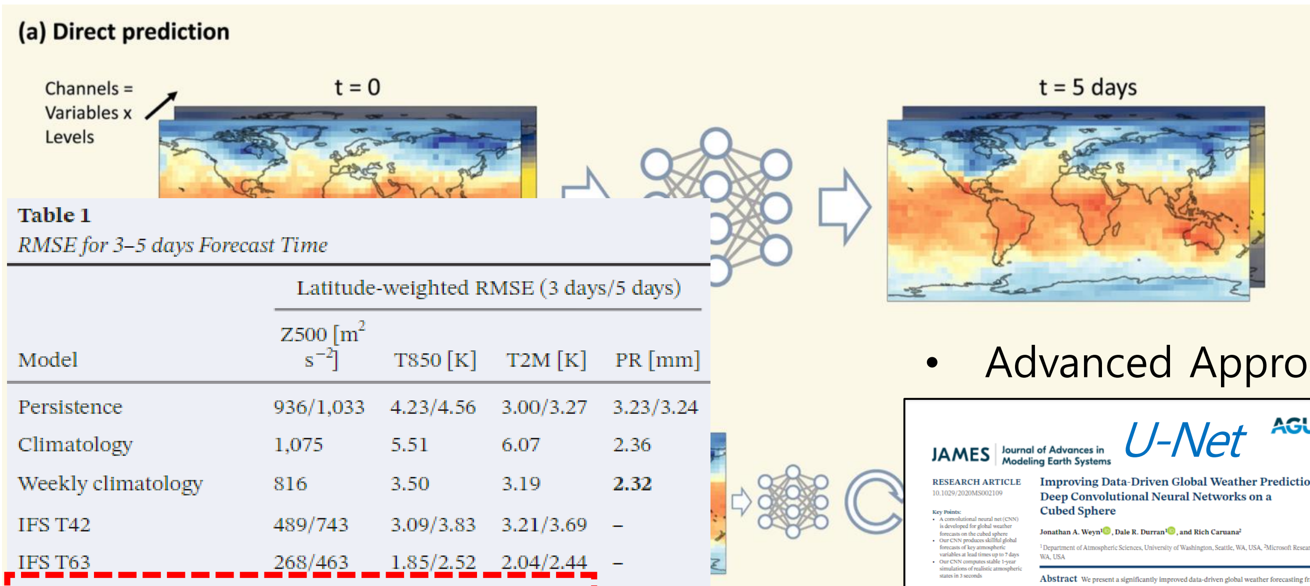
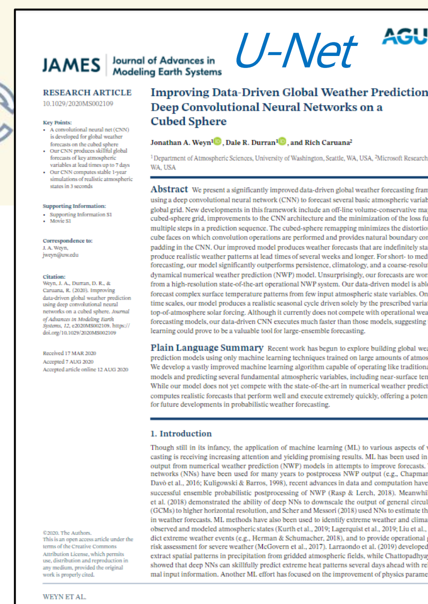


Table 1
RMSE for 3–5 days Forecast Time

Model	Z500 [$m^2 s^{-2}$]	T850 [K]	T2M [K]	PR [mm]
	Latitude-weighted RMSE (3 days/5 days)			
Persistence	936/1,033	4.23/4.56	3.00/3.27	3.23/3.24
Climatology	1,075	5.51	6.07	2.36
Weekly climatology	816	3.50	3.19	**2.32**
IFS T42	489/743	3.09/3.83	3.21/3.69	–
IFS T63	268/463	1.85/2.52	2.04/2.44	–
Operational IFS	**154/334**	**1.36/2.03**	**1.35/1.77**	2.36/2.59
Weyn et al. (2020)	373/611	1.98/2.87	–	–
Direct (ERA only)	314/561	1.79/2.82	1.53/2.32	**2.03**/2.35
Direct (CMIP only)	323/561	2.09/2.82	1.90/2.32	2.30/2.39
Direct (pretrained)	**268**/523	**1.65**/2.52	**1.42**/2.03	2.16/**2.30**
Continuous (ERA only)	331/545	1.87/2.57	1.60/2.06	2.22/2.32
Continuous (CMIP only)	330/548	2.12/2.75	2.24/2.59	2.29/2.38
Continuous (pretrained)	284/**499**	1.72/**2.41**	1.48/**1.92**	2.23/2.33

Note. All forecasts evaluated at 5.625° resolution. Best physical and data-driven methods are highlighted.
Abbreviations: IFS, integrated forecasting system; RMSE, root mean squared error.

- Advanced Approach 적용 논문



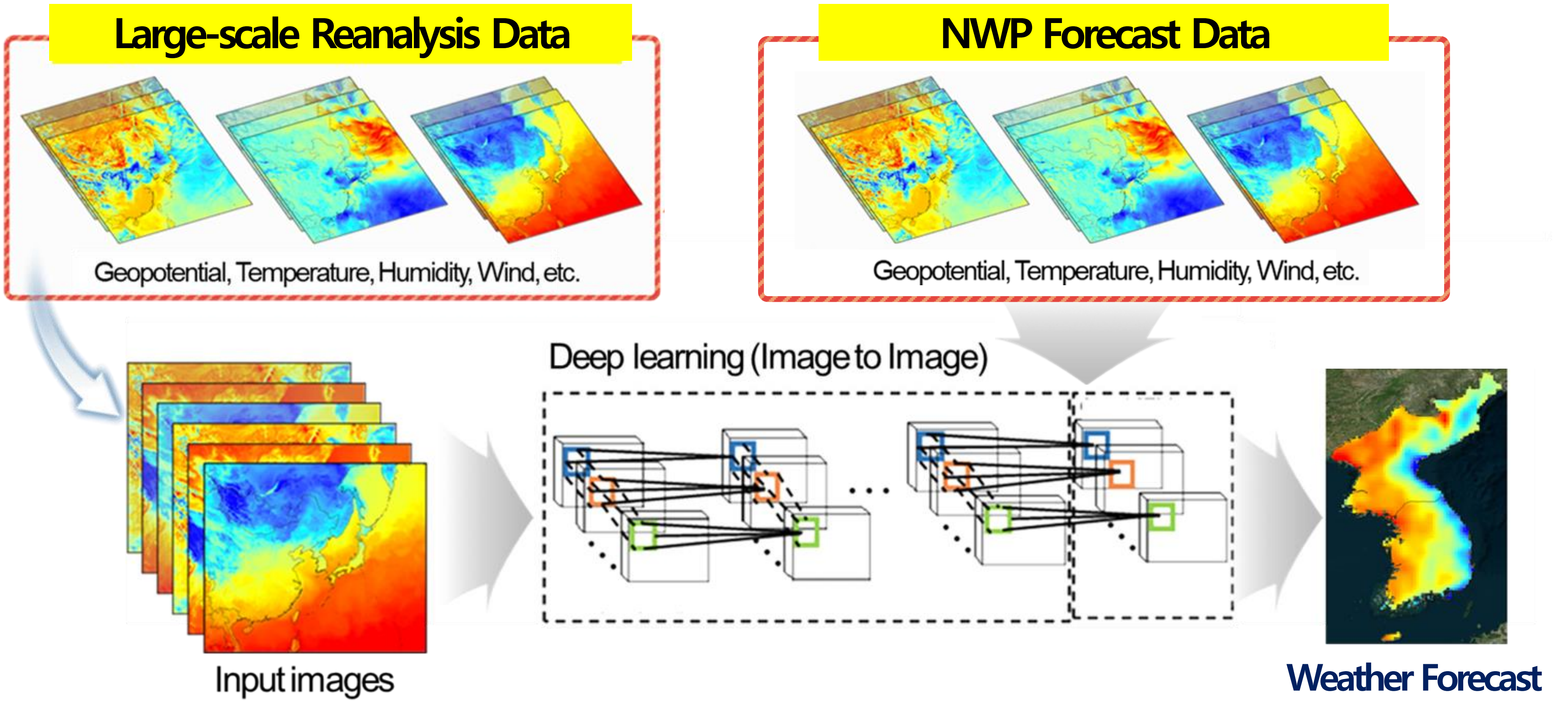
[Weyn, 2020]

[Rasp and Thuerey, 2021]

인공지능을 활용한 기상/기후 예측

Proposed hybrid approach (Data-driven modeling + NWP forecast output)

- Data-driven 접근 방식과 수치예보모델의 예측산출물을 결합하여 예측하는 방법



Weather Forecast

(e.g., Temperature, Humidity or other meteorological variables)

- 수치모델의 의존성을 벗어난 Data-driven 기법과 수치예보 모델 산출물을 함께 이용하여 예측 정확도가 향상될 것으로 기대

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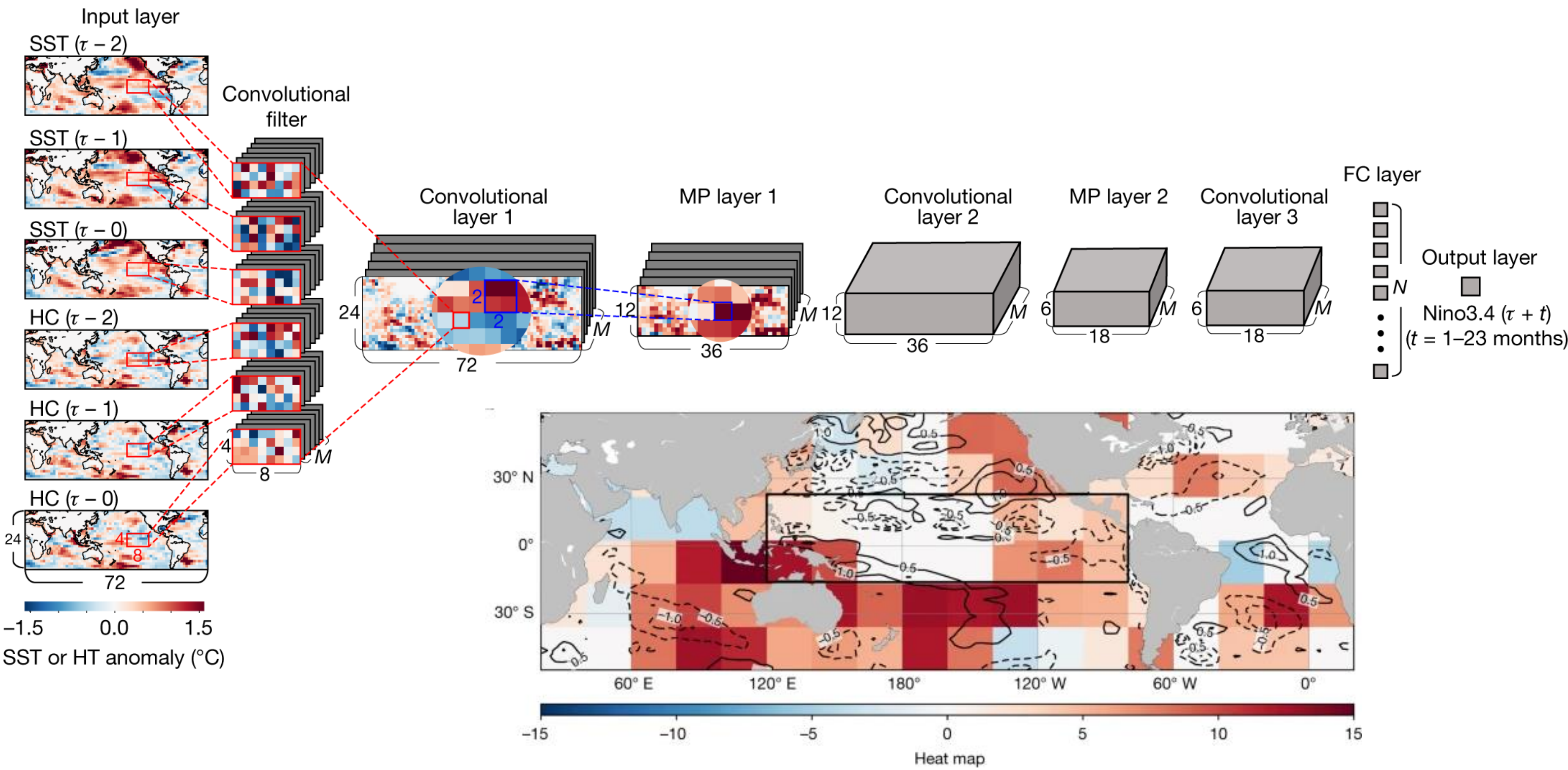
인공지능을 활용한 기상/기후 예측

인공지능을 활용한 기상/기후 예측 방법

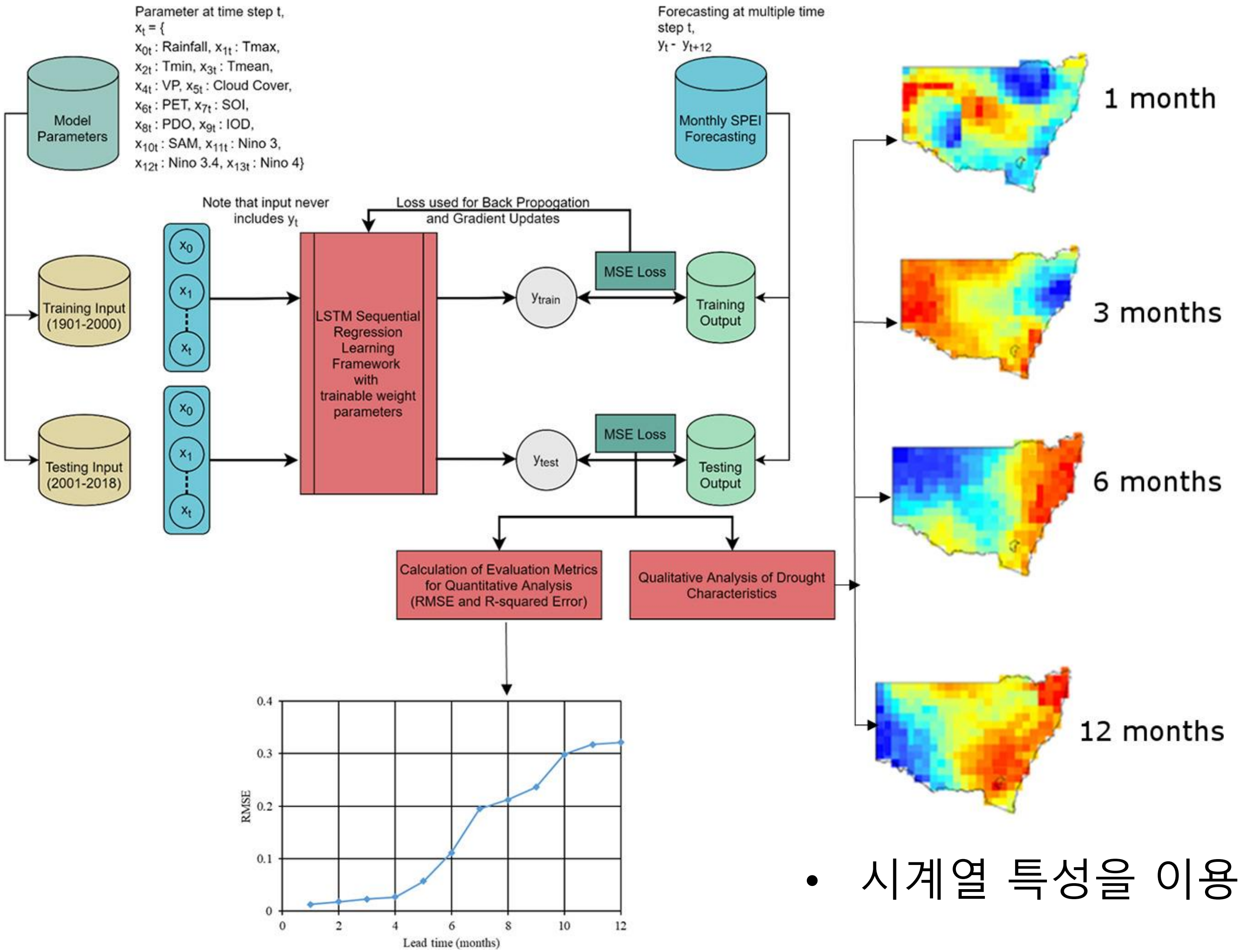


- 공간정보를 이용한 Convolutional neural network 기반 ENSO 예측

Ham, Y. G., Kim, J. H., & Luo, J. J. (2019). Deep learning for multi-year ENSO forecasts. Nature, 573(7775), 568-572.

인공지능을 활용한 기상/기후 예측

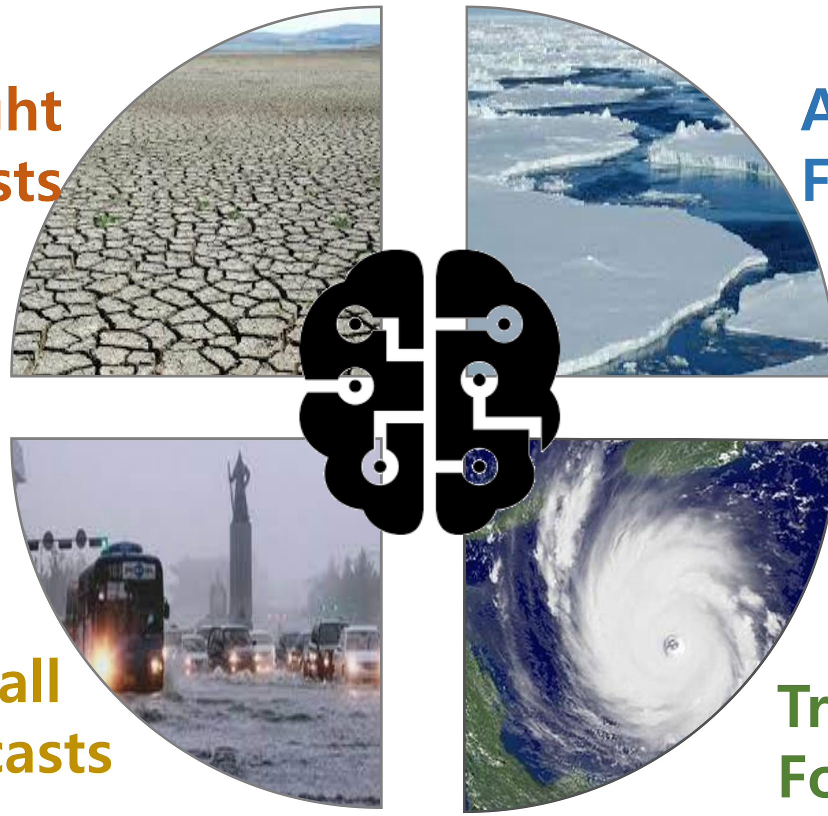
인공지능을 활용한 기상/기후 예측 방법



- 시계열 특성을 이용한 가뭄 예측

Dikshit, A., Pradhan, B., & Alamri, A. M. (2021). Long lead time drought forecasting using lagged climate variables and a stacked long short-term memory model. Science of The Total Environment, 755, 142638.

인공지능을 활용한 기상/기후 예측 사례 연구



Drought Forecasts

Arctic sea ice Forecasts

Rainfall Forecasts

Tropical cyclone Forecasts

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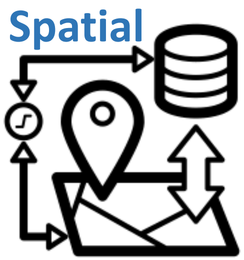
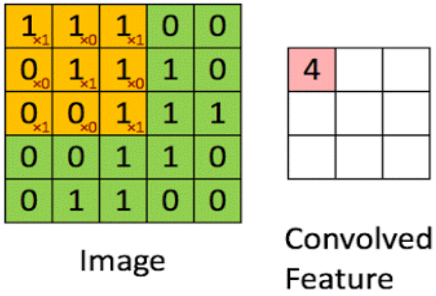
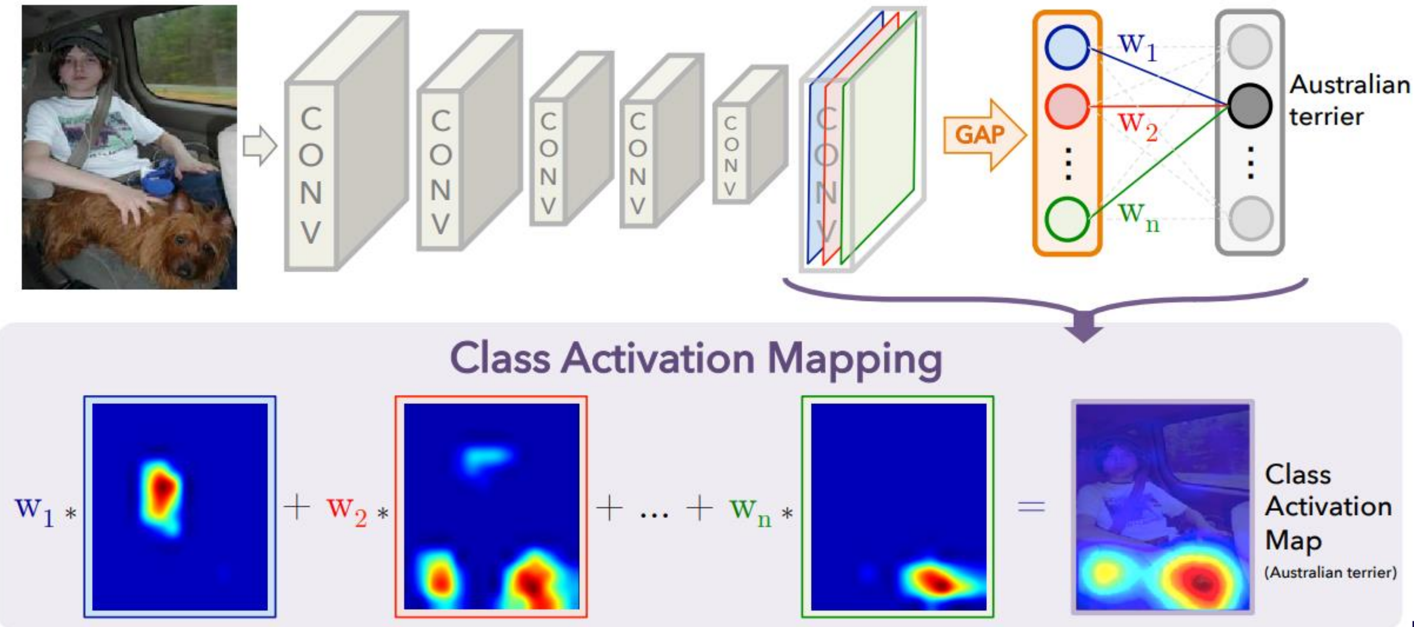
연구에 사용한 대표적인 딥러닝 기법

Convolutional Neural Network (CNN)



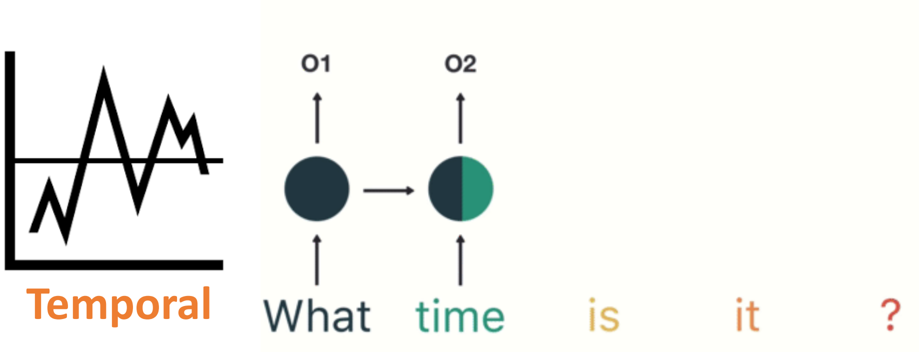




Source: https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/
https://dryjelly.tistory.com/147

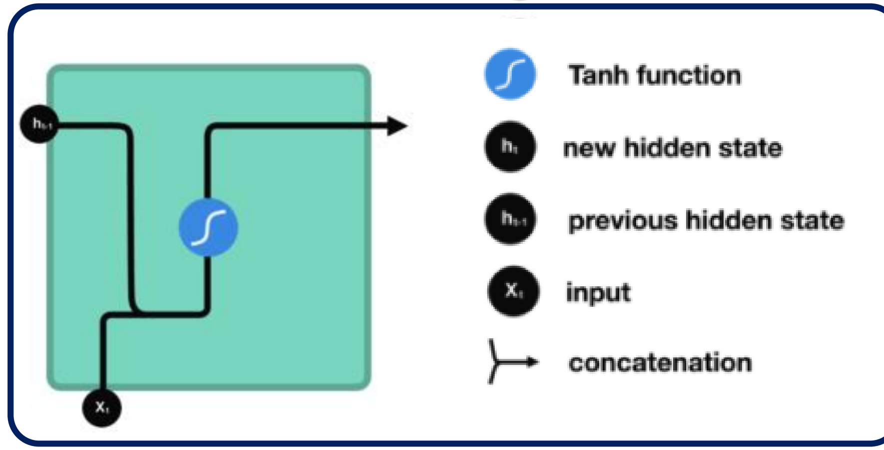
연구에 사용한 대표적인 딥러닝 기법

https://codlingual.tistory.com/87

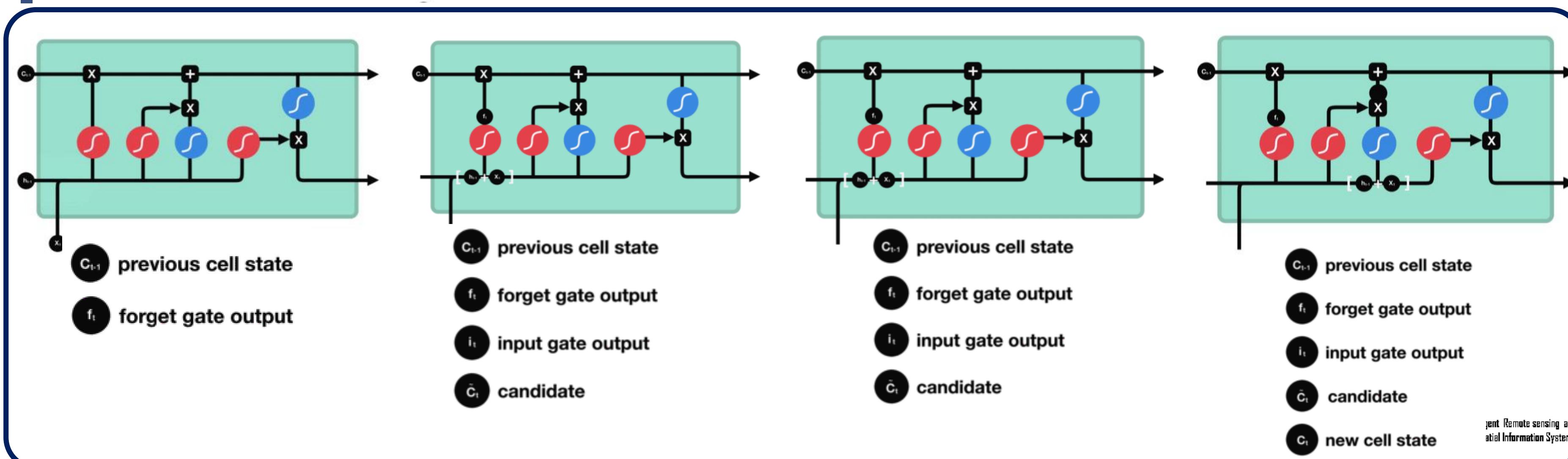


- 시계열 패턴을 고려하여 예측
- 시계열 특성이 있는 분야에 사용가능

Recurrent Neural Network (RNN)

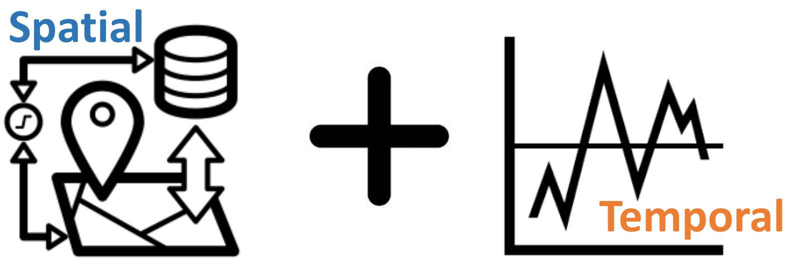


Long Short Term Memory (LSTM)

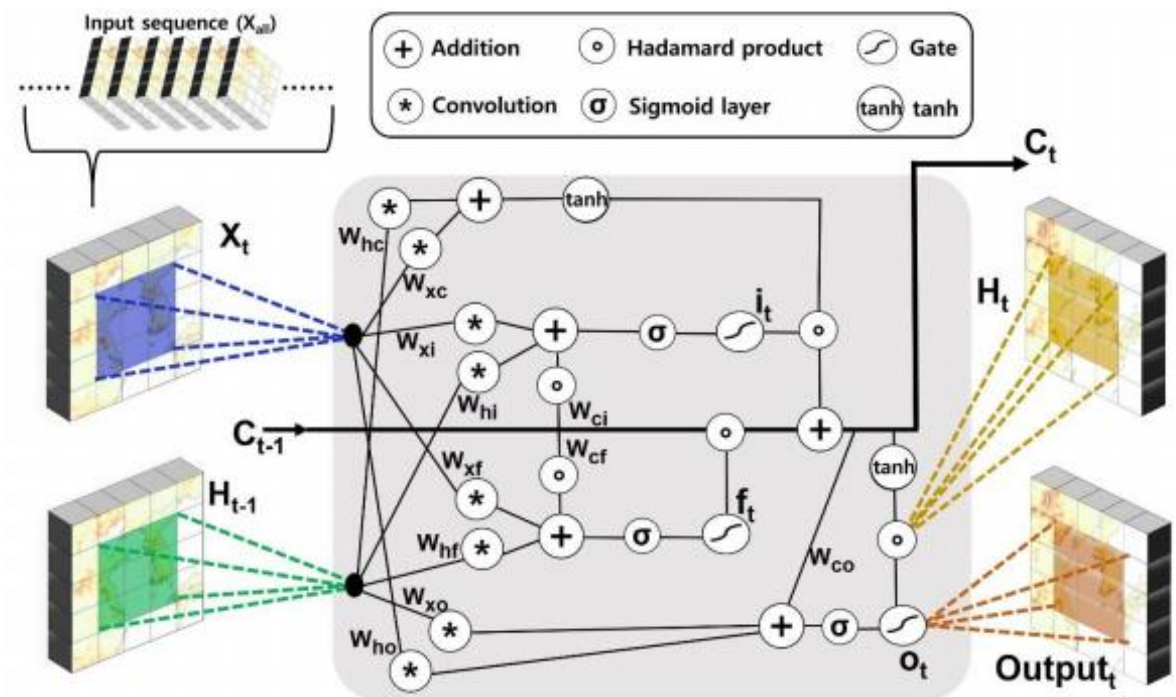


연구에 사용한 대표적인 딥러닝 기법

Convolutional Long Short Term Memory (ConvLSTM)



- 공간의 특성과 시계열 특성을 동시에 고려할 수 있다는 장점이 있음



$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} \circ C_{t-1} + b_i)$$

$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} \circ C_{t-1} + b_f) \; 6)$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tanh(W_{xc} * x_t + W_{hc} * H_{t-1} + b_c)$$

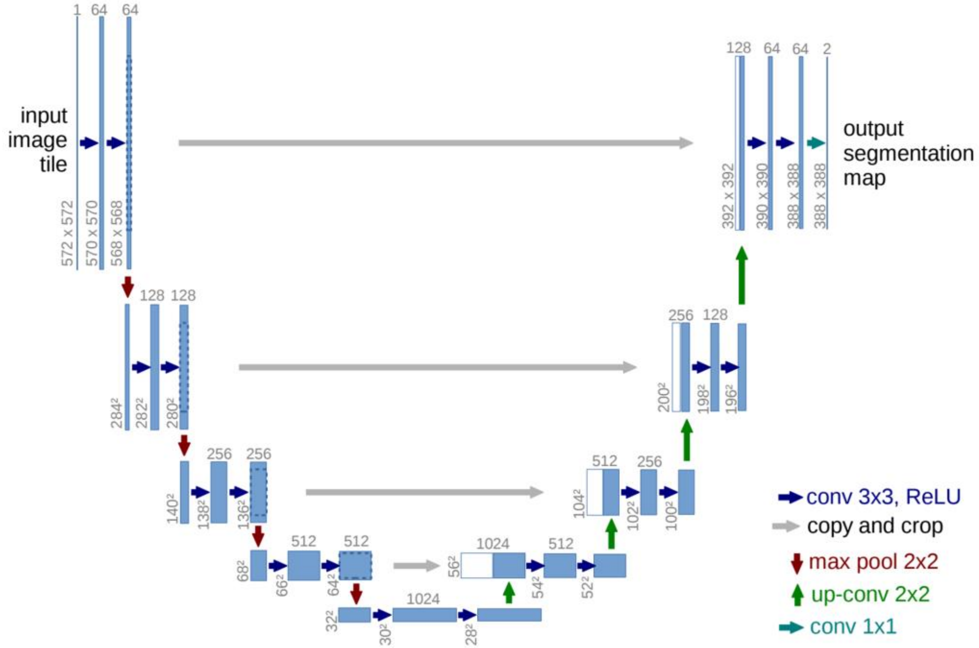
$$O_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \circ C_t + b_0)$$

$$H_t = O_t \circ \tanh(C_t)$$

Park, S., Im, J., Han, D., & Rhee, J. (2020). Short-Term Forecasting of Satellite-Based Drought Indices Using Their Temporal Patterns and Numerical Model Output. Remote Sensing, 12(21), 3499.

연구에 사용한 대표적인 딥러닝 기법

U-Net



- **Fully connected layer를 사용하지 않고 convolution 연산으로만 이뤄져 있는 fully convolutional network (FCN)의 일종**
  - 입력 크기와 동일한 크기의 출력 생성 가능
  - 모든 filter를 전체 영역에 공유하므로 메모리의 효율성
- **Encoder-decoder 구조를 통해 feature 추출**
- **Skip connection을 통해 깊은 구조에서도 원본 이미지의 고해상도 정보 손실을 보완함**

- **수축경로(Contracting Path)**

점진적으로 넓은 범위의 의미정보 추출

- **확장경로(Expanding Path)**

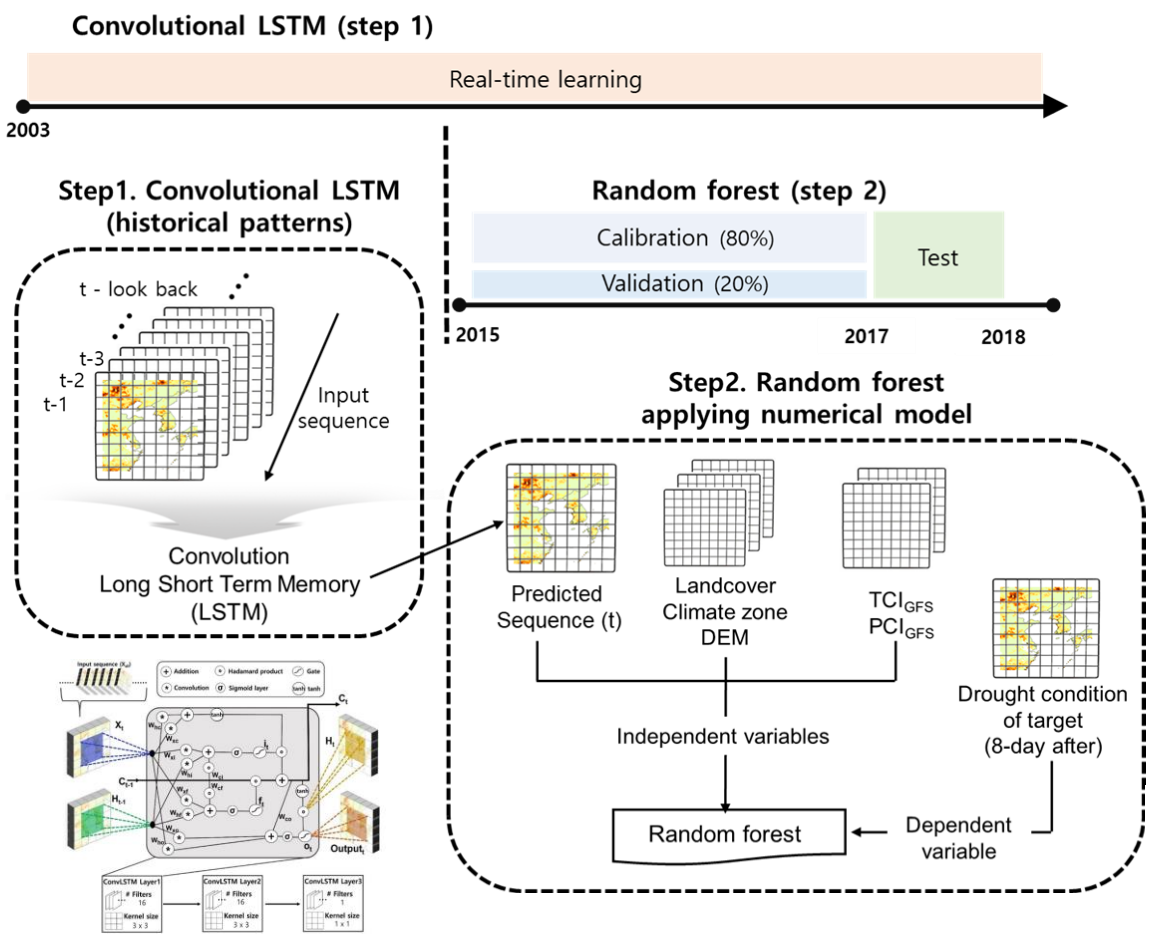
의미정보를 픽셀 위치 정보와 결합하여 픽셀마다 어떤 객체에 속하는지 구분

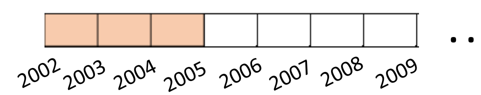
- **전환구간 (Bottle Neck)**

인공지능을 활용한 기상/기후 예측

동아시아 가뭄 단기예측

- 위성기반의 가뭄지수의 시공간적 패턴변화와 단기 기상예측자료(수치모델)을 이용하여 기계학습 (random forest)을 포함한 딥러닝 (ConvLSTM) 기반의 동아시아 가뭄을 단기 예측함





- 가뭄의 단기(8일 뒤) 예측
- 위성자료 + 수치예보모델 융합
- ConvLSTM + Random forest
- 지형자료 이용
- 실시간학습(online model)

Park, S. et al. (2020). Short-Term Forecasting of Satellite-Based Drought Indices Using Their Temporal Patterns and Numerical Model Output. Remote Sensing, 12(21), 3499.

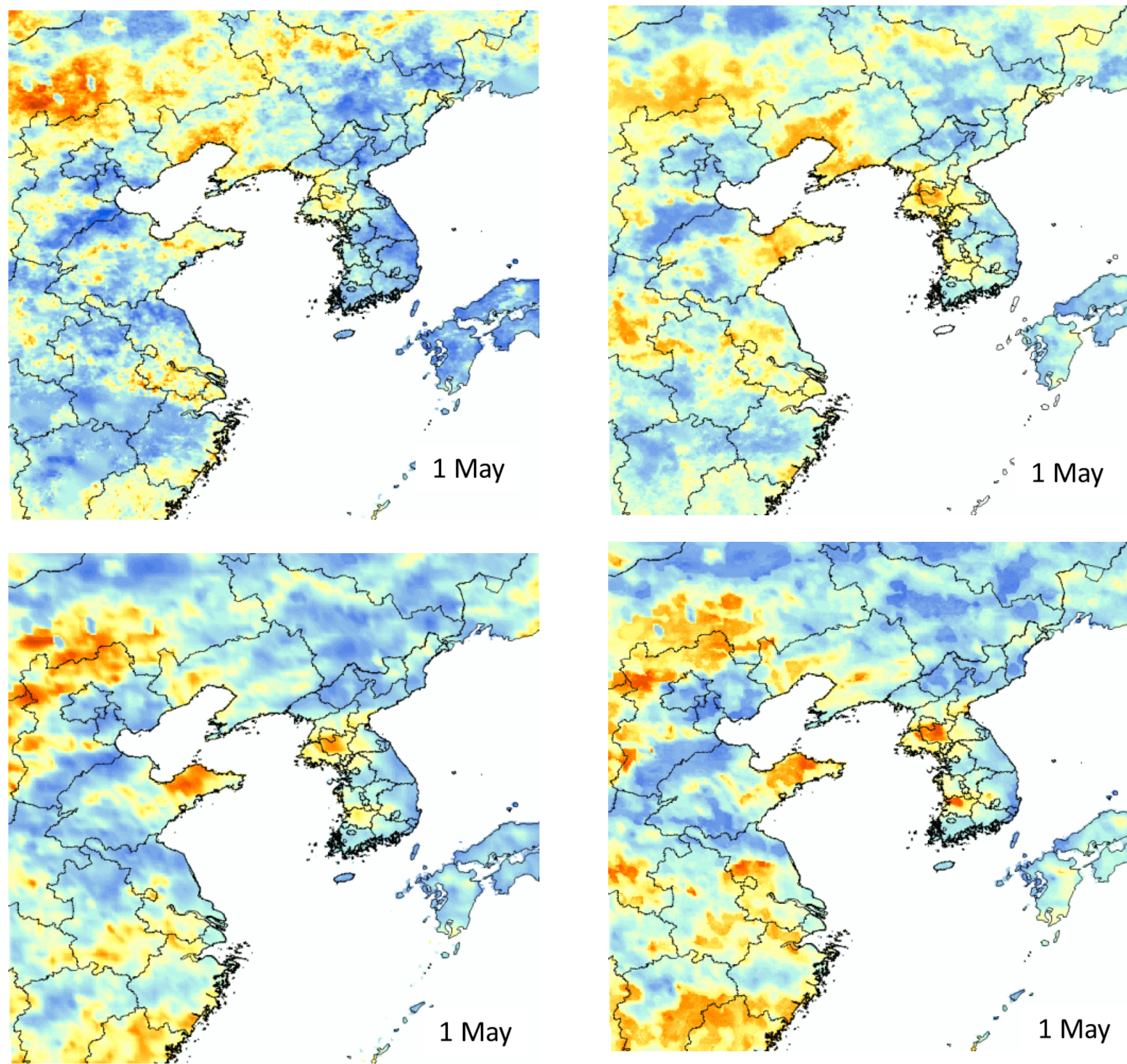
인공지능을 활용한 기상/기후 예측

동아시아 가뭄 단기예측

기존 가뭄 지수 | 예측된 가뭄지수

SDCI 가뭄지수

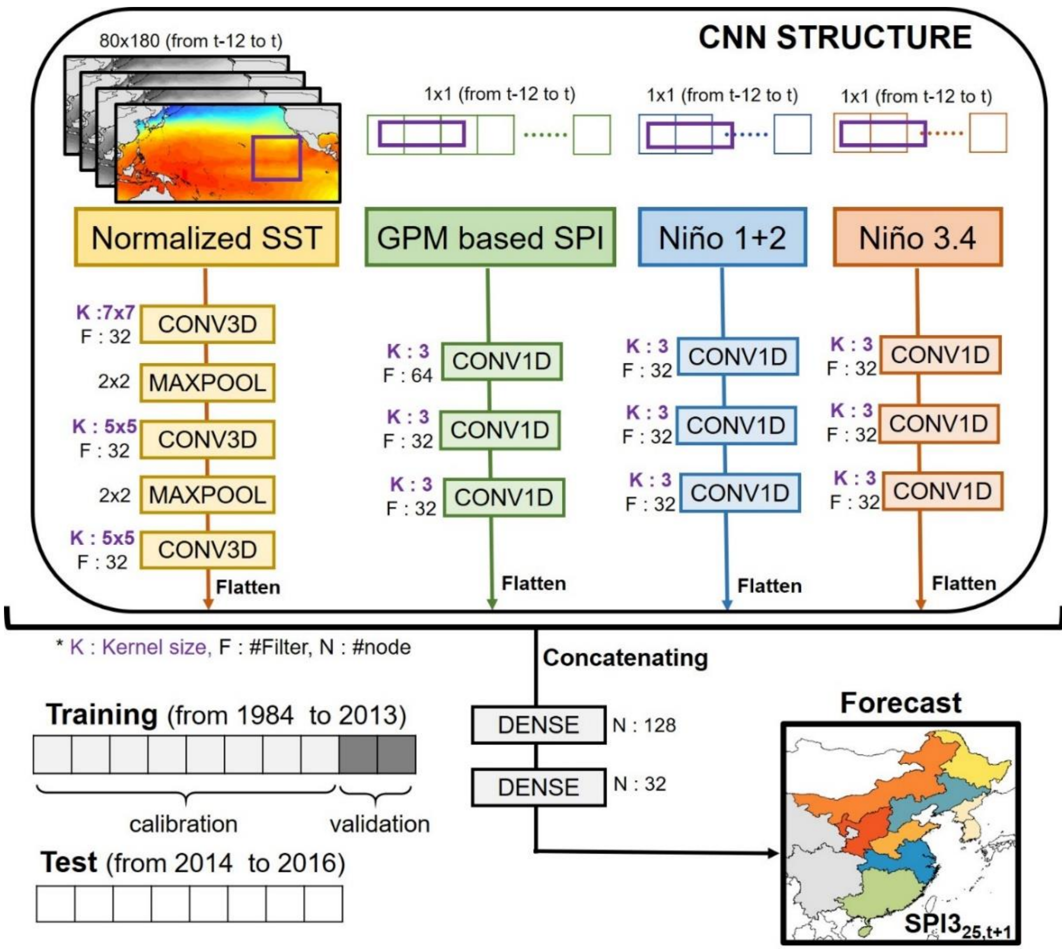
SPI 가뭄지수

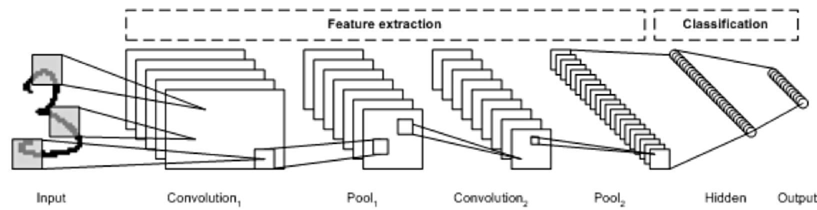


인공지능을 활용한 기상/기후 예측

SST 원격상관을 이용한 동아시아 가뭄 예측(1-3개월)

- 위성기반의 SST의 원격상관 및 가뭄의 시계열 패턴을 고려하여 CNN 기반의 동아시아 가뭄을 장기 예측함





- CNN을 이용하여 과거 12개월의 SST의 시공간적 패턴 정보를 추출함
- 과거 가뭄패턴+ 기후인자 융합

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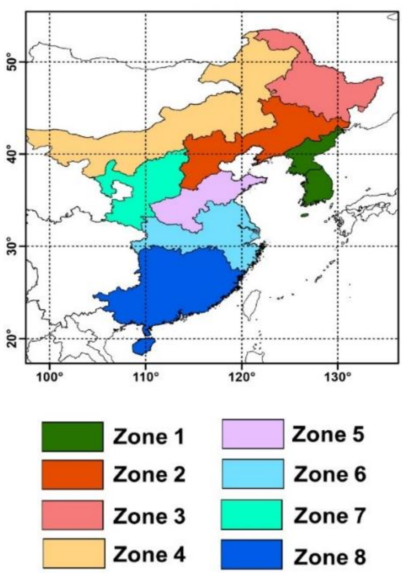
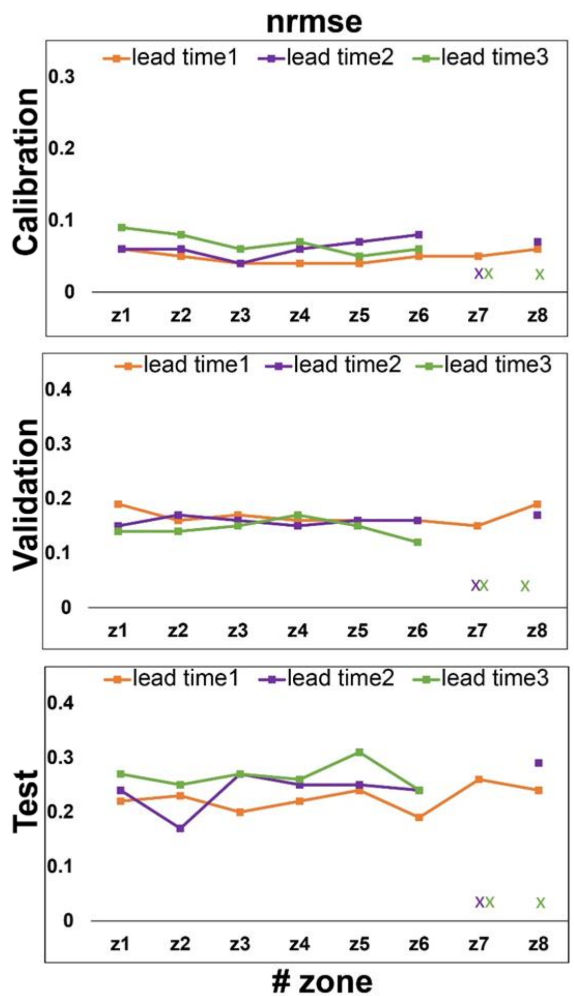
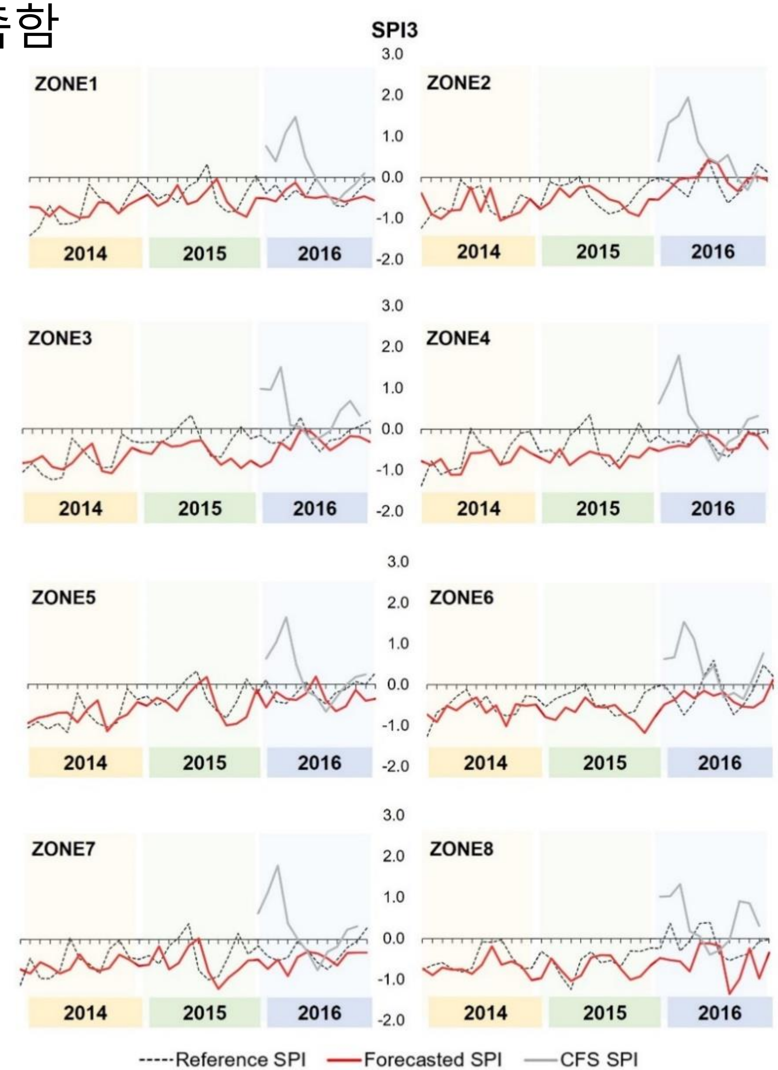
인공지능을 활용한 기상/기후 예측

SST 원격상관을 이용한 동아시아 가뭄 예측(1-3개월)

- 위성기반의 SST의 원격상관 및 가뭄의 시계열 패턴을 고려하여 CNN 기반의 동아시아 가뭄을 장기 예측함

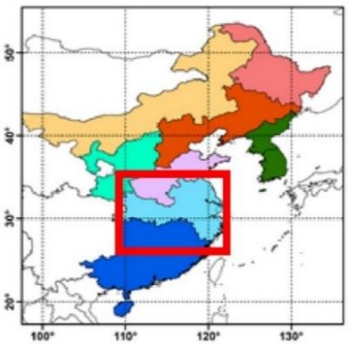


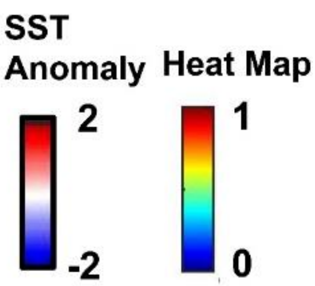


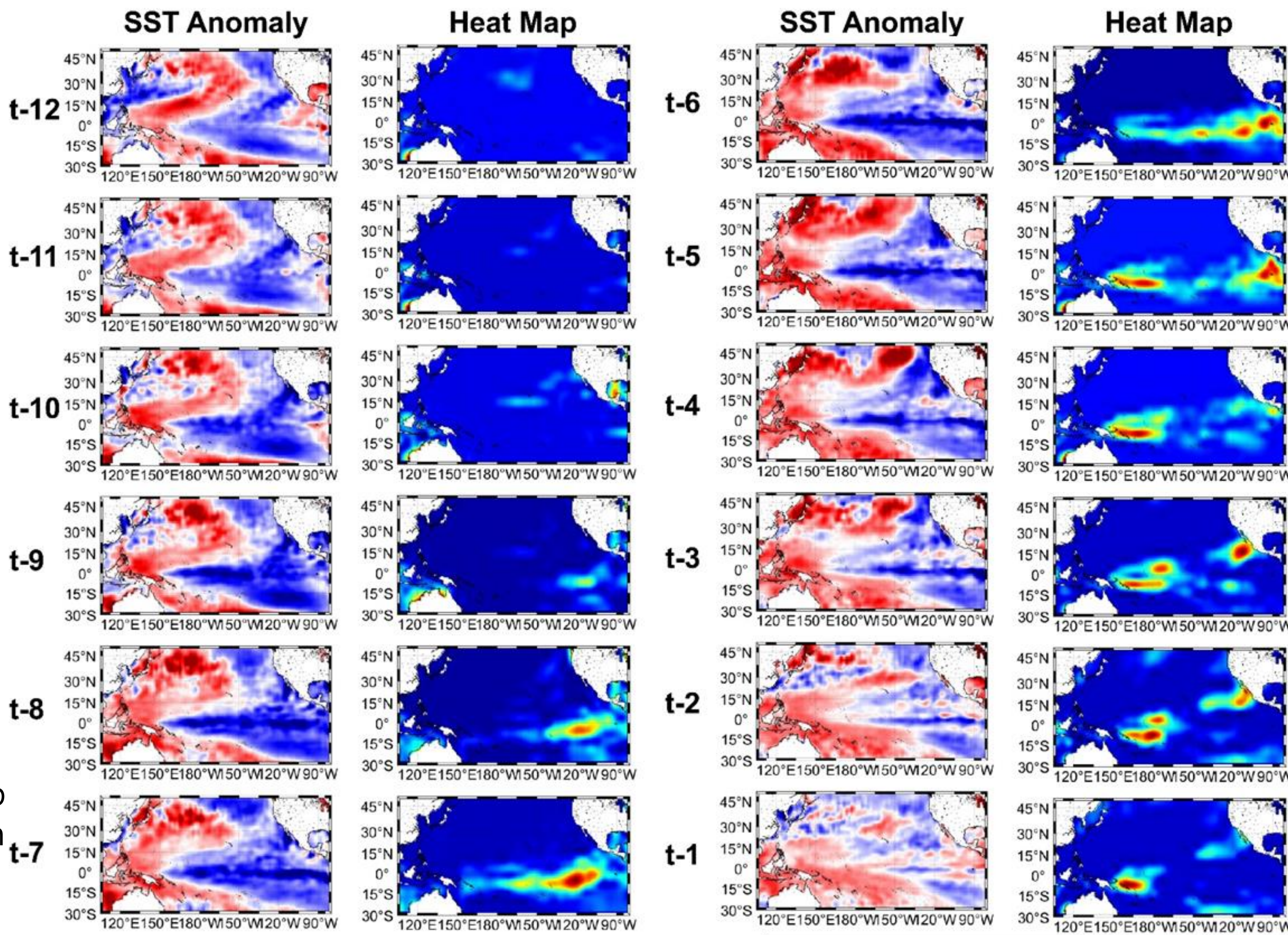


인공지능을 활용한 기상/기후 예측

SST 원격상관을 이용한 동아시아 가뭄 예측(2011년 5월 케이스)

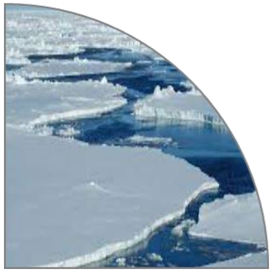






The SST anomaly (left) and Heat map (right) derived from the CNN model

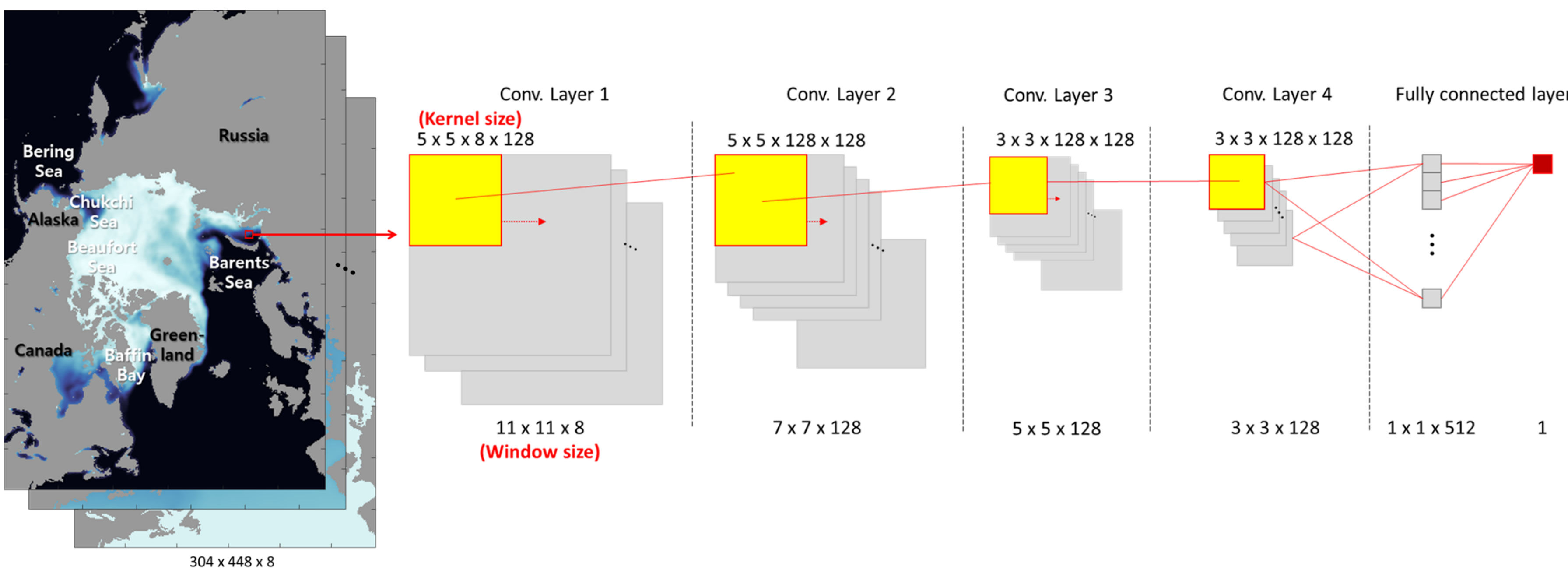
인공지능을 활용한 기상/기후 예측



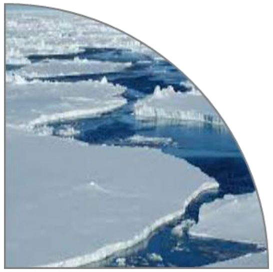
북극 해빙 농도 장기예측

- CNN 기법을 활용한 여름철 북극 해빙 3, 6, 9개월 예측 모델 개발

	variables
과거 해빙농도 (4)	• 현재 해빙 농도 • 1년 전 해빙 농도 • 과거 해빙 농도 변화 패턴 (5, 10년)
과거 해빙농도 이상치 (4)	• 현재 해빙농도 이상치 • 1년 전 해빙농도 이상치 • 과거 해빙농도 이상치 변화 패턴 (5, 10년)

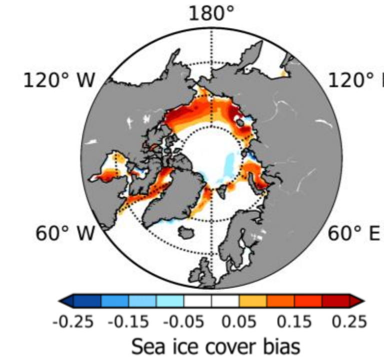


인공지능을 활용한 기상/기후 예측



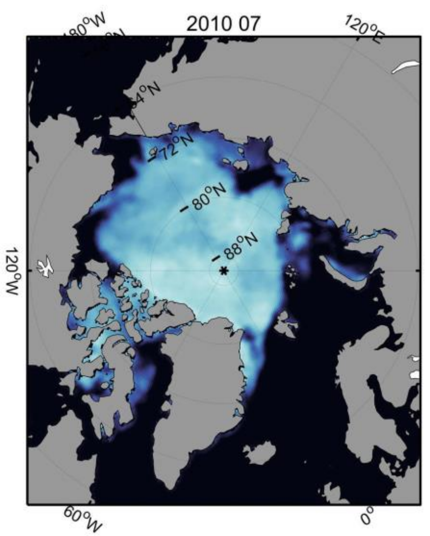
북극 해빙 농도 장기예측

- CNN 기법 활용한 7월 북극 해빙 장기 예측 결과 (25km, 2010-2019)
- 3 ~ 9개월 예측 모델 모두 10% 이하의 RMSE
- ECMWF SEAS5 예측 모델 기준, 6-8월 1개월 해빙 농도 예측결과, 10% 이상의 예측 오차를 보임

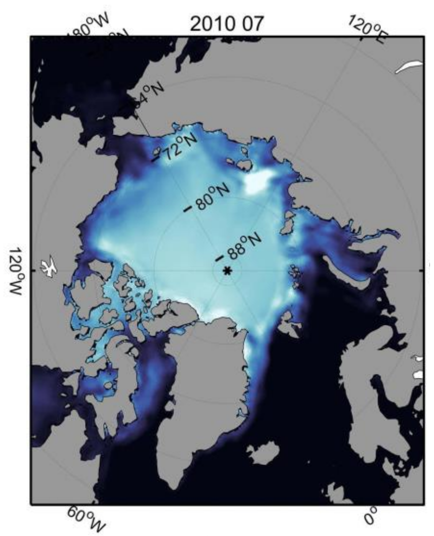


ECMWF SEAS5 1개월 예측 오차 (Johnson et al., 2019)

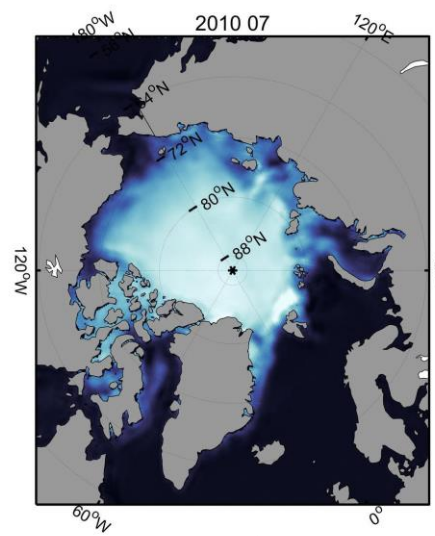
7월 해빙 농도
(2010-2019)



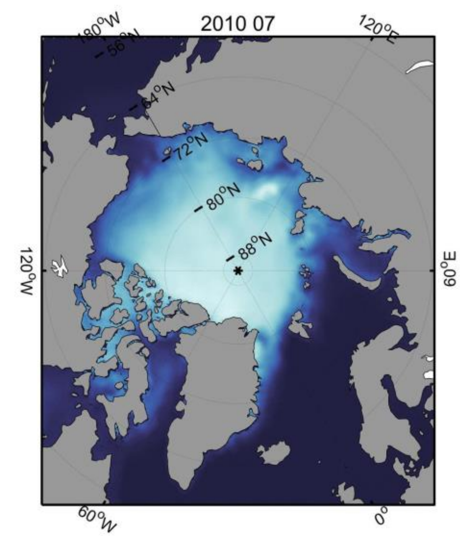
3개월 예측 결과
(RMSE = 7.08%)

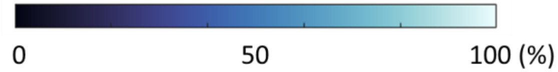


6개월 예측 결과
(RMSE = 7.87%)

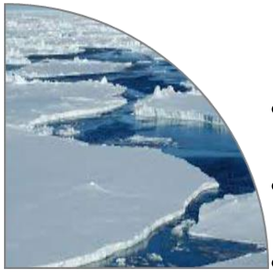


9개월 예측 결과
(RMSE = 8.06%)





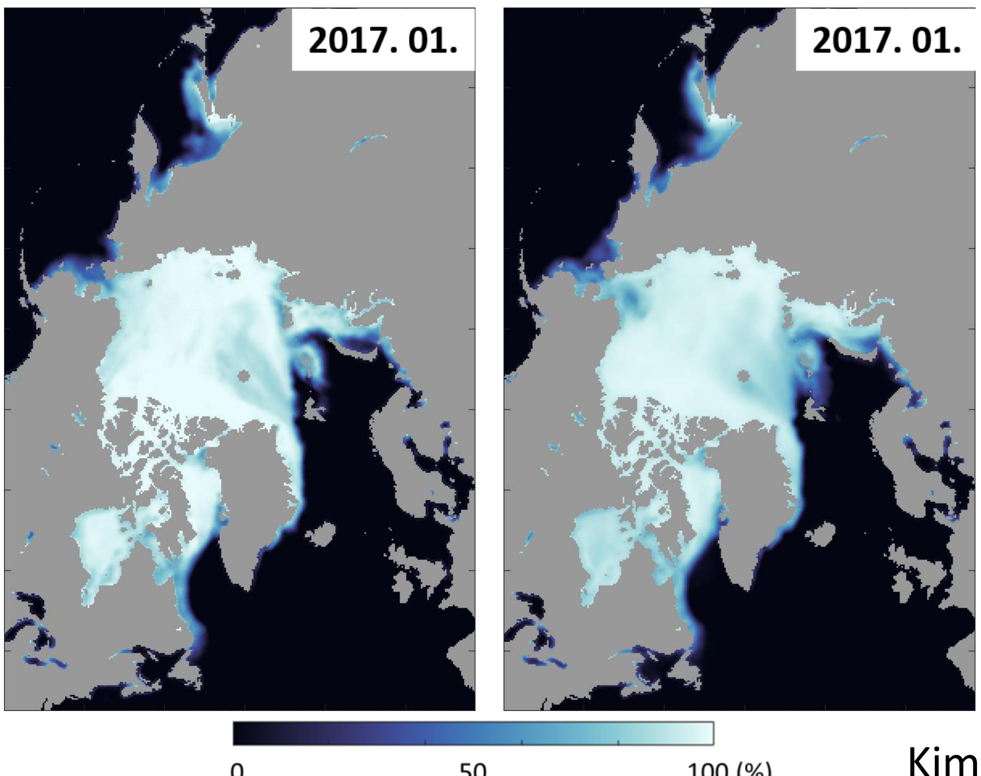
인공지능을 활용한 기상/기후 예측



북극 해빙 농도 단기 예측

- CNN 기법 활용한 북극 해빙 1개월 단기 예측
- 현재 및 과거 해빙 특성, 해양 및 대기 변수 활용 예측 모델 개발
- 전체 예측 기간에 대하여 5.76%의 RMSE를 보였으며, **과거 해빙 농도 특성**이 가장 중요한 예측 변수로 나타났으며, 뒤이어 **해수면 온도**가 중요한 것으로 나타남

2017년 월별 해빙 | **1개월 예측 결과**



상대적 변수 중요도

변수	1년 전 SIC	SIC	1년 전 SIC anomaly	SIC anomaly
변수 중요도	**1.134**	1.029	**1.095**	1.012
변수	해수면 온도	대기 온도	알베도	풍속 (v-wind)
변수 중요도	**1.035**	1.005	1.006	1.008

Kim et al. 2020. The Cryosphere.

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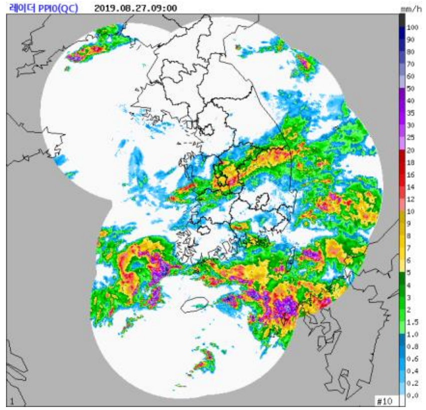
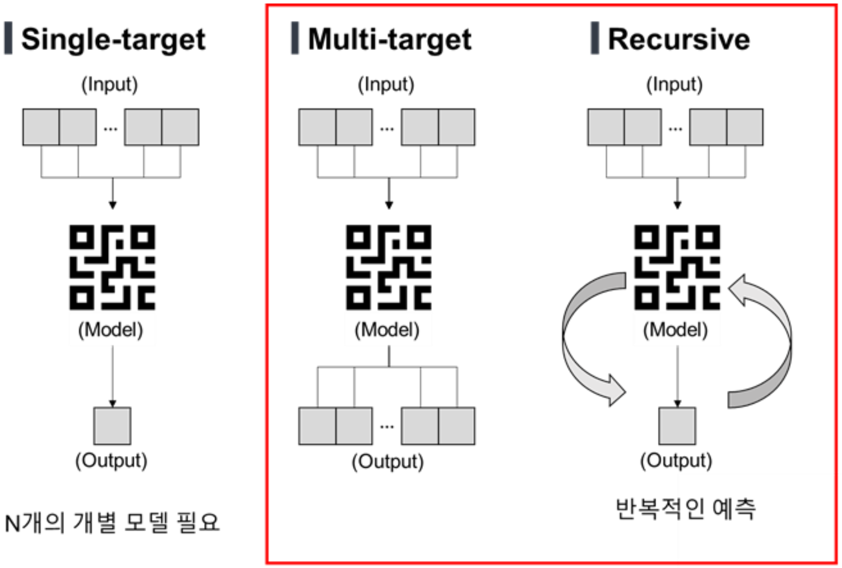
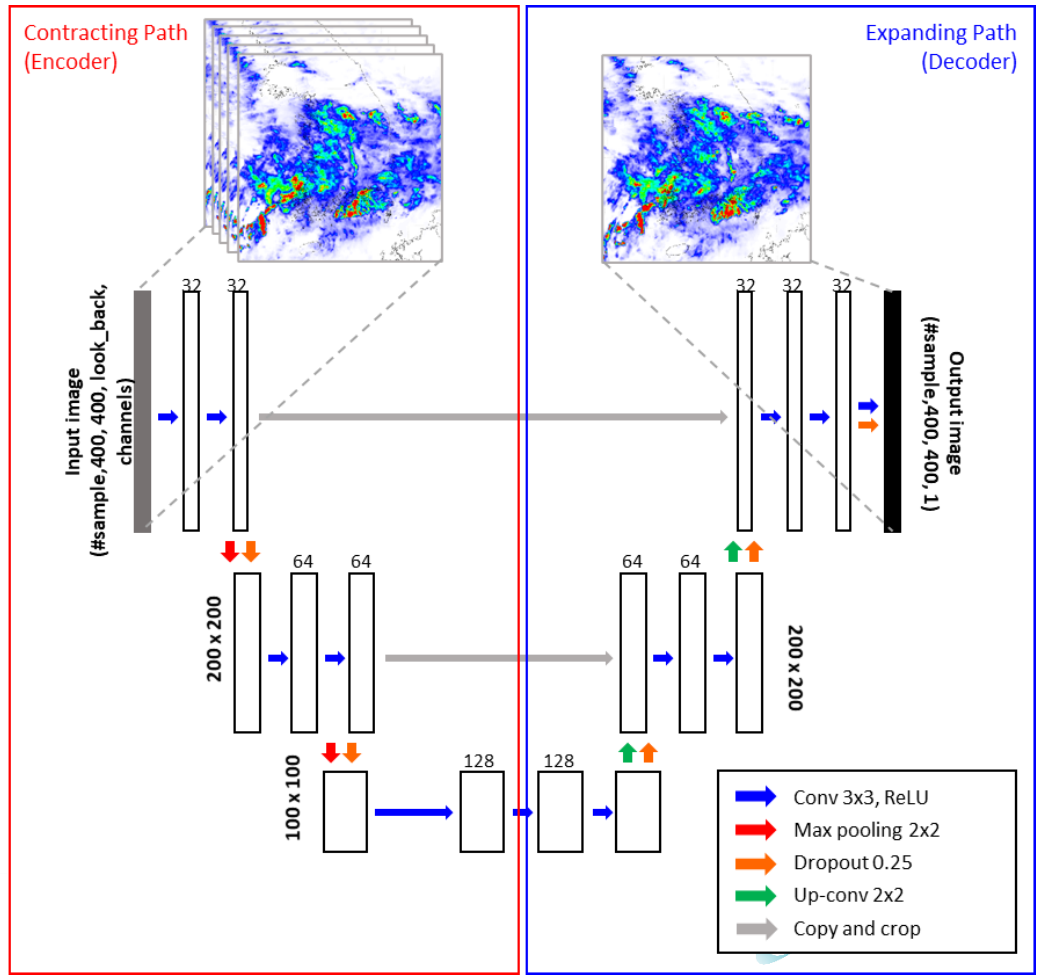
인공지능을 활용한 기상/기후 예측

초단기 강수 예측

- 실시간으로 레이더 강수 패턴을 딥러닝 모델 (CNN)에 학습하여 초단기 (0-1시간) 강수 예측을 수행함

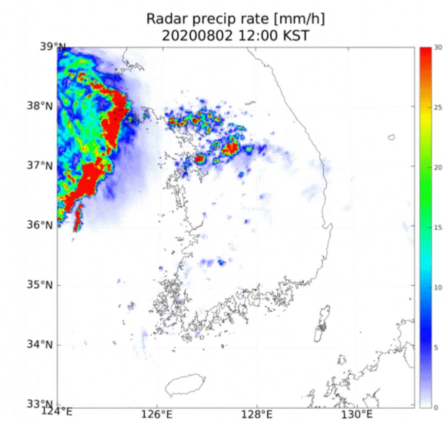




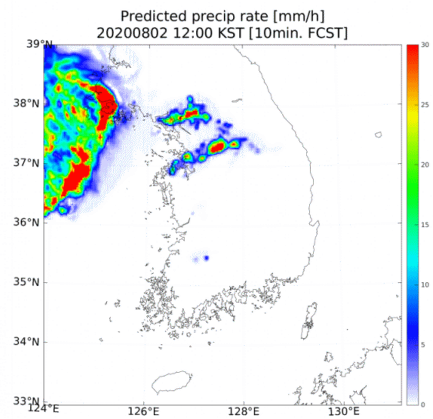


인공지능을 활용한 기상/기후 예측

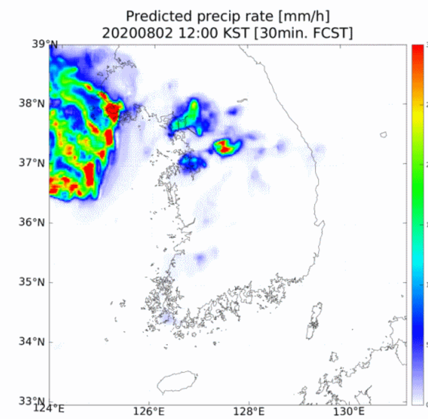
초단기 강수 예측 - 예측 시간에 따른 결과



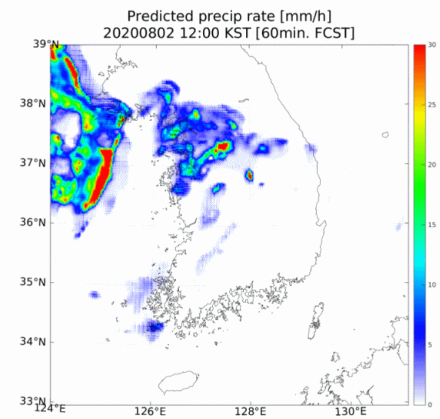
Multi-target



Fc+10min

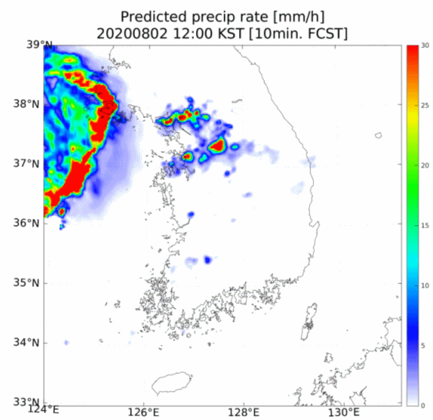


Fc+30min

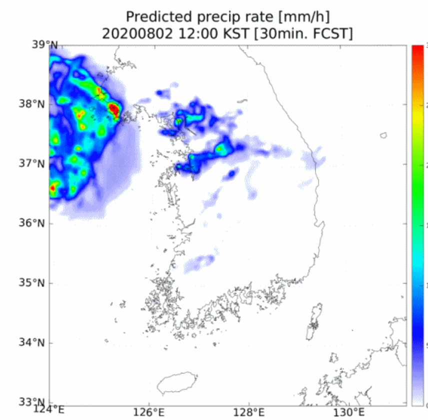


Fc+60min

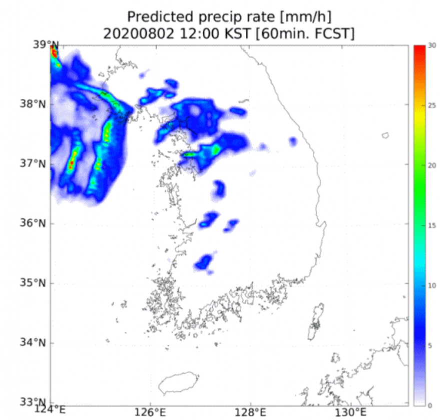
Recursive



Fc+10min



Fc+30min

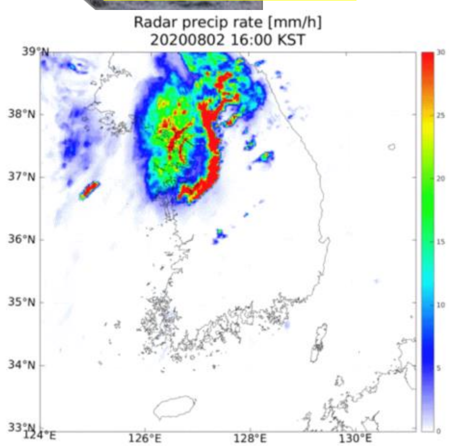


Fc+60min

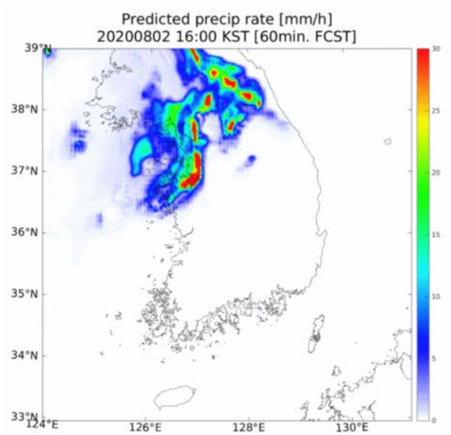
인공지능을 활용한 기상/기후 예측

초단기 강수 예측 - LDAPS 수치모델과의 비교

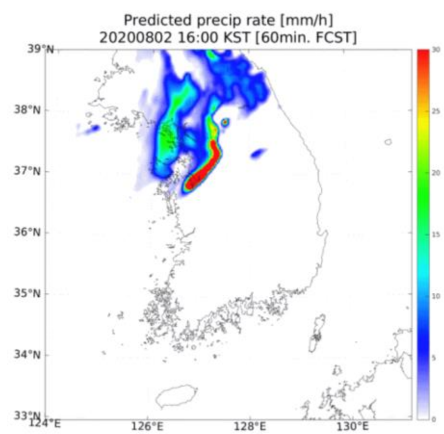
레이더 16:00



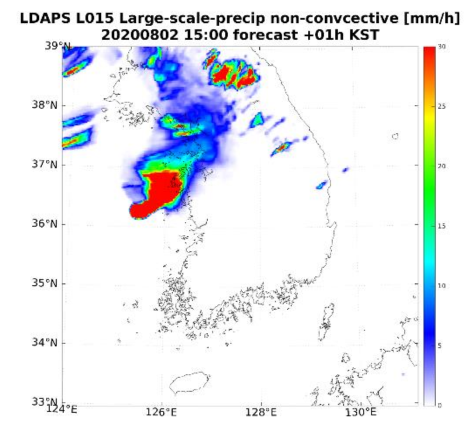
Mutli-target +01hr



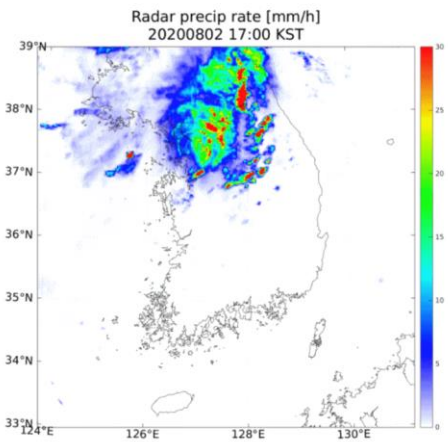
Recursive +01hr



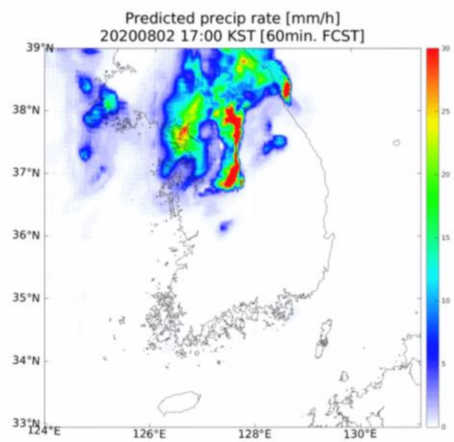
LDAPS +01hr



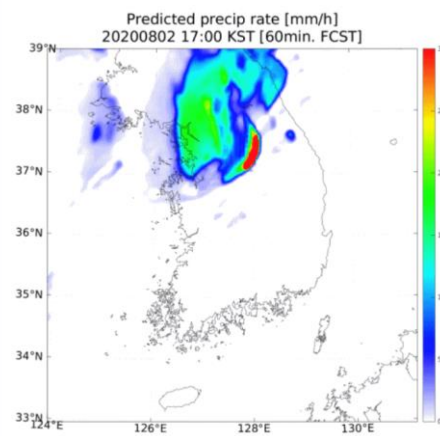
레이더 17:00



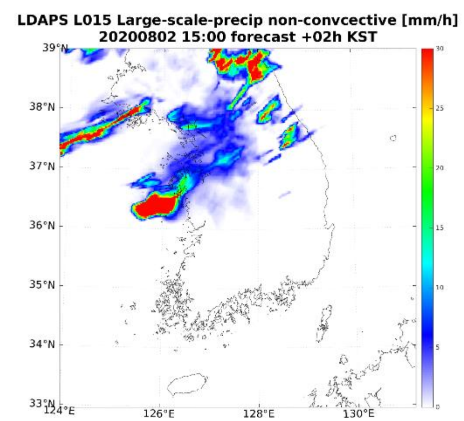
Mutli-target +01hr



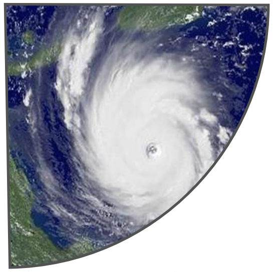
Recursive +01hr



LDAPS +02hr

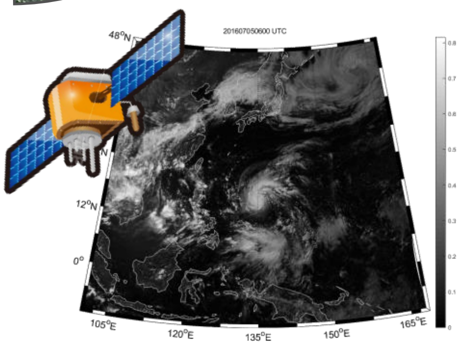


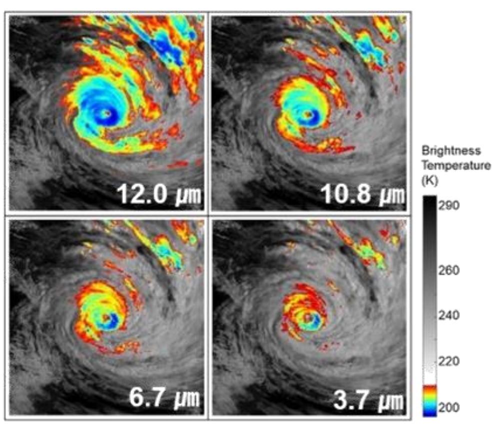
인공지능을 활용한 기상/기후 예측



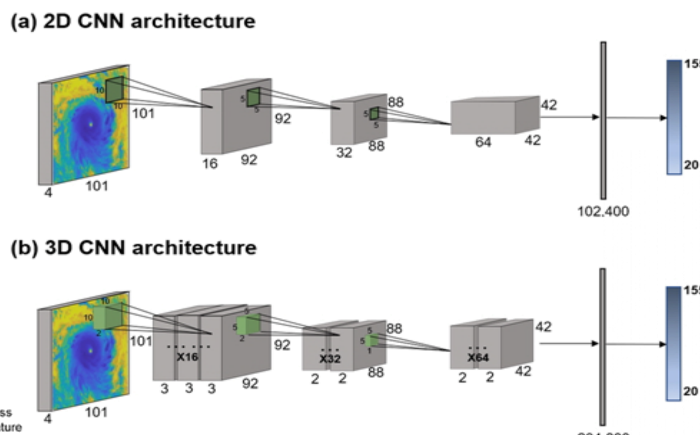
딥러닝 기반 태풍 강도 추정

- 정지궤도 기상위성기반 태풍 관측자료의 적외채널별 패턴을 딥러닝 (2D-/3D-CNNs)을 통해 분석하여 해당 태풍의 강도를 객관적으로 추출함



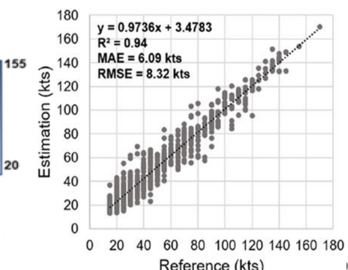


Multi spectral channels-based TC observations using geostationary satellite

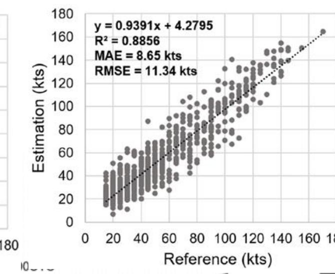


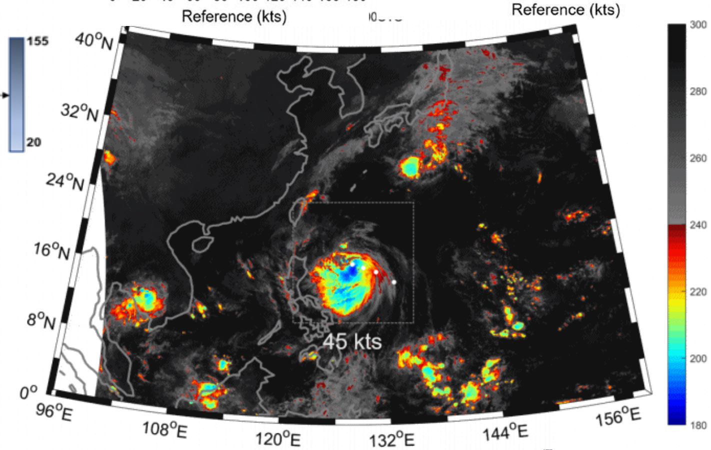
Training 2D/3D-CNNs using collected TC references

2D-CNNs based estimation results 8.32 kts RMSE



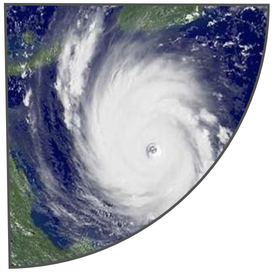
3D-CNNs based estimation results 11.34 kts RMSE





Geostationary satellite-based TC intensity estimation every 10 min

인공지능을 활용한 기상/기후 예측



딥러닝 기반 태풍 강도 추정

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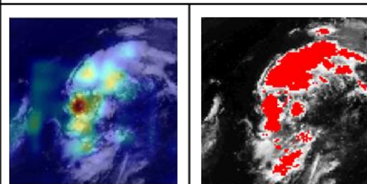
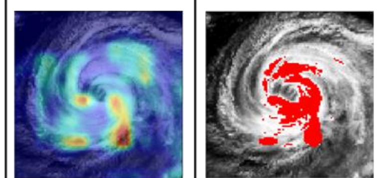
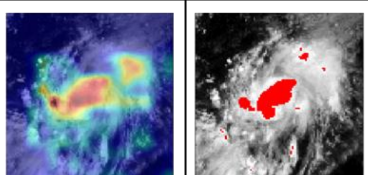
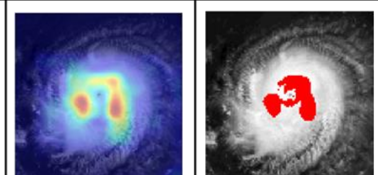
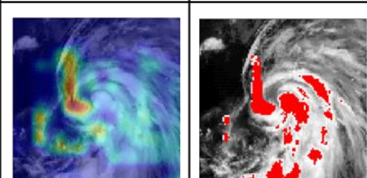
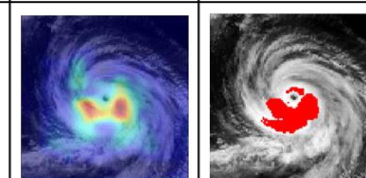
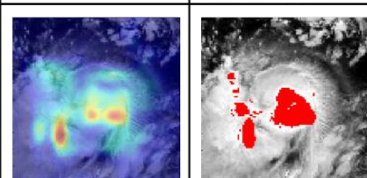
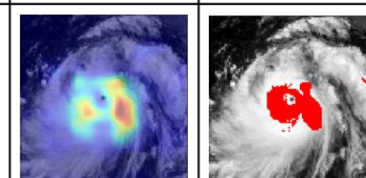
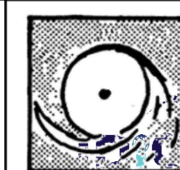
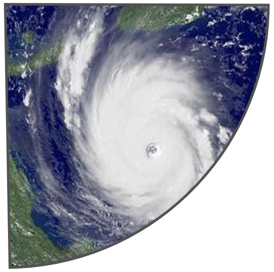
태풍 강도	딥러닝 모델 기반 태풍의 형태 분석	예보관 학습 자료	태풍 강도	딥러닝 모델 기반 태풍의 형태 분석	예보관 학습 자료
20 (Weak Topical depression)			**90** (Category 2)		
30 (Tropical depression)			**105** (Category 3)		
35 (Tropical Storm)			**115** (Category 4)		
65 (Category 1)			**145** (Category 5)		



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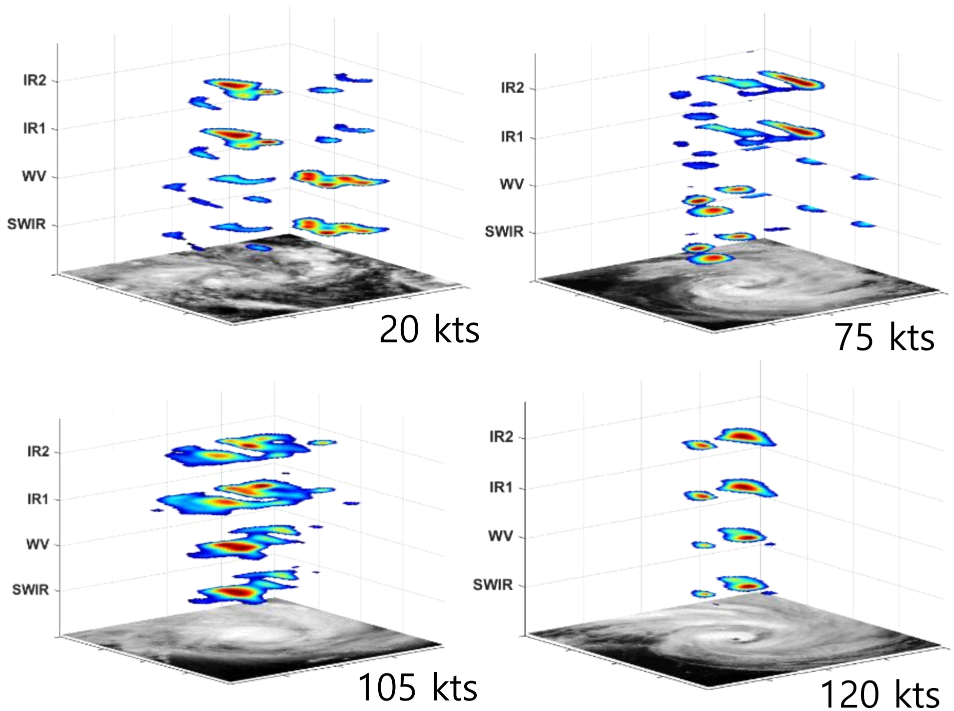
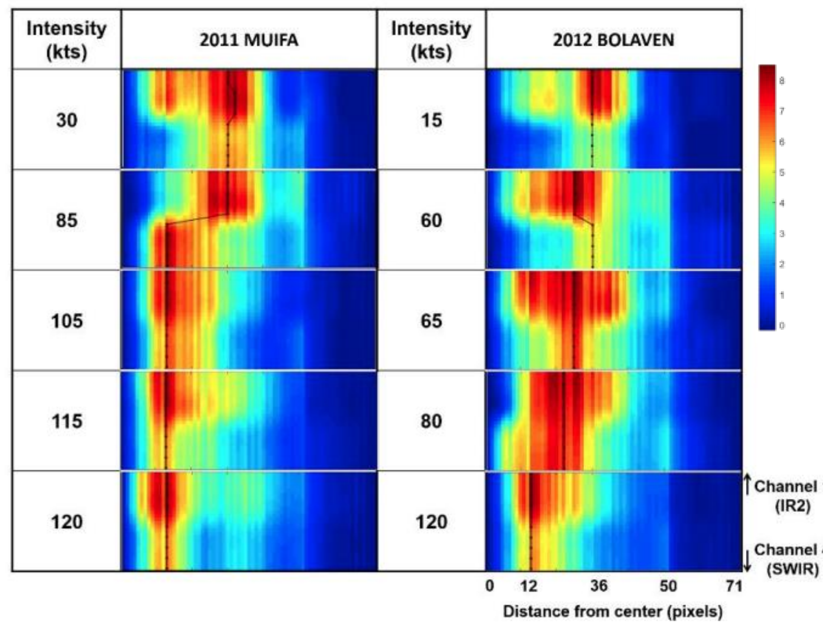
태풍 강도 별
다중 적외 채널 간 Heat map 분포의 차이



2011 MUIFA, 2012 BOLAVEN 의
강도 별 태풍의 Heat map 분포 분석



인공지능의 한계와 도전 방향

❖ AI is not a panacea

❖ Require multidisciplinary approaches

❖ Knowledge engineers for AI vs. domain experts

❖ Limitations of AI

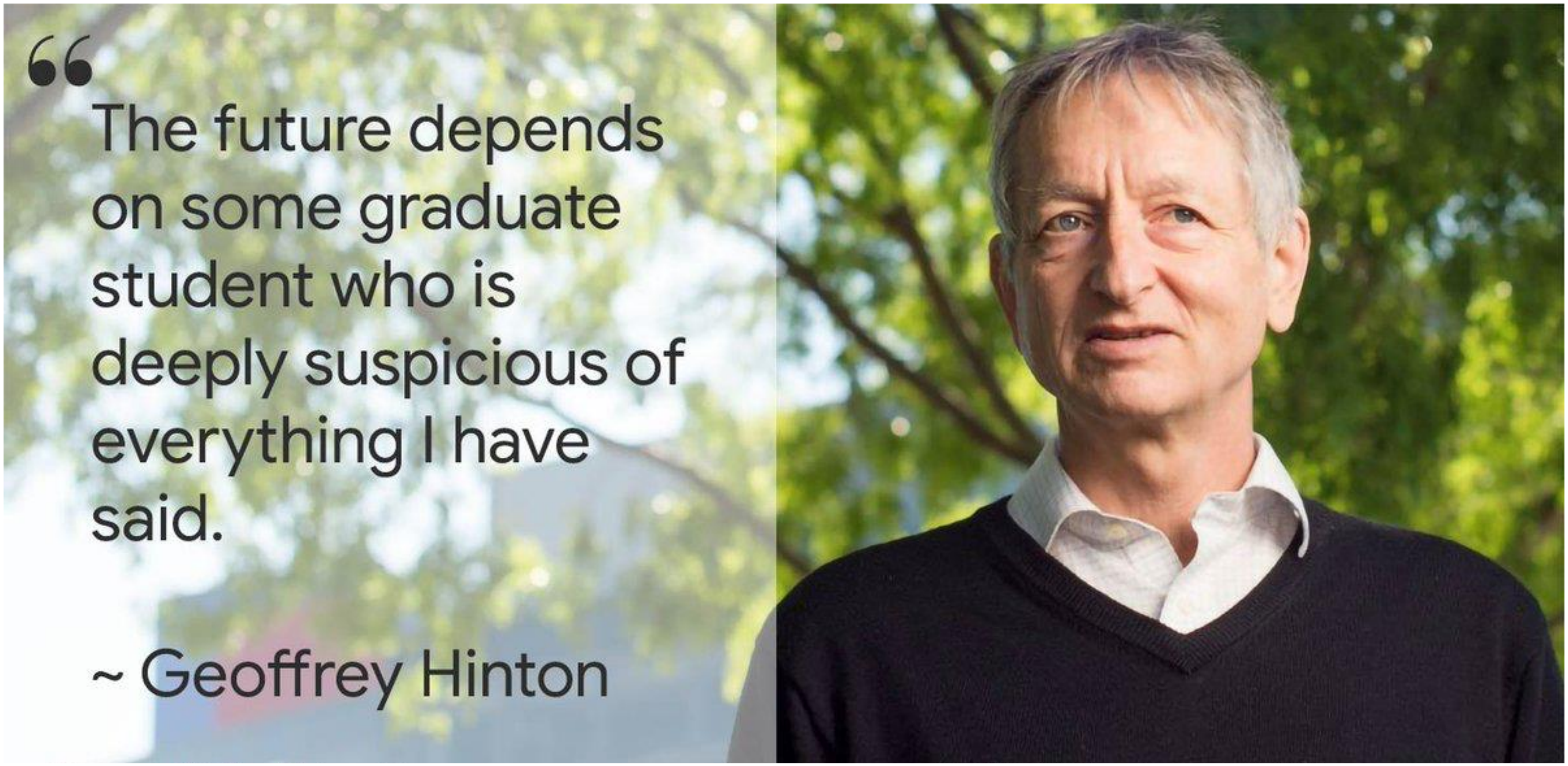
- Require too much data → no more training data
- Causation vs. correlation → ExAI (Explainable AI)
- Limited capacity of transfer; not transparent
- Not good at modeling unstable situations
- Locality → Generalization (Expandability)

❖ Based on my experience,

- Good at modeling relatively static environment such as land cover classification
- Has high uncertainty for modeling dynamic parameters especially when input variables are not well identified in relation with the target variable.
- Representation is a key to successful AI applications.

인공지능의 한계와 도전 방향

- “Science progresses one funeral at a time.”



Thank you

Questions?
ersgis@unist.ac.kr