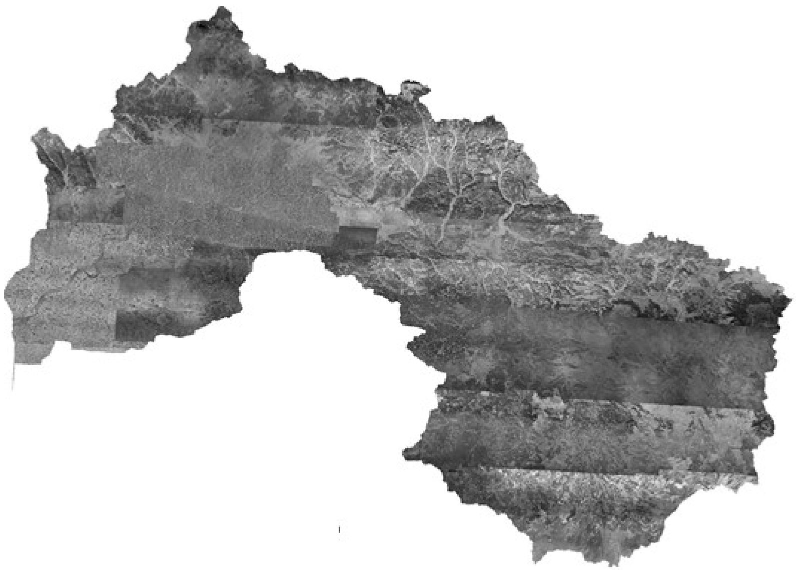
# Comparison of deep learning methods for colorizing historical aerial imagery



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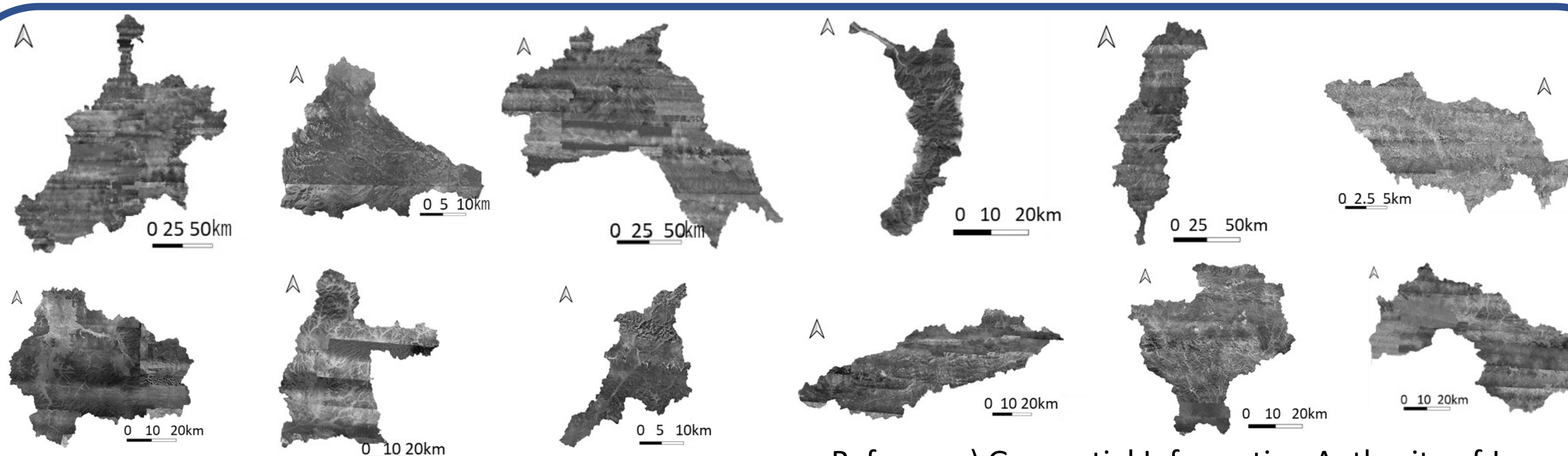
# 1.The research background and purpose

**Ortho images made from historical air photos in the middle of the 20th century**




Reference) Geospatial Information Authority of Japan

They have high potential to analyze the long-term surface evolution

Difficult to extract information from monochrome images

Needed to develop the technology of colorizing monochrome images

Trying colorizing algorithm with Neural Style Transfer(NST)

Not enough quality in the images with low feature values

**Purpose**

Trying colorizing algorithm with Cycle Generative Adversarial Network(CycleGAN) and compared to NST

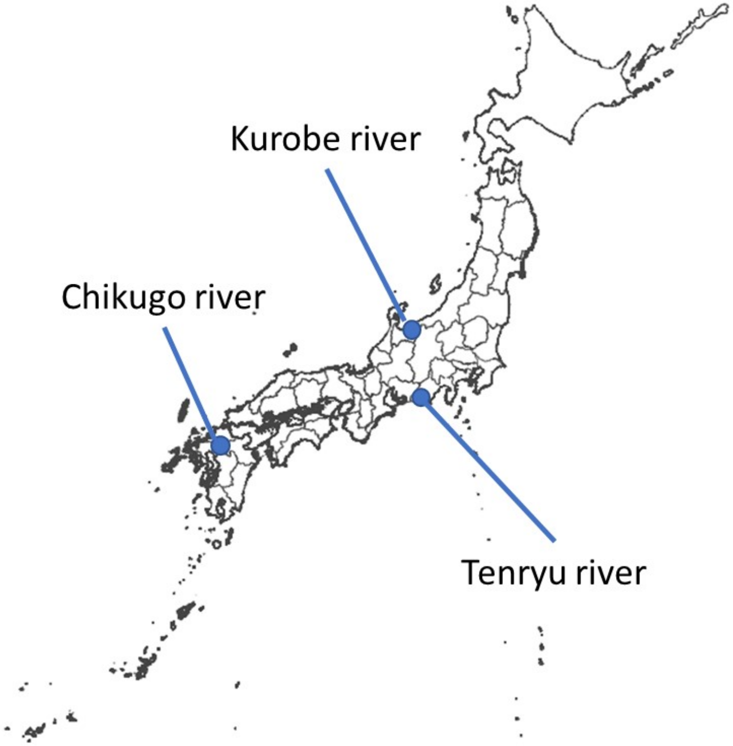
# 2.The target

The images we tried to colorize with Deep Learning

Kurobe 1)

Tenryu 2)

Chikugo 3)




Reference 1) 2) 3) Geospatial Information Authority of Japan

# 3.How to colorize monochrome images with NST

## Transfer Learning of NST:

1. Create Image Tiles:

   Extract 63,460 image tiles (100x100pixcels) in the 6 classes from river basin color images

Urban River Forest Tree Grass Paddy Field

2. Transfer Leaning of the CNN used in NST using the image tiles

   Fine-tune the CNN parameters in NST to derive the optimal model for colorization.

3. Analyze the best hyperparameters in NST with decolorized images

Hyper parameter range

| | |
|---|---|
| Contents layer | **6,7,8,9,10,11,12,13** |
| Weight Coefficients in Style layer | $0.2 \times 10^3$ $0.2 \times 10^4$ $0.2 \times 10^5$ |

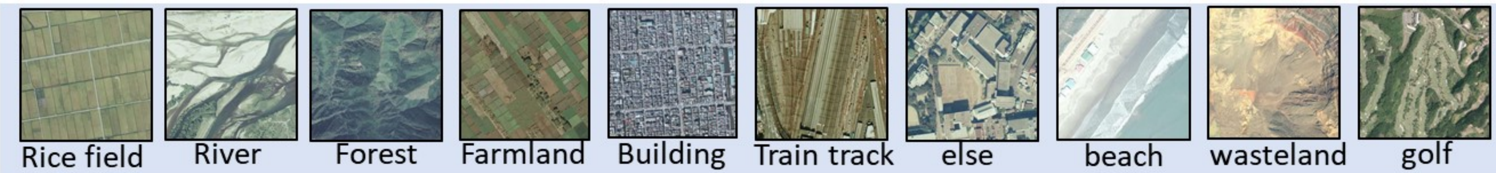
Ref.) Ishii R., Carbonneau P., and Miyamoto H.: Colorisation of archival aerial imagery using deep learning, EGU21-11925, vEGU General Assembly 2021, EGU, Online, 2021.

# 4.How to colorize monochrome images with CycleGAN

## Determining the hyper parameters

1.Training by (RGB 4000 images ・ monochrome 4000 images)

2.Recolorizing following RGB images that is decolored, one for each land use




Reference) Geospatial Information Authority of Japan

3.The one with the smallest RMSE⇒The optimal model

RGB image − Recolored image

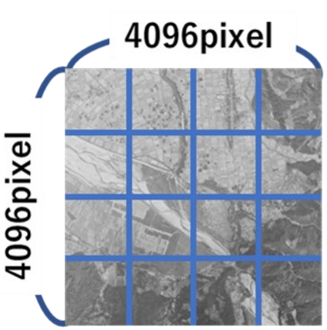
loss function coefficient

| | |
|---|---|
| Cycle consistency loss | λc |
| Identity loss | λc × λi |

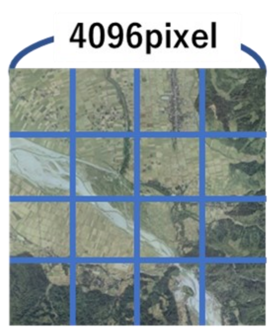
Hyperparameter Range

| | |
|---|---|
| Dropout ratios in each layers of discriminator | 0 0.2 0.3 0.4 0.5 0.6 0.7 0.8 |
| $\lambda$ c | 5 8 9 10 11 12 15 |
| $\lambda$ i | 0 0.2 0.3 0.4 0.5 0.6 0.7 0.8 |

Applying to the target




Target monochrome



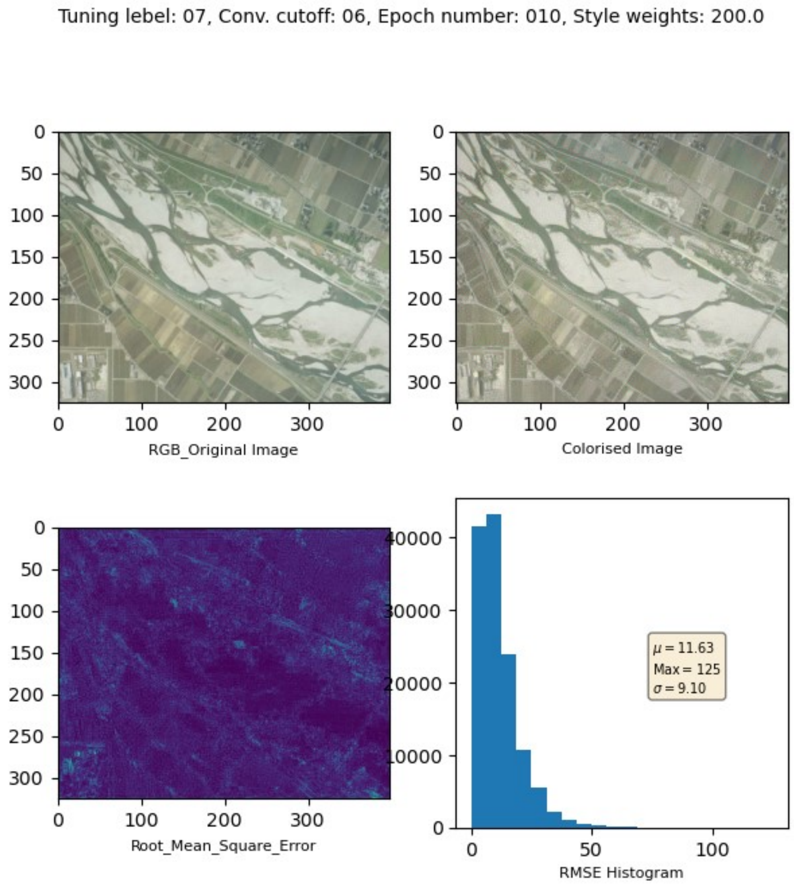

Reference RGB

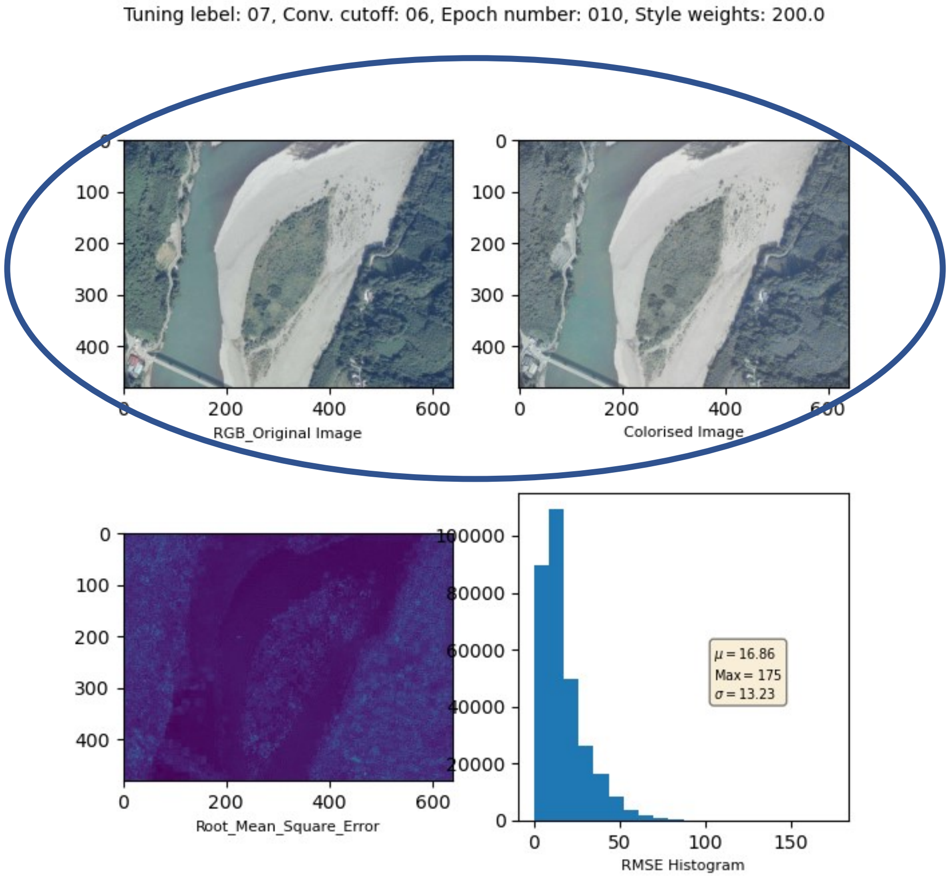
Dividing into 1024 × 1024pixels
&
Data enhancement

The numbers of training images

| | Monochrome | RGB |
|---|---|---|
| Kurobe river | 320 | 320 |
| Tenryu river | 128 | 128 |
| Chikugo river | 304 | 304 |

# 5.Result determination of the optimal hyper parameters of NST

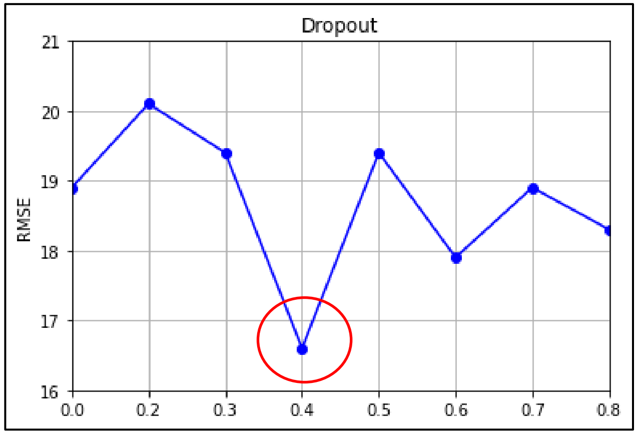


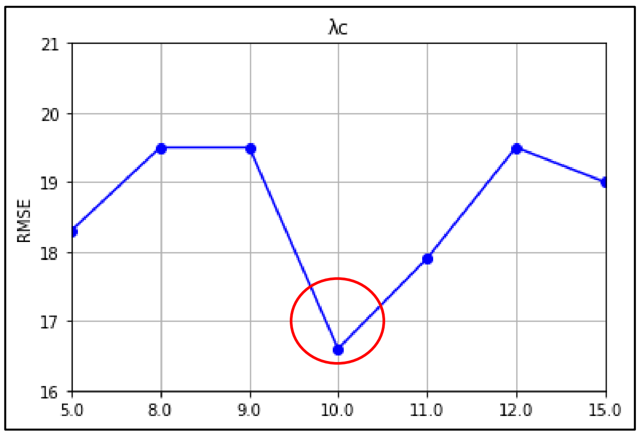



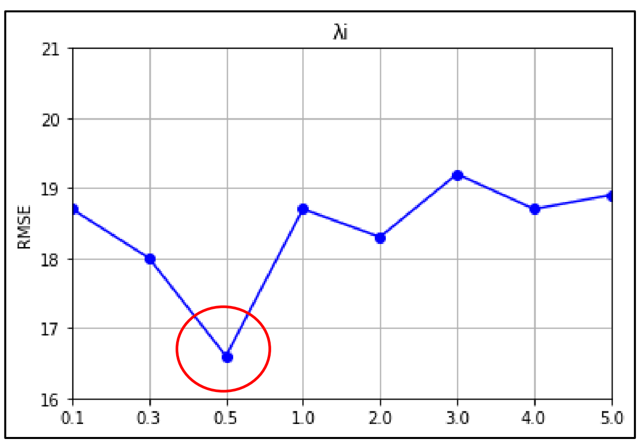

The best hyper parameter

| | |
|---|---|
| Contents layer | 6 |
| Weight Coefficients in Style layer | 10 |

# 6.Result determination of the optimal hyperparameters of CycleGAN




**Colorization in the optimal model of 10 tiles**

decoloring&recoloring

The best hyperparameter

| | |
|---|---|
| Dropout ratios | 0.4 |
| λc Cycle consistency loss coefficient | 10 |
| λi × λc Identity loss Coefficient | 0.5 × λc |

RMSE in 10 tiles :18.33

# 7.Result　comparison of NST and CycleGAN using RMSE

RGB image－Recolored image

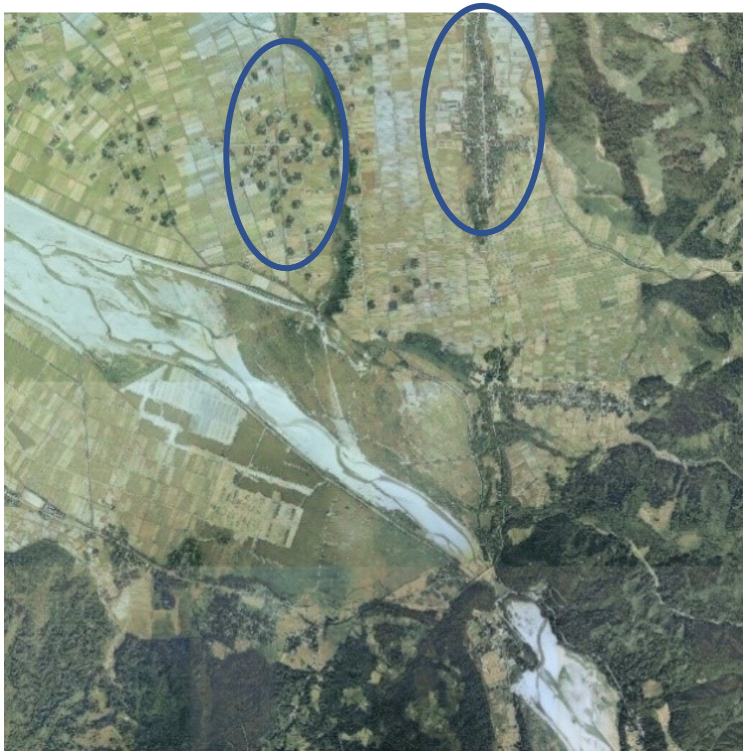
RMSE between the reference image and the recolored image

| | CycleGAN | NST |
|---|---|---|
| **Kurobe** | 15.4 | 13.7 |
| **Tenryu** | 13.7 | 9.87 |
| **Chikugo** | 18.7 | 18.8 |

# 8.Result comparison between CycleGAN and NST in Kurobe

colorizing

**Neural Style Transfer**



**Cycle GAN**

# 9.Result comparison between CycleGAN and NST in Kurobe

colorizing

**Neural Style Transfer**

**Cycle GAN**

# 10.Conclusions

## Conclusion

✓CycleGAN and NST have the same colorization accuracy in RMSE.

✓CycleGAN could improve colorized accuracy in low-feature locations.

## For the future

Application of  colorized images to land use classification